Towards an equitable solar energy transition

On reaching the solar climate goals in Amsterdam: a socioeconomic perspective on solar energy adoption using a data-driven modeling technique

Master thesis

Engineering and Policy Analysis

Faculty of Technology, Policy and Management

by

Daphne van Meggelen

Student number: 4589890

Defense: May 11th, 2023

Graduation Committee

Chairperson: Prof.dr.ir. Z. Lukszo, Engineering Systems and Services
First Supervisor: Dr.ir. R.I.J. Dobbe, Engineering Systems and Services
Second Supervisor: Dr. N.Y. Aydin, Multi-Actor Systems
External Supervisor: Christiaan Beels, EY

Executive summary

To combat the effects of climate change, there is a worldwide shift to reduced emissions and increased use of renewable energy sources. Solar energy is a vital part of this transition and necessary to be able to achieve the targets. Solar energy, including household and community-based solar photovoltaic panels, is the fastest growing source of low-carbon electricity worldwide. The rapid pace of adaptation raises questions about the negative equity and justice associated with this development. Along with the rapid growth, regional differences in solar panel adoption have been found across the world. In literature, therefore, solar panel adoption inequity has been increasingly identified as an emerging energy justice issue. Literature presents multiple socioeconomic inequities that could possibly enforce energy injustice in the context of rooftop PV installations.

Society would benefit from higher carbon reduction due to increased solar adoption. A fair distribution of solar adoption ensures widespread deployment of solar energy technology and equal spread of the benefits of current policy levers. Little is known about the geographic and socioeconomic disparity of solar panel adoption in the Netherlands, or how adoption might evolve within its volatile (geo)political context. More insights into the possible regional differences, how these are caused, and how these could evolve would benefit the equitable transition to increased renewable energy generation.

This study aims to fill these research gaps. Through filling these gaps, the study aims to answer the following main research question:

How could distributed solar panel adoption speed and disparity develop in the future and under different policy measures?

One of the research objectives is to construct an integrated, structured approach to assess the above research question. Within literature, such a cohesive approach is lacking. This thesis, therefore, aims to adopt an integrated, data-driven approach that provides a set of tools that can aid in a more structural assessment of adoption and adoption disparity, and gauging scenarios for policy-making purposes.

To answer the main research question, a Design Science Research approach is adopted. The study started with an introduction to energy justice in relation to solar panel adoption and a thorough analysis of the system at hand as part of the environment phase. In the latter, the current technological, political, social, and economic context for PV adoption in the Netherlands was examined, which resulted in a thorough understanding of the problem context as input for the design cycle. Next, in the knowledge base phase, the factors determining residential PV adoption behavior were set out. During the operationalization, the outputs of the relevance and rigor cycle are conceptualized into an artifact design. The designed artifact is a research approach enabling an integrated analysis of the solar panel adoption landscape in a municipality, with two main purposes. First, it enables to the assessment of the equity of solar panel distribution amongst the municipality. Second, it aids in policy testing, scenario evaluation, and policy-making on the solar panel system within the municipality. In this research, the artifact has been developed while simultaneously testing and demonstrating it for the municipality of Amsterdam.

Part I of the artifact includes two steps. First, it entails conducting a rooftop suitability assessment that maps the potential for residential solar energy generation by adopting a GIS-based approach. Next, a socioeconomic analysis is performed, which allows investigation of the correlation of socioeconomic factors with PV adoption and the disparity of adoption possibly leading towards a so-called "adoption gap". This statistical data analysis deploys ANOVA- and correlation analysis on empirical adoption data. The most significant socioeconomic determinants for adoption are then used in a clustering method to create groups of similar neighborhoods, which can be studied in part II of the artifact. Performing part I of the artifact results in a clear assessment of the adoption disparity, the used and the unused potential, and the factors that can aid in explaining this.

Part II of the artifact deploys a system dynamics modeling approach to simulate the adoption of solar panels from a system perspective. The context of residential PV adoption was further conceptualized from a system perspective with a causal loop diagram, and then quantified through mathematical equations and parameters. During the conceptualization and model formulation, the output of Part I of the artifact, such as the adoption rates and the neighborhood groups, is used. After testing the model, scenarios and policies analysis leads to understand the system behavior and explore the impact of policy measures on diffusion speed and diffusion disparity. This way, the model provides understanding of the structural dynamics and behavior of solar panel diffusion amongst different groups of neighborhoods and the possibility to experiment with policy levers and external developments.

Demonstrating the artifact on the municipality of Amsterdam generated several results. Part I of the artifact showed that PV adoption is unevenly spread amongst neighborhoods. Several neighborhood-clusters with high adoption rates are detected. Thus, a high disparity in adoption - an adoption gap - is observed. Contrary, rooftop suitability is spread relatively equal amongst neighborhoods. The correlations and group-differences examined in this study highlight areas where more attention may be needed and where barriers for solar adoption might exist. The results also show that there is a significant difference between PV adopters and non-adopters. The type of household property, income, type of ownership and the household composition are observed to be the most significant socioeconomic factors when comparing the results of the two statistical studies. These factors are identified as possibly the most significant adoption barriers. The inequities in adoption perceived in the neighborhood analysis points the way towards specific, targeted policy mechanisms that can tackle, mitigate, or minimize possible injustices caused by adoption disparity.

In Part II of the artifact, experiments are conducted with the system dynamics model using different configurations of netting-scheme policies, external developments, adoption rates, and leveling policies. The experiments yielded several results. First, the perceived adoption gap is expected to further widen in the future. Under the proposed netting scheme, group 2 neighborhoods achieve a marginal adoption rate of approximately 5%, and group 2 neighborhoods of approximately 25%. Under the proposed netting scheme, and without adequate policy interventions, average future PV diffusion will continue to grow only moderately. Solar panel diffusion appears to be highly impacted by the netting scheme policy in place. The difference is caused by the diverging payback times of PV under the policy options. When looking at the leveling policies, the "low-income netting scheme" and the "low-income subsidy of €1000" policies had the most promising individual results. Given that the individual policies alone do not succeed in closing the adoption gap, it is likely that a tailor-made combination of policies is most effective. A combination of a €1000 low-income subsidy, a low-income netting scheme, and a sustainability plan mandate can level the adoption percentage of group 1 to the adoption levels in group 2, reaching approximately 35% of the total number of households, which limits the adoption gap to a minimum.

Several main conclusions can be drawn from the study. First, a gap in adoption is observed. There is a significant difference between neighborhoods with high and low adoption when it comes to socioeconomic characteristics. Currently, policy levers to stimulate PV adoption benefit a small portion of households. The current netting scheme is beneficial to adoption rates but increases adoption rates mostly within several societal groups. This creates distributive justice implications: the benefits and burdens of energy policy are not equally distributed amongst citizens. The proposed netting scheme, planned to phase in 2025, will only modestly increase adoption rates compared to a lacking netting-scheme policy. Besides, without target policy interventions, the adoption gap between high and low-adoption neighborhoods will widen over time. The adoption disparity and possible justice implications emphasize the need for more targeted policy measures to minimize injustices. The leveling policies have shown to reduce the adoption gap, where a combination of policies achieves the best results. The results emphasize that more policy attention is necessary, especially when the proposed netting scheme comes into place. Targeted policies are needed to close that gap, where there is a need for a combination of all three leveling policies to narrow down the gap to a minimum.

Although the artifact is suitable for obtaining insights into the solar panel adoption disparity and diffusion dynamics, interpreting the outcomes requires a note of caution. It must be said that the system dynamics model is an abstraction of the real-world solar panel adoption context, where real-world complexity and uncertainty are present which can never be captured comprehensively in a model. Further research could provide improvements to the model by testing the model on a new local case-study area, which allows to compare results and draw more conclusions on the generalizability of the tool. Besides, the artifact has served as a suitable approach to answering the main research question in this study, but requires further validation to assess the scalability and validity of the approach. Further examining and addressing the limitations and uncertainties could improve the artifact's robustness. Furthermore, it would be interesting to include other neighborhood groups in the analysis, that are grouped based on different socioeconomic factors. Finally, the impact of renewable energy adoption on utilities could be further explored, to improve insights into the socialization of costs to consumers in the context of distributive justice.

Preface

The master thesis in front of you tries to create a clear picture of the now and the future of solar panel adoption disparity. It does so by examining real data from the municipality of Amsterdam and deploying a simulation model evaluating multiple policies. I hope that the thesis can serve as a starting point for putting adoption equity higher up on the agenda of policymakers. Addressing citizen equity is an important societal topic, and can be used to benefit the transition towards more renewable energy generation.

Defining the thesis topic and shaping the research started as a challenge. I wanted to both cover a societal topic that I feel passionate about and use research methods to my interest. When I first started my topic brainstorming, a long list of possible topics have been considered and I did not expect to end up with the research I present to you now. But I am very content and happy with the result. The process has been challenging at times, but extremely educational and valuable. I hope to both contribute to increased attention towards a topic with high societal relevance and to inspire on trusting the research process and not be afraid to come up with new ideas and methods to reach your study objective.

The realization of this thesis would not have been possible without my graduation committee. I would like to thank Zofia for being my Chair of the committee, providing me with insightful feedback, clear directions, and pleasant meetings, where there was always room for a laugh beside the serious topics we discussed. Nazli, thank you for your time, support, directions, and suggestions. And not to forget, your always spot on questions during our meetings. And of course, I would like to thank Roel for guiding me through this process and creating the time to meet every single week, even when the agenda was packed or you were on a work sabbatical in the U.S. the last weeks of my thesis. You were always available to support me with your much appreciated knowledge and feedback, or with a fun off-topic discussion. I really enjoyed this process together. Thank you for sharing your enthusiasm about the research topic, and I hope to work together on a great paper next!

To everyone within the Data & Analytics team at EY, thank you for this opportunity and the great time! I have felt extremely welcome in the team from the beginning. Your continuous interest in my progress and your motivational words are much appreciated. To Christiaan, thank you for being my supervisor on behalf of the team at EY.

Finally but not least, my friends and family have supported me through this journey a lot. I would like to thank my parents for their warmth and support. My brother, for his time and help sitting down behind my laptop with me to solve some issues I myself could not see working out at the time. I want to thank Thies, for his continuous patience, support, motivational words, and cooking-skills when I was sprinting for a deadline. And of course, my other friends and roommates who provided laughter and distracted me when needed.

All in all, these last couple of months have been a challenge at times, but a rewarding experience overall. I hope you will enjoy reading this thesis!

Daphne van Meggelen April 28, 2023

Abbreviations

ACM = Authority for Consumers and Markets
ANOVA = Analysis of Variance
AO = Invalidity benefit
BAG = "Basisregistratie Adressen en Gebouwen"
BSP = Balance service providers
BRP = Balance responsibility partners
CBS = Central Bureau of Statistics
CLD = Causal Loop Diagram
DPV = Distributed Photovoltaics
DSM = Digital Surface Model
DTM = Digital Terrain Model
GIS = Geographic Information Systems
GIS = Geographic Information Systems
LI = Low income
OA = Owners' Association (Dutch: vve, "vereniging van eigenaren")
PV = Photovoltaic
RES = Regional Energy Strategy
SD = System Dynamics
Wmo = Social Support Act
woz = Property value (Dutch: "waardering onroerende zaken")
WOM = Word of Mouth
WW = Unemployment law (Dutch: "Werkloosheidswet")

Contents

1 Introduction

1.1 Problem context

To combat the effects of climate change, there is a worldwide shift to reduced emissions and increased use of renewable energy sources. Energy is thus one of the central topics in the Agenda for Sustainable Development Goals (SDG) by the United Nations (United Nations, 2022). A fast-paced shift towards sustainable energy production and solutions is crucial to the achievement of the Paris Agreement. In this context, the Dutch national government aims to stimulate renewable energy production in order to create a sustainable energy system. The government aims to decrease the emission of greenhouse gasses in the Netherlands in 2050 by 95% compared to 1990 and to acquire 14% of its energy from sustainable sources, of which 70% renewable electricity (Ministerie van Algemene Zaken, 2022). These goals have been agreed upon in the national Climate Act on May 28, 2019. Municipalities play an important role in reaching these goals (VNG, n.d.). They have, in their turn, translated the national renewable energy targets into local targets, policies and roadmaps, aiming to contribute to reaching the national climate goals.

Solar energy is a vital part of this transition and necessary to be able to achieve the targets. In urban areas, solar photovoltaic (PV) deployment on existing rooftops has proven to be one of the most viable large-scale resources of sustainable energy (Assouline et al., 2017). Unlike other techniques, solar panels can be realized at a fast pace and can therefore greatly contribute to accelerating the transition and reaching the energy and climate targets. Accordingly, a rapid acceleration of solar energy has been witnessed across the globe. National governments have provided numerous incentives and subsidies to promote the development of residential solar panels, aiming to achieve the goal of reducing greenhouse gas emissions and mitigating climate change (Lan et al., 2021). And in line with the volatile geopolitical developments in the past years, that impacted the energy market worldwide, the desire for energy independence has driven adoption rates even higher.

Along with the rapid growth, regional differences in solar panel adoption have been found across the world. For example, Lan et al. (2021) found a high disparity in PV adoption in Australia. In their research, socioeconomic factors are successfully used to explain the regional disparity. Lukanov and Krieger (2019) investigated adoption levels in the United States and found persistently lower levels of PV adoption in disadvantaged communities, suggesting clear distributive and equity impacts of existing PV support policies, and indicating that the benefits bypass some of the state's most vulnerable populations. Darghouth et al. (2022) also identified solar inequities at national and state scale in the U.S. The observed regional differences are becoming a main concern because it means the unequal availability of solar energy services and also indicates potential social and economic inequality (Poruschi & Ambrey, 2019).

In line with many nations worldwide, the Dutch national government and local governmental bodies have provided tax incentives, feed-in tariffs, and subsidies to promote the adoption of residential solar panels. Also in the Netherlands, the residential solar panel market has witnessed rapid growth in the past years, partly due to these government incentives. Besides these incentive programs, the high energy prices over the past years and the subsequent drive for greater energy independence have increased the attractiveness of solar panel installations (Breukelman, 2021). Dutch grid operators have recorded historic growth in solar panels on residential rooftops in 2022. In the various provinces last year, the capacity of solar panels on residential roofs grew between 25 and 40 percent compared to 2021 (Netbeheer Nederland, 2023). In order to reach carbon neutrality by 2050 however, in line with the climate goals, more than tenfold of the current installed capacity is needed. According to a Dutch solar-energy expert, the low-hanging fruit has been picked and growing solar energy by a factor of ten will be technically and socially challenging. This suggests new and innovative insights into solar potential and deployment are needed, that however not only address the need for further growth to reach climate goals but also equitable growth.

Besides the possible energy justice implications, several other challenges in utilizing the full potential of solar energy exist. One of these challenges is the capacity of the electricity net and energy storage, which is under pressure due to the disbalance in energy demand and supply to the net (Deloitte, 2018). Due to the congestion on the electricity net large solar park projects are currently stalled, putting more emphasis on the integration of small-scale solar installations (NU.nl, 2021). A shortage in technicians and materials, such as converters, also slows down the installation of PV systems (Planbureau voor de Leefomgeving & van Polen, 2021). Furthermore, the solar panel adoption context is a volatile landscape, where policy levers and energy prices highly impact consumers. Insights into the potential developments of PV adoption in a municipality, and the underlying socioeconomic factors explaining this potential, can aid net operators in pro-active planning of the electricity distribution system (Liander, n.d.). The challenges faced call for both more effort in implementing existing policies and formulating new policy measures (Planbureau voor de Leefomgeving & van Polen, 2021). Insights into the potential developments of PV adoption in a municipality, and the underlying socioeconomic factors explaining this potential, can aid net operators in pro-active planning of the electricity distribution system and can aid (local) governments in exploiting renewable integration policies in a more effective way (Liander, n.d.).

1.2 Solar Energy Justice

Solar energy, including household and community-based solar photovoltaic panels, is the fastest growing source of low-carbon electricity worldwide. The rapid pace of adaptation raises questions about the negative equity and justice associated with this development. This is the main focus of the field of energy justice. Energy justice research, which is an extension of social justice, has recently emerged in the solar energy research agenda to understand the underlying reasons for the regional disparities (Poruschi & Ambrey, 2019). As the proposed research aims to include a social perspective on solar panel potential and adoption, the energy justice context related to this study is relevant to consider.

In the public debate and literature, the affordability, reliability, and sustainability of our energy supply are increasingly associated with the phenomenon of justice (Weijnen et al., 2021). Sovacool et al. (2017) define energy justice as, "a global energy system that fairly distributes both the benefits and burdens of energy services and one that contributes to more representative and inclusive energy decision-making" (p. 1). Energy justice often concerns the way in which different groups of citizens experience the benefits and burdens of the current energy supply (Weijnen et al., 2021). Several aspects of climate justice exist, of which procedural, distributive, recognition, and transformative are the most occurring in literature. *Procedural climate justice* is about processes for making decisions about the impacts of and responses to climate change that are fair, accountable, and transparent. *Distributive climate justice* deals with how the costs and benefits of climate change are spread among citizens and businesses. *Recognition climate justice* focuses on the recognition of differences alongside protecting equal rights for all. van Uffelen (2022) describes recognition justice as the adequate recognition of all actors through love, law, and status order. *Transformative climate justice* is perceived to be more of an overarching justice of the previously named types of justice, where transformative climate justice includes, and goes beyond, "the immediate and proximate challenges of distribution of costs and benefits from climate interventions" (p.36). Transformative justice thus focuses on the change that happens in a social system.

In literature, PV adoption inequity has been increasingly identified as an emerging energy justice issue (O'Shaughnessy et al., 2020a). Several studies on energy justice and the sustainable energy transition show that there is a lack of social or financial inclusion, and different types of inequities such as demographic, spatial, and temporal inequities are defined (Darghouth et al., 2022; Lukanov & Krieger, 2019; Si & Stephens, 2021; Sovacool et al., 2022; Zhang et al., 2011). Weijnen et al. (2021) see a possible future scenario unfolding, where inequality between citizens in the affordability of electricity increases. They state it is a given that incentive benefits end up mostly with the relatively prosperous and highly educated section of the population that own their residences. Besides, questions arose on the socialization of incentive schemes for solar energy to all citizens, also those who do not own solar panels. It is estimated that the transfer of wealth from households without solar panels to those with solar panels is in the region of billions of euros (Parliamentary Questions 2022Z13495, 2022). In the United States, research shows that the growth of solar deployment over the last decade has indeed not occurred equitably across socioeconomic groups. There is a clear difference between lower and higher income communities and home ownership, which is emphasized in multiple studies (Darghouth et al., 2022; Lukanov & Krieger, 2019; O'Shaughnessy et al., 2020a). Research in the U.S. also shows minimal participation from low-income households in community solar projects, with the majority of community solar subscribers being businesses, higher education institutions, government agencies, and higher-earning households (Gallucci, 2019).

In the Netherlands, 15-20% of households do not have enough income or savings to carry the costs of sustainability measures. Often, these households live in qualitatively poorer homes, and relatively a large amount of money is needed for such sustainability measures. Besides these income disparities, Si and Stephens (2021) also note racial disparities that persist even when corrected for household income and home ownership. Adding to this, Weijnen et al. (2021) state that due knowledge and 'acting ability' are also factors required to contribute to solar panel installation projects. Given the many benefits of owning solar panels - such as decreased monthly energy costs and profiting from the financial incentives, tax reductions, and subsidies - and several burdens of now owning them - such as the socialization of netting scheme costs and the dependence on volatile energy market prices - providing equal access to the technology improves the equal spread of the benefits and burdens of energy policy and improves the resilience of citizens.

Some studies argue that the observed differences might be caused by the uneven spatial distribution of solar energy, while other studies indicated that the different solar policies especially financial incentives and subsidies should account for the unbalanced PV adoption (Lan et al., 2020). However, a majority of the studies believe that this imbalance was caused by the difference in socioeconomic status. For example, Zhang et al. (2011) found that high-income households had a higher rate of PV installation. These studies identified the inequity of accessing solar panels and they also pointed out the underlying socioeconomic factors that have important implications for more regionally effective policies.

The literature base clearly presents multiple socioeconomic inequities that could possibly enforce energy injustice in the context of rooftop PV installations. O'Shaughnessy et al. (2020a) emphasizes that there is a challenge in how to address the inequities while expanding rooftop PV and maximizing its long-term benefits, and the need for justice-oriented rooftop PV policy reform. Due to these concerns, it is relevant to incorporate a socioeconomic perspective into this research. Including this perspective will allow a broader detection and analysis of the dilemmas within the solar energy problem area, and avoid privileging efficiency over social inclusion.

Given that many studies focus on income-related inequities, these studies often adhere to an adoption equity definition related to income. O'Shaughnessy et al. (2020a) for example define PV adoption equity as the degree to which PV adopter incomes reflect the incomes of the broader local population. In this study, a broader perspective on adoption equity is adopted. Adoption equity is defined as the degree to which PV adopters' socioeconomic characteristics reflect those of the broader local population.

1.3 Knowledge gaps and research objective

Residential solar energy generation has a large potential to play a versatile role in future global sustainable energy systems. Clearly, society would benefit from higher carbon reduction due to a rapid increase in solar adoption. Fair use and distribution of solar adoption ensure widespread adoption of solar energy technology. In many parts of the world, the difference in solar adoption between regions is raising concerns about adoption equity (Poruschi & Ambrey, 2019; Sovacool et al., 2022). Previous studies on solar energy adoption have shown that socioeconomic factors such as age (Sommerfeld et al., 2017), education (Vasseur & Kemp, 2015b) and income (Dharshing, 2017; Margolis et al., 2017; Veen, 2014) are correlated to adoption rates and can be used to explain adoption disparity. Little is known about the geographic and socioeconomic disparity of solar panel adoption in the Netherlands. A small selection of literature studies exists that cover this topic in the Netherlands, including the studies of Vasseur and Kemp (2015a) and Vasseur and Kemp (2015b). These studies cover statistical analysis of adoption factors based on survey data. No study on the Netherlands to date explores spatial adoption patterns. Schulte et al. (2022) state that solar panel adoption characteristics are highly local and that even within nations study outcomes differ. This emphasizes the need for local insights. More large-scale insights into the possible regional differences and how these are caused would benefit a fast and equal transition to increased renewable energy generation.

Thus, on the one hand, there is a need for additional insights into current adoption patterns and the disparity of adoption. Second, there is a need to understand how this adoption behavior and disparity might develop in the future to shape a justice-oriented rooftop PV policy reform. A selection of studies explores solar panel diffusion amongst households (Lan et al., 2020; Meehan, 2015; Morcillo et al., 2022; J. Palmer et al., 2013). These studies differ in approach and study area. J. Palmer et al. (2013) model the diffusion of rooftop solar using an agent-based modeling approach for a study area in Italy. Meehan (2015) explores residential rooftop solar diffusion and its impact on electricity and utility rates. Multiple other studies exist that explore solar panel diffusion and the so-called Utility Death Spiral (Castaneda, Jimenez, et al., 2017; Costello & Hemphill, 2014; Felder & Athawale, 2014; Grace, 2018). None of the studies however adopt a social perspective, where the focus is not only on adoption extent and speed but also on adoption equity. Some of the studies include an evaluation of policy impacts. Most of these studies examine the effect of subsidy policies - including the netting scheme - on adoption rates, such as Zhang et al. (2011) who studied panel data of households in Japan. Existing studies however often include one type of policy lever instead of multiple to allow for comparison. Besides, none of the studies cover the Netherlands as a case study area. Best et al. (2023) state that much more research is needed to support equitable policy development, through research that combines both equity and policy, as this research is currently highly limited. They further imply that future research on the links between economic distributions, policies, and solar-panel uptake is highly useful and that using actual household data and solar uptake is necessary for contributing to equitable policy development.

The possible energy justice implications identified in the previous section emphasize the need for more research on the regional difference in solar panel adoption and to understand how the difference is caused. This study aims to fill a societal knowledge gap where there is a lack of knowledge on the adoption disparity in the Netherlands, what socioeconomic factors might be used to explain the observed adoption patterns, and how the adoption might evolve in the future, under different policy levers. In the literature base, a small selection of studies on solar panel adoption and socioeconomic factors exist, however, none covered regions within the Netherlands and none study the possible future developments of solar panel adoption and adoption disparity. These knowledge gaps lead to the following main research question:

How could distributed solar panel adoption speed and disparity develop in the future and under different policy measures?

Adoption speed is defined as the number of households within a specified area installing rooftop solar installations per time period. Adoption disparity is defined as a noticeable and significant difference or dissimilarity between adoption rates of different socioeconomic groups or spatial boundaries such as neighborhoods.

To be able to answer the main research question, this study also aims to construct and adopt a structured approach for addressing both knowledge gaps. Therefore, one of the study objectives is to develop an integrated, data-driven approach that can be used to aid in a more structural assessment of adoption disparity and policy-making. From a methodological perspective, several methods exist to evaluate adoption patterns or to study future adoption diffusion. Considering adoption factors, Lukanov and Krieger (2019) used a correlation analysis approach to study trends of residential PV adoption in California. Lan et al. (2021) used a machine learning approach to understand the regional disparity of residential solar adoption in Australia. Sovacool et al. (2022) used a mixed-methods design to investigate four types of inequities associated with household solar adoption, focusing on spatial, inter-species, temporal, and demographic inequities. Other methods found in literature consider surveys (Vasseur & Kemp, 2015b) or Choice Behaviour experiments (Grbosz-Krawczyk et al., 2021). Considering adoption diffusion studies, a popular approach is the Technology Diffusion theory (Lan et al., 2020), or system-dynamics modeling (Morcillo et al., 2022). Thus, approaches exist that study either adoption characteristics or that study diffusion evolution, but up to date, no integrated approach is found in the literature base. Existing methods offer either a static examination of adoption disparity or study adoption diffusion without taking socioeconomic differences into account. This study aims to present a data-driven approach that provides a set of tools that can aid in a more structural assessment of adoption and adoption disparity, and gauging scenarios for policy-making purposes.

The main objectives of this research, therefore, are to:

- develop insight into adoption patterns and the dynamics of diffusion of residential solar panel adoption, and to;
- explore what measures could enhance a rapid and equitable deployment of solar panel adoption.
- adopt a structured approach for assessing adoption disparity and evolution.

Through fulfilling these objectives, the study aims to create insights into solar panel adoption disparity in the Netherlands and plausible future developments and propose a set of concrete policy recommendations to lever the acceleration of diffusion of solar panels in an equitable manner. Possibly, the study eventually contributes to providing a reference for governmental bodies to consider in formulating more sophisticated policies and incentives.

1.4 Research scope

The modeling approach will be demonstrated as a proof-of-concept applied to the municipality of Amsterdam. Amsterdam is a municipality with both ambitious goals and high potential in terms of rooftop area (Deloitte, 2018). The municipality of Amsterdam captured its own regional climate goals in the Roadmap Amsterdam Climate Neutral 2050. The transition to sustainable electricity generation is one of the main pillars in this roadmap: "maximizing solar energy generation of roofs" (Gemeente Amsterdam, 2022d). The municipality aims to use half of all suitable roofs by 2050.

Research has shown the municipality has a large potential for residential solar energy generation (Isabella & Verkou, 2020). However, there is still a large gap to fill in order to reach the regional climate goals. Around 70% of the suitable roofs do not yet have solar panels installed (Briels, 2022). Approximately 500.000 more solar panels need to be installed to reach the regional targets. Despite consistent growth over the past years, the adoption rates lag behind the national average (van Groesen, 2022). Applying this study to the municipality can yield insights as to why adoption progresses slower in this area. The municipality thus has high ambitions and a high potential for solar panel deployment. Besides, Amsterdam is a large municipality with citizen counts approaching 900.000, making it the largest municipality of the Netherlands (CBS, 2022b). The municipality includes 484.574 households and over 500 neighborhoods. The municipality is also found to be a suitable case-study region given the rich diversity in socioeconomic groups. The municipality is amongst the group of municipalities with the highest share of low-income households in the Netherlands (Gemeente Amsterdam, 2022b). The municipality includes many different forms of housing types (detached, apartment, etc.), ownership types (owned, rented, owner associations, etc.), and rental types (housing corporations, landlords, etc.). Besides, the inhabitants of the municipality represent a large diversity in age, education, and cultural background. The municipality is therefore found to represent a broad, inclusive reflection of Dutch society from a social, economic, and cultural perspective.

A limitation of the case study area could include the high urbanity of the municipality compared to some other municipalities in the Netherlands. This and other limitations and their implications for the research outcomes will be properly evaluated and discussed in the research discussion and conclusion.

1.5 Link with EPA program

The Master thesis research is part of obtaining a master's degree in Engineering and Policy Analysis (EPA). A typical Engineering and Policy Analysis thesis covers modeling, policy, and societal relevance of complex socio-technical systems. This research tackles a situation where there is a lack of understanding on how to shape local or national policy in a way that it efficiently stimulates reaching the climate goals, while also overcoming socioeconomic dilemmas. This knowledge gap will be tackled using modeling techniques that map the potential of solar energy in a city, explore socioeconomic factors behind neighborhood adoption patterns, and explores plausible futures of PV adoption under different policy levers and external influences. Such findings can inform municipal policymakers in enhancing their decision-making towards reaching regional and national climate goals. The research is thus located at the intersection of renewable technology diffusion, social justice, and policy-making, making it highly suitable for an EPA thesis. Technical artifacts, such as System Dynamics systems, are placed into a political multi-actor context to understand their impact and explore competent applications in the future.

1.6 Thesis outline

The report is divided into four parts, shown in figure 2. The first section includes the introduction and the methodology. The second section consists of Chapter 3, the system description, and Chapter 4, the chapter defining adoption potential and drivers. The third focuses on the operationalization, conceptualization, model formulation, and model demonstration, and includes Chapter 5, 6, 7, and 8. Finally, part three concludes with the conclusions, discussion, recommendations, and suggestions for future research in Chapters 10 and 9.

Part	Chapter	Research question	Method
Part 1	1 - Introduction		
	2 - Methodology		
Part 2	3 - System Description	RQ1	Semi-structured interviews, literature study
	4 - Solar panel adoption factors	RQ2	Literature study
Part 3	5 - Operationalization		
	6 - Potential and current state of solar panel adoption	RQ3	Rooftop suitability assessment and statistical data analysis
	7 - Model formulation and testing		System dynamics modelling
	8 - Model demonstration	RQ4	Model implementation
	8- Policy evaluation	RQ5	Model implementation
Part 4	9 - Discusion		
	10 - Conclusion and recommendations		

Figure 2: Report outline

2 Research approach and methods

This chapter describes the methods used to answer the aforementioned sub-questions and main research question.

2.1 Selection of the research strategy: Design Science approach

This research aims to understand the relationship between solar panel adoption and socioeconomic factors. It further seeks to understand the disparity of this adoption, and how it might evolve in the future under different policy levers. The approach selected to achieve these research objectives is Design Science research. Design Science research focuses on problem-solving questions and consists of a problem investigation and a design phase. This suits the research objectives, as the final research aim is to develop an integrated analysis of PV adoption that increases understanding of a real-life system. Design Science methodologies provide guidelines on the design process including the problem specification, knowledge base, the solution design, the solution demonstration, and the solution evaluation. Multiple approaches exist, of which a combination of Hevner et al. (2004) and Peffers et al. (2007) is adopted.

Design Science is a research paradigm focusing on the development and validation of prescriptive knowledge: design sciences are concerned with how things ought to be, that is, with devising artifacts to attain goals (Simon, 1996). An artifact is the object of study. It is something created by people for some practical purpose. That is, the studied artifacts are designed to interact with a problem context in order to improve something in that context (Wieringa, 2014). Design Science research is motivated by the desire to improve the environment through the introduction of new and innovative artifacts and the processes for building these artifacts (Simon, 1996). The application domain consists of the people, organizational systems, and technical systems that interact to work toward a goal (Hevner, 2007).

2.1.1 The artifact

The proposed research is a design problem: the goal is to design an artifact that will improve the problem context. In this case, the problem context is that of technology diffusion where knowledge of adoption factors and future developments under different policy levers is limited. There are four types of artifacts constituting the possible outputs of Design Science research: constructs, models, methods, and instantiations (March & Smith, 1995). The output for this research project is a data-driven approach, that can be used to increase understanding of the dynamics within a real-life system. The output (artifact) is not solely a model, but a method that situates a model in a specific social context. This touches on the idea of situated design (Greenbaum & Kyng, 1991). Greenbaum and Kyng (1991) emphasize that the context and the designer's interpretation of it are crucial to the output and outcome of the design process. The context of the problem area and thus the artifact will therefore be well established, resulting in a design that fits into the social context.

2.1.2 Design Science cycles

This research will include the three phases of design research defined by Hevner (2007), with an additional fourth phase adapted from Peffers et al. (2007). Hevner presents three inherent research cycles of Design Science research: the relevance cycle, the rigor cycle, and the design cycle.

- The **relevance cycle** bridges the contextual environment of the research project with the Design Science activities. This cycle initiates an application context that provides the requirements for the research (e.g. the opportunity/problem to be addressed) as input to the design cycle and defines the criteria for evaluating the research results.
- The **rigor cycle** connects the Design Science activities with two types of additional knowledge: the state-of-the-art knowledge base of scientific foundations, experience, and expertise that informs the research project, and the existing artifacts and processes found in the application domain. A key element in the rigor cycle is that the research results contribute to the existing knowledge base.
- The central **design cycle** combines the results from the two previous cycles to develop a new and relevant artifact. The relevance cycle provides the requirements as input for the design cycle, and the rigor cycle provides the design and evaluation theories and methods as input for the design cycle. Hevner (2007) emphasizes the importance of a proper balance between the construction and evaluation of the artifact.

of Amsterdam.

The model will be evaluated through a demonstration of the use of the artifact, applied to the municipality of Amsterdam.

- Where Hevner does not include an explicit **demonstration phase**, but rather a more implicit evaluation phase, Peffers et al. (2007) defined a six-phase Design Science process in which the demonstration phase is a separate step in the process. This will be adapted in this research, as the demonstration phase is a significant part of the research.

Figure 3 shows the framework used in this study and adapted from Hevner's Design Science cycles.

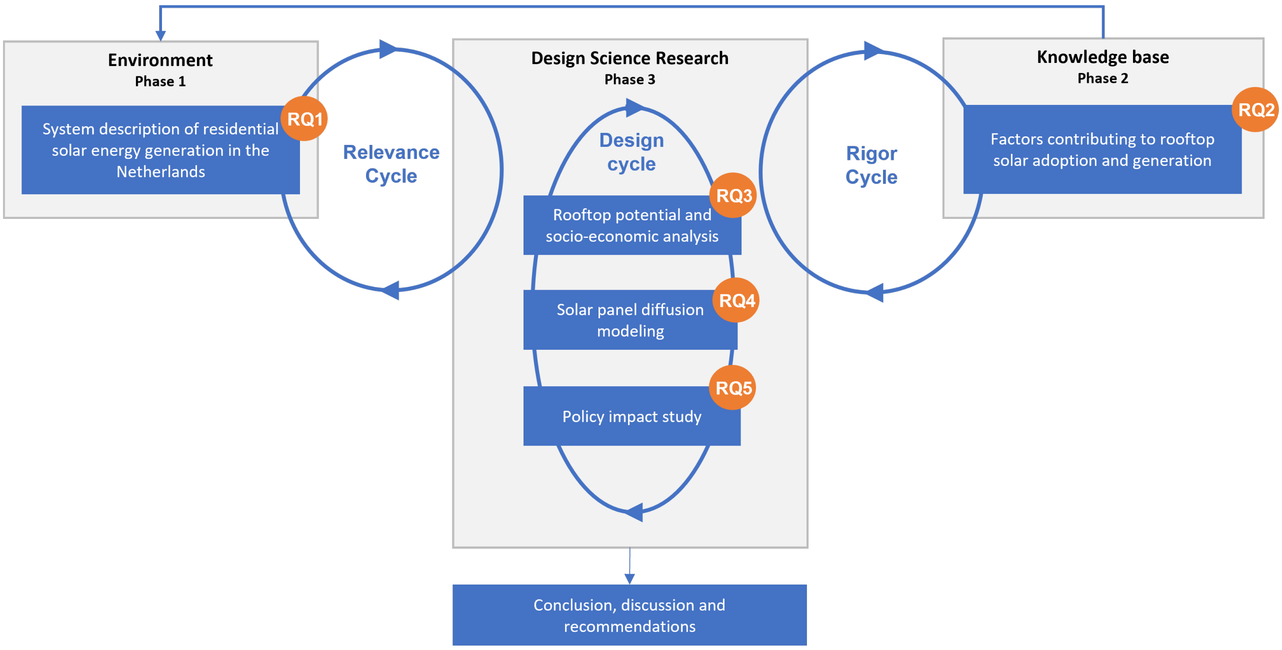


Figure 3: Design Science approach for this study adapted from Hevner (2007)

2.2 Research phases and sub-questions

The research approach follows the construction of the Design Science cycles. The Design Science research consists of three subsequent phases. In each phase, one or more sub-questions are answered. These together answer the main research question. The sub-questions are as follows:

1. What does the current landscape surrounding residential solar energy generation in Amsterdam and in the Netherlands look like, from a social, technical, economic and political perspective?
2. What factors contribute to solar panel adoption behavior?
3. What is the potential for residential solar energy generation in Amsterdam and how are observed adoption patterns correlated with various socioeconomic indicators to explain adoption disparity?
4. How might solar panel adoption disparity develop in the future
5. What are effective interventions for increasing residential PV adoption and narrowing down the adoption gap?

2.2.1 Research phase 1: Understanding the context of residential solar panel adoption in the Netherlands

Research phase one constitutes the environment phase of the Design Science cycles. This phase focuses on getting a thorough understanding of the problem context and system at hand. The phase structures the system description into four dimensions, to construct a broad sense of the existing stakeholders, policies, economic developments, and technological innovations. This way, the main objective of this sub-question is to explicate the problem environment. The following sub-question is answered in this research phase:

Sub question 1: *What does the current landscape surrounding residential solar energy generation in Amsterdam and in the Netherlands look like, from a social, technical, economic, and political perspective?*

2.2.2 Research phase 2: Exploring the factors contributing to solar panel potential and adoption

In the second research phase, a thorough understanding of the knowledge base is acquired. This phase aims to map the factors that contribute to solar panel potential and adoption, serving as input fur the artifact design. First, the factors that contribute to rooftop potential for solar generation are introduced. Next, the consumer characteristics that play a role in adoption behavior are mapped. This way, the concept of solar panel adoption is conceptualized into factors that can be used in research phase 3. Research phase 1 answers the following sub-question:

Sub question 2: *What factors contribute to solar panel adoption behavior?*

2.2.3 Research phase 3: Developing a method to study solar panel adoption disparity and dynamics

Research phase 3 reflects the design cycle of the Design Science research method. In this step, all gathered insights inform the process to design a method that allows the evaluation of adoption patterns, adoption disparity, and adoption evolution. The design process starts with an operationalization section, that translates and combines the insights from phases 1 and 2 into an artifact design. This section conceptualizes insights so that they can be used to construct the artifact design and ultimately answer the main research question.

The design process results in an integrated analysis and modeling approach. Sub-questions 3, 4, and 5 are answered using this designed approach. Sub-question 3 aims to understand adoption potential, current adoption patterns, and the socioeconomic factors correlating with the observed adoption patterns.

Sub question 3: *What is the potential for residential solar energy generation in Amsterdam and how are observed adoption patterns correlated with various socioeconomic indicators to explain adoption disparity?*

The insights from sub-question 3 are used to further develop the model for sub-question 4. For this sub-question, a model is developed that allows studying the behavior of the system of solar panel adoption over time. The next step is to use the developed method to explore the evolution of the adoption patterns that have been observed in sub-question 3. Sub-question 4 aims to understand the dynamics of solar panel adoption over time and under several policy measures and external developments.

Sub question 4: *How might solar panel adoption disparity develop in the future?*

Sub-question 5 aims to understand the dynamics of solar panel adoption disparity under leveling policy options specifically, aiming to narrow down the adoption gap.

Sub question 5: *What are effective interventions for increasing residential PV adoption and narrowing down the adoption gap?*

Finally, all insights from the research phases and sub-questions are combined to answer the main research question:

How could distributed solar panel adoption (disparity) in Amsterdam develop in the future and under different policy measures?

2.3 Research methods

This section explains what research methods have been used for the first two research phases. For the latter three sub-questions, the creative design process is used to develop a suitable approach for analyzing solar panel disparity and adoption dynamics. As such, for these sub-questions, the research methods will follow from the design process. During the design phase, the used methods will be detailed out.

Sub-question 1: (grey) literature study and semi-structured interviews
To create an understanding of the solar panel adoption landscape in Amsterdam and in the Netherlands, semi-structured interviews and reviewing (grey) literature and policy documents are used as methods to answer this sub-question. To understand the policy landscape, grey literature, and policy documents are scanned. Grey literature, specifically news articles, gives additional insights into what problems or developments exist within society. Policy documents are used for understanding current local and national regulations and climate goals.

Semi-structured interviews are conducted with several stakeholders. Semi-structured interviews are the most common qualitative research method (Qu & Dumay, 2011). This type of interviewing includes a set of questions that can be discussed in a flexible order and are mixed open and closed questions. This way of interviewing stimulates interaction with the interviewee and is found to be beneficial for investigating complex issues (Johannesson & Perjons, 2014). A prior stakeholder analysis is conducted to select interview candidates. Three stakeholders have been selected for the semi-structured interviews: municipalities, provinces, and net operators. A total of ten interviews have been conducted, of which three with net operator Stedin, three with net operator Alliander, one with the municipality of Amsterdam, and two with the province of Noord Holland. The municipality of Amsterdam is included in the net operator region of Alliander and is located within the province of Noord Holland. Besides, one interview is held with a researcher from the TU Delft, regarding Energy Justice implications in the problem area. The interviews aim to aid in determining the problem area, relevant dynamics within the system, the current challenges and dilemmas, and future opportunities and developments. Prior to the interview process, questioning is prepared and guided by identified themes in a consistent and systematic manner. In each interview, appropriate questions to the specific interviewee are asked, while adhering to the prior identified themes. Afterward, interviews are transcribed, summarized, and coded using ATLAS.ti (Qu & Dumay, 2011).

Table 1 shows the interviewees, their institute, and their role within the institute. To refer to interviews in text, reference codes are used, which are included in the most right column of the table.

Role	Institute	Reference code
Researcher Energy Justice	Delft University of Technology	DUT1
Program Manager Solar Energy	Municipality of Amsterdam	AMS1
Policymaker Energy Transition & Climate	Province Noord Holland	NH1
Spokesperson Climate & Energy	Province Noord Holland	NH2
Technical Trainee	Stedin	ST1
Grid Analyst	Stedin	ST2
Program Manager Strategic Investments	Stedin	ST3
Consultant Congestion	Alliander	AL1
Technical Trainee	Alliander	AL2
Principal Researcher	Alliander	AL3

Table 1: Conducted interviews and their reference codes

Sub-question 2: literature study (and semi-structured interviews
To answer the second sub-question, a literature review is conducted. The literature review will give theoretical insights into what is known and unknown in the field of solar panel potential and adoption. First, literature research is performed that studies in a broad sense what factors are involved in determining whether consumers adopt solar panels. Next, these factors are investigated in more detail. The insights are added onto with some insights from the semi-structured interviews, which were mainly focused on sub-question 1 but also provided some insights from sub-question 2.

Data gathering and processing
To gather data for the first and second sub-question, several literature databases combined with search engines are used. Scopus is used to find literature and Google is used to find grey literature and policy documents. Besides, the data gathered from the semi-structured interviews serves as input for these sub-questions. To structure the data from these interviews, transcripts are generated and coding is performed using the software ATLAS.ti.

For the third sub-question, which investigates adoption patterns, adoption potential, and socioeconomic correlations, several data sources are used that are retrieved from online databases. These data sources are described in more detail in the corresponding sections.

2.4 Research Flow Diagram

A detailed presentation of the research steps and their link to the research questions and used methodologies is presented in the Research Flow Diagram in Figure 4. The Research Flow Diagram presents the three research phases, consisting of research activities leading to answering the sub-questions in each chapter. The research methods are presented in the green boxes of every chapter. The arrows present research outputs of research phases that serve as input to subsequent phases. Combining the insights of all phases leads to answering the main research question.

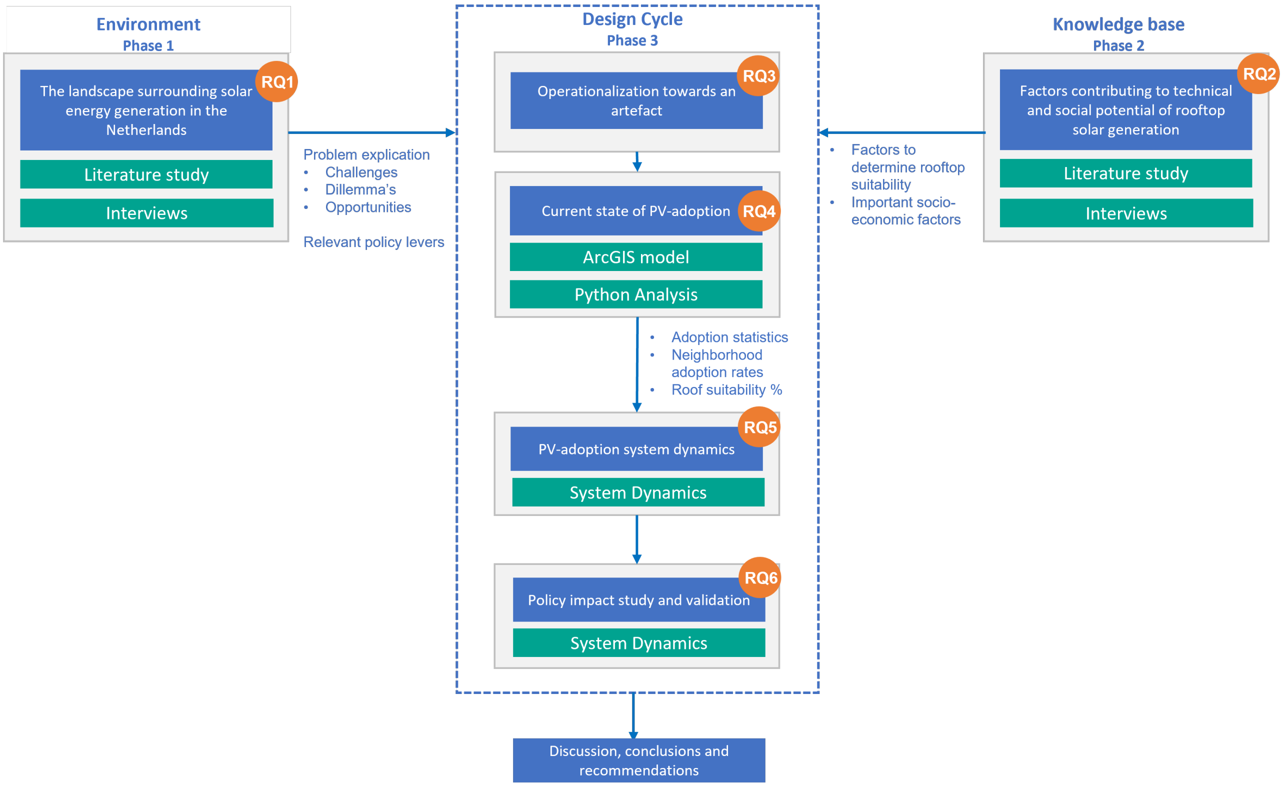


Figure 4: Research Flow Diagram

3 System description

This Chapter answers sub-question 1:

What does the current landscape surrounding residential solar energy generation in Amsterdam and in the Netherlands look like, from a social, technical, economic and political perspective?

The objective of the system description is to explicate the problem environment - the first cycle of the Design Science methodology - and to identify the existing challenges, relevant stakeholders, policy levers, and external factors impacting the system at hand.

The analysis is based on a literature study of many governmental papers and documents, as well as grey literature and policy documents. It is further elaborated upon using semi-structured interviews with experts from grid operators, municipalities, and provinces. When referring to an interview, the codes depicted in table 1 are used.

In this research, the environment is composed of a social, political, economic, and technical dimension. These dimensions are adapted from Hevner et al. (2004), who applies the method in a business domain, and altered to fit a socio-technical policy domain. Within the environment are the goals, tasks, problems, and opportunities that define the "problem" as perceived by the researcher. Framing the research activities to address policy needs assures research relevance.

This chapter starts with describing the system from a social perspective, including a stakeholder analysis. Hereafter, the political dimension is discussed, summarizing relevant laws and regulations. These are followed by the economic dimension, discussing relevant economic developments, and the technical domain, discussing what technical elements are relevant and how they influence the system.

3.1 Political

To combat climate change, both on national and EU-level numerous climate laws, policies, and targets exist. Their focus differs widely, ranging from common rules for the generation, transmission, distribution, energy storage, and supply of electricity to guidelines for the environmental sustainability of economic activities. The most important and relevant policies on the national and European Union (EU) level are described below. These are the policies, laws, and regulations that include solar energy generation at the household level.

3.1.1 International policy

Internationally, several agreements and policies exist. These documents focus on climate and renewable energy in a broad sense and set agreements on emission levels. The European Green Deal consists of European policy plans, mainly considering climate and energy. The deal aims to improve resource efficiency and the well-being of citizens with amongst others cleaner air, cleaner energy, and renewable products. While some EU-level policy documents describe general climate and emission reduction goals, some have a direct impact on residential solar generation in EU countries. Member states of the European Union have reached an agreement on stricter energy standards for buildings. New rules will apply to both new and existing commercial and residential buildings. The target, as set out in the EU's climate plans, is for all buildings to be energy neutral by 2050 (European Commission, n.d.). The strictest standards will apply to newly built buildings. In the case of existing buildings, a requirement will be imposed that when a building is extensively renovated, its overall energy efficiency rating must be improved. From 2029 onwards, solar panels will be mandatory for every newly built residence (Boven, 2018).

3.1.2 National policy

European policy and directives are 'translated' into national legislation, the legislation that applies in the Netherlands. The Dutch government aims to reduce the Netherlands' greenhouse gas emissions by 49% by 2030, compared to 1990 levels, and a 95% reduction by 2050. Climate policy is formulated to guide the reduction of greenhouse gas emissions in the Netherlands (and Europe). The energy transition ambitions of the Dutch government are rooted in the Energy Agreement of 2013, and the Climate Agreement of 2019, and are legally cemented through the Climate Act of May 2019 (Feenstra et al., 2021). The Climate Act is a framework for the development of this policy. The goals are laid down in this law and the Cabinet must adhere to these goals. The Climate Act does not state how to do this. The Climate Plan, the National Energy and Climate Plan (NECP), and the National Climate Agreement contain the policy and measures to achieve these climate goals (Ministerie van Economische Zaken Landbouw en Innovatie, 2020).

The Netherlands Authority for Consumers and Markets (ACM) published the congestion management code decision in May 2022. This allows grid operators to use existing electricity grids more intelligently. Grid operators can now conclude contracts with large-scale consumers and producers for the long term. These contracts state that they use the net less for a fee (RVO, 2017).

Looking at national policy, the netting scheme ("salderingsregeling") plays the most crucial role in the residential adoption of PV due to the increased financial benefits it offers. The net metering law, introduced to stimulate PV adoption by households by increasing financial attractiveness, obligates power companies to deduct the power that a household feeds back to the grid, from the amount of power that it consumes from the grid. This means a household pays for the resulting balance between the feeding-back amount and the consumption. When the feeding-back amount is larger than the consumption, the household receives a smaller "feeding-back tariff" per kWh for the excess amount ((Milieucentraal, n.d.)). In the remainder of this paper, the term net metering or netting scheme refers to the deduction of generated electricity on the energy bill, and net billing refers to receiving a fixed amount per injected kWh into the grid. On the deducted amount of kWh, both the distribution tariff and the energy tax are remitted.

The netting scheme has been an ongoing point of debate over the past years. In literature, incentive schemes such as the netting scheme and other net-metering alternatives are increasingly linked to notices of injustice and inequity. Keady et al. (2021) describe the existing inequities in access to household-level transition benefits such as solar net metering. Si and Stephens (2021) points to the increasing awareness of how these policies are exacerbating inequities by disproportionately benefiting wealthy communities. Lukanov and Krieger (2019) conclude in their study that there are clear distributive and equity impacts of PV support policies (e.g. net energy metering). The Dutch government is currently debating the option to out phase the net metering scheme from 2025 onwards. This entails that each year, a smaller percentage of the electricity fed back into the grid can be deducted from your consumption. Instead, households will receive a fixed, lower feeding-back tariff for each kWh fed back into the grid (Milieucentraal, n.d.). In the final stage, net metering will be phased out completely from 2031. The bill has been passed by the House of Representatives. It is now up to the Senate to decide whether this bill will pass.

There are multiple causes that sparked the debate about phasing out the net metering scheme. One of these reasons is the (un)fairness of the scheme. First of all, the net metering policy creates a redistribution issue. The costs for net metering are not fully covered by the national government. Net metering increases costs in two main ways:

- Net metering increases costs for energy suppliers. At times when there is high PV electricity generation, the market price for electricity is often also lower, because the supply of cheap power exceeds demand. The net metering scheme allows households with solar panels to offset this cheap power against the power they purchase at other times – when prices are often higher. This increases costs for energy suppliers, which they compensate for by increasing electricity unit costs for áll customers.
- It is known that PV generation increases the potential energy imbalances on the grid, due to the fluctuations in sunlight and the mismatch between generation and consumption. As net metering stimulates PV installation and feeding electricity back to the grid, the scheme contributes to imbalance on the grid and thus increases balancing costs. As prices on the 'imbalance market' are much higher than regular electricity prices, extra costs are generated by TenneT that energy suppliers pass on to their customers. Henri Bontenbal, representing the political party CDA, states that residential consumers should contribute to the system costs caused by feeding electricity to the grid: "The net metering does not allow this, costs are carried by energy suppliers and socialized to all customers" (Parliamentary Questions 2022Z13495, 2022). Imbalance price costs are estimated to be around €1-€5 /MWh (Hoogervorst, 2020; Koelemeijer & Bart, 2021).

Second, solar panel owners benefit from tax advantages. Households that produce a surplus do not pay any energy taxes, or the so-called SDE levy, nor VAT, for their own yearly consumption (Bellini, 2022). This means that users of solar panels can take advantage of tax breaks on the energy they offset against their generation.

As a result, households without solar panels are now indirectly contributing to the financial benefits for households with solar panels. These costs can rise to about €100 to €200 a year (van Weezel, 2023). And the more roofs with panels are added, the higher that amount becomes. This chafes especially because households without solar panels often have no choice. Authority Consumer and Market (ACM) recommends abolishing the scheme. According to the ACM, the scheme mainly benefits homeowners with a relatively high income (ACM, 2023). Multiple interest groups, including the Consumers' Association and the Home Owners Association, have called on the House of Representatives not to agree to the phasing out of the energy-saving scheme if there is no good alternative for (future) solar panel owners. They also suggest that the dismantling of the scheme leads to even more inequality, as the purchase of PV becomes less viable for low-income households (Donat, 2023).

Another reason for debating the continuation of the netting scheme is the emphasis of the scheme on the production of power, rather than the use of one's own power. The current scheme does not encourage small consumers to use their own generated solar energy, or store it, because of the financial benefits of feeding electricity back to the grid. This increases the pressure on the grid. Expanding the grid to prevent overloading from these mechanisms requires substantial investments. Phasing out of the netting scheme would increase the incentives for small consumers to use appliances at home at the time of energy generation (Boele, 2023).

Besides these challenges, the Cabinet states that the netting scheme has become redundant due to the sharp decline in prices for PV installations and increased efficiency. Even without the net metering benefits, it remains attractive to buy solar panels as the payback time has decreased significantly over the past years. A TNO analysis shows that the payback time of 10 solar panels in 2022 is 5 years. Should the netting scheme be phased out, the payback period will increase to around 7 years (Verheij et al., 2020a). This calculation however assumes an investment cost of 1.20 per Wp. Current price per Wp is 1.85 however, which would increase payback time. The high energy prices compensate for this, making solar panels attractive compared to other energy sources. Besides, because no tax has to be paid on the electricity stripped away, the scheme decreases the tax revenue for the government (Ministry of General Affairs, 2023).

It is clear that the netting scheme policy, both nationally and internationally, and both in politics and in literature, is controversial. The scheme is increasingly linked to notices of inequity and injustice, mainly due to the unequal access to the benefits of the scheme compared to the increasing costs for non-adopters.

Besides the netting scheme, national subsidies for residential solar energy investments are no longer in place. However, there are some national or local favorable loans available for energy-saving or sustainability investments, often with low interest rates, and some municipalities offer local subsidies or support collaborative solar panel investments. Besides, from 2023 onwards, no taxes are issued for rooftop-mounted solar panel purchases (Ministry of General Affairs, 2023). The national government also introduced an interest-free loan for households with a low income who are willing to take sustainability measures on their owner-occupied homes. In Amsterdam, the municipality offers the Energy Loan Amsterdam. This loan allows households in Amsterdam to finance sustainability investments, including solar panels. While no subsidies for residential PV adoption are in place, there are some scheme's for homeowner associations, such as the SCE (Subsidy Scheme Cooperative Energy Generation) and the SEEH (Subsidy Scheme Energy saving own Home).

Policy regarding solar energy generation is continuously under development. The federal government is currently working on a new Energy Act, and is planning to give municipalities the mandate to obligate the installation of solar panels on existing rooftops of utility buildings (buildings without residence purpose. The latter plan is aimed to commence in 2024.

3.2 Social

The social domain is investigated through stakeholder analysis. Following the stakeholder analysis, supplemented with the insights from the interviews, a list of the most relevant stakeholders is composed, together with their role within the problem area and possible justice implications.

Actor Analysis
The actor analysis focuses on stakeholders involved in the PV adoption landscape, that are an influence on the system or are influenced by the system. Actors are those parties that have a certain interest in the system and/or that have some ability to influence that system, either directly or indirectly (Enserink et al., 2022). Note that the term 'actor' and 'stakeholder' are often interchanged. However, sometimes the term 'stakeholder' is

used to refer to those groups that are mostly involved because they have an interest, or stake, in decision-making processes, while the term 'actor' is used to refer to those with the capacity to influence the decision-making or to act on decisions and their outcomes. In this analysis, the previous definition by Enserink et al. (2022) is followed. There are several methods available to support actor analysis. In practice, most use is made of approaches for stakeholder analysis.

Understanding the involved actors and their objectives and motivation is a crucial part of problem structuring within complex policy issues. Very often, the interests and/or objectives of the involved actors are not fully aligned. Understanding these interests and objectives might enrich the problem-solving process and lead to better solutions. Enserink et al. (2022) thus stress it is of great importance that a problem analysis provides insight into the range of actors involved.

Involved actors are identified through an interest-based approach as described by Enserink et al. (2022) and supplemented with knowledge gained from the interviews. The interest-based approach identifies actors who feel strongly enough about a certain policy problem or issue to act on their feelings. The general question asked here is 'Who has an interest in or feels the consequences of the issues around which the problem revolves, or the solutions that are being considered?'. Actors are identified within the problem domain and scope: the adoption of solar panels by households within municipalities in the Netherlands. Following the actor analysis, supplemented with the insights from the interviews, a selection of the most relevant actors is composed. Figure 5 present these stakeholders in a hierarchical order, including three main stakeholder categories: governmental, electricity sector stakeholders, and consumers.

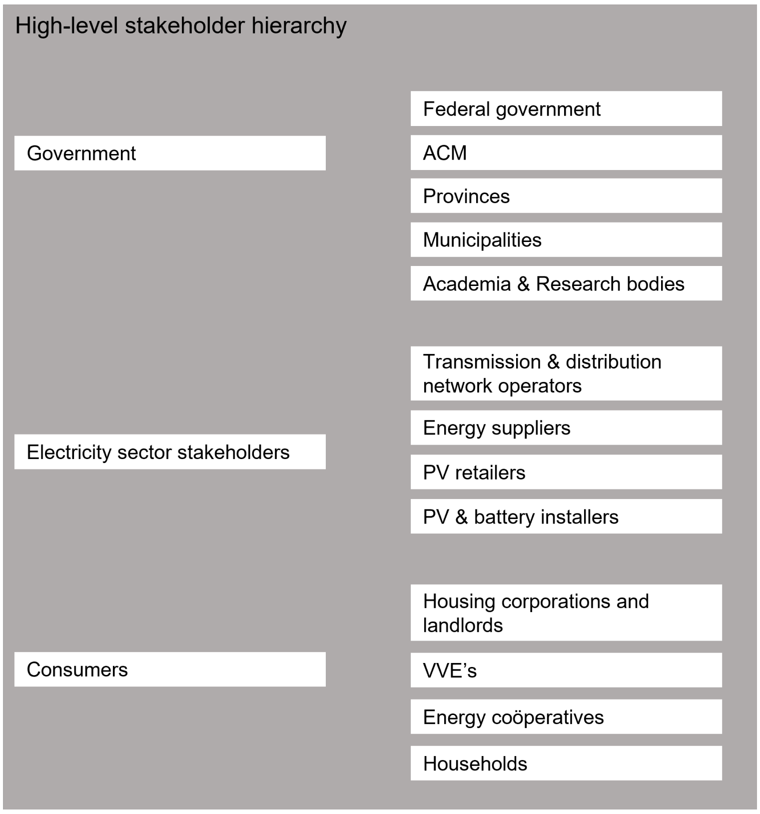


Figure 5: Hierarchy of stakeholders

The **federal government** sets out national rules, regulations, and guidelines regarding solar energy policy and climate goals. This includes amongst others the netting scheme, the Climate Law, Climate Agreement, and the zero-VAT rate on PV installation (See section 3.1). **The Ministry of Economic Affairs and Climate Policy** is mostly connected to solar energy policy. This party also initiated the phasing out of the netting scheme.

The role of the **province** in solar energy integration is at the medium-voltage level, meaning they concern with large-scale solar projects such as solar farms and solar systems on large roofs. The role of the province concerning the integration of solar panels in households is very limited (NH1, NH2). Provinces focus on reaching the goals stated in the Regional Energy Strategies (RES). To do so, they closely work together with other parties such as municipalities, grid operators, ministries, citizens, and companies. Given the recent developments with grid overload, the province and municipalities are looking to strengthen collaboration on these issues (NH2).

The actor most directly involved in stimulating and facilitating PV adoption at the household level is the **municipality** (AMS1, NH2). Municipalities implement national and own policy and act on those matters in the direct interest of their residents. Municipalities usually have local renewable energy targets, which they aim to reach amongst others by stimulating sustainability measures in households. However, most rooftops are not municipal property, and thus they can only stimulate in these cases (AMS1).

The Netherlands **Authority for Consumers and Markets** (ACM) is an independent regulator that champions the rights of consumers and businesses. ACM is charged with competition oversight, sector-specific regulation of several sectors, and enforcement of consumer protection laws (ACM, n.d.). The ACM is also responsible for the execution of the Electricity Act, grants permits to Energy Suppliers and supervises what grid operators and Energy suppliers charge to their customers.

The Dutch solar landscape offers a broad range of fundamental and applied solar research, and many **Research Institutes** are investigating materials and processes, devices, and systems. Research & Development is conducted at universities of technology like the Universities of Eindhoven, Delft, and Twente, as well as at the leading international energy research institutes ECN, TNO, and the Holst Centre. Also, large companies such as OTB Solar, Scheuten Solar, Solland Solar, and Tempress Systems have extensive research programs (van Gastel, 2012). Although the Netherlands itself has an ecosystem of companies and research institutes that cover the entire solar technology chain: from materials to device design, manufacturing equipment, software, high-end solar modules, and complete project development, the vast majority of solar panels is manufactured in Chinese factories (RVO et al., 2020).

Transmission and distribution grid (network) operators are responsible for managing the energy network in a specific region. This network includes the transportation of gas and electricity. Grid operators are not the energy suppliers. The grid operators expand and maintain the grid by laying and repairing cables and pipes. The grid operators get notified afterward when a household installed solar panels, as usually no modification of the cabling is necessary (ST3). They aim to adjust the capacity of the low-voltage grid when the impact of PV installations (in combination with electric cars or heat pumps) on the net within a neighborhood causes issues (ST3). Grid operators cooperate with provinces to achieve the goals set in the RES.

Energy suppliers deliver gas and/or electricity to business or private customers. Customers can choose an energy supplier for their own contracts. The largest energy suppliers in the Netherlands are Essent, Eneco, and Vattenfall, but there are approximately 50 energy companies active in the Netherlands (United Consumers, n.d.). Some of the large energy suppliers are not only suppliers but also energy producers, owning their own power plants, wind farms, or solar farms.

PV retailers are companies selling PV installations to households or businesses. Many retailers exist in the Netherlands, of which most also offer installation services and PV design advice. In most cases, PV retailers are also the PV installers. Due to the many retailers, market competition can keep prices relatively low.

Given the scope of the research - residential rooftop PV adoption - **households** form the most central actor within the system. Households decide on an investment in a PV installation given the many external factors (energy prices, PV prices, renewable technology popularity, etc.) and household characteristics (financial resources, perception of renewable energy sources, type of residency, rooftop availability, etc.). Some households rent a property and some households own a property. Thus, not all households own a private roof. Some households share a roof of an apartment building with other residents. All owners of apartments in a complex together form an **association of owners** (OA). All members of the OA have to decide together on the purchase of solar panels for the communal roof. The Municipality of Amsterdam counts approximately 20.000 OAs, covering 230.000 residencies. That covers 53% of all residencies in Amsterdam (Gemeente Amsterdam, 2018). OAs and rental properties form a complexity when it comes to PV adoption, due to the many involved stakeholders having to agree on an installation (AMS1). Households that rent a property have a **housing corporation** or **landlord**. For rental houses, commercial landlords or housing corporations are often responsible for the installation of solar panels.

Besides the private installation of solar panels by households, **energy cooperatives** exist that aim to collectively purchase and install solar panels, for example at public buildings. The Netherlands, currently, has around 110 energy cooperatives with the objectives of local energy generation and energy saving, as well as strengthening the community. The activities of these cooperatives consist of collective purchasing campaigns for solar panels, small-scale energy conservation campaigns for private homeowners, operating an information and advice help desk, and the reselling of electricity (Planbureau voor de Leefomgeving & van Polen, 2021).

Figure 6 shows the different stakeholders involved plotted for both interest and power. The plot is based on the power/interest matrix by Enserink et al. (2022) and is used to map actor dependencies.

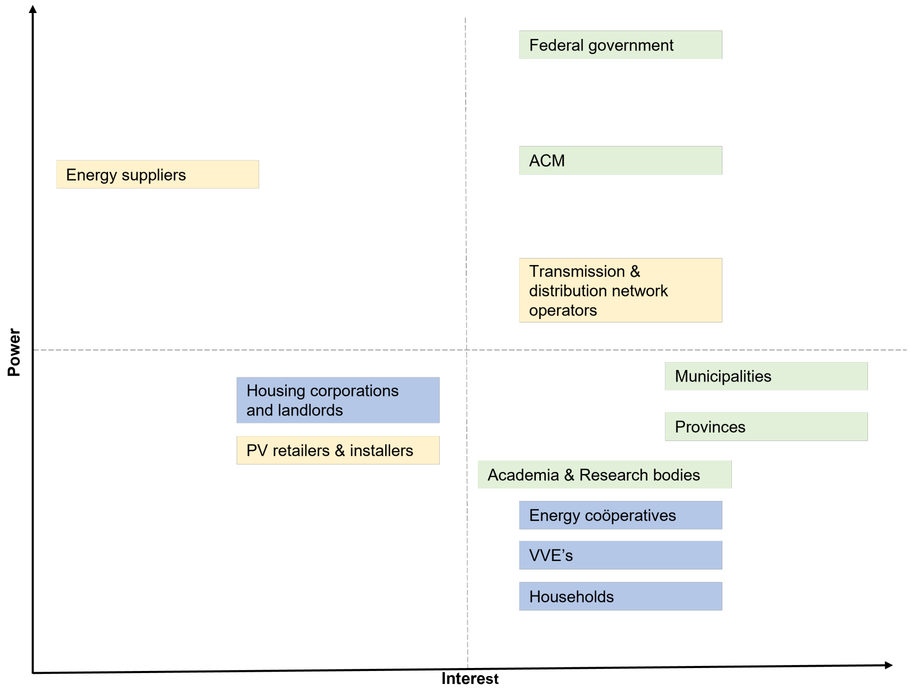


Figure 6: Hierarchy of stakeholders

The roles, responsibilities, and hierarchy of stakeholders suggest the presence of several energy justice implications. Most prominently, property renters and property sharers have no direct roof access and thus no individual decision-making power on placing solar panels on the roof's property. This form of unequal access and availability to renewable energy technology relates to *distributive justice* - the equal distribution of benefits and burdens from the energy sector - concepts and has been previously discussed in literature (Sovacool et al., 2022; Sunter et al., 2019). The hierarchy of stakeholders also reveals a large deviation in actor power. Several governmental bodies construct laws or policies that actors such as households, OAs, housing corporations, and landlords have to comply to. This diverse power spread implies that actors with low decision-making power may or may not be included in the decision-making process of actors with high decisive power. This touches upon the notion of *procedural justice*, which concerns the inclusion and equitable access to participation in the decision-making process (Si & Stephens, 2021).

3.3 Economic

The economic environment is part of the problem context and aids in understanding how the economic situation in the Netherlands might impact the problem at stake. Households are impacted by the economic situation in deciding on renewable energy investments. Besides, the economic situation creates several challenges that impact the renewable energy market.

3.3.1 Economic developments

Following several years of a COVID-19-shaped economy, the war in Ukraine is affecting the Dutch economy, which is reaching its capacity limits again after recovering from the COVID-19 recession. The economy recovered in 2021 and experienced a 4.3% expansion of economic growth in 2022. A combination of substantially higher energy prices, international trade sanctions, and heightened uncertainty due to the war in Ukraine - including the availability of energy supply - however dampens the economic outlook. The economic growth is projected to slow to 0.8% in 2023 and 1.1% in 2024 (OECD, 2022).

The shock of the war is driving energy prices higher, causing inflation in both the energy market and other goods and services. The inflation development of household electricity prices is shown in figure 7. The inflation is expected to fall from 8.7% in 2022 to 3.9% in 2023 and 2.4% in 2024 (DNB, 2022) (see figure 8). Lower-income households are particularly vulnerable and are feeling the impact of the sharp and sudden rise in energy and food prices. They spend a relatively large part of their income on energy and often have no buffer to absorb the large rise in energy prices, possibly leading to energy poverty (see section 3.3.2) (DNB, 2022).

