Sensitivity Analysis for Heating Transition Models
A case study of the CEGOIA model

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Abstract. The Dutch heating transition involves changing the heating systems of eight million buildings to a sustainable alternative by 2050. Many heating system technologies are available, but deciding which systems are cheapest for all these buildings is a difficult question to answer. Local policymakers are increasingly making use of heating transition models that estimate the feasibility and costs of systems in municipal neighbourhoods. The applicability of these models is limited by the degree of uncertainty about the future as well as the complexity in communicating the model results to policymakers. Sensitivity Analysis (SA) is a tool with which the most influential model uncertainties can be identified, quantified and communicated. So far, limited energy transition model studies have extensively used this method. A case study of SA on the CEGOIA heating transition model was performed to fill this gap and evaluate SA's value. CEGOIA calculates the costs of a variety of heating systems and optimizes the allocation of scarce energy carriers such as green gas and hydrogen to find the lowest societal costs. Sensitivities of eight heating system options were analysed in different archetypical neighbourhood contexts using Fractional Factorial analysis, the Method of Morris and the Sobol' Method. Out of an initial set of 953 parameters, a selection of 5 to 10 highly influential variables – consistent between neighbourhoods of different physical characteristics – was identified for each heating system option. High sensitivities indicate that changing the value of a parameter leads to a large change in total costs. These sets therefore describe exactly what uncertainties are crucial to evaluating what heating system is the cheapest possible solution. Variables in these sets include, but are not limited to, the price and infrastructure costs of electricity and gas, heating installation costs and insulation costs. Besides results and insights from the CEGOIA SA, further applications for SA in heating transition modelling is postulated to be able to improve the modelling process as well as better understand complex model dynamics. One recommendation is therefore to include SA as part of the toolkit for the large heating transition models currently being used in the Netherlands. The main barrier for doing so with CEGOIA is the computational time of the model, which limited the amount of parameters that could be evaluated as well as the SA techniques that could be used. Still, more systematic analysis of sensitivities in heating transition models will provide insights that ultimately aid Dutch policymakers in making robust decisions.

Keywords: Sensitivity Analysis, Model Uncertainty, Heating Transition Modelling, Method of Morris, Sobol' Method

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1. Introduction

The 2019 Dutch Climate Accord proposes a set of agreements and goals with all carbon-emitting sectors that aim to realize a 95% emission reduction by 2050 (Ministerie van Economische Zaken en Klimaat, 2019). One of five sectors recognized in these plans is the Built Environment, in which seven million residences and one million utility buildings require a sustainable heating alternative to natural gas. The Ministry of Environmental Affairs and Climate propose a decentralized approach in which municipalities direct local heating transitions focussed on a neighbourhood scale. In recent years this approach has led to the frustration of local policymakers and citizens, who perceive issues related to a lack of clarity about vision and responsibilities as well as costs (Jansma, Gosselt, & de Jong, 2020).

Models that simulate, optimize and evaluate the energy system have increasingly been used to support policymakers in their decision-making (DeCarolis et al., 2017). For instance, the Dutch government supports municipalities with Vesta MAIS modelling studies of the costs and impacts of sustainable alternatives in their neighbourhoods (Brouwer, 2019). These models can provide decisionmakers with perspective for action as well as financial insight, transparency and legitimacy, however are difficult to use (Henrich, Hoppe, Diran, & Lukszo, 2021).

It was found that municipalities rely on third party modelling expertise since the models are often found to be too complex to use. This complexity has multiple causes: the energy system of buildings is relatively complicated and many assumptions need to be made to arrive at useful scenarios with which to evaluate policy. The quality of such models is not purely technical, the ability to communicate uncertainty transparently to policymakers is crucial so that robust policy can be made (MacGillivray & Richards, 2015; Walker, Lempert, & Kwakkel, 2013). The degree to which uncertainty in heating transition models is explored is therefore of interest.

Sensitivity Analysis (SA) is the process of investigating how uncertainty in the output of a model can be apportioned to different sources of uncertainty in model inputs (Saltelli, Tarantola, Campolongo, & Ratto, 2004). This analysis is part of good modelling practice, but is often found to be done inadequately: the majority of studies evaluate the effects of changing individual parameter values one at a time which is inadequate for models with non-linear behaviour (Ferretti, Saltelli, & Tarantola, 2016).

The use of adequate SA methods to investigate the robustness of energy transition modelling based policy is increasing, but still less common than methods such as Life Cycle Assessments and Cost-Benefit Analysis (Bottero, Dell'anna, & Morgese, 2021). What's more is that SA studies that focus on heating typically limit scopes to individual building energy models, from which few policy implications can be derived (Mastrucci, Pérez-López, Benetto, Leopold, & Blanc, 2017; Menberg, Heo, & Choudhary, 2016). In an integrated study of uncertainty in UK energy transition pathways, Pye, Sabio, & Strachan (2015) demonstrated the value that SA can have for identifying important developments that leads to robust policymaking. To add to this discussion this study presents a SA case study of CEGOIA, a privately developed heating transition model.

