To Redefine, Not Reinforce

A Spatial Decision Support System with Generative Design Model for Exploring Optimal Improvements to Existing Street Networks for Enhancing Equity of Accessibility

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Abstract

Transport decision-making determines people's level of accessibility and deeply influences an individual's access to social and economic opportunities and the quality of life. Socially vulnerable populations are highly dependent on yet often more likely to have less access to transport services and experience lower accessibility. This creates and reinforces social and spatial inequalities by trapping people in disconnected neighborhoods and segregated areas that continue to be deprived of access to opportunities. This research aims to develop a Spatial Decision Support System (SDSS) to explore how re-purposing existing streets for walking and biking could influence the accessibility of vulnerable neighborhoods to support decision-making in enhancing equity of accessibility.

In the SDSS, equity of accessibility is formulated as a generative design (GD) problem, named the Street Allocation Decision Problem (SADP), a single-objective optimization problem that searches for generated designs with the maximum weighted improvement in accessibility per unit of its cost. A GD model is built to solve SADP. Lastly, an operational framework is developed to guide prospective users in tuning and operating the SDSS for their specific context, problem, and objective.

The SDSS is tested on a toy problem, a 0.09km^2 area in The Hague, The Netherlands. The toy problem is small in scale, easy and fast to implement and useful for initial testing of the model. Preliminary results have demonstrated the feasibility of the model. This is the first and humble attempt at developing an SDSS for enhancing equity of accessibility with a GD model. However, there are shortcomings in methodology and result quality, which compromise the practicality of the model and the interpretability of results. Although, only a proof of concept at the moment, the SDSS is a valuable starting point due to its advantages, such as transparency, modularity, humane-ness, and flexibility. This SDSS is built to involve decision-makers in the design process, which could serve as a useful learning experience for questioning and understanding what is the problem, what is considered equitable, and what are possible solutions. The SDSS has the potential to facilitate learning during transport decision-making in experimental settings or as explorative aids in early design stages.

Keywords: Equity. Accessibility. Generative design. Spatial decision support system. Network design problem. Network optimization. Street allocation decision problem.

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Notations

$\boldsymbol{\alpha}$	Vector of accessibility
$\boldsymbol{B}$	Assignment matrix assigning spatial units to vertices
$\boldsymbol{C}$	Two-dimensional array storing the closest vertex for every POI
$\boldsymbol{D}_{\mathbf{c}}$	Two-dimensional array storing the smallest travel distances to reach every POIs in category c from all vertices
$\boldsymbol{D}$	Two-dimensional array storing the smallest shortest paths to every POI category for all vertices
$\boldsymbol{d}$	Vector of the smallest shortest path from every vertex to a POI category
$\boldsymbol{l}$	Vector of the length of every edge in the decision variable
$\boldsymbol{P'}$	Two-dimensional array storing the POI category(ies) represented by each vertex
$\boldsymbol{P}$	Assignment matrix assigning categories to POIs
$\boldsymbol{v'}$	One-dimensional array storing the vulnerability index of spatial units every vertex represents
$\boldsymbol{v}$	One-dimensional array storing the vulnerability index of every spatial unit
$\boldsymbol{x}$	Vector of decision variable
$\mathcal{D}$	Set of k number of vector $\boldsymbol{d}$
σ_{fix}	Fixed cost of street allocation project
σ_{unit}	Cost per unit length of street allocation project
a	Number of edges in the decision variable
c	A POI category
G_{base}	Base graph representing the entire street network of the toy problem
G_{design}	Graph of generated design
G_{start}	Edge-induced subgraph of G_{base}
k	Number of POI category
m	Number of edges
n	Number of vertices
o	Number of POI
o_{k}	Number of POI in a POI category
s	Number of spatial units

Chapter 1

Introduction

Transportation has a paramount influence on the quality of life and livability of cities. It connects people to essential economic and social opportunities, such as employment, health care, and education, facilitates access to leisure activities, and enables social interactions [1]. Aside from various observed urban injustices, academic and policy literature concerned with equity in urban transportation systems has called attention to the unfair distribution of transport-related infrastructure and services amongst urban dwellers, as well as the associated social and economic impacts. Historically, transportation planning and evaluation are dominated by the mobility-based approach, which centers around travel time reduction and travel speed optimization, and focuses primarily on private vehicle infrastructure [2]. It follows a 'predict and provide' formula, forecasting demand and expanding infrastructural capacity accordingly to maximize traffic flows and minimize congestion [3]. Besides economic and environmental problems related to the transportation system, such as urban sprawl, noise and air pollution, traffic fatalities, and fossil fuel consumption, urban transport resources and externalities are often unequally distributed spatially and socially [4]. This segregates people by class, race, and occupation, and deprives parts of the population of the means of transport that match their needs, thereby impeding their participation in society [5, 6]. Therefore, it has become evident that the traditional approach to transport planning is insufficient in addressing existing social inequalities, and in addition, it may exert a reinforcing effect on segregation and social exclusion. With sustainability and equity growing in significance in urban planning and policies, it has been acknowledged that urban transport systems need to be redesigned to become more socially sustainable in order to tackle some of the major challenges facing 21st-century cities [7].

Along such aspiration, transport equity is extensively studied to understand how urban transportation is spatially distributed and experienced differently amongst segments of the population, as well as the potential urban dynamics driving this phenomenon and their consequences on quality of life. Transport equity concerns the distribution of transport benefits (e.g. resources, infrastructure, services) and costs (e.g. air and noise pollution, use of space, forced relocation) [5, 8]. In addition, there is the notion of *need* with regards to this distribution, which suggests that transport systems should be designed to meet the heterogeneous needs of people to guarantee good accessibility for all [9]. Factors such as age, disability, gender, income, educational level, and ethnicity could determine individuals' physical condition, perception of safety, travel budget, the types of neighborhoods they reside and the types of destinations of interest - which all have an influence on the choice behavior of travelers and the transport modes that are accessible to them [9, 10]. For example, elderly and disabled individuals are less likely to be able to drive, lower-income families have less budget for commuting, and the younger population needs safe and easy access to education. Accessibility refers to the ease with which people can reach their destinations of interest depending on the land-use and transport systems, temporal constraints, and individual needs and capabilities [10]. From a transport equity perspective, accessibility is a key measure as it captures the range of possibilities people have at their disposal and the level of freedom provided by the transport systems, which helps to better understand people's quality of life [11]. Thus, it can be argued that it is *accessibility* that should be distributed equitably when planning practice progressively moves beyond optimizing transport network efficiency to mobility for all [1]. Such is especially the case when policies intend to design solutions that meet the needs of the most disadvantaged groups of the population so they are ensured to have access to an equal range of opportunities [12]. Past research has observed that socially vulnerable populations, such as people with low-income and ethnic backgrounds, are more likely to be deprived of quality transport services (e.g. longer travel time and a higher percentage of income spent on transportation) and experience higher exposure to pollution and risks associated with transportation [13–15]. This reinforces existing social and spatial inequalities by trapping people in poverty and segregated areas that continue to be deprived of access to economic and social opportunities. Hence, it is highly relevant and important for decision-makers to understand the impact of their transport decisions on equity of accessibility in order to achieve economically productive, socially sustainable, and inclusive cities [16]. Furthermore, policies should address the needs of vulnerable groups so they are ensured to have access to an equal range of opportunities [12].

The problem of inequitable distribution of accessibility can be considered an 'ill-structured' or 'wicked' problem (visit Appendix B for a detailed description of its wickedness) [17]. 'Wicked problem' refers to complex social problems, such as persisting poverty and climate change, for which there exists no definitive formulation of the problem due to the nature of the problem [17]. The nature of these problems include the difficulty in drawing system boundary - unlike a mathematical problem, social problems are interlinked with one another and could involve multi-faceted physical phenomena that cannot be clearly separated from other connected phenomena. They also are inherently multi-actors, so the plurality of objectives, varying worldviews, and conflicting interests contribute to the challenge of defining the problem. This makes the problem definition a problem itself, in which the journey of exploring possible directions for solutions is precisely how the problem definition can be developed

[17]. In addition, addressing wicked problems comes with great pressure as it is a ‘one-shot operation’, in which any solution implemented will have irreversible impacts, including unexpected consequences. With the presence of complex human decision-making processes and multi-faceted physical phenomena, it is difficult to devise solutions to tackle wicked problems that are multi-dimensional, multi-criteria, multi-actor, and multi-value in nature [18].