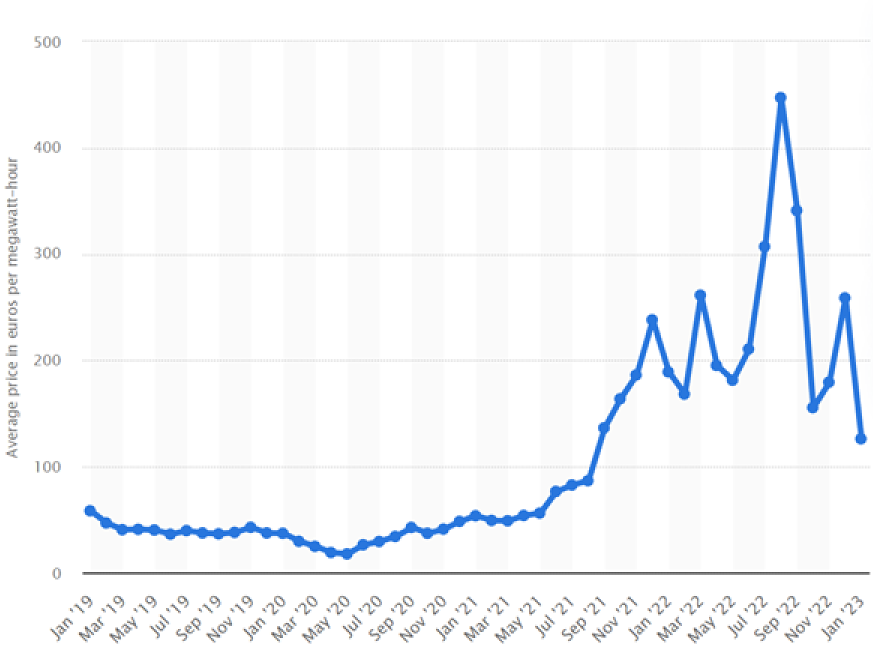


Figure 7: Development of household electricity prices. Source: (Statista, 2023)

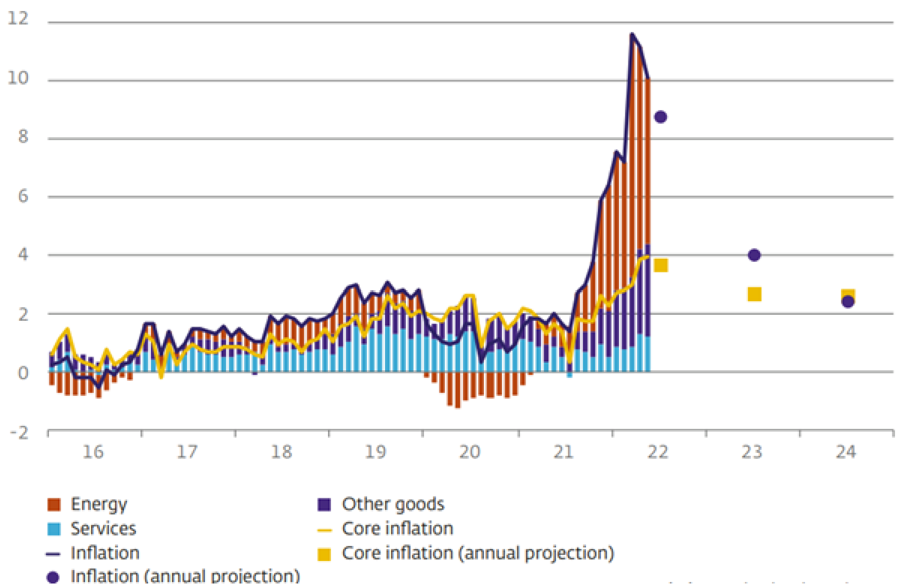


Figure 8: Development of inflation. Source: (DNB, 2022)

To compensate for the sharp rise in energy prices and the increased financial load on households, the government introduced several measures. These include a lower energy tax on electricity, a higher energy tax refund and a reduced VAT on energy from 21% to 9% (in 2022). For lower-income households, the government offers extra measures. Households with an income around the social minimum are entitled to an energy surcharge of approximately €1300. Municipalities will receive €300 million to help residents in poorly insulated houses save energy. Next to all this, the government announced a price cap for gas and electricity for small consumers of energy, from 1 January to 31 December 2023 (Ministry of Economic Affairs & Policy, 2023).

Besides the challenge of inflation, the labour market is extremely tight again immediately after the COVID-19 recession. Staff shortages are being felt across the whole economy. It is expected that employment will barely grow in the coming years. Besides, the supply of labour is also reaching its limits. The tightness of the labour market and higher inflation are driving wage rises higher. The unemployment rate is projected to average 3.3% in 2022, and is expected to rise to 3.6% in 2023 and 3.4% in 2024.

The tightness of the labour market has a clear impact on the solar PV market in the Netherlands. The renewable energy market, including the PV market, experiences a severe shortage of technicians and mechanics which limits the growth of the market (Stil, 2022). The Dutch Planbureau even stated that the shortage is a threat to reaching the climate goals (Weterings et al., 2022).

3.3.2 Energy poverty

The energy crisis has led to an increase in energy-poor households. The increase is caused by a sharp rise in both energy prices and prices of other goods. This increased the costs of living for all households, and thus also increased the share of energy costs households pay relative to their income. When the energy burden (energy quota) of a household is equal to or more than 10% of their spendable income, the Dutch government speaks of energy poverty. The municipality of Amsterdam is amongst the areas in the Netherlands where energy poverty has increased sharpest since 2020 (Mulder et al., 2023). Within this municipality, the increase in energy poverty highly differs per neighbourhood and is, besides the household income, also related to the type of buildings. In the city centre, buildings are relatively old and poorly isolated, which increases changes in energy poverty. In the West, there are relatively many small residencies and almost solely multi-household residencies (apartments). In the South-East of Amsterdam, energy poverty occurs the most, where 14% of the households are classified as "energy poor". In the South-East, this high number is mainly caused by the share of low-income households, given that energy consumption is around the average. The municipality of Amsterdam states that in general, neighbourhoods that experience high numbers of energy poverty have a high share of low-income households (Gemeente Amsterdam, 2022c).

Related to energy justice, energy poverty is becoming a widespread problem in both developing and developed economies, including the Netherlands. Energy poverty is an indicator related to the pressure of energy costs on the disposable household income (Weijnen et al., 2021). Most countries use a threshold of 10% of the household income to indicate energy poverty. TNO defines energy-poor households as households that have to deal with a low income in combination with an excessively high energy bill and/or a home of (very) poor energy quality. TNO investigated that in the Netherlands, 1 out of 13 households experience energy poverty in 2022. This number has increased significantly compared to previous years, mainly due to the sudden increase in energy prices. The financial compensation measures introduced by the Dutch government have limited the increase in energy poverty by 2020 and 2022. Without these measures, it is estimated that the energy poverty number would have doubled compared to 2020 (Mulder et al., 2023).

In recent years, researchers have contended that the issue of energy poverty is a key dimension of the broader energy justice paradigm (Jenkins et al., 2016). G. Walker and Day (2012) claim that, at its core, energy poverty is 'fundamentally a complex problem of distributive injustice' (p. 69), and suggests that this is underpinned by further injustices in recognition and policy-making procedures. Other studies have built upon this work to establish energy poverty as a form of injustice (Christman & Russell, 2016; Sovacool et al., 2016). Looking at energy poverty within the solar energy domain, distributed solar energy has large potential benefits for alleviating energy burdens for low-income households, and thus decreasing energy poverty (Si & Stephens, 2021). It is however the households that experience energy poverty that cannot afford the technology.

3.3.3 The PV market in the Netherlands

The European market, including the Dutch solar market, is growing significantly. The market experienced a reduction in costs for solar panels due to increased competition, tightened European climate objectives, increased political support, and the introduction of the European recovery plan. These are important drives of the solar market. (Intersolar Europe, 2022). The European market experienced the third-largest growth worldwide in 2021.

In 2021, solar power was the largest energy source for renewable electricity. Specifically, the role of distributed systems increased. Policy incentives, such as the netting scheme, drove distributed PV capacity to increase enormously in 2020 and 2021. That same policy incentive causes the Dutch market to fall behind compared to other Western markets when it comes to the self-consumption of generated electricity. The main reason for this is the focus on production due to the advantages of the net metering system.

In the Netherlands, demand for solar panels also increased due to the high energy prices. Partially because of the netting scheme, the Netherlands is one of the largest growing solar energy markets in Europe. The vast majority of solar panels are installed on roofs. The number of households with solar panels passed the 1.5 million mark in the second half of 2021. In total, 1.3 GW of newly installed capacity was added to the residential part of the sector. The growth of residential installed solar capacity is shown in figure

Regarding the costs of solar panels, on average, the price of the modules steadily decreased in the period of 1985 to 2020. The nominal price of panels has however risen steadily in 2021. This is due to the scarcity of resources and high transportation costs. Fierce competition in the low-cost sector keeps the prices relatively low (DNE Research, 2022).

Just as in other markets, the COVID pandemic has had a great impact on the sector of solar energy modules. Where the demand for solar panels surprisingly increased sharply, so did the shortage of different resources for the production of solar panel systems. Solar panel suppliers thus had little opportunity to meet the rising demand for solar panels (NVDE, 2022). Where the PV industry mostly dealt with a shortage in resources for solar panels in the previous years - ranging from glass to silicum to eva-foil – in 2021 and 2022 it is the converter producers that deal with problems due to the chip crisis. Converters contain chips that regulate that electricity from the solar panel is converted to electricity usable by households. Manufacturers of converters point to the chip shortage to explain the current supply problems (van Gastel & Stultiens, 2022). The raw materials for chips are scarce, and many chip manufacturers experienced production problems due to the COVID pandemic (Teije, 2022). On top of this, many stakeholders in the supply chain experience increased transportation costs due to the COVID pandemic and rising fuel prices. These developments caused a worldwide shortage of converters, and to a lesser extent batteries, slowing down the supply of solar panels and increasing the waiting times for solar panel deliveries (Teije, 2022).

3.4 Technical

Within the technical dimensions, the PV market is discussed in Section 3.4.1. The electricity grid is discussed in Section 3.4.2.

3.4.1 PV market

Based on technology, the market is segmented into monocrystalline silicon, thin-film, multi-crystalline silicon, and others. The multi-crystalline segment dominated the global market in 2020 with over 95% market share (RVO et al., 2020). This segment has a wide range of applications in this market and it is widely used in the commercial, residential, and industrial segments.

The monocrystalline silicon segment is expected to grow at the highest pace during the forecast period. Monocrystalline silicon sun-energy panels are more widely used in solar rooftop systems. These panels are commonly preferred for large-scale solar PV installations. Such solar panels are used in different sectors, such as industrial, commercial, or residential. Many manufacturers are also shifting from multi-crystalline to monocrystalline solar cells due to their high efficiency, compact design, and durability (Fortune Business Insights, 2022).

The shift to more efficient monocrystalline wafers accelerated in 2021, with the technology capturing almost all crystalline PV production. In parallel, more efficient cell design (PERC) is also expanding its dominance with almost 75% market share. New, even higher-efficiency cell designs (using technologies such as TOPCon, heterojunction, and back contact) saw expanded commercial production and captured about 20% of the market in 2021.

3.4.2 The Electricity Grid

High and low voltage grids
For the largest share, the Netherlands is dependent on the large-scale generation of electricity in power stations, which is transported and distributed from power stations to the end users. In the transport- and distribution network, there are no storage possibilities. Up to date, storing electricity is only affordable for small amounts in batteries.

The Dutch main transport network for electricity, also called the transmission network, consists of the high-voltage grid, which is used for transporting electricity at 110,000 volts (110kV) and higher and has a frequency of 50 Hz, in line with European Standards (Our high voltage grid (TenneT, n.d.). The high-voltage grid is the system that is visible above ground: the electricity pylons in the Dutch landscape and the electricity transport cables connected to them. The Dutch transmission network is directly connected to that of Germany and Belgium. The high-voltage grid is managed by TenneT, which is responsible for maintaining and ensuring a balance in supply and demand on the grid, securing electricity supply, transmitting electricity from producers to regional distributors, and facilitating the energy market. Our high voltage grid (TenneT, n.d.) The electricity flowing through the grid is generated from various sources. These include fossil fuels (natural gas, coal, lignite, oil), renewable sources (wind, solar, biomass, geothermal), and nuclear energy.

Households are not directly connected to the transmission network. Only some large industrial consumers are directly connected to this grid. TenneT transmits electricity from the source to regional distributors, which in turn supply power to consumers, or directly to large consumers. This is done by connecting the high-voltage grid and the distribution grids at high-voltage substations or switching substations. At these 'nodes', transformers convert the high voltage to low voltage, suitable for use by households, businesses, and organizations (Chappin, 2022). The intricate distribution networks do not fall under the responsibility of the national transmission network operator (TenneT) but under the responsibility of regional distribution net operators (including Stedin, Enexis, and Liander).

Balance on the electricity network
Because the electricity grid lacks storage solutions, there is a need to balance the demand and supply at any time. It is the responsibility of TenneT to manage the balance on the grid at a frequency of 50 hertz at all time and to ensure that no shortages or surpluses arise. Maintaining this balance is challenging, given the many different consumer patterns of all individual customers, the fluctuating supply of renewable energy by wind and sun, and the absence of large-scale storage possibilities for electricity. Especially shortages in electricity can lead to fallouts of parts of the electricity network (Chappin, 2022).

Because of the lack of large-scale storage solutions, at any moment there could be more electricity being fed to the net than there is being taken from the net. Solar energy projects and solar panels at households contribute to the mismatch between demand and supply, due to the unpredictable and fluctuating load. These developments mainly cause high fluctuations between summer and winter.

TenneT manages the balance in cooperation with balance service providers (BSP) and balances responsibility partners (BRP). Each supplier or buyer with a connection to the grid carries balance responsibility and needs to be connected to a BRP. A BRP is financially responsible for any imbalances that occur in his/her portfolio of grid allocation points and delivers portfolio forecasts to TenneT. BRPs have the ability to correct their own imbalance by changing load or production behind their allocation points or trading with another BRP. If an imbalance occurs in the Netherlands, TenneT sends a signal to the BSP who then activates balancing energy to reinstate the system balance. If the BRP contributed to an imbalance in the system, the BRP has to pay TenneT. or if the imbalance supported the system, the BRP will receive the imbalance price from TenneT. The costs for imbalance are being passed on to customers, causing increased electricity prices (Vattenfall, n.d.).

Another consequence of the limited storage options accounts for households with solar panels specifically. Because energy storage is a challenge, without a battery it is impossible to store electricity, e.g. electricity generated in summer until winter. A solution to this is the use of small-scale batteries for decentralized energy systems. The batteries are expensive, however, and still offer limited storing capacity for the price (van Zoelen, 2022). Besides, due to the advantages of the netting scheme, it is still relatively attractive to deliver electricity back to the grid, instead of investing in local energy storage (NH1, ST1). Batteries as part of a decentralized energy system are however seen as an important solution to balance and capacity problems on the grid. These problems will be elaborated on in the next section.

Grid congestion

Grid congestion occurs due to transmission constraints: a lack of transmission line capacity to transport electricity without exceeding thermal, voltage, and stability limits designed to ensure reliability (NRG, 2018). The demand for the transport of electricity, both at the producer and at the consumer, is larger than the available transmission capacity of the existing grid. Overall, there are two types of congestion: delivery congestion and feeding-back congestion. Delivery congestion occurs when the demand from an energy consumer is higher than the supplying transmission line capacity. This happens for example when many large consumers are connected to the grid within a small area. Feeding-back problems occur when for example generators of renewable electricity feed back unused electricity to the grid, at places where the grid is not adapted to two-way traffic (ST1, AL1).

The increased traffic of electricity causing grid congestion problems has several causes. One development that increased traffic on the grid is the changed electricity market. There has been a shift from a centralized energy system, where energy is generated at a few large sources and dispatched to consumers through somewhat one-way traffic, to a decentralized system where energy is also generated by consumers and fed back to the grid (ST1). This development results in increased traffic in new directions, where locations, where energy can be generated, do not match with the current capacity spread of the electricity net (Limited grid capacity endangers strong Dutch Solar growth (Dutch New Energy, 2021). This causes problems with feeding electricity back to the grid. The shift to a decentralized energy system is a development that has a large impact on grid operators in the Netherlands, who have to adjust the grid capacity to the shifted demand and supply of electricity to avoid grid congestion.

The congestion in the electricity net occurs most apparently in rural, sparsely populated areas, where traditionally there has been relatively little offtake of electricity. The grid, once built on the basis of a predictable production and offtake model, is not designed to cope with large peaks, particularly in these rural areas. Large-scale solar parks - a development of recent years - that want to establish themselves precisely in sparsely populated areas (cheap land and space), make great demands on the grid when transporting the peaks in generated solar power. Especially if several large producers of renewable energy in a region want access to the grid, the risk of overload is apparent. In addition, in urban areas, there is the problem that, due to the rapidly growing demand for data centers and the electrification of industry, grid operators are unable to increase the grid's capacity fast enough to meet all the demand (source: interview). Under the new connection policy adopted by the Ministry of Economic Affairs,1 Dutch transmission system operator TenneT is required to connect all new generation capacity to the transmission grid regardless of whether sufficient transmission capacity is available (van Blijswijk & de Vries, 2012).

A second development is the increased generation of renewable electricity due to environmental concerns and climate targets. Lower carbon emissions mean more electrification. The share of generated electricity increases and more renewable solar and wind projects arise. Another development is the increased demand for electricity over the years due to economic growth, the large housing assignment the government is facing, and the rapid digitalization of society, resulting in overall more traffic on the electricity grid (Liander, n.d.).The trends named above have the most impact on the grid when they cause increased traffic of electricity at one or a concentrated location.

Voltage issues on the grid

On the lower-voltage grid, where PV installations by small consumers or businesses are attached, congestion is still limited but solar panel installations mainly impact the voltage of the grid (AL1, AL3, ST3). Voltage issues arise when high levels of electricity are transported to the grid at the same time, mainly when the grid capacity is not built for such levels of transported electricity. To date, voltage issues occur frequently in neighborhoods with a large share of renewable energy generation. An important element in these issues at the low voltage grids is the simultaneity of consumption and generation of electricity. This issue arises both on a daily and yearly basis.

On a daily basis, generally, household energy consumption and generation of electricity by PV systems are not simultaneous. This means that for a large share of the consumption, which generally has its peaks in the morning, late afternoon, and evening, electricity is demanded from the grid. Only a small share of the generated electricity by solar panels is directly used. The remaining of this generated electricity is fed back to the grid. Especially when high levels of simultaneously generated solar energy by households are being fed back to the grid, voltage issues can occur.

On a yearly basis, PV electricity generation widely varies between different seasons due to the seasonal nature of radiation intensity. As the radiation intensity is impacted by hours of light and weather conditions, solar radiation is on average much higher during summer months compared to winter months. Thus, during summer months solar panels yield more electricity than in winter months. The average energy consumption of households however shows a contradictory pattern, where more electricity is demanded during winter months, such as for heating and lights. During the summer months, when PV yield is high, the increased transport on the electricity grid results in more voltage problems than during the winter.

A solution to voltage issues on the grid is an expansion of the grid capacity. When in a specific neighborhood for example, a large share of the households adopts solar panels, it is very likely that voltage issues occur and the grid needs adaptation (ST3).

3.5 Main conclusions Chapter 3

The relevance cycle revealed relevant policy measures, stakeholders, possible adoption barriers, and external influences that can serve as input for the Design Science Research cycle. Besides, the cycle aided in explication the problem at hand and identifying the relevant challenges and dilemmas. Doing so, this section answers research question 1:

What does the current landscape surrounding residential solar energy generation in Amsterdam and in the Netherlands look like, from a social, technical, economic and political perspective and through an energy justice lens?

The main findings resulting from the first research question are summarized below.

The impact of relevant policy levers on the system
The (grey) literature review and interviews have given a clear overview of the policies that currently influence the system or that might do so in the future. Policies currently in place include the netting scheme, tax subsidies, and in the year 2023, the energy price cap. The netting scheme policy is the most crucial policy momentarily. It significantly impacts PV adoption behavior, raises questions about energy-justice matters, and increases pressure on the grid and electricity system. Doing so impacts many stakeholders including households, grid operators, utility companies, and policymakers. The netting scheme policy in specific is an ongoing point of debate both in politics and in literature, as the scheme is increasingly linked to notices of injustice and inequity. This is mainly due to the fact that the scheme can cause distributive injustices: the benefits of the scheme are not equally accessible to households and the costs of the scheme are socialized to all citizens.

The impact of important external factors on the system
Many external factors have been revealed during the relevance cycle that directly or indirectly impacts the system of PV adoption. The price of PV systems and energy prices impact the adoption decision-making. Geopolitical developments have played an important role over the past years, increasing uncertainty in the energy market and energy prices. PV efficiency has increased over the years and, together with solar radiation, increases the potential electricity yield for consumers and thus increases PV attractiveness. Public awareness for renewable energy generation has accelerated over the past years, which has greatly contributed to favorable policy incentives and increased adoption rates for renewable energy generation. A shortage of materials and technicians has both impacted the speed of PV adoption and installation and the speed of grid expansion.

The main identified challenges
Grid congestion and voltage issues. Increasing capacity on the grid is the main challenge for grid operators, given the limited resources and capital. Grid expansion is needed because of voltage issues and congestion issues. The non-simultaneousness of demand and supply is an important cause of the pressure on the grid: demand and supply are often not at the same time. Households can experience the increased pressure on the grid through PV converters that shut off due to overvoltage on the grid.

Anticipating PV adoption. The municipality and grid operators experience anticipating PV adoption by households as a challenge, given the largely unpredictable nature of consumer PV adoption. Predictions are complicated because of the many socioeconomic factors and external "drivers", such as electrification of the industry, the netting scheme, and the energy prices. Therefore, additional insights into explanatory variables of adoption are useful. Scenarios are needed to evaluate future development given the significant impact of external factors.

The main identified adoption barriers

Municipalities distinguish several target groups when it comes to PV adoption, including homeowners, OAs, commercial renters, and housing corporations. There is a large difference in complexity between these groups. The adoption barriers for solar panels are partially clear, however, non-adopters are not a very clear target group. Several observed adoption barriers through the interview process are the ownership of property, access to a roof, household income, and language/information barriers. These adoption barriers indicate that some groups within society have limited opportunities for purchasing a PV installation. For some households, the initial investment of a PV purchase is too high. These households also cannot benefit from the advantages of the netting scheme. Besides, PV generation and specifically the netting scheme cause additional costs for grid operators and utility companies such as balancing costs, as customers with solar panels increase the pressure on the grid. These costs, together with the netting scheme costs, are socialized to all customers, which creates justice complications.

Energy justice implications following from the system description

The identified system and its stakeholders, external drivers, challenges, and barriers reveal multiple possible inequities caused by justice implications. The diversity in actor power could imply procedural justice complication: not all actors might have equal participation in the decision-making process. This injustice can exist between actor groups (grid operators vs. citizens) but also within actor groups: different socioeconomic characteristics such as income or race can influence decisions making power (Si & Stephens, 2021). The netting scheme policy has implications for distributive justice: not all citizens experience the benefits and burdens of the policy equally. Recognition of injustice results more implicitly from the injustices above, where it is about recognizing the rights of different groups, particularly the underserved groups or minorities. Several literature studies identify the injustices named above - although none cover the Netherlands as a study area. In the United States for example, Si and Stephens (2021) identified societal groups that have less political power than other target groups and less ability to participate or be represented in the solar-energy policy process.

Energy poverty, a nation often linked to energy justice, is an increasing problem in the municipality of Amsterdam. Though residential solar energy generation has a large potential for alleviating energy burdens and thus decreasing energy poverty, it is the households that experience energy poverty that cannot afford the technology.

The system explication and literature studies clearly point towards possible justice implications that can arise in the solar energy field. Most literature research covers geographic areas outside of the Netherlands. To properly understand the justice implications at stake, a clear assessment of the solar adoption behavior is necessary. The remaining study will focus on identifying socioeconomic groups that are under-served when it comes to solar panel adoption, and how external drivers and policy levers impact this.

4 Residential solar energy adoption and generation

Whether households adopt solar panels, is determined by several factors. Research question 2 aims to map these factors as described in previous studies:

What factors contribute to the technical and social potential of rooftop solar generation through PV-systems?

By answering this research question, insights can be used for the operationalization towards a design artifact. This section covers a definition of solar panel adoption potential, including the main factors determining adoption behavior, in Section 4.1. Next, these factors are explicated in more detail. Section 4.2 describes the rooftop suitability factors, and Section 4.3 describes the consumer characteristics related to adoption behavior.

4.1 PV adoption behaviour

A comprehensive literature study is conducted on solar panel adoption and potential studies. This literature review revealed that many factors come to play during the adoption decision-making process. On the one hand, adoption behavior is determined by consumer characteristics (Bouaguel & Alsulimani, 2018), (Vasseur & Kemp, 2015b), (Lan et al., 2021), and more. Consumer characteristics include demographic factors, as well as perceptions of external factors that influence the decision-making process. On the other hand, rooftop suitability forms a direct physical determinant of PV adoption. To structure the factors influencing the adoption decision-making process, the diagram in figure 9 is constructed. This diagram is not conclusive but gives an overview of factors that have been noted in the literature to influence PV adoption. A limited fraction of the literature spends attention on external drivers (such as electricity prices) as a separate factor of influence. Rather, these factors are embedded in the consumers' behavioral and psychographic characteristics. This way, it is assumed that the *perception* of consumers of these external drivers impacts their choice for adoption.

The factors presented in the diagram are explained and detailed in the sections below. Section 4.2 discusses the rooftop photovoltaic potential and Section 4.3 discusses the consumer characteristics.

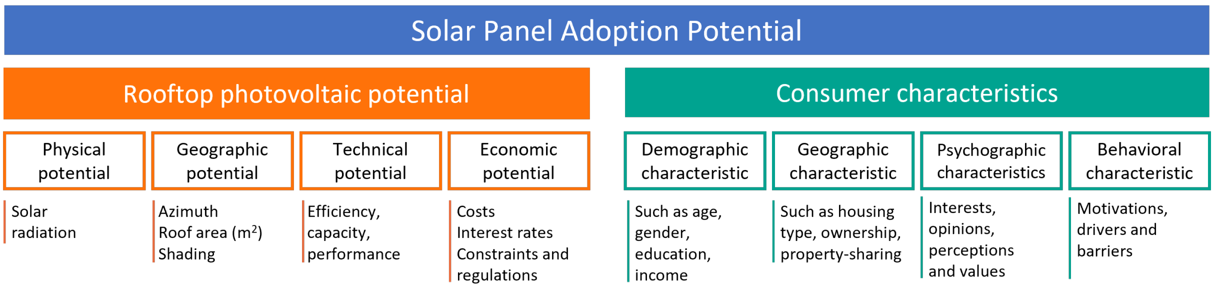


Figure 9: Representation of determinants for solar panel adoption. Source: author

4.2 Rooftop photovoltaic potential

In order to understand rooftop photovoltaic potential, a basic understanding of photovoltaic technology is necessary. Therefore, this section starts off with an introduction to electricity generation through photovoltaic technology. Next, the important factors for electricity generation are discussed. Finally, rooftop characteristics determining rooftop suitability are described.

4.2.1 PV systems: Solar cells and electricity generation

Solar panels, or photovoltaic cells are used to convert solar power into electricity. Photovoltaic (PV) is a combination of the words photo ('light') and voltaic (electricity). PV converts solar irradiance into electricity that can be used in on-grid and off-grid applications (Boxwell, 2012). When the sun shines onto a solar panel, energy from the sunlight is absorbed by the PV cells in the panel. This energy creates electrical charges that move in response to an internal electric field in the cell, causing electricity to flow (Veen, 2014). The more light and the higher the intensity of the light, the greater the flow of this current. Several applications of solar panel systems exist, such as rooftop-mounted systems or solar parks. Given the scope of this study, this section focuses on rooftop-mounted PV systems.

4.2.2 Rooftop installations

Solar Panel types

Two main types of solar panels are currently available on the commercial market: crystalline silicon panels and thin-film panels. The division is based on the material properties of the semiconductor that makes up a solar panel. In the current market, crystalline silicon panels account for >90% of total production worldwide (Tozzi et al., 2020). Within these two main types, module technologies differ based on the material used and/or the structure of the panel, giving each technology unique characteristics. Important panel attributes include efficiency, performance at high temperatures, and production costs. The efficiency is the fraction of the total energy a solar panel can convert to usable electric energy. Besides, panels differ in production costs and commercial market prices, whereas in general panels with higher efficiency are more complex to produce, and thus more expensive (Tozzi et al., 2020).

Generally, solar panel systems consist of several elements, besides the panels described above, a solar panel system includes an inverter, a power meter connecting the system to the utility grid, racking, and possibly a battery system. Racking ensures that the panels are securely attached to the roof. An overview of the components of a grid-connected residential solar panel system is shown in figure 10.

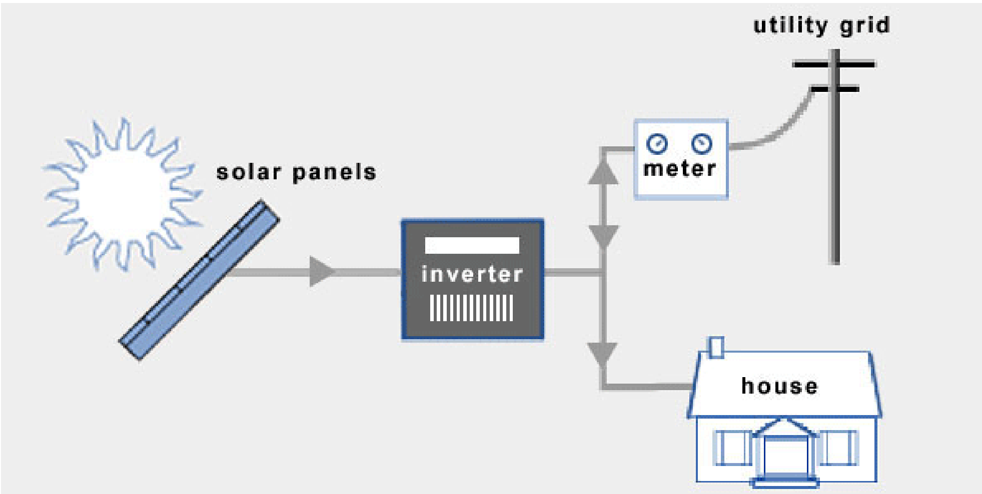


Figure 10: Components of a grid-connected residential solar panel system. Source: Solar Electric (n.d.)

Converters and batteries

Solar panels rarely power electrical equipment directly. The current from all the connected solar panels is collected and fed into an inverter. This inverter changes the direct current (DC) from the panels into alternating current (AC), which allows using the electric current for appliances at home or to feed electricity back into the grid (Boxwell, 2012). A battery can be used to store electricity from the moment of generation to the moment it is needed for consumption. In the Netherlands, the march of battery-storage solutions is limited given the high prices of these systems (NH1, ST1).

Grid-connected systems

In the Netherlands, most commercial PV installations are grid-connected (AL2). Grid-connected solar systems are systems directly connected to the national utility grid. Some of the produced electricity is directly consumed by the owners. During the day when the sun is shining, these systems transport (sell) excess electricity to the grid which is then used elsewhere. During the night, when there is no sunshine, consumers buy electricity from the grid as required. Grid-connected solar systems have largely contributed to the shift towards a distributed electricity system in the Netherlands (Al1).

4.2.3 Electricity generation factors

A wide range of factors influences the electricity generation of PV systems, of which the most important ones are described below.

- Solar irradiance. The quantity of power coming from solar sources per unit area is known as irradiance (Boxwell, 2012). The energy produced by a photovoltaic module is directly related to the availability of solar energy and is, therefore, location dependent. Incoming solar radiation (insolation) originates from the sun and is modified as it travels through the atmosphere and reaches topography and surface features. The radiation is intercepted at the earth's surface as direct, diffuse, and reflected radiation (see figure 11). Direct radiation is received in a direct line from the sun. Diffuse radiation is scattered by atmospheric objects such as clouds and dust. The reflected radiation is reflected from surface features such as the ground. The sum of the direct, diffuse, and reflected radiation is called total or global solar radiation. Generally, direct radiation and diffuse radiation contribute most to the total radiation, and reflected radiation only constitutes a small proportion. Therefore, in most radiation models only the direct and diffuse radiation are included (ArcGIS Documentation, 2021a). Irradiance usually fluctuates according to the weather and the sun's location in the sky. The location of the sun changes throughout the day due to changes in the sun's altitude (the angle between the sun's rays and the horizontal plane) and the azimuth angle (the angle between true north and the projection of the sun rays onto the horizontal) (Fouad et al., 2017).

- The module temperature. A PV cell converts a small portion, approximately less than 20%, of the irradiance into electrical energy while the remaining is converted into heat (Fouad et al., 2017). Solar panels can warm up to temperatures above 70°, making it crucial that the panels keep their performance under high temperatures (Tozzi et al., 2020).
- Dust accumulation. Some of the sunlight can be blocked from the PV module due to the presence of dirt or dust. This causes a considerable amount of losses in the generated power since the solar irradiance is scattered on the surface of the solar panel (Meral & Diner, 2011).
- Shading. Shadows, caused by trees, buildings, or other objects near roof installations, lower the power output from PV panels. Viitanen and Halonen (2014) showed that the power output can be reduced up to 80% when only 5-10% of the panel is shaded.
- System degradation. PV panels degrade over time, due to a degradation of PV materials, cells, corrosion, or broken connectors. A panel is considered degraded when it reaches a level below 80% of its initial power. On average, solar panels are expected to last 25 to 30 years.
- Performance ratio. The performance ratio is a measure of the quality of a PV panel that is independent of location. The performance ratio is stated as percent and describes the relationship between the actual and theoretical energy outputs of the panel. Performance ratio ranges from 46% to 105% (A. Walker & Desai, 2011).
- System sizing: the number of PV modules installed. A PV system has to generate enough energy to cover the energy consumption of the loads and the energy used by the system itself.
- System surface area. The larger the surface area of a PV system, the higher the potential electricity yield.
- Panel efficiency. A PV panel has an energy conversion efficiency, which represents the percentage of collected power that is converted when a PV cell is connected to an electrical circuit. The efficiency, therefore, depends on the PV panel, the surface area of the panel, and the solar irradiance (Boxwell, 2012).
- PV material. Different photovoltaic materials exist and each has its own efficiency. Solar cell materials include crystalline silicon, thin-film (such as cadmium telluride and copper indium gallium diselenide) and perovskite photovoltaics (U.S. Energy Department, n.d.). Crystalline silicon cells are the most efficient among the current commercially-available solar cell technologies.

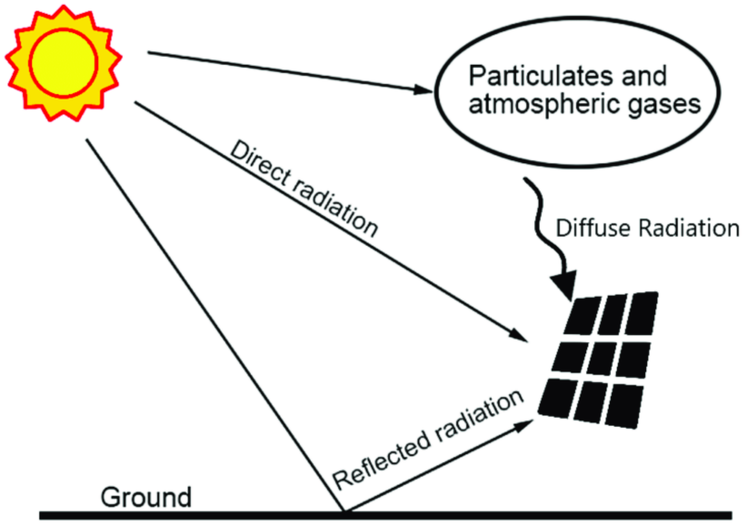


Figure 11: There are three types of insolation: direct, diffused, and reflected radiation. Source: ArcGIS Documentation (2021a)

4.2.4 Rooftop suitability assessment

Several attempts and various methods for urban solar PV roof suitability determination exist within literature, where the earliest literature dates back to 2010. The number of studies in this field increased significantly during the past 10 years, mainly due to technological advancements, the need for precise knowledge of solar energy resources for electricity production, the rising energy crisis, and environmental concerns (2021). A clear shift can be seen when comparing the literature on this topic between 2010-2015 to the literature between 2015-2020: statistical sampling approaches disappeared and Artificial Intelligence approaches appeared and immediately became the largest share. The attempts differ in approach, method, data, project scale, and focus. The methods include physical and empirical models, geostatistical methods, constant-value methods, sampling methods, geographical information systems (GIS) methods, light detection and ranging (LiDAR)-based methods, and machine learning methods (2017). Many papers, however, adopt a combination of these methods.

Several roof characteristics are important in determining the rooftop photovoltaic potential. The selection of variables used strongly depends on the project scales, data availability and method used. Overall, regardless of the methodologies and project scales, different sub-potentials can be determined and studied in order to assess rooftop photovoltaic potential. These sub-potentials are shown in figure 12, which is adapted from Fakhraian et al. (2021).

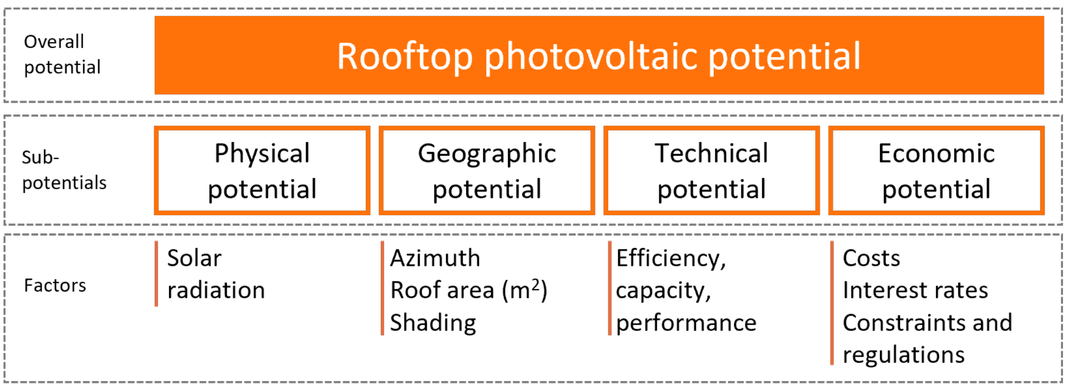


Figure 12: Sub-potentials and factors for rooftop photovoltaic potential determination, adapted from Fakhraian et al. (2021)

The physical potential is the solar power available, that is, the solar irradiance coming to the zones of interest. It represents the resource's maximum energy received from the sun by the roof area. The geographical potential is the portion of the physical potential captured over the restricted area, more specifically here the available area for PV installation on roofs. It essentially considers factors such as rooftop geometry, other buildings, and trees, shading effects, structures on rooftops, rooftop inclinations, and rooftop slopes (Fakhraian et al., 2021). The daily and monthly energy production from PV panels is for example strongly influenced by the module orientation. The technical potential is the actual electricity generated by the PV panel by transforming the solar energy received by the available roof area into electrical energy. The technical potential considers the technical characteristics of the solar photovoltaic technology such as the efficiency and performance, as described above. The economic potential represents the installation's economic attractiveness under current market conditions. This sub-potential takes into account installation costs, maintenance costs, installation lifetime, interest rate, and governmental regulations. The technical potential is based on the assumption that building owners will only consider investing in rooftop photovoltaic installations when these facilities are economically justifiable (Fath et al., 2015).

4.3 Factors contributing to adoption behavior

Consumers have different personal characteristics and traits that influence adoption behavior. There is an extensive body of literature on PV adoption factors, motives, and intentions. Research into PV adoption has traditionally focused on financial drivers and economic analyses, but a growing body of social science energy research has broadened the focus to include a range of non-financial factors that influence energy behavior (Bach et al., 2020). Research on attribute preferences and perceptions ((Vasseur & Kemp, 2015b), (Dharshing, 2017), (Schulte et al., 2022)), socioeconomic adopter characteristics ((Margolis et al., 2017), (Sommerfeld et al., 2017), (Balta-Ozkan et al., 2015), (Lan et al., 2021)), and behavioral characteristics ((Sun et al., 2020), (Vasseur & Kemp, 2015b), (Zhang et al., 2011)) have developed a nuanced understanding of the drivers and barriers of PV adoption. The study is wide-ranging in terms of methodological approaches and case-study locations. While not a systematic review nor an exhaustive list of PV adoption research, this Section summarized the diversity of factors influencing the adoption process.

Within literature, several dimensions of PV adoption understanding are observed. Studies cover amongst others consumers' preferences, perceptions, demographic variables, behavioral characteristics, motivations, and barriers. To structure the insights that have already been informed by literature, broadly four types of dimensions are distinguished to understand PV adoption behavior, inspired by Vasseur and Kemp (2015b): demographic characteristics, geographic characteristics, psychographic characteristics, and behavioral characteristics.

- Demographic characteristics refer to age, gender, family composition, education level, housing type, and income (Vasseur & Kemp, 2015b). Geo-demographic segmentation involves a combination of geographic and demographic factors. This segmentation is based on the notion that people who live close to one another are likely to have similar financial means, tastes, preferences, lifestyles, and consumption habits (Schiffman & Wisenblit, 2021).
- Geographic characteristics include characteristics related to the living situation and area of consumers, such as the housing type, housing situated, ownership, and number of residents per dwelling.
- Psychographic characteristics, or lifestyle characteristics, refer to activities, interests, opinions, attitudes, and values (Vasseur & Kemp, 2015b). These include perceptions of product characteristics and governmental incentives.
- Behavioral characteristics divide consumers into groups according to their motive to buy/benefits sought (price, esthetic, functionality, idiosyncratic preferences), readiness to buy, and occasions (events that stimulate the purchase). Behavioral characteristics include the motivations and the barriers to adopting a PV system.

This study focuses on socioeconomic influences on PV adoption. However, it is deemed necessary to understand the broader context of solar panel adoption behavior in order to properly study its diffusion. Looking at the dimensions above, this study includes demographic characteristics and geographic characteristics, which are taken together in this study in the term socioeconomic characteristics. For each of the dimensions, findings from literature are discussed below.

Psychographic characteristics
Considering psychographic variables, Vasseur and Kemp (2015b) find that climate change is a concern for people with a positive attitude toward PV. The price of a system is a major issue perceived by all respondents in their study. Adopters consider the costs for PV affordable, while non-adopters view the costs as too high. A study by

Dharshing (2017) revealed that the environmental attitude had significantly positive impacts on PV adoption. The results of a study by Schulte et al. (2022) imply that with stronger environmental concern and a stronger propensity to innovation, the perception of the benefits of PV systems increases.

Many studies suggest that solar PV systems markets rely heavily on governmental support policies (Hsu, 2012), (Parker & Paul, 2008). Within studies on psychographic characteristics, a share of attention, therefore, goes toward the perception and importance of governmental support. Sun et al. (2020) report that crucial factors for the diffusion of solar energy systems are financial incentives, government-led initiatives, and reductions in investment costs.

Perceptions and values are impacted by a consumer's environment. Several studies investigated the so-called "peer effect". Palm (2017) report that the participants in their study acknowledged peer effects as important for their adoption decision, although they had in general been seriously contemplating PV adoption before the effects. The study concludes that the main function of peer effects appears to have been a confirmation that PV works as intended, rather than the procreation of unexpected insights or the provision of more advanced information. Noll et al. (2014) state that positive peer effects for PV can increase the likelihood of adoption and decrease the length of decision time. They find that peer effects had mainly occurred through existing and rather close social relationships, rather than between neighbors that did not already know each other. Salazar et al. (2013) also confirmed that peer groups like colleagues, family, and friends may affect the decision to choose environmentally friendly products rather than conventional ones.

Behavioral characteristics

Behavioral characteristics study the motives, barriers, and drivers of PV adoption. In terms of motives, Veen (2014) found that financial benefits were the most important motive for households who install and use a PV system, followed by environmental concern, independence from energy suppliers, and being self-supporting. The findings from Sun et al. (2020) do not support the positive influence of environmental concern on the attitude toward rooftop PV installation. They do agree that financial motives are the main motive for PV adoption.

In terms of barriers and drivers, many studies find similar results. High investment costs and long capital payback times are the main barriers for households for installing PV systems in the study of Veen (2014). Uncertainty and/or knowledge gaps about (future) subsidies and legislation and about (future) technology development were found as barriers. Knowledge gaps are also observed to be an adoption barrier by Vasseur and Kemp (2015b). These authors also observe that for the vast majority of non-adopters, the high investment costs of PV are the most important barrier followed by a large distance with low energy yield. Similarly, Sun et al. (2020) find that high costs are the primary barrier to installing PV systems, and they suggest a strong preference for capital incentives to reduce investment costs is needed. They conclude that subsidies and incentives are among the key drivers of global solar PV systems. Zhang et al. (2011), who also studied adoption barriers and drivers, reported that the high capital costs were identified as a barrier to households' willingness to install PV panels, while also indicating that government subsidies, housing investment, and environmental awareness had significant positive impacts on the PV adoption outcome could be used to promote the PV installation among households.

Demographic characteristics

When looking at demographic characteristics, many studies have demonstrated that socioeconomic differences contribute to the regional disparity of PV adoption. There is some general consensus on the direction of the relationship between demographic characteristics and PV adoption. Studies suggest that households are typically between 45-64 years old have high or middle incomes, and own their home (Veen, 2014), (Vasseur & Kemp, 2015b), (Sommerfeld et al., 2017), (Sardianou & Genoudi, 2013), (Dharshing, 2017), (2017). Regarding education, studies differ in observations. Vasseur and Kemp (2015b) find that adopters have a higher education than non-adopters. This is in line with the findings from Sardianou and Genoudi (2013), Dharshing (2017), and Balta-Ozkan et al. (2015). Sommerfeld et al. (2017) however found education, as well as income, to be less significant. Their study showed the greatest significance of dwelling type, home ownership, household composition, and age.

Sardianou and Genoudi (2013) also find that income had a positive impact on people's likelihood to adopt PV and that marital status and gender were not statistically significant. Unique from other studies, Margolis et al. (2017) find the number of rooms and house age to be key influential variables. Balta-Ozkan et al. (2015) found that the number of PV installations in a region was negatively related to its density, the average number of households, and the share of home ownership, while positively related to the share of detached homes.

To summarize, previous studies have proved that socioeconomic variables play a significant explanatory role in residential PV adoption across the world. While many studies examine individual relations of factors with PV adoption, Lan et al. (2021) investigated the intercorrelation of socioeconomic factors and concluded that variables interplay with each other to condition their individual explanatory effect on the regional difference of residential solar PV adoption. For example, a high income is found to be a stimulant for adoption, but the concurrence of a high income with home ownership or property-sharing may discourage PV adoption.

Geographic characteristics
Multiple studies linked home ownership, dwelling type or property-sharing to adoption behavior (Sommerfeld et al., 2017), (Balta-Ozkan et al., 2015), (Vasseur & Kemp, 2015b). Balta-Ozkan et al. (2015) find that the number of PV installations in a region was negatively related to the share of home ownership, while positively related to the share of detached homes. Citizens who have their own houses have a more positive attitude towards PV adoption than the respondents who rent. Concerning housing type, Vasseur and Kemp (2015b) report that the majority of the respondents with solar panels in their research live in the middle of row dwelling. Living in an apartment is identified as a physical barrier.

There seems to be consensus on the importance of home ownership and attitude towards PV adoption. The domestic sector in the Netherlands is divided into three types of ownership: (1) owner-occupied sector in which the residents themselves are the decision makers, (2) private rental sector in which private landlords make the investment decision, (3) public rental sector in which housing associations make the investment decision (Vasseur & Kemp, 2015b). Each sector represents a different type of decision-maker with respect to the purchase of PV.

Bach et al. 2020 notes that besides the more well-studied technical and economic factors, there are various place-specific societal factors influencing uptake, including social and cultural differences. These societal factors can vary within and between countries. socioeconomic differences are also not just perceived on a national scale. Even within a given country, research findings are not always consistent.

Technology diffusion studies
Technology diffusion theory seeks to explain how, why, and at what rate technologies spread. Diffusion studies cover a broad range of studies and methods. Generally, diffusion studies evaluate the adoption of a technology by a population, where the diffusion speed and extent depend on several factors including the nature and quality of the innovation, how information about the innovation is communicated, and the characteristics of the population into which it is introduced.

During a diffusion process, consumers go through different stages. This process is referred to as the innovation-decision process. It consists of the following five stages: knowledge, persuasion, decision, implementation, and confirmation. First, a consumer becomes aware of an innovation and some knowledge is gained on the presence of that innovation. Next, the consumer starts to form a certain attitude, either towards the innovation at the persuasion stage. At this stage, he or she seeks further information about the innovation actively. During the decision stage, the consumer takes part in activities that end with the adoption or rejection of the innovation. The implementation stage refers to the period when the consumer has adopted the innovation and is deploying it. Finally, the confirmation stage occurs for some time after adoption or rejection where the individual is convinced of his or her own decision to adopt or reject (Rogers, 1962).

The diffusion of innovation theory provides an understanding of the rationales for household consumers to purchase solar panels. The studies are used to identify some of the factors described in Section 4.3.

4.4 Main conclusions Chapter 4

This section covers research question 2:

"*What factors contribute to solar panel adoption behavior?*"

The potential for residential solar panel adoption broadly depends on rooftop suitability and consumer characteristics. Considering rooftop suitability, the factors to be examined depend on the methodology used. Generally, rooftop photovoltaic potential can be divided into four sub-potentials: technical potential, geographic potential, physical potential, and economic potential. Generally, when assessing roof suitability, one examines a combination of these factors.

Considering the adoption behavior of solar panels, it appears adoption choice behavior is complex, and determined by amongst others: demographic characteristics, geographic characteristics, behavioral characteristics, and psychographic characteristics. In literature, these characteristics have been identified through numerous studies and methods, of which the technology diffusion theory is a popular approach. Within the existing studies, there appears to be consensus on the general directions of some factors, e.g. the negative effects of perceived barriers, as well as the positive effects of perceived benefits and general personal motivations (such as environmental attitude). Given the focus of this study, a socioeconomic perspective of PV adoption, several characteristics are found to be significant in the literature. These factors include the consumers' income, house ownership, property-sharing, age, and dwelling type. On some variables, literature studies differ in conclusions. There is no clear consensus on the relationship between gender and education. It however remains difficult to compare study results. Uncertainties remain related to the inconsistent use of predictors, different operationalizations of predictors, differences in dependent variables assessing PV adoption, and different contextual and political environments (e.g. subsidy programs, different market maturity states) (Schulte et al., 2022).

With the literature study results in mind, it is important to note that PV adoption factors are highly location-specific, especially socioeconomic factors. Research at different locations has yielded contradicting results in the past, and differences are not just at the national scale. This location sensitivity for the investigation of energy behaviors may help to explain why some previous studies have produced different findings regarding the drivers and barriers of PV adoption. Differences on the one hand occur due to different political environments. But even within a given country, research findings are not always consistent (Bach et al., 2020). This observation has two main implications. On the one hand, it emphasizes the need for local investigation of adoption factors instead of generalization of the findings from the literature review to this study. Second, it emphasizes the need for targeted policy designs that are based on place-specific societal factors, instead of a one-size-fits-all perspective.

It should also be noted that the technology diffusion process is a complex decision-making mechanism. This section is not conclusive of the factors that might play a role but aim to map the factors that are most relevant to this study.

5 Operationalization towards a Design artifact

Chapters three and four described the relevance and rigor cycle of the Design Science Approach. The central design cycle combines the results from the two previous cycles to develop a new and relevant artifact that enables answering the main research question. This section will build upon these results and operationalize them into a suitable artifact design.

In the relevance cycle, the landscape surrounding solar panel adoption was investigated, including the political, technical, social, and economic context. The analysis, performed with literature research and semi-structured interviews, revealed the important system elements and dynamics, and the current challenges and perceived dilemmas, from a multi-actor perspective. An XLRM diagram is composed of presenting the main external factors (X), policy levers (L), relationships within the system (R), and performance metrics (M), that have come forward during the relevance cycle (see figure 13). During this cycle the dynamic nature of the system and its sensitivity towards external factors and policy levers became apparent.

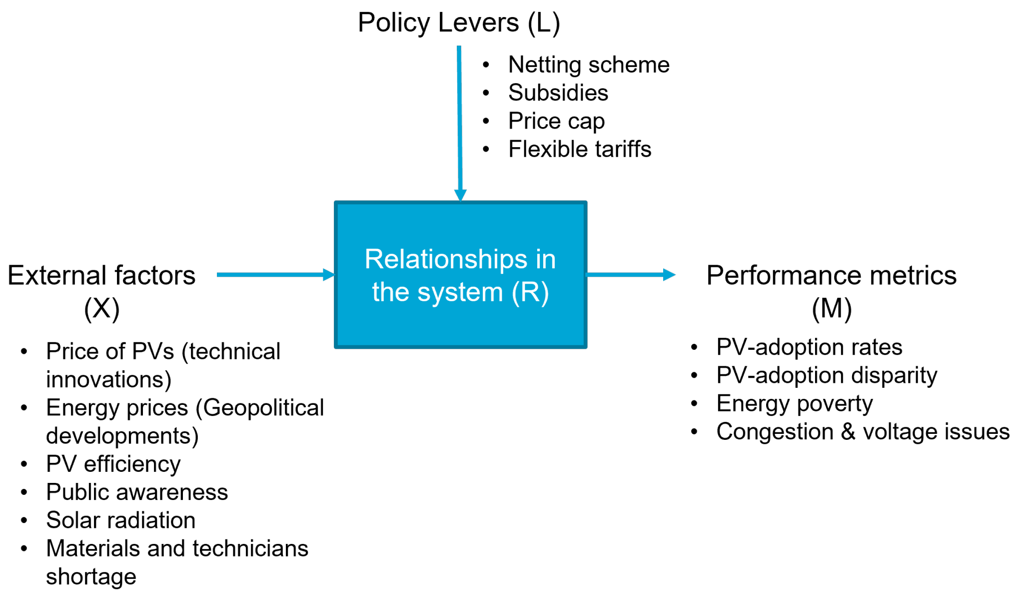


Figure 13: XLRM diagram for the studied PV adoption system. Source: author.

The rigor cycle shaped the understanding of the factors that seem to influence PV adoption choices by consumers, both considering rooftop suitability and socioeconomic context. It is learned that factors influencing solar panel adoption can roughly be divided into socioeconomic factors, rooftop suitability, and psychographic variables. Many socioeconomic variables have been linked to relate to PV adoption in previous studies, however, due to the local characteristics of these factors, it is difficult to scale these findings to other locations. Therefore, the studies have served as an inspiration for the socioeconomic analysis is this study.
The outputs of the rigor and relevance cycle are used to formulate an artifact that can answer the main research question. To be able to answer the research question, firstly, there is a need to understand the current state of PV adoption, how this adoption is spread amongst different groups in society, and what socioeconomic factors correlate with PV adoption. Although factors behind PV adoption behavior are complex, interrelated, and multi-dimensional, insights into what socioeconomic characteristics correlate with PV adoption might increase understanding of adoption behavior, and aid in targeted policy-making in the future. Second, there is a need to understand how PV adoption might develop in the future, under different external factors and policy measures. Understanding the dynamics of PV adoption allows us to inform measures to stimulate PV adoption and the disparity of the adoption amongst different societal groups. This Section proposes an artifact design to address both objectives.

The results so far emphasize the need for an integrative and dynamic analysis of PV adoption. A static approach, i.e. solely investigating what adoption patterns are currently perceived, does not suffice in addressing how PV adoption can be improved. An understanding of how the system reacts to external factors and policy measures over time is needed to properly understand PV adoption dynamics. The proposed artifact therefore includes an integrated approach, that evaluates both the current state of PV adoption and the dynamics of the system over time. The approach thus essentially consists of two, connected, parts. The initial artifact design is shown in figure 14.

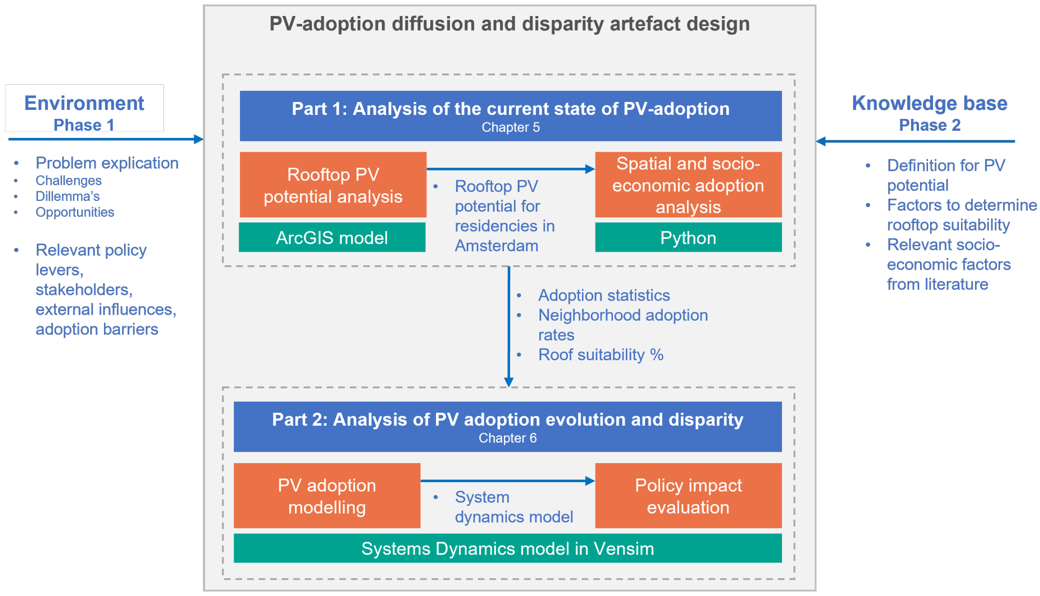


Figure 14: Artifact design

5.0.1 Part I: The spatial and socioeconomic analysis

First, in order to move towards a method to analyze the dynamics of PV adoption, a proper assessment of the current state of and potential for PV adoption is needed. This analysis should investigate adoption potential, current adoption patterns, how adoption is spread amongst different neighborhoods, and whether a so called "adoption gap" exists. The analysis is split into two sub-parts: an investigation of the spatial rooftop PV potential and a study on neighborhood socioeconomic data and corresponding adoption patterns. The aim of the spatial analysis is to investigate what the rooftop PV potential is for residential PV deployment in Amsterdam. In Section 4.2, it is explained that rooftop PV potential consists of physical, geographic, and technical potential. All of these will be covered to assess the overall rooftop PV potential for residencies in Amsterdam.

To be able to accurately investigate adoption patterns and, more specifically, why some neighborhoods have lower adoption patterns than others, it is important to determine what the potential for rooftop solar generation is per neighborhood. Little to no PV adoption could be caused by lacking rooftop potential for electricity generation within a neighborhood. Therefore, prior to investigating the relationship between adoption and socioeconomic factors, the rooftop PV potential is considered.
Many methods of estimating rooftop PV potential have been developed, ranging from simple multipliers of total building space (Molnár et al., 2022) to methods that employ complex geographic information systems (GIS) (Yesilmaden & Dogru, 2019) or three-dimensional (3D) models (Han et al., 2022). Some studies assess solely either the physical, geographic, or technical potential, while others take an integral approach to cover all three. Geographic Information Systems (GIS) is a technology that connects location and attributes, which facilitates spatial investigation, data capture, presentation, and analysis (Goodchild, 2009). Melius et al. (2013) identifies three main approaches to estimating rooftop suitability: constant-value methods, manual selection, and methods based on geographic information systems (GIS). The manual selection methods were found to produce detailed results but were labor-intensive, and cannot be replicated on a large scale. The constant value methods were quick. On the other hand, these did not reproduce local characteristics. GIS-based methods supplied detailed maps and may be automated. The GIS-based methods provide more precision than constant-value methods while handling much larger data sets than manual selection. They require either orthophotography or LiDAR data as input for their models (D. Palmer et al., 2016). In more recent years, Artificial Intelligence (AI) approaches, such as machine learning, also increasingly appeared in the literature. AI approaches like machine learning are explored because of the model scalability, computational power, and ability to automatically detect obstacles, materials, slopes, and areas from satellite imagery ??. AI approaches are however time-consuming to

develop and train and require extensive data sources and data quality (Assouline et al., 2018).

For this analysis, a GIS-based approach is chosen to analyze the rooftop PV potential of residential rooftops. This approach is found to be suitable given the high precision of results, the availability of necessary data for the study area, and the ability to handle large data sets. Several previous applications have proven the accuracy and suitability of this method (Margolis et al., 2017).

For the second analysis, adoption patterns and socioeconomic neighborhood statistics are analyzed using descriptive statistics and correlation analysis in Python. The overall geospatial distribution of PV adoption is examined, including the temporal dynamics of solar uptake since 2016, and a correlation study of PV deployment with predictor variables. These predictor variables are socioeconomic neighborhood indicators that cover multiple themes including population, income, and education. An analysis at the neighborhood level is chosen based on the availability of data and the level of granularity that is wished for. Considering the availability of data, at the individual household level very little data is available due to privacy reasons. A dataset was acquired on the postal code level, which is more granular than the neighborhood level, but the quality of the dataset was poor and included a lot of missing data points. The data on the neighborhood level was of good quality and included more than 100 socioeconomic indicators within different themes and little missing data. Besides, in the performed interviews it came forward that policy plans at the municipality level are often formed at the neighborhood level, which makes analysis at this granularity suitable.

5.0.2 Part II: Modelling PV adoption (disparity)

Second, the spatial adoption patterns and distributions derived from the first step of the design cycle, are used to develop a dynamic simulation model of PV adoption in the municipality. The model aims to investigate how the adoption rates and disparity of PV adoption might develop in the future, and how several policy measures and external influences influence the system. Besides, it is investigated what policy measures can be used to close a possible adoption gap and how effective these are. To model PV adoption dynamics, a System Dynamics approach is chosen.

What is System Dynamics?
System Dynamics (SD) is a method to describe, model, simulate and analyze dynamically complex issues and/or systems in terms of processes, information, organizational boundaries, and strategies. SD allows us to identify desirable system changes and test them in a 'virtual laboratory' (Pruyt, 2013). It is a widely adopted approach used to understand the behavior of a complex system as determined by its components. In other words, a change in each component will affect the final behavior of the complex system.

The system dynamics approach has emerged as a robust methodology to analyze and simulate complex feedback systems. By simulating various scenarios, a better comprehension of the dynamic behavior of systems over time can be obtained. The central elements of the system dynamics methodology encompass variables in mathematical equations, which present stocks and flows, as well as causal relationships. By employing computer simulations, the actual influence of the social system under a policy can be observed in a laboratory setting to comprehend the implied causal feedback in the system. Consequently, a "policy laboratory" can be established through system dynamics, which allows decision-makers to simulate diverse policy scenarios. The system dynamics approach in this study is adopted from Pruyt (2013). The resultant findings can subsequently be utilized to enhance the quality of their decisions. Hence, the formulation of system dynamics is appropriate for this study (Hsu, 2012).

Why System Dynamics?
System dynamics is a modeling approach based on a systems perspective, commonly used to design and evaluate public policy, to aid policymakers in the development of policy dealing with complex and dynamic systems, such as energy systems and infrastructure. A number of recent studies use system dynamics to model renewable energy systems on a broader scale. System dynamics is commonly used to model the implementation of solar and other renewables into the energy system.

Several System Dynamics studies have been performed regarding PV adoption rates and dynamics under netting schemes and feed-in-tariffs. Many of these papers focus on the so-called "utility death spiral", or on the effect of policy levers such as feed-in-tariffs on PV adoption (Castaneda, Franco, et al., 2017) (Costello & Hemphill, 2014) (Grace, 2018) (Meehan, 2015) (Felder & Athawale, 2014). The utility death spiral is a phenomenon that may occur when a greater ratio between the electricity tariff and the cost of solar PV sparks the adoption of solar PV by households. With more PV systems in place, electricity demand falls, which forces utilities to raise charges in order to compensate for energy usage reduction and to help recover costs. The rise in retail rate accelerates PV adoption and further charge increases, inducing a utility death spiral (Castaneda, Jimenez, et al., 2017).

Most closely related to the objective of this study, Morcillo et al. (2022) assess the speed, extent, and impact of the diffusion of residential solar PV in three case study areas: the United Kingdom, Colombia, and Brazil. Their focus is on at what locations the energy transformation towards sustainable energy sources can take place, how fast it could take place, and how different stakeholders are affected. They deem SD as a suitable method for such studies given its ability to capture multidimensional and complex problems. The authors do assess technological diffusion rates but do not distinguish between different societal groups.

Agnew et al. (2018) explores residential solar and battery adoption dynamics in Australia using causal loop modeling. Their research objective was to identify what ambiguous and multi-dimensional problems relate to the adoption and integration of residential PV and battery adoption. The focus here was mainly on battery adoption, what non-financial and financial reinforcing feedback loops encourage battery storage uptake, and what impact is perceived on the electricity market. Though a different focus, the modeling approach can be used as a source of inspiration for this study.

Hidayatno et al. (2020) studied the effectiveness of two policy instruments (net billing and net metering) by analyzing and understanding the dynamic complexity of household rooftop PV adoption using a system dynamics approach incorporated with a policy analysis framework. Though the study assessed the diffusion process for the country's population as a whole, and not how adoption differs between groups, they successfully used the method of system dynamics to do so. The authors also emphasize the importance of taking a systems perspective to acquire a sufficient understanding of the dynamic complexity of solar energy development for a better evaluation of energy policy.

Though SD has made significant contributions to understanding both current and previous energy transitions, it has not specifically addressed the questions of this study. No study distinguishes between adoption rates of different socioeconomic groups or neighborhoods. While several studies investigate the impact of incentivizing policy levers, no study exists that includes other policies than net metering or feed-in-tariffs, or leveling, tailored policies that aim to increase adoption equality. Besides, none of these models use actual case-study data, such as growth or adoption rates, as observed in previous years. Last, no prior study has used the Netherlands as a case-study area before. Therefore, there is an opportunity for a systematic approach to assess the speed and disparity of PV adoption using this method, to further add on to the existing literature. A novelty of this study is therefore to develop a model-based framework, that includes both the spatial analysis as presented in Section 6, followed by a system-dynamics approach presented in Section 7.

5.0.3 Moving towards a demonstration of the artifact

This section described the operationalization of the relevance and rigor cycle into an artifact that allows the to answer the main research question. In Section 6, part I of the artifact is demonstrated for the case study area Amsterdam. In Section 7, the development of the System Dynamics model of Part II of the artifact is described, followed by the demonstration of the model and the results in Section 8.

6 Design artifact part I: Current state of residential PV adoption

This chapter aims to analyze the overall state of PV adoption, existing adoption patterns, and (unused)potential by assessing both the rooftop suitability and socioeconomic features of residents in Amsterdam, given that the psychographic variables are out of scope for this research. This section thereby answers research question 3:

What is the potential for residential solar energy generation in Amsterdam and how are observed adoption patterns correlated with various socioeconomic indicators to explain adoption disparity?

The performed steps are explained in Section 6.1.2 and Section 6.3. The results are discussed in Section 6.4.

The current state of residential PV potential and adoption is assessed following two main steps. First, the rooftop potential for residential PV adoption is assessed through estimating the rooftop suitability of residencies, using the geospatial tool ArcGIS Pro. Next, rooftop suitability data, current PV installations data, and socioeconomic data are combined in a Python analysis to examine the correlation between socioeconomic factors and PV adoption, and possibly explain adoption patterns between neighborhoods. The steps are explicated in detail below. Assessing the rooftop PV potential and socioeconomic factors behind current adoption rates enables an understanding of adoption patterns and geographic disparity, why some neighborhoods have higher adoption rates than others, what neighborhoods have a high potential for PV adoption, and why potential rooftops might not have solar panels installed yet.

6.1 Assessing rooftop PV potential: Rooftop suitability analysis

To assess the rooftop suitability using a GIS-based approach and the geospatial tool ArcGIS, several inputs are needed. These include Digital Surface Models, address data, and building footprint data. The data is processed to determine the shading, tilt, and azimuth of each residential rooftop at a resolution of 0.5 m2. A set of criteria is applied to determine which residential rooftops are suitable for PV deployment. Once the suitable rooftop area is quantified, the potential PV electricity generation is calculated. The following approach has been tested and validated by numerous sources (Dahal et al., 2021; Koch et al., 2022; Margolis et al., 2017; Nicoletti, 2018). The approach is outlined in detail below.

6.1.1 Input data

Digital Surface Model
Digital Surface Models (DSM) depict the topography of the Earth's surface, including objects above the terrain (such as buildings). Contrary, Digital Terrain Models (DTM) do not include buildings or vegetation. DSM data is obtained through LiDAR techniques. LiDAR data offers height information with a high degree of accuracy and short-time acquisition. Unlike photogrammetry, which relies on aerial images, LiDAR technology is less sensitive to cloud cover and shadows. The high geometric detail of LiDAR data enables to calculate the solar radiation of an area of interest and subsequently find suitable roof areas for PV installation (Marešová, 2014). The LiDAR aerial scanning results in a collection of unstructured 3D points (point clouds). These raw LiDAR data allow the generation of digital surface models (DSM) of the ground surface. LiDAR data is attainable at various resolutions for the Netherlands.

For this study, DSM data is obtained from the ArcGIS database in the form of a 50 cm Digital Surface Model. The DSM data obtained includes the whole surface of the Netherlands and is generated in 2020-2021. In ArcGIS, the dataset is shaped to the boundaries of the municipality of Amsterdam.

Building data and footprints
To distinguish different buildings and rooftops and to be able to select residencies from other types of buildings, building data from the *Basisregistratie Adressen en Gebouwen* (BAG) 2.0 is used. The dataset includes all addresses and buildings in the Netherlands and includes both building information and building footprints in the form of polygon shapefiles. Building information includes building identification, construction year, building status (in use, in construction, e.g.), building purpose (residential, commercial, public, e.g.), the number of residencies in the building, and the surface area.

This data is downloaded through the ArcGIS Database. In ArcGIS, the dataset is fitted to the municipality of Amsterdam. For Amsterdam, the dataset includes data for about 545.950 addresses, of which 115.876 addresses are residential buildings.

Neighborhood boundaries

To scope the analysis on the municipality of Amsterdam, and to be able to distinguish adoption patterns between different neighborhoods, municipal and neighborhood boundaries are provided by the Central Bureau of Statistics (CBS), in the form of polygon shapefiles.

Solar radiation data

Solar radiation data is provided by the ArcGIS Pro Solar Radiation toolset. The solar radiation analysis tools calculate insolation across a landscape or for specific locations, based on methods from the hemispherical viewshed algorithm developed by Rich (1990) and further developed by Fu and Rich (2000). The total amount of radiation calculated for a particular location or area is given as global radiation. The calculation of direct, diffuse, and global insolation is repeated for each feature location or every location on the topographic surface, producing insolation maps for an entire geographic area (ESRI, n.d.).

6.1.2 Method

Figure 15 summarizes the GIS-based method for estimating rooftop PV suitability. Given the high resolution of the DSM file and the large study area, the surface model is divided into multiple parts to limit the simulation time of each separate run.