2. CEGOIA

The CEGOIA model performs an economic and energetic evaluation of various sustainable heating systems applied to real-world neighbourhoods and subsequently optimizes the allocation of energy carriers within a region to arrive at the lowest cost assignation of heating systems. The model is privately developed and used by CE Delft to advise Dutch policymakers about the heating transition (Meyer & van de Poll, 2021). It uses a diverse set of data, including information about real-world buildings, infrastructure and heat sources (**Fig 1**). Roughly 1000 parameters are additionally used to model the dimensioning of energy demand and various heating systems.

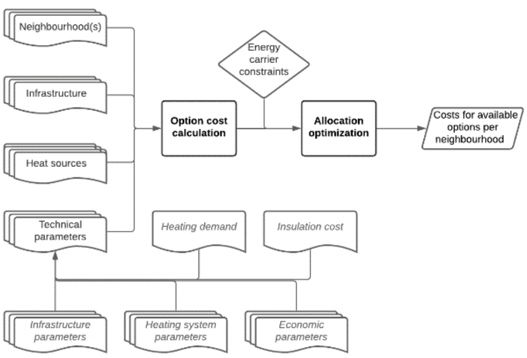


Fig 1: Simplified overview of CEGOIA model functions and inputs.

The model is based around the concept of *options*, which represent specific heating systems coupled with additional interventions necessary to implement the systems in a neighbourhood (**Fig 2**).

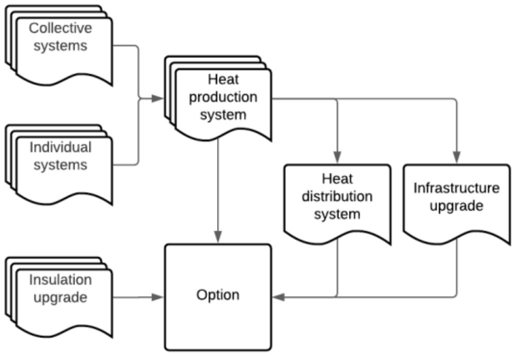


Fig 2: CEGOIA heating system option attributes

CEGOIA is in continuous development so that functionality required to answer specific questions can be added on the fly. As such, there are several modules and niche heating system options included in the model which were not included in this analysis.

3. Methodology

The purpose of the CEGOIA SA is to identify a set of key uncertainties and quantify their sensitivities to be generalizable to different contexts and heating system options. Typical ingredients for SA include a set of input parameters with probabilistic uncertainty distributions, an experimental design with which to vary parameter values and an output value for which to construct sensitivity measures (Morio, 2011). Since CEGOIA calculates costs for different systems using different sets of parameters, eight heating systems were evaluated, for each of which separate analysis was performed: 1) Air-based heat pump, 2) Ground-based heat pump, 3) Condensing boiler, 4) Hybrid heat pump, 5) Pellet boiler, 6) HT heat net, 7) MT heat net and 8) LT heat net. The output value used to base sensitivity is the annualized total costs of the heating system option. The model was set to evaluate the costs of options in 2050 and the analysis region was restricted to only one neighbourhood. Because of CEGOIA model logic (**Fig 1**), this resulted in not evaluating the effects of limited availability of energy in the study.

3.1. SA techniques

Sensitivity Analysis techniques are generally divided into two classes: Local and Global. Local techniques focus on the effects of individual parameters on model outcomes, whereas Global SA (GSA) varies the entire input space by which interaction effects are considered (Saltelli & Annoni, 2010). The analysis assumed no previous knowledge about model uncertainty and (non)-linearity behaviour. As such, an initial Uncertainty Analysis (UA) was done using a two-way Fractional Factorial experiment design (Saltelli et al., 2008). This is a Local method that is computationally cheap.

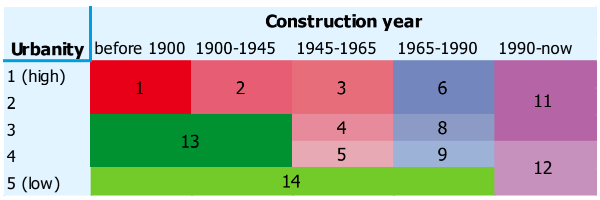
The second technique used is the Method of Morris (MM), by which Elementary Effects (EE) of parameters are calculated (Ziehn & Tomlin, 2017). MM is computationally inexpensive and captures indirect model effects, because of which it is often used as a screening method for models with large input spaces (Campolongo, Cariboni, & Saltelli, 2007).

The third and final method used is the Sobol' method, by which sensitivity indices of first and total-order effects are estimated (Sobol' & Kucherenko, 2009). Sobol' index estimation requires a large number of model runs, because of which these indices could only be estimated for eight model parameters. The experiment designs and sensitivity measure calculation of all three methods were generated using the contributions of Herman & Usher (2018).

3.2. Archetypal neighbourhoods

Real-world neighbourhoods have diverse physical characteristics, many of which influence the viability of heating system options. Particular characteristics of note for the heating transition were found to include the socio-economic characteristics of inhabitants, dimensioning and age of infrastructure as well as the number, age, function and type of buildings (Mutani & Todeschi, 2020). Collective heat sources from which heat nets can source energy are also highly location-specific.