Considering the ’wickedness’ of inequitable distribution of accessibility, this research is an attempt in applying generative design (GD) approach to support decision-making in improving the accessibility of vulnerable neighborhoods. GD refers to methodological design approaches that abstract the problem or ideas of desired functionality (of solutions) to sets of mathematical and/or computational rules and proceedings, and automate parts of the design process to computer [19]. Conceptually, GD is a suitable methodology to deal with ill-structured problems, like inequitable distribution of accessibility. Firstly, the design process focuses on developing the mathematical formulation of the design problem, basically converting the problem of design to sequences of decision problems, and in a way shifts the design process from being implicit to explicit [20]. This guarantees a transparent and reproducible scientific approach to understanding ill-structured problems, their potential solutions, and the relationships between the two. Secondly, by leveraging the power of computation, it guarantees the quality of design alternatives while satisfying a plethora of objectives and considerations inherent to ill-structured problems [19]. Thirdly, by framing equity of accessibility as a design problem, the research focuses on providing decision-support at an earlier stage of transport planning or design. Ex-Ante equity analysis is ideal as transport planning involves high investment and long-term and irreversible impacts. Lastly, the research develops a Spatial Decision Support System (SDSS) with GD model to involve designers (transport decision-makers in the case of this research) during the design processes, despite automating design generation to computers. This is key in making the generated designs useful in practice, by ensuring the decision-makers can integrate their domain and context-specific knowledge through the design processes: 1) it helps to improve the quality of solutions; 2) decision-makers can learn how their perceived equity manifests in reality (embodied by designs); 3) through involving in the process and learning along the way, they can meaningful interpret the social values of the designs.

1.1 Research Objective and Questions

The goal of this research is to develop a Spatial Decision Support System (SDSS) for exploring how repurposing existing streets for walking and biking influence the accessibility of vulnerable neighborhoods to support decision-making in enhancing equity of accessibility. The research is guided by the following research question: **How can optimal improvements of existing street networks be identified to enhance equity of accessibility and decision support be provided?** The research question is supported by the following sub-research questions:

1. How to formulate improvement of equity of accessibility as a GD problem?
2. How to apply the GD approach to support decision-making?
3. How to provide space for decision-makers to participate in the design process?

This research strives to contribute to existing progress in supporting decision-making towards more socially and spatially equitable distribution of transport benefits and resources. The main deliverable of this research is a SDSS, consisting of: (i) a GD model that identifies optimal improvements to existing street networks, which induces the highest weighted improvement in accessibility per unit of cost; and (ii) an operational framework to guide potential users to tailor the use of the model to their specific contexts and objectives. The model is tested on a small area of 0,09 km^2 in The Hague, referred to as the toy problem in this research.

1.2 Scope

This research focuses on the physical effects of the built environments (street network) on accessibility. This is a specific intervention from a range of possible options which are out of the scope. For example, implementing land use measures to increase the number of and proximity to amenities or changes in the timetabling of desired services are also important in facilitating accessibility. Such can be said for non-physical interventions, such as the perception of safety, which are crucial in creating the conditions necessary for people to reach their destinations of interest. Accessibility is defined as the ease with which people can reach all categories of points of interest (POI): mobility, active living, recreation, food choices, community space, education, and health well-being. The transport modes under study are walking and cycling. The choice is made as the research hopes to support policy efforts in promoting sustainable urban mobility. This furthermore considers inter-generational equity, to ensure that the impacts on future generations are considered in today's decision-making [5]. The research has formulated the problem as a Street Allocation Decision Problem and defined *improvement* as a decision to allocate a street segment to be made accessible for walking and/or biking. By working within the constraints of existing infrastructures, the research aims to explore how re-purposing streets for walking and biking influence accessibility for disadvantaged neighborhoods.

This research defines equity as vertical equity with regards to income and social class, in which a design will be deemed equitable if it favors economically and socially disadvantaged groups [5]. The focus is on the distribution of benefits generated by the transport system. Transport-related burdens and costs are excluded but are equally important issues to be considered in transport equity-driven decision-making [21]. Lastly, this research is a humble attempt at transcribing the equity of accessibility problem into a generative design problem, which gives considerable attention to the process of how the model comes about. The project does not thoroughly explore the various choices of algorithms fitted for the problem.

1.3 Chapters Overview

Chapter 2 reviews literature and past work relevant to this research. Followed by Chapter 3 describing the research methodology. Next, Chapter 4 introduces the Street Allocation Decision Problem, Chapter 5 explains the data processing procedures, and Chapter 6 introduces the GD model. Chapter 8 show preliminary results of the toy problem. Chapter 9 discusses the key takeaways from the results and limitations of the research and suggests possible directions for future research. Lastly, Chapter 10 concludes this research.

Chapter 2

Relevant Literature and Work

This chapter reviews past literature and works relevant to defining and operationlising the concepts of accessibility and equity, to understanding generative design as a design methodology, and a brief introduction to transport network design problem. The chapter ends by highlighting the knowledge gap along with the motivations of filling this gap.

2.1 Accessibility: Beyond Space-time Compression

Transport planning has historically followed a mobility-oriented approach. Mobility refers to the movement of people and goods and mobility-oriented planning has focused on optimizing network efficiency and resorted to solutions that accommodate an ever-increasing flow of vehicles, such as increasing road capacity and the construction of new roads [3, 22]. However, this approach is gradually deemed obsolete as cities are progressively striving for higher livability, sustainability, and inclusivity, and transport planning objectives are shifting from efficiency and speed to traffic safety, the adoption of low-carbon transport modes, and meeting the needs of different regions and/or social groups [23]. This change has enriched the planning approach to include non-transport aspects of urban life and shifted the narrative to an accessibility-oriented approach [2, 24].

Accessibility is a well-established concept and there has been substantial literature on developing various ways to operationalize it for application in urban and transport planning. Accessibility is generally defined as the ease of reaching opportunities or desired destinations [1, 25]. It is also often defined as the number of places that can be reached from a specific point given travel time and/or cost [24, 26]. Geurs and Van Wee (2004) identified four components that are theoretically important in defining and measuring accessibility: (i) transport component refers to the transport system in which its infrastructure, quality, and distribution determine the amount of time, cost, and convenience for people to travel; (ii) land-use component refers to the spatial distribution of opportunities (such as jobs, shops, health, social and recreational facilities) but also distribution of people; (iii) temporal component considers the availability of opportunities and transport services at different times of the day; (iv) individual component refers to the needs and abilities of individuals, such as income, educational level, household situation, physical conditions, which influence their level of access to transport modes and the types of destination they desire (see Figure 2.1) [10]. Accessibility provides a more comprehensive view of travel by unraveling the interplay of transport, land-use, and human factors that determines the ease with which one can reach basic services and desired locations.

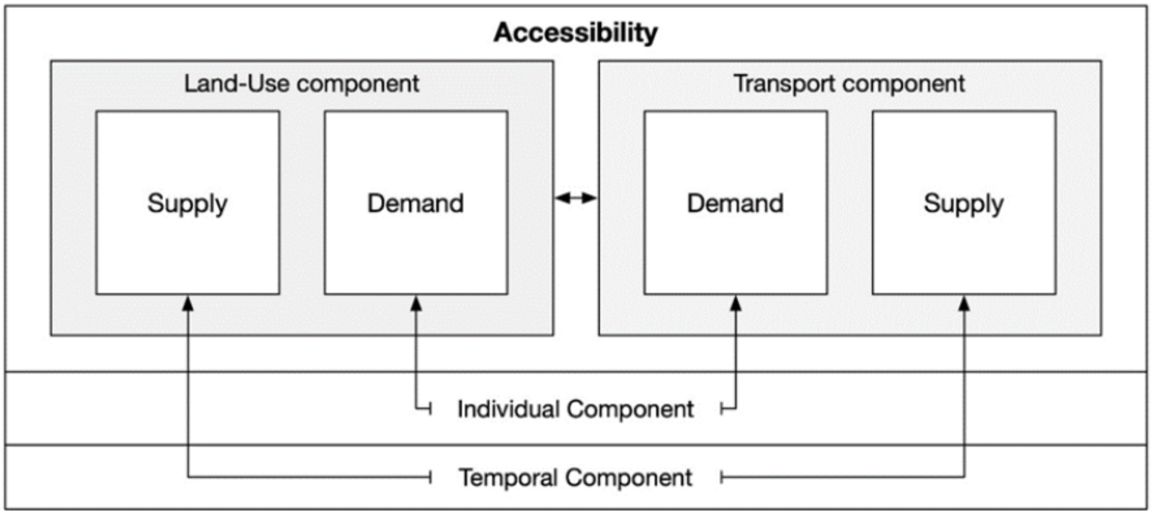


Figure 2.1. Simplified visualization of accessibility components and their relationships, from [27].

A multitude of accessibility measures has been developed, which vary in the main objective, theoretical basis, and application. The selection of accessibility measures is anything but a trivial task. The comprehensiveness of accessibility makes operationalizing, establishing clear evaluation metrics, and interpreting results all more difficult and time-consuming than the mobility-oriented approach. The lack of time, data, software, and/or skills and knowledge have been identified as barriers to its practical implementation [28]. The challenge is to find the right balance between scientific rigor and usefulness of practitioners [1]. The complicated measures may be more difficult to interpret whereas simpler measures may be less theoretically sound. There are four criteria for evaluating the usefulness and limitations of accessibility measures to guide the selection process [10].