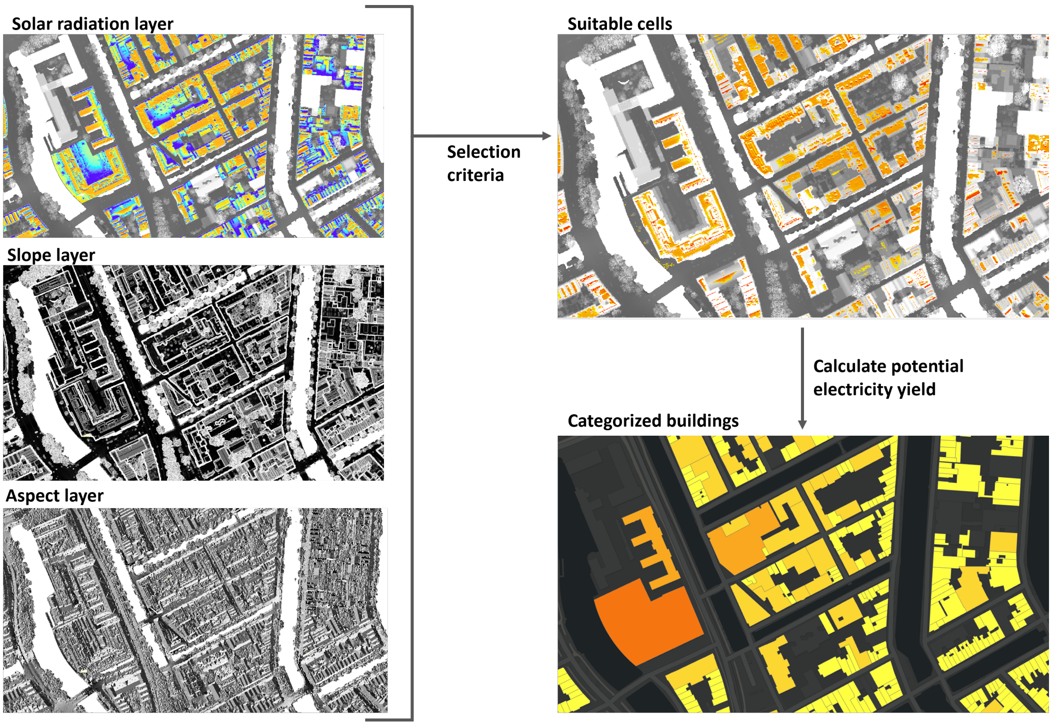


Figure 15: Steps for determining the suitability of roof area for PV. Source: author.

The simulation starts with importing the DSM, building footprint, and neighborhood data. The first step is to compute a solar radiation layer, that contains the amount of solar radiation received on each rooftop. This is done by taking the DSM layer as input and calculating the annual received solar radiation for each building footprint. Radiation is calculated based on a sophisticated model that takes into account the position of the sun throughout the year and at different times of the day. The model is based on the hemispherical viewshed algorithm developed by Rich (1990) and Fu and Rich (2000). Since radiation can be greatly affected by topography and surface features, a key component of the models' algorithm requires the generation of an upward-looking hemispherical viewshed for every point in the Digital Surface Model (ArcGIS Documentation, 2021b). The hemispherical viewsheds are similar to upward-looking fish-eye photographs. The amount of visible sky plays an important role in the insolation at a location, e.g. a point located in an open field receives more solar radiation than a point at the ground in between four high buildings. The sophisticated model calculates the received solar radiation for each point location on a map based on the direct and diffuse radiation (see Section 4.2.3) resulting in the total global radiation. The calculations for direct, diffuse, and global insolation are repeated for each location on the topographic surface, producing insolation maps for an entire geographic area (ArcGIS Documentation, 2021a). In ArcGIS, the Area Solar Radiation toolbox is used to compute the above calculations. Through using this method, obstacles that may block sunlight such as nearby trees or buildings, the slope, and the orientation of the surface are taken into account. The output is a raster layer where each cell value contains the amount of solar radiation in watt-hours per square meter (Wh/m^2) at that location. As a reference year for the solar radiation data, the year 2022 is used. Radiation is calculated on a one-hour interval, using 16 calculation directions. The solar radiation raster uses watt-hours per square meter as its unit of measurement. To reduce the size of the raster values, the raster layer is converted to kilowatt-hours per square meter (kWh/m^2).

Roof suitability is determined by roof slope, received solar radiation, and rooftop orientation (azimuth). To identify suitable rooftops for solar panels, four selection criteria are applied:

- Suitable rooftops should have a slope of 45 degrees or less. The optimal slope for PV installations in the Netherlands is 37°, and for south-facing installations (Schepel et al., 2020). Steeper slopes tend to receive less sunlight.
- Suitable rooftops should receive at least 800 kWh/m^2 of solar radiation (Koch et al., 2022).
- Suitable rooftops should have at least 30 square meters of suitable roof surface (ESRI, n.d.).
- Suitable rooftops should not face north. North-facing rooftops in the northern hemisphere receive insufficient sunlight (Schepel et al., 2020). Slopes that face north have an aspect value of less than 22.5 or more than 337.5 degrees. Slopes that are (almost) flat (10 degrees or less) are not removed, regardless of their aspect.

To apply the above criteria, several steps are performed using the Surface Parameters toolbox. To determine the rooftop slope, a slope raster layer is created. Each cell in the slope raster contains a slope value ranging from 0° to 90°. This allows selecting surfaces with a slope of 45 degrees or less. To determine rooftop orientation, an aspect raster layer is created. Each cell of the aspect layer contains a value expressing orientation in degrees, with 0 being north and 180 being south. This allows for removing slopes that face north. Next, areas with low solar radiation (<800 kWh/m^2) are removed.

Applying the above criteria results in a map showing the amount of received solar radiation each suitable raster cell receives. Next, data will be aggregated to determine the amount of solar radiation each building receives on average in a year. For every building, the area covered by suitable cells (in m^2) and their average solar radiation (kWh/m^2) are calculated. The number of suitable cells, the area covered by suitable cells (m^2), and the average solar radiation (kWh/m^2) received by the cells are outputs. The cells are then aggregated for each individual building. Next, buildings are selected that have at least 30 square meters of suitable roof surface. The result is a map with all suitable buildings, and for each building, the suitable area and mean solar radiation per square meter.

For each building's suitable area, the total amount of solar radiation received per year is calculated, using the following formula:

$$(Area * Mean)/1000$$

Solar radiation is converted from kWh to MWh by dividing by 1000. Finally, for each building, the received solar radiation per building per year is converted to electric power production potential. Power production depends not only on solar radiation but also on panel efficiency and performance ratio. The U.S. Environmental Protection Agency estimates an average solar panel efficiency of 16.3% and a performance ratio of 86% (EPA, 2021). To determine electric power production potential, the following formula is used:

$$Suitable\,cells * 0.16 * 0.86$$

Where *suitable cells* are the usable area of suitable cells in MWh. Each suitable building is symbolized according to the amount of potential electricity yield, as shown in figure 16.

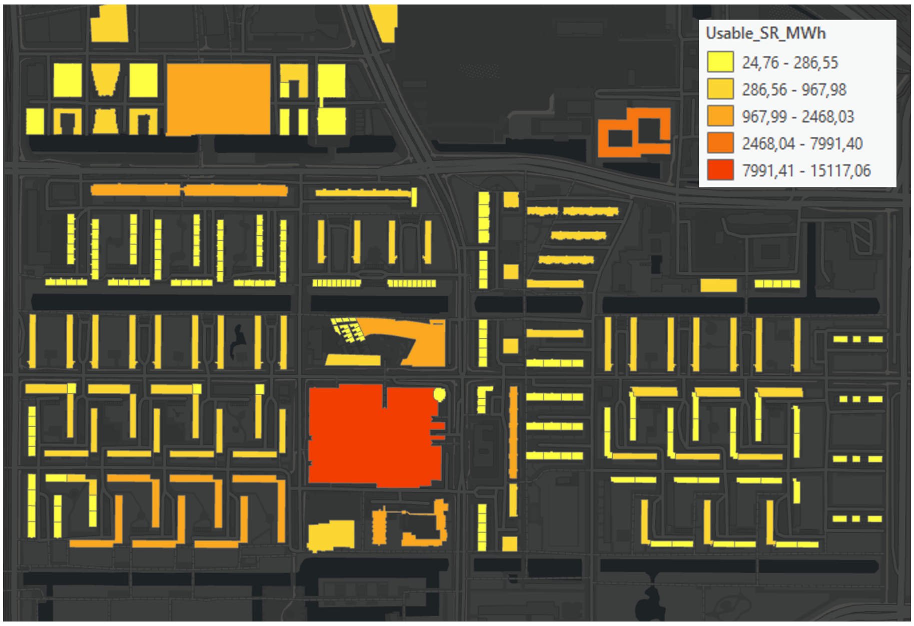


Figure 16: Example of categorization of suitable buildings

6.2 Suitability assessment validation

To validate the results of the suitability simulation, several steps are performed. The validation steps are intended to ensure that:

- the model thresholds are appropriately set to capture the rooftops that are deemed appropriate for residential PV
- unsuitable rooftops were excluded
- suitable rooftops are not wrongfully removed

First of all, suitable rooftop cells are compared to Google Earth imagery. Comparing the results with satellite imagery allows us to check how the model deals with roof objects such as chimneys, shadows, roof windows, and dormers. Taking such objects into account prevents wrongfully selecting inappropriate roofs as suitable for PV. An example comparison is shown in figure 17. A random selection of buildings has been compared using visual inspection, and the used model appears to take roof objects into account in an appropriate way, removing chimneys from the usable area and taking shadows into account.

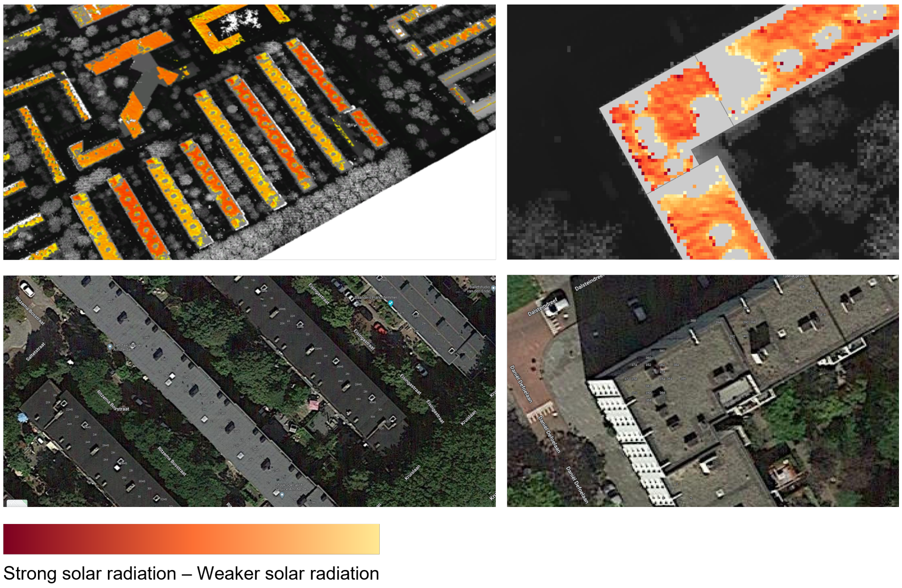


Figure 17: Example of validation through visual inspection of satellite imagery

Second, randomly selected buildings were compared to the Zonatlas (Vermaas & Hoogendijk, 2021). The Zonatlas is a commercial online tool that computes the suitability of rooftops for several municipalities in the Netherlands. The tool can be used to compare individual buildings from both analyses, but no large-scale comparison is possible as the Zonatlas only allows retrieving suitability results of one building at a time. The comparison with the Zonatlas is used to determine whether the assumptions and outcomes of this analysis are in line with the outcomes of a tool that has a similar objective.

The Zonatlas takes several similar assumptions, such as a panel efficiency of 15% (compared to 16% in this study) and a performance ratio of 86% (identical to this study). The Zonatlas uses three categories for suitability (very suitable, suitable, and less suitable) compared to the five categories in this study. When comparing several randomly selected buildings from the study area, it appeared that all of the buildings that were classified as suitable in this study were also classified as suitable by the Zonatlas. Several buildings that were classified as "suitable" by the Zonatlas, were classified as unsuitable in this study. It is deemed likely that this is caused by less strict selection criteria considering the minimal suitable roof surface area by the Zonatlas. This observation led to conducting a more thorough investigation of the minimum required roof area thresholds used in the literature. The ArcGIS default minimum area is 30m^2. The Zonatlas minimum suitable area is 11m^2. In literature, thresholds differ. Several sources use 28-30m^2 as a minimum suitable surface area (Assouline et al., 2017; Fortson, 2021) while other studies use 10-16,5m^2 as minimum required surface (Hong et al., 2017; Melius et al., 2013; van der Wilt, 2022). The required surface area depends on several factors, such as the type of solar panels, the radiation intensity, and the electricity consumption of a household (Assouline et al., 2017). In the Netherlands, the average PV system size is 10 solar panels, which require approximately 16,5m^2 of roof surface. This minimum is used in this study, but given that space is needed between the roof edge and the solar panels, and in between the solar panels, the ArcGIS model will adopt a minimum of 20m^2. Based on the validation with the Zonatlas, other literature sources, and relevant data from the Netherlands, the minimum required surface for PV is thus adjusted to 20m^2 in this study.

Third, the model outcomes have been compared against the PV installation database. This database contains the PV installations for the municipality of Amsterdam from the years 2016 until 2021 (Gemeente Amsterdam, 2021). This comparison is used to compare calculated potential yield to actual yield from the database and to compare the suitability of rooftops with actual PV installations. Comparing the calculated potential yield in this study with the actually generated electricity from current installations in the database is difficult, however, as this model estimates the maximum potential yield if all suitable cells are covered with solar panels. In reality, some buildings do not cover their full roof area with solar panels. Therefore, for the calculated potential values it is evaluated whether the data is in the same order of magnitude as the actual generation data, which was true for the randomly selected buildings that were tested.

6.3 Assessing socioeconomic PV adoption patterns

The previous section described the technical potential of rooftop solar adoption. As described in Chapter 4, PV adoption depends on both technical potential and socioeconomic factors. This section explains how socioeconomic adoption patterns are analyzed. The results are described in Section 6.4.

The technical rooftop suitability analysis generates insights into the technical potential for PV adoption in households and how this potential is spread amongst different neighborhoods. This socioeconomic analysis aims to use these insights, combined with current adoption numbers and socioeconomic neighborhood data, to study the current state and spread of PV adoption, e.g. what neighborhoods and what type of residencies have many or few solar panels installed? And what socioeconomic factors are correlated to the % of PVs installed?

6.3.1 Data

- socioeconomic data at the neighborhood level. This dataset, retrieved from the Central Bureau of Statistics, includes 212 socioeconomic indicators. The factors cover thirteen themes: population, living, income, energy, education, labor, social security, healthcare, business, motor vehicles, facilities, surface, and urbanity. Data is included at the municipality, district, and neighborhood levels. Data from 2020 is used, as this is the most recent dataset with the least missing values. From the 212 variables, a selection will be made based on the insights from the previous sections.
- socioeconomic data at the residence level. Some data is available at the residence level, such as construction year, energy labels, roof access, and property ownership. However, due to privacy reasons, most data is only available at neighborhood level.

6.3.2 Method

The rooftop suitability analysis resulted in a dataset with all residencies in Amsterdam, including a suitability categorization, and for the suitable rooftops a suitable surface area and potential electricity yield. Besides this, the dataset already contained general information such as building function, construction year, and building status (see Section 6.1.1).

In ArcGIS, the residence building dataset is combined with the solar panel dataset. First, from the solar panel dataset, only solar panels installed on residencies are selected. Next, building footprints from the residence building dataset is linked to the current PV installation locations. This results in a dataset that contains all residential buildings in Amsterdam, building data, address data, the suitability of the rooftop of that building, and whether these buildings have solar panels installed.

All residential buildings are categorized on whether they have (1) a suitable roof for PV, (2) no suitable roof for PV, and on having (3) a suitable roof and PV installed or (4) a suitable roof, and no PV installed. These categories can be used to aggregate the data to neighborhood level.

Next, in ArcGIS, all residential buildings are aggregated to neighborhood level, and combined with the socioeconomic neighborhood characteristics dataset. socioeconomic data is obtained at the neighborhood level, as this allows a more granular analysis of geographic differences than an analysis at the district level. Besides, little data is available at the individual residence level due to privacy reasons, therefore the analysis mostly focuses on neighborhood characteristics and patterns. As policymakers and grid operators often target policy measures at the neighborhood level (Al2, ST2, AMS1), an analysis at the neighborhood level is deemed applicable. The complete dataset is exported for further analysis in Python.

In Python, the complete dataset is studied using descriptive statistics and correlation analysis. The overall geospatial distribution of PV adoption is examined, including the temporal dynamics of solar uptake since 2016, and a correlation study of PV deployment with predictor variables. Based on the review of household PV studies in Section 4, 95 socioeconomic variables that may explain the household PV installation disparity have been selected from the database, covering the themes population, living, income, energy, education, labor, social security, healthcare, motor vehicles, and urbanity are studied. During data exploration, a smaller selection of variables that include high data quality will be selected.

For each neighborhood, several variables are computed:

- the number of PVs per residence for each year (2016-2021)
- the number of PVs per citizen for each year (2016-2021)
- the growth of PVs per neighborhood for each year, in absolute numbers and growth percentages
- the growth of PVs per citizen for each year, in absolute numbers and growth percentages

Adding variables expressing the number of PV installations per citizen allows comparison between neighborhoods indifferent to the number of households in that neighborhood. Besides, the average prices for PV installations over the years 2016 until 2021 have been added as variables to the dataset. These prices are obtained from Milieu Centraal (Milieucentraal, 2022).

6.4 Results spatial analysis

The spatial analysis investigated the current spread of solar panel adoption amongst the neighborhoods and the potential for solar panel installations per neighborhood. The figures described in this section have been plotted during the suitability analysis in ArcGIS. The figures are provided in Appendix A.2, where several are highlighted in the main text.

Figure 18 shows the total yearly growth of residential rooftop PV installations over the years 2016-2021. Steady growth can be seen from approximately 4.000 households with PV in 2016 to 16.000 in 2021. This means that in 2016, the household adoption percentage was 1% compared to 4% in 2021.

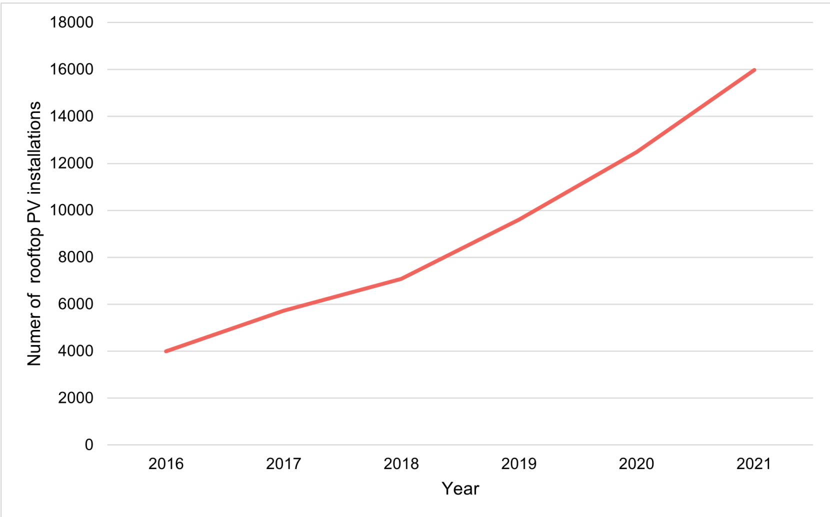


Figure 18: Growth of residential PV installations in the municipality of Amsterdam over the years 2016 - 2021

Figure 19 shows the number of residential PV installations per neighborhood. It can be observed that mostly the outer neighborhoods have high numbers of PV. It is, however, when looking at adoption rates, more accurate to study the PV installations per household, which is shown in figure 69. This figure shows similar results, where several clusters of high-adoption neighborhoods can be perceived in the northeast, southwest, and southeast. The center of Amsterdam structurally has low adoption rates. It should be noted that the inner center of Amsterdam contains several monumental buildings and restricted areas for in-sight PV installations. However, this area is much smaller than the observed low-adoption neighborhoods in this study.

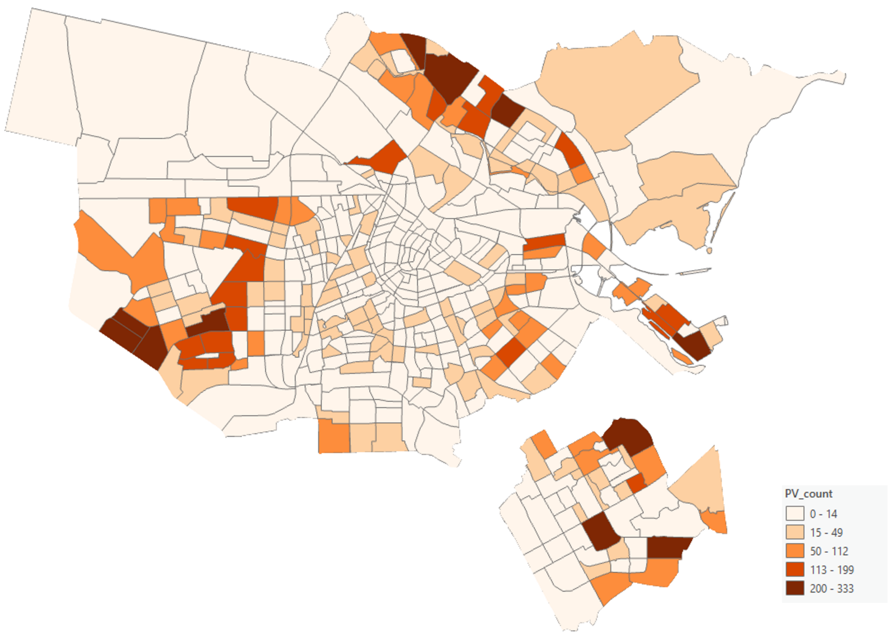


Figure 19: Number of residential PV installations in each neighborhood

Next, the suitability of rooftops within neighborhoods is assessed. Figure 70 shows the total potential usable electricity yield in MWh per neighborhood. Notably, rooftop suitability is spread amongst the whole city, in contrast to the observed clusters of adoption that are generally located at the outer borders of the municipality. Several neighborhoods show little to no potential electricity yield. These have been studied in more detail. Most of these neighborhoods contain little to no residential buildings, such as neighborhoods that are mainly recreational areas. Examples are the "Vondelpark buurt" and the "Oeverlanden", which mainly consist of parks, water, or public buildings.

Figure 20 shows the potential electricity yield per citizen. Expressing the potential yield per citizen is a useful way in comparing how the potential for rooftop solar generation is spread geographically. The figure shows that for most neighborhoods, the potential electricity yield per citizen is similar. Several neighborhoods show outliers, with a high above-average potential electricity yield. When investigating several of these individual neighborhoods, it appears these neighborhoods have a relatively low number of citizens compared to the residential suitable roof space available.

Figure 71 shows the unused potential of suitable residential rooftops per neighborhood, as a percentage of the total suitable rooftops. The figure can be used to detect neighborhoods with high unused potential, however, it can be misleading when there are only a few residencies that do not have solar panels. In that case, the unused potential is 100%, though the actual potential electricity yield might not be that high in that neighborhood. In that case, one can best refer to figure 70. The figure can however be useful to distinguish between areas of high unused potential.

To compare, figure 72 shows the number of suitable rooftops per neighborhood. The figure shows a similar pattern as figure 70. Again, some neighborhoods show little to no suitable rooftops due to a low number of residencies in that neighborhood, or because of small rooftops.

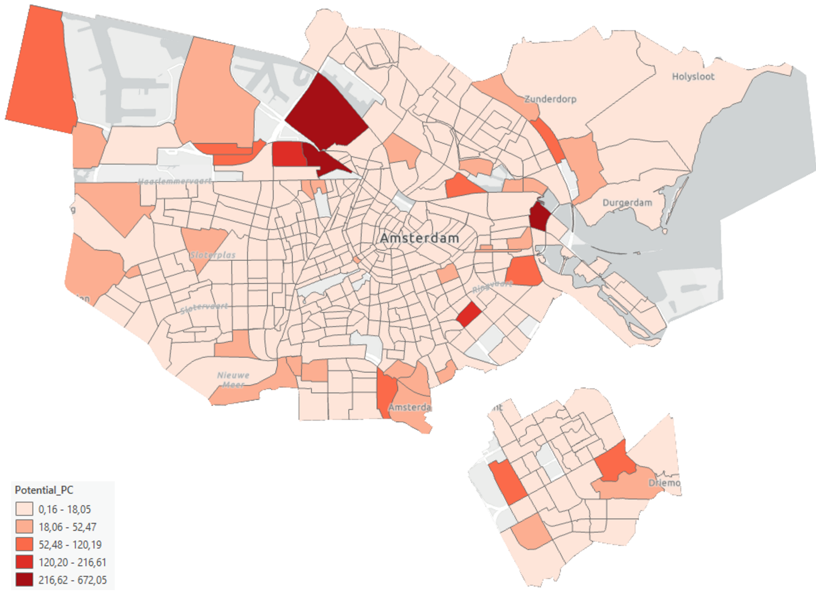


Figure 20: Usable rooftop surface in potential electricity yield (MWh) for each neighborhood per citizen

From the results in figures 19 and 69, a high disparity in adoption can be observed when comparing adoption rates at neighborhood level. Most notably, some neighboring neighborhoods have highly diverging adoption rates. This raises questions as to why some neighborhoods have high adoption and some have low adoption, and why two neighborhoods next to each other can have such different adoption behavior. These questions will be further investigated in Section 6.5. From the results in figure 20 it appears that although PV adoption per citizen is not evenly spread across the municipality, the potential electricity yield per citizen is spread more equally.

6.5 Results socioeconomic analysis

The results of the socioeconomic analysis are structured as follows: first, in Section 6.5.1 the data is explored and distributions are plotted. Next, in Section 6.5.3, the data is described using descriptive statistics and correlation metrics. This is done for each of the included socioeconomic themes separately, to limit the number of variables per analysis. In Section 6.5.4, a more detailed analysis is done of the neighborhoods with high levels of unused potential. Finally, in Section 6.5.5, the observed adoption gap is discussed.

6.5.1 Data exploration and distributions

In Python, the necessary packages for data gathering, data cleaning, statistical and correlation analysis, and data visualization are imported. These packages include pandas, geopandas, numpy, seaborn, matplotlib, scipy, statsmodels and sklearn.

The dataset has been pre-processed in ArcGIS to combine solar panel, suitability, and neighborhood data into one complete dataset. The dataset is imported and explored for data quality, consistency, and missing values. The dataset initially contains 484 neighborhoods and 212 socioeconomic attributes, of which 95 socioeconomic variables are selected for further analysis based on their relevance for the study purpose and the outcomes of the analysis in Section 4. Several columns require altering of the data to ensure consistency of the data types amongst variables. Neighborhoods that have zero inhabitants, or less than five households, are removed from the dataset. Neighborhoods with zero inhabitants are not relevant for the study purpose, and neighborhoods with less than five households have a large share of missing values due to data privacy. To limit the volume of the analysis, from the 95 socioeconomic variables, a selection is made for further analysis. The variables covering the themes income, population, residencies, energy consumption, education, and vehicles are selected given these themes are most relevant for the study purpose, based on the insights from the literature review in Chapter 4. In order to properly compare neighborhoods, variables that represent counts are transformed into percentages of the number of citizens.

First, the data distributions are explored to get an idea of the characteristics of the neighborhoods in the study area. All plotted distributions are shown in Appendix A.3. In 2021, most neighborhoods have 0-10 households with solar panels (see figure 21), and 0-0.02 solar panels per citizen (figure 74).

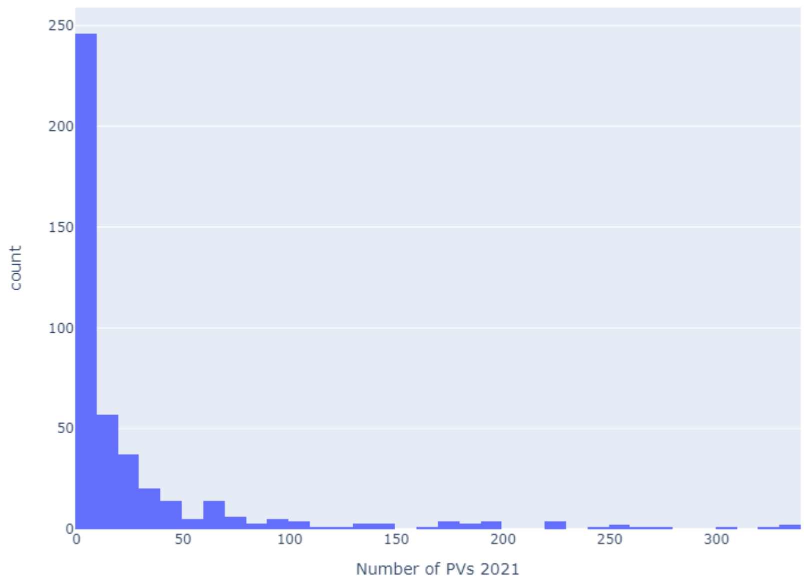
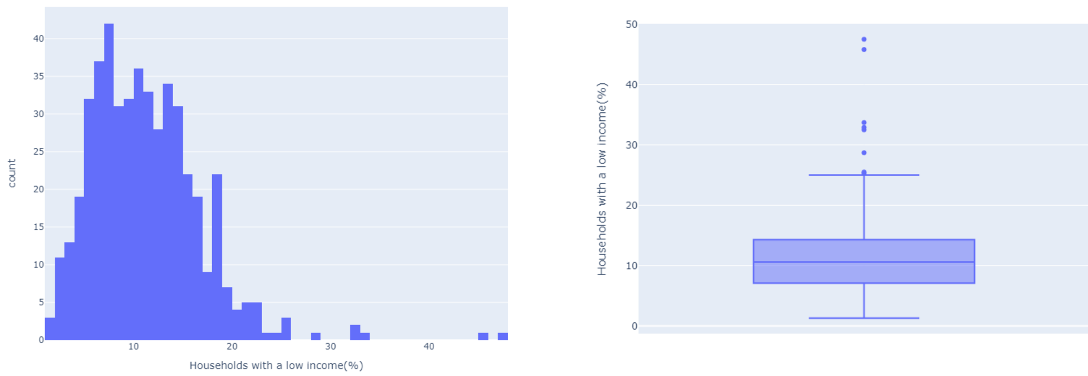


Figure 21: Distribution of PV installations per neighborhood in 2021

The distribution of the number of households is spread more evenly, meaning that the number of households highly varies between different neighborhoods. This emphasizes the need to analyze the number of PVs per household instead of the absolute number of PV installations. The percentage of residencies with a housing corporation widely varies, where most neighborhoods have 0-60% of housing corporation residencies. However, neighborhoods exist where all residencies are connected to a housing corporation.

When looking at the distribution of the percentage of households with a low income in figure 22a and figure 22b , an average of 11.2% low-income households is observed. To compute the variable "percentage of households with a low income", CBS standardized the households' incomes and redistributed them to the price level of 2000. A low income is defined as a maximum income of the 1979 welfare benefit of 9249 euros. Although most neighborhoods have an average low-income household percentage between 0-20%, there are some outliers that have more than 30% of low-income households. The average of 11.2% in Amsterdam is above the average in the Netherlands. Only the municipality of Rotterdam has a higher percentage of low-income households (CBS, 2021).

The standardized average household income (figure 79a and figure 79b in Appendix A.3) has an average of €34.000. A majority of the households have an average standardized income between €20.000 and €40.000 euros, with a dozen of households that score above average.



(a)

(b)

Figure 22: Distribution of the percentage of households with a low income for each neighborhood in 2021

The percentage of multi-household residential buildings represents the percentage of households that share the building their residence is situated in, with other residencies. Notably, many neighborhoods have high percentages of multi-household residencies, with even several neighborhoods that only have multi-household residencies (see figure 77 in Appendix A.3). Looking at the city of Amsterdam, this is expected given the high number of apartments in the city centre and flats in outer neighborhoods.

Looking at the percentage of rental properties in figure 23, a majority of the neighborhoods have at least 50% rental properties compared to owned properties.

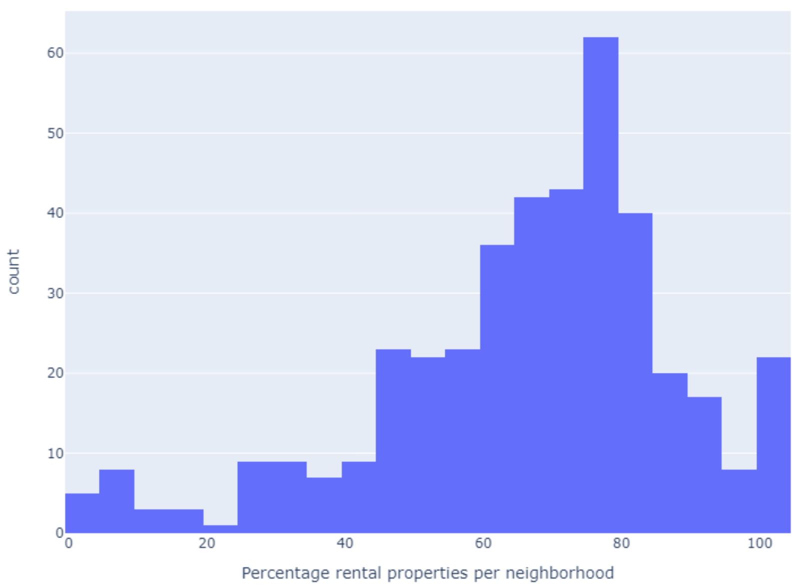


Figure 23: Distribution of the percentage rental properties for each neighborhood in 2021

Average woz values, in figure 78, are mostly between 250.000 and €600.000, which is quite a wide range. Few outliers exist with an average woz value of above €1.000.000.

The characteristics of the neighborhoods are important to take into account in any further analysis. The most notable characteristic of the municipality is the number of multi-household residencies and the high share of rental properties. Besides, there is relatively a high percentage of low-income households in the municipality, especially when comparing the numbers on a country level.

6.5.2 Comparing low and high PV adoption neighborhoods

It is useful to understand whether neighborhoods with high or low adoption rates differ from each other in terms of socioeconomic characteristics. To analyze this, the neighborhoods are categorized into groups based on their adoption intensity, specifically, the PV per citizen.

To allow comparison between neighborhoods regardless of the number of inhabitants, several new variables are computed:

- For all neighborhoods and for each year, the average "*PV per household*" and "*PV per citizen*" are computed, to enable comparison between neighborhoods regardless of the number of inhabitants.
- The "*yearly growth percentage*" per neighborhood is computed for each year in the dataset
- The "*absolute yearly growth*" per neighborhood is computed for each year in the dataset. Growth rates vary from 1731 new PV adopters in 2017 to 3501 new adopters in 2021.
- Adoption rates are computed for each neighborhood and each year. The adoption rate is defined as the number of households that have adopted PV in a certain year as a percentage of the total number of households in that neighborhood. The yearly adoption rates vary between 0.22% in 2016-2017 to 0.52% in 2020-2021.

Neighborhoods are then categorized into four groups based on their PV adoption: very low PV adoption, low PV adoption, medium PV adoption, and high PV adoption. The categories are formed using the 0.25, 0.5, and 0.75 quantiles, resulting in equal groups for analysis. Given there are 444 neighborhoods in the cleaned dataset, each group contains 111 neighborhoods.

To test whether the categorized PV adoption groups significantly differ from each other based on the socioeconomic variables, one-way ANOVA tests are performed for each of the variables. A one-way ANOVA (analysis of variance) compares the means of two or more groups for one dependent variable. A one-way ANOVA is a suitable test when the study includes more than two groups (in this study, there are four groups). There is one independent variable and one dependent variable. The assumption of a normal distribution is not required but the sample data does require equally sized groups, independently observed sample, and continuous dependent variables (Ross & Willson, 2017). The data meets these requirements, thus a one-way ANOVA test can be performed.

ANOVA tests are hypothesis based. By default, ANOVA assumes all the sample groups' means are equal (the null hypothesis). The statistical tests evaluate whether the null hypothesis can be accepted. If not, one or more groups' means differ from the others (the alternative hypothesis) (Zubair, 2022). The hypothesis is tested based on the F-value, which represents the variation between sample means divided by the variation within the samples. The higher the F-value, the higher the variation between sample means relative to the variation within the samples. Based on the F-value, the ANOVA test calculates a p-value (Feldman, 2018). The ANOVA tests are performed and the null hypothesis is rejected when the p-value is below the 0.05 significance level.

Many of the socioeconomic variables present significant p-values, and thus a significant difference in the sample means between the PV adoption groups. Insignificant differences were found for the percentage mortality, the percentage of citizens from Morocco and the percentage of citizens from Turkey, the average gas consumption, the average number of citizens with an AO benefit (invalidity benefit), the average number of vehicles, and the average number of Wmo-client (social security benefit clients). For the significant variables, although the difference in means per group might be significant, the absolute difference can be small. What is most interesting, is what variables present the highest difference in the means between groups. This can be derived from the F-value. The following variables have the highest difference in means per group:

- Population density (number of citizens per km2)
- Percentage of citizens between the years 0-14 (%)
- Percentage of citizens between the years 25-44 (%)
- Percentage of married and unmarried citizens (%)

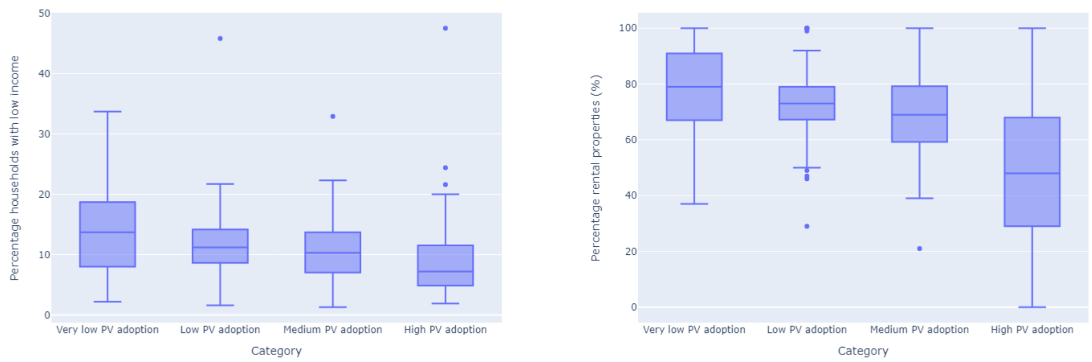
- Percentage of single-citizen households (%)
- Percentage of households with children (%)
- Average household size (# of citizens per household)
- Percentage of citizens with a Western European migration background (%)
- Percentage of single-household residencies and percentage multi-household residencies (%)
- Percentage rental properties and percentage owned properties (%)
- Percentage of households with a low income and percentage of households with a high income (%)
- The average electricity consumption per household (%)
- And the percentage of highly-educated citizens (%).

A significant difference in the means of groups does not necessarily mean that the difference is linked or correlated with PV adoption. The actual distributions of the significant variables with a high F-value are therefore visually inspected using distribution plots. The distribution plots are included in Appendix A.4. Some examples are highlighted below.

When inspecting the *population density*, for example, the ANOVA test revealed a significant difference between the groups. Visual inspection of the distributions of this variable however reveals that the variable is likely not linked to a certain adoption rate (figure 86).

For several of the variables, visual inspection leads to presume there might be a (linear) correlation between the socioeconomic variable and PV adoption. From the distribution graphs, it appears that :

- High-adoption neighborhoods on average have a higher average electricity consumption, average household size, percentage of children, and percentage of married citizens compared to low-adoption neighborhoods.
- High-adoption neighborhoods on average have a lower share of multi-household residences, rental properties, citizens between the ages 25-44, low-income households, highly educated citizens, and citizens with a western-European migration background, compared to low-adoption neighborhoods.
- The population density does not seem to be logically related to PV adoption.



(a) The percentage of low-income households (%) (b) The percentage of rental properties (%)

Figure 24: Distributions per PV adoption category

To be able to draw more conclusions on the relationship between variables and their direction, a regression and correlation analysis is performed.

6.5.3 Regression and correlation analysis

Both a regression and correlation analysis is performed on the individual socioeconomic factors in the study to examine not only the explanatory ability of these variables but also their relative weight. All variables are included, not only the significant variables from the prior ANOVA analysis, to be able to compare results between the two.

First, given the large set of independent variables, multicollinearity amongst the indicators is investigated. A preliminary correlation analysis was run on the data using all indicators. A correlation plot is computed and for each of the variables, a variance inflation factor (VIF) is calculated. VIF measures the ratio between the variance for a given regression coefficient with only that variable in the model versus the variance for a given regression coefficient with all variables in the model (Forthofer et al., 2007). A higher VIF means the more correlated a predictor is with the other predictors. The multicollinearity analysis revealed that many indicators are correlated with each other. This multicollinearity is expected and caused by the fact that many variables are somewhat each other's opposites or complementary variables, such as the percentage of households with a low income and the percentage of households with a high income. Or, the percentage of households with low buying power and the percentage of households with low income, and the percentage of married vs the percentage of unmarried residents. To eliminate multicollinearity, a selection of the variables is used for further analysis.

An ordinary least squares (OLS) multiple regression model for solar adoption was run on the data using all indicators. The OLS model is run with both PVs per citizen and PVs per household as the dependent variable, to test the performance for both possible dependent variables. For both dependent variables, several of the predictors variables including the WOZ value, the percentage of households with a low income, the percentage of households with a high income, and the average income per citizen were found to be statistically significant at the $p < 0.05$ level. The dependent variable *PV per household* had a slightly larger R-squared error of 0.82 compared to *PV per citizen* of 0.78. This means that the degree of variance in PV adoption can be explained for 82% and 78% respectively by the independent variables.

While the regression analysis allows controlling for confounding effects between the explanatory variables, it does not provide clear information about the relative influence of each of the predictor variables on solar adoption rates (Lukanov & Krieger, 2019). Therefore, a more detailed correlation analysis is performed based on the results of the previous analysis. The Spearman's rank correlation coefficients between residential PV adoption (PV per citizen and PV per household) and the independent variables per theme (income, population, residencies, energy consumption, education, and vehicles) are computed. As the underlying data contains outliers and not all variables are normally distributed, Spearman correlation is chosen as the correlation metric. This metric deals well with rank-ordered data and outliers (de Winter et al., 2016). The analysis is performed per theme to limit the extent of the data per analysis.

Given the large amount of independent variables, even when the dataset is divided into multiple variable themes, a Bonferroni correction is performed for each of the variables. The Bonferroni correction is a multiple-comparison correction used when several dependent or independent statistical tests are being performed simultaneously (Weisstein, 2023). The reason for performing a Bonferroni adjustment is that while a given alpha value may be appropriate for each individual comparison, it is not appropriate for the set of all comparisons. In order to eliminate multiple spurious positives, the alpha value needs to be lowered to account for the number of comparisons being performed (Hayes, 2021). Therefore, for each variable, the adjusted p-value is computed which is equal to its alpha divided by the number of variables.

An overview of the investigated variables and their explanation is found in Appendix A.1. The results for each theme are discussed below.

Income
The theme income includes 18 variables. The 18 income-related variables contain several similar, opposites, or complementary variables (e.g. % households with low income and % households with low buying power). Therefore, a selection of the income variables is chosen for further analysis. Of the complementary or opposing variables, only one variable is chosen. In the original dataset, separate variables are included for four different types of social benefit schemes (AO, WW, AOW, and social assistance). These are combined into one variable representing the total amount of citizens receiving social benefits in a neighborhood. The results of the correlation matrix of the selected variables are summarized in figure 25, where Spearman's rank correlation coefficients for every pair of variables are displayed on the right side of the diagonal. The full overview of correlations is

presented in Appendix A.5. Histogram distributions of the variables are shown along the diagonal, revealing non-normal distributions for all variables. Left of the diagonal is scatter plots with fitted trend lines, which are generally non-linear.

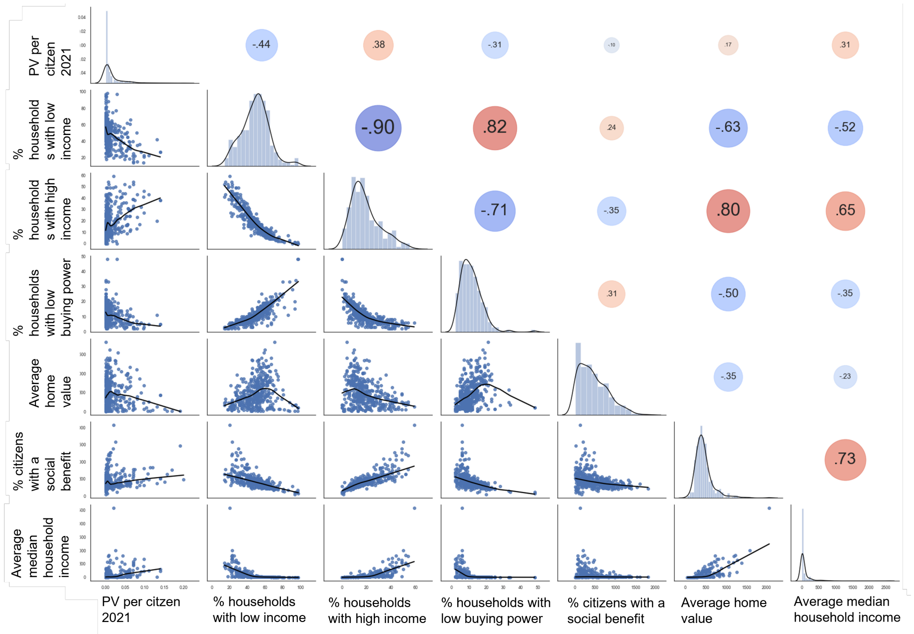


Figure 25: Correlation matrix for residential solar adoption (PV per citizen) and income-related variables. Spearman correlation coefficients are displayed to the right of the diagonal. Histogram distributions are displayed on the diagonal, and scatterplots with fitted lines are left of the diagonal.

Of the five predictors, four are statistically significant in explaining variations in residential solar adoption, at at least the $p < 0.05$ significance level. Only the number of citizens with a social benefit is not statistically significant. Of the significant variables, the percentage of households with a low income is most strongly correlated with PV adoption (-0.42), followed by the percentage of households with a high income (0.37), the median household income (0.37), the percentage of households with low buying power (-0.34) and the average home value (0.10). The first four variables have similar weights but also represent similar variables, which explains why these variables are all similarly correlated and significant.

Population

The theme population includes 29 variables, covering amongst others age, marital status, population density, household characteristics, and cultural backgrounds. For the full list, see Appendix A.1. All variables are tested for correlation significance with the dependent variable PV installations per citizen. Of the 29 variables, 21 are statistically significant. The full overview of significance values and correlation coefficients is shown in Appendix A.6. To summarize the results, it appears that the most correlated variables are age, marital status, and household composition. Figures 26 and figure 27 highlight some of these correlations.

When looking at age, a high percentage of children (citizens from 0 until 14 years old) positively correlates with a high PV adoption rate (0.48), and a high percentage of citizens between 25 and 44 years old negatively correlates with the PV adoption rate (-0.38). The age group 25-44 years includes groups such as students and job starters that possibly do not have a stable salary or the capital to invest in solar panels, are saving for other matters such as buying a house, or have not settled yet and are frequent movers. Sovacool et al. (2022), who also noted a lagging adoption among young adults and middle-aged people, investigated the causes and found that young children, mortgages, being a student, or renting properties before being able to afford to buy one were the main reasons for this.

Considering household composition, the household size most strongly correlates (0.59) with PV adoption, followed by the percentage of single-person households (-0.58) and the percentage of households with children (0.54). For marital status, the percentage of married citizens positively correlates with PV adoption (0.52), and correspondingly the percentage of unmarried citizens correlates negatively (-0.43).

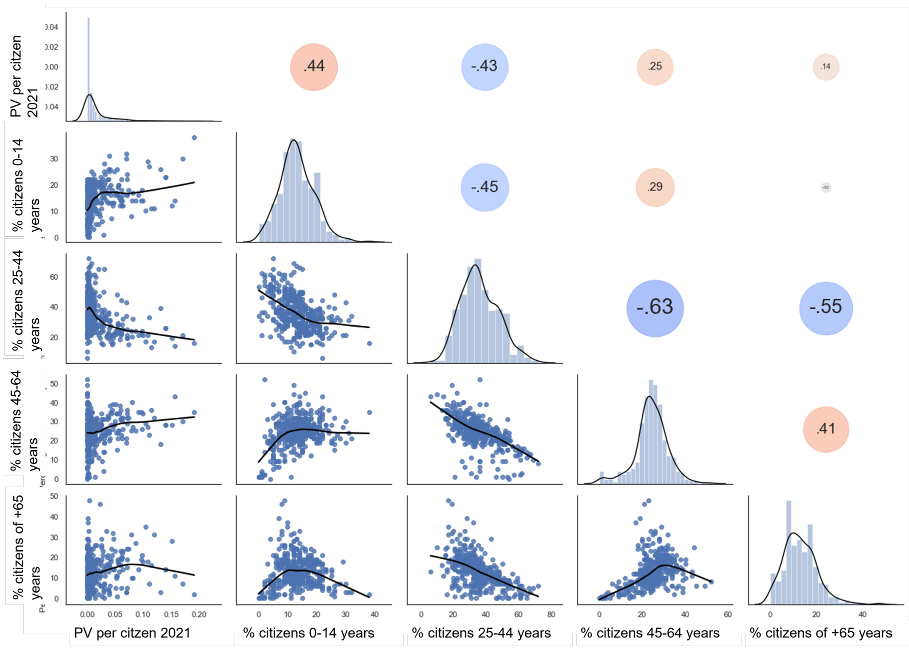


Figure 26: Correlation matrix for residential solar adoption (PV per citizen) and age-related variables. Spearman correlation coefficients are displayed to the right of the diagonal. Histogram distributions are displayed on the diagonal, and scatterplots with fitted lines are left of the diagonal.

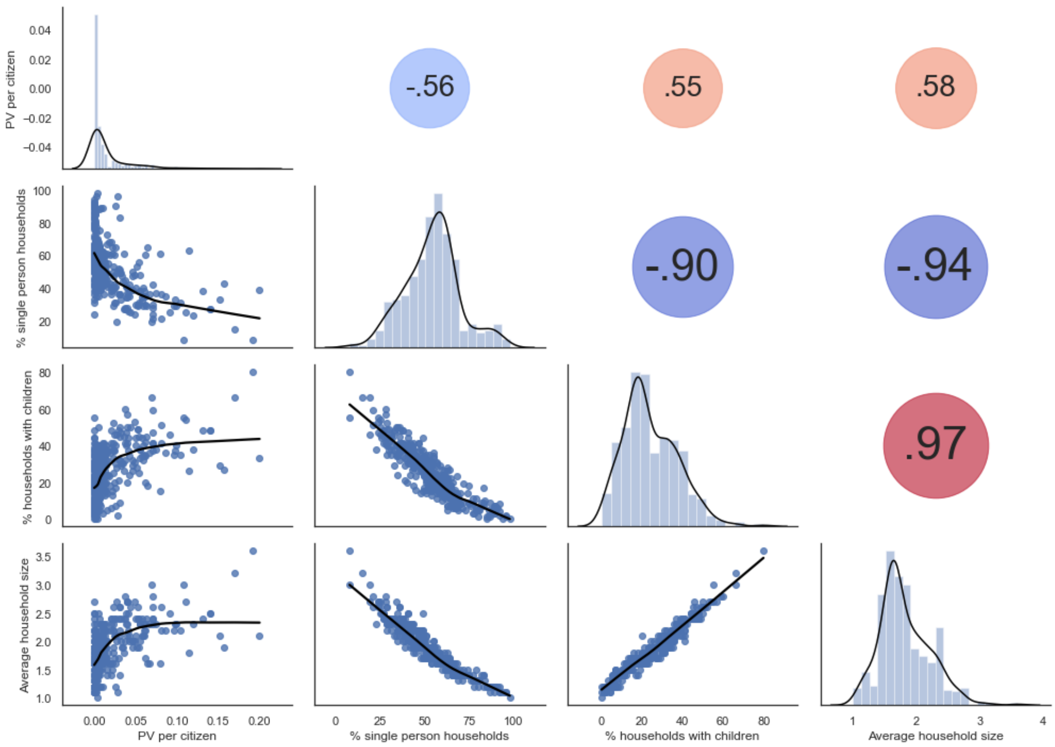


Figure 27: Correlation matrix for residential solar adoption (PV per citizen) and household-related variables. Spearman correlation coefficients are displayed to the right of the diagonal. Histogram distributions are displayed on the diagonal, and scatterplots with fitted lines are left of the diagonal.

Residencies

The theme residencies includes 11 variables. All 11 variables are tested for correlation significance with the dependent variable PV installations per citizen. Of the 11 variables, 10 are statistically significant. The full overview of significance values and correlation coefficients is shown in Appendix A.7. To summarize the results, it appears that the most correlated variables are the percentage of single-family homes (-0.79), the percentage of owned properties (+0.62) versus rental properties (-0.62), and the woz-value (+0.17). Figure 28 highlights the strongest correlations.

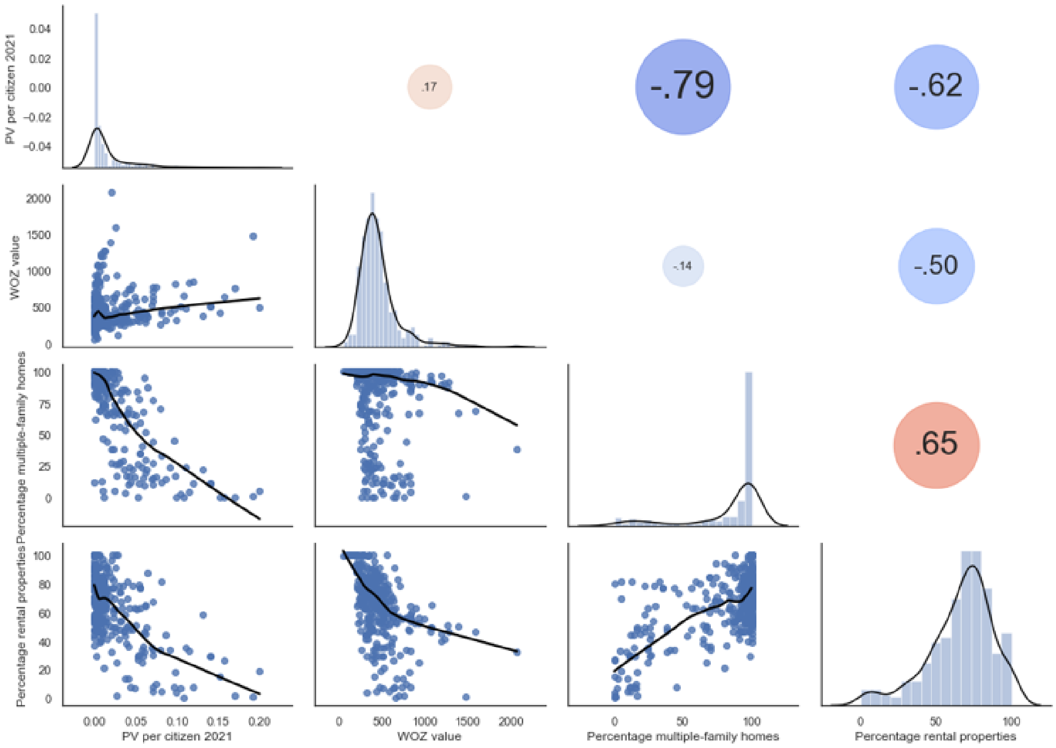


Figure 28: Correlation matrix for residential solar adoption (PV per citizen) and residence related variables. Spearman correlation coefficients are displayed to the right of the diagonal. Histogram distributions are displayed on the diagonal, and scatterplots with fitted lines are left of the diagonal.

Education

The theme education includes six variables in the original dataset. As the variables for "highly education citizens", "Secondary educated citizens" and "lower educated citizens" are absolute numbers per neighborhood, these variables are transformed into percentages by dividing the values by the number of citizens. One new variable is added: the total percentage of educated citizens. For all seven variables, the Spearman correlations are computed. Of the seven variables, all variables are significant at the 0.05 level except for the variable "Percentage secondary educated citizens". Figure 29 shows the visualized correlations of the four most significant variables. Although the variables significantly correlate with the dependent variable, the correlation coefficients exhibit a relatively weak association between the indicators and the dependent variable.

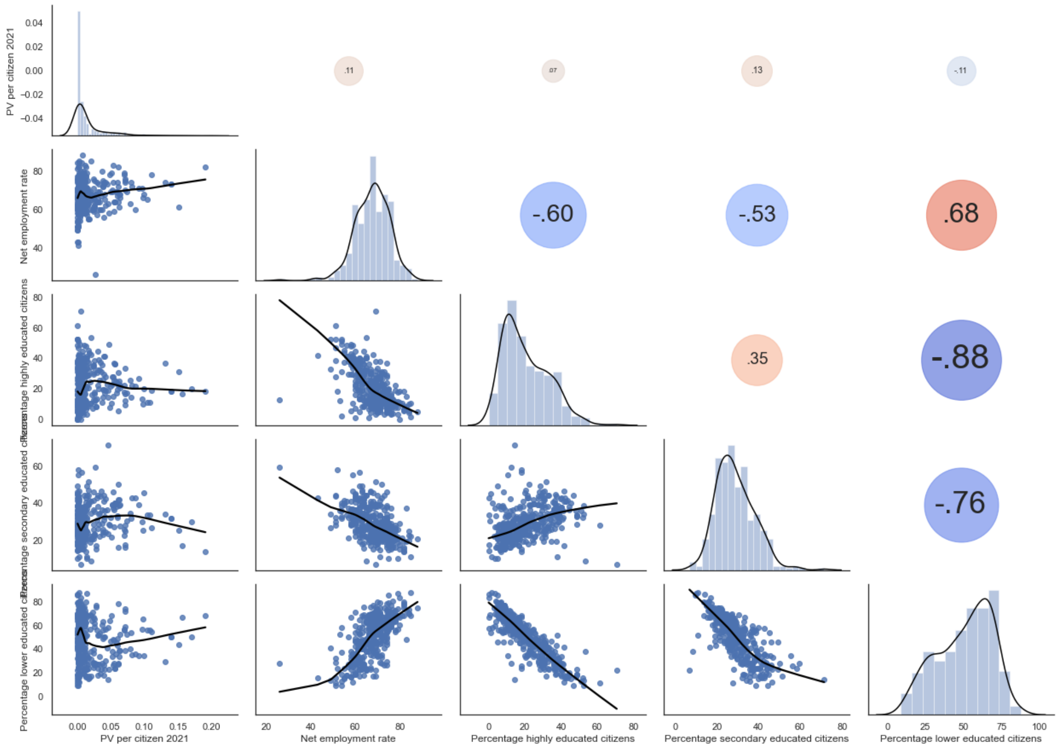


Figure 29: Correlation matrix for residential solar adoption (PV per citizen) and education-related variables. Spearman correlation coefficients are displayed to the right of the diagonal. Histogram distributions are displayed on the diagonal, and scatterplots with fitted lines are left of the diagonal.

Vehicles
The vehicle theme contains six variables, of which three relevant variables are selected: passenger vehicles per household, vehicles with gasoline fuel, and vehicles with other fuel. For the variables "vehicles with gasoline fuel" and "vehicles with other fuel" the percentage values are computed. The Spearman correlations are presented in Appendix A.10. Of the variables, only the number of passenger vehicles per household is significant (+0.59), meaning that in neighborhoods with high adoption rates, there is on average also a high number of vehicles per household. The correlation is shown in figure 30.

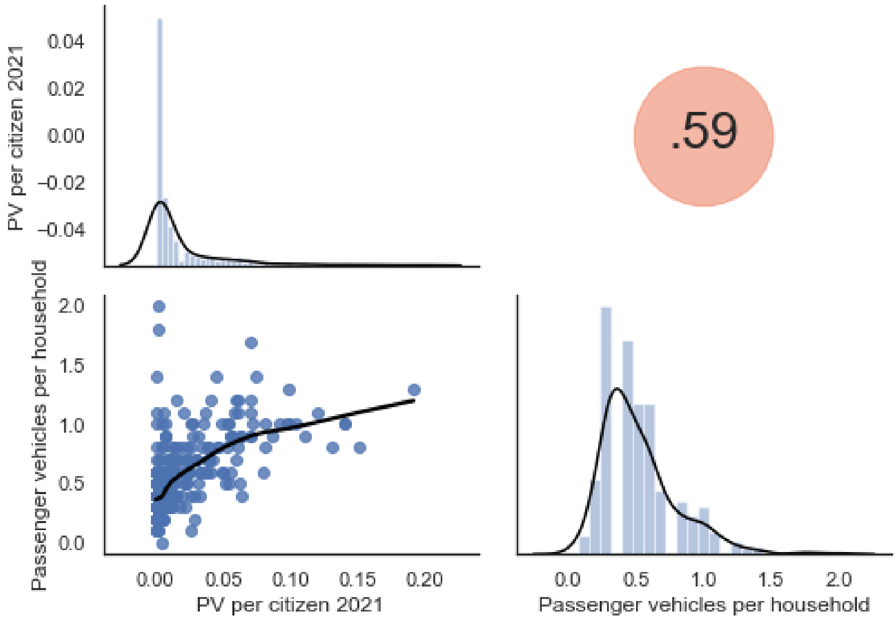


Figure 30: Correlation matrix for residential solar adoption (PV per citizen) and the number of passenger vehicles per household. Spearman correlation coefficients are displayed to the right of the diagonal. Histogram distributions are displayed on the diagonal, and scatterplots with fitted lines are left of the diagonal.

6.5.4 Unused potential

When a neighborhood has low adoption rates, this does not necessarily mean that the adoption rate can be improved in this neighborhood. Possibly the neighborhood has a low number of suitable rooftops. To incorporate this, the variable "unused potential" is analyzed. This variable represents the residencies with a suitable roof but without PV installed as a percentage of the total number of residencies.

The unused potential per neighborhood is strongly correlated with the number of PVs per household: on average, when the number of PVs per household in a neighborhood is low, the unused potential in that neighborhood is high (coefficient: -0.72, p-value: 0.00). The distributions- and ANOVA tests from Section 6.5.1 and Section 6.5.2 have been repeated for the unused potential variable by, again, creating groups based on the percentage of unused potential. The results of the two analyses are very similar. The most significant difference is that for the "unused potential", the number of vehicles is statistically significant between the two groups, which was not the case when exploring the ANOVA results of the adoption-based groups, and the average F-values for the "unused potential" groups are slightly lower. This means that roughly, neighborhoods with a low adoption rate also have much-unused potential.

6.5.5 Investigating the adoption gap

The results of the spatial and socioeconomic analysis so far lead us to think that a distinction can be made between several neighborhoods based on PV adoption rates and socioeconomic factors. The results show that there is a significant difference between the means of multiple socioeconomic indicators between groups with very low, low, medium, or high adoption rates or unused potential. In other words: neighborhoods that have high adoption rates significantly differ from neighborhoods with low adoption rates.

In Part 2 of the Design artifact, PV adoption evolution between socioeconomic groups will be further analyzed. To formulate these groups, the outcomes of the analysis in this Section are used. Not all variables can be included. It is chosen to focus on three variables that seem to significantly differ between adoption groups (as investigated in the ANOVA analysis) and that strongly correlate with PV adoption (as investigated in the correlation analysis). The three chosen variables are the **percentage of rental properties**, the **percentage of multi-household residencies**, and the **percentage of low-income households**. These variables strongly correlate with PV adoption rates (coefficients of -0.62, -0.71, and -0.43 respectively) and significantly differed between the PV adoption categories from the ANOVA tests (with F-values of 167.8 for the percentage multi-household residencies, 28.3 for the percentage low-income households and 52.1 for the percentage rental properties).

Therefore, the neighborhoods in Amsterdam have been clustered according to their scores for these three factors, to create sub-populations of neighborhoods to investigate in the system-dynamics model. The neighborhoods are clustered using the k-means clustering method in Python. Clustering methods partition data points into groups, or clusters, based on their similar attributes. Clusters are defined as groups of data objects that are more similar to another object in their cluster than they are to data objects in other clusters (Arvai, 2020). Thus, the clustering method allows to create groups of similar neighborhoods in Amsterdam.

The k-means clustering method is an unsupervised machine learning technique used to identify clusters of data objects in a dataset (Arvai, 2020). There are many different types of clustering methods, but k-means is one of the oldest and most approachable. The technique requires a few steps, presented in figure 31.

Algorithm 1 k-means algorithm

Specify the number k of clusters to assign.
Randomly initialize k centroids.
repeat
    expectation: Assign each point to its closest centroid.
    maximization: Compute the new centroid (mean) of each cluster.
until The centroid positions do not change.

Figure 31: Steps of the k-means algorithm for clustering. Source: (Arvai, 2020)

The clustering method is used to create similar groups of neighborhoods based on their percentage of low-income households, their percentage of multi-household residencies, and their percentage of rental properties. The optimal number of groups is determined using the elbow method and resulted in three clusters. A visualization of the categorization of the neighborhoods is shown in figures 32, 33 and 34, plotting each neighborhood's value for the percentage of low-income households, the percentage multi-household residencies and the percentage of rental properties.

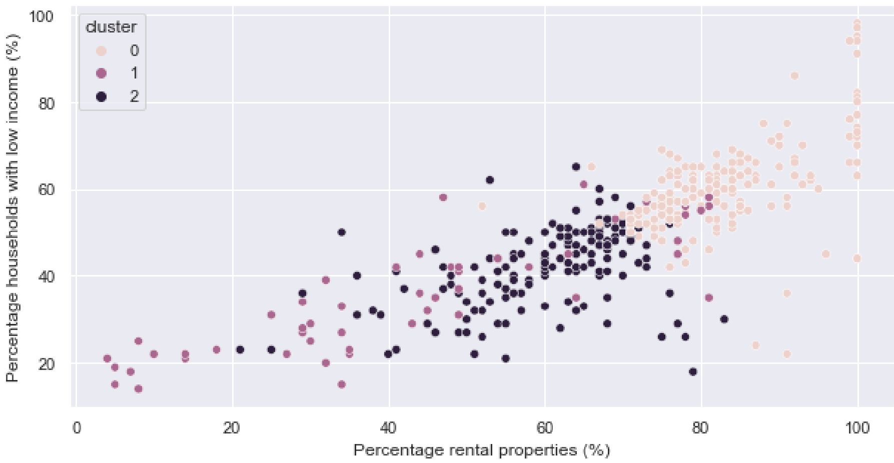


Figure 32: Correlation plot showing the classification of the three clusters, with the percentage of households with a low income and percentage of rental properties per neighborhood

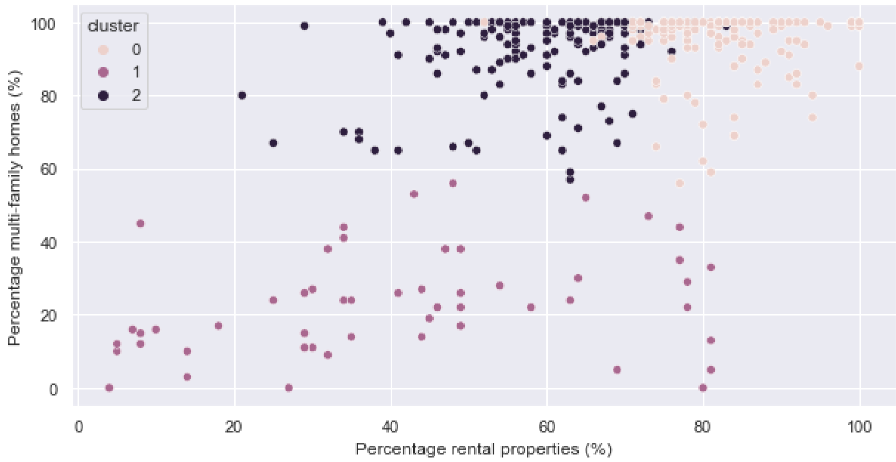


Figure 33: Correlation plot showing the classification of the three clusters, with the percentage of multi-household properties and percentage of rental properties per neighborhood

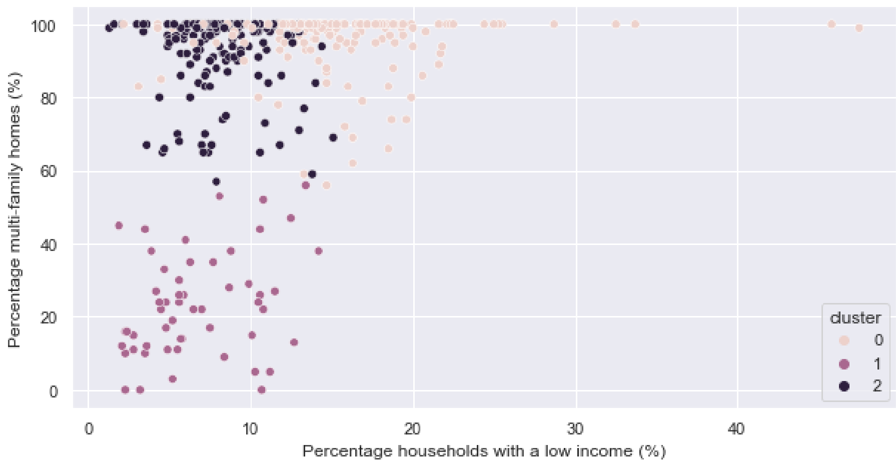


Figure 34: Correlation plot showing the classification of the three clusters, with the percentage of multi-household properties and percentage of rental properties per neighborhood

The three clusters of neighborhoods each have varying adoption rates, historic adoption patterns, and socioeconomic characteristics. For each of the clusters, the number of citizens, the number of households per cluster, and the socioeconomic variables that have been used for clustering are shown in Table 2. The yearly growth of the number of PV installations per citizen is shown in figure 35.