Fig 3: Classification of archetypal neighbourhoods



To deal with the heterogeneity of real neighbourhoods an archetypal approach was used. This approach is typical when evaluating effects in diverse systems and allows for conclusions about model sensitivities in different contexts (Marchau, Walker, Bloemen, & Popper, 2019). Mastrucci et al. (2017) demonstrated the viability of this approach in a GSA of a simplified building model that surrogate models based on specific construction periods and building types. They concluded such typification capture significant contextual differences with a high degree of conformity to the original model.

A novel archetypal classification approach was used for CEGOIA based on the density of neighbourhoods and the dominant construction period of buildings within it

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using the classification (based on the scheme in **Fig**) and subsequent aggregation of Dutch neighbourhoods using a public dataset (Centraal Bureau voor de Statistiek, 2020). Due to time constraints, five archetypes were evaluated ().

Even considering only those parameters directly related to individual heating systems, CEGOIA and heating transition models, in general, have a larger than conventional number of input parameters on which to use SA (Sheikholeslami, Razavi, Gupta, Becker, & Haghnegahdar, 2019). Three types of parameters can be distinguished: spatial parameters which describe the region's physical characteristics, scenario parameters which describe the changes to the current energy system context to the future one and modelling parameters, with which economic and energetic impacts are modelled. Spatial characteristics have been accounted for in the archetypical approach. Scenario and modelling parameters, therefore, remain for varying under SA.

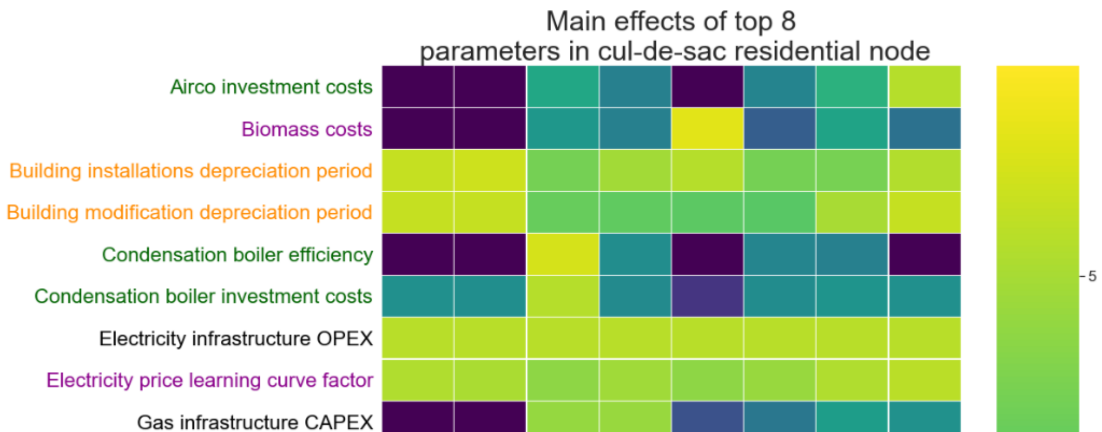
Table 1: Selected neighbourhoods for SA

Archetype	Description
2	High urbanity '**first ring**', predominantly built between 1900 and 1945
3	High urbanity '**post-war**', built between 1945 and 1965
6	High urbanity suburban 'Bloemkoolwijk' or '**cul-de-sac**' built between 1965 and 1990
11	High and moderate urbanity **recent** construction, built after 1990
14	Non-urban (**rural**) areas, with diverse construction periods

3.3. Parameter grouping and probability distributions

By reducing the number of input variables to vary more powerful SA techniques can be used (Saltelli et al., 2008)**.** The screening was therefore done in conjunction with factor grouping (Anderson, You, Wood, Wood-Sichra, & Wu, 2015). SA methods assume input variables are not interdependent, but in practice, this is not always the case. By grouping sets of input parameters together, independency can be assured and the number of variables to vary decreased. By doing so, however, the assumption is introduced that variable values correlate perfectly. This is not a valid assumption in most cases, and so it must be recognized that the explanatory power of SA using factor grouping is decreased. Still, the method was used for CEGOIA to arrive at a set of parameters with which SA could be performed in a realistic timeframe.

Because of the high number of input variables, probability distributions for the uncertainty of parameter



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values were gathered using expert elicitation with the help of the NUSAP (Number Unit Spread Assessment Pedigree) framework (Funtowicz & Ravetz, 1990).

Three CEGOIA model developers were involved in the definition of the distributions in **Figure 4** which were subsequentially assigned to model parameters. One symmetrical and two skewed uncertainty distribution were deemed suitable, and uncertainty about a parameter's value was labelled with certain, uncertain or very uncertain. This method was previously employed by Pye et al. (2018) to generate distributions on input variable uncertainty for SA.

4. Results

Three SA techniques were used for the screening and sensitivity evaluation of CEGOIA parameters. Analyses were done for five different neighbourhoods. The model took two to three days for evaluating each of the fifteen SA experiments.