1. **Theoretical basis**: An accessibility measure should reflect the aforementioned components of the concept. It should be sensitive to changes in the transport system and land-use system, i.e. the amount of time, cost, and effort to travel from an origin to a destination with a specific transport mode, as well as the amount, quality, and distribution of opportunities. The measure

should consider the temporal difference in the availability of opportunities and transport services. Lastly, it should incorporate individual needs and abilities into account. In practice, accessibility measures tend to focus on one or a selection of components [1].

2. **Operationalisation**: This concerns the extent to which a measure can be used in practice, depending on the availability of data, models and techniques, time, and budget it requires.

3. **Interpretability and communicability**: Those involved in planning and decision-making should be able to understand and interpret the measure well for meaningful contribution in formulating new public policy, planning practice, and engaging relevant stakeholders with different backgrounds.

4. **Usability in social and economic evaluation**: The measure of accessibility can be used to evaluate social and/or economic impacts of land-use and transport changes. This concerns the extent to which a measure can show, for example, changes in the number of opportunities or travel time, for groups of individuals. Social evaluation involving equity will benefit from a spatially differentiated and disaggregated accessibility measure. Economic evaluation often involves direct economic benefits from land-use and transport projects (e.g. cost-benefit analysis) and indirect and 'wider' economic effects (e.g. production function approach estimates the contributions of the infrastructural project to long-term macro-economic benefits in terms of GDP) [29]. The social evaluation aspect is arguably more relevant to the objective of this research.

2.2 Equity: Fairness in Transport Contexts

Transport planning decisions are inevitably experienced differently by groups of population and across space within an urban environment. There has been an extensive amount of research in conceptualizing and developing methods to measure transport equity in order to build more insights into guiding urban and transport decision-making toward more equitable policies. This line of literature focuses on building conceptual clarity about what constitutes equity and fair distribution and constructing ways to measure and evaluate the fairness of the distribution [5, 21, 30, 31].

Equity refers to the distribution of impacts (benefits and costs) and whether such distribution is fair over members of society [5, 32]. Equity is not solely about the distribution of resources, the implicit inquiry is rather on how this distribution affects the lives and well-being of different groups of people, for example in terms of exposure to environmental externalities and their capability to access opportunities across space [33]. Two types of equity are generally evaluated in transport planning: horizontal and vertical equity [5]. The former favors uniform distribution of impacts among individuals and groups considered equal in ability and need, such that public resources be allocated equally to each group or that all users shall bear the costs of transport services [5, 31]. The latter requires that disadvantaged groups be identified and favors a distribution that provides more or better to the identified groups in order to compensate for overall inequality [5]. The two are not mutually exclusive, in fact they often overlap, but they also conflict as a particular decision is deemed horizontally equitable but vertically inequitable [34]. For instance, horizontal equity as an objective requires transit passengers to pay as much as one uses but vertical equity demands subsidy provision for the disadvantaged [35]. Therefore, the equity evaluation of a decision depends on how fairness is defined. Equity is objectively desirable but there is no objective or standard way to define a particular equity objective. Such planning decision depends on and should reflect community needs and values [5]. Transport equity analysis is thus ad hoc and always involves moral judgment, values, and context-specific information upon implementation [23]. Given the subjective nature of equity analysis, the challenge is of formulating an explicit equity objective from the several types of equity, the various ways to categorize people, the multitude of potential impacts to consider, and the multiple ways to measure the impact (see Figure 2.2) [5, 31]. The answers to these questions depend on the nature of the problem under study and the concerns and values of the involved stakeholders and communities [5].

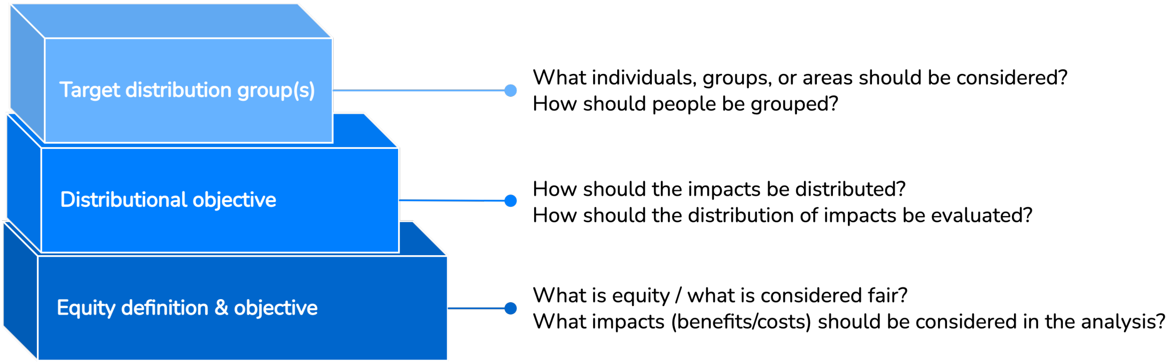


Figure 2.2. Key building blocks for formulating an explicit equity objective.

2.3 Generative Design: Designing Logic over Object

Generative design (GD) refers to design methodology that utilizes algorithmic or rule-based processes for the combinatorial generation of design alternatives [36, 37]. It is an emerging methodology that has been applied to designing products or systems in various domains, such as aircraft components, building designs, and urban block layouts. Since it is a relatively new design approach, there is a lack of a clear definition so the terminology is often used to describe a broad range of loosely related methodologies [38]. In general, GD differs from other computational design methodologies because "during the design process the designer does not interact with materials and products in a direct way, but via a generative system of some sort" [38]. The generative system refers to a system encoded with the computational specification on the principles of design formation - in other words, it specifies the abstract set of rules and proceedings for creating designs [39, 40]. GD, therefore, refers to methodical design approaches that begin with abstract ideas of desired functionality and then systematically explore and deduce a large of design alternatives through mathematical and/or computational means [41]. This bridges the gap of the 'logical leap in design,' alluding to the jump from an abstract desired functionality of a design to the final concrete form, which tends to happen during the design process driven by designers' knowledge and intuition [20, 42]. In a sense, GD methodology converts a design problem to sequences of decision problems that are solvable with algorithms, shifting the design processes from being implicit to explicit [20].

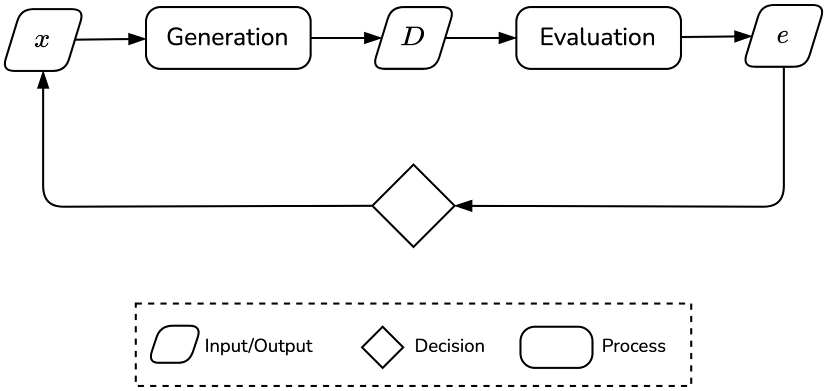


Figure 2.3. Flowchart of Generative Design methodology.

An overview of GD methodology is presented in Figure 2.3. The designers are required to formulate the design objective, requirements, and constraints into rules of generative systems, such as parameters, variables, and initial configurations to generate a range of design possibilities. Then, based on an input x, the generation process produces designs D based on the set rules, which are then evaluated based on design objectives and performance requirements. Based on the performance of the designs (e), designers can select satisfying design alternatives or adjust any steps in the design process or even the objective to produce more desirable outcomes. The process iterates until satisfactory design(s) is found. The flexibility to adjust the design process according to intermediate learning and outputs helps to understand the problem, properly define the objective and requirements, and reach progressively satisfactory solutions [43].

Even though the design process has some level of autonomy, GD approaches do not deem human designers superfluous. The point is to preserve designers' domain knowledge in the design process while leveraging the power of computation for generating a large number of diverse design alternatives and satisfying a complex plethora of demands and considerations at the same time [41]. This is especially the case for multi-actor, multi-disciplinary, and multi-objective situations, where computation can address the issues of speed, accuracy, and complexity and support designers in exploring the solution space in greater breadth and depth, even if time and resources are limited [44].