	G
High % rental properties, high % multi-household properties and high % low-income households	1
Low % rental properties, Low % multi-household properties and low % low-income households	2
Medium % rental properties, high % multi-household properties and medium % low-income households	3

Table 2: Descriptive statistics for the three neighborhood clusters

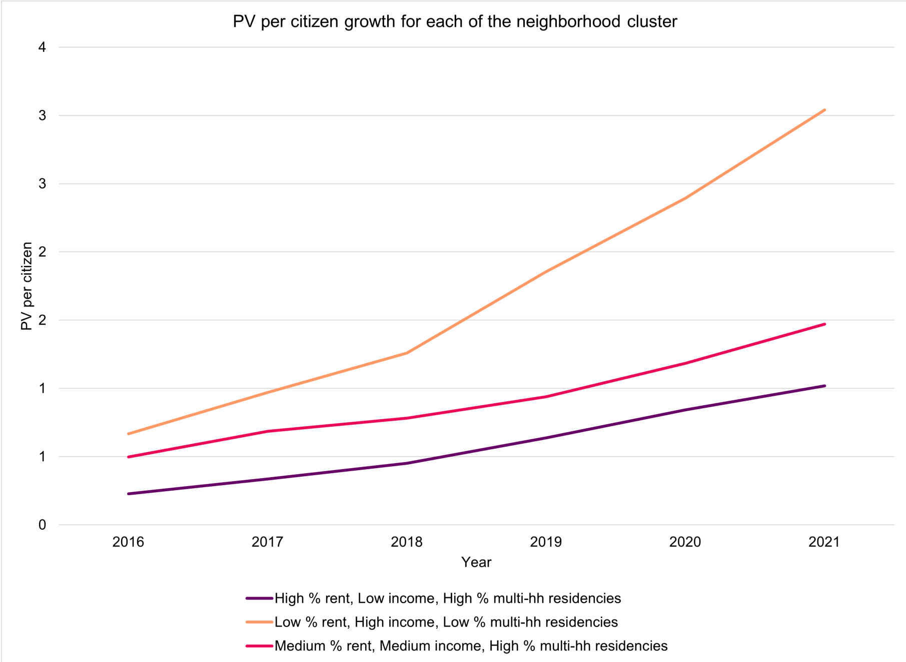


Figure 35: Growth of the number of PV installations per citizen for each of the neighborhood clusters, from the years 2016-2021

6.6 Main conclusions Chapter 6

This chapter aimed to answer research question 3:

What is the potential for residential solar energy generation in Amsterdam and how are observed adoption patterns correlated with various socioeconomic indicators to explain adoption disparity?

To answer this question, an assessment of the rooftop potential for solar panels is conducted and the relationship between socioeconomic factors and spatial adoption patterns is investigated. The rooftop suitability assessment showed that PV adoption is spread disparately amongst the neighborhoods of Amsterdam. Contrary, the potential electricity yield per citizen for rooftop solar generation is spread rather equally, with a few outliers of high potential per citizen.

The study revealed that in 2021, approximately 4% of households in Amsterdam have solar panels installed on their roof. From an ANOVA analysis it was found that, for multiple socioeconomic indicators, neighborhoods with the highest adoption rates significantly differ from neighborhoods with the lowest adoption rates. The strongest differences between neighborhoods based on adoption rates include:

- The percentage of multi-household versus single-household properties (F=167.8, p=0.0)
- The percentage of rental properties versus owned properties (F=53.75, p=0.0)
- The percentage of households with a low income versus a high income (28.5, p=0.0)
- The average electricity consumption (F=52.98, p=0.0)
- The average household size (F=84.07, p=0.0)
- The percentage of households with children (F=75.34, p=0.0)
- The percentage of single-person households (F=68.65, p=0.0)

A correlation analysis revealed that many variables correlate significantly with the adoption rate in a neighborhood. The strongest correlations found are:

- The percentage of low-income households (-0.43, p=0.0).

- The percentage of children of 0-14 years (+0.48, p=0.00)
- The percentage of single-person households (-0.58, p =0.00)
- The average household size (+0.59, p=0.00)
- The percentage of single-household residencies (+0.62, p=0.00)
- The percentage rental properties (-0.79, p=0.0)

The percentage of rental properties, the percentage of multi-household residencies, and household income have come forward during the interviews as important possible barriers to PV adoption (AMS1, NH2). Notably, these factors have also come forward as important correlating factors with PV adoption rates in this Section. Several of the outcomes in this study are in line with findings from other studies. The importance of home ownership, age, income, and property-sharing also came forward as important determinants during the literature study in section 4. These findings are in line with some of the findings by (Sommerfeld et al., 2017), (Balta-Ozkan et al., 2015), (Vasseur & Kemp, 2015b). Balta-Ozkan et al. (2015). Where Margolis et al. (2017) found the number of rooms and house age to be key influential variables, this study did not reveal the significance of these variables. Besides, Balta-Ozkan et al. (2015) found the number of households to be a significant variable, but this study had contrary results for this variable. The varying results between different studies highlight the local characteristics of PV adoption patterns and the care that should be taken when generalizing results to other regions.

It should be noted that correlations do not necessarily imply causation. There are numerous confounding demographic and socioeconomic factors that can influence the rates of rooftop solar adoption that were not taken into account in this study. Some of these include linguistic isolation or housing burden (Lukanov & Krieger, 2019). The studied variables are meant for exploration and are not conclusive. The correlations examined in this study, however, do highlight areas where more attention may be needed and where barriers to solar adoption might exist. The results also show that there is a significant difference between PV adopters and non-adopters. The type of household property, income, type of ownership, and household composition are observed to be the most significant socioeconomic factors when comparing the results of the two statistical studies. These results will be used for further investigation of the evolution of adoption patterns in Part II of the artifact.

7 Design artifact part II: System Dynamics Approach

This chapter describes the PV adoption system dynamics model and its structure. The model is conceptualized based on the theoretical understanding of the problem, local case study data, and stakeholder input. First, in Section 7.1, the model objective and requirements are discussed, and in Section 7.2.2, the system boundary is outlined. Section 7.2.5 - 7.2.7 give an overview of the conceptual model, the model components, and the model assumptions. In Section 7.3, the model formalization is described. In Section 7.4 the model is validated using structural and behavior-oriented tests, and finally in Section 8 experiments are conducted and results are discussed.

7.1 Model objective and requirements

The purpose of the model is to study the dynamics of PV adoption (amongst different socioeconomic neighborhoods), under the presence of several policy levers. The model aims to analyze the extent, speed, and disparity of PV adoption over time. The model requirements are defined by the model objectives, complemented by the insights from the relevance and rigor cycle. In short, the model should:

- Allow analysis of the extent, speed, and disparity of PV adoption
- Be able to investigate dynamics over a specified time
- Be able to capture relevant adoption dynamics as given by the previous research phases
- Be able to incorporate both socioeconomic and geographic insights from the previous research phases into the model
- Evaluate scenarios based on external developments and under different policy measures

In short, a model is needed that is flexible enough to allow experimentation and the analysis of potential policy interventions. Additionally, the model should be able to dynamically describe PV adoption development over the long term. On the other hand, the model must be general enough that the model is applicable to other municipalities (with their own data).

The model outcomes of interest are presented in table 3.

Category	KPI	Unit
Social indicators	Adoption percentage overall	% of total households
	Adoption percentage per socio-economic group	%
	Used potential of suitable rooftops	%
	Energy bill PV vs. non PV	€/household/month
	Energy bill as percentage of spendable income	%
Solar / climate goal indicators	Installed residential PV capacity	MW (MegaWatt)/citizen
	Installed capacity per socio-economic group	MW/citizen

Table 3: Model outcomes of interest

Uncertainty regarding model parameter values and model structure is not explicitly modeled in the system dynamics approach (Kelly et al., 2013). This makes it necessary to execute a scenario and sensitivity analysis, to explore the impacts of uncertainties on model behavior and incorporate them in a policy (intervention) analysis (J. Sterman, 2000) (Pruyt, 2013).

7.2 Model design

7.2.1 Method

In SD models, links between parameters and variables represent direct causal relations. This allows SD models to be used to explore the complex behavior of the interaction between structures to gain insights, in order to transform the structure of the system into more desirable behaviors (Pruyt, 2013). Thus, one needs to be able to perceive, identify or assume direct causal relations.

First, a conceptual model is made in the form of a Causal Loop Diagram (CLD) to identify the main relationships, factors, and subsystems affecting the system. Afterward, a detailed stock-flow diagram (SFD) is developed to model the system of adoption, followed by the formulation of the model equations.

SD simulation models are mostly displayed/constructed using Stock-Flow Diagrams. An example is shown in figure 36. The diagrams consist of boxes (stocks) and arrows (inflows or outflows), auxiliary variables, causal links between variables, and causal links with delay signs. The stock variable accumulates: it integrates flows over time. Shadow variables are used in SD models to include a variable in a sub-model that is elsewhere defined. Shadow variables are shown in between brackets in grey: <Shadow variable>.

Two common uses of SD modeling are (i) to explore plausible futures, and (ii) to study the implications of different policies. Another common use of SD modeling is to learn about a system and the link between system structure and behavior (Pruyt, 2013).

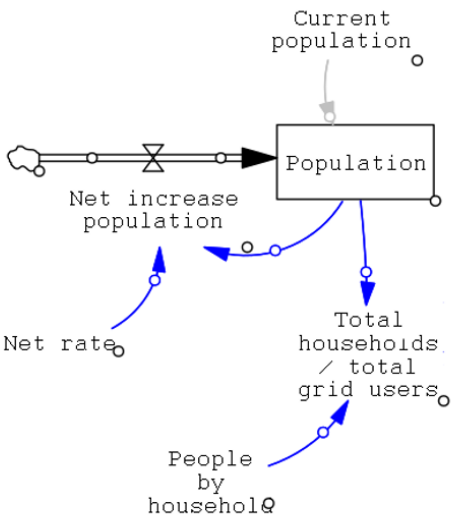


Figure 36: Example of a stock-and-flow system. Source: author.

Figure 37 shows the used model components and their visual representation. Sensitivity variables (purple boxes) are included in the model to allow conduction a sensitivity analysis.

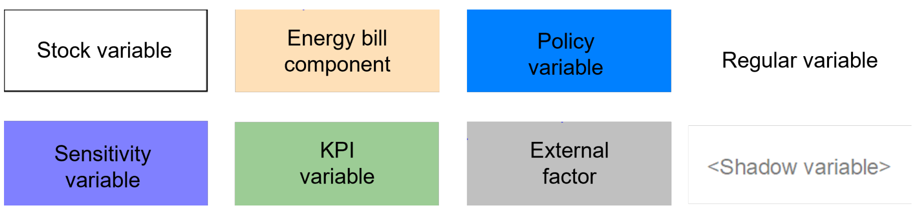


Figure 37: Model components of the System Dynamics model

7.2.2 Model boundaries

It is very important to carefully delimit system and model boundaries. All (potentially) important elements which influence other parts of the system and are also significantly influenced by elements of the system, should be modeled as endogenous variables. Endogenous variables thus are variables that are determined by other variables within the model. All elements that (could) seriously impact the system –but that are not sufficiently influenced by the system– become exogenous variables. All other elements omitted (Pruyt, 2013). Table 4 describes the boundaries of this study.

The model studies grid-connected rooftop PV adoption by households. Thus, only the residential sector is in the scope of this study. Besides variable boundaries, the model has a distinct geographic boundary: PV adoption in the municipality of Amsterdam is studied. The SD model retains this geographic boundary, similar to the previous analysis in, as this allows to use case study data obtained in the analysis, and study adoption dynamics between socioeconomic neighborhood groups in this municipality. Several factors are not limited to the boundaries of the municipality of Amsterdam, such as electricity prices and PV installation costs, which are national.

Endogenous	**Exogenous**	**Excluded**
Thoroughly modelled endogenous variables	PV installation costs	PV battery technology development and adoption
Households installing rooftop solar	Inflation (national)	PV capacity expansion
PV payback times	Geopolitical developments	Change in grid costs and load losses due to rooftop solar
Energy bills PV and non-PV	Fixed distribution and transmission costs	Annual PV system degradation
	Market electricity price (national)	PV installations at business or public buildings
Superficially modelled endogenous variables	Population growth in Amsterdam	Grid defection by households
Addition in energy supplier margin due to rooftop solar	Household electricity demand in Amsterdam	Increase in PV capacity due to technological advancements
	Electricity generation	Grid capacity
	Average MWs installed per rooftop solar adopter	
	Time to install rooftop solar	
	Expected annual kWhs produced per kW of solar in the Netherlands	
	Shortage of technicians and materials	
	Energy tax tariffs	
	PV self-consumption rate	
	Percentage of suitable roof surface	

Table 4: The endogenous, exogenous, and excluded model variables, indicating model boundaries

The annual PV system degradation rate is a year-to-year decline in the DPV system's output due to, for example, the aging of equipment over time. This factor is not considered in this study, as the model does not allow the modeling of individual PV systems and their lifetime.

7.2.3 External influences

The XLRM diagram presented in Section 5 is used as input for setting model boundaries. Several external factors have been identified in Chapter 3 that impact the PV adoption system, but are not influenced by the system itself. These are presented as the external factors in the XLRM diagram. The external factors can be included in the model as exogenous factors. Not all external factors are included. The modeled external factors are the price of PVs (driven by technical innovations), the energy prices (driven by geopolitical developments), the PV efficiency, and the shortage of materials and technicians. It has deliberately been chosen to leave public awareness and solar radiation out of the simulation model, to reduce model complexity and uncertainty. The impact of the solar radiation level is limited in the face of the current modeling objectives. The causal effects of public awareness on adoption patterns in Amsterdam are unknown and difficult to determine and are therefore also left out of scope. The factors of geopolitical developments, inflation, and technicians and materials shortages and their incorporation into the model are explained in more detail below.

Geopolitical developments have caused turbulent developments in energy prices over the past years. Where initially gas prices increased significantly, electricity prices followed accordingly. The future development of these prices is highly uncertain. Electricity prices here indicate the market price (wholesale price) for electricity. The CPB estimates that electricity wholesale prices remain dependent on gas prices, and assume that the electricity prices will increase similar to the tariffs for gas (CPB, 2022b) in the future. Given the uncertain nature of this variable, scenarios are included in the modeling process. The CPB developed three scenarios for price developments. These scenarios are adopted in this study, to account for the uncertain development of this variable. The scenarios cover a base case, a low-price scenario, and a high-price scenario, shown in figure 38.

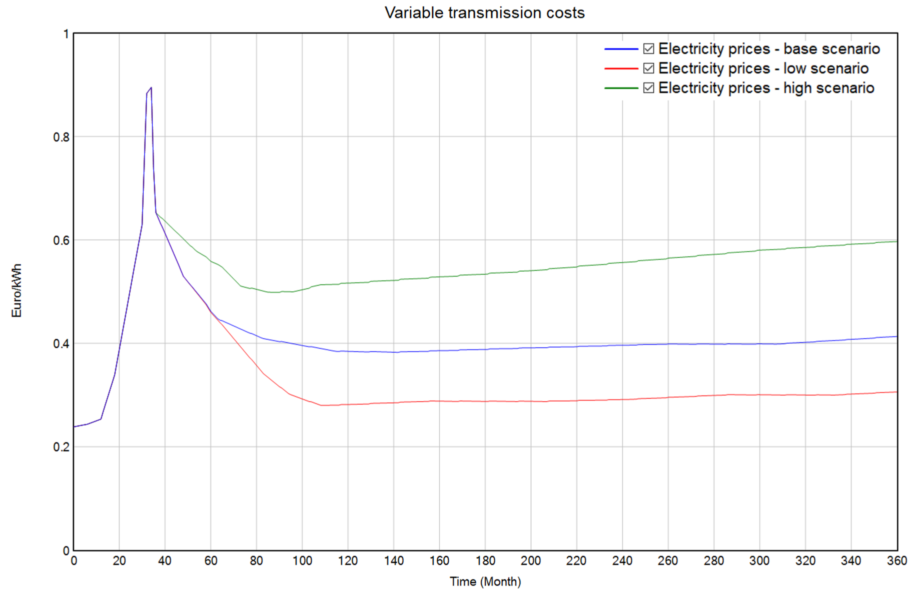


Figure 38: Plausible scenarios for wholesale electricity prices used in this study, and developed by the CPB

A distinction is made between geopolitical developments and **inflation**. Geopolitical developments are included as a separate scenario here because these developments specifically have impacted the energy market severely over the past years. While these developments also caused inflation in other sectors through increased energy prices, the macroeconomics of geopolitical developments and inflation are complex, and thus the inflation factor is modeled separately in the model. This also allows analyzing increased prices of for example PV modules separately. For inflation, three scenarios are included: low inflation, a base case, and high inflation scenario. In the base case, there is no inflation. In the low inflation scenario, inflation decreases to 85% and in the high inflation scenario, inflation increased to 115%.

The **shortage in technicians and materials**, which impacted the PV industry over the past years, mainly affects the time to install PV in this model. This creates a shorter or extended delay in the flow from potential PV adopters to PV adopters. For this variable, there are two scenarios: a base case and an increased shortage in technicians and materials. In the base case, the delay in installations of PV systems is 6 months, in the increased shortage scenario, this delay is 12 months. Besides, it is assumed that the delay causes a slight decrease of 10% in the adoption rate, as households might refrain from adopting PV when waiting times are so long.

7.2.4 Policy interventions

The impact of several policy measures is simulated in the system dynamics study. This section describes the included policy measures. The current existing policies have been identified in Section 3.1. These include the current netting scheme, the proposed netting scheme, the price cap, the zero-interest loan for lower incomes, the tax deduction on PV installations, and the feed-in tariff (after 2030).

Two additional policy options are included in the model. Almost all of the existing policy measures are general policies, not targeting specific groups of citizens. The additional policies are leveling policies that aim to stimulate PV adoption in under-served groups and thus aim to shrink the adoption gap. These are included to explore the effect of leveling, targeted policies, and have been identified through literature research and interviews.

First, a subsidy for lower-income (LI) households is introduced. Currently, the only form of active subsidy is a tax for all citizens. Previous research has shown that low- or middle-income specific financial incentives work significantly more effectively than general financial incentives (O'Shaughnessy et al., 2020b).

Second, an extended netting-scheme is proposed for LI households. This policy measure can be used when the proposed netting scheme is in place. The proposed netting scheme is expected to increase payback times for PV investments, making the purchase less viable for low-income households. An extended netting-scheme for low-income households allows these adopters to profit from the current netting scheme for the first years after investment until the investment is earned back. This duration should be set by the government based on actual average payback times.

The third additional investigated policy measure is a sustainability mandate for landlords, OAs, and housing corporations. Interviews with stakeholders revealed that one of the barriers to adoption includes the complicated

	Policy	Explanation	Currently in place?
General policies	Netting scheme (current and proposed)	Allows deducting (a percentage of) the power that households feed back to the grid, from the amount of power that it consumes from the grid	Current scheme in place, proposed scheme active from 2025 onwards
	Subsidies	A tax rebate that removes the VAT tax of 21% of a PV-installation purchase	Yes
	Feed-in tariff (after 2030)	Excess electricity fed back to the grid and that exceeds one's consumption is sold to the utility for a feed-in tariff	Yes. For the proposed netting scheme, the minimum feed-in tariff is set to be 80% of the retail tariff.
	Renewable energy loan	For renewable energy investments, households can request a loan with low interest rates	Yes
	Price cap	A maximum electricity tariff of €0,40/kWh for households, under a specified consumption limit	In the year 2023
Leveling policies	Subsidy for LI-households	Subsidy for PV-installation purchase for LI-households	No, for investigation purpose in this study
	Zero-interest loans for LI-households	Zero-interest loans for renewable energy purchases by LI-households	Yes, in the municipality of Amsterdam specifically
	Extended netting scheme for LI-households	Allowing LI-households to profit from the netting-scheme when purchasing a new installation, up untill the investment is paid back	No, for investigation purpose in this study
	Mandate sustainability plan	Mandate a sustainability plan for OA's and housing corporations	No, for investigation purpose in this study

Table 5: Current and studied policies

decision-making process of residents of OA's and housing corporation residencies. This policy measure entails mandating a sustainability plan for these parties, lifting some of the barriers that exist in these cases.
An overview of the policy measures included in the system dynamics model is presented in table 5.

7.2.5 Conceptual model

A conceptual model, representing the main factors and relationships in the system, is created in the form of a Causal Loop Diagram (CLD). This section describes the main model elements through the CLD presentation. A detailed description of model dynamics follows in Section 7.2.6 and 7.3. CLDs contain variables and the direct causal relationship between them. Relationships are either positive or negative. A positive relationship between variables A and B means that (i) an increase in A causes B to rise above what it would have been otherwise and (ii) a decrease in A causes B to fall below what it would have been otherwise. A negative relationship between variables A and B means that (i) an increase in A causes B to fall below the value would have had otherwise and (ii) a decrease in A causes B to rise above what it would have been otherwise (J. Sterman, 2000).

The conceptual model is shown in figure 39. Inputs, policy interventions and external factors are shown respectively on the left, top and bottom of the CLD. The policy interventions are explained in more detail in Section 7.2.4.

The purple stock-flow diagram represents the PV adoption by households. Although the adoption-decision process is complex, and besides financial motivations other socioeconomic factors and psychographic factors play a role, the final decision is often made based on a financial metric such as the payback time. Therefore, in this model the flow from potential household adopters to household adopters is represented by the adoption rate, which is in turn determined by the payback period of rooftop solar. Rai and Sigrin (2012) investigated the economics behind PV adoption decision-making, and found that PV adopters generally use the expected payback period as the financial decision making criterion, and not other metrics such as the Net Present Value. Therefore, the payback period is used in this simulation. The socioeconomic factors influencing adoption choices are embedded in the empirical adoption rates used in the model, further described in Section 7.2.6.
The population of potential household adopters grows according to the population growth in the municipality, and depends on the percentage of available suitable rooftop (the technical potential). The expected savings from rooftop solar and the price of a PV system make up the payback period of rooftop solar. The expected savings from rooftop solar depend on the system efficiency, the financial incentives posed by the Netting Scheme policy, the self-consumption rate, the interest on a sustainability loan and the subsidies on PV installation costs.

The netting policy is an important factor in determining the expected savings from rooftop solar, as it impacts the expected savings in two ways. First, through the amount of generated electricity one is allowed to deduct from the consumption on the energy bill. Second, the netting scheme influences the self-consumption rate of consumers. When all generated electricity can be deducted from the consumption, there is little incentive to use one's own generated electricity (ST_2, ST_3,AL_1). When the netting scheme becomes less financially attractive, consumers will likely adjust their self-consumption. The feed-in-tarrif plays a role here aswell, as it determines the worth of the injected electricity to the grid, dependent of what netting scheme policy is in place. Currently, only the amount exceeding consumption is compensated using the feed-in tariff. Under the proposed netting scheme, a higher percentage of injected electricity will be compensated with a fixed feed-in tariff.

The orange arrows indicate a feed-back loop that represents the death spiral hypothesis (Castaneda, Franco, et al., 2017; Costello & Hemphill, 2014; Felder & Athawale, 2014; Grace, 2018; Meehan, 2015). The death spiral hypothesis, as described in Section 5, represents the vicious cycle where increased PV adoption results in increased costs for utilities, who in turn raise their tariffs, thus increasing the attractiveness of solar panels compared to grid electricity, which in turn results in more PV adoption. For every household installing rooftop solar, utilities lose some revenue. Depending on the netting scheme policy in place, the utility company is obligated to pay a tariff for the injected electricity by households, and the generated electricity by households replaces some or all of the kWhs of electricity they would have otherwise bought from the utility. As such, the utility makes less sales and experiences reduces revenues. Utilities respond, under the principle of cost recovery, by increasing their electricity rates, which impacts the expected savings from rooftop solar, making the technology more attractive. This results in more households who are willing to install rooftop solar, creating a reinforcing loop.

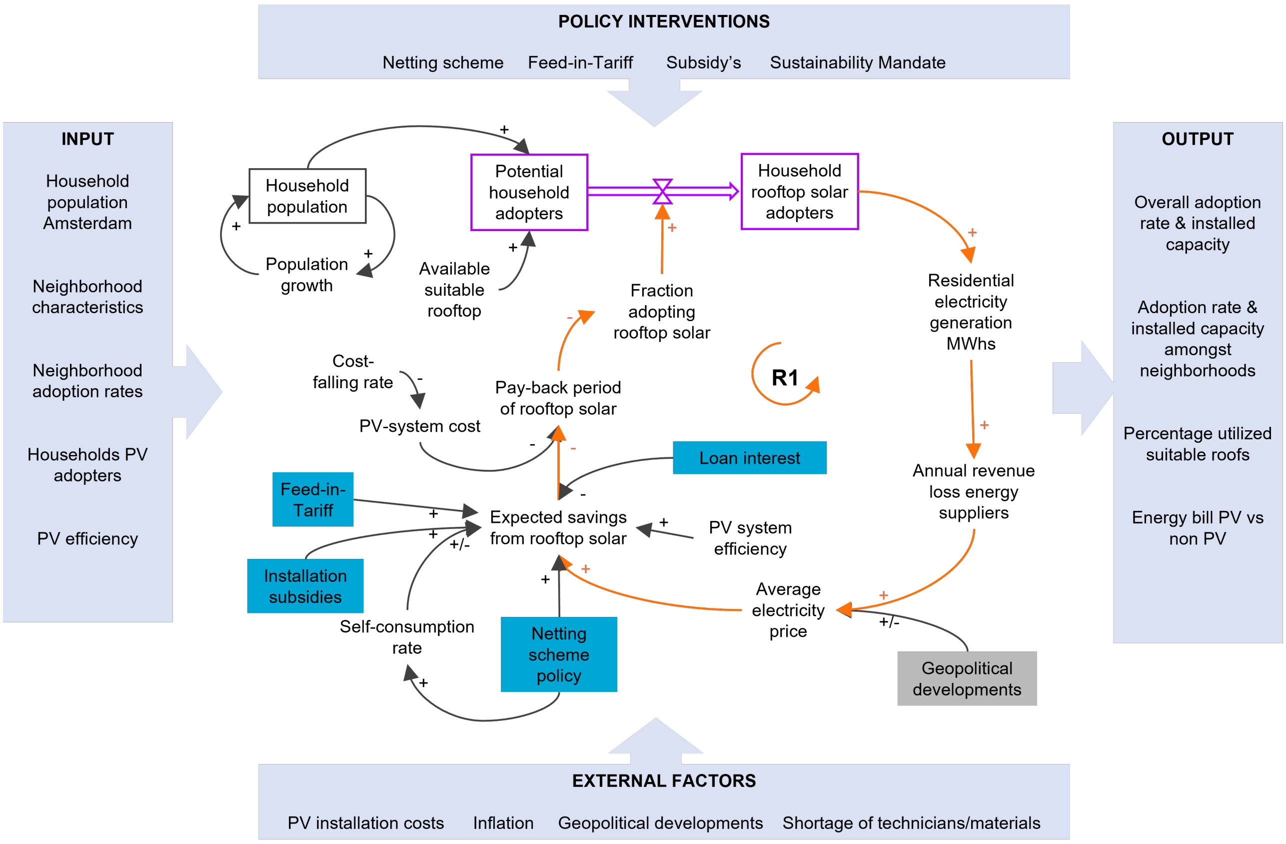


Figure 39: Causal Loop Diagram representing the main variables and relations in the System Dynamics model

7.2.6 Main model dynamics

PV adoption

Modelling PV adoption - the flow from potential adopters to adopters - is not straightforward. Chapter 4 describes that PV adoption depends of several factors, including technical potential, socioeconomic factors and psycho-graphic factors. In renewable-technology diffusion studies, different methods to model technology adoption are available.

One of the most widely adopted methods is the Bass-Diffusion model, which is a mathematical model used to depict the spread of an innovation, as a function of information-related technology such as advertising and word of mouth (Morcillo et al., 2022). The Bass model is a general model, used to depict many different types of innovation diffusion such as innovation diffusion in retail service, industrial technology, agriculture, and the educational, pharmaceutical and consumer-durables markets (Mahajan et al., 1993). In the case of PV adoption, the Bass model considers how information is disseminated through potential households to convert them to PV system adopters.

The Bass model is applied in this study to account for the adoptions through the factors of imitation (word-of-mouth) and innovation. These factors are included to replicate the phenomenon that over time, adoption increases even though the product price might remain constant. This independent increase in adoption is generated by the fact that households imitate adoption behavior (the word-of-mouth effect) and technology products increase in popularity (the innovation effect) (Mahajan et al., 1993).

To determine the fraction of households adopting based on financial motivations, empirical data is used to compose an adoption curve. Given the rich amount of data available for this study, adoption rates can be determined for each neighborhood for the past six years. Therefore, it is chosen to model product diffusion based on empirical data of adoption rates at given years and payback periods. The data from Chapter 6 can be used to derive the historic adoption rates. This method allows capturing more adoption mechanics, as product price and adoption barriers are embedded in the actual perceived adoption rates. Besides, this allows to model the impact of policy interventions on product diffusion more adequately and to distinguish different groups of customers by using multiple adoption rates from the empirical data.

All together, the adoption rate (flow from potential adopters to rooftop solar adopters) is thus determined by the adoption curve that estimates adoption rates at certain payback times, a word-of-mouth effect, and an innovation effect.

The utility death spiral
The utility death spiral, which has often been the topic of investigation in previous renewable integration SD studies, results from the utilities' need to increase tariffs to compensate for the reduction in electricity demand. The increased tariffs further promote PV adoption, resulting in an increased fall in demand, causing a reinforcing cycle.

Distributed PV impacts utility revenue in multiple ways. First of all, it generates gross utility revenue loss through self-consumption of PV-generated electricity and through grid-injection of PV-generated electricity (Castaneda, Franco, et al., 2017):

- Self-consumption of generated electricity by consumers reduces retail sales for utilities, directly decreasing their revenue. Any distributed PV generation that is used to supply the customer directly with electricity for consumption is said to be self-consumed. Self-consumption allows PV owners to reduce or eliminate the variable utility charge portion of their electricity bills. The amount of self-consumed electricity by PV adopters is no longer taken from utilities, reducing their sales and marginal electricity price (Castaneda, Franco, et al., 2017).

- Grid injection of PV-generated electricity increases costs for utilities as they have a purchase obligation for the injected electricity. If the PV system generates more electricity than the consumption of the consumer at that moment, the PV customer essentially "sells" the energy to the energy supplier. This can happen in multiple ways, such as net metering or net billing. In the Netherlands, this currently happens through both schemes, working towards only net billing after 2030. From the utility viewpoint, these payments for PV grid injections are additional expenditures. However, there are also reduced expenditures as these grid injections offset purchasing or generating wholesale electricity. Thus, the difference between the sell rate for grid injections and the utility's avoided costs, driven in large part by the wholesale electricity price, is a key driver of distribution utility financial impacts.

Second, distributed PV also results in avoided costs including reduced wholesale electricity purchase costs or avoided energy generation costs and avoided distribution line losses. For a utility, the self-consumption of distributed PV generation leads to reduced expenditures related to purchasing or generating wholesale electricity and, in some cases, may reduce some future fixed capital and associated operations and maintenance costs. In most cases, under pre-existing tariff designs, this may still lead to an under-recovery of distribution system fixed costs because utilities often recover a (sometimes substantial) portion of the fixed costs incurred for maintaining the network from the volumetric energy charge component of their retail tariff.

Utilities adjust their retail tariff to their changed revenue. The change in tariff thus depends on the extent of distributed PV deployment, the reduced utility sales and revenue due to PV, and the extent to which utilities pass through reduced revenue to consumers. To decide on the pass-through rate, utilities formulate future revenue requirements. The impact of distributed PV on utility rates is not easy to assess and differs per utility company. However, many studies on the utility death spiral have successfully used SD to assess these effects in a simplified manner, such as (Castaneda, Franco, et al., 2017), (Morcillo et al., 2022) and (Castaneda, Jimenez, et al., 2017). All studies showed that increased penetration of distributed residential PV, at different degrees of penetration, led to a moderate increase in utility rates due to lost revenues, meaning that the revenue losses were on average larger than the revenue increases due to rooftop PV. The tariff increase was found to be higher at higher degrees of PV penetration. Morcillo et al. (2022) estimates that electricity prices for households without PV will increase by about 20% by 2035 .

Distributed PV also impacts grid operators, as has been described in Section 3.4, mainly in the form of voltage issues. Interviews with grid operators revealed that although PV-related problems are expected to increase in the future, distributed PV-related cost increases will remain minimal for consumers due to several reasons:

- Grid operators can acquire low-interest loans with long depreciation periods. Therefore the growth of investments by grid operators is not equal to the growth in fixed grid costs paid by consumers.
- Wholesale customers pay relatively more than small consumers such as households.
- Grid losses currently are much more driving the increased costs for consumers than investment costs. These costs are more directly passed on to consumers. The increased grid losses are caused by the high energy prices.
- Grid investments for expansion often occur because new customers are connected to the grid, which results in more customers who pay a grid contribution. Replacement or reinforcement of the grid does result in increased rates for consumers, however, many investments are planned regardless of increased PV integration. Grid operator Liander (operating in Amsterdam) is already planning to replace all low-voltage cables nonetheless of the PV adoption rates.

In this study, the impact of PV adoption and electricity demand on electricity tariffs will be included but modeled in a simplified manner. In reality, the tariff determination is complex, and different utility companies handle in different manners. However, literature shows that the general effect of PV adoption on utility electricity tariffs is known, and similar dynamics are observed in all studies.
Given the geographic extent of the SD model in this study, it is difficult to model national pricing mechanics. Not only PV adoption in Amsterdam impacts utility revenues, but PV adoption in the whole country. Therefore, a simplification is made that electricity retail prices increase according to the extent of PV adoption increase and based on findings in the studies by (Castaneda, Franco, et al., 2017), (Morcillo et al., 2022) and (Castaneda, Jimenez, et al., 2017).

7.2.7 Model assumptions

System dynamics models are highly aggregated and simplified representations of reality. Most SD models thus contain many assumptions, aggregations, simplifications, and uncertainties (Pruyt, 2013). These are often necessary and justifiable, based on either the need for simplicity or the lack of available data/knowledge on the relationship. The list below describes and justifies the assumptions upon which this model was based:

- Households with PV systems do not require battery support for the storage of energy and thus remain grid connected. Grid defection in the Netherlands requires extensive energy storage solutions to store electricity from summer to winter. Given that battery solutions remain expensive, especially solutions that have the capacity to store energy from summer to winter, grid defection by households is therefore deemed unfeasible and is not incorporated into the model. Some studies acknowledge that grid defection is not yet an economically feasible option (Sabadini & Madlener, 2021). Solar-battery systems are not considered in this model.
- PV system sizes adopted by households are the same for each household and remain constant during simulations. The system size is fixed at 10 solar panels per installation with a capacity of 350 kWp (van der Wilt, 2022) , which is a good representative of the average solar panel on the market in the Netherlands. PV system efficiency is also assumed to be constant for each household and throughout the simulation period. PV efficiency is defined as the ratio of energy output from the solar cell to input energy from the sun. In addition to reflecting the performance of the solar cell itself, the efficiency depends on the spectrum and intensity of the sunlight and the temperature of the solar cell (PVEducation, n.d.). The PV efficiency is set at 85%, which is an accepted average for the Netherlands (Verheij et al., 2020b).
- Energy consumption is assumed to be equal for all households. The average for households in Amsterdam is used in the model, which is 233 kWh per month and 2800 kWh per year (Planbureau voor de Leefomgeving

& van Polen, 2021). It is assumed that electricity consumption gradually decreases until 2030, in line with projections of the Netherlands Bureau for Economic Policy Analysis (Planbureau voor de Leefomgeving & van Polen, 2021), of which one of the reasons is the stricter energy efficiency requirements for electric devices. Any other external influences that might impact the average energy consumption are left out of scope.

- The simulation period is 30 years, starting in 2019. The model starts in 2019 so that the years 2019-2022 can be simulated and model outcomes can be compared with actual observed data from these years, to validate the model outcomes.
- It is assumed that households purchase PV installations using a low-interest loan provided by Dutch national government, with a yearly rent of 3,5% with a duration of 10 years (Nationaal Warmtefonds, 2022).
- For simplicity, no difference between distribution utilities is considered. This entails that electricity prices are equal for all households in the simulation. No distinction is made between different types of contracts.
- As the modelled case study includes only the municipality of Amsterdam, the case study area is too small to properly and extensively model the effects of a possible death-spiral, which happens mostly at national level. Therefore, the death-spiral effect is modeled in a simplified way, informed by previous research on the dynamics of the death-spiral.
- Considering the death-spiral effects, this model includes the impact of rooftop PV on the variable electricity costs, as interviews with grid operators revealed the impact on the fixed grid costs are marginal, and are expected to rise nonetheless (AL_3).
- The effects of rooftop solar diffusion on the utility's grid costs are thus not taken into account in this model. Besides that it is not expected that these costs will directly impact consumers (AL_3), it also appears that there does not yet exist a proper method of analysis for quantifying the large-scale impact of PV on the grid, voltage issues and the change in grid costs attributable to rooftop solar diffusion for the region of Amsterdam. Any estimations made in literature could be used as proxies, however grid impact is highly region-specific, depending on the quality and age of the grid, and thus proxies would create high uncertainty in the results. Given the impact is not necessary to model PV adoption, it is chosen to leave this variable out of scope.
- Newly built residencies more often come equipped with PV installations. Thus, possibly, amongst new households in the study area, several households might already be equipped with solar panels. However, the magnitude of this relationship is unknown. This mechanic is therefore, for simplicity, not included in the model.
- An assumption is made for the sake of simplicity that there are no birth, death or migration processes between the sub-populations
- The impact PV adoption has on electricity tariffs is difficult to determine, as the exact impact of PV on company revenue has to be assessed, and every utility company has its own policy to deal with such tariff impacts. The tariff impact also depends on the extent to which utilities pass revenue loss caused by distributed PV on to ratepayers versus absorbed by the company, and on the mechanism through which the rate adjustment is passed (every 3 months, every year, etc.).
- The lifetime of rooftop solar systems, and thus the need to replace a system, is not taken into account to avoid the complexity of the model.
- For the income-based leveling policies, the "low-income definition" of the municipality of Amsterdam is adopted. Under this definition, a household with a collective income below €30.000 is considered a low-income household. This requirement is used in the further analysis for the eligibility of LI-subsidies.

7.3 Model implementation

This section describes the implementation of the model by elaborately discussing each sub-model.
The simulation model
The model has a time unit of 1 month and a time-step of 1. This allows to model the monthly fluctuations of PV generation. The model starts simulation at the initial time t=0, which corresponds to the year 2019. The

model simulates 360 months, corresponding to 30 years, resulting in a simulation period from 2019 to 2049.

The model is divided into several submodels. Each of these submodels will be explained in this section. A list of additional formulas is included in Appendix C.0.1.

Population and PV adoption sub-model
The population and PV adoption sub-model contain the main stock and flow simulation. This Stock and Flow model simulates the whole population of the municipality of Amsterdam. The simulation of the sub-populations (neighborhood groups) is detailed later on in this section.

The sub-model, shown in figure 40, contains a stock for the population (number of citizens) in Amsterdam, which increases with a net rate of 1% each year. The net increase has been calculated using the yearly population statistics from the CBS (CBS, 2022a). To transpose the population to a total number of households (grid users), the population is divided by the average people by household in Amsterdam of 1,8.

The potential rooftop solar adopters are the percentage of the total household population with a suitable rooftop. This stock grows according to population growth. The percentage of households with a suitable rooftop is determined by the author during the spatial analysis in ArcGIS in Section 6 , and is set at 60%.

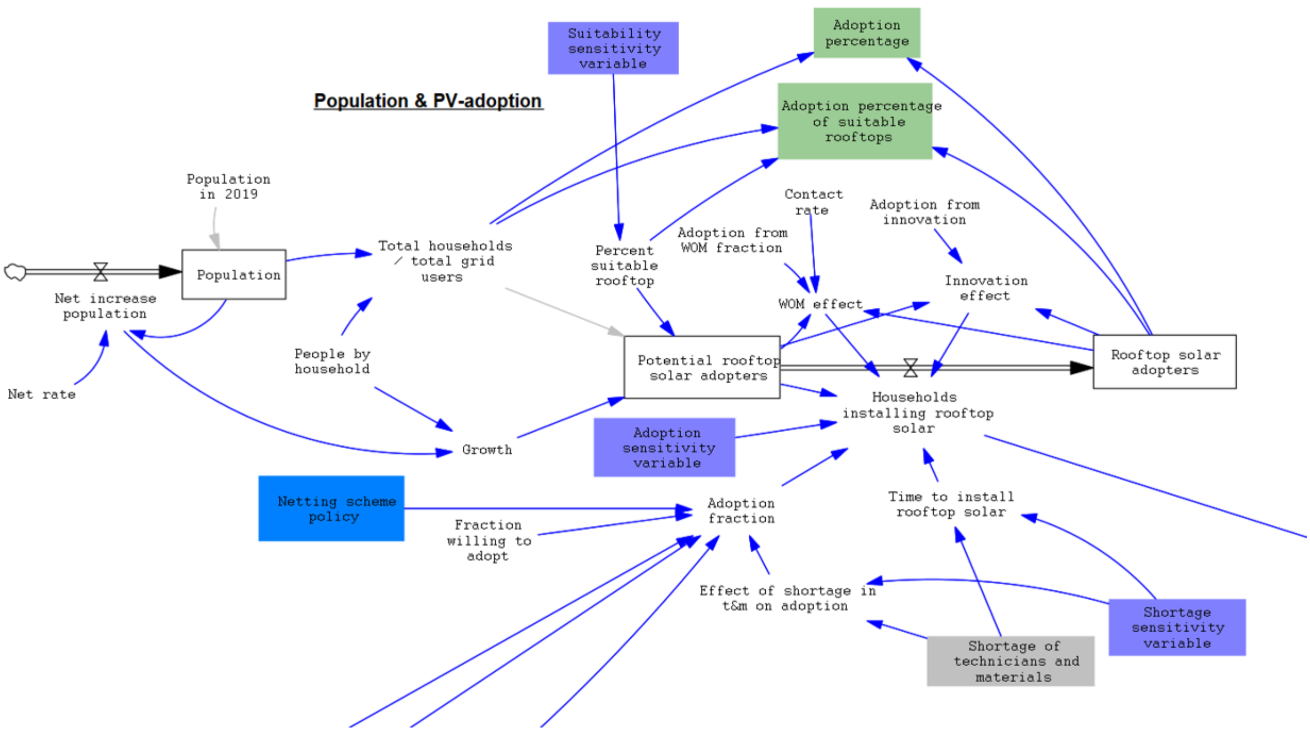


Figure 40: PV adoption sub-model

The flow from the stock of potential rooftop solar adopters to rooftop solar adopters, the households installing rooftop solar, is determined by the adoption fraction, the innovation effect, and the WOM effect. The adoption rate is divided by 12 as the model uses one-month timesteps, while the adoption rates are yearly. The flow is delayed by the time to install rooftop solar (initially set at six months), which is affected by a possible shortage of technicians and materials.

Households installing rooftop solar = DELAY1((((Potential rooftop solar adopters(Adoption fraction*Adoption sensitivity variable))+WOM effect+Innovation effect)/12, 6)*

Based on the payback period of PV systems, a certain fraction of the potential rooftop solar adopters will install a PV system each year. The adoption fraction is determined by a graphical function (figure 41), which is calibrated against the available empirical data analyzed in Chapter 6. As the empirical data includes adoption fractions from the years 2016 - 2021 with average payback times from 7,5 to 6 years, some data points are missing from the function. These have been informed by the shape of similar graphical functions revealed in other studies on PV adoption rates (Maximillian, 2018) (Grace, 2018), and adapted to the empirical data in this study. The final adoption fraction is determined by the fraction willing to adopt and the payback time under different formulations of the netting scheme policy.

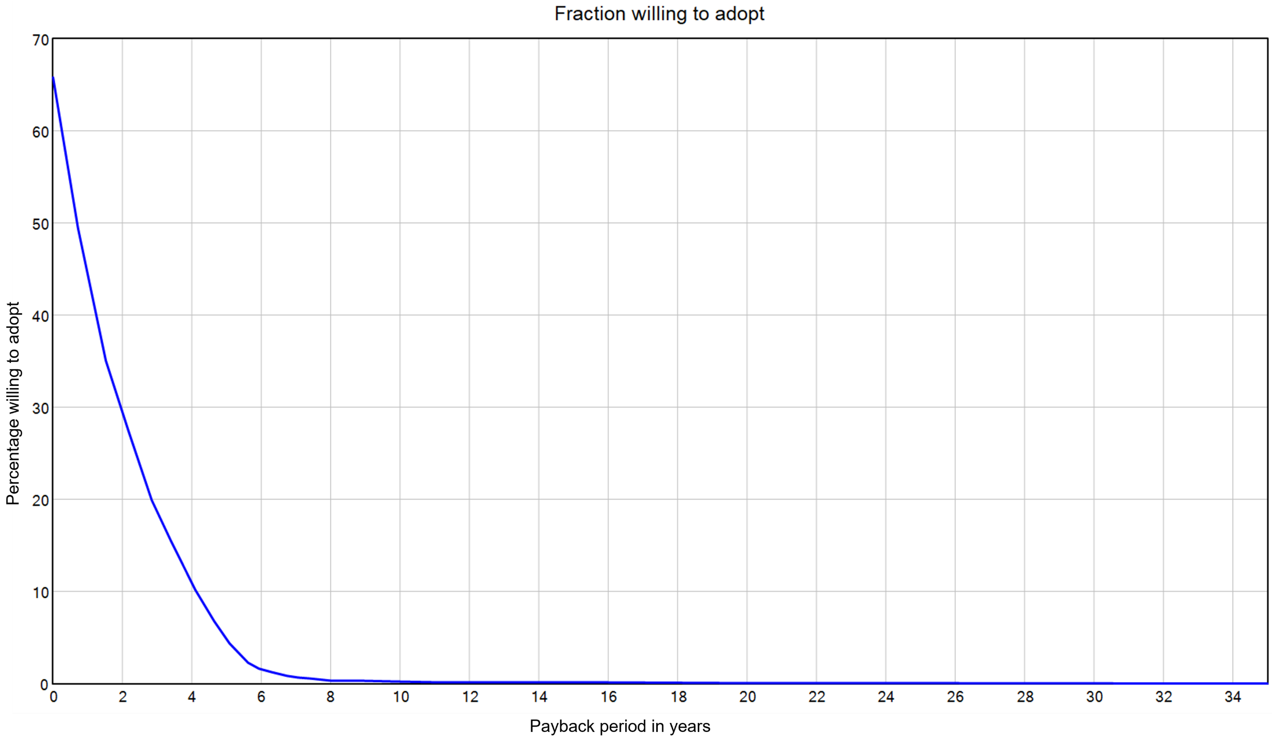


Figure 41: Graphical representation of the average willingness to adopt for households in Amsterdam

Additionally, the adoption rate is also affected by a 'word-of-mouth' (WOM) effect and an innovation effect. The WOM effect represents the fact that rooftop solar adopters will spread the word about their investment to friends, family, and neighbors through a 'contact rate', some of whom will then become adopters themselves. Such an effect is often included in models looking to replicate the diffusion of technology (Morcillo et al., 2022), (Castaneda, Jimenez, et al., 2017), (Castaneda, Franco, et al., 2017) (J. Palmer et al., 2013), and is part of the Bass diffusion model. The innovation effect represents the effect that technological products increase in popularity over time, due to mass-media attention and advertising, and thus result in more adoption (Mahajan et al., 1993).

The contact rate of the WOM effect represents the number of contacts per year that each solar adopter would have with a potential solar adopter. A certain fraction of these contacts will result in the potential adopter becoming an actual adopter. The same goes for the innovation effect. Accepted values for the adoption from WOM and the adoption from innovation are 0,02. The structure of the WOM effect and innovation effect have been informed by Bass (1969) and J. D. Sterman (2002).

PV attractiveness sub-model
The PV attractiveness sub-model calculates payback times for PV installations under different Netting Scheme formulations: the current netting scheme, the proposed netting scheme, and no netting scheme. The calculations for the payback periods have been adapted from Verheij et al. (2020b), who previously published research on payback periods for PV installations. payback periods are calculated assuming that the Netting Scheme variant in place remains the same for the remainder of the simulation.

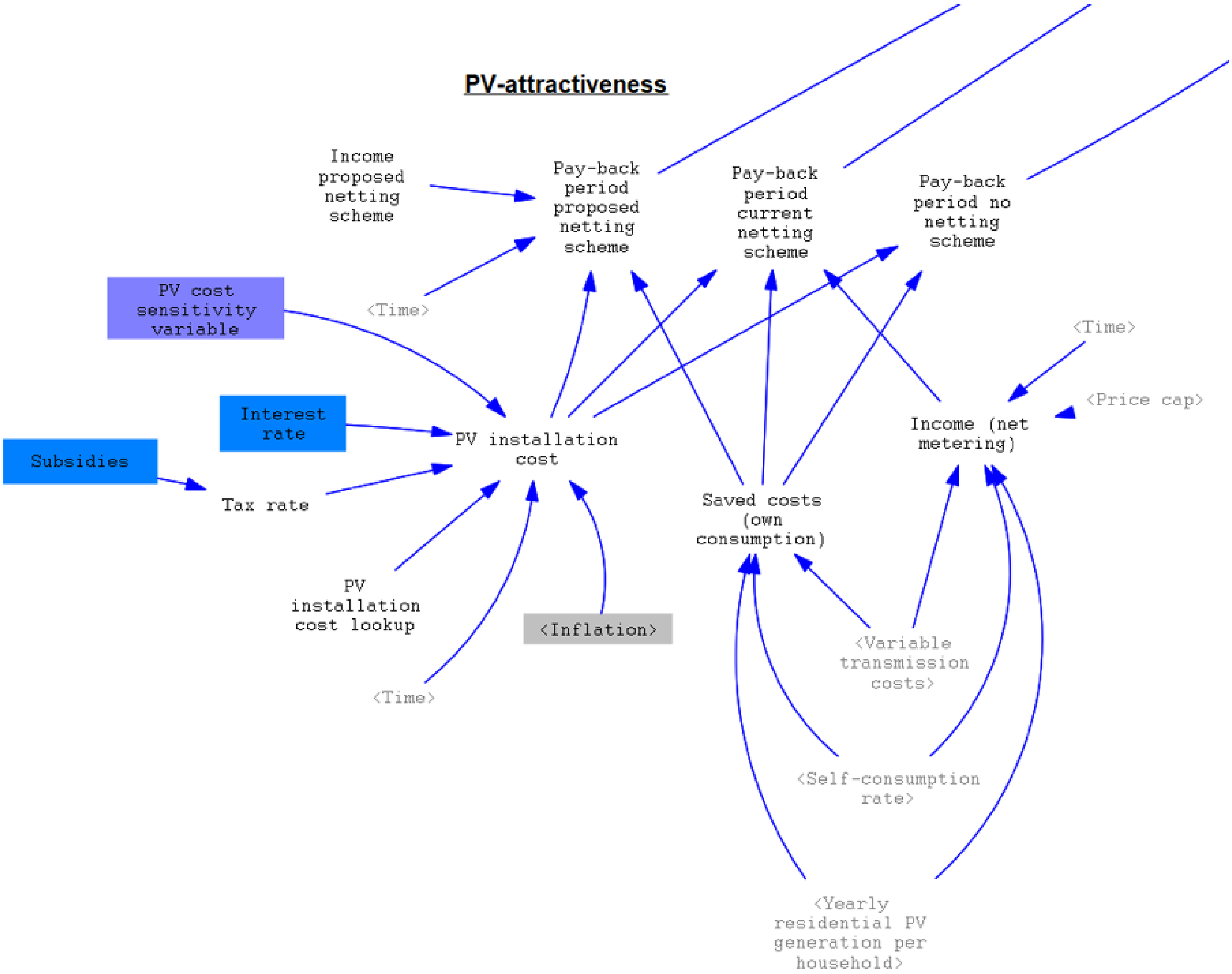


Figure 42: PV attractiveness sub-model

An investment in solar panels is earned back by avoided expenses and generated income. The general payback period is defined using the following formula:

$$\frac{\text{initial investment in PV system}}{\sum \text{yearly avoided expenses and income for electricity generation}}$$

The calculation does not take maintenance costs into account. Interest rates on loans are embedded in the PV installation costs.

The avoided expenses are costs for consuming electricity from the grid when own-generated electricity is not consumed directly. The income results from the feeding-back of electricity to the grid when it is not directly used by the consumer. This latter factor can be divided into a share that can be netted (as of 2031 this is not possible anymore) and a share that cannot be netted. For this share, the consumer receives a feed-in tariff.

Under the current netting scheme, the electricity that is fed back to the grid can be fully offset against the number of kWh the small consumer uses at another time up to and including the amount of the total annual offtake. Therefore, under the current netting scheme, the income from feeding electricity to the grid is equal to the avoided costs from direct self-consumption.

The payback period for PV installations bought under the current netting scheme is calculated using the saved costs (own consumption), the income of net metering, and the PV installation costs. The payback period when no netting scheme is in place, depends on the PV installation costs and the saved costs from direct self-consumption. The payback period of the proposed netting scheme depends on the PV installation costs, the saved costs through direct self-consumption, and the income from net metering. The latter factor includes a complicated calculation for this case, as each year a different percentage of generated electricity can be netted. payback periods thus strongly depend on the year in which the system is bought. To simplify the model calculations, the estimated income per year under the proposed netting scheme is derived from an investigation by TNO TNO2020. The income from net metering depends on the variable transmission costs, or on the price cap when this policy measure is in place.

It is assumed that households purchase PV installations using a low-interest loan provided by the Dutch national government. The PV installation costs consist of several factors: a flat system price, the paid interest, and a tax rate. PV system costs decline on average by 3,5% per year (Verheij et al., 2020b). The interest rate is currently on average 3,5% (Warmtefonds, n.d.). The tax rate on PV installations is currently 0%, instead of 21%. The calculation of the PV installation costs is then as follows:

*PV installation cost lookup(Time)*Tax rate*Inflation)*((1+Interest rate)*^{10})

Electricity costs sub-model
This sub-model simulates the electricity costs for consumers. The submodel is shown in figure 43.

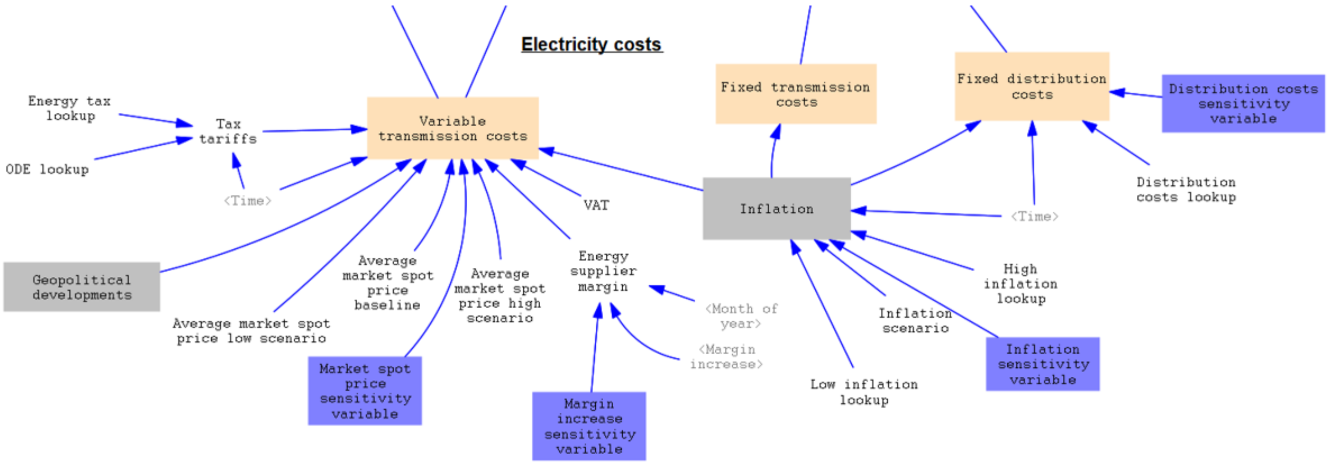


Figure 43: Electricity price submodel

The electricity costs for consumers (the components of an electricity bill) consist of:

- Fixed distribution costs. The costs paid to the energy supplier for delivering energy.
- Fixed transport costs. These are the costs paid for being attached to and receiving energy through the electricity grid. The costs are paid by consumers to the energy supplier, which in turn transfers the payments to the grid operator. The costs are monitored and fixed each year by the Authority Consumer and Market (ACM).
  - Capacity tariff
  - Meter rate
  - Grid connection fee
- An energy tax reduction. This is a fixed amount that consumers receive back from their paid energy taxes. The Dutch government sees part of the energy consumption as a basic necessity, thus no taxes have to be paid for that amount (Rijksoverheid, 2023).
- Variable costs:
  - Costs for consumption (electricity tariff in €/kWh * consumption in kWh): the retail electricity price
  - Energy tax
  - Renewable Energy Raise (ODE) ("Opslag Duurzame Energie") until 2022. From 2023 onwards, the ODE is combined with the Energy tax (Rijksoverheid, 2023).
  - VAT

The electricity bill components are shown in orange boxes in the systems diagram.
The retail electricity price consists of a market spot price, the price for which the utility company purchased the energy, and a risk and profit margin (ACM, 2017), (de Boer & Stet, 2022). The variable transmission costs paid by consumers consist of the retail electricity price and (energy) taxes. The composition of the variable costs paid by consumers in the Netherlands is shown in figure 45.

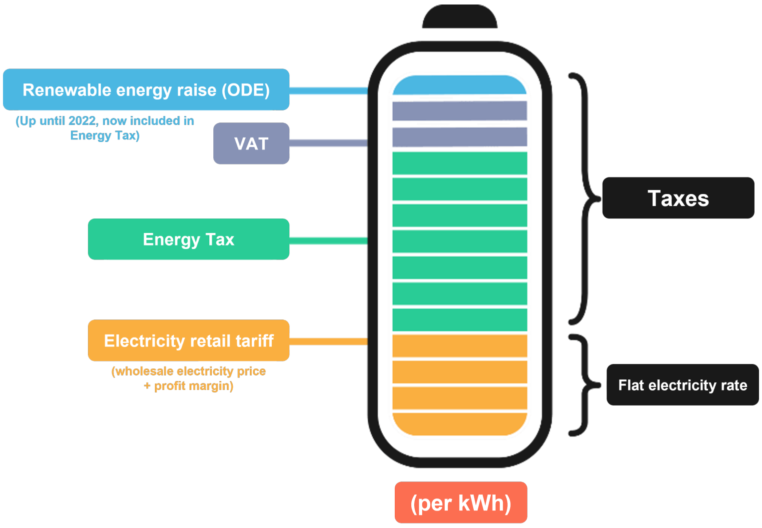


Figure 44: Composition of the variable electricity tariff paid by households in the Netherlands. Source: author.

In Section 7.2.3, it is explained that the development of the average market spot price is uncertain, partially due to possible geopolitical developments. Thus, three scenarios are used to model the average market spot price: a low, medium, and high scenario. For the ODE and the energy tax, the projections by the Planbureau voor de Leefomgeving (2019) are adopted. The energy supplier margin has an initial value of €0,02/kWh. The energy supplier margin is expected to slightly increase in the future, mainly due to the energy transition (ACM, 2020). The margin increases according to the factor *Margin increase*, which is determined in the capacity & utility impact sub-model.
The fixed transmission costs are set at €70/year, which is the current average, and increase according to the inflation rate. The fixed distribution costs have an initial value of €257, and are expected to increase to over €600 over the coming 30 years. The distribution costs, which are exogenous in this model, are expected to increase significantly in the future due to increased investment and maintenance costs of grid operators. The cost increase is adopted from projections by research institutes that forecast the growth of distribution costs (Planbureau voor de Leefomgeving & van Polen, 2021), (PWC, 2021).

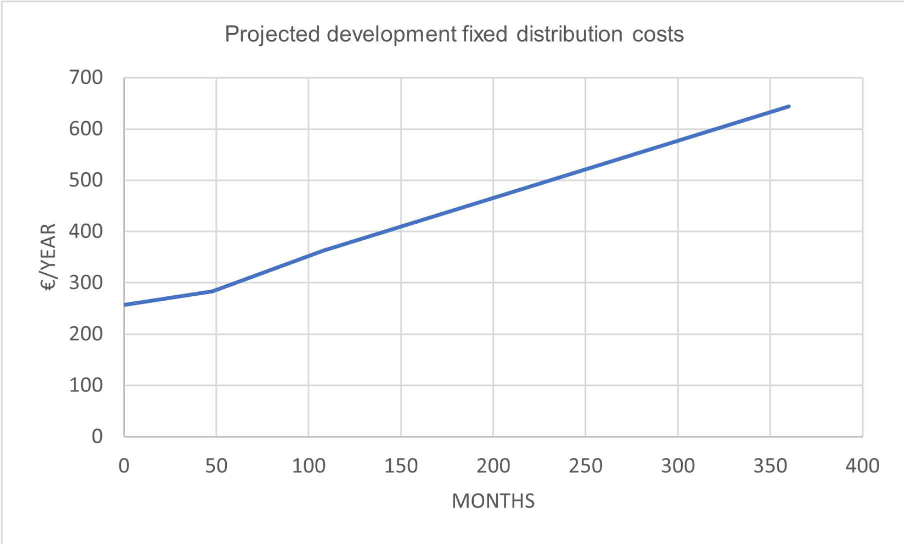


Figure 45: The projected growth of the fixed distribution costs. Source: Author, based on (Planbureau voor de Leefomgeving & van Polen, 2021; PWC, 2021).

The variable transmission costs are then a sum of the tax tariffs (energy tax and until 2023 the ODE), the average market spot price for the chosen scenario, and the energy supplier margin, multiplied by the VAT percentage of 21% and the inflation factor:

*Variable transmission costs = (((Average market spot price *scenario*(Time)+Energy supplier margin)*Inflation)+Tax tariffs)*(1+VAT)*

Energy bill sub-model

The energy bill for PV adopters and non-adopters is calculated in this sub-model. The sub-model is presented in figure 46.

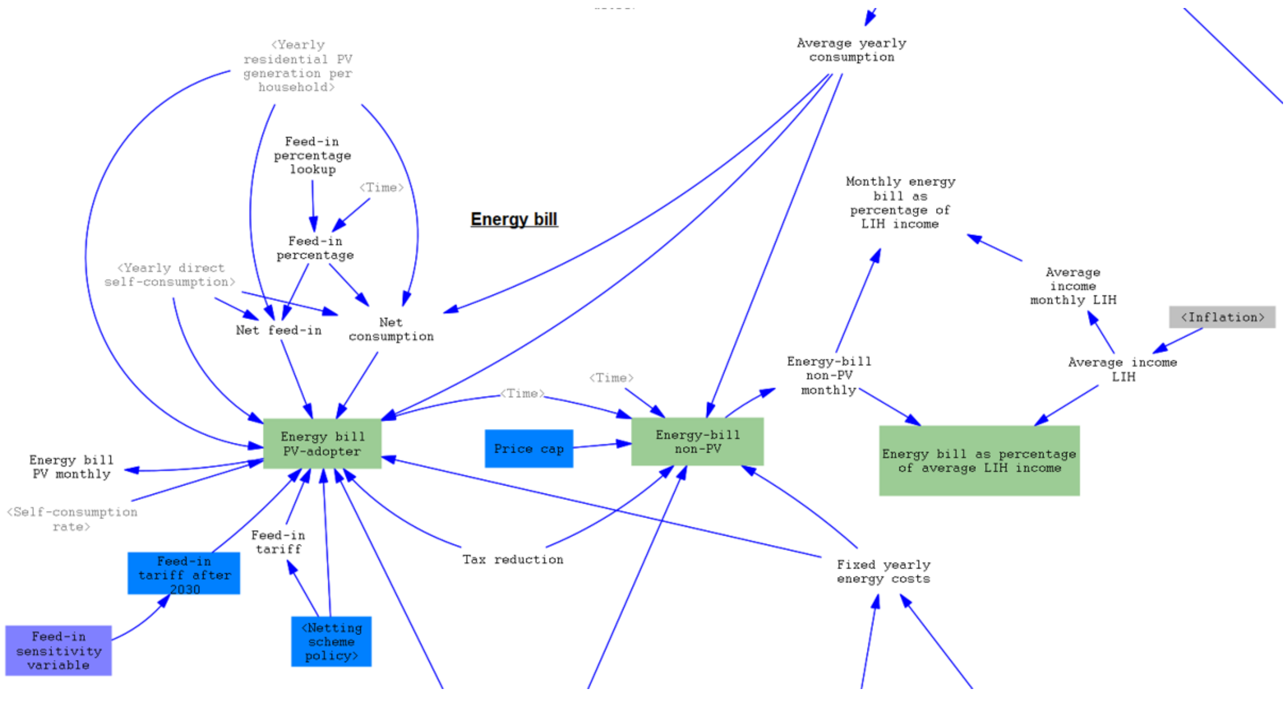


Figure 46: Energy bill sub-model

The energy bill for non-adopters consists of the fixed transmission costs in that year, the fixed distribution costs in that year, the variable transmission costs in that year multiplied by the consumption from the grid, and a tax reduction. The tax reduction for the years 2019-2023 is known, however, the future values are not. Therefore, it is assumed that the tax reduction amount for the remaining simulation period is equal to the value in 2023, which is €493,27. Besides, in the year 2023, there is a price cap in place on variable electricity costs. Up until a certain consumption limit and when regular variable transmission costs exceed the price cap value, the electricity price is limited to the €0,40/kWh. For this simulation, it is assumed that average consumption remains below the price cap consumption limit. The energy bill for non-adopters is then calculated by:

*Electricity bill non-adopter = IF THEN ELSE(Time>=48 :AND: Time<=60 :AND: Variable transmission costs>0.4, (Average yearly consumption*Price cap)-Tax reduction(Time)+Fixed yearly energy costs, (Average yearly consumption*Variable transmission costs)-Tax reduction(Time)+Fixed yearly energy costs)*

The energy bill for PV adopters is slightly more complicated. The bill depends on the type of netting scheme in place, the feed-in tariffs, the direct self-consumption, and the height of consumption vs generation. For simplicity, it is a justifiable assumption to assume that on average, yearly electricity generation exceeds yearly electricity consumption.

Under the current netting-scheme, the energy bill of a PV adopter consists of the fixed yearly energy costs, the difference between yearly generation and yearly consumption multiplied by the feed-in tariff, and a tax reduction:

PV adopter electricity bill under current netting scheme = Fixed yearly energy costs-((Yearly residential micro PV generation per household-(Average yearly consumption))"Feed-in tariff")-Tax reduction(Time))*

Under no netting scheme, a household receives a fixed amount per kWh for the electricity injected into the grid (the feed-in tariff) and pays for the electricity they do not generate at the same time as consumption and thus consume from the grid. The calculation for the bill then is:
Electricity bill PV-adopter, no netting scheme = (Average yearly consumption-(Yearly residential micro PV generation per household"Self-consumption rate")) * Variable transmission costs + Yearly residential micro PV generation per household*(1-"Self-consumption rate")*"Feed-in tariff"))*
Under the proposed netting scheme, the electricity bill highly depends on the allowed feed-in percentage in that year. A netto feed-in and netto consumption are calculated to be able to incorporate the yearly degrading feed-in percentage.

Netto feed-in =((Yearly residential PV generation per household-"Yearly direct self-consumption")(1-"Feed-in percentage"))*

Netto consumption = Average yearly consumption-((Yearly residential PV generation per household-"Yearly direct self-consumption")"Feed-in percentage")*

The electricity bill under the proposed netting scheme is then calculated as follows:
*Electricity bill PV-adopter, proposed netting scheme = ((Netto consumption*Variable transmission costs)+Fixed yearly energy costs)-("Netto feed-in"*"Feed-in tariff after 2030")-Tax reduction(Time)*

For the calculation of the energy bill of PV adopters, the electricity price cap is also taken into account, meaning that a conditional statement is included first: *Time>=48 :AND: Time<=60 :AND: Variable transmission costs>0.4*. This means that in the year 2023, the consumers pay the price-cap price when the market electricity price exceeds €0.40/kWh.
To monitor the height of the energy bill compared to the average income of low-income households, the yearly energy bill of non-adopters is transposed to a monthly average. Then, the ratio is calculated using the average income for low-income households adjusted for inflation.

Demand and generation sub-model
The demand and generation sub-model simulates monthly and yearly electricity generation by adopters, the rate of self-consumption versus grid-fed electricity, and the average consumption of households in Amsterdam. The sub-model contains several other measures simulating grid demand and grid-fed electricity. Not all are used for further analysis in this study but can be used when extending the model to further analyze grid-impact. The relevant variables are explained below.

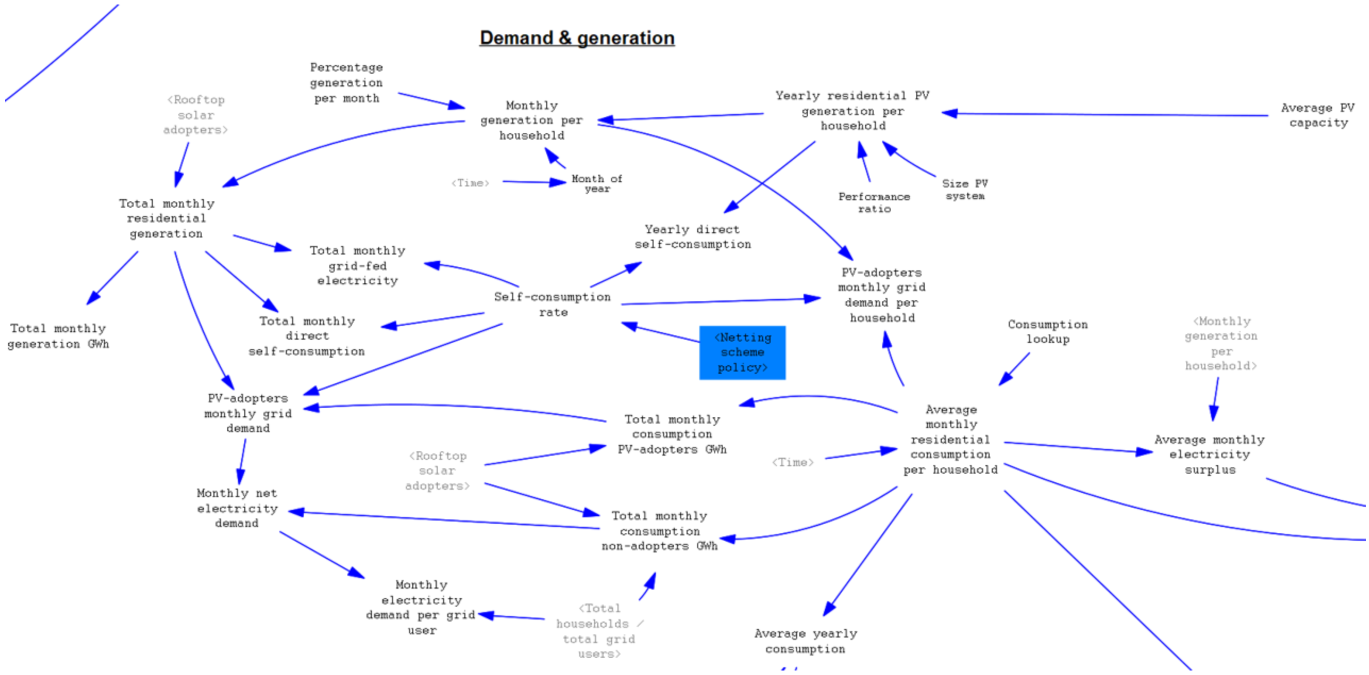


Figure 47: Demand and generation sub-model

The yearly residential PV generation per household is calculated using the PV system size in a number of panels, the performance ratio, and the capacity of the panels. The average capacity for PV systems currently on the market is 3.5 kW peak or 350 watt peak (Verheij et al., 2020b), the average system size is 10 panels (Verheij et al., 2020b), and the performance ratio for the Netherlands is 85% (A. Walker & Desai, 2021). The average yearly residential electricity generation is then calculated using:
*Average yearly residential electricity generation = Size PV system*Performance ratio*(Average PV capacity*100)*

The average yearly electricity generation in reality is not spread equally over the year. In summer months, more electricity is generated due to higher solar radiation levels. The average yearly electricity generation is converted to a monthly generation pattern using the percentage spread of total generation over the year. For example, in August, 20% of the total yearly amount is generated. The percentage spread over the year is calculated for the Netherlands and adopted from Milieucentraal (n.d.). The formula for the generation per month is:
*Monthly generation per household = (Percentage generation per month(Month of year)/100)*Yearly residential PV generation per household*

What percentage of generated electricity households consume themselves or feed back to the grid, is determined by the self-consumption rate. Any PV generation that is used to supply the customer directly with electricity for instantaneous consumption is said to be "self-consumed." Self-consumption allows DPV system owners to reduce or eliminate the variable utility charge portion of their electricity bills, as consumption from the grid is replaced by consumption from their DPV system (Zinaman & Darghouth, 2020).