4.1. Screening

Fractional Factorial analysis of 265 (grouped) model variables representing 695 CEGOIA parameters was done as a first screening test. Alikeness between options (**Figure 5**) was evaluated using the Main Effects to get an indication of how alike options are. Correlation is dictated by the similarity in heating techniques and temperature at which heat is delivered, indicating that sensitivities of correlating options will be similar.

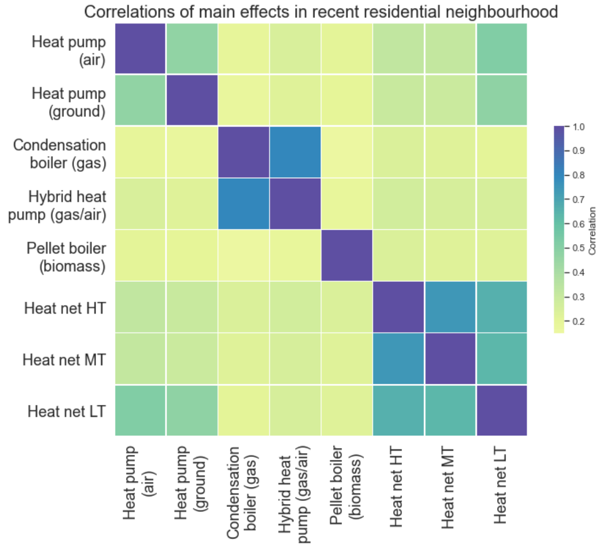

Fig 5: Correlation of heating system options based on the estimated parameter Main Effects

The individual parameter effects found using this method indicated in **Figure 6** suggest that there is a small set of parameters that has a significant impact on all heating system options. These are the costs related to electricity and depreciation periods of building modifications (insulation) and installations (heat production and distribution systems). Lighter colours in **Figure 6** indicate a higher effect on total system cost observed when that single parameter is increased; note that no interaction effects are included. Effects coloured dark green can be considered insignificant due to the relatively low confidence associated with FF analysis. Further parameters that have high direct effects are specific to heating systems: heat pumps are sensitive to the investment costs of the heat pumps, costs of radiators and insulation. Boilers are sensitive to costs related to gas, heat nets are sensitive to the connection costs and simultaneity factor with which the nets are dimensioned.

Based on results from FF analysis a reduction of parameters to 119 (grouped) model variables representing 491 CEGOIA parameters was done. These parameters were used for the application of the Method of Morris. **Figure 7** contains results indicating indirect effects for an hybrid heat pump, whilst **Figures 8, 9 and 10** contain direct effect results for respectively a, air heat pump, hybrid heat pump and MT heat net. In **Figure 7**, the absolute Elementary Effects are plotted on the x-axis and the standard deviation of the option is plotted on the y-axis. The standard deviation that is estimated by the Method of Morris is a stand-in for the indirect effect of the parameter (Morio, 2011). In relative terms, the covariance of insulation costs and heating demand was found to be high (0,5+), whereas many of the other parameters have ratios that are at the lower end. In general it can thus be said there are few interaction effects in the model. This implies that the use of

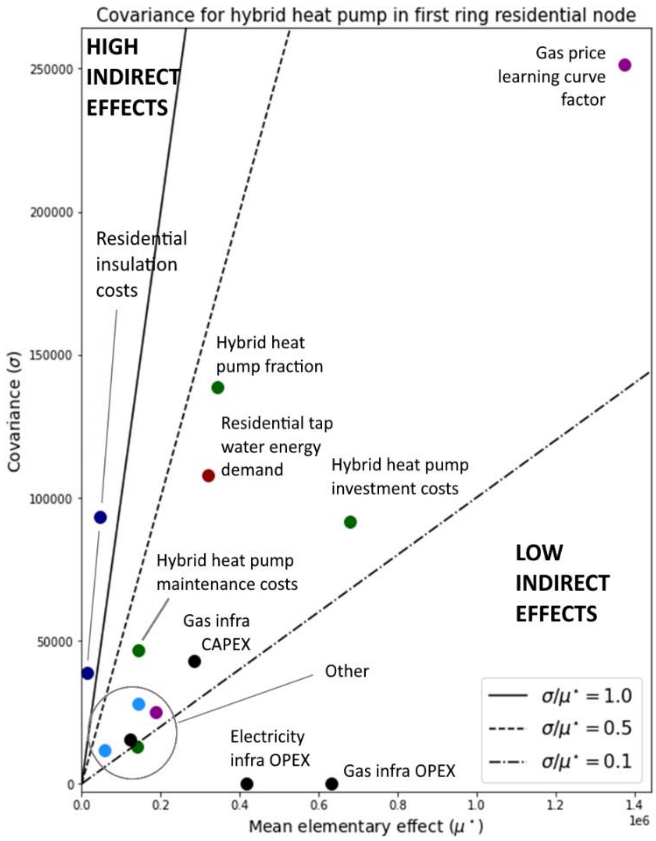

Fig 7: Elementary Effects of hybrid heat pump and related direct (x-axis) and indirect (y-axis) effects