2.4 Transport Network Design Problem

Network design problem (NDP) refers to problems that involve the selection of optimal choices that can be represented conceptually as the selection of a subset of vertices and/or edges in a graph, given some sort of costs or constraints [45, 46]. NDPs often involve design decisions from a discrete set of alternatives, with which the design problems are formulated as integer or mixed-integer programming problems. NDP is prominent in dealing with all sorts of issues that arise in transport planning, design, and management [47, 48]. At the operational level, traffic slow control and scheduling problems are examples of short-term decisions that can be supported by NDP. At the tactical level, NDP is used to support decisions for the effective use of existing infrastructure, such as determining the one-way street orientation or allocation of streets as bus lanes. Lastly, the strategic level is a higher level of decision-making that defines the infrastructure of the transport system, with which investments have long-term impacts, such as building new or expanding streets and designing bus routes [45, 47]. Generally, these problems are referred to as the urban transportation network design problem (UTNDP). UTNDP can be further specified into, for example, road network design problems (RNDP), transit network design problems (TNDP), and multi-modal network design problems (MMNDP), which deal with different components of the urban transportation systems [49].

2.5 Knowledge Gap

This chapter has discussed the literature on the measure of accessibility in transport decision-making, the conceptualization and operationalization of equity in transport contexts, generative design (GD) as a methodical design approach, and briefly introduced the transport network design problem (NDP). This section will proceed by synthesizing research at the intersections of the above-mentioned topics, followed by identifying the knowledge gap (Figure 2.4).

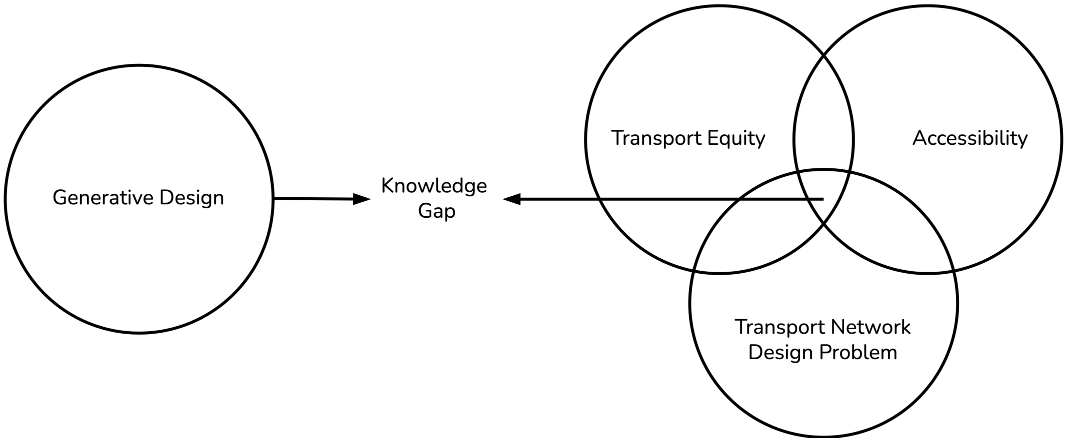


Figure 2.4. Visualization of the intersections between the literature on accessibility, transport equity, and network design problems, and the knowledge gap of this research.

Transport equity literature, to a large extent, concerns the equitable distribution of accessibility [6, 50]. From a theoretical perspective, accessibility is a key measure of transport equity as it captures the range of possibilities different people have at their disposal, and the level of freedom provided by the transportation system [11]. The main goals of such research are to analyze how people experience transport and land-use systems differently due to social, spatial, or individual factors - they are useful to draw attention to the poorer and socially-disadvantaged neighborhoods or populations and to justify policies that redistribute transport resources towards the currently disadvantaged and provide equitable transport for all [23]. For example, studies have been conducted on equity of accessibility to employment and education for different income groups [51, 52], to health care facilities [53], and access to urban public facilities in general for a number of socially disadvantaged groups [54].

Within the transport NDP literature, there has been more and more research that incorporates equity criteria into the formulation of NDP [55]. Transport planning can be extremely costly and exerts long-term impacts on people's lives, thus the motivation for such research is to integrate direct or indirect social equity impacts into the planning. Unlike NDP with equity objective, the transport equity literature discussed previously performs evaluation on the existing transport systems, which is more an analysis of the status quo, and NDP in this context is considering equity at an earlier stage of planning. NDP is also suitable for this endeavor as it directly deals with the distribution of benefits and externalities between different demographic groups and geographic areas [56]. Behbahani *et al.* (2019) provides an overview of studies conducted to design or evacuate transport networks with respect to equity [55]. The reviewed literature include, for instance, NDP is formulated as a multi-objective problem that seeks to maximize highway investment efficiency and minimize intraregional and interregional difference in accessibility to improve horizontal and vertical equities [57]; a network design model that maximizes accessibility then evaluates the statistical distribution of accessibility among all center (Gini coefficient) and among all centers in the same region (Theil index) [58]; and a bi-level integer programming model that maximizing equity of congestion and travel time, which is tested on eight objective functions and considered two population groups; protected (deprived) and unprotected [59]. The literature on the formulation of the transport NDP with respect to equity have experimented with various mathematical expression of equity in a variety of infrastructure investment problems and contributed to building systematic frameworks and methods to help decision-makers integrate equity analysis into an earlier stage of planning [55].

The review of relevant works has identified several intersections between accessibility, transport equity, and NDPs. However, a cross path between GD and the rest has not yet been found. This research seeks to fill this gap by incorporating an NDP that optimizes equity of accessibility through the GD approach (Figure 2.4). The motivations to fill the knowledge gap are several. Firstly, as observed earlier, equity of accessibility literature tends to contribute to decision-making through analysis of existing transport systems and transport NDPs involving equity objectives provide decision support in the earlier stage of planning or design through optimization. The benefit of using GD is to approach the problem as a design problem, similar to NDP, but make the entire process leading to the optimization also decision-support-oriented instead of only providing insights from optimization outputs. As discussed prior, equity problems in transport planning are unique, open-ended, and ill-structured, since they involved the subjective definition of what is equitable, as well as context- and problem-specific knowledge. Imagine the transport decision-makers and planners as designers, the GD approach is able to involve them in every stage of the design process. This integrates decision-makers' domain and context-specific knowledge into defining the problem and choosing the desired inputs to ensure the model embodies equity as close to the intended definition as possible. Decision-makers can iterate between problem definition and design generation, enriching their understanding of how their idea of equity manifest in designs - basically learning about the problem while learning about the solutions. In addition, by having the decision-makers evaluate designs to understand their physical (structural, function) and social sense, helps guide the search process and improve the quality of solutions. In a way, this research argues that GD adds a humane layer to transport NDP, which is very much necessary when the objective involves equity considerations, to interpret the social implications of designs.

2.6 To Redefine, Not Reinforce

This research is an attempt to fill the identified knowledge gap by applying a generative design (GD) approach to support decision-making that aims at improving equity of accessibility through a network design problem (NDP). The GD approach has the advantage of having a flexible, modular, and extensible optimization system that can involve decision-makers in every stage of the design process. The choice of accessibility measure will be evaluated upon its theoretical basis, operationalization, interpretability and communicability, and usefulness in social evaluation. The GD model will be based upon clearly defined equity definition and objective and the corresponding distributional objective and target distribution group(s). Building upon past literature and work, this research hopes to contribute to guiding decision-making towards the more equitable design of transport systems by humanizing the optimization processes, with the hope of providing a methodical way to redefine what an urban transport system could be, instead of reinforcing the current urban dynamics.

Chapter 3

Research Methodology

This chapter explains the research methodology, presents the case study, and listed the data requirements.

The research methodology is composed of several iterative processes to formulate equity of accessibility as a generative design (GD) and assist decision-support (Figure 3.1). **Problem formulation** is the process of conceptualizing the objective and problem through reviewing related literature and work and examining data availability. This entails a process of clearly defining the concepts used for describing and thinking about the problem and transcribing them into a series of well-defined mathematical statements. The intention is to 'provide the language in which problems and solutions are defined and communicated' and set the stage for problem-solving [60]. In the problem formulation, equity of accessibility is formulated as a GD problem with clear design and solution spaces, with which an objective function is formulated to guide optimization and used as a measure of the effectiveness of designs. **Model formulation** involves developing a set of steps for solving the formulated problem.

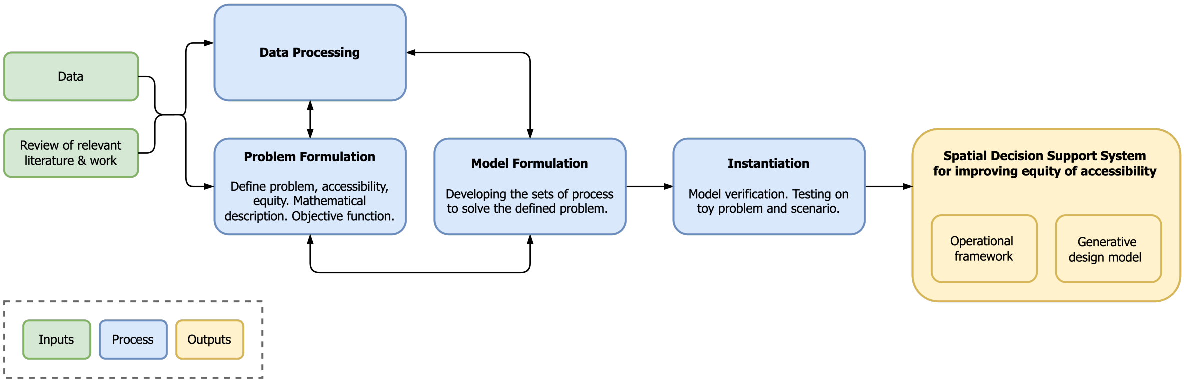


Figure 3.1. Overview of research design.