The netting scheme policy impacts the self-consumption rate. The self-consumption rate in the Netherlands is estimated at 30% (Verheij et al., 2020b) under the current netting scheme. The policy removes the incentive to use one's generated electricity instantaneously given the financial benefits of feeding electricity back to the grid (AL_1, ST_3). As long as 100% of the generated electricity can be netted, direct self-consumption and feeding back will deliver the same savings on energy consumption. This will likely change when the netting scheme changes. The impact on the self-consumption rate under the proposed netting scheme, or under no netting scheme, is however unknown. The percentage of self-consumption can only increase a certain amount, as most households consume most of their electricity in the evenings when there is no sun. The change in self-consumption behavior is expected to be limited (AL_3), therefore the assumed self-consumption under the proposed netting scheme or no netting scheme is a maximum of 40%, in line with the variable boundaries set by Verheij et al. (2020b).

To calculate the average yearly electricity surplus, the amount of kWh generated by PV adopters that exceeds the consumption of households, the following variable is simulated:

Average monthly electricity surplus = Monthly generation per household-Average monthly residential consumption per household
This variable is relevant to calculate the amount of generated electricity that households receive a feed-in tariff for, under the current netting scheme.

The average monthly yearly consumption by households currently is 233 kWh/month, and is expected to slightly decrease over the coming years (Planbureau voor de Leefomgeving & van Polen, 2021). The development of consumption is shown in figure 48.

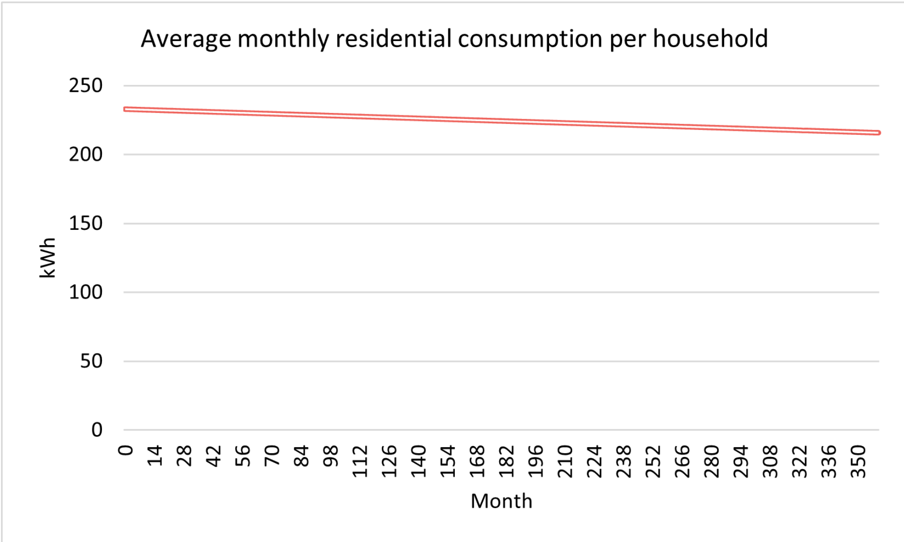


Figure 48: Average monthly consumption per household. Source: author, based on (Planbureau voor de Leefomgeving & van Polen, 2021)

Installed capacity & utility impact sub-model
The total installed residential capacity is modeled using a stock and flow diagram. The yearly capacity growth is calculated by multiplying the yearly increase in PV adopters with the average capacity of a PV system of 3.5 kW. To compute the residential installed capacity in MW, the residential capacity in kW is divided by 1000.

As discussed in Section 7.2.6, PV generation by households affects utility revenues through the concept of the utility-death spiral. To approach that effect in this simulation, the two main cost drivers of revenue loss are simulated: the direct loss of sales and the increased costs for imbalance. Many previous studies have simulated the utility death spiral, mostly focusing on the lost revenue due to decreased sales (Castaneda, Jimenez, et al., 2017), (Castaneda, Franco, et al., 2017), (Grace, 2018). Few studies also included the saved generation costs by utilities, given the decreased demand. This factor is left out of scope in this research. Imbalance costs are included in this research as well, given the severity of the problem as understood from the performed interviews.

The electricity tariff is thus expected to increase as PV penetration increases (Costello & Hemphill, 2014), (Felder & Athawale, 2014). Given the geographic extent of the SD model in this study, it is difficult to model national pricing mechanics. Not only PV adoption in Amsterdam impacts utility revenues, but PV adoption in the whole country. Therefore, a simplification is made that electricity retail prices increase according to the extent of PV adoption costs increase and based on findings in the studies by (Castaneda, Franco, et al., 2017), (Morcillo et al., 2022), and (Castaneda, Jimenez, et al., 2017).

Imbalance costs increase as the generation by distributed PV increases. The imbalance costs are estimated in several studies and range from 0,6 euro cent to 2 euro cents per kWh. The estimation from the Dutch PBL is followed, which uses a value of 1,3 euro cent per kWh (Koelemeijer & Bart, 2021).

The revenue loss by utilities depends on the netting scheme in place. Under the current netting scheme, it can be assumed that the revenue loss is equal to the MWhs produced by solar adopters (Meehan, 2015). Utilities also pay a fixed feed-in tariff for the surplus of electricity. The monthly revenue loss increase is then equal to:
Monthly revenue loss under the current netting scheme = (Average monthly residential consumption per house-

*hold*Rooftop solar adopters*Variable transmission costs) + (Average yearly electricity surplus*Rooftop solar adopters*"Feed-in tariff").*

Under no netting scheme, the revenue loss is equal to the monthly self-consumption by PV adopters, which is the amount these consumers no longer purchase from the utility:
*Monthly revenue loss without netting scheme = Total monthly direct self-consumption*Rooftop solar adopters*Variable transmission costs.*

Under the proposed netting scheme, the revenue loss gradually decreases as the net-metering percentage decreases. The revenue loss depends on the net consumption per PV adopter (the percentage of consumption they are not allowed to deduct from the energy bill), the net feed-in per PV adopter, the total number of adopters, and the feed-in tariff after 2030:
*Monthly revenue loss under the proposed netting scheme = (Average monthly residential consumption per household-Net consumption)*Variable transmission costs+("Net feed-in"*Rooftop solar adopters*"Feed-in tariff after 2030")*

It is assumed that utilities adjust their margin for expected losses. Therefore, in the simulation model, the margin increase is determined by the average and expected growth of the imbalance cost increase and the revenue loss through a SMOOTH function:
Margin increase = (SMOOTH(Growth imbalance costs, 120)+SMOOTH(Growth revenue loss, 120))

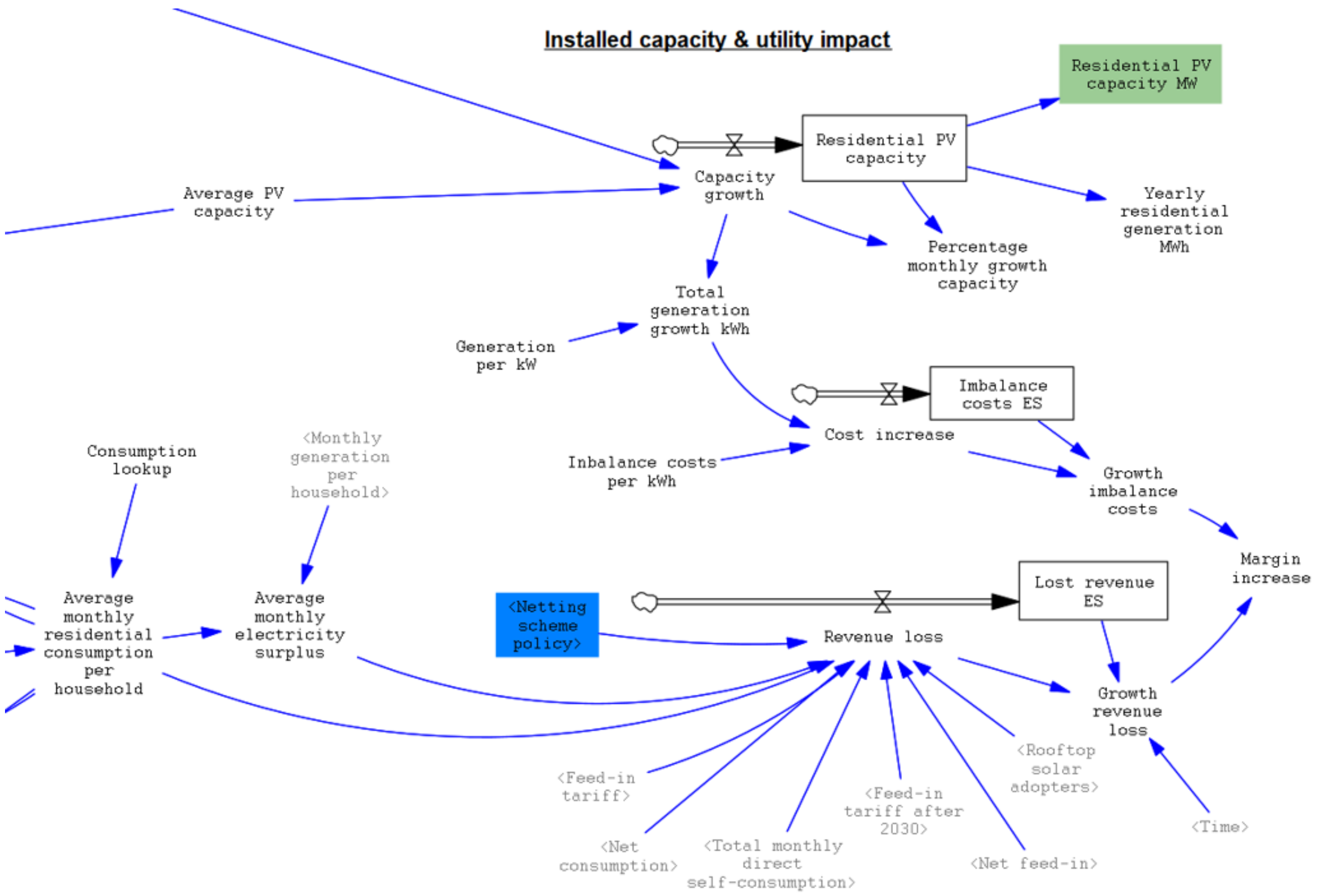


Figure 49: Installed capacity and utility impact sub-model

Sub-population adoption simulations
To explore the perceived adoption gap as described in the results of 6 and the plausible future developments of this gap, the PV adoption is simulated for sub-populations of neighborhoods of the municipality of Amsterdam. The sub-populations simulated in this study are taken from the adoption disparity analysis in Section 6.5.5. In this section, neighborhoods have been clustered based on the attributes "percentage rental properties", the

"percentage multi-family properties" and the "percentage households with a low income", given that these three factors are important correlating factors with PV adoption. In this sub-model, the PV adoption disparity and future development between these groups are explored.

The neighborhood clustering resulted in three neighborhood groups, of which the two most deviating groups are modeled:

- The group with a high percentage of rental properties, a high percentage of low-income households, and a high percentage of multi-household residencies: **Group 1**
- The group with a low percentage of rental properties, a low percentage of low-income households, and a low percentage of multi-household residencies: **Group 2**

For each of these groups, the PV adoption process is modeled separately. Although not only the percentage of rental properties, multi-household properties, and household income determine PV adoption, the groups based on these attributes are used to demonstrate how PV adoption might evolve within two different groups of neighborhoods that have had diverging adoption rates in the past.

The sub-models for the two groups are shown in figure 50 and 51. Similar to the overall PV adoption sub-model, the historic adoption rates for the sub-groups are extracted to construct a graphical function that represents the adoption rate at a given payback period. The stocks for "potential rooftop solar adopters" and "rooftop solar adopters" now represent the two groups respectively including the corresponding number of households and the initial number of PV adopters.

The sub-models include the PV adoption stock and flow and the residential PV capacity stock and flow. For each of the groups, the adoption fraction is computed based on the payback period, which increases the rooftop solar adopters in that group with the "customers installing rooftop solar" flow. For the rooftop solar adopters, a maximum of adopters is built in based on the percentage of suitable rooftop that is available (60% for both groups). The sub-populations grow according to the overall population growth and are proportional to the percentage of households in that group from the total number of households. Group 1 initially contains 234.055 households, which is 23% of the total initial households. Of the yearly household growth, 23% is thus assigned to this group. Group 2 initially contains 45.680 households, which is approximately 10% of the total initial households.

For both groups, the adoption fraction can increase with the "policy impact sustainability plan", representing the impact that the "mandate sustainability plan" policy would have on the adoption rate. When this policy is in place, the adoption curve moves right, meaning that at a given payback time, a higher fraction of the population will adopt solar panels. The effects of these policies are estimated, based on the percentage of rental properties and multi-household properties in a group (and thus the extent to which rental properties and shared roof ownership currently form a barrier to adoption). For Group 2 this effect is estimated at a 30% increased adoption rate, given a shared-property percentage of 80%. For Group 1, this effect is estimated at a 15% increased adoption rate, given a shared-property percentage of 40%.

To simulate the leveling policies "LI-subsidy" and "LI-netting scheme", the PV adoption sub-model for Group 1 is extended. The PV installation costs for this group are calculated separately, as it should be able to incorporate the effect of a low-income subsidy on the payback period, and thus on the adoption fraction. Besides, low-income groups can acquire a loan with a zero interest rate. The LI-subsidy variable has an initial value of €0, meaning no subsidy is in place, and has a value of €1000 when the LI-subsidy is activated. It can however be adjusted easily. The PV-installation costs for Group 1 are then calculated using the following formula:

*PV installation cost Group 1 = ((PV installation cost lookup(Time)+(PV installation cost lookup(Time)*Interest rate Low Income*10))*Subsidies)-"LI-subsidy"*

The payback periods are then calculated the same way as in the main PV adoption sub-model.

When the proposed netting scheme is in place and the LI-netting scheme policy is activated, households with a low income can extend the duration of the current netting scheme instead of shifting towards the proposed netting scheme. Therefore, when the LI-netting scheme is in place, the adoption fraction of this group is calculated using the payback period of the current netting scheme, instead of the proposed netting scheme payback period. To simulate this, a second variable for adoption fraction is built in "adoption fraction Group 1-2", which takes the adoption fraction under the LI-netting scheme as input when this policy is in place, and the regular adoption fraction from "adoption fraction Group 1" when this policy is not in place.

In the simulation, it is assumed that the leveling policies for lower-income households only affect Group 1, and that 50% of the households in this category can make use of the LI-subsidy and loan. This assumption is based on requirements for the low-income loan eligibility, and the average standardized household income of €30.000 in this neighborhood group. Although in reality, it could be the case that there are some households with a low income in Group 2, this simulation represents averages of population groups.

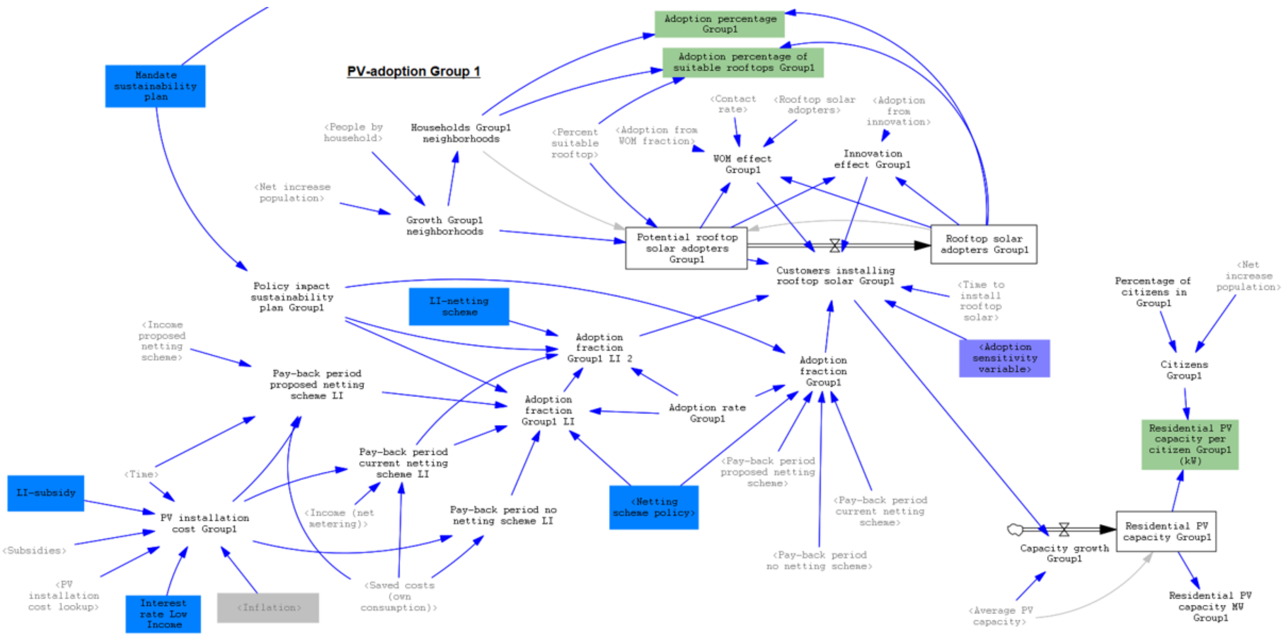


Figure 50: Sub-model for the neighborhoods in Group 1

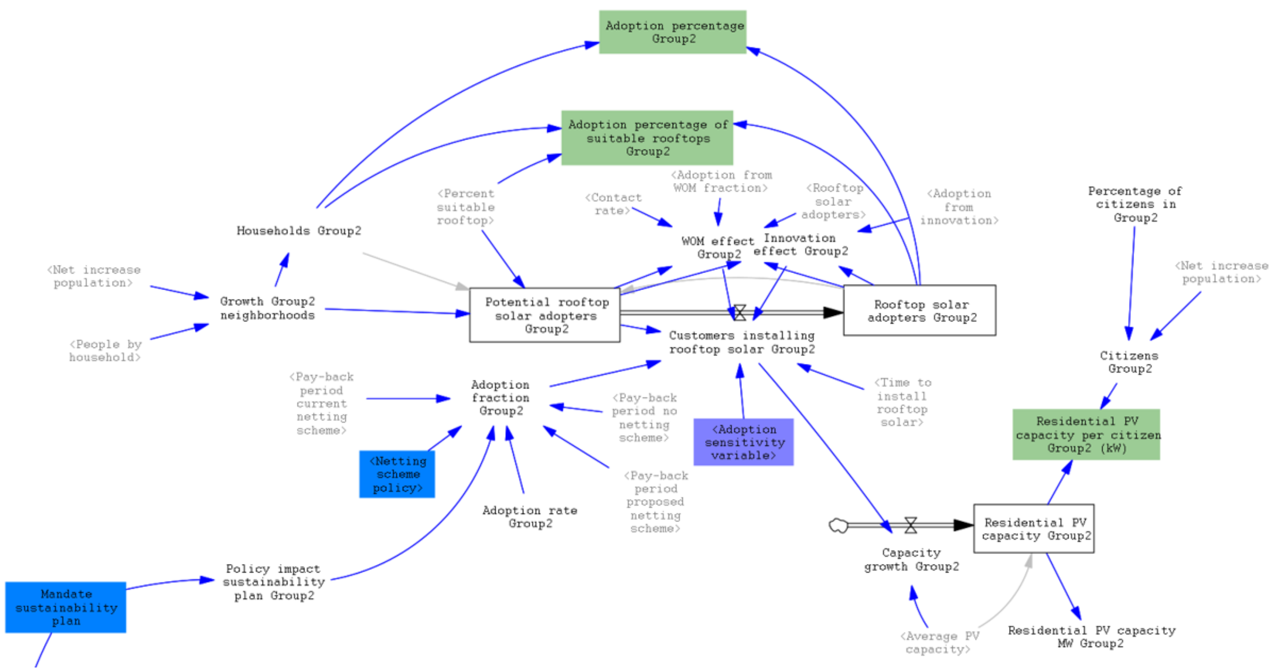


Figure 51: Sub-model for the neighborhoods in Group 2

7.4 Model evaluation

Before starting to interpret the behavior of a model and/or performing policy analyses with the model, one first needs to turn to model testing. Model testing is a process to uncover errors, improve models, learn, and build confidence in the usefulness of models for particular purposes and in the recommendations that follow from modeling studies (Pruyt, 2013). Model testing is not about whether the model is 'right', but rather if the model serves its purpose (J. Sterman, 2000). As stated by Forrester and Senge (1980), the ultimate objective of validation is to obtain confidence in a model's soundness and usefulness as a policy tool. Valid models/modeling are therefore models/modeling that are believed to be useful for their intended purpose.

An important reason for SD model testing is to test whether SD models generate the right outputs for the right reasons, for SD models are supposed to be operational causal models. That is, all model variables need to correspond to system elements and each relation is assumed to be causal. However, the most important purposes are to learn and to build confidence in the model and its usefulness for the intended purpose (Pruyt, 2013). With the model purpose in mind, several validation procedures have been conducted to gain insight into the model's behavior, usefulness, and limitations.

Validation methods in System Dynamics can roughly be divided into two main categories: structural validation and behavioral validation. Structural validation tests if the model structure and parameters correctly present real-world structures and values. Behavioral validation tests whether the model outcomes are plausible. This study adopts a series of validation methods as described in literature by Forrester and Senge (1980) and J. Sterman (2000).

7.4.1 Direct structure tests for structural validity

Direct structure tests are used to check whether the relations and assumptions in the model are based on accepted theories and that all important variables are included in the model. It is also important to check whether the equations and model hold under extreme conditions (Pruyt, 2013).

1. Boundary adequacy test
The boundary adequacy test assesses whether the model boundaries and submodels are accurately chosen and aligned with the intended purpose of the model. It involves a comparison of the actual structure of the real world with the structure of the model to determine if important concepts are represented accurately within the model. To conduct this evaluation, a qualitative comparison is made between the CLD diagram (as shown in Figure 39) and the input parameters of the model with the components of the actual hydrogen supply chain. Although the list of variables and subsystems that are excluded from the model may be endless, the importance lies at the relevance of the included and excluded concepts with respect to the intended purpose of the model.

All of the chosen key performance indicators are products of the endogenously modeled variables. A variable that is modeled as exogenous, but could also have been included endogenously is the PV prices. Several studies model the PV prices as endogenous using a "learning curve", meaning that technology prices decrease over time due to a higher demand combined with increased competition and technological advancements. It is deliberately chosen to model this variable as exogenous as the geographic scope of the study is too narrow to properly model the price-decline effect on PV systems, and numerous projections of PV price declines were available in literature to use instead.

Likewise, grid distribution costs are modeled exogenous and based upon projected future developments adopted from literature. This variable could be modeled endogenously when the geographic scope of the model is extended to the national level. However, modeling the impact of PV on distribution grid costs and investments is highly complicated and probably out of scope given the intended model purpose.

2. Structure verification
Structural validation examines the aggregation level of the model compared to reality. Several high-level aggregations of the model are compared to real-world results or other projections in literature.

To start with, the population and household growth for 2019-2023 is compared with actual data. On January 1st, 2022, Amsterdam counted 881.933 citizens. The modeled value at this date is 882.156. In 2049, the modeled population is 1.069.670, compared to the expected population in 2050 by the municipality of 1.070.000

(Gemeente Amsterdam, 2022a). These projections versus real-world values are aligned.

Adoption percentages are compared to other literature studies. Although limited are available, few are found that are suitable for comparison. The Dutch PBL estimates an adoption percentage of 30% in 2030. This is in the same order of magnitude as the projected percentages in this study, under the current netting scheme. Under the proposed netting scheme, the simulation model projects lower adoption percentages, however, the PBL study appears to be based on the current netting scheme as well. Van Westering et al. (2016) simulated three scenarios for residential PV adoption until 2050 and resulted in a minimum adoption percentage of 10%, a base case percentage of 30%, and an upper bound of 50%. These estimations are also in line with the modeled results in this study in base case circumstances.

Lastly, the development of electricity bill prices is compared to projections of the PBL. They projected an increase in energy bills ranging from 1.300 to 1.900 in 2030. The simulation model on average computes an electricity bill of 1000 for the year 2030. This is lower than the PBL projection but in the same order of magnitude. The PBL projection however also includes gas costs and is executed before the significant increase in electricity prices in 2022.

3. Dimensional consistency
Vensim offers a built-in unit check tool that allows to automatically test the dimensional consistency. No unit errors are presented, meaning that for each equation the units match on both sides of the equation.

4. Parameter verification
Parametric validity evaluates the value and the meaning of each model parameter. For example, whether the parameter has a clear, real life counterpart (J. Sterman, 2000). Through translating real world concepts into simplified mathematical variables and equations, the use of fabricated parameters or variables is inevitable.

The "fraction willing to adopt" variable attempts to capture the adoption behavior of households based on their willingness-to-pay and payback times. The variable reflects a simplification of an intangible real world concept. Although empirical data is used, it is impossible to accurately predict adoption behavior by households. However, given the embedded validation of diffusion models in literature, the method is an accepted approach.

Likewise, the policy impact of the sustainability plan mandate is a nonphysical factor that is embedded in the model to account for the effect this policy has on adoption rates. The shortage in technicians and materials variable is also represents an intangible, real world concept which represents the effect that a shortage in technicians and materials in real-life has on adoption rates and speed.The significance and implications of the value for these parameters is further discussed in Section 9.2.

7.4.2 Structural behavior tests for behavioral validity

Structure-oriented behavior tests are used to test whether the modes of behavior, frequencies and mechanisms causing the behavior and other characteristics correspond to what one would expect (Pruyt, 2013). Unexpected results and responses to extreme conditions are then explored in detail. Sensitivity analysis is a very important structure-oriented behavior test for identifying parts of the model to which model behavior is particularly in/sensitive. For example, parameters, functions or structures that have a minor/major influence on the behavior when slightly changed.

5. Extreme conditions test
The extreme condition test evaluates the behavior of the system under extreme circumstances for a number of input parameters. The test reveals possible faults in model equations because the modeler can check the credibility of the model outcomes under extreme conditions and compare them to real-world expected behavior (Forrester & Senge, 1980). This way, the test reveals the model's ability to behave outside normal or expected patters. The extreme condition test is evaluated for several model variables: the adoption percentage, the installed capacity, the energy bill and the pay-back period. The table with inputs for the extreme condition tests is displayed in table 6. The visualisations of the outcomes are displayed in Appendix B.3. The tests are performed for the proposed netting scheme. The results of all the named variables are assessed and included in the appendix, but main results are summarized below.

Tested parameters	Base case value	Low extreme	High extreme
Electricity price	Lookup function (€/kWh)	-400%	+400%
PV installation costs	€4800 in 2019	€500 in 2019	€13.000 in 2019
Self-consumption rate	40% under the proposed netting scheme	0%	100%

Table 6: Setup for the extreme conditions test

The extreme conditions are tested for the electricity price, the PV-installation costs and the self-consumption rate. The extreme settings for electricity prices are expected to lead to very high or very low adoption rate. Very high electricity prices are expected to lead to high adoption rates, given the high attractiveness of PV-generated electricity compared to grid electricity. Contrary, low grid electricity prices are expected to lead to very low adoption rates, as PV-installation costs do not create enough financial benefits for many households to acquire a PV-system. For the PV installation costs, again, the extreme settings are expected to lead to very high or very low adoption rates, where high installation costs lead to low adoption rates and vice-versa. Similarly to the electricity price, the PV installation costs impact the attractiveness of PV electricity compared to grid electricity. Considering the self-consumption rate, an extremely low self-consumption rate is expected to lead to a low adoption rate, and an extremely high self-consumption rate is expected to lead to an extremely high adoption rate.
The outcomes are collected in figures in Appendix B.3. The following behavior is detected:

- An extremely high electricity price results in a very high adoption percentage (40%, equal to 98% of suitable rooftops), and an extremely low electricity price results in low adoption rates (only a few percentage points increase compared to the beginning of simulation). The high prices result in a payback time of on average 9 years, compared to 6 years in the base case. Extremely low electricity prices result in an average payback time of 4 years.
- Extremely low PV installation costs result in a very high overall adoption percentage (43%) and a 100% adoption of suitable rooftops, and very high installation costs result in very low adoption rates (no increase compared to the beginning of simulation time). The payback time under high installation costs increases to approximately 15 years, compared to 1 year under low installation costs.
- An extremely high self-consumption rate leads to an overall adoption percentage of 39% and adoption of suitable rooftops of 98%, and an extremely low self-consumption rate results in a very low adoption (no increase). The payback period of PV increases to approximately 30 years under a low self-consumption rate and decreases to 3 years under a high self-consumption rate.

The model behavior from the extreme condition tests corresponds with the expected behavior of the real-world system. Even under extreme conditions, the model remains stable and the outputs react accordingly. The test also provides useful preliminary insights into the model behavior. For example, a high self-consumption rate seems to have a proportionally higher impact on the payback time of PV installations than a lower self-consumption rate. Besides, the results show where barriers to diffusion exist, as both the PV installation costs and electricity prices significantly impact the adoption rates. Surprisingly, the self-consumption rate also significantly impacts the adoption percentage. This is due to the lower financial benefits of PV-generated electricity compared to grid electricity.

6. Sensitivity Analysis
Sensitivity Analysis is the computation of the effect of changes in input values or assumptions (including boundaries and model functional form) on the outputs' ((**morgan-1990**), p39). Defined like this, Sensitivity Analysis (SA) refers to the analysis of the effect of relatively small changes to values of parameters and functions on the behavior (behavioral sensitivity) or preference for a particular policy (policy sensitivity), starting from a base case (Pruyt, 2013).

The aim of the sensitivity analysis is to detect which parameters are most strongly moving the model. From there, it provides insight into which model parameters are most important and demands thorough attention of the modeler (J. Sterman, 2000).

In SD, it is not common to include policies in the sensitivity analysis, because the response of the system to policies is investigated in the policy testing phase of modeling (J. Sterman, 2000). The sensitivity analysis is deducted for the parameters shown in table 7. These variables are chosen as they represent some form of uncertainty about their development in the future. For the distribution costs, PV installation costs, and electricity market prices, projections from multiple studies are used. The percentage of suitable rooftops is derived from this study, however as computations of suitability might differ, this variable includes uncertainty. For the imbalance costs, estimations vary in literature and a best estimate is used in the simulation. All variables are tested for a base case input with a range of plus and minus 20%. The range is kept constant for each parameter to allow comparing the influence of individual variables. The sensitivity analysis is performed under both the current and proposed netting scheme policies, to be able to analyze sensitivities in both situations.

Tested model variables	**Base value**	**Lower**	**Upper**
Imbalance costs per kWh	€0.0013 per kWh	€0.0008	€0.0018
Distribution costs	Increasing from €257/year to €640/year	-20%	+20%
Inflation	0%	-20%	+20%
Market spot price	Stabilizing towards €0.18/kWh	-20%	+20%
PV cost	€5400 declining to €2700	-20%	+20%
Adoption intensity	(see figure 38)	-20%	+20%
Percentage of suitable rooftops	60&	-20%	+20%

Table 7: Sensitivity analysis input variables, base values and upper and lower tested limits

First, a univariate sensitivity analysis is executed. All output graphs are displayed in Appendix B.4. The results show that the model is most sensitive toward the electricity market spot price, inflation, and PV installation costs. These sensitivities seem to be in accordance with the real-world system. The model is least sensitive toward the imbalance of costs and utility margin. This implies that varying the parameters does not have a significant influence on the model. This can be explained by the fact that the cost increase per kWh for imbalance is minimal in the model, and mainly come to play at the national level.

Second, a multivariate sensitivity analysis is performed, with the input of all parameters for a range of +/- 20%. The multivariate sensitivity analysis evaluates the sensitivity of the *adoption percentage*, the *number of PV adopters*, and the *installed PV capacity* to a combined set of input parameters over the sensitivity space. Given that the output variables are similar and depend on each other in the simulation model, results will not deviate significantly between these output variables. The multivariate analysis is performed for both the current and the proposed netting scheme. All results of the multivariate analysis can be found in Appendix B.4.3.

Figure 52 shows the multivariate sensitivity of the adoption percentage for the current netting scheme. Figure 53 shows this for the proposed netting scheme. Despite the complexity of the system, its behavior is some variation of linear growth, which can be accelerated or slowed down depending on adoption rates, external factors, or applied interventions.

The results show no unexpected behavior. For the proposed netting scheme, the lower boundaries of adoption show that under certain circumstances, the adoption rate is significantly low that there is barely any increase in adoption. The results also show that it is useful to thoroughly investigate the parameters during the experiments as these seem to influence adoption rates significantly under both policy schemes. The results also show the model is sensitive to the netting scheme policy in place, as results widely differ for the adoption rates under both scheme's.

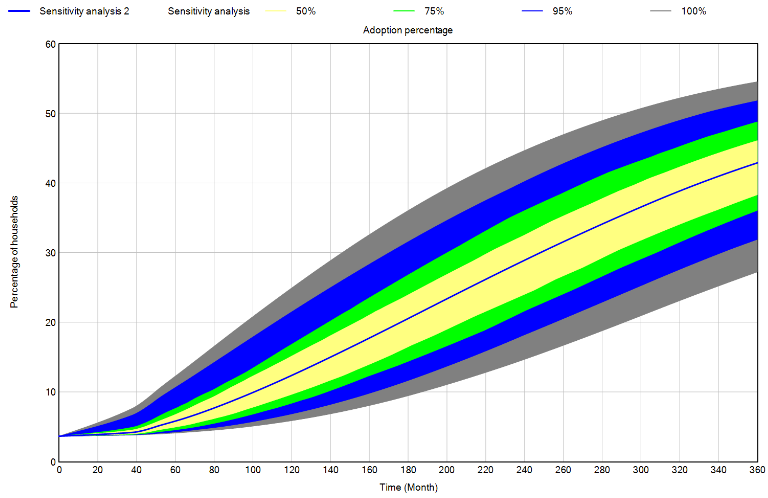


Figure 52: Multivariate sensitivity analysis of the adoption percentage under the current netting scheme

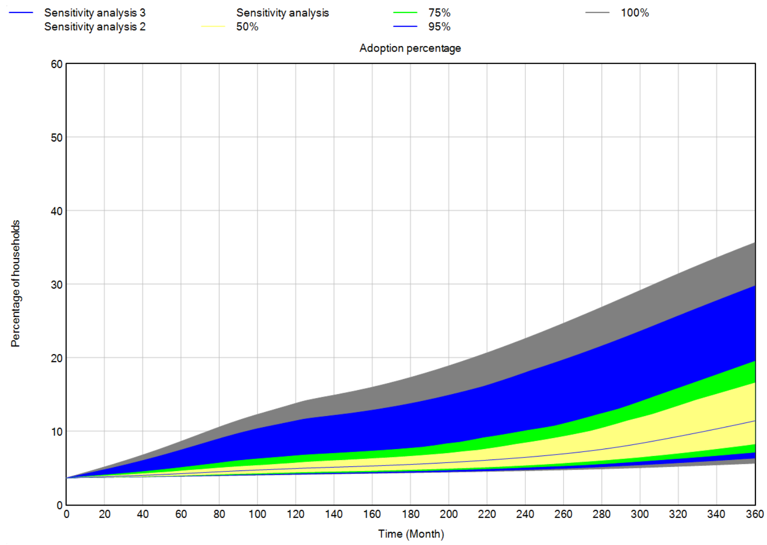


Figure 53: Multivariate sensitivity analysis of the adoption percentage under the proposed netting scheme

7.4.3 Validation conclusions and implications for model experimenting

The structural and behavioral tests provided the confidence that the SD model can be used for further experimentation. The model boundaries were adequately chosen for the purpose, aggregation level, and scope of this study. Parameters and their projections have been adopted from reliable sources and are always embedded in multiple sources. The dimensions of all units are correct, and the model shows reasonable behavior under the sensitivity tests. The model outcomes are comparable to other PV adoption projections, although limited is available. The extreme condition tests revealed expected model behavior, even under extreme conditions. The sensitivity test revealed the models' sensitivity towards inflation and PV installation costs. This will be adequately dealt with in further analysis, and scenarios will be conducted using the inflation and PV installation costs.

7.5 Main conclusions Chapter 7

In this section, a system dynamics model is developed and described that allows to simulate PV adoption behavior of the population as a whole and of sub-groups and allows for experimenting with policy levers and external scenarios. This way, the model generates insights in the extent, speed and disparity of PV adoption over time. The model measures the overall adoption percentage and that of two subgroups: group 1 with a high percentage of rental properties, a high percentage of low-income households, and a high percentage of multi-household residencies, and an opposite group 2. The model allows for analyzing policy impact of several general policies (including the netting scheme) and several leveling policies (including a low-income subsidy, a low-income netting scheme and a sustainability plan mandate).

The model is thoroughly validated using direct structure tests, to test structural validity, and structural behavior tests, to test behavioral validity. The validation tests provided the confidence that the SD model can be used for further experimentation. The sensitivity test revealed the models' sensitivity towards inflation and PV installation costs, which will be adequately dealt with during experimentation and interpretation of results. In Section 8, the model will be used for experimentation.

8 Design artifact part II: Experimental Design and Results

In this chapter the system dynamics model developed in Section 7 is used for simulation. This is done by performing experiments on the model. This way, this section aims to answer research questions 4,
How might solar panel adoption disparity develop in the future?
and 5,

What are effective interventions for increasing residential PV adoption and narrowing down the adoption gap?

The experimental design involves varying policies and external developments as well as critical assumptions concerning household adoption rates. Given that the adoption rates are based on empirical data, but not all data points were available, missing data points have been estimated based on existing studies (Dharshing, 2017; Maximillian, 2018; J. Palmer et al., 2013). To deal with the uncertainty this poses, the adoption rates are varied using a bandwidth of 20%. Each experiment represents a combination between a scenario and a policy. According to Kwakkel (2018): "a scenario is understood as a point in the uncertainty space, while a policy is a point in the decision space". The uncertainty space is a multi-dimensional space bounded by the value ranges of the uncertain factors in the simulation. A scenario is any point within this space. The decision space is a multi-dimensional space bounded by the value ranges of the policy options. Each experiment represents a different combination of two points in the uncertainty space and in the decision space. This way, each experiment will yield a different simulation result.

The output variables are identified in Table 3. The simulation is run for 30 years - 360 - months using the experiments outlined in Section 8.1. In Sections 8.2-8.4, the experiments are conducted and results are discussed.

8.1 Experimental setup

Table 8 presents the policy levers and external factors that will be adjusted for experiments during the simulation study. Not all policies presented in Section 7.2.4 are included in the experimental setup. To limit the number of experiments, the value for the feed-in tariff (under the current and proposed netting scheme) and the price cap (only active in 2023) remain constant during all simulations. Besides, it is assumed that the renewable energy loan with low interest and the tax rebate stay in place.

Type	**Variable**	**Possible values**
Policies	Netting scheme	No, current, new
	LI subsidy	€0, €500, €1000
	Sustainability-plan mandate	Not active, active
	LI netting scheme	Not active, active
External factors	Geopolitical developments	Low, base case, high scenario
	Inflation	Low (-15%), base case, high (+15%)
	Shortage of technicians and materials	None, shortage

Table 8: Policies and external factors used for the experimental setup

The experiments are split into three groups. The first set of experiments tests the different netting scheme policies and different calibrations of the adoption rate. The second set of experiments tests the proposed netting scheme under different external influences. The sensitivity analysis revealed that the model is most sensitive toward electricity market spot prices, PV installation costs, and inflation. These variables have therefore been included in the scenario testing. The geopolitical development scenarios represent the impact of the electricity market spot price on the system. The inflation scenarios cover both the impact of PV installation costs and inflation. The last set of scenarios tests the leveling policies to investigate how to close the adoption gap. For the second and third sets of experiments, the proposed netting scheme is used as a policy measure, given the fact that at the time of writing, it is highly likely the policy will indeed go into effect. Table 20 in Appendix B.5 shows the full list of combinations of variable values that make up the experiments. In the sections below the experiments are discussed per set.

The most important results are discussed below. Appendix C.0.2 provides extra visualizations of the experimental results.

8.2 Netting-scheme experiments

In the netting scheme experiments, the model is simulated under the three different variants of the netting scheme policy and using different calibrations for the adoption ratio (see table 9). Scenarios 1, 1.2, and 1.3 reflect the current policy regulation in the Netherlands. The results are plotted for the adoption percentage, installed residential PV capacity, and the adoption percentage of suitable rooftops.

Experiment	Netting scheme	LI subsidy	Sustainability plan (SP) mandate	LI-netting scheme	Geopolitical developments (GD)	Inflation	Shortage of technicians and materials (t&m)	Adoption rate
1	Current	-	-	-	Base case	Base case	Base case	Base case
1.2	Current	-	-	-	Base case	Base case	Base case	Low adoption
1.3	Current	-	-	-	Base case	Base case	Base case	High adoption
1.4	Current	-	-	-	Low	Low	Base case	Base case
1.5	Current	-	-	-	High	High	Base case	Base case
1.6	Current	-	-	-	Low	Low	Base case	Low
1.7	Current	-	-	-	Low	Low	Base case	High
1.8	Current	-	-	-	High	High	Base case	Low
1.9	Current	-	-	-	High	High	Base case	High
2	Proposed	-	-	-	Base case	Base case	Base case	Base case
2.2	Proposed	-	-	-	Base case	Base case	Base case	Low adoption
2.3	Proposed	-	-	-	Base case	Base case	Base case	High adoption
3	None	-	-	-	Base case	Base case	Base case	Base case
3.2	None	-	-	-	Base case	Base case	Base case	Low adoption
3.3	None	-	-	-	Base case	Base case	Base case	High adoption

Table 9: Experiments varying different netting-scheme options, external influences and adoption rates

The adoption percentage at the start of the simulation, in 2019, is 3,5%. Currently, in 2023, the adoption percentage is approximately 5% (see Section 6). The graphs in figures 54, 104, and 103 show the adoption percentage, installed capacity in MW and the adoption percentage of suitable rooftops respectively. Adoption under the proposed netting scheme is significantly lower compared to the current netting scheme. This is caused by the higher payback period of PV under the latter policy (see figure 55). Under the current netting scheme, the payback period is expected to decline from approximately 7 years in 2019 to 2,5 years when purchased in 2049. Under the proposed netting scheme, the payback period is expected to increase from 2022 to 2030 to a maximum of 8,7 years, followed by a steady decrease to about 5,2 years when purchased in 2049. Under no netting scheme, the payback period swiftly increases to more than 16 years, and then gradually declines to about 6 years at the end of the simulation. The steady decrease in payback time under all of the three policy options is caused by a simultaneous decrease in PV installation costs and increased grid-electricity costs. While net savings from PV gradually increase over the years, as electricity prices rise, the decrease in PV installation costs plays the largest role in the decline of the PV payback time.

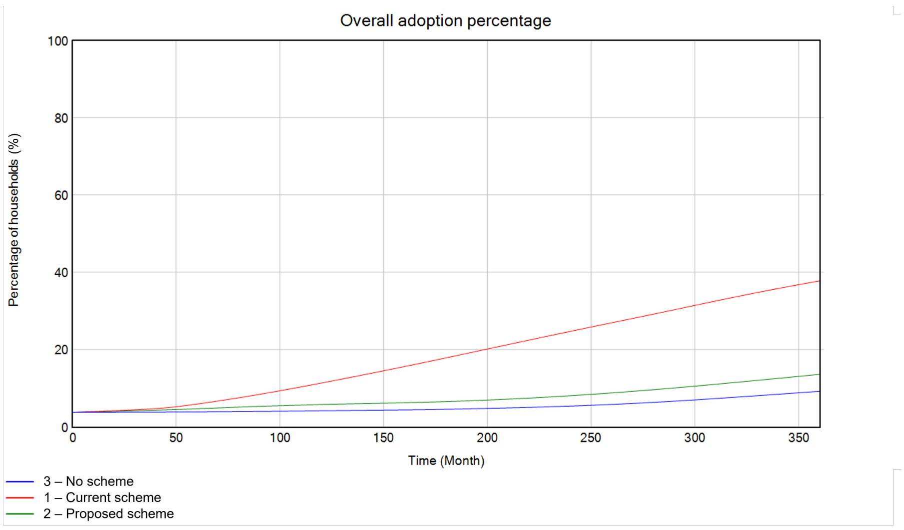


Figure 54: Overall adoption percentage for experiments 1-3

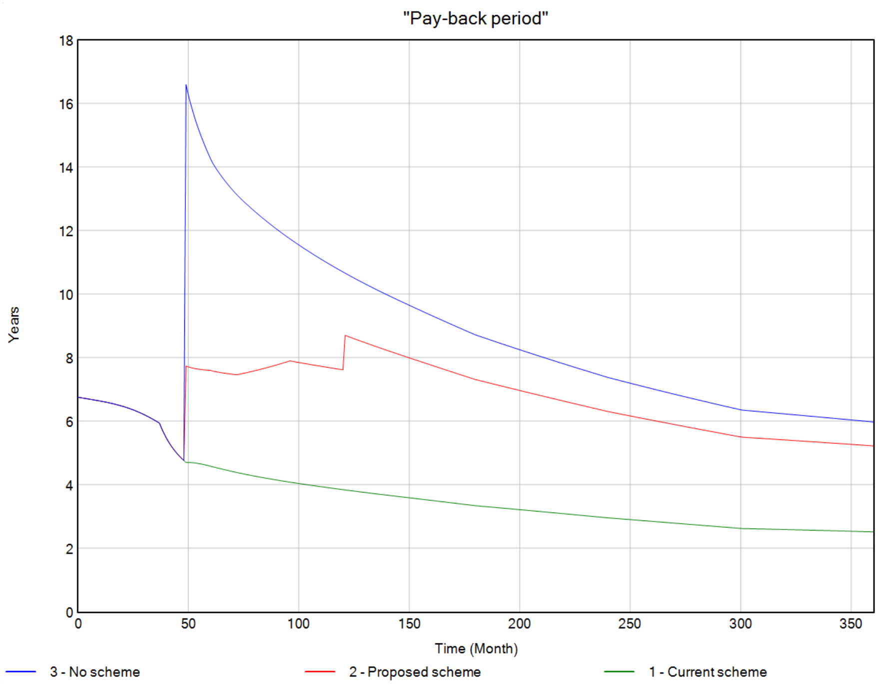


Figure 55: Payback periods for PV installations under the current, proposed and no netting scheme

The same outputs under varied adoption rates are shown in figure 56 until figure 106 and show that under the current netting scheme, the adoption percentage increases towards approximately 30-35% (see figure 56). Under the proposed netting scheme, the adoption percentage increases towards 11-13%. Under no netting scheme, the adoption percentage increases towards 8-10%.

Considering the adoption percentage of households with suitable rooftops, in figure 105, this adoption rate increases towards 54-58% under the current netting-scheme, 18-22% percent under the proposed netting scheme and 16-18% under no netting scheme. The initial installed capacity in 2019 is 52MW (CBS, 2020). For the current netting scheme, installed capacity increases towards 620-700 MW in 30 years, compared to 210-230 MW under the proposed netting scheme and 180-200 MW under no netting scheme (figure 104-2).

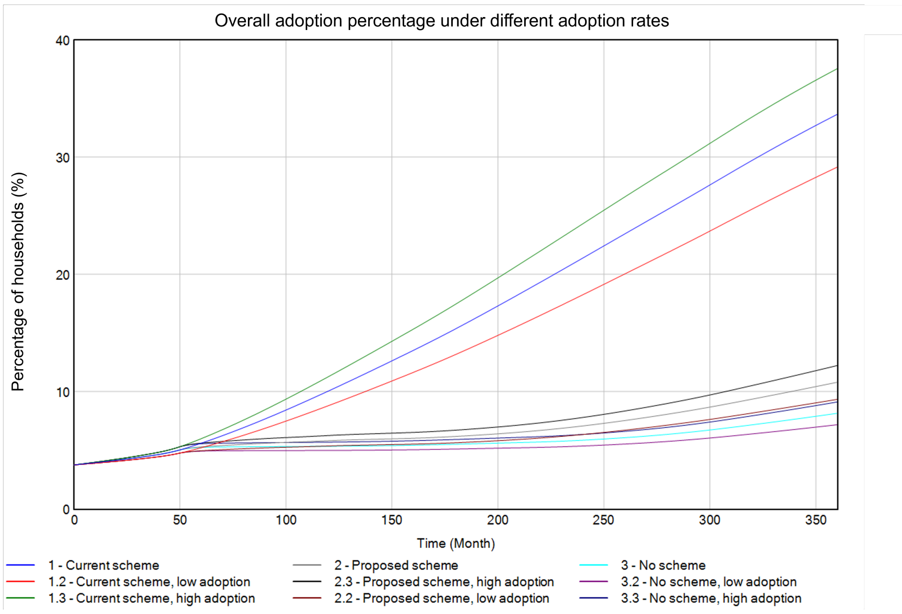


Figure 56: Adoption results for experiments 1-3 under different adoption rates

Looking at the two sub-population groups, the neighborhoods with a low percentage of rental properties and a low percentage of low-income households (group 2), vs. the neighborhoods with a very high percentage of rental properties and a very high percentage of low-income households (group 1), the adoption patterns significantly diverge. Under the current netting scheme, adoption percentages rise to 44-46% for the group 2 neighborhoods, and to 20-26% for the group 1 neighborhoods. Under the proposed netting scheme, where adoption for the group 2 neighborhoods rises to approximately 25%, and for group 1 neighborhoods to 4-8%. Under no netting scheme, adoption achieves a maximum of around 20% for group 2 neighborhoods and 5% for group 1 neighborhoods.

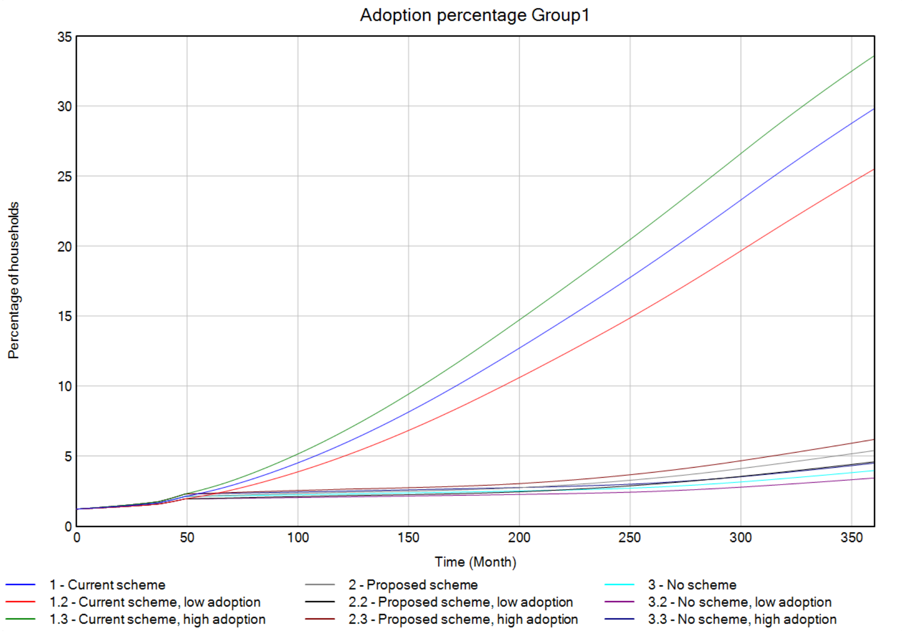


Figure 57

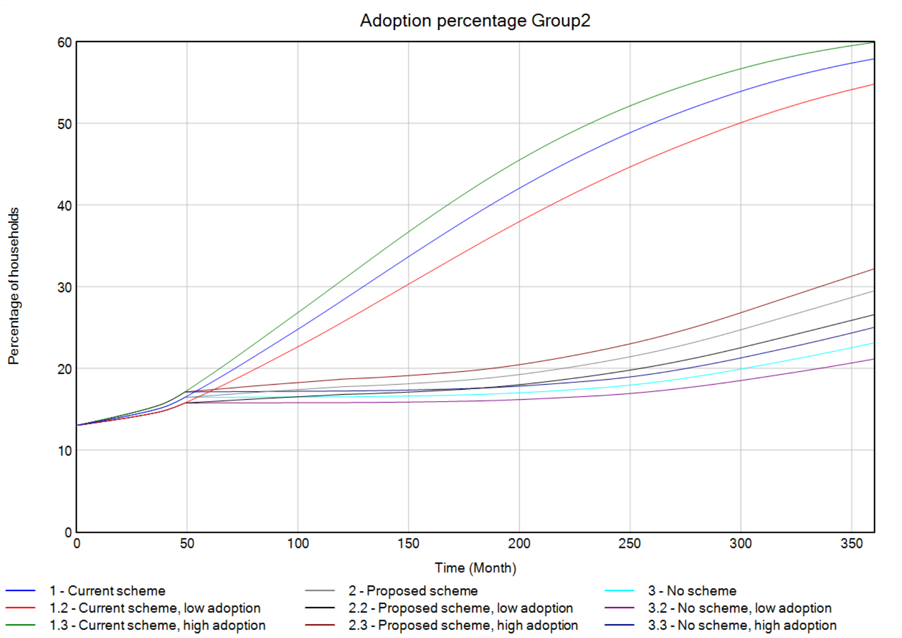


Figure 58

To analyze the payback periods under the netting scheme policies in more detail, extra experiments are run for the current and proposed netting scheme under different scenarios (scenarios 1.5 and 1.6 for the current netting scheme). Using scenarios 1 until 1.6 and 2-2.3, 9, and 10, the payback periods for different scenarios can be compared. These are shown in figure ?? and ??.

Under the current netting scheme, payback times decline from 6.8 years in 2019 to 2-3 years in 2049, depending on external influences. Payback time is highest when there are low geopolitical developments and low inflation, as electricity prices are low, making PV less attractive compared to high energy prices. Although inflation is high, geopolitical developments seem to influence the payback time more strongly. Similarly, payback time is lowest when there are high geopolitical developments and high inflation, where PV is now a more attractive alternative compared to grid electricity.

Under the proposed netting scheme, the payback period starts at 7.2 years in 2019 and decreases towards 4-5.5 years in 2049. The decline is strongest under the high GD, high inflation scenario (scenario 10), and weakest under the low GD low inflation scenario, similar to the payback period of the current netting scheme.

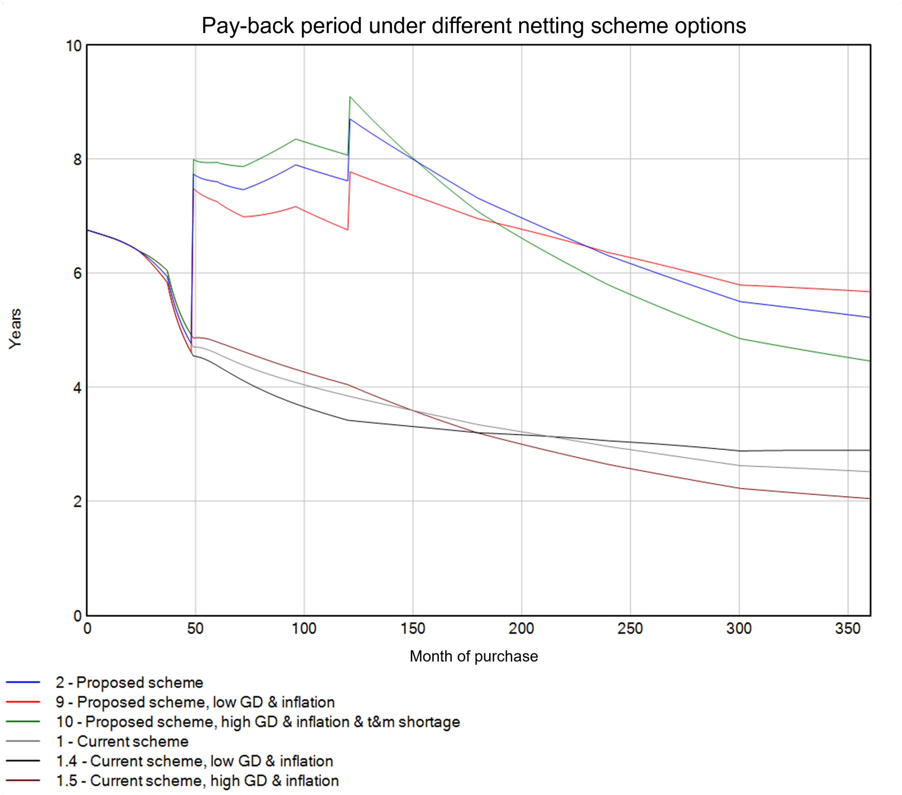


Figure 59: Payback times of the current and proposed netting scheme under different scenarios

8.3 External influence scenarios

Table 10 presents the experiments covering the external influence scenarios. The experiments explore the development of the KPIs under different scenarios for geopolitical development, inflation, or combinations of both. The netting scheme is kept constant for all experiments with the proposed scheme. The results of the experiments are shown in figures 60 - 62 and in Appendix C.

Experiment	Netting scheme	LI subsidy	Sustainability plan (SP) mandate	LI-netting scheme	Geopolitical developments (GD)	Inflation	Shortage of technicians and materials (t&m)	Adoption rate
4	Proposed	-	-	-	Low	Base case	Base case	Base case
5	Proposed	-	-	-	High	Base case	Base case	Base case
6	Proposed	-	-	-	Base case	Low	Base case	Base case
7	Proposed	-	-	-	Base case	High	Base case	Base case
8	Proposed	-	-	-	Base case	Base case	High	Base case
9	Proposed	-	-	-	Low	Low	Base case	Base case
10	Proposed	-	-	-	High	High	High	Base case

Table 10: Experiments covering geopolitical developments and inflation scenarios

The adoption percentages under different geopolitical and inflation scenarios different quite nominative, where the minimum adoption percentage is 9% at the end of the simulation period, versus the highest percentage being 16,5% at the end of the simulation period. For scenarios with low geopolitical developments (meaning low electricity prices, scenario 4), high inflation (scenario 7), and a high shortage of technicians and materials (scenario 8), adoption percentages remain the lowest.

The low electricity prices in scenario 4 result in a less attractive investment in PV systems, given that prices for consuming electricity from the grid are not very high. Savings from PV compared to non-PV are thus lower and the payback period for PV systems is higher compared to a scenario with higher electricity prices.

A shortage in technicians and materials decreases the willingness to adopt and creates a longer delay in the adoption rate. This decreases and postpones adoption. High inflation causes PV installation costs to increase. This increase (and decrease at low inflation) is shown in figure **??**. The increased costs for PV installations result in a longer payback period, and thus a less attractive investment. Although electricity prices (fixed and variable) also increase under high inflation, the impact of the increased payback period is more important in determining the PV adoption rates.

High adoption scenarios can be perceived under the high geopolitical developments scenario (scenario 5), high geopolitical developments and high inflation (scenario 10), and the low inflation scenario (6). The sharp increase in adoption that can be perceived under high electricity prices and high inflation (scenarios 5 and 10), reflects what can be perceived in the Netherlands nowadays. Many households feel the need for independence from utilities and market energy prices (van de Weijer, 2022). Increased geopolitical unrest, combined with increased electricity prices, enlarges the wish of many citizens to become more independent. Scenario 6 increases adoption rates by significantly decreasing the cost for PV installations, and thus the payback period of PV installment.

It should be noted that the study's scenarios are now evaluated separately. However, in reality, it could well be that several external influences impact each other. In the past, for example, geopolitical developments surrounding the war in Ukraine sparked not only energy prices but prices in many other sectors. The geopolitical developments, mainly those surrounding Ukraine, have however been severely significant for the energy industry, much more so than inflation, that it is chosen to model this variable separately.

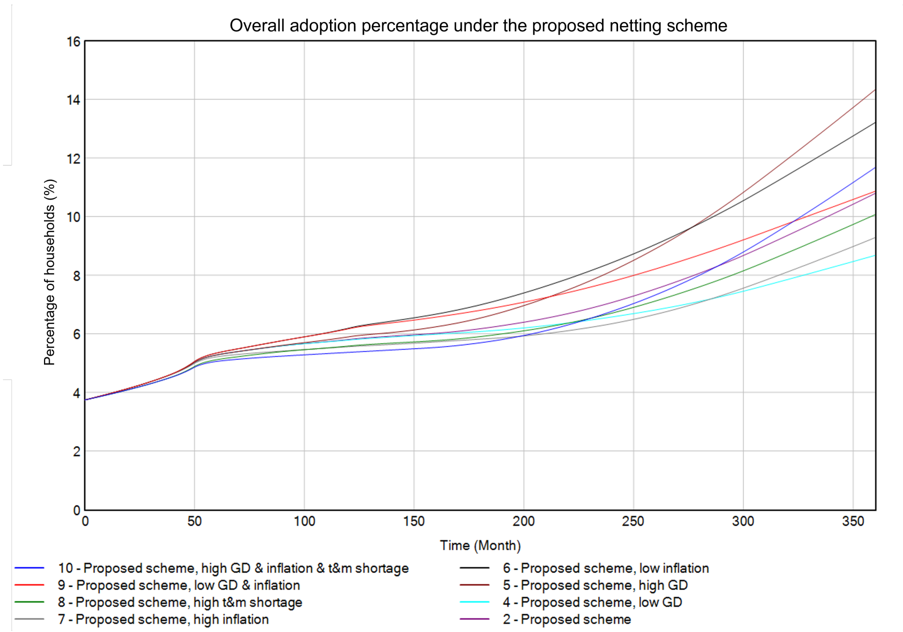


Figure 60: Results of experiments 4-10: overall adoption percentage

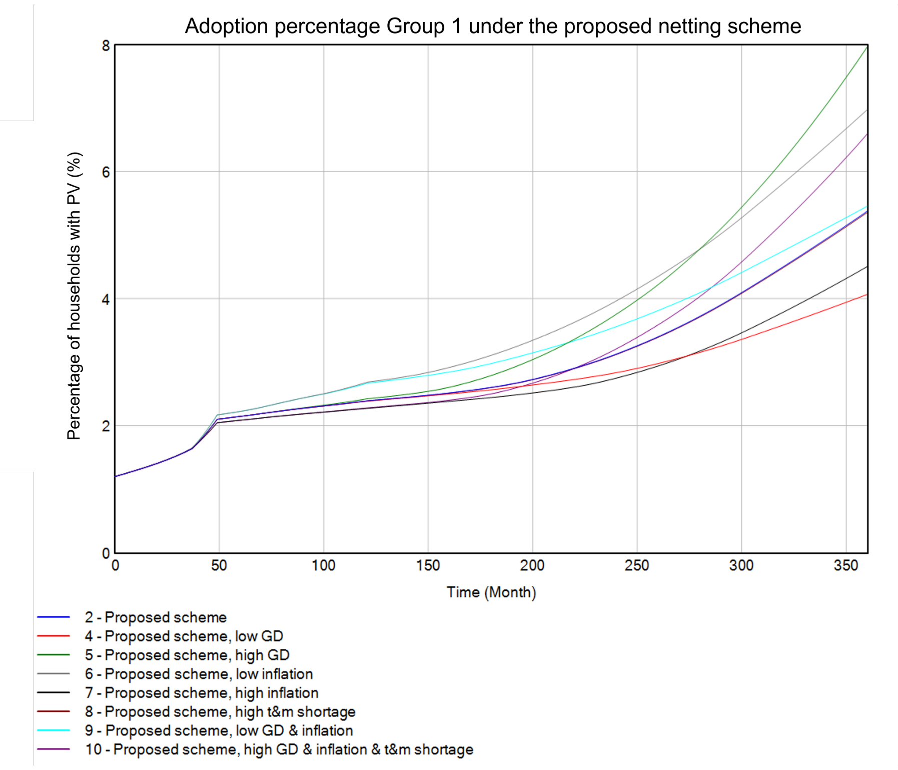


Figure 61: Results of experiments 4-10: overall adoption percentage Group 1

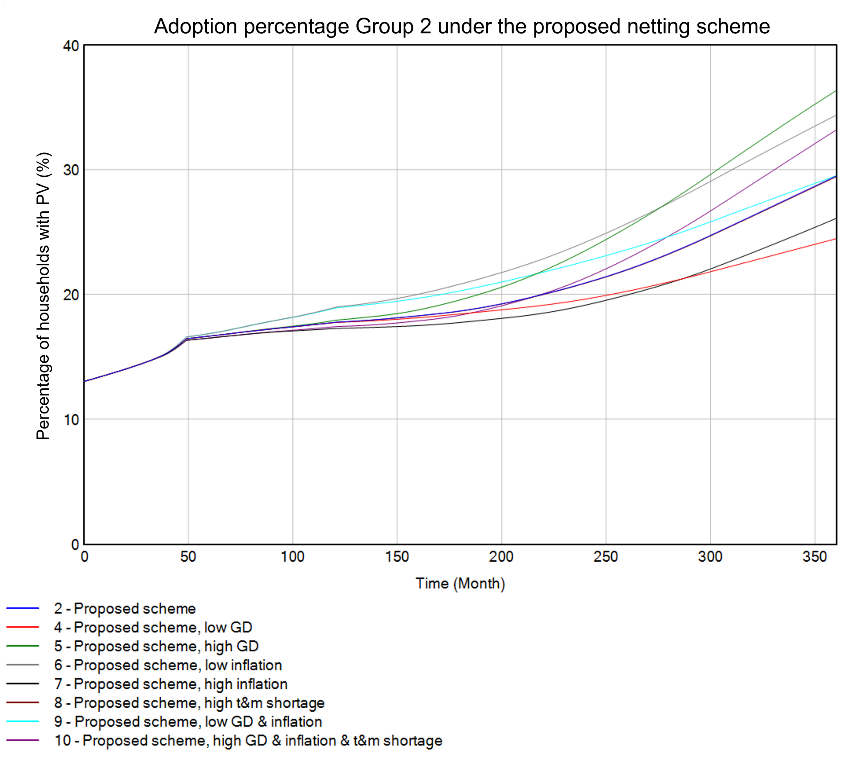


Figure 62: Results of experiments 4-10: overall adoption percentage Group 2

8.4 Leveling policy implementation scenarios

Experiments 11 - 26 (see table 11) cover the different configurations possible with the leveling policies "LI-netting scheme", "LI-subsidy" and "Sustainability plan mandate". The results are discussed per the policy below.

Experiment	Netting scheme	LI subsidy	Sustainability plan (SP) mandate	LI-netting scheme	Geopolitical developments (GD)	Inflation	Shortage of technicians and materials (t&m)	Adoption rate
11	Proposed	€500	-	-	Base case	Base case	Base case	Base case
12	Proposed	€1000	-	-	Base case	Base case	Base case	Base case
13	Proposed	€500	-	-	Low	Low	Base case	Base case
14	Proposed	€500	-	-	High	High	High	Base case
15	Proposed	€1000	-	-	Low	Low	Base case	Base case
16	Proposed	€1000	-	-	High	High	High	Base case
17	Proposed	-	Yes	-	Base case	Base case	Base case	Base case
18	Proposed	-	Yes	-	Low	Low	Base case	Base case
19	Proposed	-	Yes	-	High	High	High	Base case
20	Proposed	-	-	Yes	Base case	Base case	Base case	Base case
21	Proposed	-	-	Yes	Low	Low	Base case	Base case
22	Proposed	-	-	Yes	High	High	Base case	Base case
23	Proposed	-	Yes	Yes	Base case	Base case	Base case	Base case
24	Proposed	€1000	Yes	-	Base case	Base case	Base case	Base case
25	Proposed	€1000		Yes	Base case	Base case	Base case	Base case
26	Proposed	€1000	Yes	Yes	Base case	Base case	Base case	Base case

Table 11: Experiments covering leveling policies

Low-income subsidy

The low-income subsidy is a fixed amount that low-income households can request back from the government after a PV-installation purchase. Two amounts of 500 and 1000 euros are chosen for the simulation. The two variants are simulated under different scenarios. The results are shown in figure 63.

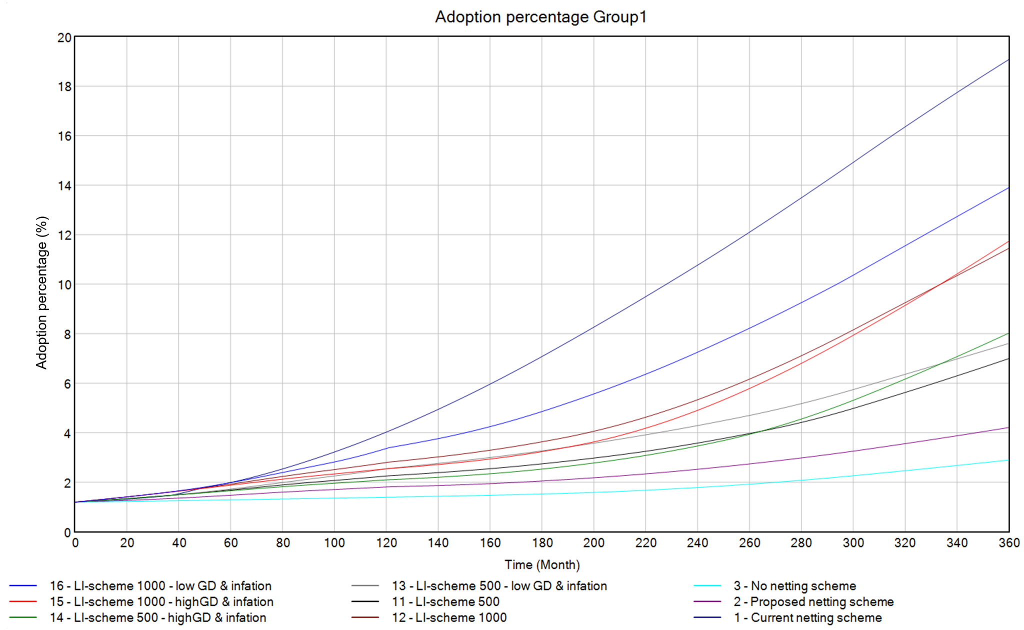


Figure 63: Adoption percentages for the neighborhoods in group 1 under different configurations of the LI-subsidy

As expected, all experiments with a subsidy policy in place achieve better results than no subsidy in place (scenario 2). Besides, also as expected, a subsidy of 1000 euros achieves better results than a subsidy of 500 euros. The best results are achieved when there are high electricity prices and inflation. The adoption percentage then increases from 4% to about 14%, which is still far below the average of the group 2 neighborhoods, which reach an adoption of 35-40% in this scenario. The high electricity prices make PV more attractive than grid electricity, and the inflation impacts the households in this category less as the price for a PV system is kept low with the subsidy allowance.