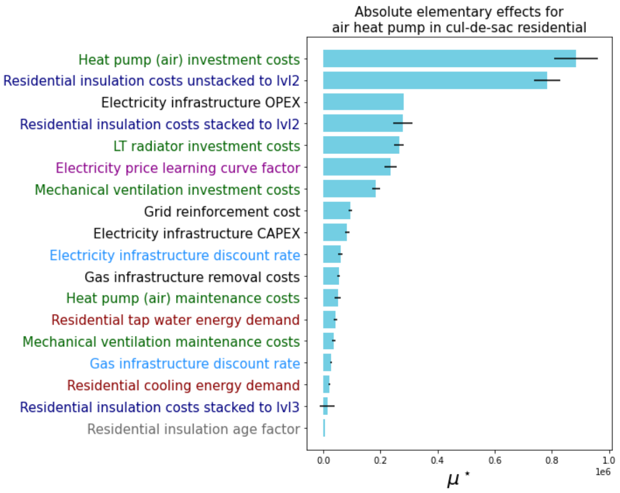

Fig 8: Elementary Effects for air heat pump

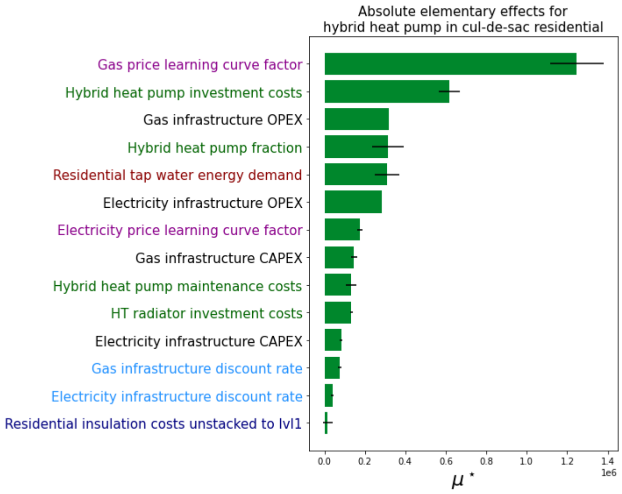

Fig 9: Elementary Effects for hybrid heat pump

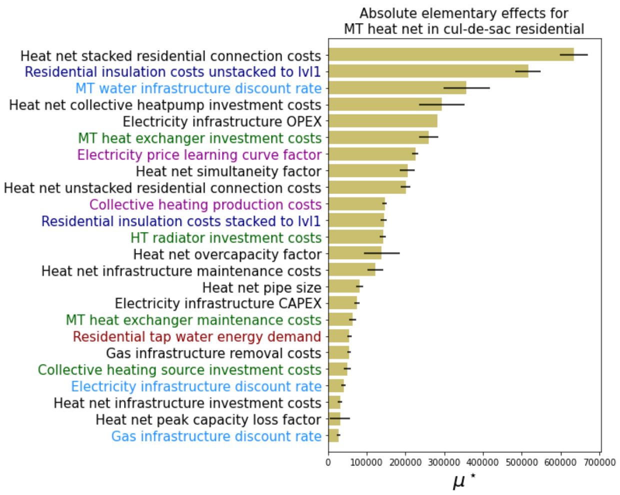

Fig 10: Elementary Effects for MT heat net

Local SA techniques can be a decent estimator for what actual sensitivities are in heating transition models such as CEGOIA.

Figures 8 reports that for a typical Dutch house in a typical Dutch neighbourhood the costs of insulation and the costs for the heat pump itself are the main sources of sensitivity; changes in these values influence how cheap or expensive the total system will be the most. Other parameters of note are the electricity price, radiator and ventilation costs. Although often a topic when discussing electrification, grid reinforcement costs have a relatively small effect. Because the cul-de-sac neighbourhood uses averaged data from real neighbourhoods, this implies that reinforcement costs are not often going to be a deciding factor in choosing an alternative. The OPEX costs for electricity infrastructure is a parameter that is very influential in each of the heating system options. Yet, in the big picture, they may not be very important to decision making in the heating transition. This is because these costs are about the same for any of the heating system options evaluated by CEGOIA. After all, all buildings are required to be connected to – and pay for – the electricity grid.

Figures 9 concerns hybrid heat pumps results. Their costs are found to mostly be influenced by the price of gas and the investment costs for the pump itself. The fraction of electricity/gas is also important. If hybrid heat pump installers can realize low investment costs as well as a high fraction of electricity use without spending much money on insulation this option will often be the cheapest in comparisons.