An iterative cycle between data processing, problem, and model formulation is necessary. In order to define a problem that reflects the situation being modeled, it requires a frequent check on the meaning of the data and its structure. Furthermore, the problem should be amenable to computational techniques, but likewise, the model and the choices made to build its steps should concern the social meaning of the problem and its variables. This is especially important as this research works with a social problem, and the process of transcribing it into a mathematical description and employing computational means for problem-solving will ultimately be bounded by a subjective interpretation and abstraction of the problem. Therefore, it was an iterative process of ensuring the methods reflect these interpretations and abstractions consistently.

After the GD model is formulated and built, **instantiation**, which is the implementation of the model to demonstrate usefulness and feasibility to their intended purposes [60, 61], is carried out to show preliminary results with respect to the toy problem (explained in Section 3.1). The methodology is an attempt to formulate a real-world problem of transport equity as a design problem, with the objective of supporting decision-making with computer-aided design generation. The main contribution is precisely this translation process. The main output is the SDSS that consists of the GD model and a corresponding operational framework. The operational framework is developed to guide prospective users to operate the SDSS for their context-specific problem and objective related to equity of accessibility. Each of the processes in Figure 3.1 is described in detail by a proceeding chapter. Problem formulation is outlined in Chapter 4, data processing in Chapter 5, and model formulation in Chapter 6. The chapters are organized in such order to present the workflow logically despite its iterative nature.

3.1 Case Study and the Toy Problem

The case study of this research is in The Hague, the Netherlands. The Mobility Transition Strategy 2022-2040 (‘Strategie Mobiliteitstransitie 2022-2040’) is a plan initiated by The Hague municipality with the goals of ensuring the city is liveable, traffic safe, and accessible. The plan proposes six main goals to carry out their ambitions:

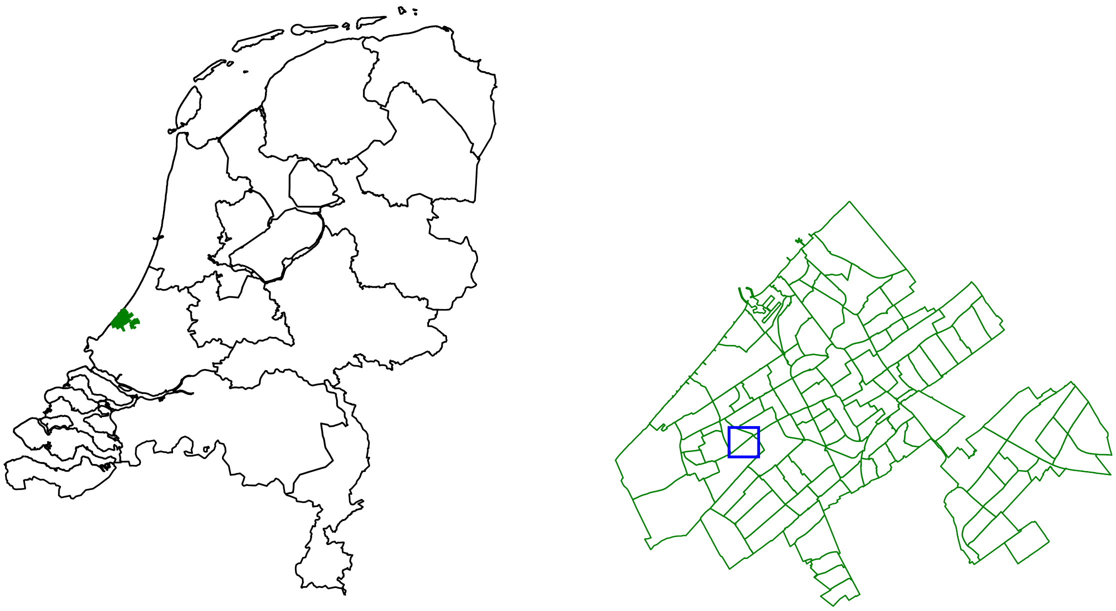
1. Safe (‘Veilig’): Targeting zero road casualties per year.
2. Efficient (‘Efficiënt’): More efficient use of space and infrastructure for mobility, improve traffic flow, and make public transport faster.
3. Clean (‘Schoo’): Align mobility with environmental and climate ambitions.
4. Tailor-made (‘Op maat’): A transport system that provides the needs of all residents and mobility policy takes into account the spatial and social differences amongst the city’s neighbor-

hoods/districts.

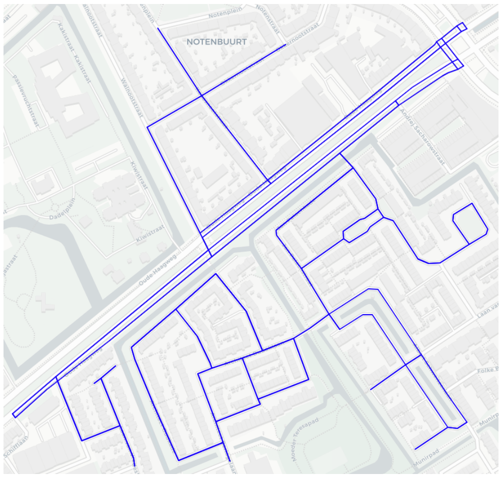
5. Affordable (‘Betaalbaar’): Provide mobility solutions for every budget.
6. Connected (‘Verbonden’): Establish good connections with other metropolitan regions at home and abroad.

Accessibility, especially of low-carbon transport modes, is a crucial part of The Hague’s mobility goals. Thus, The Hague as a case study is highly relevant and it will be interesting to see if the model produces useful insights that contribute to the city’s goals. The Hague is also chosen considering the good availability of street networks and socioeconomic data. Most importantly, familiarity with the city under study is important for the purpose of this research. Existing knowledge and experience with the city’s street network, and social and spatial distribution of people are useful in contextualizing the data, abstracting the problem, and interpreting the social value of the variables and results.

This research takes an area of 0,09 km^2 from The Hague (the center point is 52°03’37.3”N, 4°15’19.6”E) as the toy problem for developing and testing the methods and generative design model (Figure 3.2). A toy problem is a small and simplified representation of a complicated or complex real-world problem/system of interest. Mathematical abstraction of reality is easier with a toy problem and it is beneficial in the context of developing a complete and clear set of mathematical notation for a new problem. The advantages are also that a toy problem is easy to implement and performing an exhaustive search of the problem space and faster execution are possible. This is helpful for testing the model. Certainly, the point is to contribute to understanding and solving real-world problems and develop techniques for toy problems that are transferable to larger ones [62].



(a) Map of the Netherlands. **(b)** Map of The Hague.



(c) Map of the toy problem area.

Figure 3.2. Overview of the toy problem location with three maps: (a) A map of The Netherlands, the green area indicates The Hague. (b) A map of The Hague, the blue square points out the toy problem location. (c) A map of the toy problem area, the blue lines represent the street networks. Source of spatial data for the maps: First-level administrative divisions shapefile of The Netherlands [63], neighborhood shapefile of The Hague [64], and street networks of the toy problem [65].

Chapter 4

Problem Formulation

This chapter formulates equity of accessibility as a generative design (GD) problem, named the Street Allocation Decision Problem (SADP). Problem formulation corresponds to a level of reality simplification that accommodates data structure and availability.

4.1 Definition and Measure of Key Concepts

4.1.1 Accessibility

To operationalize accessibility, the research by Nicoletti et al. (2022) is adopted. They define and quantify the notion of accessibility as the weighted average shortest path distance to all point of interest (POI) categories [66]. It captures the transport and land-use components of accessibility in which the ease with which people can reach essential goods and services is affected by the spatial distributions of amenities across the urban landscape and the transport infrastructure. Different types of urban amenities are classified into seven POI categories: mobility, active living, recreation, food choices, community space, education, and health well-being. The categories are created for ease of analysis while reflecting the types of essential services and socioeconomic opportunities that are prerequisites for good livability. This research excludes the weight assignment to the POI categories, which was done to weight the POIs by their service importance in the accessibility calculation (for example, hospitals are given higher importance than bars). It is excluded to decrease the number of elements that needed to be considered while designing this research's method and model, but this research recognizes the importance of weight assignment to provide accessibility calculating with more theoretical soundness. Thereby, this research defines accessibility as the average shortest path distance to all point of interest (POI) categories. It is important to mention that the use of the shortest path for calculating accessibility assumes individuals' travel behaviors are determined by finding the smallest distance to the destination. This is an assumption since there are other physical and cognitive reality factors that influence the route choice of pedestrians and cyclists besides taking the shortest one, such as perception of safety and comfort, climatic pleasure, scenery, and the amount of traffic [67].