Sustainability plan mandate for OAs and housing corporations

The sustainability plan (SP) mandate requires landlords, OAs, and housing corporations to come up with a sustainability plan, of which installing solar panels is a possible inclusion. The SP mandate shifts the adoption curve to the right, resulting in a higher adoption percentage for the same payback period, because adoption barriers related to rented properties are now partially lifted. For the simulation, a 30% increase in the adoption rate is tested. The results show that a maximum increase of 9% can be reached, under the high geopolitical developments, high inflation, and high shortage of technicians and materials, followed close by the low geopolitical developments and low inflation scenario. Both scenarios make PV more attractive, one by increasing grid electricity prices and one by decreasing PV installation rates. Inflation seems to be the smaller influence in this case, as the effect of inflation is smaller than the effect of high electricity prices due to geopolitical developments.

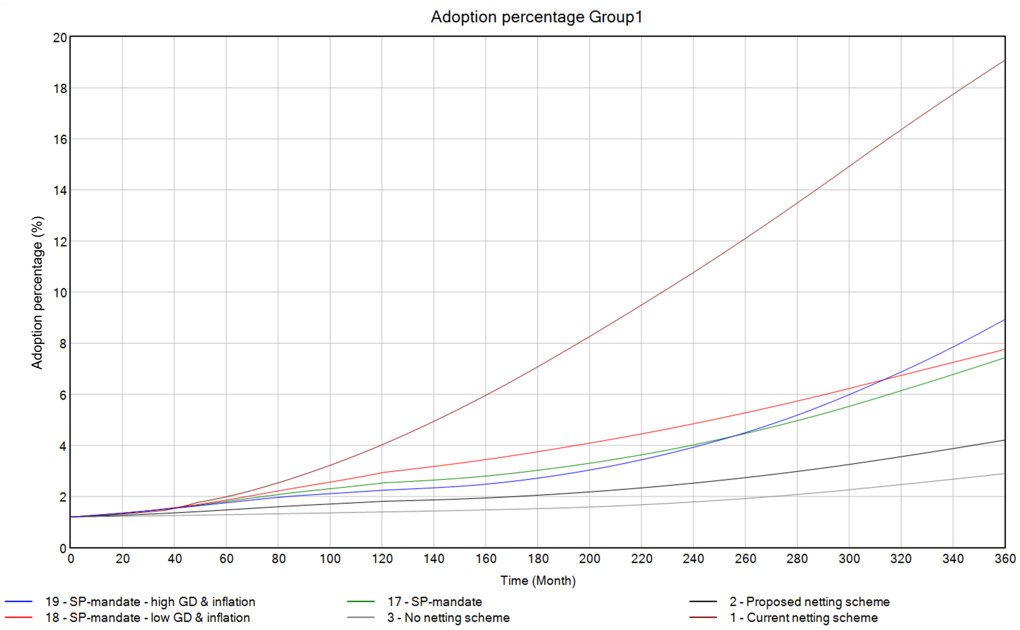


Figure 64: Adoption percentages for the neighborhoods in group 1 under different configurations of the Sustainability Plan mandate

Low-income netting scheme allowance

The low-income netting scheme allows LI-households to profit from the current netting scheme benefits for as long as the PV installment has not yet paid itself back. The LI-netting scheme works similarly to the base case scenario, where the current netting scheme is also in place. Under this policy measure, an adoption percentage of 17% is achieved at the end of the simulation (see figure 121), which is the highest achieved adoption percentage of all leveling policies.

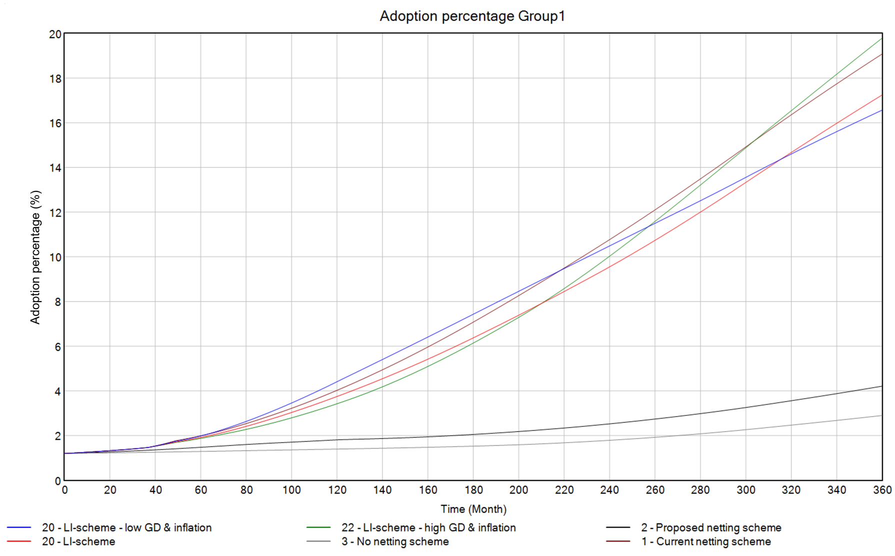


Figure 65: Adoption percentages for the neighborhoods in group 1 under different configurations of the LI-netting scheme

Combination of leveling policy measures

Each stand-alone policy achieves improvement in PV adoption, however, a combination of policies might be more effective. These combinations make up experiments 23-26. The results of these experiments are shown in figure 66 and in Appendix C.

As expected, a combination of all three policy measures works best for increasing PV adoption rates of group 1 neighborhoods. A combination of three policies however could be unrealistic given the unfairness towards other socioeconomic groups. The two best scoring combinations are a combination of a €1000 subsidy and an SP mandate, achieving an adoption percentage of approximately 27%, closely followed by a combination of the LI scheme and an SP mandate, achieving an adoption percentage of approximately 26%. Notably, experiments 23, 25, and 26 achieve better adoption rates than the current netting scheme in place.

The achieved results are compared with the adoption percentage and the installed capacity per citizen of group 2 under the base case scenario. The comparison of results is shown in figures 66 and 122. Under the proposed netting scheme, group 2 achieves an adoption of about 30%. With a combination of leveling policies, this adoption rate can be closely approached. Deploying all three leveling policies achieves an adoption rate of 36%, which encompasses the adoption rates in group 2.

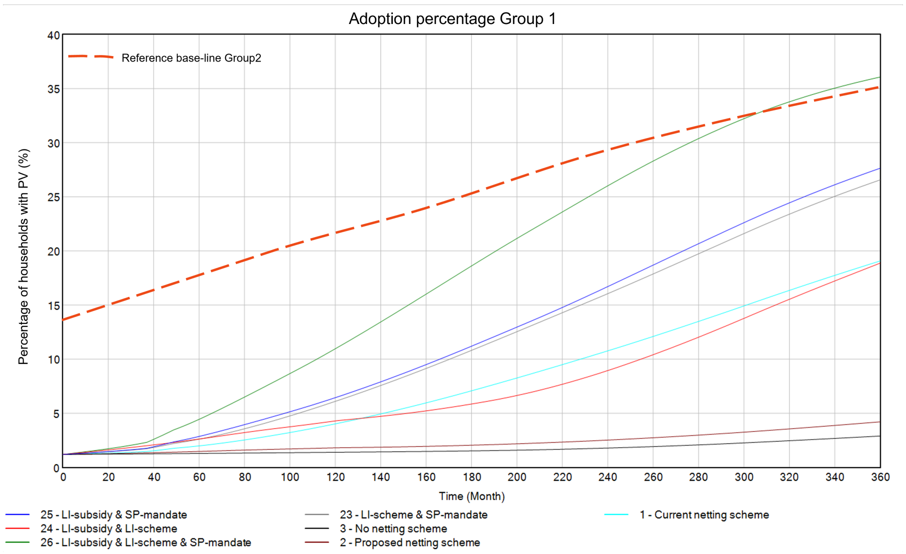


Figure 66: Adoption percentages for the neighborhoods in group 1 under different combinations of leveling policy measures, compared with the adoption percentage of group 2 in the base case

8.5 Consumer electricity costs development

For both solar adopters and non-adopters, the electricity costs per month are computed to allow a comparison of the monthly energy cost burdens. Besides, the energy burden of electricity costs of an average low-income household is computed. This allows to relate the energy costs to the concept of energy poverty.

Figure 67 shows a comparison of the monthly electricity costs for adopters versus non-adopters under the proposed netting scheme. The graph shows that for adopters, the costs are significantly higher compared to non-adopters, and at some point are even negative, meaning they receive money back from the energy supplier. Due to the increasing costs of grid operators, for both groups, the electricity costs will steadily decrease over time.

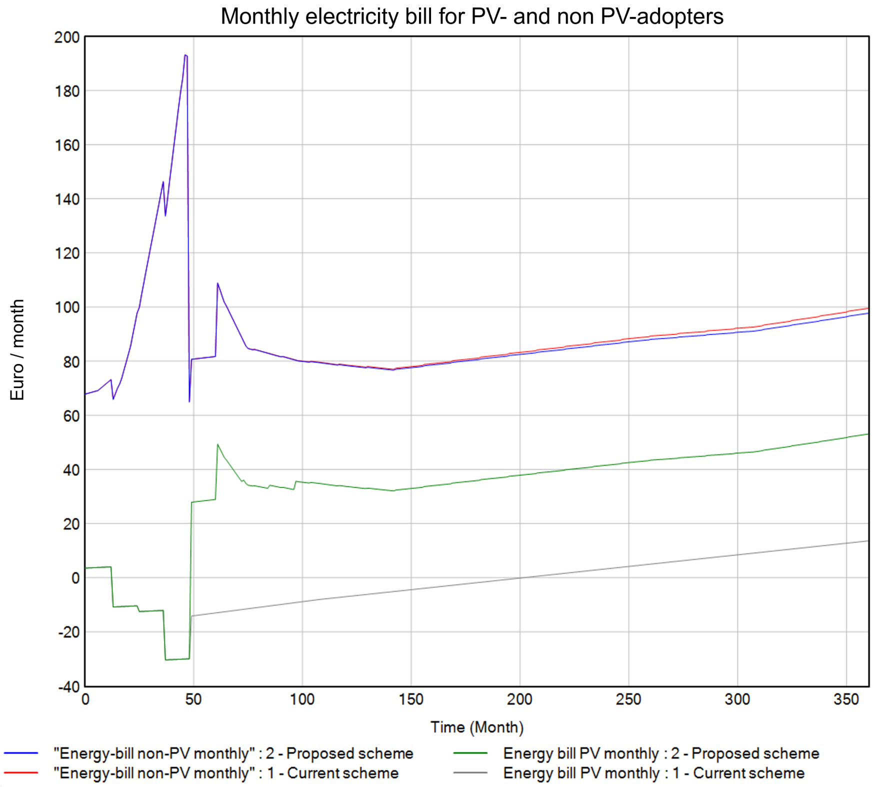


Figure 67: Energy bill for PV adopters and non-adopters under different netting scheme options

Figure 68 shows the monthly electricity bill for non-adopters as a percentage of the average low-income household in the Netherlands. The average low income is adapted from the CPB Netherlands Bureau for Economic Policy Analysis (CPB, 2022a). It should be noted that for the definition of energy poverty, an energy quota (the percentage of income spent on energy) of 10% is used, but this percentage is based on a total of the electricity and gas costs. This study only includes electricity costs. Nonetheless, the figure shows that during 2022, when electricity prices are extremely high, the energy quota rises to 12%, which indicates energy poverty for the average low-income household. The figure also shows that under the high inflation, high geopolitical developments, and a high shortage of technicians, the share of energy costs of the total average low-income increases to above 10%. This percentage would only be higher if gas costs were to be included. The results clearly point towards an increasing chance of energy poverty for low-income households under the steadily increasing electricity prices and show that monthly electricity costs for adopters are significantly higher than for PV adopters.

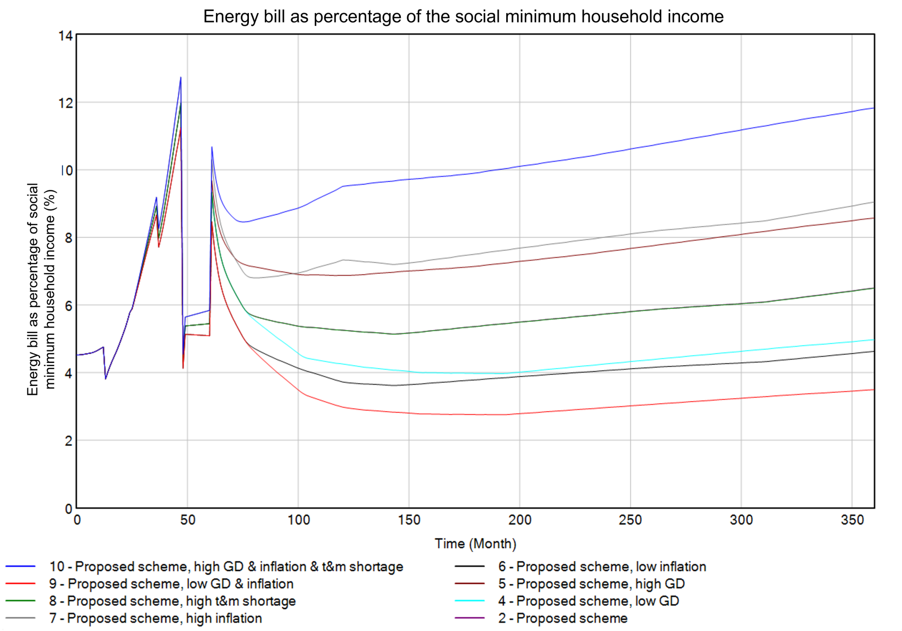


Figure 68: Energy bill as a percentage of the average low-income for non-adopters under different netting scheme options

8.6 Main conclusions Chapter 8

This section aimed to answer research questions 4 and 5. To start with research question 4: *how might solar panel adoption disparity develop in the future?*. Adoption appears to be highly affected by the netting scheme policy in place. For the current netting scheme policy, adoption percentages of 37-49% can be achieved in 30 years time, depending on adoption rates and external developments. For the proposed netting scheme, the simulated adoption percentages achieved 9,5-17,5%, depending on adoption rates and external developments. This difference is caused by the large difference between payback times for both netting schemes. For the current netting scheme, the payback time decreases to 2-3 years, while for the proposed netting scheme, the payback time decreases to 4-5.5 years.

The difference between the adoption of group 1 and group 2 neighborhoods is large under both the current and the proposed netting scheme. Under the current netting scheme, group 1 neighborhoods still achieve an adoption percentage of 18-31%, which is significantly lower than the group 2 neighborhoods which achieve 42-52% adoption. Under the proposed netting scheme, the adoption rates are 5-9% for group 1 neighborhoods compared to 24-28% for group 2 neighborhoods at the end of the simulation period. It is notable that for both socioeconomic groups and the overall adoption rate, the adoption under the proposed netting scheme is significantly lower than under the current netting scheme.

Most remarkable is the extremely low adoption rate for group 1 neighborhoods under the proposed netting scheme. Under this policy lever, the payback period does not decrease significantly enough over the years to stimulate a high adoption rate for group 1 neighborhoods. However in the group 2 neighborhoods, the adoption percentage under the proposed netting scheme is still high enough to reach an adoption rate of almost four times higher.

To answer research question 5 - *What are effective interventions for increasing residential PV adoption and narrowing down the adoption gap?* - experiments are conducted with leveling policies. The "LI-netting scheme" and the "LI-subsidy" policies had the most promising results. Compared to the proposed scheme base case, the "LI-netting scheme" can increase adoption percentages from 5,5% to approximately 17%. Under high geopolitical developments and inflation, the LI-subsidy achieves an adoption percentage of 11,5%.

It is likely that a tailored made combination of policies is most effective. Combining the three policy levers could achieve an adoption percentage of 35%, which thereby approaches the adoption percentage of the group 2 neighborhoods of also 35% under the proposed scheme. A policy combination including all three policies is however questioned given the large economic advantages awarded to group 1 neighborhoods. The policy results can however guide future policy-making as it aids in understanding what policy measures could be used and what their impact could be. The policies can then possibly be combined with other, not modeled policy solutions to increase success. Further suggestions are discussed in Section 10.

It should be noted that SD models are simplifications of reality, and are most suitable for studying (changes in) model behavior. Thus, given the nature of System Dynamics modeling, the modeling results are perceived to be most useful for comparing the relative performance of policy levers and scenarios, instead of absolute achieved adoption percentages.

9 Discussion

This section reflects on the methodology and discusses the limitations of the model and the policy analysis and the implications of these limitations. Furthermore, this section provides suggestions for further research.

9.1 Reflection on the methodology

9.1.1 GIS-based rooftop suitability assessment

The GIS-based rooftop suitability approach proved to be appropriate for the study purpose. The method provides the desired outputs for examining rooftop suitability in a municipality, allows for altering suitability assumptions to fit different geographic locations, and enables the use of own data sources as well as directly imported data from the ArcGIS environment.

A limitation of the methodology is that GIS-based methods are time-intensive and computer-resource intensive. Solar radiation calculation is computationally demanding, and the computation time for solar radiation mapping in ArcGIS significantly increases for larger study areas. For the municipality of Amsterdam, which has a surface of 219,49 km^2 of which 165,50 km^2 land, the surface had to be split into seven sections to reduce the computation time of the individual runs. For all seven sections together, computation time added up to 160 hours. Though computation time also depends on the study area, data quality, data granularity, simulation period (a month, a year, etc.), and computer capacity, other studies that have applied similar methods also experienced similar computation times (Marešová, 2014), (Wolfs, 2017). When there is a wish for reduced computation time, one could consider other approaches such as machine learning, however, proper skills are needed to be able to apply such methods. Besides, extensive and high-quality data is needed for accurate assessments.
Another limitation of the GIS-based approach in ArcGIS is the relatively complicated validation process. Mostly manual validation is required to verify the correctness of roof classifications, which is time-consuming. Besides, validation is complex as the GIS-based computation requires several assumptions on roof suitability, which might differ in other studies and thus requires care when comparing. This limitation is dealt with by carefully examining the assumptions and methods used by studies that have been used for comparison.

A final limitation of the ArcGIS approach is the need for detailed surface area data. For this study, height data at a resolution of 0.5m^2 is used. For all municipalities in the Netherlands, this data is freely available. Possibly in other countries worldwide, however, this data might be more challenging to obtain. Alternatively, less fine-grained data could be used, which reduces the accuracy of the computations.

9.1.2 socioeconomic data analysis approach

An advantage of the statistical data-analysis approach is that the used methods (i.e. ANOVA analysis, correlation analysis) are generally well-grounded in literature, assumptions of the methods are known, and results can be easily interpreted and visualized. A pitfall of the method is that it requires sufficient data, high data quality, extensive data pre-processing, and compliance with several statistical assumptions that vary per statistical method. A limitation of correlation analysis is that results should be interpreted with caution. It might be natural to assume casual relationships, while correlation does not imply causation. Besides, correlation analysis cannot be used to explore the presence or effect of other variables outside of the two being explored. Finally, the range of observations influences the correlation coefficient. These limitations have been dealt with carefully during the research. Overall, the method was found suitable for the intended purpose.

9.1.3 System dynamics approach

System dynamics has been demonstrated to be an appropriate method for modeling the diffusion of solar panel adoption amongst households for several reasons. SD allowed for making the complex system behavior visible and understandable in a transparent and quantitative manner. As SD provides insight into the entire system mechanism, the method fits the exploratory characteristic of this research. Besides, the method enabled simplification of a complex system, while still maintaining trust in the validity of the model outcomes. This way, the application of SD appeared to be appropriate for the level of aggregation of this research. The method allows modeling PV adoption disparity amongst different socioeconomic groups while allowing both local and country-level policy testing. The method also allowed modeling the decision-making of a neighborhood group as a whole. Finally, the problem contained a number of mechanisms for which SD has previously proven to be a suitable modeling method, such as the technology diffusion process.

A limitation of the use of system dynamics for this research is the lack of possibility to include geographic or spatial analysis. Part 1 of the designed artifact included a geographic perspective on PV adoption, where disparity could be easily visualized. Translating the outputs of the SD model back to geographic developments is not simple as the method does not allow for a spatial representation of modeling results. In the future, other methods for SD modeling could be explored, such as Python.

9.2 Discussion of limitations

9.2.1 Limitations of the rooftop suitability analysis in ArcGIS

1. Potential electricity yield.
   Electricity yield strongly depends on the type of solar panels. In ArcGIS, estimations for potential electricity yield are based on average system efficiency. In reality, electricity yield can deviate. However, for the purpose of estimating rooftop suitability and thus solar panel potential, this estimation is deemed justifiable.

2. Suitability definition.
   In this study, it was chosen to consider rooftop suitability from a household perspective, meaning a PV installation should economically be viable. In ArcGIS, the minimum available roof surface for solar panels is defined as $20m^2$. This minimum is set because smaller roof surfaces likely do not yield enough electricity for a PV-system investment to be profitable. Some other studies use less strict minimum surface areas such as $15m^2$. Using a minimum suitable surface area is not conclusive, as electricity yield depends on system size and efficiency. Using a lower minimum suitable surface will increase the number of suitable rooftops.

3. Exclusion of suitability factors.
   The rooftop suitability assessment does not consider a number of elements that fall outside of the scope of the study, such as the accessibility of roofs, roof material (defining the carry capacity for PV installations), and monumental buildings. In future research, these could be included in the analysis, though these factors limiting roof suitability are considered exception cases. The factors that have been included in this study are perceived to be well representative of the general suitability of rooftops for PV and have been shown to reproduce accurate results in other studies (Margolis et al., 2017), (Wolfs, 2017), (Dahal et al., 2021).

9.2.2 Limitations of the socioeconomic data analysis

1. Level of analysis and data granularity.
   The analysis of socioeconomic indicators and PV adoption is performed at the neighborhood level. A neighborhood statistic represents the average of a neighborhood. For this analysis, it is assumed that households and residencies within neighborhoods are somewhat alike. Of course, , averages might not be representative of the whole neighborhood population. The purpose of the study however is to identify socioeconomic and spatial PV disparity, for which neighborhood-level data is found to be the most suitable and available data source. Besides, when using the results of the study, targeted policy measures can be formulated at the neighborhood level. Besides, in the socioeconomic data set, the financial-related indicators exclude students. This means that this population group is not represented in the financial indicators.

2. Correlation does not imply causation.
   That two factors correlate does not necessarily mean that one causes the other. The fact that correlation does not imply causation, is one of the most important cautions in correlation statistics (Green, 2012). Human preconceptions about the way things work might tempt one to think of causation when sometimes there is merely correlation. Correlation between two factors can be caused by a third factor, a con-founder effect. In this study, it is therefore clearly noted that the studied correlation effects do not imply causation. The results are merely used to be able to evaluate adoption disparity amongst different socioeconomic sub-populations. The study does not intend to explicate the exact causes of adoption disparity. This should be kept in mind when interpreting the results of the study.

3. Multicollinearity amongst indicators.
   The study included a wide range and extensive amount of socioeconomic factors. Although in this study each of these are treated as distinct, they are in fact deeply interconnected. Different types of inequities

or inequalities can compound each other. Besides, several socioeconomic factors might in fact be intrinsically correlated to income. In future studies, this could be explored by correcting neighborhood indicators, such as education or ethnic background, for income differences in neighborhoods. The wide amount of socioeconomic indicators that might be interconnected can result in multicollinearity effects. Multicollinearity has been assessed in this study to account for the effects in the further interpretation of the results. The effect is mitigated by including a Bonferroni correction. A more extensive analysis of the deep interconnectedness of socioeconomic factors could add to the results of this study.

9.2.3 Limitations of the System Dynamics Analysis

1. Simplification of the PV adoption diffusion process
   The adoption behavior of solar panels is complex. Many variables come into play that influences one's willingness or ability to adopt solar panels. This model adopts economic, social, and regulatory drivers for the diffusion of solar panels. These drivers are represented by exogenous price variables, policy levers, and adoption rates. The socioeconomic characteristics of a population are captured in the adoption function: given a certain technology price, a (sub)population with specific socioeconomic characteristics shows a certain adoption behavior. Other drivers for PV adoption are not modeled, such as psychographic indicators, environmental drivers, and technology popularity. For example, Vasseur and Kemp (2015a) state that psychographic features impact the choice for PV adoption. Morcillo et al. (2022), included an advertising factor in their PV-diffusion model. This model excluded these factors. Psychographic features and environmental drivers are factors that are difficult to abstract into model variables, and data on these features at the neighborhood level lack. Attempting to include these would increase model uncertainty, but could also provide a more holistic view of the diffusion process. Since this model uses empirical adoption rates, it could be argued that any psychographic population behavior is embedded into the empirical adoption rates, however, this would also imply that these factors do not change over time.

   Low or high adoption rates (within neighborhoods) are most often probably not caused by one socioeconomic indicator or adoption barrier. In fact, a low adoption rate within a neighborhood is likely to be caused by a combination of rooftop suitability, socioeconomic factors, adoption barriers, and psychographic factors. This should be taken into account when interpreting the results of the simulation study. Within both the studied neighborhood groups and the population as a whole, other factors play a role in determining adoption behavior. Some of these factors have been identified in this study. The study mostly shows, regardless of the complex factors behind PV adoption, how the system might behave in the future and that there is a significant gap in adoption between societal groups which both creates inequities and limits renewable climate goals.

   The study examines adoption patterns for two different neighborhood groups, that have been categorized based on the percentage of rental properties, the percentage of multi-household residencies, and the percentage of households with a low income. These indicators came forward during the analysis in Chapter 6, and have therefore been chosen for further, detailed analysis in the system dynamics study. However, the socioeconomic study revealed other indicators that significantly correlate with high or low adoption rates in neighborhoods. Given the limited time, it was chosen to focus on these two factors that were observed to be highly significant from both the relevance, rigor cycle and socioeconomic analysis. No other societal groups have been studied yet.

2. Simplification of the adoption evolution process
   modeling the effect of policy levers on the system behavior can bring uncertainty in the outcomes. For financial-incentive-related policies, the effect is more straightforward to model given the quantifiable impact of the policy on the payback time of PV installations. The effect of the "sustainability plan mandate" policy is more complex to evaluate, given there is no empirical data on the impact of this policy to date. The effect of this policy is therefore estimated based on the characteristics of the neighborhood groups. When considering the implementation of such a targeted policy lever, it is advised to perform additional research on the effects of this policy on adoption behavior.

   The model uses average monthly adoption rates and average system sizes. The effect that multi-household residencies for example might have larger PV systems installed, is not modelled. Besides, for the whole simulation, socioeconomic neighborhood data from the year 2021 is used. To reduce model complexity, it is assumed that these indicators remain constant over the period of analysis.

3. Local versus national modeled dynamics.
Several dynamics in the model are simulated at the local level, while other dynamics require modeling at the national level. PV adoption is modeled locally, as local case-study data is used. It is desired and even necessary to model such processes at a local level using local case-study data, given the role of specific case-study characteristics on PV adoption disparity. Other mechanisms in the simulation model are however national. For PV pricing, this is not problematic. When one, however, wants to incorporate a "learning by doing" feedback loop, where PV installation prices decrease due to increased adoption of the technology and technological innovation, this national process is difficult to match with the small-scale and locally modeled PV adoption. PV adoption in the case-study area only (the municipality of Amsterdam) is too limited to impact PV prices on a national level. When one wants to include such national dynamics, an estimation of national impact needs to be incorporated.

   The same accounts for the modeling of electricity price and margin increase effects. These require modeling at a larger scale in order to properly assess the effect of PV adoption on utility costs and electricity prices. In this study, estimations are therefore made to replicate this effect. More suitable to include in local modeling of PV adoption is the impact of adoption on voltage issues on the local electricity grid. This could be used to estimate local PV adoption increases and in combination with grid quality information, assess weak spots on the grid that might need prioritization for expansion. To do so, one can use neighborhood adoption evolution from the SD model and translate this to real-life neighborhoods.

   Incorporating an agent-based modeling perspective could be useful for generating additional insights into the technology diffusion process, as this allows modeling individual household (agent) behavior. This approach needs estimations or generalizations of individual household behavior, but these can be based on the analyzed adoption rates and socioeconomic neighborhood data as discussed in this study. In agent-based modeling, it is however more difficult to trace back the chain of events causing the results of the simulation. Besides, agent-based modeling is focusing on the micro-level decision-making structures of actors. To model this, a different modeling process for adoption and additional data sources are necessary.

4. Exclusion of PV-system size and expansion
Unit scaling as an effect of cumulative adoption is not regarded in the model. The PV-system capacity is normalized in the model, and therefore the system size is a constant factor in the model. Expansion of existing PV installations, e.g. adding an extra four panels to ten already installed panels, is not modeled.

5. Simplification of the Utility Death Spiral effect
The utility death spiral is a well-investigated phenomenon in literature. The exact extent of the effects of this phenomenon is debated in the literature. Therefore, this phenomenon is modeled with caution in this study and the effects on the model are validated using research sources. Future research could expand the model by detailing this effect.

6. System dynamics modeling caution
It should be noted that the diffusion process of PV amongst the municipality of Amsterdam, and its disparity amongst different socioeconomic groups, remains an abstraction of the modelers' vision of the real-world system. Although bias in the model construction is inevitable in system dynamics modeling (J. Sterman, 2000), this is limited as much as possible through careful data selection and construction of the model components. Input data such as parameter assumptions are adopted from reliable sources and validated by comparing multiple other studies or sources. Similarly, the final SD model structure is a result of different sources from literature about the technology diffusion process, electricity generation through PV systems, and PV adoption market effects. Besides, the model is tested with accepted methods for SD validation.

   Nevertheless, caution should be paid when using the model and interpreting its results. The model is not validated by experts. An expert opinion could provide a new perspective on the model structure, assumptions, and bias. Besides, when interpreting the model and its results, it should be kept in mind that the model is a simplification of reality, and aims to provide insights into the dynamics of the system as a whole. Therefore, the model can be used to provide insights into system behavior, but the results should be interpreted with the described model limitations in mind.

7. Limited scenario testing opportunities
System Dynamics is a valuable tool for investigating system behavior and testing model and policy sensitivity. However, its usefulness for policy analysis is limited due to the constraints on extended model exploration and policy analysis options. The required manual input is time-consuming, which restricts the number of model analysis runs that can be conducted. To address this issue, this study analyzed three exogenous scenarios (geopolitical developments, inflation, and shortage of technicians and materials) and four policy scenarios in different, selected combinations, resulting in 26 tested combinations. While this approach provided insights into the effects of policy severity and timing within the system's legitimate boundaries, its limitations include the difficulty of searching for plausible scenarios and quantifying other scenarios that could trigger diffusion acceleration.

8. Uncertainty in the model.
During the System Dynamics modeling and experimenting process, the uncertainty space is thoroughly explored using sensitivity analysis and scenario exploration. There however remains uncertainty about whether the selected uncertainty and decision spaces are an accurate and complete representation of plausible future developments. This uncertainty is inherent to system dynamics modeling and could be reduced by using a robust policy search method (see Section 9.3).

9. Incorporation of energy poverty and energy injustices.
In the system dynamics model, the electricity bill as a percentage of the average low-income household is calculated. This calculation is based on the average expenditure on electricity of a Dutch household. Energy poverty can be caused by a high expenditure, a low income of a poorly isolated residence. Households with poorly isolated residencies often have higher energy expenses, thus it is expected that a larger share of the households with energy poverty will have high expenditures than the average used in the model. Besides, the model only includes electricity costs, while the assessment of energy poverty usually includes both electricity and gas costs. Therefore, the energy quota calculated in this model is an approach of the share of energy costs of the average low-income households (the energy burden), instead of an exact assessment of energy poverty.

9.3 Recommendations for future research

- The study adopted a newly developed approach to assessing PV adoption equity and evolution in a structured, integrated manner. The approach consists of multiple steps, of which each step has been individually validated during the study. Future research could build upon the developed approach as a whole and perform a more extensive validation of the scalability and robustness of the approach and the validity of the policy outcomes. A suggestion would be to evaluate the approach with experts in the field of energy policy-making and energy justice, and with other relevant actors that could use the policy outcomes, such as municipalities and governments.

- This study applied a social perspective on the PV adoption process. Other perspectives on PV adoption are useful to investigate. One suggestion is that of grid operators, in the form of a grid impact analysis. In this study, it is suggested that PV adoption impacts the capacity and voltage issues on the grid and that clustering of PV adoption can increase these effects. Though an expert interview revealed that grid investments costs due to PV are likely not the reason for increased costs for consumers (thus decreasing the chance of socialization of these costs to non-adopters), assessment of the impact on the grid is useful for grid operators aiming to pro-actively act upon plausible future adoption behavior. This study revealed that adoption patterns are different between neighborhoods and that there is a risk of clustering of PV installations. According to experts, clustering of PV can increase grid issues, but the impacts need to be further explored.

  Assessing the grid impact of distributed renewable energy generation however is highly complex, and exceeds the abilities of the methodologies used in this study. No suitable proxy for assessing grid impact has been found in literature so far, that was suitable for including in the system dynamics structure. Further research could be done on ways to incorporate grid impact into the study.

- The developed model in this study could be deployed for the investigation of other sub-populations by using different socioeconomic factors to construct neighborhood groups. This study used the socioeconomic indicators that came forward as some of the most correlated with PV adoption. However, other variables came forward as important correlated indicators, and other studies might also reveal socioeconomic indicators worth investigating. Following from this research, other suggestions are racial differences and educational backgrounds and following from other studies, linguistic isolation and housing burden (Lukanov & Krieger, 2019).

- Several studies in the literature suggest that there are clear distributive and equity impacts of PV support policies such as net metering and that the benefits of PV adoption are largely bypassing less-advantaged communities (Keady et al., 2021; Lukanov & Krieger, 2019; O'Shaughnessy, 2021; Si & Stephens, 2021; Sovacool et al., 2022). Accordingly, this study has identified several forms of injustice that are prevalent in the solar energy landscape, either through the literature research, interview process, or modeling process. The modeling process mainly touched upon notices of distributional justice: socioeconomic inequities in adoption are identified and modeled through future developments. Future research could focus more on the other forms of energy justice that are prevalent in the residential solar panel adoption landscape in the Netherlands: procedural justice, recognition justice, and transformative justice. Generally, future research could ground the perceived possible injustices by empirically evaluating citizens' perceptions of injustice, for example through field research and interviews with citizens in Amsterdam. Kieskamp (2023)investigated justice perceptions regarding energy policy in the Dutch city of Tilburg, and found that the interviewees' perceptions of injustice regarding distribution and procedures could oftentimes be traced back to a lack of recognition for their distinct needs and vulnerabilities in the first place. It is useful to investigate the perceptions of justice in the municipality of Amsterdam accordingly. As another example, this study slightly touches upon procedural justice in the conclusion section regarding the recommended policy steps, however, a more detailed assessment of the policy steps in light of procedural justice would increase decision-making equity even more. Another example is that future research could focus on the quantification of inequalities or injustices caused by PV-related policy, such as the socialization or cross-subsidization of netting-scheme costs and increased utility and grid costs. Such a study could serve as an explication of the socialization of grid investments and utility revenue losses.

- To extend the system dynamics model, several dynamics could be added or extended based on the current study:

  - The impact of renewable energy adoption on utilities could be further explored. PV adoption impacts utilities financially by increasing balancing costs and reducing revenue. The impact on electricity tariffs is simplified in this study but could be further investigated.

  - A feedback loop that is excluded from this analysis but could be included in future research is the impact of PV adoption on PV system prices. This could for example be done through incorporating learning curve effects (Morcillo et al., 2022).

- This study implied translating a spatial analysis (part 1 of the artifact) to a non-spatial analysis (part 2 of the artifact). To still incorporate the spatial element of adoption disparity, sub-populations of neighborhoods are investigated. However, future research could translate the system dynamics outcomes back to spatial insights, by visualizing simulated adoption patterns on a map of the municipality.

- To deal with the limited scenario testing opportunities presented by the system dynamics approach, a robust policy search and deep-uncertainty assessment could be adopted. The Exploratory Modeling & Analysis (EMA) workbench, developed by (Kwakkel, 2017), could provide a suitable methodology. The workbench is an open-source toolkit for supporting decision-making under deep uncertainty. The method can be used to subject the system dynamics model in this study to an optimization algorithm which will yield a list of robust policies.

  The sensitivity analysis in this study revealed the model is most sensitive towards changes in the market electricity prices, PV installation costs, and inflation. These variables have been used for scenario testing in this study but would be suitable to study in a robust policy search and deep-uncertainty assessment for further analysis. Contrary to exploring the most suitable policy combinations by hand, the EMA workbench allows one to search the decision space to find optimal policy combinations and best or worst scenario's based on these external factors. Besides, a search in the decision space of the possible combinations of leveling policy options under the many possible values for external factors could significantly improve the robustness of the leveling policy options. In short, though this study included scenario testing of external factors and uncertainties, a robust policy search and deep-uncertainty assessment could improve insights into the robustness of policies, where the focus should be on the market electricity prices, PV installation costs, and inflation.

- Earlier in this study, it is suggested that PV adoption behavior and socioeconomic trends behind this behavior are highly local. It would be interesting to apply the artifact in this study to another municipality in the Netherlands or abroad to be able to compare model outcomes and validate the scalability of the approach towards other geographic regions.
- The simulation model in this study investigates the system behavior of residential solar panel adoption based on the assumption PV systems are bought through a one-time investment using a loan. Other financing options could be investigated, such as the effect of leasing schemes.
- The case-study area in this research is a highly urban environment. It might be interesting to explore possible differences with rural areas. A hypothesis could be that in rural areas, the share of multi-household properties is lower, thus other adoption barriers have a more prominent role. Vasseur and Kemp (2015b) in their study on adoption and non-adoption in the Netherlands found that a majority of the group of adopters lives in a village, while the group of non-adopters lives in a city. Under non-adopters in rural areas, other adoption barriers and diffusion behavior might be visible.

10 Conclusion and recommendations

This final chapter will draw conclusions on the results presented in this study. First, in section 10.1 an overview of the main research findings will be given and the main research question is answered. The research contributions will be discussed in section 10.2. Finally, recommendations for policymakers will be given in section 10.3.

10.1 Overview of the main research findings

The purpose of this study was to gain quantitative insight into the dynamics of solar-panel diffusion and assess the impact of policies and external developments on the disparity of adoption. Through a Design Science Research approach, an artifact was designed that enables to achieve the research objective in two main steps. The analysis was performed for the municipality of Amsterdam. The local analysis allowed for incorporating detailed case-study data on the adoption patterns of different neighborhood groups.

The study started with a thorough analysis of the system at hand during the environment phase of the Design Science methodology. The current technological, political, social, and economic context for PV adoption in the Netherlands was examined. Next, in the knowledge base phase, the factors determining the potential for PV adoption were set out. During the operationalization, the outputs of the relevance and rigor cycle are conceptualized into an artifact design. The designed artifact is a research approach enabling an integrated analysis of the solar panel adoption landscape in a municipality, with two main purposes. First, it enables assessment of the equity of solar panel distribution amongst the municipality. Second, it aids in policy testing, scenario evaluation, and policy-making on the solar panel system within the municipality. In this research, the artifact has been developed while simultaneously testing and demonstrating it for the municipality of Amsterdam.

Part I of the artifact includes conducting a rooftop suitability assessment that maps the potential for residential solar energy generation by adopting a GIS-based approach. Next, a socioeconomic analysis is performed, which allows investigating of the correlation of socioeconomic factors with PV adoption and the disparity of adoption possibly leading towards a so-called "adoption gap". This statistical data analysis deploys ANOVA- and correlation analysis on empirical adoption data. The most significant socioeconomic determinants for adoption are then used in a clustering method to create groups of similar neighborhoods, which can be studied in part II of the artifact. Performing part I of the artifact results in a clear assessment of the adoption disparity, the used and the unused potential, and the factors that can aid in explaining this. The outcomes are used to assess socioeconomic adoption inequalities and energy justice implications.

Part II of the artifact deploys a system dynamics modeling approach to simulate the adoption of solar panels from a system perspective. The context of residential PV adoption was further conceptualized from a system perspective with a causal loop diagram and then quantified through mathematical equations and parameters. During the conceptualization and model formulation, the output of Part I of the artifact, such as the adoption rates and the neighborhood groups, is used. After testing the model, scenarios and policies analysis leads to understanding the system behavior and exploring the impact of policy measures on diffusion speed and diffusion disparity. This way, the model provides an understanding of the structural dynamics and behavior of solar panel diffusion amongst different groups of neighborhoods and the possibility to experiment with policy levers and external developments.

Combining both artifact parts results in a set of tools that can aid more structural assessment of adoption and adoption disparity, and gauging scenarios for policy-making purposes. Demonstrating the artifact on the municipality of Amsterdam resulted in a set of findings that were used to answer the main research question:

How could distributed solar panel adoption speed and disparity develop in the future and under different policy measures?

To answer this question, the developed artifact is demonstrated for the municipality of Amsterdam. First, the current state of PV adoption is described (artifact part I). From there, plausible future developments are evaluated (artifact part II). The answers to the sub-research questions are included in each of the chapters' conclusions.

The main findings from part I of the artifact:

- PV adoption is unevenly spread among neighborhoods. A smaller group of neighborhoods has high adoption rates, compared with a larger group of neighborhoods with lower adoption rates. Several neighborhood clusters with high adoption rates are detected. Thus, a high disparity in adoption is observed.
- Rooftop suitability is spread relatively equally amongst neighborhoods. When looking at the potential electricity yield per citizen, the potential is rather evenly distributed with the exception of several outliers that have an above-average potential electricity yield per citizen.
- The correlations and group differences examined in this study highlight areas where more attention may be needed and where barriers to solar adoption might exist. The results also show that there is a significant difference between PV adopters and non-adopters. The type of household property, income, type of ownership and household composition are observed to be the most significant socioeconomic factors when comparing the results of the two statistical studies. These factors are identified as possibly the most significant adoption barriers. The inequities in adoption perceived in the neighborhood analysis point the way toward specific, targeted policy mechanisms that can tackle, mitigate, or minimize possible injustices caused by adoption disparity.
  - When comparing neighborhoods with low and high adoption rates, it is observed that neighborhoods with low adoption rates significantly differ from neighborhoods with high adoption rates. Many statistically significant variables explained this difference, including citizen age, household composition, type of property, property ownership and income.
  - The correlation analysis revealed many statistically significant variables correlating with the level of PV adoption in a neighborhood. These factors include the percentage of low-income households, the percentage of children, the percentage of single-person households, the percentage of rental properties, and the percentage of multi-household properties.
  - Many of these studies are in line with These findings are in line with some of the findings by (Sommerfeld et al., 2017), (Balta-Ozkan et al., 2015), (Vasseur & Kemp, 2015b). Balta-Ozkan et al. (2015). Where Margolis et al. (2017) found the number of rooms and house age to be key influential variables, this study did not reveal the significance of these variables. Besides, Balta-Ozkan et al. (2015) found the number of households to be a significant variable, but this study had contrary results for this variable. The varying results between different studies highlight the local characteristics of PV adoption patterns and the care that should be taken when generalizing results to other regions.
- The results show that the adoption of solar panels in Amsterdam over the past years has not occurred equitably across socioeconomic groups. The disparity in adoption, both from a spatial and socioeconomic perspective, points towards demographic inequalities in solar panel adoption. These demographic adoption inequalities can result in distributive justice issues. Solar adoption has been driven strongly by government incentives (Si & Stephens, 2021). The incentives provided generally apply only to those who buy a PV system outright. The incentive programs, therefore, have ended up targeting only a selection of socioeconomic groups: middle- and high-income households, homeowners, and households with roof access. Households without solar panels cannot profit from the benefits of the scheme, and experience burdens by the socialization of program and utility costs. For some households, non-adoption is voluntary, for others, it can be due to financial inability, the lack of decision-making power over their roof (renters), the unsuitability of their roof, or the lack of access to a roof. This implicates unequal access to the benefits of incentive schemes, an important notion within the concept of distributive energy justice.
- Moving towards part II of the artifact design, a clustering algorithm was used to automatically divide neighborhoods into similar groups based on the percentage of rental properties, the percentage of multi-household residencies, and the percentage of low-income households. These are used to study the development of PV adoption under several policy levers and external drivers.

The main findings from part II of the artifact:

- An adoption gap is perceived that is expected to further widen in the future under all netting-scheme regulations. Under the current netting scheme, group 1 neighborhoods achieve an adoption percentage of 20%, whereas group 2 neighborhoods achieve an adoption percentage of 42%. Under the proposed netting scheme, group 2 neighborhoods achieve a marginal adoption rate of approximately 5%, and group 2 neighborhoods of approximately 25%. Given the adoption percentages in 2019 are 1% for group 1 and 13% for group 2, the model shows the adoption gap will widen over time.

- It can be concluded from the policy and scenario analyses that without adequate policy interventions, the average future PV diffusion will continue to grow only moderately. The simulation with differing netting-scheme policies demonstrates the considerate difference in adoption extent and speed under no netting scheme, the current, and the proposed netting scheme. Solar panel diffusion thus appears to be highly impacted by the netting scheme policy in place. The difference is caused by the diverging payback times of PV under the policy options. The lack of policies thus intensifies the financial barriers to adoption.
- A gap in adoption is observed when comparing the diffusion of PV in two neighborhood groups with low (group 1) and high (group 2) percentages of rental properties, low-income households, and multi-household properties. Without intervention, the adoption gap widens over time. Under the proposed netting scheme, neighborhoods in group 1 experience minimal adoption rates. The payback time for PV does not decrease significantly enough over time to stimulate higher PV adoption rates in this group. Several other studies conclude that general incentives - such as the netting scheme - are ineffective at increasing adoption equity (Brown et al., 2020; Vaishnav et al., 2017).
- The analysis of the leveling policies revealed several insights. First, all policies individually yield better results, regardless of the external scenarios. The "low-income netting scheme" and the "low-income subsidy of €1000" policies had the most promising individual results. Through these policy levers, adoption percentages in 30 years' time could be increased from approximately 6% in the base case to approximately 17% and 11,5% respectively (equal to 40% and 35% respectively of the suitable rooftops).
- The analyses of separate policies compared to combined policies reveal two insights. First, given that the individual policy levers do not succeed in closing the adoption gap, it is likely that a tailor-made combination of policies is most effective. A combination of a €1000 low-income subsidy, low-income netting scheme, and sustainability plan mandate can level the adoption percentage of group 1 to the adoption levels in group 2, reaching approximately 35% of the total number of households. This means the adoption gap is reduced to almost zero. The best two-policy combination is the low-income netting scheme combined with the low-income subsidy of €1000, or a combination of the low-income subsidy with the sustainability plan mandate, which enables approaching an adoption percentage of approximately 27%.
- Of the observed external drivers, geopolitical developments (representing the market electricity price) significantly impact the speed and extent of PV diffusion. High geopolitical unrest, which has in the past increased energy uncertainty and energy prices, increases the attractiveness of PV adoption and thus drives increased adoption rates. Inflation rates have a significant but much lower impact on adoption rates. These results suggest that energy prices are a stronger driver of PV adoption than PV installation costs.
- The exploration of policy options and their impact of PV diffusion is perceived to be most useful when comparing the relative performance (how different policy levers perform compared to one another) of the options at hand, instead of absolute performance (exact achieved adoption percentages).
- Though many studies assess the impact of net metering on adoption rates, few other studies combine policy impact and adoption equity or assess targeted policy levers. O'Shaughnessy et al. (2020a) investigated the impact of policies and business models on income equity in rooftop solar adoption and found that targeted incentives at low-and-middle incomes were effective in increasing adoption equity. The study also found positive results for PV leasing and low-income loans, of which the first was not included in this study and the second is already in place in the Netherlands at the time of writing.

Several main conclusions can be drawn from the study. First, a gap in adoption is observed: solar deployment in Amsterdam over the last years has not occurred equitably across socioeconomic groups. There is a significant difference between neighborhoods with high and low adoption when it comes to socioeconomic characteristics such as income, home ownership, and roof access. This points toward demographic inequalities in solar panel adoption. Accordingly, policy levers to stimulate PV adoption currently benefit a small portion of households. Solar adoption has been driven strongly by such government incentives (Si & Stephens, 2021). The incentive programs therefore have ended up targeting only a selection of socioeconomic groups: middle- and high-income households, homeowners and households with roof access. Households without solar panels cannot profit from the benefits of the scheme, and experience burdens by the socialization of program and utility costs. For some households, non-adoption is voluntary, for others, it can be due to financial inability, the lack of decision-making power over their roof (renters), the unsuitability of their roof or the lack of access to a roof. This implicates unequal access to the benefits of incentive schemes, an important notion within the concept of distributive energy justice.

Second, the current netting scheme is beneficial to adoption rates, but increases adoption rates mostly within several societal groups. The proposed netting scheme, planned to be introduced in 2025, will only modestly increase adoption rates compared to a lacking netting-scheme policy. Besides, without target policy interventions, the adoption gap between high and low-adoption neighborhoods will widen over time, thus increasing demographic adoption inequities and distributive justice issues. Additionally, the electricity costs for non-adopters will continue to be significantly higher than that of PV adopters, with a risk of socialized costs by governments, grid operators, and energy suppliers - though the latter is included in the model to a limited extent. The energy burden for non-adopters will significantly increase, and very low-income households reach an energy quota of 4-12% of their income. The leveling policies have been shown to reduce the adoption gap, where a combination of policies achieves the best results. The results emphasize that more policy attention is necessary, especially when the proposed netting scheme comes into place. Under-served and under-represented communities should be identified and acknowledged. Targeted policies are needed to close the adoption gap, where there is a need for a combination of all three leveling policies to narrow down the gap to a minimum.

Considering the different energy justice principles, this study mostly touches upon distributive justice implications. The analysis of socioeconomic neighborhood groups allowed for assessing the inequality of the distribution of adoption and thus the spread of benefits and burdens of energy policy amongst society - the main principle of distributive justice. Although not explicitly touched upon in this study, it is important to recognize the implications of other forms of energy justice. Procedural justice implications should be taken into account when further evaluating the policy levers presented in this study - the policies should be implemented granting equal chances at participation in the decision-making processes. Specifically, attention should be paid to including the under-served communities, e.g. the neighborhoods with low incomes, high shares of rental properties, and high shares of multi-household properties. Besides, to address citizens' perceptions of injustice, a multi-dimensional approach is required that addresses both socio-demographic inequalities through for example leveling policy levers (to improve distributional justice), integrating extended participation procedures (to improve procedural justice), and integrating recognition into energy policy (to improve recognition justice). The latter injustice is often overlooked but covers a central challenge to address citizens' more fundamental sense of misrecognition and build trust with citizens.

Although the outcomes of socioeconomic variables and their relation to adoption patterns differ within the literature, due to geographic differences, the overall adoption equity findings are in line with multiple studies that investigated adoption disparity and inequalities outside of the Netherlands (Lan et al., 2021; O'Shaughnessy et al., 2020a; Si & Stephens, 2021; Sovacool et al., 2022). Sovacool et al. (2022) for example clearly document demographic inequity and disparities in ownership in the UK and even state solar energy adoption can exacerbate these inequalities. Lukanov and Krieger (2019), who evaluated adoption equity in California, also conclude that there are clear distributive and equity impacts of PV support policies (e.g. net metering) and that benefits of PV adoption are largely accruing within less-advantaged communities. The authors identify economic burdens - such as housing burden and poverty rates - as significant barriers to solar adoption, which is in line with the significance of household income in this study. The authors however also indicate linguistic isolation and low education levels as important adoption barriers, which have not been tested or found significant in this study. It should be noted that the studies named above all follow different methodologies, and no other system dynamics approach was available for comparison.

Closing the adoption gap is an important step in tackling the justice implications that current adoption incentives oppose. However, tackling these justice implications requires a multifaceted approach, covering both local and national policy, the socialization of costs by governments, grid operators, and utilities, and adoption barriers such as income and roof access. This study aimed to gather insights on both the observed inequities and the policy levers at hand to achieve more equal adoption patterns, aiding in a justifiable road map towards renewable energy for all. The study resulted in a set of tools that, while not perfect yet, form an artifact that can be used to facilitate a more fine-grained insight into these justice issues and their possible routes for resolution.

The performed research steps have been evaluated using multiple evaluation methods including sensitivity analysis and direct structure tests. The used methods - GIS modeling, statistical data analysis, and system dynamics modeling - have been demonstrated to be appropriate methods within the artifact and to answer the main research question. The methods present several limitations that need to be taken into account when interpreting the results. Several important limitations follow. First, caution is needed when interpreting correlation results, as correlating factors do not imply causation. Second, the adoption diffusion process is simplified and probably does not include a perfect representation of adoption factors in real life. Third, several loops are simplified, such as the utility death spiral. These limitations could be addressed in further research, to increase the robustness and usability of the artifact design. Finally, further evaluation of the artifact as a method to assess adoption inequities and policy impacts is needed. A more extensive validation should be performed to assess the robustness and scalability of the approach and the validity of the policy outcomes. This can establish the approach as a well-grounded and universally applicable method to assessing adoption equity and evolution across the Netherlands and abroad.

10.2 Contributions of this research

The contributions of this research are two folded. On the one hand, the study generated new insights into the diffusion of solar panel technology in Amsterdam, contributing to societal relevance. On the other hand, the study developed an approach that adds to the existing literature base and that can be applied in other case studies. Both contributions will be discussed below.

10.2.1 Scientific contributions

This study made several scientific contributions. First of all, the study adds to the existing knowledge base by presenting a data-driven, integrated, and scalable approach for investigating solar panel adoption patterns and future developments. That, though it needs additional validation to establish it as a grounded approach, can serve as an inspiration for other studies. The approach uniquely combines multiple research methods - GIS-modelling, statistical data analysis, and System Dynamics - to create overarching insights into the behavior and dynamics of the system and the possible inequities it presents. Other studies found in the literature that investigate adoption behavior and equity most often deployed either one of the approaches - an assessment of socioeconomic factors and their relation to adoption rates (Darghouth et al., 2022; Lan et al., 2021; Lukanov & Krieger, 2019; Sovacool et al., 2017; Vasseur & Kemp, 2015a) or an assessment of adoption evolution and policy impact (Hsu, 2012; Meehan, 2015; O'Shaughnessy, 2021; Palm, 2017) - where this study uniquely combined both. Many existing system dynamics studies on solar panel adoption focus on the impact of the netting scheme, or the utility-death spiral effect (Castaneda, Jimenez, et al., 2017; Grace, 2018; Meehan, 2015), where this study adopted a focus on adoption disparity and leveling policies specifically.

Second, this study added to the existing knowledge base by studying solar panel diffusion amongst sub-populations. Previous solar panel diffusion studies examined case-study populations as a whole (Castaneda, Jimenez, et al., 2017; Grace, 2018; Meehan, 2015), and did not allow for studying sub-groups. Therefore, general adoption curves were used to estimate the effect of policies such as the netting scheme, while in reality, different consumers react differently to such changes in the political landscape and external drivers. Besides, few previous solar panel diffusion studies assessed the impact of targeted policies instead of general policies, or the impact of numerous external developments. Most in line with this study, O'Shaughnessy (2021) assessed the impact of policies on income equity in rooftop solar adoption, including several leveling policies. Similarly, they find that financial leveling policies increased adoption equity in the past. This study added to the existing knowledge by investigating additional measures - such as the low-income netting scheme - and by simulating adoption disparity into the future under different external scenarios.

Finally, the developed method allowed for studying local adoption characteristics, which is deemed necessary for a proper analysis of adoption behavior, while also incorporating both local and national policy levers. Up to date, no approach existed that used local insights into adoption patterns to study the effects of both general and leveling policies at the local case-study level.

10.2.2 Societal relevance

The research aimed to fill an existing gap of knowledge on solar panel adoption in Amsterdam. The research touched upon several lacking pieces of knowledge. First of all, there was a lack of knowledge on the current adoption patterns in Amsterdam, specifically how adoption is distributed geographically and socioeconomically, and what socioeconomic factors are linked to explain these observed adoption patterns. In the literature base, several studies on solar panel adoption and socioeconomic factors exist, however, none covered regions within the Netherlands, and none covered such a broad range of socioeconomic factors all at once. Besides, no previous study combined adoption patterns and socioeconomic data with the potential for solar energy generation, to incorporate the potential for adoption in the analysis. Incorporating this factor allowed for understanding whether perceived adoption patterns could also be caused by unequally distributed potential, where this study showed that potential is rather equally distributed geographically, while adoption is not.

Where Lan et al. (2021) used a machine learning approach to understand the regional disparity of solar panel adoption in Australia by investigating numerous socioeconomic factors, this study adopted a statistical data analysis approach. Nonetheless the different adopted methods and geographic focus, the results of the studies corroborate in the sense that both identified household income as an important determinant for adoption rates. Contrary, Lan et al. (2021), who investigated 18 socioeconomic indicators compared to more than 80 in this study, emphasize the role of population density, which is less significant in this study given the high average density of the whole study area. Other studies investigating socioeconomic factors had several similar and several contradicting results, such as similar findings in the importance of home-ownership, age, income, and property-sharing (Sommerfeld et al., 2017), (Balta-Ozkan et al., 2015), (Vasseur & Kemp, 2015b). Balta-Ozkan et al. (2015), but contradicting findings in the importance of the number of rooms, house age, and number of households (Balta-Ozkan et al., 2015; Margolis et al., 2017). These differences highlight the local characteristics of PV adoption patterns and that the effects of socioeconomic characteristics on adoption should be understood regionally, where this study added to the knowledge base by generating additional insights into the adoption characteristics of the Netherlands specifically.

Second, insights into the possible future developments of solar panel adoption and adoption disparity lacked. Specifically, what the evolution of solar panel adoption might look like under different policy levers and external drivers. Given the proposed new netting-scheme policy, planning to go into action in 2025, insights into the impact of this new policy on the diffusion and disparity of solar panel adoption can aid in assessing what the impact of this political change is on reaching solar climate goals. Besides, several leveling policies are studied, that aim to narrow down the adoption disparity amongst socioeconomic groups. Currently and to the best knowledge of the author, no studies exist that examine the impact of such leveling policies.

Finally, the study contributed in the fact that it made some observations of the inequalities and justice implications that exist within the residential solar panel adoption landscape. Whilst this study did not thoroughly analyze all possible forms of injustice, our analysis nevertheless clearly demonstrates some forms of distributive injustices and points to measures that can be taken within policy and strategy for PV to improve the justness of future deployments. The study highlights several adoption barriers and several geographic areas and socioeconomic sub-populations that are under-served in terms of solar panel deployment and may need more targeted policy measures to fully utilize the potential for solar energy, and to overcome unequal distribution of the benefits and burdens of solar energy policy. The results of this study provide a reference for governmental bodies to consider the regional difference and make more sophisticated policies and incentives.

10.2.3 Scalability of the designed artifact

For this study, the designed artifact was used to provide local insights into the system behavior of solar panel adoption. Results and conclusions drawn from this specific case study are therefore not directly generalizable to other locations. The designed artifact is however an integrated, scalable approach that can be applied for analysis in other municipalities or regions. The designed artifact hereby serves as an approach to tackle similar study objectives or problem statements. The artifact is meant to set out a strategy for an inclusive approach to assessing adoption, adoption disparity, and plausible future developments in a case study area, thereby providing guidelines on possible policy interventions. Perhaps, the methodologies named in this study can be altered to appropriately suit a local case study.

For replication of the artifact as described in this study, local case-study data is required. For part I of the artifact, this includes adoption data, socioeconomic neighborhood data, building data, solar radiation data, and LiDAR data. For all municipalities in the Netherlands, this data can be freely obtained. For part II of the artifact, several additional data are needed for model parameters. These include electricity prices, feed-in-tariffs, fixed energy costs, average PV prices, average PV capacity, and the average system performance ratio, all of which can easily be adjusted in the SD model.

The artifact is most directly usable for municipalities in the Netherlands, given that the System Dynamics model is constructed based on the Dutch electricity system (i.e. the composition of energy bills) and the Dutch policy landscape. The model can however be altered to fit other policy or electricity contexts. When considering replication of the artifact, it is stressed that the limitations of the methodologies discussed in Section 9 are carefully considered.

10.3 Recommendations for policy-makers

The identified adoption inequities and the expected widening of the adoption gap over time resulting from this study emphasize the need for appropriate attention by policymakers toward equal PV adoption. Besides the prevalent justice implications, the under-utilization of rooftop space in under-served neighborhoods could reduce or at least decelerate the realization of the benefits of rooftop PVs as a clean energy resource by reducing PV market potential. Thus, complicating the achievement of local renewable energy goals. The study yields several recommendations for policymakers:

- The first recommendation is to identify and acknowledge under-served and under-represented communities and the presence of distributive justice implications. This study has aimed to contribute to this, however, it is the policymakers that can act upon it. Addressing the perceived disparities and inequities within a municipality is an important step in diminishing justice implications, and benefits both socioeconomic equalities and renewable energy generation. It is advised to further investigate the perceptions of citizens regarding the forms of injustice described in this paper, and other possible energy justice conceptions. A study that can serve as inspiration for such an assessment of citizen perception is that of Kieskamp (2023), who explored this in the region of Tilburg, the Netherlands. Besides, addressing these inequalities can have a self-sustaining effect. By shifting adoption into under-served neighborhoods, the presented policy levers could catalyze peer effects in those regions, which may generate self-sustaining increases in adoption in those areas (Balta-Ozkan et al., 2021).
- Adopt a targeted, tailor-made approach. PV adoption target groups can be complex. Numerous adoption barriers, socioeconomic variables psychographic variables can contribute to adoption behavior. Different adoption barriers need different solutions. It is advised to adopt a tailored approach for different target groups, focusing on three large target groups that have under-served markets: low-income households, rental-property households, and shared-property households. Suggestions for approaches are included below.
- The generated insights into socioeconomic characteristics and their relation to adoption patterns highlight the areas where more attention is needed and where barriers to solar adoption might exist. At a local, or municipal level, these insights can be used for targeted policy measures or campaigns. It is advised to further investigate the (solutions to) adoption barriers in under-served neighborhoods through collaboration with citizens, landlords, and housing corporations. Such explorations can reveal possible underlying mechanisms or barriers or structural societal inequities that go beyond adoption inequity, that could be tackled to improve justice on a much broader spectrum.
- Explore additional measures to go hand-in-hand with the possible policy levers, to accelerate and reinforce results. It is advised to adopt a multi-dimensional approach, consisting of not only policy levers but also including local initiatives and campaigns to actively mobilize stakeholders such as households, OA's, landlords, and housing corporations. Other studies show that authority support and coordination can benefit PV adoption and aid in mobilizing households (2018).
- The low adoption rates in neighborhoods with low property ownership and high shared property suggest it is worthwhile to further explore closer collaboration with owner associations, landlords, and housing corporations. The socioeconomic analysis in part I of the artifact design made clear that renters, non-homeowners, and property-sharers are more excluded from solar PV deployment due to housing tenure and ownership type. A sustainability-plan mandate, as explored in this study, could be further investigated to address this target group.
- The low adoption rates in neighborhoods with a high share of low-income households suggest exploring other financing options. The financial incentive policies in this study have shown to increase adoption rates, but other options are possible. It is advised to explore the deployment and promotion of a leasing-contract or shared-ownership-business models (2022) for PV as an alternative for low-income households and owners of rental properties. Other than the (local) loan options currently in place, a leasing option removes the high upfront investment costs of a solar panel system purchase. To utilize the positive effects lease constructions could possibly bring, these constructions should be structured such that market players can profit but to the extent that the leasing option still benefits (low-income) households enough to be able to make use of the option.

On the other hand, the study provided insights in the system behavior of PV adoption and the effectiveness of policy levers. Broadly, our results suggest that policymakers can increase adoption equity through measures that address specific barriers to adoption and shift PV deployment patterns into previously under-served areas. Local pilot studies can be used to increase practical knowledge on the suitability of these policy options. The results that can be achieved through the deployment of policy levers can be accelerated through local engagement programs and community initiatives.

Another suggestion at the local scale is to investigate options to make use of suitable small-surface roof space. When aiming to utilize most of the potential at rooftops in Amsterdam, it might be useful to investigate ways in which municipalities can place small PV installations on suitable rooftop areas, that would not be financially attractive enough for consumers to invest in themselves. Given that the final decision for PV purchasing is mostly determined by financial motives such as payback time, these smaller suitable roof areas might remain unused.

References

ACM. (n.d.). The Netherlands Authority for Consumers and Markets. https://www.acm.nl/en/about-acm/our-organization/the-netherlands-authority-for-consumers-and-markets

ACM. (2017). *Besluit maximumtarieven* (tech. rep.).

ACM. (2020). *Openbare versie benchmarkstudie consumenten energiemarkt 2020* (tech. rep.).

ACM. (2023). ACM steunt voorstel voor afbouw salderingsregeling. https://www.acm.nl/nl/publicaties/acm-steunt-voorstel-voor-afbouw-salderingsregeling

Agnew, S., Smith, C., & Dargusch, P. (2018). Causal loop modelling of residential solar and battery adoption dynamics: A case study of Queensland, Australia. *Journal of Cleaner Production*, *172*, 2363–2373. https://doi.org/10.1016/J.JCLEPRO.2017.11.174

ArcGIS Documentation. (2021a). How solar radiation is calculated. https://desktop.arcgis.com/en/arcmap/latest/tools/spatial-analyst-toolbox/how-solar-radiation-is-calculated.htm

ArcGIS Documentation. (2021b). Modeling solar radiation. https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-analyst/modeling-solar-radiation.htm

Arvai, K. (2020). K-Means Clustering in Python: A Practical Guide. https://realpython.com/k-means-clustering-python/

Assouline, D., Mohajeri, N., & Scartezzini, J. (2017). Quantifying rooftop photovoltaic solar energy potential: A machine learning approach. *Solar Energy*, *141*, 278–296. https://doi.org/10.1016/j.solener.2016.11.045

Assouline, D., Mohajeri, N., & Scartezzini, J. L. (2018). Estimation of Large-Scale Solar Rooftop PV Potential for Smart Grid Integration: A Methodological Review. *Studies in Systems, Decision and Control*, 173–219. https://doi.org/10.1007/978-3-319-74412-4{_}11

Bach, L., Hopkins, D., & Stephenson, J. (2020). Solar electricity cultures: Household adoption dynamics and energy policy in Switzerland. *Energy Research & Social Science*, *63*, 101395. https://doi.org/10.1016/J.ERSS.2019.101395

Balta-Ozkan, N., Yildirim, J., & Connor, P. M. (2015). Regional distribution of photovoltaic deployment in the UK and its determinants: A spatial econometric approach. *Energy Economics*, *51*, 417–429. https://doi.org/10.1016/J.ENECO.2015.08.003

Balta-Ozkan, N., Yildirim, J., Connor, P. M., Truckell, I., & Hart, P. (2021). Energy transition at local level: Analyzing the role of peer effects and socio-economic factors on UK solar photovoltaic deployment. *Energy Policy*, *148*, 112004. https://doi.org/10.1016/J.ENPOL.2020.112004

Bass, F. M. (1969). A New Product Growth for Model Consumer Durables. *https://doi.org/10.1287/mnsc.15.5.215*, *15*(5), 215–227. https://doi.org/10.1287/MNSC.15.5.215

Bellini, E. (2022). Eneco to slash net-metering tariffs, Dutch consumer association asks for minimum threshold. https://www.pv-magazine.com/2022/08/30/eneco-to-slash-net-metering-tariffs-consumer-association-asks-for-minimum-threshold/

Best, R., Marrone, M., & Linnenluecke, M. (2023). Meta-analysis of the role of equity dimensions in household solar panel adoption. *Ecological Economics*, *206*, 107754. https://doi.org/10.1016/J.ECOLECON.2023.107754

Boele, G. (2023). Less room for offsetting for small-scale solar generation. https://www.abnamro.com/research/en/our-research/less-room-for-offsetting-for-small-scale-solar-generation

Bouaguel, W., & Alsulimani, T. (2018). The Potential of Solar Energy in Saudi Arabia: The Residential Sector. *J3ea*, *14*(18). https://doi.org/10.3390/SU141811356

Boven, L. (2018). Work to do: solar panels mandatory on all new EU homes from 2029 onwards. https://innovationorigins.com/en/work-to-do-solar-panels-mandatory-on-all-new-eu-homes-from-2029-onwards/

Boxwell, M. (2012). *Solar Electricity Handbook A simple, practical guide to solar energy: how to design and install photovoltaic solar electric systems 2012 Edition*. Greenstream Publishing. www.GreenstreamPublishing.com

Breukelman, F. (2021). Hoge energieprijzen maken zonnepanelen nóg aantrekkelijker. https://www.zonneplan.nl/blog/hoge-energieprijzen-maken-zonnepanelen-nog-aantrekkelijker

Briels, S. (2022). Dashboard Zon op dak: hoeveel zonnepanelen kunnen er nog bij? https://readar.com/dashboard-zon-op-dak/

Brown, M. A., Soni, A., Lapsa, M. V., & Southworth, K. (2020). Low-Income Energy Affordability: Conclusions from a Literature Review. www.osti.gov

Castaneda, M., Franco, C. J., & Dyner, I. (2017). Evaluating the effect of technology transformation on the electricity utility industry. *Renewable and Sustainable Energy Reviews*, *80*, 341–351. https://doi.org/10.1016/J.RSER.2017.05.179

Castaneda, M., Jimenez, M., Zapata, S., Franco, C. J., & Dyner, I. (2017). Myths and facts of the utility death spiral. *Energy Policy*, *110*, 105–116. https://doi.org/10.1016/J.ENPOL.2017.07.063

CBS. (2020). StatLine - Zonnestroom; vermogen zonnepanelen woningen, wijken en buurten, 2020. https://opendata.cbs.nl/#/CBS/nl/dataset/85447NED/table?ts=1677576170811

CBS. (2021). Armoede en sociale uitsluiting. https://longreads.cbs.nl/armoede-en-sociale-uitsluiting-2021/

CBS. (2022a). Huishoudens; samenstelling, grootte, regio, 1 januari.

CBS. (2022b). Inwoners per gemeente. https://www.cbs.nl/nl-nl/visualisaties/dashboard-bevolking/regionaal/inwoners

Chappin, É. (2022). TB141E - Introductie in Energie- en Industriesystemen. https://eduweb.eeni.tbm.tudelft.nl/TB141E/?elektriciteit-netwerken

Christman, B., & Russell, H. (2016). Readjusting the political thermostat: fuel poverty and human rights in the UK. *Journal of Human Rights in the Commonwealth*, *2*(2). https://doi.org/10.14296/JHRC.V2I2.2273

Costello, K. W., & Hemphill, R. C. (2014). Electric Utilities' 'Death Spiral': Hyperbole or Reality? *The Electricity Journal*, *27*(10), 7–26. https://doi.org/10.1016/J.TEJ.2014.09.011

CPB. (2022a). Raming aantal personen/ huishoudens onder de lage-inkomensgrens in 2021 en 2022.