Figures 10 shows the effects of MT heat net parameters. The connection costs of heat nets, insulation costs, collective heat pump investment costs and the discount rate used for MT heat net infrastructure are the most influential parameters. Developments that decrease the connection costs will have the biggest effect on the choice of MT heat nets. The discount rate – which is set to 6% in CEGOIA – is of particular interest. These rates are set by heat net investors to reflect the profitability of an investment. Lower discount rates result in a cheaper total system, and could be realized by collectivizing heat net investment by public institutions. Other parameters that are also of notable consequence are the electricity price, costs of the collective heat source and further heat net specific parameters such as the simultaneity factor, overcapacity factor and pipe sizing. Somewhat surprisingly the costs of the heat from a collective heat source is not as influential as the collective heat pump – which is required to meet peak demand.

After using MM a further selection of parameters was done for which to determine model sensitivity using Sobol' indices. Because the Sobol method is very computationally expensive, only seven parameters could reasonably be included in this analysis. These were chosen from the parameters that were consistently found to be influential amongst options and unsurprisingly comprise mostly scenario parameters rather than modelling ones. Several of the selected parameters were constructed from further grouping:

- **Insulation costs**: Includes all costs associated with insulation upgrades: every energetic performance level, building type and building period for both residential and utility applications.

- **Heating system costs**: Covers investment costs and maintenance costs of production (like heat pumps and pellet boilers), and distribution systems (radiators).
- **Gas infrastructure costs**: Covers the CAPEX, OPEX as well as the removal costs for gas infrastructure, and represents the trend of adding or removing new gas infrastructure.
- **Heat net infrastructure costs**: Encapsulates a wide range of costs, specially selected based on their appearance on the heat maps. Includes connection costs, peak factors and provisions.
- **Gas price**: The cost of (green) gas in 2050 based on the learning curve factor.
- **Electricity price**: The cost of electricity in 2050 based on the learning curve factor.

4.2. Sensitivities

The sensitivities of eight heating system options were attributed to seven parameters. Aggregated results displayed in **Table 2** show that the costs of each system can generally be explained by a handful of trends. Heat pumps are equally sensitive to the costs of the heat pump and insulation costs. Condensing boilers and hybrid heat pumps are sensitive to the price of gas, insulation and heating systems. Pellet boilers are found to be principally sensitive to heating system costs, but it must be noted that biomass costs were not included in this analysis. Heat nets vary significantly in their sensitivity. LT heat nets are notably much less sensitive to heat net infrastructure costs, but more sensitive to the costs of insulation and heating installation.

Between neighbourhoods, it was found that older neighbourhoods have a much higher sensitivity to insulation costs than recent ones, and more rural neighbourhoods had higher sensitivities to infrastructure costs. Other than these differences, sensitivity results for the heating options are generally similar and so results in **Table 2** provide a way to rank the importance of uncertainties related to the included parameters.

5. Discussion and limitations

Three analyses were performed on CEGOIA. Fractional Factorial analysis results proved useful for identifying influential parameters as well as to quantify the likeliness of the different heating system options. Perhaps unsurprisingly, significant correlations were found between heating system options that use similar technologies, such as heat net and heat pump options. Although such results are not shocking to those that are familiar with the model, quantifying such relationships is useful to someone without tacit knowledge about the model's dynamics.

The distribution of parameter effects for each heating system option was found to conform to a Pareto-like distribution, in practice resulting in one to three variables having a very large effect, a handful having a medium effect, about a dozen variables having a weak effect and the others having little to no effect on the costs of an option. The types of variable that came up was fairly consistent throughout all options, such as heating system investment costs and energy price. This suggests that it is possible to reduce the total number of parameters whilst keeping the analysis meaningful.

Using MM it was found that insulation costs and heating demand do have significant effects on the model outcome, most of which is expressed through interactive effects with other variables. In contrast, certain infrastructure variables were found to have no indirect effect on the model outcome at all. The other factors were all found to have some indirect effects, although their ratio of indirect over direct effects can be considered to be generally low. For CEGOIA, these results imply that the direct effect observed by changing a single input variable is somewhat representative of the sensitivity of the model to that variable, as long as that variable is not insulation or energy demand related.

The Sobol method was used to determine general sensitivities of CEGOIA heating options to seven impactful partially grouped variables. Within this selection of variables, it was again found that the effect of higher-order interactions was on the low side overall. Sensitivities of heating system options were generally similar in different neighbourhoods, although insulation is more important in

Table 2: Sensitivities of CEGOIA to seven trend parameters, averaged over five neighbourhoods.

CEGOIA Sensitivities	Air heat pump	Ground heat pump	Condensing boiler	Hybrid heat pump	Pellet boiler	HT heat net	MT heat net	LT heat net
Insulation costs	40%	36%	0%	0%	0%	0%	6%	26%
Heating system costs	41%	46%	2%	15%	79%	2%	1%	23%
Gas infrastructure costs	0%	0%	16%	23%	0%	0%	0%	0%
Electricity infrastructure costs	12%	11%	7%	11%	16%	14%	9%	9%
Heat net infrastructure costs	0%	0%	0%	0%	0%	76%	75%	30%
Gas price	0%	0%	72%	47%	0%	0%	0%	0%
Electricity price	2%	1%	0%	0%	0%	1%	1%	2%

older neighbourhoods and infrastructure in less dense neighbourhoods. The sensitivities of CEGOIA heating options were found to be a useful way of highlighting the major trends that are important in determining the total system costs.