4.1.2 Equity

To operationalize the notion of equity, the distributional goal of this problem formulation focuses on allocating streets for walking and cycling to maximize accessibility for the most vulnerable neighborhoods. Two aspects need to be further elaborated: what is vulnerability and how to execute maximization.

Firstly, the vulnerability index is a composite measure aggregated from disadvantage score and population density to identify spatial units that are comparably more 'in need' and thus should be prioritized in the optimization. The vulnerability index follows the rationale that a disadvantaged area should be considered first in transport resource provision than a less disadvantaged area in order to achieve an equitable outcome, with which the former is more likely to be deprived of and dependent upon good transport resources for accessibility. In addition, if two neighborhoods are equally disadvantaged but one is densely populated and the other not, the former should be prioritized as a larger population would be affected by improvement in accessibility. Therefore, population density is used for the efficient allocation of limited transport resources and budget. The vulnerability index of each spatial unit (vi) is calculate as follows:

$$\text{scaled\_value} = \frac{\text{actual\_value} - \text{minimum\_value}}{\text{maximum\_value} - \text{minimum\_value}} \tag{4.1}$$

$$v_{\text{i}} = (\text{disadvantage\_score}_{\text{scaled}} * \text{population\_density}_{\text{scaled}})^{\frac{1}{2}} \tag{4.2}$$

The calculation follows the method for calculating the Human Development Index (HDI) [68]. Firstly, the disadvantage score and population density are scaled to values between 0 and 1 with min-max normalization (Equation 4.1). Re-scaling the data allows both variables to contribute proportionately to v_{i}. Then, v_{i} is calculated as the geometric mean (equally weighted) of the disadvantage score and population density (Equation 4.2). Geometric aggregation reduces the degree of compensability between the individual variables, i.e. a low value in a variable would not be compensated by a high value in another variable, which is a major limitation of arithmetic aggregation [68]. The disadvantage score and population density are considered of equal importance in determining vulnerability in this research. This choice is believed to fit the research objective as the composite indicator will prioritize highly disadvantaged and populated neighborhoods in order to arrive at generated designs that improve accessibility for as many potentially-disadvantaged individuals as possible, thereby enhancing equity.

4.2 Formulating the Street Allocation Decision Problem

The street network, neighborhoods, and POIs of the toy problem are represented by a graph G_{base}. Let $G_{\text{base}} = (V, E, l)$ be a directed, weighted multi-graph with non-negative edge length l for each $e \in E$ on each ordered pair of vertices $u, v \in V$, and let $n := |V|$ and $m := |E|$. G_{base} is a 'base graph' that represents the street network of the toy problem in its entirety. All existing streets should be in G_{base}. An edge represents a street segment and a vertex represents a street intersection - but also:

1. the neighborhood it is located in, and the vulnerability index of the neighborhood becomes an attribute of each vertex;
2. the POI(s) closest to it, and the category of the POI(s) becomes an attribute of each vertex.

Parallel edges between the same pair of vertices occur when a transport mode has its own separated lane in real life, such as protected bike lanes that are physically separated from the main road). Every edge has an attribute that describes the types of roads it represents and the transport modes it allows. Based on this attribute, the edges are classified as bikeable and/or walkable (e.g. an edge representing a bike lane is bikeable but one representing a neighborhood road is both bikeable and walkable). Based on the classification, let $G_{\text{start}} = (V', E', l')$ be an edge-induced subgraph of G_{base} with $V' \subseteq V$ and $E' \subseteq E$, which is composed of the set of edges classified as accessible to a transport mode (either bikeable or walkable in this case). G_{start} is the 'starting graph' that represents all streets currently accessible to a transport mode.

Given the difference between the edge set E of G_{base} and E' of G_{start}, the design space emerges. The binary decision variable $\boldsymbol{x}$ to the problem is a set of a number of edges which are present in E but absent in E':

$$\boldsymbol{x} := [x_{\text{i}}]_{a \times 1} \in \{0, 1\}^a \tag{4.3}$$

$$x_{\text{i}} = \begin{cases} 1 & \text{if } e' \in E \setminus E' \text{ is added to the generated design} \\ 0 & \text{otherwise} \end{cases} \tag{4.4}$$

The design space consists of the missing edges in G_{start} are the streets currently not allocated to a transport mode according to the street classification. The goal is to explore the impact on accessibility when adding missing edges to G_{start}: given a finite set of edges, determine the combination of edges to add to G_{start} so that the weighted improvement in accessibility is maximized in G_{design}.

4.2.1 Objective Function

The Street Allocation Decision Problem (SADP) can now be formally defined as follow:

Maximize:

$$\frac{\boldsymbol{v}^T \left(\boldsymbol{\alpha}\left(\boldsymbol{x}^{(t+1)}\right) - \boldsymbol{\alpha}\left(\boldsymbol{x}^{(t)}\right)\right)}{\sigma_{\text{fix}} + \mathbf{1}^T \left(\sigma_{\text{unit}}\left(\left(\boldsymbol{x}^{(t+1)} - \boldsymbol{x}^{(t)}\right) \odot \boldsymbol{l}\right)\right)} \tag{4.5}$$

Given:

t	discrete time step
σ_{fix}	fixed cost of street allocation project
σ_{unit}	cost per unit (meter) of street allocation project

Where:

$$\boldsymbol{v} := [v_{\text{i}}]_{n \times 1} \in [0,1]^n \tag{4.6}$$

$$\boldsymbol{\alpha} := [\alpha_{\text{i}}]_{n \times 1} \tag{4.7}$$

$$\boldsymbol{l} := [l_{\text{i}}]_{a \times 1} \tag{4.8}$$

The objective function calculates the weighted improvement in accessibility induced by a design per unit of its total cost. Firstly, the components of the objective function will be explained. $\boldsymbol{v}$ is the vulnerability index and $\boldsymbol{\alpha}$ is the accessibility of vertices in the network. $\boldsymbol{l}$ is a vector of the length (meter) of each of the edges in the decision variable. $\boldsymbol{x}^{(t)}$ denotes decision variable before intervention at discrete time step t, which means $x_{\text{i}} = 0$. $\boldsymbol{x}^{(t+1)}$ represents the decision variable of an intervention (generated design) at discrete time step $t+1$ to denote a difference between the decision variable 'before and after' the intervention or one can image it as a distinction between the 'this and that'. Accessibility is calculated by a computational function with network analysis that takes in $\boldsymbol{x}$, generates a new graph accordingly, and then calculates and outputs the accessibility of vertices. Thereby, $\boldsymbol{\alpha}(\boldsymbol{x}^{(t)})$ expresses the accessibility of the network before the intervention, in other words, the accessibility of G_{start}. And $\boldsymbol{\alpha}(\boldsymbol{x}^{(t+1)})$ is the accessibility of a network with intervention, in other words, accessibility of G_{design}. Basically, the objective function finds the difference between the accessibility of the former and the latter, in other words, the *improvement (change) in accessibility* induced by an intervention. Then, it weights the improvement by vulnerability index. The multiplication of $\boldsymbol{v}^T$ and improvement in accessibility involves multiplying the vulnerability index of every vertex with the improvement it experiences. Thus, the single, unitless value product from the multiplication will be greater for designs that bring about significant improvement to highly vulnerable vertices.

The denominator of the objective function is the total cost of an intervention, which is the sum of fixed cost (σ_{fix}) and the total unit cost (σ_{unit}), which is σ_{unit} multiplied by the sum of lengths of edges added by the intervention, denoted by $\sigma_{\text{unit}} \left(\left(\boldsymbol{x}^{(t+1)} - \boldsymbol{x}^{(t)} \right) \odot \boldsymbol{l} \right)$. The subtraction of the before and after decision variables in the unit cost calculation is explicitly denotes that the edges considered in the calculation are the differences between G_{start} and G_{design}. The objective function thereby outputs the weighted improvement in accessibility induced by a design per unit of its total cost, and the SADP seeks to find the optimal solution that generates the maximum weighted improvement in accessibility per unit of its total cost. It concerns resource allocation that considers equity and cost-efficiency.