CPB. (2022b). *Scenario's energieprijzen CPB* (tech. rep.).

Dahal, A., Chhetri, B., Sharma, K. R., & Neupane, M. (2021). Assessment of Solar Photovoltaic Potential of Building Rooftops Using Photogrammetry and GIS. *The Geographic Base*, *8*(01), 31–46. https://doi.org/10.3126/TGB.V8I01.43467

Darghouth, N. R., O'Shaughnessy, E., Forrester, S., & Barbose, G. (2022). Characterizing local rooftop solar adoption inequity in the US. *Environmental Research Letters*, *17*(3), 034028. https://doi.org/10.1088/1748-9326/ac4fdc

de Boer, S., & Stet, C. (2022). The Basics of Electricity Price Formation. https://www.rabobank.com/knowledge/d011318792-the-basics-of-electricity-price-formation

Deloitte. (2018). *State of the State-onderzoek: Zonnepanelen kunnen de helft van de Nederlandse elektriciteitsbehoefte opwekken* (tech. rep.). https://www2.deloitte.com/nl/nl/pages/data-analytics/articles/zonnepanelen.html

de Winter, J. C., Gosling, S. D., & Potter, J. (2016). Comparing the Pearson and Spearman correlation coefficients across distributions and sample sizes: A tutorial using simulations and empirical data. *Psychological Methods*, *21*(3), 273. https://doi.org/10.1037/MET0000079

Dharshing, S. (2017). Household dynamics of technology adoption: A spatial econometric analysis of residential solar photovoltaic (PV) systems in Germany. *Energy Research & Social Science*, *23*, 113–124. https://doi.org/10.1016/J.ERSS.2016.10.012

DNB. (2022). *Economic Developments and Outlook* (tech. rep.). https://www.dnb.nl/en/publications/publications-dnb/edo/economic-developments-and-outlook-june-2022/

DNE Research. (2022). *Dutch Solar Trend Report* (tech. rep.). https://www.solarsolutions.nl/trendrapport/

Donat, J. (2023). Geen afbouw salderingsregeling zonder goed alternatief. https://www.consumentenbond.nl/zonnepanelen/geen-afbouw-salderingsregeling-zonder-goed-alternatief

Dutch New Energy. (2021). Dutch Solar Trend Report. https://www.dutchnewenergy.com/trend-reports/

Enserink, B., Bots, P., van Daalen, E., Hermans, L., Kortmann, R., Koppenjan, J., Kwakkel, J., Ruijgh-van der Ploeg, T., Slinger, J., & Thissen, W. (2022). *Policy Analysis of Multi-Actor Systems*. TU Delft Open. https://doi.org/10.5074/T.2022.004

EPA. (2021). Green Power Equivalency Calculator - Calculations and References. https://www.epa.gov/green-power-markets/green-power-equivalency-calculator-calculations-and-references

ESRI. (n.d.). How solar radiation is calculated. https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-analyst/how-solar-radiation-is-calculated.htm

European Commission. (n.d.). Nearly zero-energy buildings. https://energy.ec.europa.eu/topics/energy-efficiency/energy-efficient-buildings/nearly-zero-energy-buildings_en

Fakhraian, E., Alier, M., Dalmau, F. V., Nameni, A., & Guerrero, J. C. (2021). The Urban Rooftop Photovoltaic Potential Determination. *Sustainability 2021, Vol. 13, Page 7447*, *13*(13), 7447. https://doi.org/10.3390/SU13137447

Fath, K., Stengel, J., Sprenger, W., Wilson, H. R., Schultmann, F., & Kuhn, T. E. (2015). A method for predicting the economic potential of (building-integrated) photovoltaics in urban areas based on hourly Radiance simulations. *Solar Energy*, *116*, 357–370. https://doi.org/10.1016/J.SOLENER.2015.03.023

Feenstra, M., Middlemiss, L., Hesselman, M., Straver, K., & Tirado Herrero, S. (2021). Humanising the Energy Transition: Towards a National Policy on Energy Poverty in the Netherlands. *Frontiers in Sustainable Cities*, *3*. https://doi.org/10.3389/frsc.2021.645624

Felder, F. A., & Athawale, R. (2014). The Life and Death of the Utility Death Spiral. *The Electricity Journal*, *27*(6), 9–16. https://doi.org/10.1016/J.TEJ.2014.06.008
Feldman, K. (2018). F-value (ANOVA). https://www.isixsigma.com/dictionary/f-value-anova/
Forrester, J. W., & Senge, P. M. (1980). Tests for building confidence in system dynamics models. *TIMS Studies in the Management Sciences*, *14*, 2019–2228.
Forthofer, R. N., Lee, E. S., & Hernandez, M. (2007). Linear Regression. *Biostatistics*, 349–386. https://doi.org/10.1016/B978-0-12-369492-8.50018-2
Fortson, C. (2021). Roof requirements for solar panel installation. https://securedroofingandrestoration.com/solar-panel-roof-requirements/
Fortune Business Insights. (2022). *Solar Photovoltaic Market Share, Growth & Trends, 2028* (tech. rep.). https://www.fortunebusinessinsights.com/industry-reports/solar-pv-market-100263
Fouad, M. M., Shihata, L. A., & Morgan, E. S. I. (2017). An integrated review of factors influencing the perfomance of photovoltaic panels. *Renewable and Sustainable Energy Reviews*, *80*, 1499–1511. https://doi.org/10.1016/J.RSER.2017.05.141
Fu, P., & Rich, P. M. (2000). A geometric solar radiation model and its applications in agriculture and forestry A GEOMETRIC SOLAR RADIATION MODEL AND ITS APPLICATIONS IN AGRICULTURE AND FORESTRY*, 357–364. http://www.gemlab.ukans.edu,
Gallucci, M. (2019). Energy Equity: Bringing Solar Power to Low-Income Communities. https://e360.yale.edu/features/energy-equity-bringing-solar-power-to-low-income-communities
Gemeente Amsterdam. (2018). Inzicht in VvE's. https://onderzoek.amsterdam.nl/artikel/project-inzicht-in-vve
Gemeente Amsterdam. (2021). Zonnepanelen - toename van aantal en vermogen. https://maps.amsterdam.nl/zonnepanelen/?LANG=nl
Gemeente Amsterdam. (2022a). Amsterdam groeit weer | Website Onderzoek en Statistiek. https://onderzoek.amsterdam.nl/interactief/dataverhaal-bevolkingsprognose
Gemeente Amsterdam. (2022b). Armoedemonitor 2021: Kerncijfers Armoede in Amsterdam. https://onderzoek.amsterdam.nl/publicatie/armoedemonitor-2022
Gemeente Amsterdam. (2022c). Energiearmoede in Amsterdam 2021. https://onderzoek.amsterdam.nl/publicatie/energiearmoede-in-amsterdam-2021
Gemeente Amsterdam. (2022d). Policy: Climate neutrality. https://www.amsterdam.nl/en/policy/sustainability/policy-climate-neutrality/
Girardeau, H., & Pattanayak, S. K. (2018). Environment for Development Centers Household Solar Adoption in Low-and Middle-Income Countries: A Systematic Review. www.efdinitiative.orgorcontactinfo@efdinitiative.org.
Goodchild, M. (2009). Geographic information systems and science: today and tomorrow. *15*(1), 3–9. https://doi.org/10.1080/19475680903250715
Grace, W. (2018). Exploring the Death Spiral: A System Dynamics Model of the Electricity Network in Western Australia, 157–170. https://doi.org/10.1007/978-3-319-69844-1{_}15
Grbosz-Krawczyk, M., Zakrzewska-Bielawska, A., Glinka, B., & Glińska-Neweś, A. (2021). Why Do Consumers Choose Photovoltaic Panels? Identification of the Factors Influencing Consumers' Choice Behavior regarding Photovoltaic Panel Installations. *Energies 2021, Vol. 14, Page 2674*, *14*(9), 2674. https://doi.org/10.3390/EN14092674
Green, N. (2012). Correlation is not causation. https://www.theguardian.com/science/blog/2012/jan/06/correlation-causation
Greenbaum, J., & Kyng, M. (1991). *Design at Work*. Taylor & Francis.
Han, J. Y., Chen, Y. C., & Li, S. Y. (2022). Utilising high-fidelity 3D building model for analysing the rooftop solar photovoltaic potential in urban areas. *Solar Energy*, *235*, 187–199. https://doi.org/10.1016/J.SOLENER.2022.02.041
Hayes, A. (2021). What Is the Bonferroni Test (Correction) and How Is It Used? https://www.investopedia.com/terms/b/bonferroni-test.asp
Hevner, A. R. (2007). A Three Cycle View of Design Science Research. *Scandinavian Journal of Information Systems*, *19*(2), 4. http://community.mis.temple.edu/seminars/files/2009/10/Hevner-SJIS.pdf
Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. *MIS Quarterly: Management Information Systems*, *28*(1), 75–105. https://doi.org/10.2307/25148625
Hidayatno, A., Setiawan, A. D., Wikananda Supartha, I. M., Moeis, A. O., Rahman, I., & Widiono, E. (2020). Investigating policies on improving household rooftop photovoltaics adoption in Indonesia. *Renewable Energy*, *156*, 731–742. https://doi.org/10.1016/J.RENENE.2020.04.106

Hong, T., Lee, M., Koo, C., Jeong, K., & Kim, J. (2017). Development of a method for estimating the rooftop solar photovoltaic (PV) potential by analyzing the available rooftop area using Hillshade analysis. *Applied Energy*, *194*, 320–332. https://doi.org/10.1016/j.apenergy.2016.07.001

Hoogervorst, N. (2020). *Kosten van klimaatneutrale elektriciteit in 2030. Operationalisering voor de Startanalyse 2020* (tech. rep.).

Hsu, C. W. (2012). Using a system dynamics model to assess the effects of capital subsidies and feed-in tariffs on solar PV installations. *Applied Energy*, *100*, 205–217. https://doi.org/10.1016/J.APENERGY.2012.02.039

Intersolar Europe. (2022). European Photovoltaics Market Experiences Robust Growth, Despite the Coronavirus Pandemic. https://www.intersolar.de/market-trends/growth-of-european-photovoltaics-market

Isabella, O., & Verkou, M. (2020). PV Advent Calendar. https://www.ams-institute.org/urban-challenges/urban-energy/solar-panel-potential-amsterdam-roof-tops-considering-local-grid-infrastructure/

Jenkins, K., McCauley, D., Heffron, R., Stephan, H., & Rehner, R. (2016). Energy justice: A conceptual review. *Energy Research & Social Science*, *11*, 174–182. https://doi.org/10.1016/J.ERSS.2015.10.004

Johannesson, P., & Perjons, E. (2014). *An Introduction to Design Science*. Springer.

Keady, W., Panikkar, B., Nelson, I. L., & Zia, A. (2021). Energy justice gaps in renewable energy transition policy initiatives in Vermont. *Energy Policy*, *159*, 112608. https://doi.org/10.1016/j.enpol.2021.112608

Kelly, R. A., Jakeman, A. J., Barreteau, O., Borsuk, M. E., ElSawah, S., Hamilton, S. H., Henriksen, H. J., Kuikka, S., Maier, H. R., Rizzoli, A. E., van Delden, H., & Voinov, A. A. (2013). Selecting among five common modelling approaches for integrated environmental assessment and management. *Environmental Modelling & Software*, *47*, 159–181. https://doi.org/10.1016/J.ENVSOFT.2013.05.005

Kieskamp, I. (2023). *The inclusion of energy vulnerable citizens in the Dutch energy transition: A comparative analysis between perspectives on energy justice in policy and of energy vulnerable citizens in Tilburg, the Netherlands* (Doctoral dissertation). Radboud University. Groningen. https://theses.ubn.ru.nl/handle/123456789/14459

Koch, H., Lechner, S., Erdmann, S., & Hofmann, M. (2022). Assessing the Potential of Rooftop Photovoltaics by Processing High-Resolution Irradiation Data, as Applied to Giessen, Germany. *Energies*, *15*(19). https://doi.org/10.3390/EN15196991

Koelemeijer, R., & Bart, S. (2021). *Nationale kosten van maatregelen gericht op het realiseren van doelstellingen uit het energieakkoord 2013* (tech. rep.). PBL. Den Haag.

Kwakkel, J. H. (2018). Open exploration — Exploratory Modeling Workbench. https://emaworkbench.readthedocs.io/en/latest/indepth_tutorial/open-exploration.html

Kwakkel, J. H. (2017). The Exploratory Modeling Workbench: An open source toolkit for exploratory modeling, scenario discovery, and (multi-objective) robust decision making. *Environmental Modelling & Software*, *96*, 239–250. https://doi.org/10.1016/J.ENVSOFT.2017.06.054

Lan, H., Gou, Z., & Cheng, B. (2020). Regional difference of residential solar panel diffusion in Queensland, Australia. *https://doi.org/10.1080/15567249.2020.1736214*, *15*(1), 13–25. https://doi.org/10.1080/15567249.2020.1736214

Lan, H., Gou, Z., & Lu, Y. (2021). Machine learning approach to understand regional disparity of residential solar adoption in Australia. *Renewable and Sustainable Energy Reviews*, *136*, 110458. https://doi.org/10.1016/J.RSER.2020.110458

Liander. (n.d.). Voorkom zelf terugleverproblemen met zonnepanelen. https://www.liander.nl/consument/energie-opwekken-en-terugleveren/spanningsproblemen/voorkomen

Lukanov, B. R., & Krieger, E. M. (2019). Distributed solar and environmental justice: Exploring the demographic and socio-economic trends of residential PV adoption in California. *Energy Policy*, *134*, 110935. https://doi.org/10.1016/J.ENPOL.2019.110935

Mahajan, V., Muller, E., & Bass, F. M. (1993). New-product diffusion models. *Handbooks in Operations Research and Management Science*, *5*(100), 349–408. https://doi.org/10.1016/S0927-0507(05)80031-3

March, S. T., & Smith, G. F. (1995). Design and natural science research on information technology. *Decision Support Systems*, *15*(4), 251–266. https://doi.org/10.1016/0167-9236(94)00041-2

Marešová, E. (2014). *LIDAR based estimation of roof-top photovoltaic potential of Wageningen Case of Wageningen Municipality* (Doctoral dissertation). Wageningen University. Wageningen. https://edepot.wur.nl/309907

Margolis, R., Gagnon, P., Melius, J., Phillips, C., & Elmore, R. (2017). Using GIS-based methods and lidar data to estimate rooftop solar technical potential in US cities. *Environmental Research Letters*, *12*(7), 74013. https://doi.org/10.1088/1748-9326/AA7225

Maximillian, S. (2018). *Residential PV Adoption: Exploration on Communication Channels' Influence through Consumers' Psychological Decision Making* (Doctoral dissertation). Delft University of Technology. Delft.

Meehan, C. (2015). *Residential Rooftop Solar and the Utilities Death Spiral: A system dynamics analysis of the potential effects of rooftop solar diffusion on utilities' electricity rates and CO2 emissions* (Doctoral dissertation). Universitetet i Bergen and Universidade Nova de Lisboa, Radboud Universiteit Nijmegen. Nijmegen.

Melius, J., Margolis, R., & Ong, S. (2013). Estimating Rooftop Suitability for PV: A Review of Methods, Patents, and Validation Techniques. (NREL/TP-6A20-60593). https://doi.org/10.2172/1117057

Meral, M. E., & Diner, F. (2011). A review of the factors affecting operation and efficiency of photovoltaic based electricity generation systems. *Renewable and Sustainable Energy Reviews*, *15*(5), 2176–2184. https://doi.org/10.1016/J.RSER.2011.01.010

Milieucentraal. (n.d.). Hoe werken zonnepanelen? https://www.milieucentraal.nl/energie-besparen/zonnepanelen/hoe-werken-zonnepanelen/

Milieucentraal. (2022). Prijs en opbrengst zonnepanelen. https://www.milieucentraal.nl/energie-besparen/zonnepanelen/kosten-en-opbrengst-zonnepanelen/

Ministerie van Algemene Zaken. (2022). Klimaatakkoord. https://www.rijksoverheid.nl/documenten/rapporten/2019/06/28/klimaatakkoord

Ministerie van Economische Zaken Landbouw en Innovatie. (2020). Climate policy. https://www.government.nl/topics/climate-change/climate-policy

Ministry of Economic Affairs & Policy, C. (2023). Price cap for gas, electricity and district heating. https://www.government.nl/topics/energy-crisis/cabinet-plans-price-cap-for-gas-and-electricity

Ministry of General Affairs. (2023). Plan kabinet: afbouw salderingsregeling zonnepanelen. https://www.rijksoverheid.nl/onderwerpen/energie-thuis/plan-kabinet-afbouw-salderingsregeling-zonnepanelen

Molnár, G., Ürge-Vorsatz, D., & Chatterjee, S. (2022). Estimating the global technical potential of building-integrated solar energy production using a high-resolution geospatial model. *Journal of Cleaner Production*, *375*, 134133. https://doi.org/10.1016/J.JCLEPRO.2022.134133

Morcillo, J., Castaneda, M., Jímenez, M., Zapata, S., Dyner, I., & Aristizabal, A. J. (2022). Assessing the speed, extent, and impact of the diffusion of solar PV. *Energy Reports*, *8*, 269–281. https://doi.org/10.1016/J.EGYR.2022.06.099

Mulder, P., Batenburg, A., & Dalla Longa, F. (2023). *Energiearmoede in Nederland 2022: een actuele inschatting op nationaal en lokaal niveau* (tech. rep.). Amsterdam, TNO. https://repository.tno.nl/islandora/object/uuid%3A6ba9df79-a65e-4f34-970b-ebffdc8c0853

Nationaal Warmtefonds. (2022). Energiebespaarlening voor particulieren - Warmtefonds. https://www.warmtefonds.nl/particulieren?gclid=CjwKCAjwq-WgBhBMEiwAzKSH6LAYfNaqatOKVZLObthJRnrdqorAqLxT_qtvlriOPGoLElA8H9CLjRoCQUcQAvD_BwE

Netbeheer Nederland. (2023). In 2022 historische groei zonnepanelen op woningdaken. https://www.netbeheernederland.nl/nieuws/in-2022-historische-groei-zonnepanelen-op-woningdaken--1602

Nicoletti, L. (2018). *Roof Solar Potential at UBC: Assessing Suitability of Campus' Building Roofs for Solar Energy Capture* (tech. rep. 10.13140/RG.2.2.27123.04647). University of British Columbia - Vancouver. University of British Columbia - Vancouver. https://www.researchgate.net/publication/349574430_Roof_Solar_Potential_at_UBC_Assessing_Suitability_of_Campus%27_Building_Roofs_for_Solar_Energy_Capture

Noll, D., Dawes, C., & Rai, V. (2014). Solar Community Organizations and active peer effects in the adoption of residential PV. *Energy Policy*, *67*, 330–343. https://doi.org/10.1016/J.ENPOL.2013.12.050

NRG. (2018). Transmission congestion & constraints: Market impediment or opportunity? https://www.nrg.com/insights/energy-education/transmission-congestion---constraints.html

NU.nl. (2021). Nauwelijks meer ruimte voor zonneparken op bomvol stroomnet. https://www.nu.nl/klimaat/6167439/nauwelijks-meer-ruimte-voor-zonneparken-op-bomvol-stroomnet.html

NVDE. (2022). *Tekorten aan materialen verder toegenomen* (tech. rep.). https://www.nvde.nl/

OECD. (2022). Economic Outlook. https://www.oecd-ilibrary.org/sites/f6da2159-en/1/3/1/index.html?itemId=/content/publication/f6da2159-en

O'Shaughnessy, E. (2021). Toward a more productive discourse on rooftop solar and energy justice. *Joule*, *5*(10), 2535–2539. https://doi.org/10.1016/j.joule.2021.08.006

O'Shaughnessy, E., Barbose, G., Wiser, R., Forrester, S., & Darghouth, N. (2020a). The impact of policies and business models on income equity in rooftop solar adoption. *Nature Energy 2020 6:1*, *6*(1), 84–91. https://doi.org/10.1038/s41560-020-00724-2

O'Shaughnessy, E., Barbose, G., Wiser, R., Forrester, S., & Darghouth, N. (2020b). The impact of policies and business models on income equity in rooftop solar adoption. *Nature Energy*, *6*(1), 84–91. https://doi.org/10.1038/s41560-020-00724-2

Palm, A. (2017). Peer effects in residential solar photovoltaics adoption—A mixed methods study of Swedish users. *Energy Research & Social Science*, *26*, 1–10. https://doi.org/10.1016/J.ERSS.2017.01.008

Palmer, D., Cole, I., Betts, T., & Gottschalg, R. (2016). Assessment of potential for photovoltaic roof installations by extraction of roof tilt from light detection and ranging data and aggregation to census geography. *IET Renewable Power Generation*, *10*(4), 467–473. https://doi.org/10.1049/iet-rpg.2015.0388

Palmer, J., Sorda, G., & Madlener, R. (2013). Modeling the Diffusion of Residential Photovoltaic Systems in Italy: An Agent-Based Simulation. *Stochastic Models eJournal*. https://doi.org/10.2139/SSRN.2278120

Parker & Paul. (2008). Residential solar photovoltaic market stimulation: Japanese and Australian lessons for Canada. *Renewable and Sustainable Energy Reviews*, *12*(7), 1944–1958. https://ideas.repec.org/a/eee/rensus/v12y2008i7p1944-1958.html%20https://ideas.repec.org//a/eee/rensus/v12y2008i7p1944-1958.html

Parliamentary Questions 2022Z13495. (2022). Beantwoording Kamervragen over de salderingsregeling. https://www.rijksoverheid.nl/documenten/kamerstukken/2022/09/23/beantwoording-kamervragen-over-de-salderingsregeling

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A Design Science Research Methodology for Information Systems Research. *Journal of Management Information Systems*, *24*(3), 45–77. https://doi.org/10.2753/mis0742-1222240302

Planbureau voor de Leefomgeving, P. (2019). *Achtergronddocument het Klimaatakkoord: Effecten en aandachtspunten* (tech. rep.).

Planbureau voor de Leefomgeving, P., & van Polen, S. (2021). *Ontwikkelingen in de energierekening tot en met 2030* (tech. rep.). PBL. Den Haag. https://www.pbl.nl/sites/default/files/downloads/pbl-2020-ontwikkelingen-in-de-energierekening-tot-en-met-2030-4306.pdf

Poruschi, L., & Ambrey, C. L. (2019). Energy justice, the built environment, and solar photovoltaic (PV) energy transitions in urban Australia: A dynamic panel data analysis. *Energy Research & Social Science*, *48*, 22–32. https://doi.org/10.1016/J.ERSS.2018.09.008

Pruyt, E. (2013). *Small System dynamics models for big issues : triple jump towards real-world complexity*. TU Delft Library.

PVEducation. (n.d.). Solar Cell Efficiency. https://www.pveducation.org/pvcdrom/solar-cell-operation/solar-cell-efficiency

PWC. (2021). *De energietransitie en de financiële impact voor netbeheerders* (tech. rep.). Amsterdam.

Qu, S. Q., & Dumay, J. (2011). The qualitative research interview. *Qualitative Research in Accounting & Management*, *8*(3), 238–264. https://doi.org/10.1108/11766091111162070

Rai, V., & Sigrin, B. (2012). Economics of Individual Decision-Making : Buy vs . Lease Differences in the Adoption of Residential Solar.

Rich, P. M. (1990). Characterizing plant canopies with hemispherical photographs. *Remote Sensing Reviews*, *5*(1), 13–29. https://doi.org/10.1080/02757259009532119

Rijksoverheid. (2023). Energiebelasting. https://www.rijksoverheid.nl/onderwerpen/milieubelastingen/energiebelasting

Rogers, E. M. (1962). *Diffusion of Innovations*. The Free Press.

Ross, A., & Willson, V. L. (2017). One-Way Anova. *Basic and Advanced Statistical Tests*, 21–24. https://doi.org/10.1007/978-94-6351-086-8{_}5

RVO. (2017). Wetgeving zonne-energie. https://www.rvo.nl/onderwerpen/zonne-energie/wetgeving

RVO, FME, TKI Urban Energy, & Top Sector Energy. (2020). *Solar Energy Guide* (tech. rep.). https://www.rvo.nl/

Sabadini, F., & Madlener, R. (2021). The economic potential of grid defection of energy prosumer households in Germany. *Advances in Applied Energy*, *4*, 100075. https://doi.org/10.1016/J.ADAPEN.2021.100075

Salazar, H. A., Oerlemans, L., & Van Stroe-Biezen, S. (2013). Social influence on sustainable consumption: evidence from a behavioural experiment. *International Journal of Consumer Studies*, *37*(2), 172–180. https://doi.org/10.1111/J.1470-6431.2012.01110.X

Sardianou, E., & Genoudi, P. (2013). Which factors affect the willingness of consumers to adopt renewable energies? *Renewable Energy*, *57*, 1–4. https://doi.org/10.1016/J.RENENE.2013.01.031

Schepel, V., Tozzi, A., Klement, M., Ziar, H., Isabella, O., & Zeman, M. (2020). The Dutch PV portal 2.0: An online photovoltaic performance modeling environment for the Netherlands. *Renewable Energy*, *154*, 175–186. https://doi.org/10.1016/J.RENENE.2019.11.033

Schiffman, L. G., & Wisenblit, J. L. (2021). Consumer Behavior and Technology. *Consumer Behavior, Global Edition*, 32–55. https://www.perlego.com/book/827329/consumer-behavior-global-edition-pdf

Schulte, E., Scheller, F., Sloot, D., & Bruckner, T. (2022). A meta-analysis of residential PV adoption: the important role of perceived benefits, intentions and antecedents in solar energy acceptance. *Energy Research & Social Science*, *84*, 102339. https://doi.org/10.1016/J.ERSS.2021.102339

Si, Y., & Stephens, J. C. (2021). Energy Justice Through Solar: Constructing and Engaging Low-Income Households. *Frontiers in Sustainable Cities*, *3*. https://doi.org/10.3389/frsc.2021.632020

Simon, H. A. (1996). *The Sciences of the Artificial*. MIT Press (MA).

Solar Electric. (n.d.). Solar Systems Explained - Grid-tie Vs. Battery Backup Vs. Hybrid. http://www.solarelectricinc.com/solar-electric-system-types

Sommerfeld, J., Buys, L., Mengersen, K., & Vine, D. (2017). Influence of demographic variables on uptake of domestic solar photovoltaic technology. *Renewable and Sustainable Energy Reviews*, *67*, 315–323. https://doi.org/10.1016/J.RSER.2016.09.009

Sovacool, B. K., Burke, M., Baker, L., Kotikalapudi, C. K., & Wlokas, H. (2017). New frontiers and conceptual frameworks for energy justice. *Energy Policy*, *105*, 677–691. https://doi.org/10.1016/j.enpol.2017.03.005

Sovacool, B. K., Barnacle, M. L., Smith, A., & Brisbois, M. C. (2022). Towards improved solar energy justice: Exploring the complex inequities of household adoption of photovoltaic panels. *Energy Policy*, *164*, 112868. https://doi.org/10.1016/J.ENPOL.2022.112868

Sovacool, B. K., Heffron, R. J., McCauley, D., & Goldthau, A. (2016). Energy decisions reframed as justice and ethical concerns. *Nature Energy*, *1*. https://doi.org/10.1038/NENERGY.2016.24

Statista. (2023). Monthly wholesale electricity prices in the Netherlands 2019-2023. https://www.statista.com/statistics/1314549/netherlands-monthly-wholesale-electricity-price/

Sterman, J. (2000). *Business Dynamics-Systems Thinking and Modeling for a Complex World*. Irwin/McGraw-Hill. https://books.google.com/books/about/Business_Dynamics.html?hl=nl&id=CCKCQgAACAAJ

Sterman, J. D. (2002). System Dynamics: Systems Thinking and Modeling for a Complex World. *Engineering Systems Division (ESD) Working Paper Series*. https://dspace.mit.edu/handle/1721.1/102741

Stil, H. (2022). Laadpaal? Zonnepaneel? Het tekort aan mensen om ze neer te zetten blijft maar groeien. https://www.parool.nl/nederland/laadpaal-zonnepaneel-het-tekort-aan-mensen-om-ze-neer-te-zetten-blijft-maar-groeien~ba129737/

Sun, P.-C., Wang, H.-M., Huang, H.-L., & Ho, C.-W. (2020). Consumer attitude and purchase intention toward rooftop photovoltaic installation: The roles of personal trait, psychological benefit, and government incentives. *Taiwan. Energy & Environment*, *104*(40), 21–39. https://doi.org/10.1177/0958305X17754278

Sunter, D. A., Castellanos, S., & Kammen, D. M. (2019). Disparities in rooftop photovoltaics deployment in the United States by race and ethnicity. *Nature Sustainability*, *2*(1), 71–76. https://doi.org/10.1038/s41893-018-0204-z

Teije, S. (2022). Levering zonnepanelen stagneert door tekort aan omvormers. https://www.ad.nl/wonen/levering-zonnepanelen-stagneert-door-tekort-aan-omvormers~a67ae302/?cb=1cb8bff5be2eac8f80e88141c11e3438

TenneT. (n.d.). Our high voltage grid. https://www.tennet.eu/grid/our-high-voltage-grid

Tozzi, A., Schepel, V., & Klement, M. (2020). Dutch PV Portal. https://www.tudelft.nl/ewi/over-de-faculteit/afdelingen/electrical-sustainable-energy/photovoltaic-materials-and-devices/dutch-pv-portal

United Consumers. (n.d.). Energiebedrijf: Goedkope Energiemaatschappij. https://www.unitedconsumers.com/blog/energie/energiebedrijven.jsp

United Nations. (2022). SDG Indicators. https://unstats.un.org/sdgs/report/2022/

U.S. Energy Department. (n.d.). Solar Photovoltaic Cell Basics. https://www.energy.gov/eere/solar/solar-photovoltaic-cell-basics

Vaishnav, P., Horner, N., & Azevedo, I. L. (2017). Was it worthwhile? Where have the benefits of rooftop solar photovoltaic generation exceeded the cost? *Environmental Research Letters*, *12*. https://doi.org/10.1088/1748-9326/aa815e

van der Wilt, P. (2022). Hoeveel zonnepanelen heb ik nodig? | Consumentenbond. https://www.consumentenbond.nl/zonnepanelen/hoeveel-zonnepanelen

van de Weijer, B. (2022). Oorlog in Oekraïne geeft duurzame energie wereldwijd een enorme duw voorwaarts. https://www.volkskrant.nl/nieuws-achtergrond/oorlog-in-oekraine-geeft-duurzame-energie-wereldwijd-een-enorme-duw-voorwaarts~b8b542d3/

Van Westering, W., Zondervan, A., Bakkeren, A., Mijnhardt, F., & Van Der Els, J. (2016). Assessing and mitigating the impact of the energy demand in 2030 on the Dutch regional power distribution grid. *ICNSC 2016 - 13th IEEE International Conference on Networking, Sensing and Control*. https://doi.org/10.1109/ICNSC.2016.7478981

van Blijswijk, M. J., & de Vries, L. J. (2012). Evaluating congestion management in the Dutch electricity transmission grid. *Energy Policy*, *51*, 916–926. https://doi.org/10.1016/J.ENPOL.2012.09.051

van Gastel, E., & Stultiens, E. (2022). Groothandels: tekort aan omvormers voor zonnepanelen houdt nog heel 2022 aan. https://solarmagazine.nl/nieuws-zonne-energie/i27463/groothandels-tekort-aan-omvormers-voor-zonnepanelen-houdt-nog-heel-2022-aan

van Gastel, E. (2012). *Solar Magazine* (tech. rep.). https://solarmagazine.nl/

van Groesen, K. (2022). Bijna 1 op de 5 woningen heeft zonnepanelen. https://weblog.independer.nl/persbericht/bijna-1-op-de-5-woningen-heeft-zonnepanelen/

van Uffelen, N. (2022). Revisiting recognition in energy justice. *Energy Research & Social Science*, *92*, 102764. https://doi.org/10.1016/j.erss.2022.102764

van Weezel, T. (2023). Minister Jetten wil af van regeling voor zonnepanelen, waarom steunen GroenLinks en PvdA hem niet? https://www.volkskrant.nl/nieuws-achtergrond/minister-jetten-wil-af-van-regeling-voor-zonnepanelen-waarom-steunen-groenlinks-en-pvda-hem-niet~b661a473/

van Zoelen, B. (2022). Regio waarschuwt: knelpunten op Amsterdams stroomnet staan klimaatdoelen in de weg. https://www.parool.nl/amsterdam/regio-waarschuwt-knelpunten-op-amsterdams-stroomnet-staan-klimaatdoelen-in-de-weg~bfe68828/

Vasseur, V., & Kemp, R. (2015a). The adoption of PV in the Netherlands: A statistical analysis of adoption factors. *Renewable and Sustainable Energy Reviews*, *41*, 483–494. https://doi.org/10.1016/j.rser.2014.08.020

Vasseur, V., & Kemp, R. (2015b). A segmentation analysis: the case of photovoltaic in the Netherlands. *Energy Efficiency*, *8*(6), 1105–1123. https://doi.org/10.1007/S12053-015-9340-8/FIGURES/6

Vattenfall. (n.d.). Wat zijn onbalanskosten? https://www.vattenfall.nl/grootzakelijk/energiemarkt/onbalanskosten/

Veen, L. E. M. (2014). Domestic Solar Energy Collection: The Sunny Side of Life?

Verheij, F., Menkveld, M., & Usmani, O. (2020a). *Effect afbouw salderingsregeling op de terugverdientijd van investeringen in zonnepanelen* (tech. rep.). TNO. https://repository.tno.nl/islandora/object/uuid%3A764ab15e-d480-4e50-bc73-27716c240917

Verheij, F., Menkveld, M., & Usmani, O. (2020b). *Effect afbouw salderingsregeling op de terugverdientijd van investeringen in zonnepanelen* (tech. rep.). TNO. Delft. https://repository.tno.nl/islandora/object/uuid%3A764ab15e-d480-4e50-bc73-27716c240917

Vermaas, N., & Hoogendijk, E. (2021). Zonatlas Amsterdam. https://openresearch.amsterdam/nl/page/74332/zonatlas-amsterdam

Viitanen, J., & Halonen, L. (2014). Electrical efficiency study of alternating current and direct current power topologies in office building with integrated photovoltaics in Matlab-Simulink environment. *Journal of Renewable and Sustainable Energy*, *6*(3). https://doi.org/10.1063/1.4880775

VNG. (n.d.). Datavoorziening Energietransitie Gebouwde Omgeving. https://vng.nl/projecten/datavoorziening-energietransitie-gebouwde-omgeving

Walker, A., & Desai, J. (2021). *Understanding Solar Photovoltaic System Performance* (tech. rep.). National Renewable Energy Laboratory (NREL).

Walker, A., & Desai, J. (2011). *Understanding Solar Photovoltaic System Performance: An Assessment of 75 Federal Photovoltaic Systems* (tech. rep.). https://www.energy.gov/sites/default/files/2022-02/understanding-solar-photo-voltaic-system-performance.pdf

Walker, G., & Day, R. (2012). Fuel poverty as injustice: Integrating distribution, recognition and procedure in the struggle for affordable warmth. *Energy Policy*, *49*, 69–75. https://doi.org/10.1016/j.enpol.2012.01.044

Warmtefonds. (n.d.). Voorbeelden Energiebespaarlening. https://www.warmtefonds.nl/particulieren/voorbeelden-energiebespaarlening

Weijnen, M. P. C., Lukszo, Z., & Farahani, S. (2021). *Shaping an Inclusive Energy Transition* (1st ed.). Springer Publishing. https://doi.org/10.1007/978-3-030-74586-8

Weisstein, E. W. (2023). Bonferroni Correction. https://mathworld.wolfram.com/BonferroniCorrection.html

Weterings, A., Bakens, B., Ivanova, O., den Nijs, S., Thissen, M., Bijlsma, I., Pestel, N., & Planbureau voor de Leefomgeving. (2022). *Inzicht in arbeidsmarktknelpunten voor de uitvoering van het klimaatbeleid* (tech. rep. PBL-4931). Publisher PBL. https://www.pbl.nl/

Wieringa, R. J. (2014). *Design Science Methodology for Information Systems and Software Engineering*. Springer Publishing.

Wolfs, T. (2017). A GIS-based approach to estimate the geographic potential for rooftop solar PV: Developing a database at building-level for Denmark. https://projekter.aau.dk/

Yesilmaden, H. M., & Dogru, A. O. (2019). Finding the best locations for photovoltaic panel installation in urbanized areas. *Fresenius Environmental Bulletin*, *28*(2), 619–625.

Zhang, Y., Song, J., & Hamori, S. (2011). Impact of subsidy policies on diffusion of photovoltaic power generation. *Energy Policy*, *39*(4), 1958–1964. https://doi.org/10.1016/J.ENPOL.2011.01.021

Zinaman, O., & Darghouth, N. (2020). *Distributed solar utility tariff and revenue impact analysis* (tech. rep.). National Renewable Energy Laboratory (NREL). www.nrel.gov/publications.
Zubair, M. (2022). Statistical Comparison Among Multiple Groups With ANOVA. https://towardsdatascience.com/statistical-comparison-among-multiple-groups-with-anova-d4ac27f6e59e

A Appendix: Artifact part I

A.1 Included socio-economic variables

Theme	Variable	Unit
Population	Number of inhabitants	#
	Men	#
	Women	#
	Percentage of people 0 to 15 years	%
	Percentage of people 15 to 25 years	%
	Percentage of people 25 to 45 years	%
	Percentage of people aged 45 to 65	%
	Percentage of people aged 65 and over	%
	Percentage of people unmarried	%
	Percentage of people married	%
	percentage divorced	%
	Percentage married	%
	Birth total	#
	Birth relative	#
	Total mortality	#
	Mortality relative	#
	Population density inhabitants per km2	# / km2
	Number of households	#
	Percentage of single-person households	%
	Percentage of households without children	%
	Percentage of households with children	%
	Average household size	# citizens / household
	Percentage of persons with western migration background	%
	Percentage of persons from non-western migration background	%
	Percentage of people from Morocco	%
	Percentage from the Netherlands Antilles and Aruba	%
	percentage from Suriname	%
	percentage from Turkey	%
	Percentage of other persons with a non-western migration background	%
Residencies	WOZ value	€ x 1000
	Percentage single-family homes	%
	Percentage multiple-family homes	%
	Percentage inhabited	%
	Percentage owned properties	%
	Percentage rental properties	%
	Percentage housing corporation	%
	Percentage other landlords	%
	Percentage ownership unkown	%
	Percentage construction year from 2000	%
	Percentage construction year until 2000	%

Table 12: Variables used for detailed analysis

Income	Number of income recipients	#
	Percentage of persons with lowest income	%
	Percentage of persons with highest income	%
	Percentage of households with lowest income	%
	Percentage of households with highest income	%
	Households below social minimum	%
	Percentage of households with low income	%
	Households up to 110 percent of social minimum	%
	Households up to 120 percent of social minimum	%
	Median wealth of private household	€ / year
	Average property value	€ x 1000
	Number of inhabitants	#
	Total unemployment benefits	#
	AO benefits total	#
	Total general social assistance benefits	#
	Number of people with AOW benefits total	#
	Average income per income recipient	€ / year
	Average income per inhabitant	€ / year
	Average standardized income of households	€ / year
	Median assets of private households	€
	Total benefits	#
Energy	Average gas consumption	m3 / year
	Average gas consumption rental properties	m3 / year
	Average gas consumption owned properties	m3 / year
	Average electricity consumption	kWh / year
	Average electricity consumption rental properties	kWh / year
	Average electricity consumption owned properties	kWh / year
Education	Net employment rate	%
	Percentage employed	%
	Percentage self-employed	%
	Percentage highly educated citizens	%
	Percentage secondary educated citizens	%
	Percentage lower educated citizens	%
Vehicles	Passenger vehicles per household	%
	Percentage of vehicles with gasoline fuel	%
	Percentage of vehicles with other fuel	%
	Percentage housing corporation	%
	Percentage other landlords	%
	Percentage ownership unkown	%
	Percentage construction year from 2000	%
	Percentage construction year until 2000	%

Table 13: Variables used for detailed analysis

A.2 Spatial analysis results

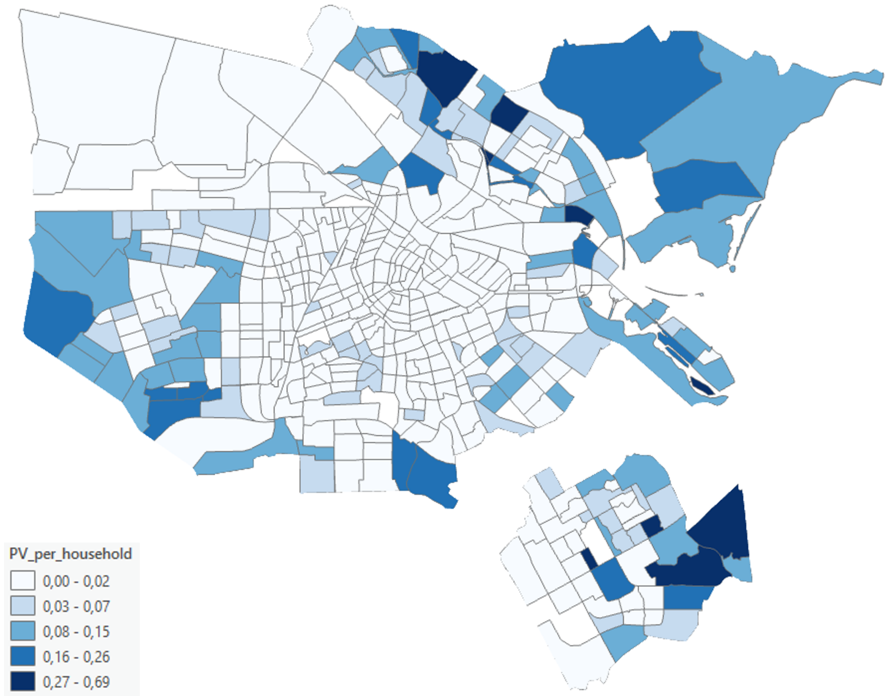


Figure 69: PV installations per citizen in each neighborhood

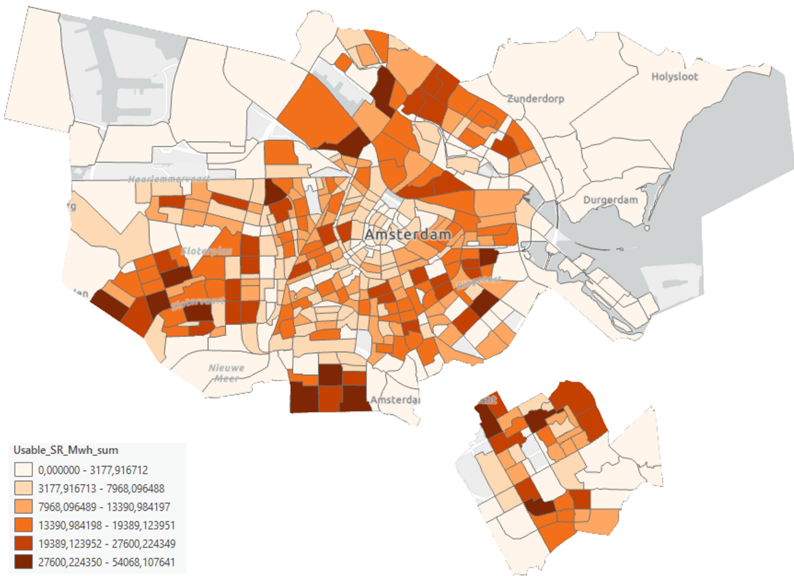


Figure 70: Usable rooftop surface in potential electricity yield (MWh)

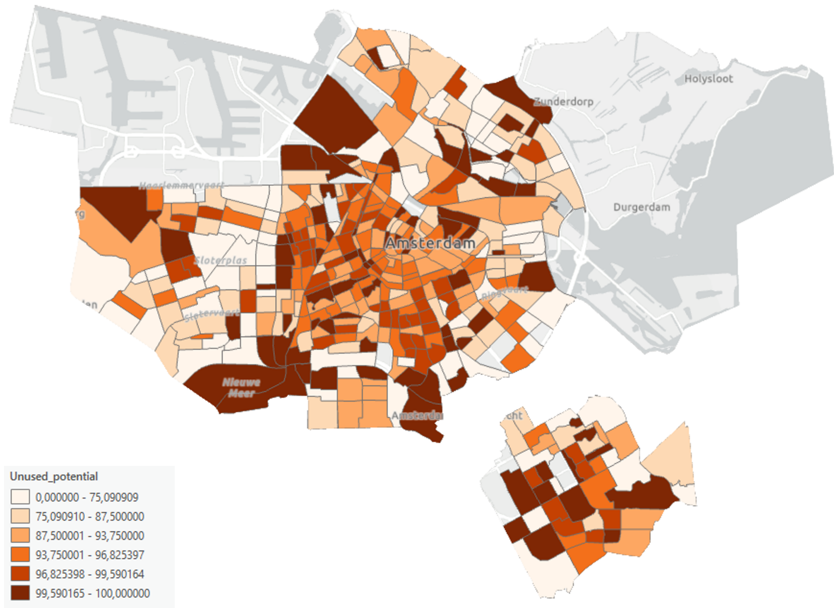


Figure 71: Unused potential residential rooftops, as a percentage of the total residential rooftops in a neighborhood

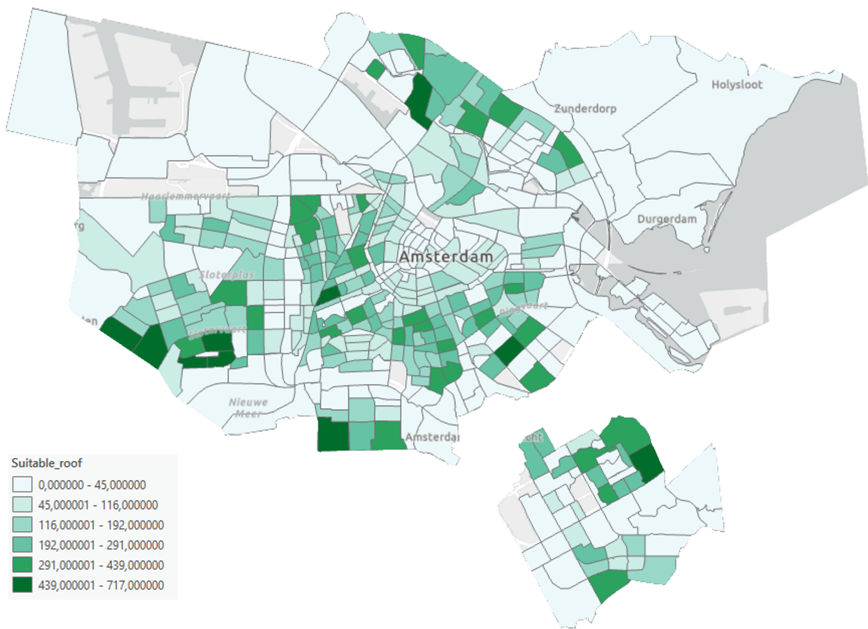


Figure 72: Suitable residential rooftops per neighborhood

A.3 Data exploration and distributions

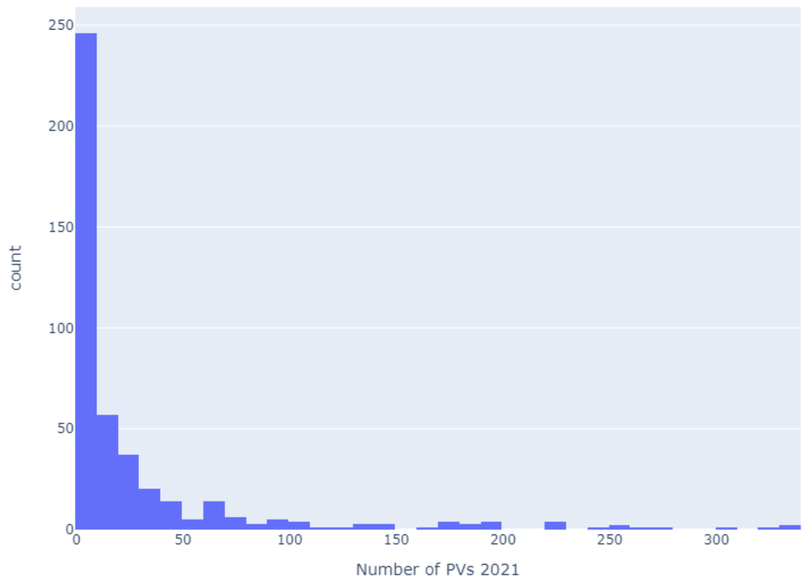


Figure 73: Distribution of PV installations per neighborhood in 2021

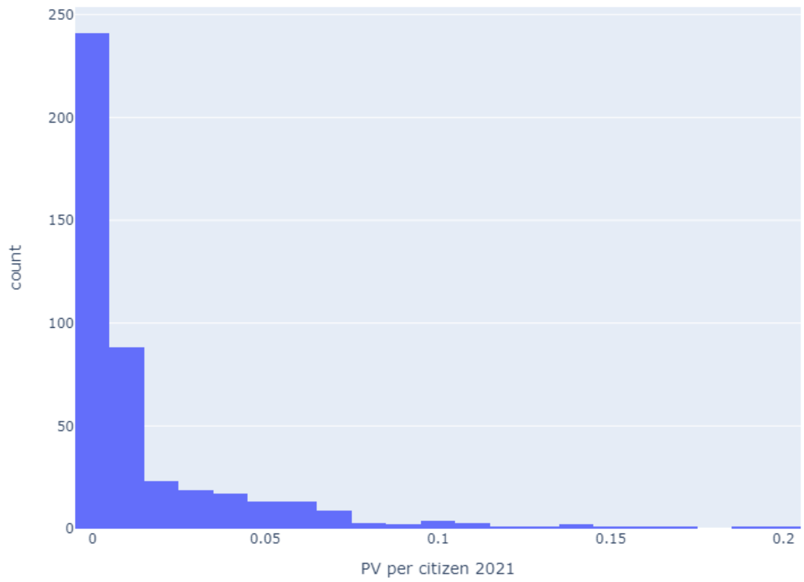


Figure 74: Distribution of PV installations per citizen for each neighborhood in 2021

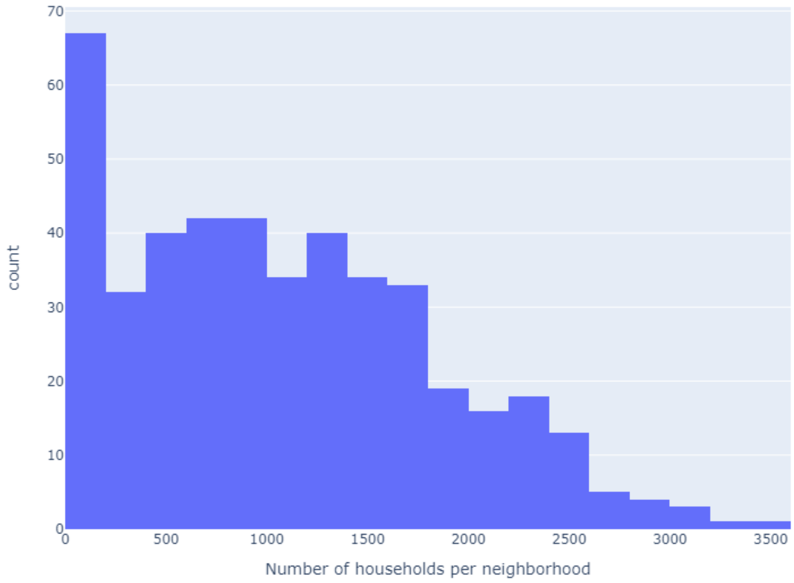


Figure 75: Distribution of the number of households per neighborhood in 2021

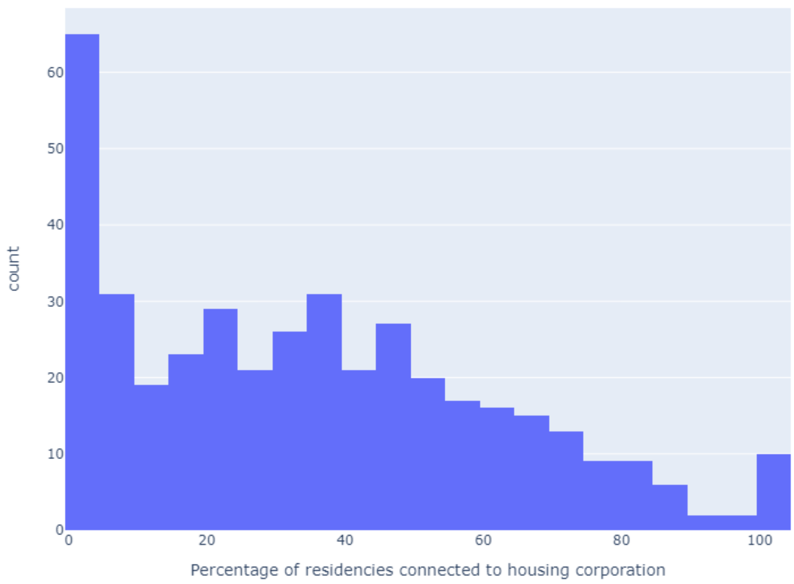


Figure 76: Distribution of the percentage of residencies under a housing corporation for each neighborhood in 2021

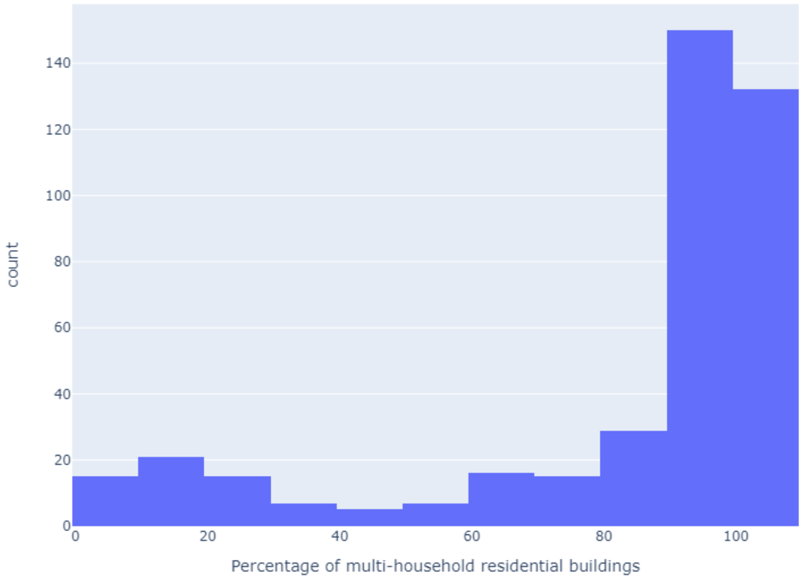


Figure 77: Distribution of the percentage multi-household residential buildings for each neighborhood in 2021

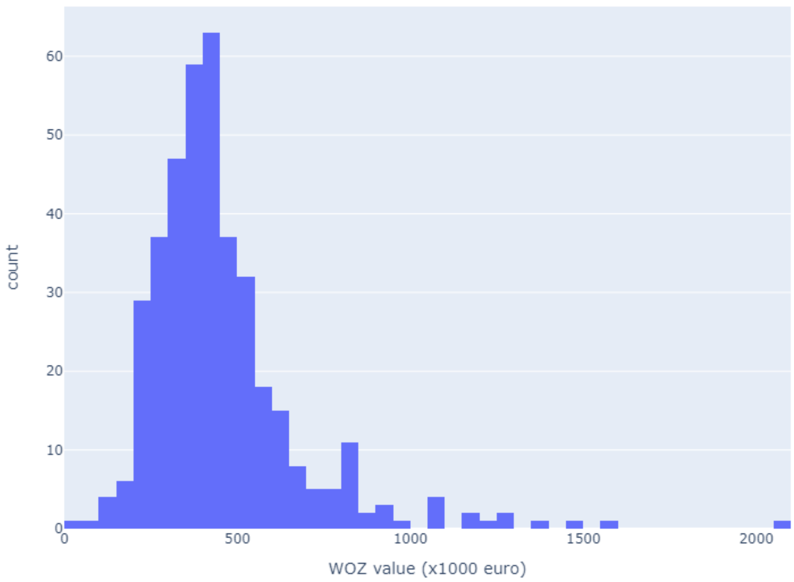
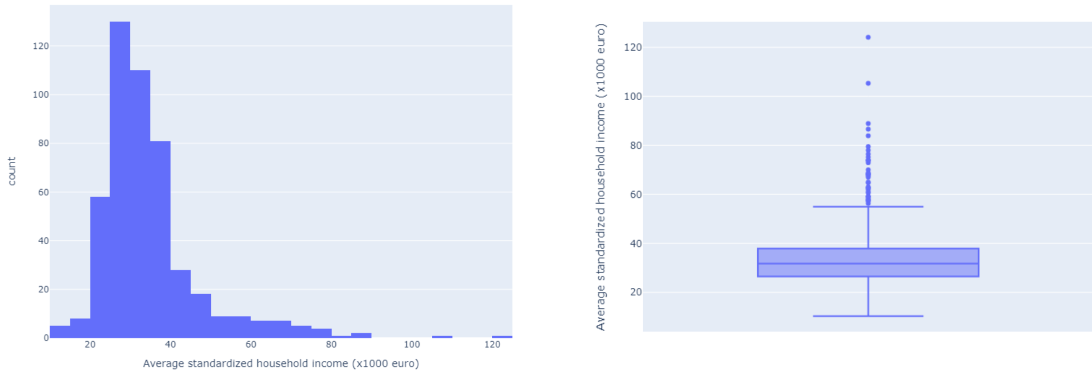


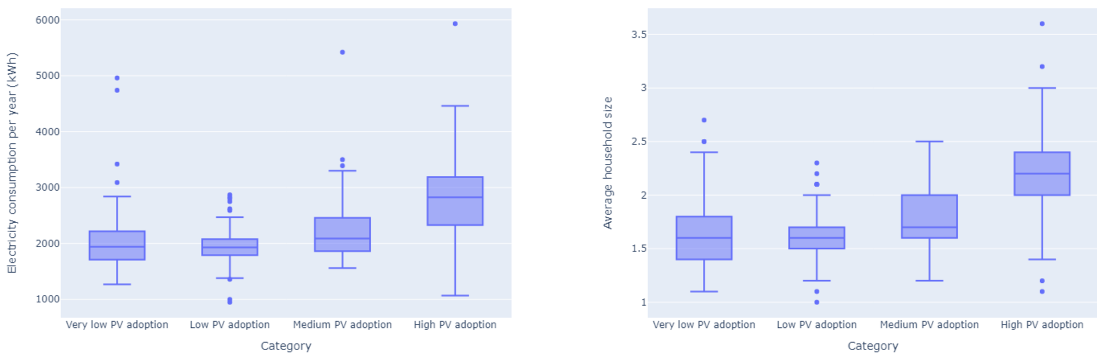
Figure 78: Distribution of average woz values for each neighborhood in 2021



(a) (b)

Figure 79: Distribution of the standardized household income for each neighborhood in 2021

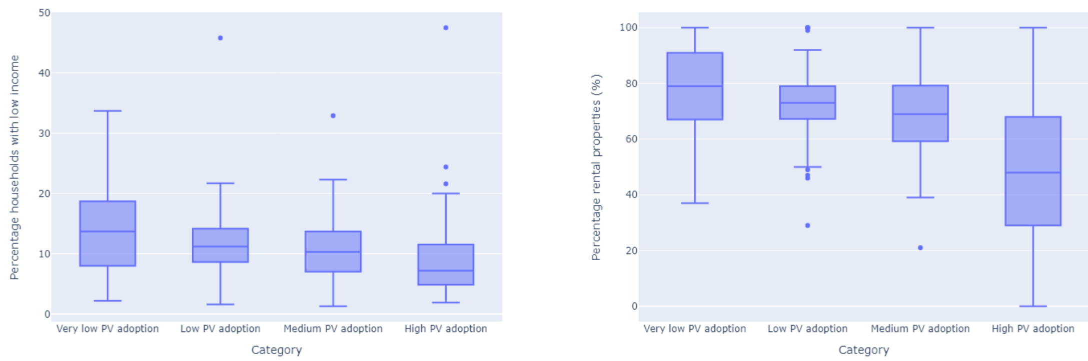
A.4 Group comparison distributions



(a) Distribution of the average electricity consumption (kWh) per household per PV adoption category

(b) Distribution of the average household size per PV adoption category

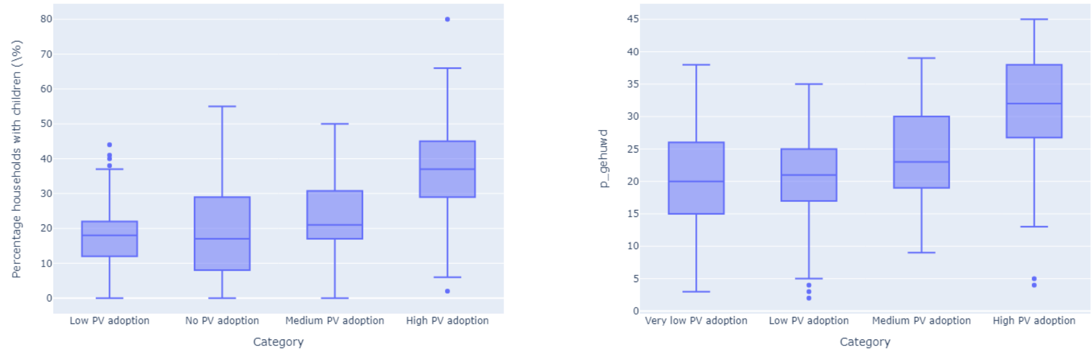
Figure 80: Group comparison distributions



(a) Distribution of the percentage low-income households per PV adoption category

(b) Distribution of the percentage rental properties per PV adoption category

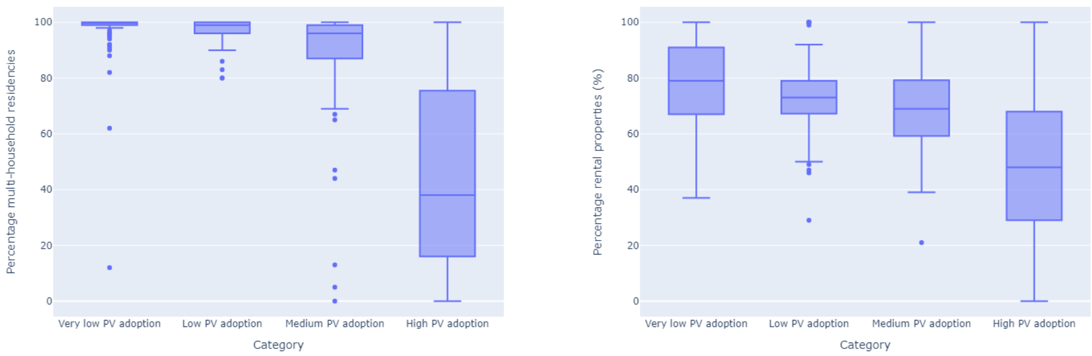
Figure 81: Group comparison distributions



(a) Distribution of the percentage children per PV adoption category

(b) Distribution of the percentage married citizens per PV adoption category

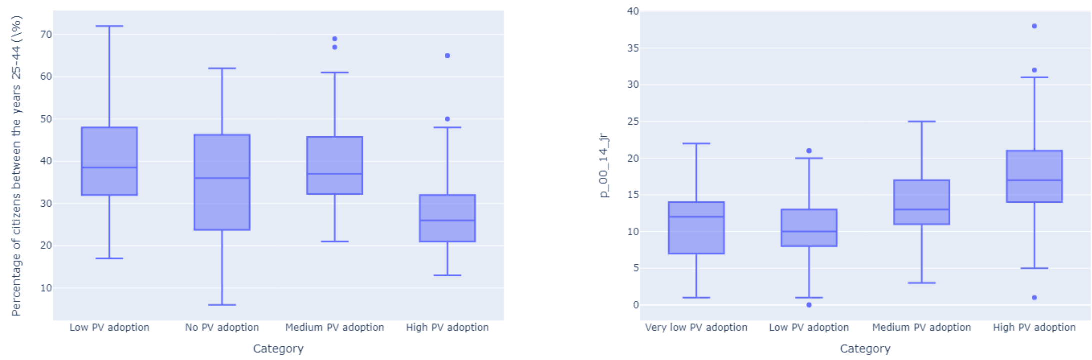
Figure 82: Group comparison distributions



(a) Distribution of the percentage multi-household residencies per PV adoption category

(b) Distribution of the percentage rental properties per PV adoption category

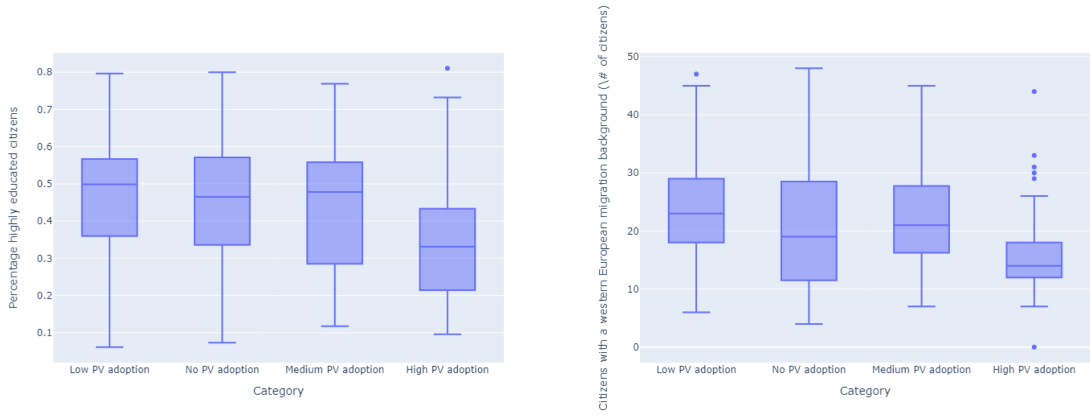
Figure 83: Group comparison distributions



(a) Distribution of the percentage 24-44 year old citizens per PV adoption category

(b) Distribution of the percentage 0-14 year old citizens per PV adoption category

Figure 84: Group comparison distributions



(a) Distribution of the percentage high-educated citizens

(b) Distribution of the percentage citizens with a western-European migration background

Figure 85: Group comparison distributions

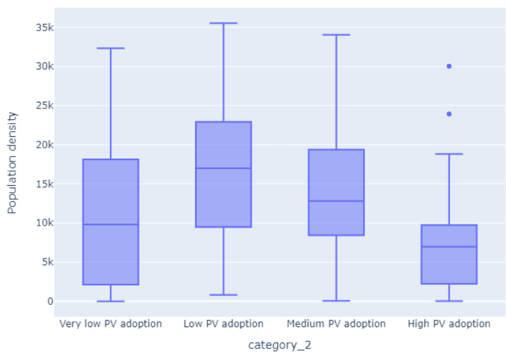


Figure 86: Distribution of the population density per PV adoption category

A.5 Socio-economic analysis - income correlation results

Variable	p_value	coefficient	Adjusted p-value	Significant?
Number of income recipients	0.01	0.13	0.21	FALSE
Percentage of persons with lowest income	0.00	-0.18	0.01	TRUE
Percentage of persons with highest income	0.00	0.15	0.06	FALSE
Percentage of households with lowest income	0.00	-0.45	0.00	TRUE
Percentage of households with highest income	0.00	0.40	0.00	TRUE
Households below social minimum	0.00	-0.33	0.00	TRUE
Percentage of households with low income	0.00	-0.34	0.00	TRUE
Households up to 110 percent of social minimum	0.00	-0.31	0.00	TRUE
Households up to 120 percent of social minimum	0.00	-0.30	0.00	TRUE
Median wealth of private household	0.00	0.35	0.00	TRUE
Average property value	0.00	0.16	0.05	FALSE
Number of inhabitants	0.00	0.14	0.06	FALSE
Total unemployment benefits	0.36	0.04	9.68	FALSE
AO benefits total	0.11	0.08	3.03	FALSE
Total general social assistance benefits	0.07	-0.09	1.85	FALSE
Number of people with AOW benefits total	0.00	0.14	0.09	FALSE
Average income per income recipient	0.04	0.10	1.00	FALSE
Average income per inhabitant	0.51	0.03	13.86	FALSE
Average standardized income of households	0.00	0.39	0.00	TRUE
Median assets of private households	0.00	0.23	0.00	TRUE
Total benefits	0.12	0.08	3.24	FALSE

Table 14: Significance values, Spearman coefficients and Bonferroni adjusted p-values for the income related variables

A.6 Socio-economic analysis - population correlation results

Variable	p_value	coefficient	Adjusted p-value	Significant?
Number of inhabitants	0,00	0,14	0,03	TRUE
Men	0,00	0,14	0,04	TRUE
Women	0,00	0,15	0,02	TRUE
Percentage of people 0 to 15 years	0,00	0,48	0,00	TRUE
Percentage of people 15 to 25 years	0,86	0,01	11,16	FALSE
Percentage of people 25 to 45 years	0,00	-0,38	0,00	TRUE
Percentage of people aged 45 to 65	0,00	0,20	0,00	TRUE
Percentage of people aged 65 and over	0,00	0,15	0,02	TRUE
Percentage of people unmarried	0,00	-0,44	0,00	TRUE
Percentage of people married	0,00	0,52	0,00	TRUE
percentage divorced	0,00	-0,15	0,02	TRUE
Percentage married	0,00	0,25	0,00	TRUE
Birth total	0,00	0,16	0,01	TRUE
Birth relative	0,00	0,18	0,00	TRUE
Total mortality	0,07	0,09	0,92	FALSE
Mortality relative	0,43	0,04	5,62	FALSE
Population density inhabitants per km2	0,00	-0,18	0,00	TRUE
Number of households	0,49	0,03	6,40	FALSE
Percentage of single-person households	0,00	-0,58	0,00	TRUE
Percentage of households without children	0,00	0,23	0,00	TRUE
Percentage of households with children	0,00	0,54	0,00	TRUE
Average household size	0,00	0,59	0,00	TRUE
Percentage of persons with western migration background	0,00	-0,33	0,00	TRUE
Percentage of persons from non-western migration background	0,24	-0,06	3,08	FALSE
Percentage of people from Morocco	0,18	0,07	2,39	FALSE
Percentage from the Netherlands Antilles and Aruba	0,03	-0,11	0,37	FALSE
percentage from Suriname	0,19	0,06	2,46	FALSE
percentage from Turkey	0,19	0,06	2,53	FALSE
Percentage of other persons with a non-western migration background	0,00	-0,27	0,00	TRUE

Table 15: Significance values, Spearman coefficients and Bonferroni adjusted p-values for the population related variables

A.7 Socio-economic analysis - residency correlation results

Variable	p-value	Coefficient	Adjusted p-value	Significant?
PV per citizen 2021	0,00	1,00	0,00	TRUE
PV per household 2021	0,00	1,00	0,00	TRUE
WOZ value	0,00	0,15	0,03	TRUE
Percentage single-family homes	0,00	0,74	0,00	TRUE
Percentage multiple-family homes	0,00	-0,74	0,00	TRUE
Percentage inhabited	0,00	0,18	0,00	TRUE
Percentage owned properties	0,00	0,49	0,00	TRUE
Percentage rental properties	0,00	-0,49	0,00	TRUE
Percentage housing corporation	0,00	-0,23	0,00	TRUE
Percentage other landlords	0,00	-0,22	0,00	TRUE
Percentage ownership unkown	0,05	-0,10	0,60	FALSE
Percentage construction year from 2000	0,00	-0,14	0,05	FALSE
Percentage construction year until 2000	0,00	0,14	0,05	FALSE

Table 16: Significance values, Spearman coefficients and Bonferroni adjusted p-values for the residence related variables

A.8 Socio-economic analysis - energy correlation results

Variable	p value	Coefficient	Adjusted p-value	Significant?
Average gas consumption	0,00	0,27	0,00	TRUE
Average gas consumption rental properties	0,00	0,19	0,00	TRUE
Average gas consumption owned properties	0,00	0,31	0,00	TRUE
Average electricity consumption	0,00	0,49	0,00	TRUE
Average electricity consumption rental properties	0,00	0,43	0,00	TRUE
Average electricity consumption owned properties	0,00	0,50	0,00	TRUE

Table 17: Significance values and Spearman coefficients for the energy related variables

A.9 Socio-economic analysis - education correlation results

Variable	p_value	coefficient	p_value_new	Significant?
Net employment rate	0,01	0,12	0,13	FALSE
Percentage employed	0,02	-0,11	0,22	FALSE
Percentage self-employed	0,02	0,11	0,22	FALSE
Percentage highly educated citizens	0,00	0,16	0,01	TRUE
Percentage secondary educated citizens	0,02	0,11	0,21	FALSE
Percentage lower educated citizens	0,00	-0,15	0,03	TRUE

Table 18: Significance values and Spearman coefficients for the education related variables

A.10 Socio-economic analysis - vehicle correlation results

Variable	p_value	coefficient	p_value_new	Significant?
Passenger vehicles per household	0,00	0,56	0,00	TRUE
Percentage of vehicles with gasoline fuel	0,49	0,03	1,95	FALSE
Percentage of vehicles with other fuel	0,20	-0,06	0,78	FALSE

Table 19: Significance values and Spearman coefficients for the vehicle related variables

B Appendix: Artifact part II - System Dynamics model

B.1 Model parameters

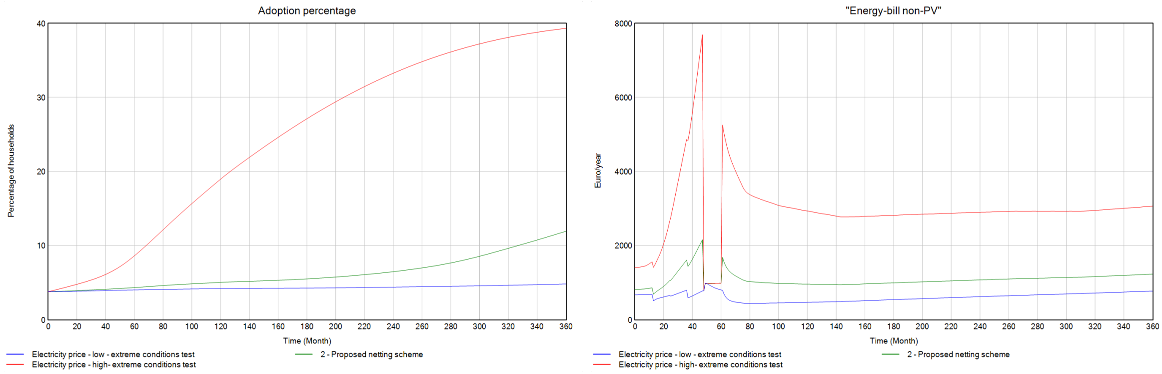
A table with all parameters, their modelled values and the corresponding source will be included.