The inclusion of more parameters in this analysis could have provided many more specific insights. However, the computation time required for this SA is not insignificant and hindered the use of more elaborate analysis, especially using the Sobol method. The NUSAP approach used for defining parameter ranges was found to be useful, but further research should be supplemented by desk research for parameters with high uncertainty. The grouping of parameters and archetype approach was found to be a useful assumption with which to reduce the complexity of analysis, although care must be taken in applying results to real neighbourhoods that local circumstances matter.

6. Conclusions

Sensitivities found for CEGOIA were evaluated for eight different heating system options and five neighbourhoods with diverse physical characteristics. For each option, a set of ten to twenty parameters were found to have any significant influence on the total costs of the sustainable heating system. Generally speaking, the costs are very sensitive to a set of only one to five parameters. These parameters are often the price of the energy carrier(s) used by the system, the investment costs and efficiency of the heat production system and the costs for infrastructure. For heat nets, in particular, several parameters affecting heat net dimensioning were found to be of influence. The most important of these is the connection costs of buildings to the net.

Other parameters that contribute significantly to the model outcome are the maintenance of the heat production system and investment costs into the heat distribution system. The costs of insulation become more significant as the age of buildings in the neighbourhood gets older. The (heat) energy demand of buildings was found to not have much direct influence on the system costs. Indirectly, however, both insulation and energy demand were found to contribute significantly to the costs of the overall system.

With these results statements can be made about the confidence in CEGOIA predictions. A general observation is that as a whole, the margin of uncertainty in results is quite high. As a consequence, the decision of whether a certain option is going to be cheaper than another is often very uncertain. For this reason it is important to further investigate whether an option is more or less uncertain than another, and which developments are the primary drivers of the uncertainty. To reduce uncertainty in the heating transition policymaking should furthermore be based on controlling these developments.

Heating transition models often have a lot of input variables that could be considered for evaluation with SA. Spatial data should be systematically varied to be able to interpret the effect of the context in which the model is used. A way to do this is by creating typical contexts, such as the archetypical neighbourhoods that were constructed for CEGOIA. SA techniques are practical so long as the number of parameters and the time to calculate the model results is limited. Several ways to reduce the number of parameters exist and apply to heating transition models. These include the grouping of factors that are natural to move together and the screening of parameters with basic SA techniques.

The calculation time for CEGOIA was found to be a limiting factor to SA. More details about – and a higher level of confidence in sensitivity results, are attainable with more model runs. A further research recommendations for the CEGOIA model specifically is therefore to invest in optimizing the model for SA and investigating more parameter sensitivities using the Sobol' method, possibly considering one heating system at a time.

References

Anderson, W., You, L., Wood, S., Wood-Sichra, U., & Wu, W. (2015). An analysis of methodological and spatial differences in global cropping systems models and maps. *Global Ecology and Biogeography*, *24*(2), 180–191. https://doi.org/10.1111/geb.12243

Bottero, M., Dell'anna, F., & Morgese, V. (2021). Evaluating the transition towards post-carbon cities: A literature review. *Sustainability (Switzerland)*, *13*(2), 1–32. https://doi.org/10.3390/su13020567

Brouwer, M. (2019). *Het ene model is het andere niet: Zes rekenmodellen voor de energietransitie in de gebouwde omgeving onderzocht*. Arnhem.

Campolongo, F., Cariboni, J., & Saltelli, A. (2007). An effective screening design for sensitivity analysis of large models. *Environmental Modelling and Software*, *22*(10), 1509–1518. https://doi.org/10.1016/j.envsoft.2006.10.004

Centraal Bureau voor de Statistiek. (2020). Wijk- en buurtstatistieken. Retrieved from https://www.cbs.nl/nl-nl/dossier/nederland-regionaal/wijk-en-buurtstatistieken

DeCarolis, J., Daly, H., Dodds, P., Keppo, I., Li, F., McDowall, W., … Zeyringer, M. (2017). Formalizing best practice for energy system optimization modelling. *Applied Energy*, *194*, 184–198. https://doi.org/10.1016/j.apenergy.2017.03.001

Ferretti, F., Saltelli, A., & Tarantola, S. (2016). Trends in sensitivity analysis practice in the last decade. *Science of the Total Environment*, *568*, 666–670. https://doi.org/10.1016/j.scitotenv.2016.02.133

Funtowicz, S. O., & Ravetz, J. R. (1990). *Uncertainty and quality in science for policy*. (W. Leinfellner, Ed.), *Ecological Economics* (1st ed., Vol. 6). Dordrecht: Kluwer Academic Publishers. https://doi.org/10.1016/0921-8009(92)90014-J

Henrich, B. A., Hoppe, T., Diran, D., & Lukszo, Z. (2021). The Use of Energy Models in Local Heating Transition Decision Making: Insights from Ten Municipalities in The Netherlands. *Energies*, *14*(2), 423. https://doi.org/10.3390/en14020423