Chapter 5

Data Processing

This chapter explains the Data Processing procedure of the Spatial Decision Support System (SDSS). The SDSS takes the spatial data of street networks, demographics, and socioeconomics and processes them into the vertex and edge properties for the generative design (GD) model. The research uses the following data:

- **Street network**: This research builds the network with OpenStreetMap (OSM) street network data [65]. The dataset is open source with universal coverage across most geographic regions and features various transport modes. All non-private OSM streets and paths are extracted ('network_type' = 'all'), and the data are returned as vertices (street intersections) and edges (street segments).
- **Point of interest (POI)**: Urban amenity is one of the map features of the OSM data. They are extracted for the accessibility measure.
- **Socioeconomic data**: Socioeconomic data: The 'disadvantage score' ('de achterstandsscore') of The Hague in 2020 published by Den Haag in Cijfers is downloaded to build indicator for characterizing the vulnerability of neighborhoods [64]. The data is at the neighborhood ('buurten') resolution and is composed of five indicators that together provide a comprehensive understanding of a neighborhood's level of deprivation:
    1. the average personal income;
    2. the average property value of homes ('WOZ-waarde');
    3. the share of ethnic cultural populations;
    4. the share of inhabitants on social benefits;
    5. the share of re-locations in the last three years.

- **Population density and Spatial unit**: The population density data for The Hague is collected from the European Commission's Global Human Settlement Layer (GHSL). It is raster data with 9-arcsec grid resolution, encoding the number of people per grid for 2015 (WGS84, EPSG:4326) [69]. The grid of the GHSL layer is used to define the spatial unit of this research.
- **Shapefiles**: The first-level administrative divisions shapefile of The Netherlands [63] is used for plotting and neighborhood shapefile of The Hague [64] is for data processing.

Figure 5.1 shows processing processes for each dataset and the output from every process. The following sections will explain the three main streams of data transformation depicted in Figure 5.1: (i) processing of OSM street network into G_{base} and G_{start}, (ii) processing of OSM amenity data and assigning them as vertex attribute, and (iii) calculating the vulnerability index with population density and disadvantage score.

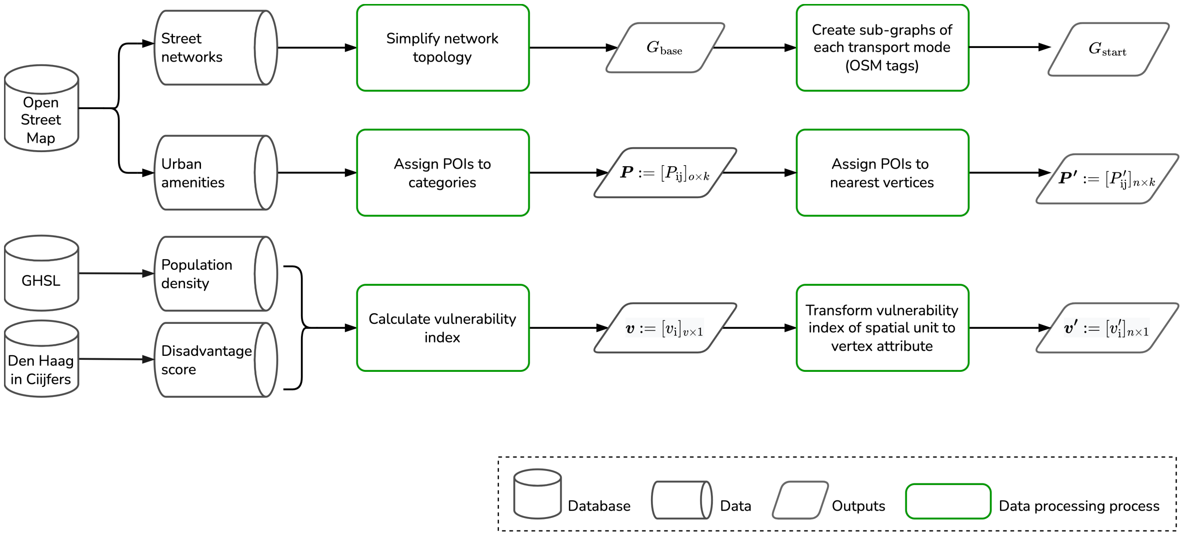


Figure 5.1. Flowchart of the data processing procedure in the Spatial Decision Support System.

5.1 Street Network Data

OSM street networks are extracted using OSMnx [70]. OSMnx allows the types of network to be specified when obtaining the data, the options include: 'all_private', 'all', 'bike', 'drive', 'drive_service', and 'walk'. To build a G_{base} that represents the street network of the toy problem, a custom filter is used to customize the OSM parsing. The custom filter is identical to the OSM query filter for 'all' network types, except that some specific street types are excluded, as they are not relevant for the purpose of this research, such as 'steps' and 'service'. With the custom filter, the street network was downloaded and converted to a non-planar, directed, weighted multi-graph G. Next, the OSMnx consolidate intersection tool is used to simplify graph G by merging clusters of topologically close vertices and rebuilding the graph [71]. The consolidated graph is $G_{\text{base}} = (V, E, l)$ (Figure 5.2). Acquiring and simplifying all networks (i.e. pedestrian and biking networks) together will ensure that the different transport modes share the same sets of vertices and edges after network topology consolidation. If simplification is done separately for each transport mode, they will result in different sets of consolidated vertices due to the inherent differences in the network topology of each mode. Consistent sets of vertex and edge indices are key to this research methodology as vertices and edges are bookkept by their indices, and data are often organized in arrays and called by indices.

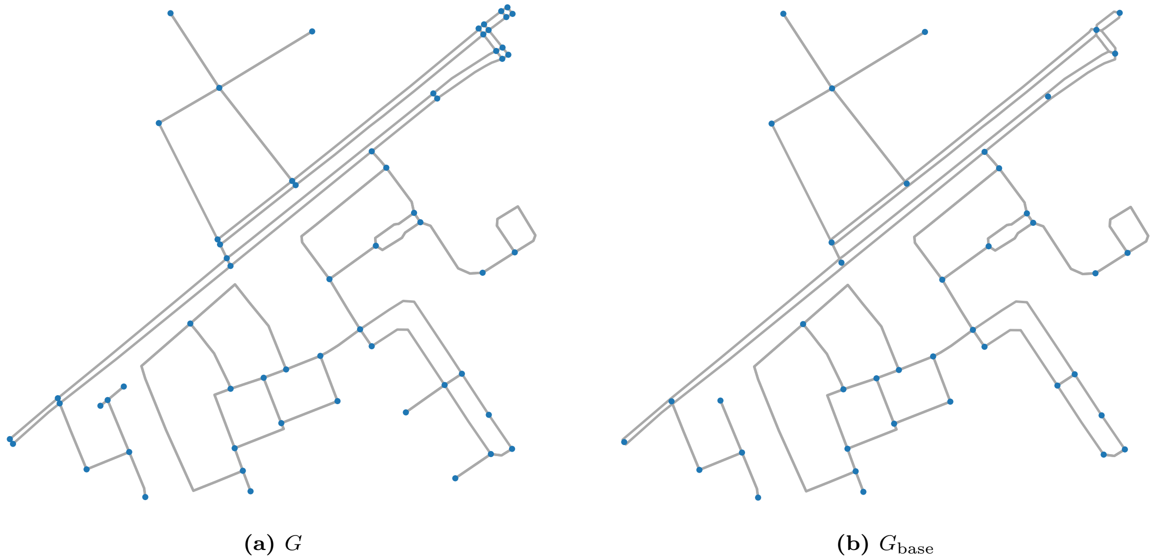
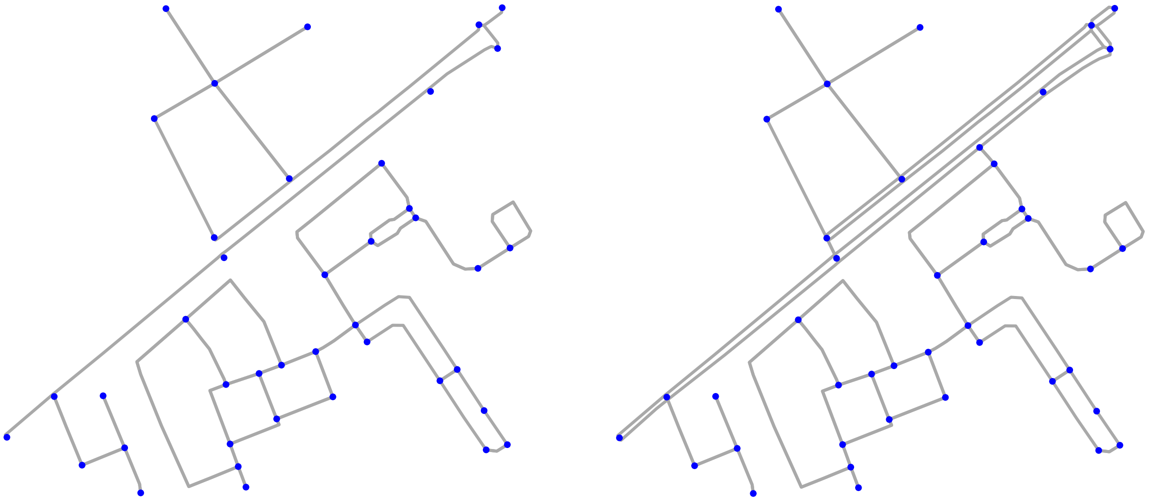

(a) G **(b)** G_{base}

Figure 5.2. Street network of the toy problem before (a) and after (b) intersection consolidation with OSMnx to simplify network topology.