B.2 Model variables

A table with all model variables, their value range and units will be included.

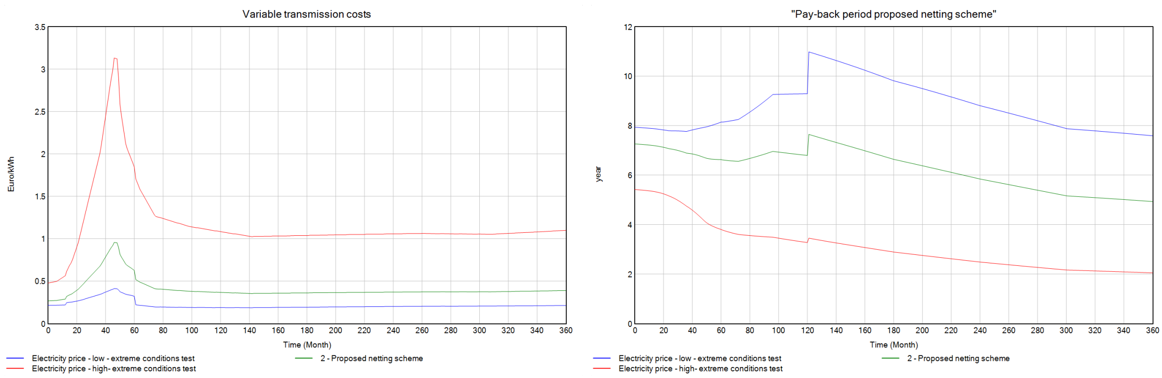
B.3 Extreme Conditions Test

Electricity price



(a) (b)

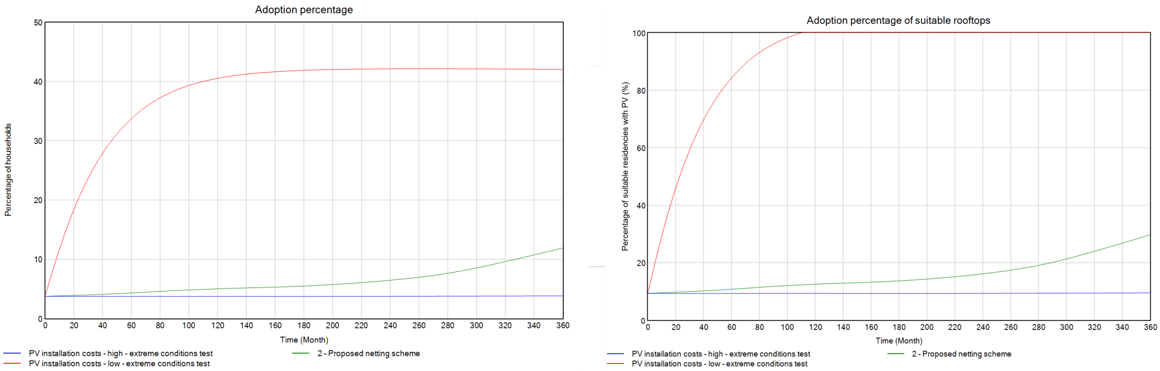
Figure 87: Extreme condition test results for the electricity price



(a) (b)

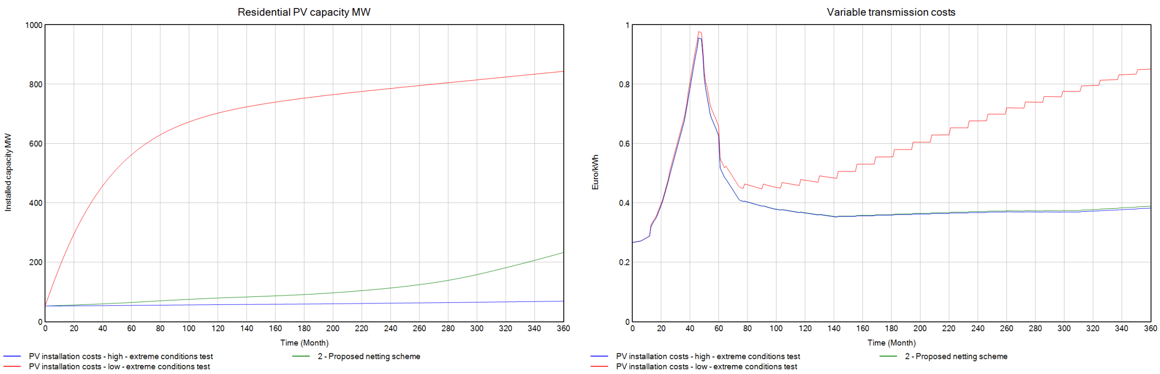
Figure 88: Extreme condition test results for the electricity price

PV installation costs



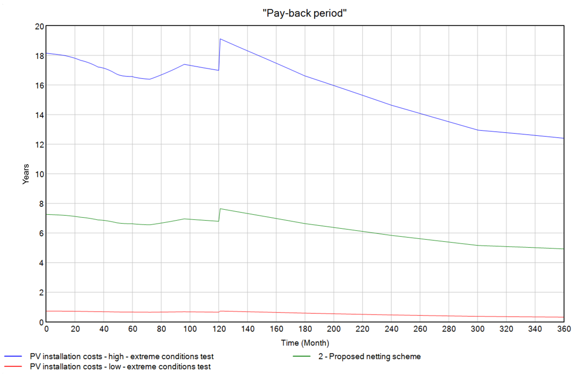
(a) Overall adoption percentage (b) Adoption percentage of suitable rooftops

Figure 89: Extreme condition test results for the PV installation costs



(a) Installed capacity (b) Variable transmission costs

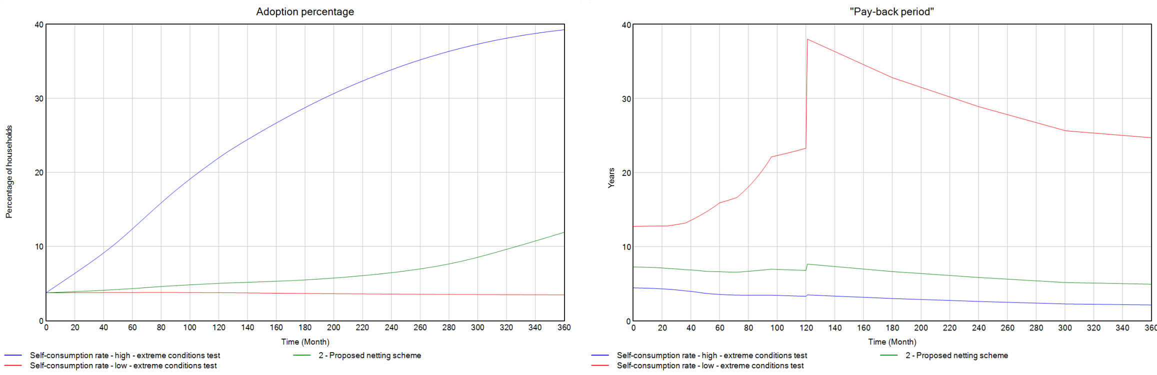
Figure 90: Extreme condition test results for the PV installation costs



(a) payback period

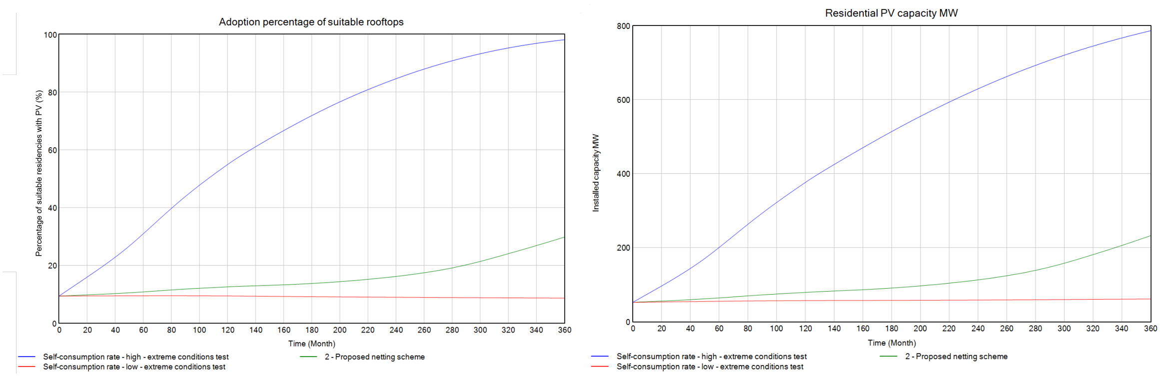
Figure 91: Extreme condition test results for the PV installation costs

Self-consumption rate



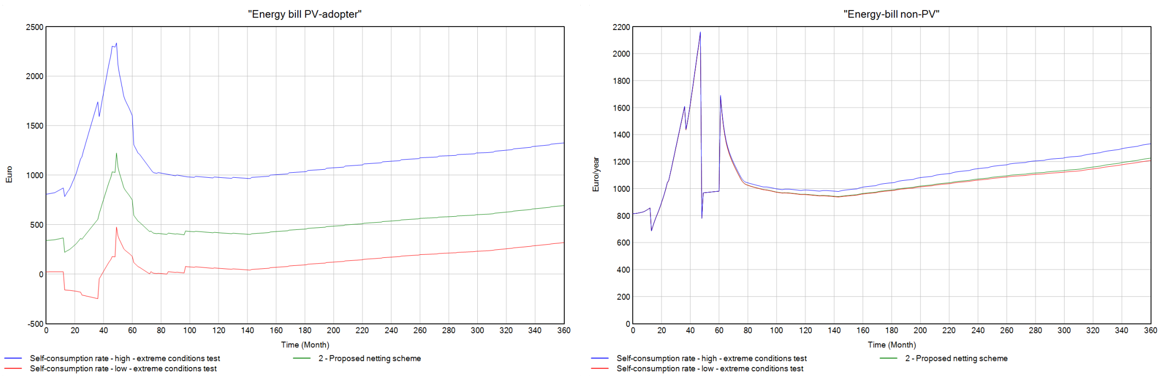
(a) Overall adoption percentage (b) Payback period

Figure 92: Extreme condition test results for the self-consumption rate



(a) Adoption percentage of suitable rooftops (b) Installed capacity

Figure 93: Extreme condition test results for the self-consumption rate

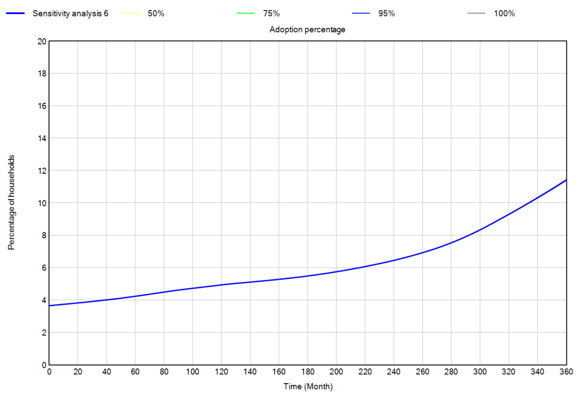


(a) Energy bill PV adopter (b) Energy bill non-PV adopter

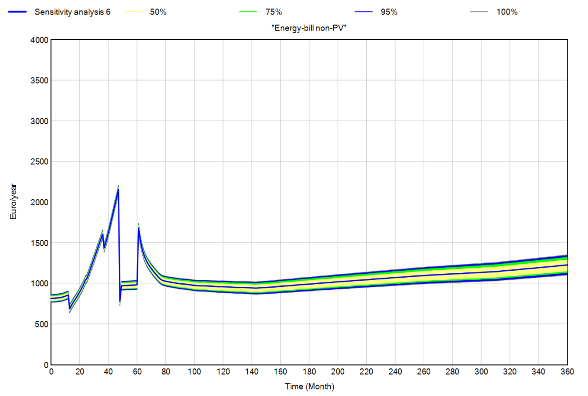
Figure 94: Extreme condition test results for the self-consumption rate

B.4 Sensitivity Analysis

B.4.1 Univariate analysis under the proposed netting scheme

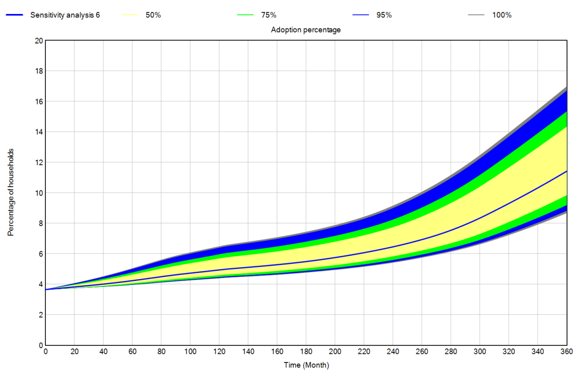


(a) Univariate sensitivity analysis for the imbalance costs per kWh

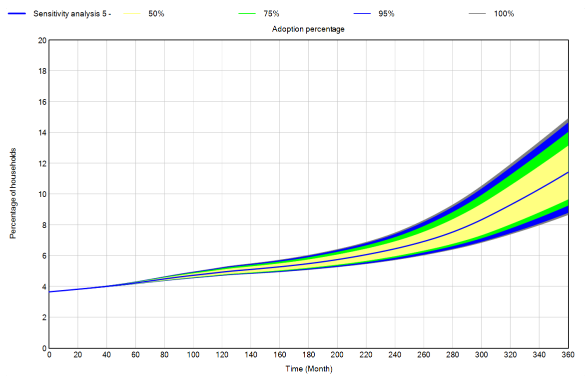


(b) Univariate sensitivity analysis for the distribution costs

Figure 95: Univariate sensitivity test results

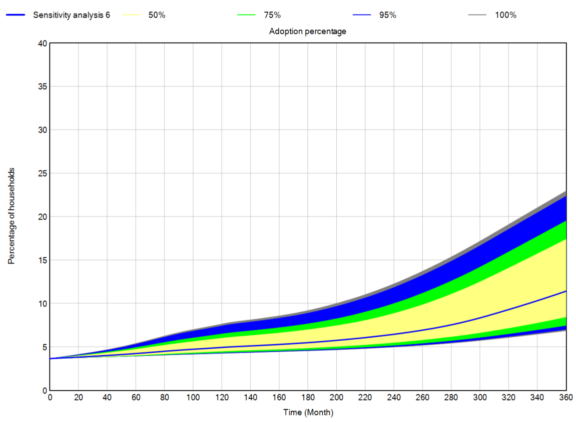


(a) Univariate sensitivity analysis for the inflation factor

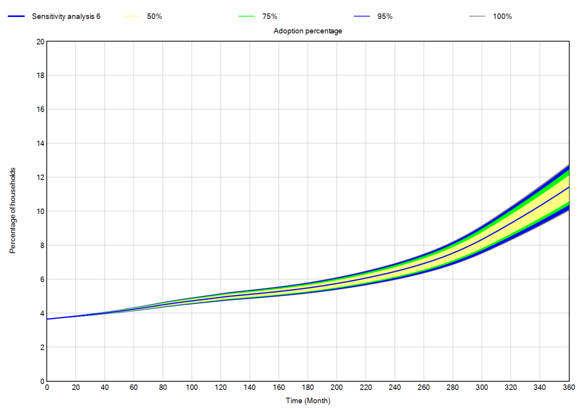


(b) Univariate sensitivity analysis for the market spot price

Figure 96: Univariate sensitivity test results



(a) Univariate sensitivity analysis for the PV installation cost



(b) Univariate sensitivity analysis for the adoption rate

Figure 97: Univariate sensitivity test results

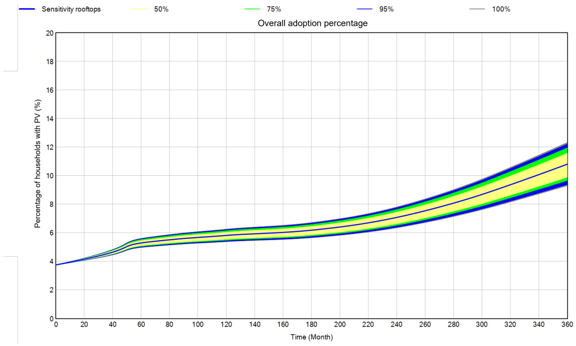
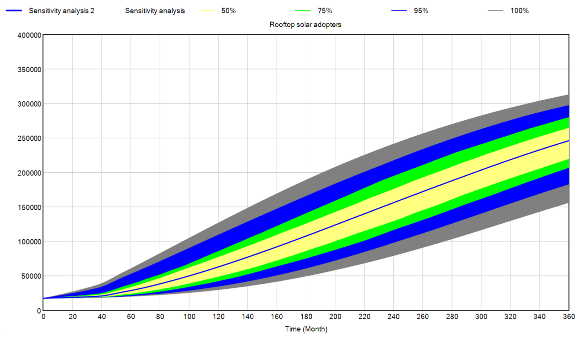
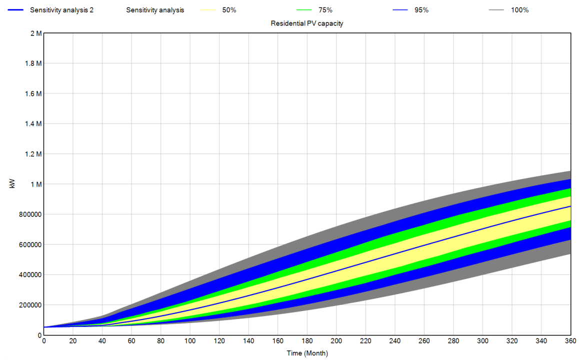


Figure 98: Univariate sensitivity analysis for the percentage of suitable rooftops

B.4.2 Multivariate sensitivity analysis under the current netting scheme

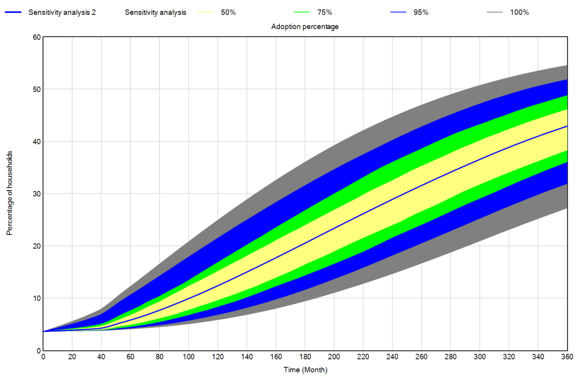


(a) Multivariate sensitivity analysis of the number of adopters under the current netting scheme



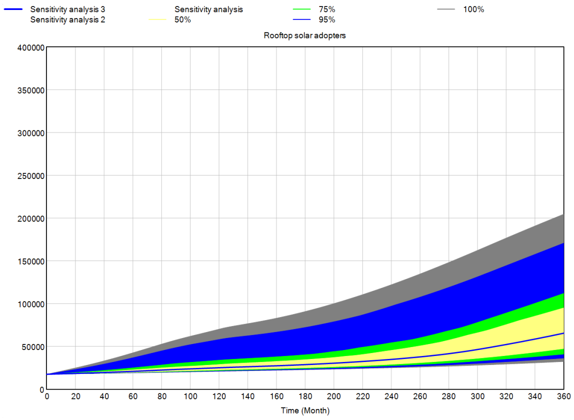
(b) Multivariate sensitivity analysis of the installed residential capacity under the current netting scheme

Figure 99: Multivariate sensitivity test results

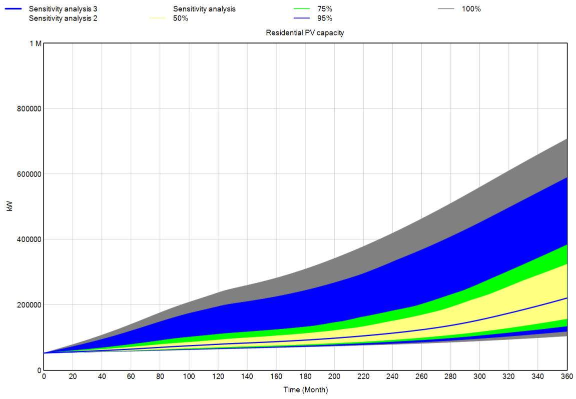


(a) Multivariate sensitivity analysis of the adoption percentage under the current netting scheme

B.4.3 Multivariate sensitivity analysis under the proposed netting scheme

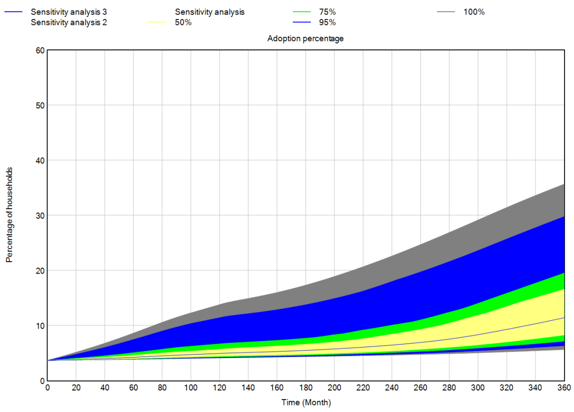


(a) Multivariate sensitivity analysis of the number of adopters under the proposed netting scheme



(b) Multivariate sensitivity analysis of the installed residential capacity under the proposed netting scheme

Figure 101: Multivariate sensitivity test results



(a) Multivariate sensitivity analysis of the adoption percentage under the proposed netting scheme

B.5 Full experimental setup

Experiment	**Netting-scheme**	**LI subsidy**	**Sustain-ability plan (SP) mandate**	**LI-netting scheme**	**Geopolitical developments (GD)**	**Inflation**	**Shortage of technicians and materials (t&m)**	**Adoption rate**
1	Current	-	-	-	Base case	Base case	Base case	Base case
1.2	Current	-	-	-	Base case	Base case	Base case	Low adoption
1.3	Current	-	-	-	Base case	Base case	Base case	High adoption
1.4	Current	-	-	-	Low	Low	Base case	Base case
1.5	Current	-	-	-	High	High	Base case	Base case
1.6	Current	-	-	-	Low	Low	Base case	Low
1.7	Current	-	-	-	Low	Low	Base case	High
1.8	Current	-	-	-	High	High	Base case	Low
1.9	Current	-	-	-	High	High	Base case	High
2	Proposed	-	-	-	Base case	Base case	Base case	Base case
2.2	Proposed	-	-	-	Base case	Base case	Base case	Low adoption
2.3	Proposed	-	-	-	Base case	Base case	Base case	High adoption
3	None	-	-	-	Base case	Base case	Base case	Base case
3.2	None	-	-	-	Base case	Base case	Base case	Low adoption
3.3	None	-	-	-	Base case	Base case	Base case	High adoption
4	Proposed	-	-	-	Low	Base case	Base case	Base case
5	Proposed	-	-	-	High	Base case	Base case	Base case
6	Proposed	-	-	-	Base case	Low	Base case	Base case
7	Proposed	-	-	-	Base case	High	Base case	Base case
8	Proposed	-	-	-	Base case	Base case	High	Base case
9	Proposed	-	-	-	Low	Low	Base case	Base case
10	Proposed	-	-	-	High	High	High	Base case
11	Proposed	€500	-	-	Base case	Base case	Base case	Base case
12	Proposed	€1000	-	-	Base case	Base case	Base case	Base case
13	Proposed	€500	-	-	Low	Low	Base case	Base case
14	Proposed	€500	-	-	High	High	High	Base case
15	Proposed	€1000	-	-	Low	Low	Base case	Base case
16	Proposed	€1000	-	-	High	High	High	Base case
17	Proposed	-	Yes	-	Base case	Base case	Base case	Base case
18	Proposed	-	Yes	-	Low	Low	Base case	Base case
19	Proposed	-	Yes	-	High	High	High	Base case
20	Proposed	-	-	Yes	Base case	Base case	Base case	Base case
21	Proposed	-	-	Yes	Low	Low	Base case	Base case
22	Proposed	-	-	Yes	High	High	Base case	Base case
23	Proposed	-	Yes	Yes	Base case	Base case	Base case	Base case
24	Proposed	€1000	Yes	-	Base case	Base case	Base case	Base case
25	Proposed	€1000		Yes	Base case	Base case	Base case	Base case
26	Proposed	€1000	Yes	Yes	Base case	Base case	Base case	Base case

Table 20: Full experimental setup

C Appendix: Artifact part II - System Dynamics modeling and results

The most important model equations that are not included in the main text are included in this appendix. For the sub-models, some equations are equal to those in the mail model. In that case, the equation is only included once, for the main model.

C.0.1 Model equations

Main model

Adoption fraction = IF THEN ELSE(Netting scheme policy=1, ((Fraction willing to adopt("Pay-back period current netting scheme"))/100)*"Effect of shortage in tm on adoption", IF THEN ELSE(Netting scheme policy=2, ((Fraction willing to adopt("Pay-back period proposed netting scheme"))/100)*"Effect of shortage in tm on adoption", ((Fraction willing to adopt("Pay-back period no netting scheme"))/100)*"Effect of shortage in tm on adoption"))

WOM effect = ((Potential rooftop solar adopters*Rooftop solar adopters*Contact rate*Adoption from WOM fraction)/(Potential rooftop solar adopters+Rooftop solar adopters))/12

Innovation effect = ((Potential rooftop solar adopters*Rooftop solar adopters*Adoption from innovation)/(Potential rooftop solar adopters+Rooftop solar adopters))/12

Adoption percentage of suitable rooftops = MIN((Rooftop solar adopters/("Total households / total grid users"*Percent suitable rooftop))*100, 100)

PV installation costs = (PV installation cost lookup(Time)*PV cost sensitivity variable*Tax rate*Inflation)*((1+Interest rate)î0)

Self-consumption rate = IF THEN ELSE(Netting scheme policy=1, 0.3*"Self-consumption rate sensitivity variable", IF THEN ELSE(Netting scheme policy=2, 0.4*"Self-consumption rate sensitivity variable" , 0.45*"Self-consumption rate sensitivity variable"))

Neighborhood subgroups

Customers installing rooftop solar group1 = ((((Potential rooftop solar adopters Group1*(Adoption fraction Group1 LI 2)*0.7)*Adoption sensitivity variable)+((Potential rooftop solar adopters Group1*(Adoption fraction Group1)*0.3)*Adoption sensitivity variable)++WOM effect Group1+ Innovation effect Group1)/Time to install rooftop solar)/12

Customers installing rooftop solar group2 = (((Potential rooftop solar adopters Group2*(Adoption fraction Group2*Adoption sensitivity variable))+WOM effect Group2+Innovation effect Group2)/Time to install rooftop solar)/12

Adoption fraction group1 - 2 = IF THEN ELSE("LI-netting scheme"=1, ((Adoption rate Group1("Pay-back period current netting scheme LI"))/100)*Policy impact sustainability plan Group1, Adoption fraction Group1 LI)

Adoption fraction group1 - 1 = IF THEN ELSE(Netting scheme policy=1, ((Adoption rate Group1("Pay-back period current netting scheme LI")))/100*Policy impact sustainability plan Group1, IF THEN ELSE(Netting scheme policy=2, ((Adoption rate Group1("Pay-back period proposed netting scheme LI")))/100*Policy impact sustainability plan Group1, ((Adoption rate Group1("Pay-back period no netting scheme LI")))/100*Policy impact sustainability plan Group1))

PV installation cost group1 = ((PV installation cost lookup(Time)*Inflation+(PV installation cost lookup(Time)*Inflation*In rate Low Income*10))*Subsidies)-"LI-subsidy"

C.0.2 Simulation results

Experiments 1, 2, 3

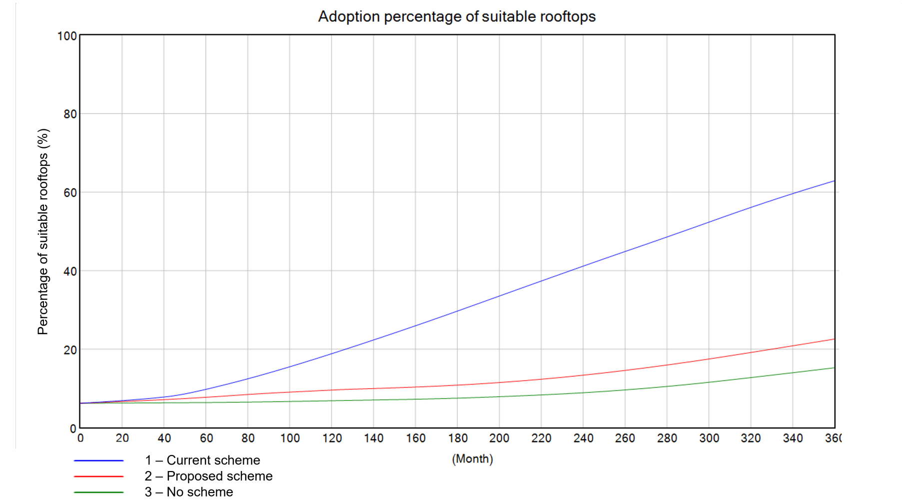


Figure 103: Adoption percentage of suitable rooftops for experiments 1-3

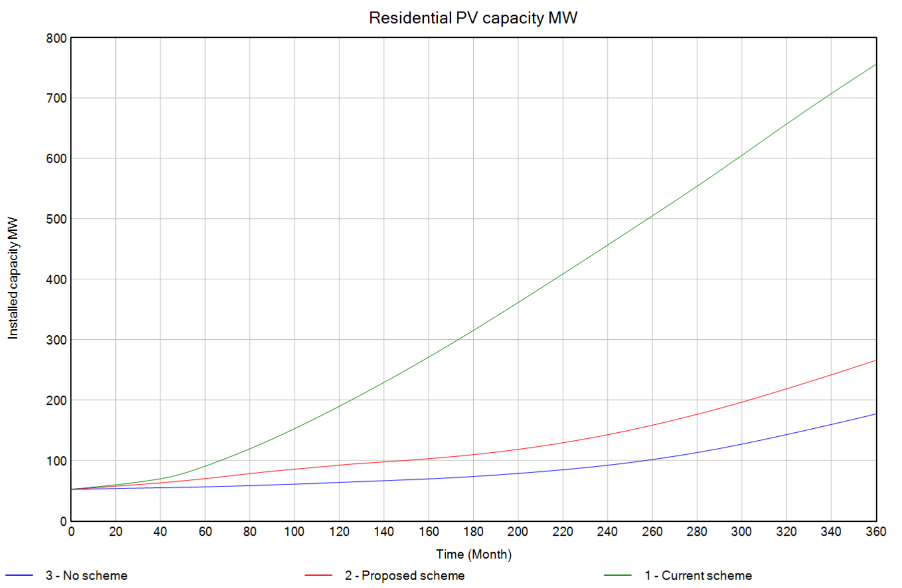


Figure 104: Total installed capacity for experiments 1-3

Experiments 1, 2, and 3 with varying adoption rates

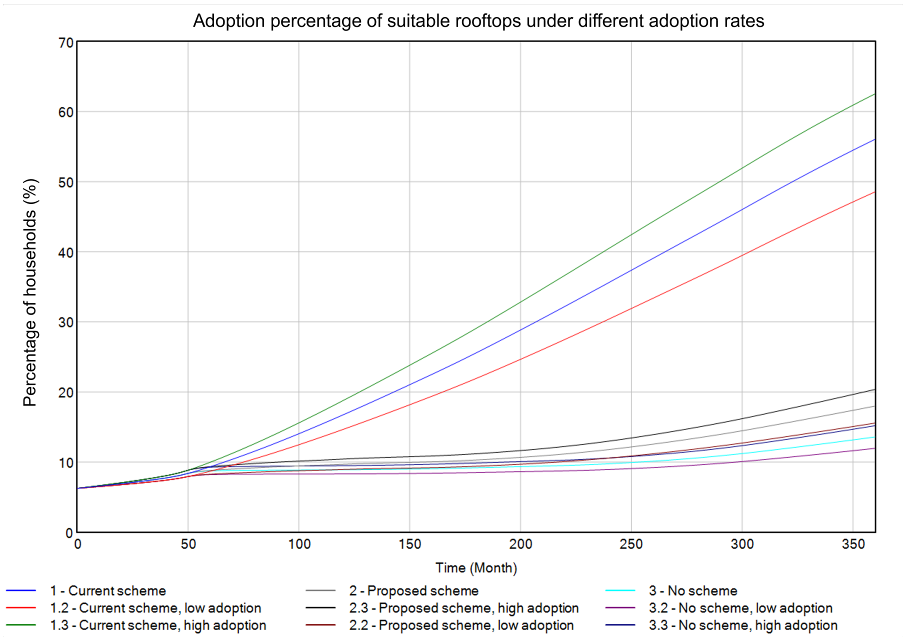


Figure 105: Adoption results for experiments 1-3 under different adoption rates

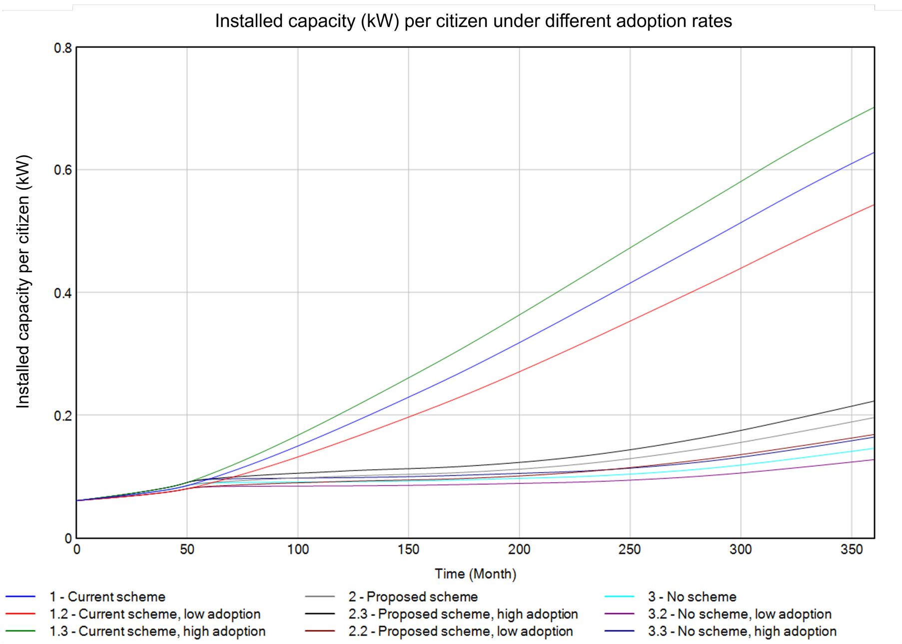


Figure 106: Installed capacity results for experiments 1-3 under different adoption rates

Experiments 1, 2, and 3 with varying adoption rates, for subgroups 1 and 2

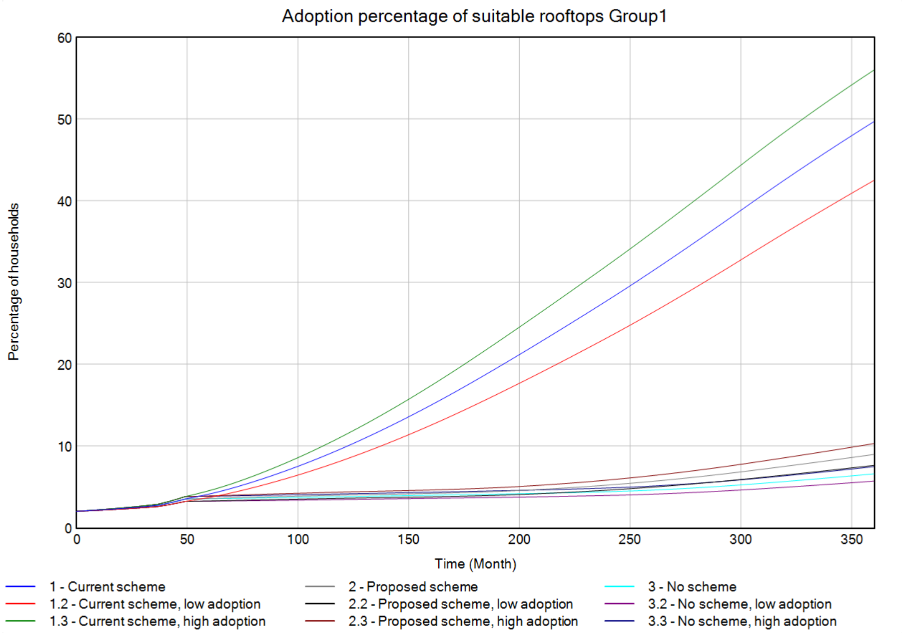


Figure 107: Adoption percentage of suitable rooftops for group 1

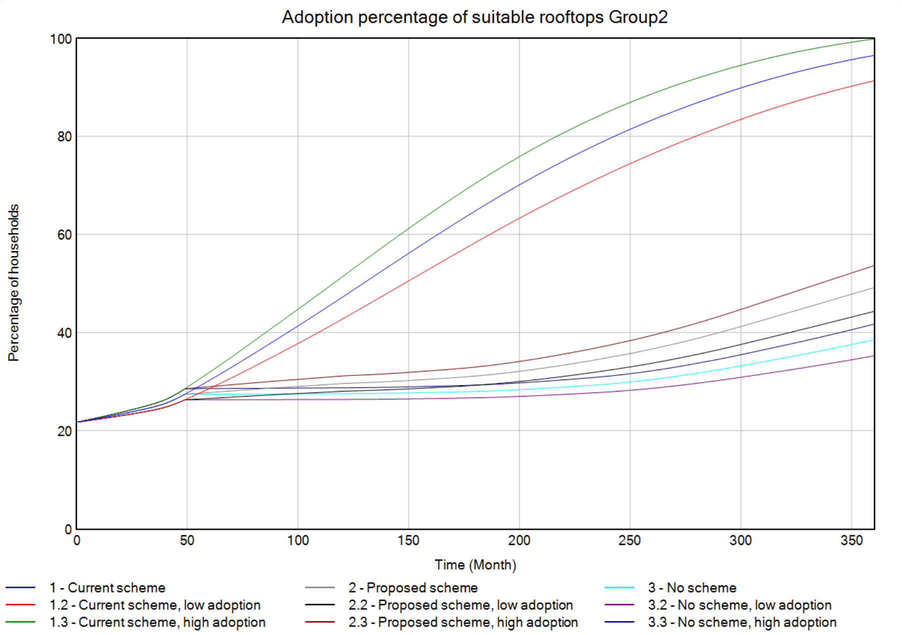


Figure 108: Adoption percentage of suitable rooftops for group 2

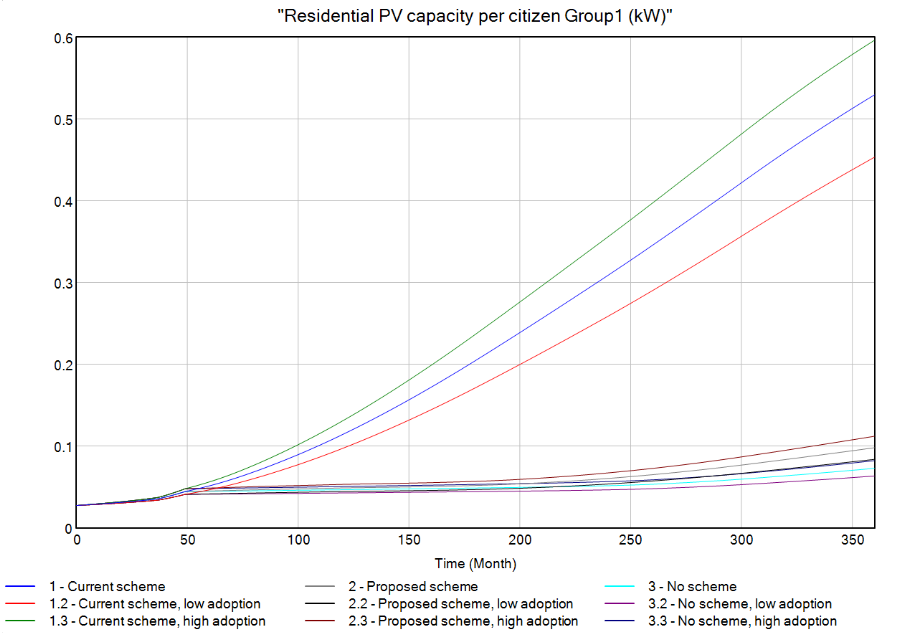


Figure 109: Installed capacity per citizen for group 1

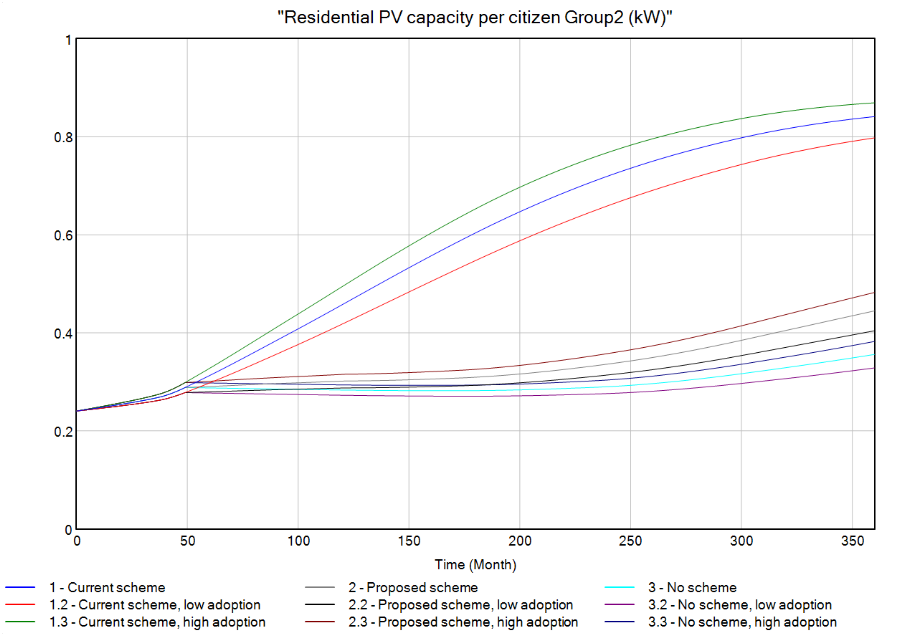


Figure 110: Installed capacity per citizen for group 2

Payback periods under different netting scheme options and scenario's

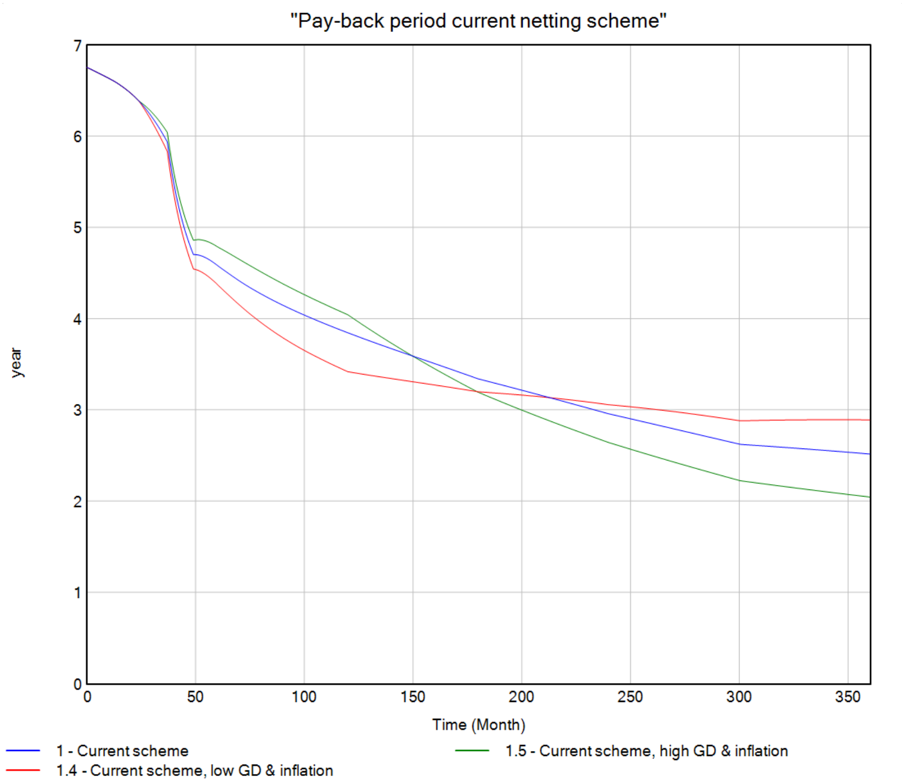


Figure 111: Payback times of the current and proposed netting scheme under different scenario's

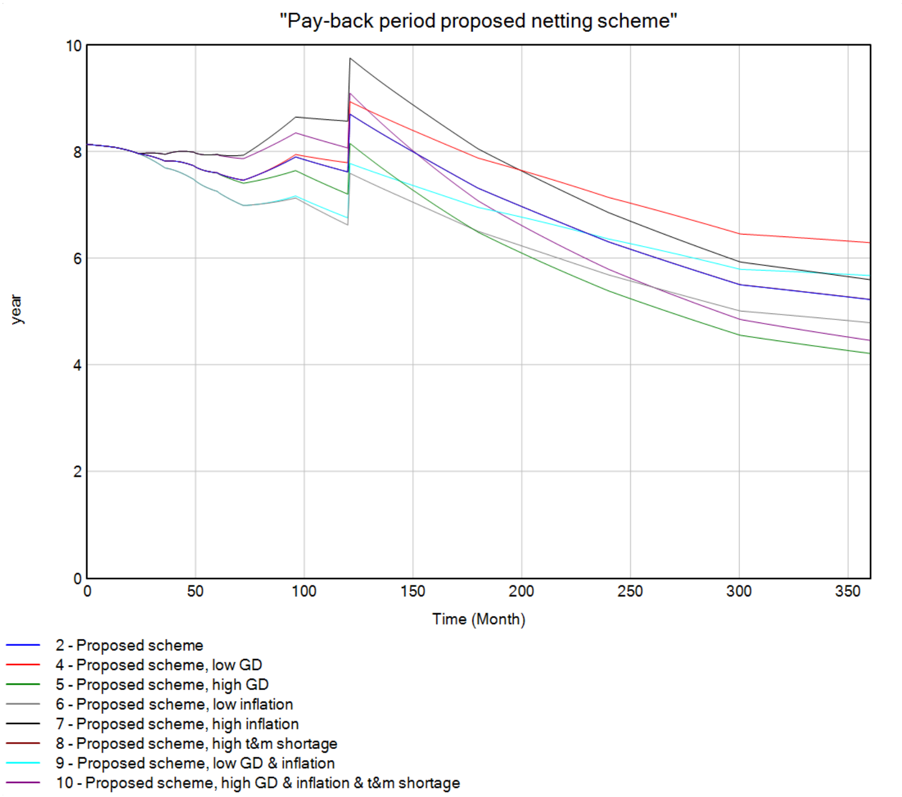


Figure 112: Payback times of the current and proposed netting scheme under different scenario's

Results of experiments 4-10: External influence scenario's

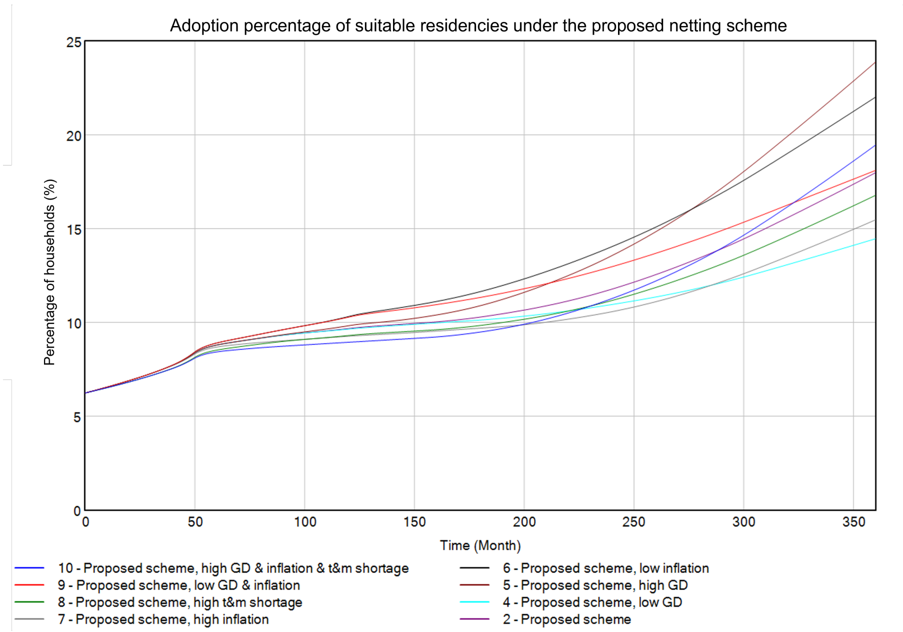


Figure 113: Results of experiments 4-10: adoption percentage of suitable rooftops

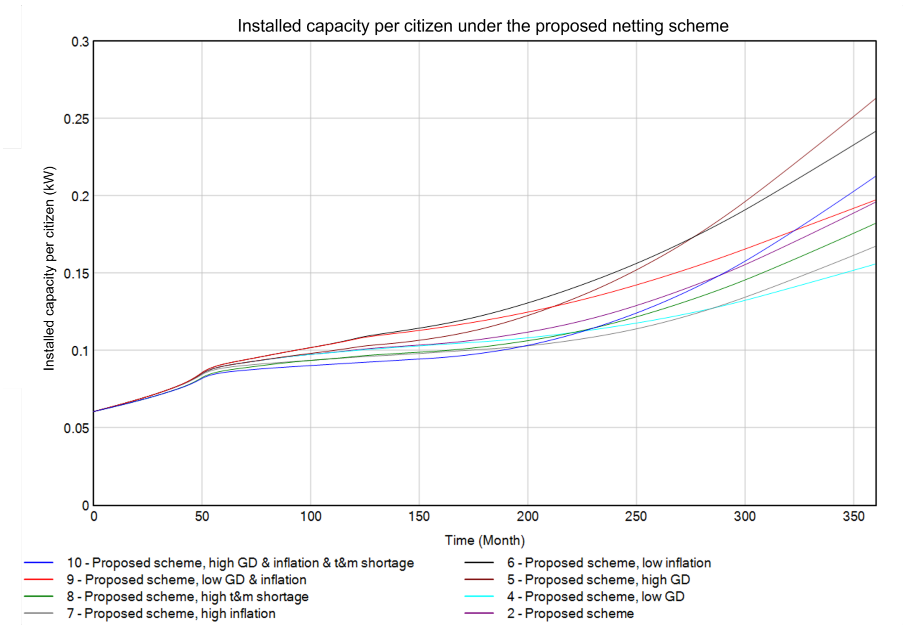


Figure 114: Results of experiments 4-10: installed capacity per citizen

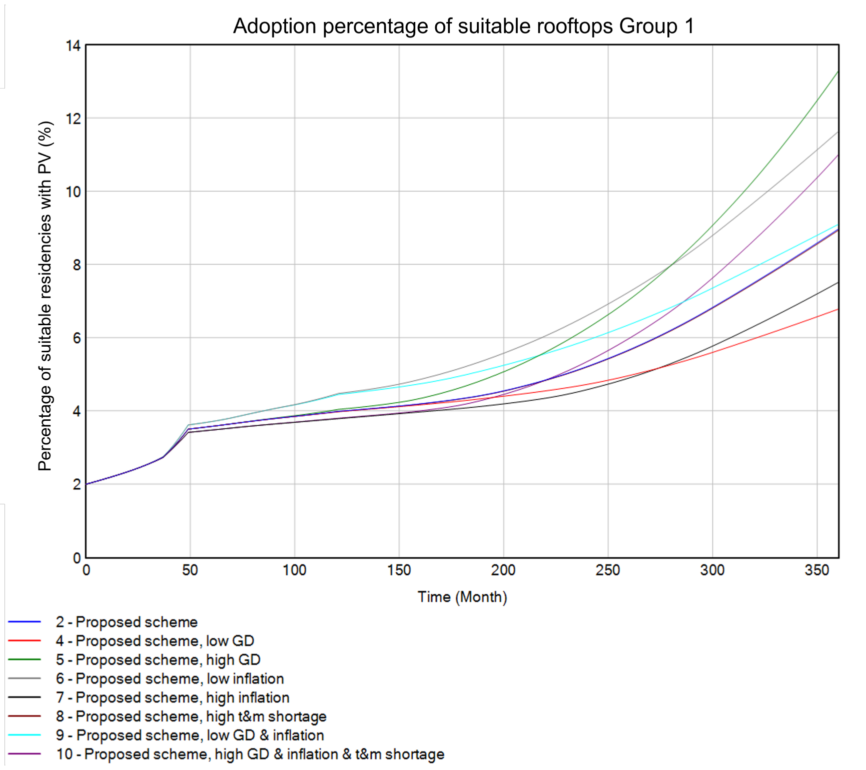


Figure 115: Results of experiments 4-10: overall adoption percentage of suitable rooftops in Group 1

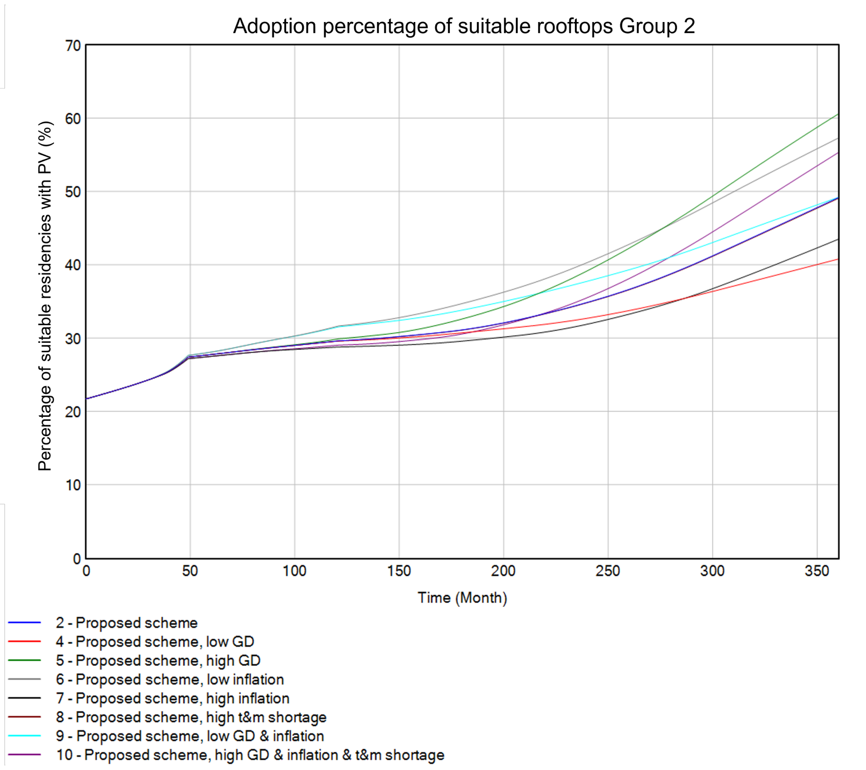


Figure 116: Results of experiments 4-10: overall adoption percentage of suitable rooftops in Group 2

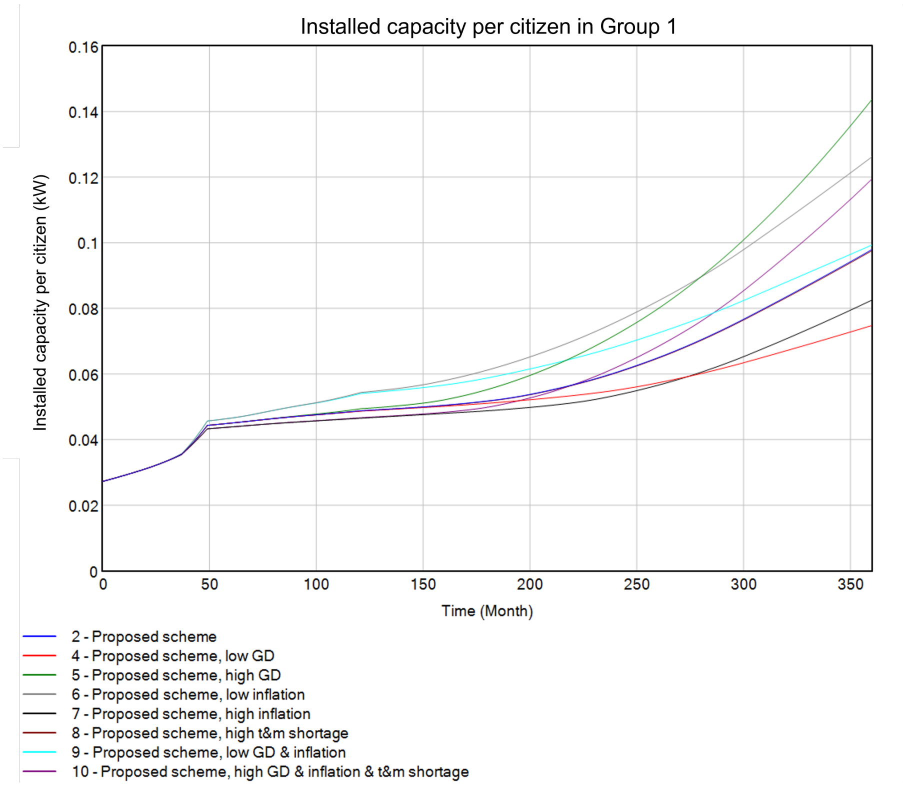


Figure 117: Results of experiments 4-10: installed capacity per citizen in Group 1

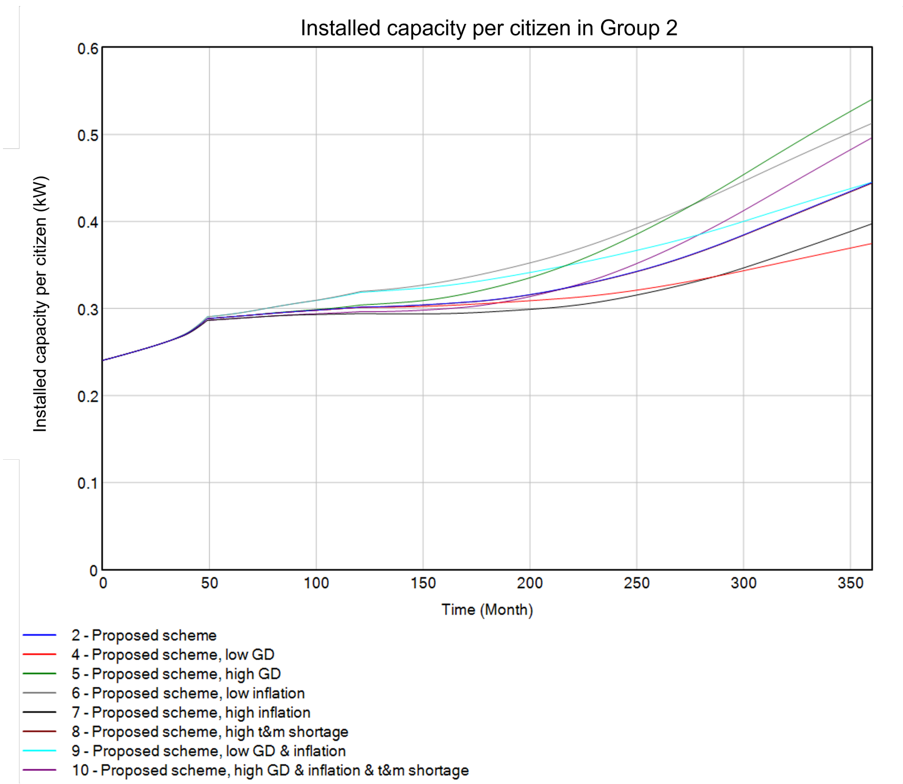


Figure 118: Results of experiments 4-10: overall adoption percentage of suitable rooftops in Group 2

PV installation costs under different scenario's

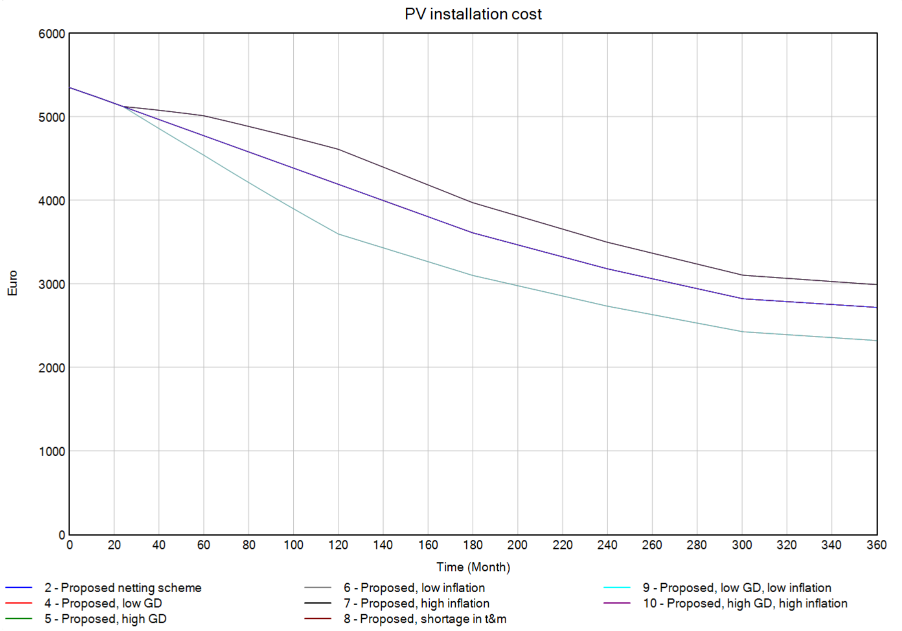


Figure 119: Average PV installation costs under different scenario's

Leveling policy experiments - Sustainability plan mandate

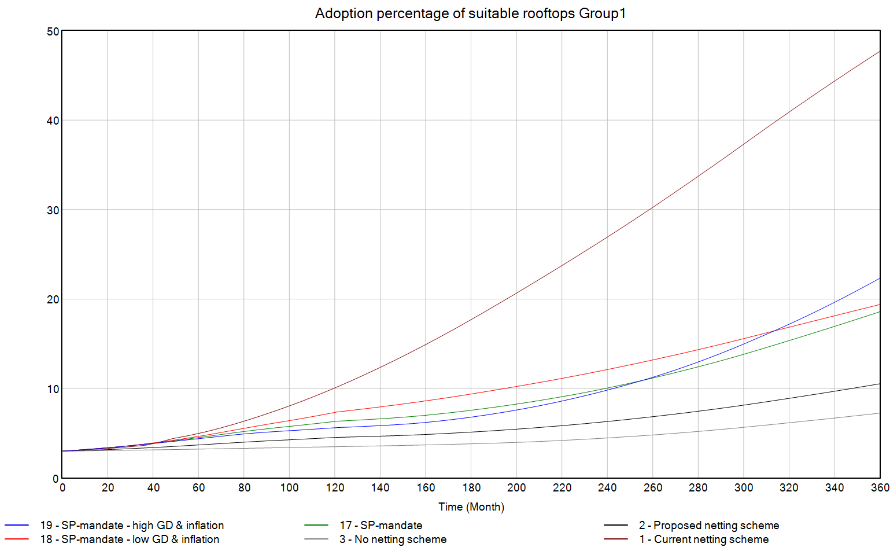


Figure 120: Adoption percentages of the suitable rooftops for the neighborhoods in group 1 under different configurations of the Sustainability Plan mandate

Leveling policy experiments - Low-income netting scheme allowance

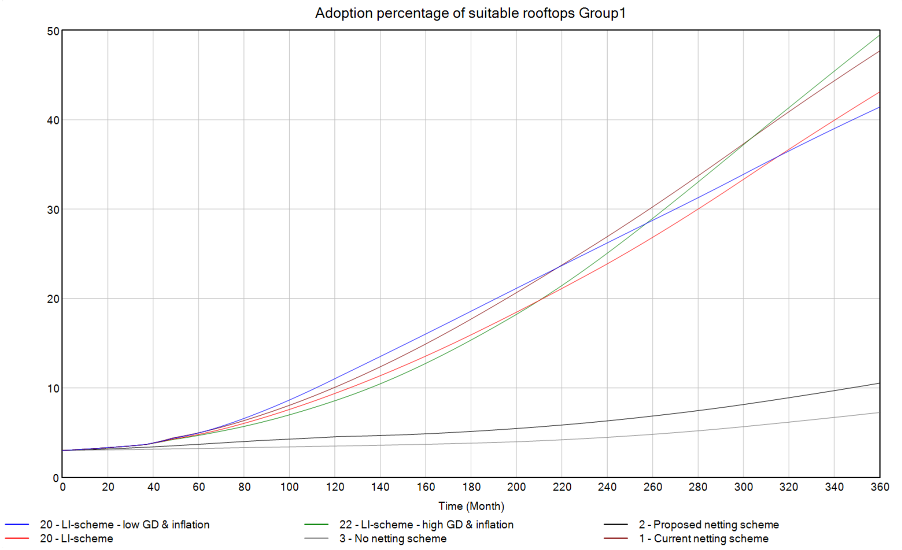


Figure 121: Adoption percentages for the neighborhoods in group 1 under different configurations of the LI-netting scheme

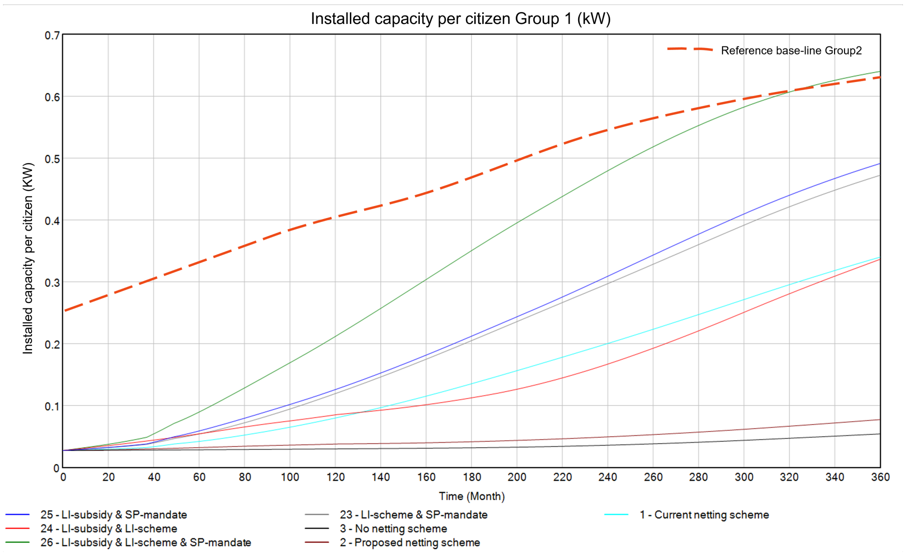


Figure 122: Installed capacity of group 1 neighborhoods under different combinations of leveling policy measures, compared with the installed capacity of group 2 in the base case