Herman, J., & Usher, W. (2018). SALib : Sensitivity Analysis Library in Python (Numpy). Contains Sobol , SALib : An open-source Python library for Sensitivity

Analysis, *41*(April), 2015–2017. https://doi.org/10.1016/S0010-1

Jansma, S. R., Gosselt, J. F., & de Jong, M. D. T. (2020). Kissing natural gas goodbye? Homeowner versus tenant perceptions of the transition towards sustainable heat in the Netherlands. *Energy Research and Social Science*, *69*(July), 101694. https://doi.org/10.1016/j.erss.2020.101694

MacGillivray, B. H., & Richards, K. (2015). Approaches to evaluating model quality across different regime types in environmental and public health governance. *Global Environmental Change*, *33*, 23–31. https://doi.org/10.1016/j.gloenvcha.2015.04.002

Marchau, V., Walker, W., Bloemen, P., & Popper, S. (2019). *Decision Making Under Deep Uncertainty. From Theory to Practice*. *Springer*.

Mastrucci, A., Pérez-López, P., Benetto, E., Leopold, U., & Blanc, I. (2017). Global sensitivity analysis as a support for the generation of simplified building stock energy models. *Energy and Buildings*, *149*, 368–383. https://doi.org/10.1016/j.enbuild.2017.05.022

Menberg, K., Heo, Y., & Choudhary, R. (2016). Sensitivity analysis methods for building energy models: Comparing computational costs and extractable information. *Energy and Buildings*, *133*, 433–445. https://doi.org/10.1016/j.enbuild.2016.10.005

Meyer, M., & van de Poll, F. (2021). *CEGOIA Gebruikershandleiding*. Delft. Retrieved from https://www.ce.nl/cegoia-warmte-gebouwde-omgeving

Ministerie van Economische Zaken en Klimaat. (2019). *Klimaatakkoord*. *Ministerie van Economische Zaken en Klimaat*. Den Haag. Retrieved from https://www.klimaatakkoord.nl/binaries/klimaatakkoord/documenten/publicaties/2019/06/28/klimaatakkoord/klimaatakkoord.pdf

Morio, J. (2011). Global and local sensitivity analysis methods for a physical system. *European Journal of Physics*, *32*(6), 1577–1583. https://doi.org/10.1088/0143-0807/32/6/011

Mutani, G., & Todeschi, V. (2020). Building energy modeling at neighborhood scale. *Energy Efficiency*, *13*(7), 1353–1386. https://doi.org/10.1007/s12053-020-09882-4

Pye, S., Li, F. G. N., Petersen, A., Broad, O., McDowall, W., Price, J., & Usher, W. (2018). Assessing qualitative and quantitative dimensions of uncertainty in energy modelling for policy support in the United Kingdom. *Energy Research and Social Science*, *46*(March), 332–344. https://doi.org/10.1016/j.erss.2018.07.028

Pye, S., Sabio, N., & Strachan, N. (2015). An integrated systematic analysis of uncertainties in UK energy transition pathways. *Energy Policy*, *87*, 673–684. https://doi.org/10.1016/j.enpol.2014.12.031

Saltelli, A., & Annoni, P. (2010). How to avoid a perfunctory sensitivity analysis. *Environmental Modelling and Software*, *25*(12), 1508–1517. https://doi.org/10.1016/j.envsoft.2010.04.012

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., … Tarantola, S. (2008). *Global Sensitivity Analysis: The Primer*. Chichester: John Wiley & Sons Ltd.

Saltelli, A., Tarantola, S., Campolongo, F., & Ratto, M. (2004). *Sensitivity Analysis in Practice: A Guide to Assessing Scientific Models*. Chichester: John Wiley & Sons Ltd.

Sheikholeslami, R., Razavi, S., Gupta, H. V., Becker, W., & Haghnegahdar, A. (2019). Global sensitivity analysis for high-dimensional problems: How to objectively group factors and measure robustness and convergence while reducing computational cost. *Environmental Modelling and Software*, *111*(February 2018), 282–299. https://doi.org/10.1016/j.envsoft.2018.09.002

Sobol', I. M., & Kucherenko, S. (2009). Derivative based global sensitivity measures and their link with global sensitivity indices. *Mathematics and Computers in Simulation*, *79*(10), 3009–3017. https://doi.org/10.1016/j.matcom.2009.01.023

Walker, W. E., Lempert, R. J., & Kwakkel, J. (2013). Deep Uncertainty: Uncertainty in Model-Based Decision Support. *Encyclopedia of Operations Research and Management Science*, *1*(1), 395–402. Retrieved from https://pdfs.semanticscholar.org/8e6b/c8cd6c880e54c68e6c1c71a9f9a5a5781283.pdf

Ziehn, T., & Tomlin, A. S. (2017). Efficient Tools for Global Sensitivity Analysis Based on High-Dimensional Model Representation. In G. P. Petropoulos & P. K. Srivastava (Eds.), *Sensitivity Analysis in Earth Observation Modelling* (pp. 297–318). Amsterdam: Elsevier. https://doi.org/10.1016/B978-0-12-803011-0.00015-X