To create the edge-induced sub-graphs (G_{start}) of G_{base} for walkable and bikeable networks, a system to classify street segments according to the specific mode permissions and restrictions is created. OSM streets (edges) are tagged with key and key value that describes the geographic attributes they represent. The key crucial for the classification is 'highway' and the key value denotes the types of roads represented, such as 'pedestrian', 'primary', 'busway', 'cycleway', and 'residential'. However, although some key values clearly indicate which types of mode are permitted or restricted on a street (e.g. 'cycleway' is only accessible to bikes and 'motorway' to vehicles), most of the key values do not express a clear indication (e.g. 'living_street' prioritizes pedestrians but is accessible for bikes and cars with speed limits). This unclear indication can be observed upon a closer inspection of the OSM highway keys supported by satellite images (Appendix C). Following the methodology of Gil (2015), a binary street classification is set up to classify the highway tags into different transport modes (Table 5.1). The walkable and/or bikeable classification of streets is supported by a combination of examining satellite images, highway key values [73], and personal experiences of The Hague's street network. Based on the classification, G_{start} is built with NetworkX for walkable and bikeable networks respectively (Figure 5.3) [74].

Table 5.1. List of all relevant 'highway' key values in the OSM dataset on the street network of The Hague and indication of the transport mode they are accessible to (0 = inaccessible and 1 = accessible) for the toy problem.

Key value	**Car**	**Bike**	**Pedestrian**
unclassified	1	1	1
cycleway	0	1	0
tertiary	1	1	1
residential	1	1	1
secondary	1	1	1
pedestrian	0	1	1
primary	1	1	1
living_street	1	1	1
motorway	1	0	0
motorway_link	1	0	0
trunk	1	0	0
trunk_link	1	0	0
primary_link	1	1	1



(a) G_{start} of the pedestrian network.

(b) G_{start} of the bike network.

Figure 5.3. Edge-induced sub-graphs of the pedestrian and bike networks, composed of walkable and bikeable edges in the toy problem, respectively.

5.2 Assigning Urban Amenities to Vertices

This section details the transformation of OSM urban amenity data into vertex attributes to prepare the network for accessibility calculation.

The OSM amenity data is obtained and categorized into seven categories (Mobility, Active Living, Recreation, Food Choices, Community Space, Education, and Health and Well-being) following the method of Nicoletti *et al.* (2022). The method collects OSM keyword tags on all urban amenities relevant to the categories, such as ‘hospital’, ‘education’, and ‘park’, and utilizes the tags to extract more than 50 types of urban amenities through the OSM API [66]. The extracted data are geospatial points with amenity names and their associated geographic locations (latitude and longitude). They represent the POIs in this research. The POIs are then grouped into seven categories based on the subjective assignment of the authors of Nicoletti *et al.* (2022). The complete list of amenities and their corresponding category is listed in Appendix D and the detailed method and code are provided by the authors [66]. POIs in the toy problem and their categories are shown in Figure 5.4a. Proceeding the data extraction and categorization, the following mathematically denotes the process of assigning POIs to vertices and results in a two-dimensional array that shows the POI category(ies) represented by every vertex:

$$\mathbf{P}' = \mathbf{CP}. \tag{5.1}$$

Given:

$$\boldsymbol{P'} := [P'_{\mathrm{ij}}]_{n \times k}, \tag{5.2}$$

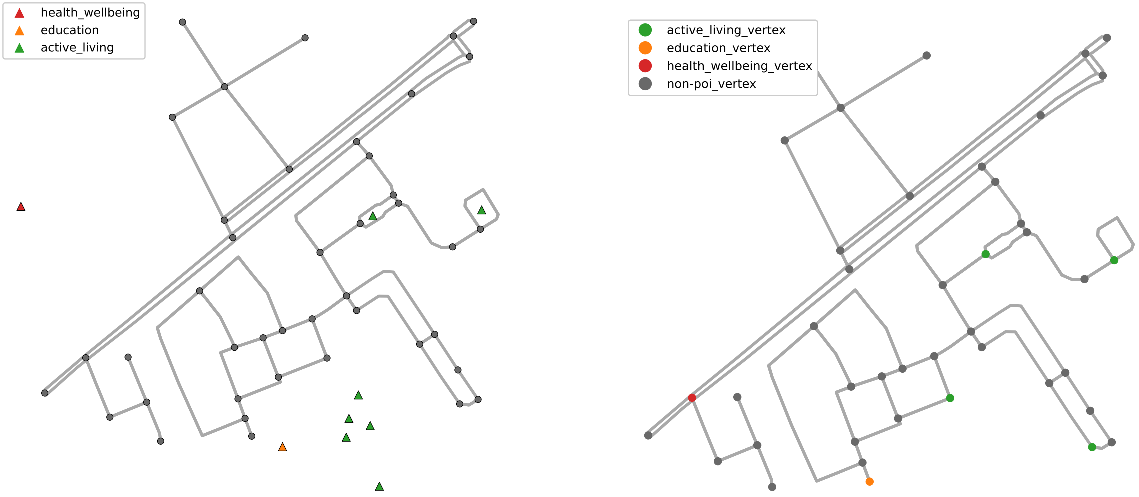
$$\boldsymbol{P} := [P_{\mathrm{ij}}]_{o \times k}, \tag{5.3}$$

$$\boldsymbol{C} := [C_{\mathrm{ij}}]_{n \times o}, \tag{5.4}$$

where:

n	the number of vertex in the toy problem,
o	the number of POI in toy problem,
k	the number of POI categories.

Firstly, the categorized POIs from the method of Nicoletti *et al.* (2022) is arranged into matrix $\boldsymbol{P}$, that assign every POI to a POI category (Equation 5.3). The nearest_points function from Shapely is employed to find the closest vertex in the toy problem for every POI and the outputs are organized into assignment matrix $\boldsymbol{C}$, which assigns the POI to its nearest vertex (Equation 5.4). Lastly, the multiplication product of $\boldsymbol{C}$ and $\boldsymbol{P}$ is the main output of this section: array $\boldsymbol{P'}$. If a vertex is assigned a POI, $\boldsymbol{P'}$ shows its corresponding category. It is possible that a vertex is assigned more than one POIs and thus represents more than one POI category. Figure 5.4b visualizes $\boldsymbol{P'}$.



(a) POIs of the toy problem.

(b) G_{base} of toy problem with POI as vertex attribute.

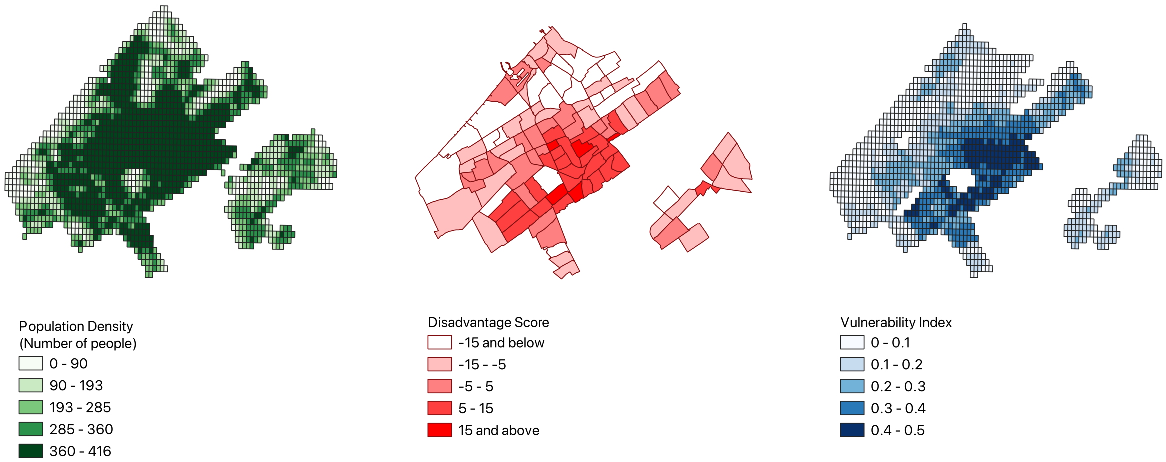
Figure 5.4. OpenStreetMap urban amenities data is assigned to vertices of toy problem as an attribute.

5.3 Assigning Socioeconomic Attributes to Neighborhoods

This section details the processing of data for defining the spatial unit of this research and calculating and assigning the vulnerability index to vertices.

The GeoTIFF file of the downloaded Global Human Settlement Layer (GHSL) data of The Hague is imported into QGIS as a raster layer to process the population density data and define the spatial unit of this research. The grid resolution is 9-arcsec, encoding the number of people living per grid. The grid of the raster layer is used to define the spatial unit of this research. 1 arcsec is approximately 30.87m, thereby every spatial unit is approximately 0.077km^2.

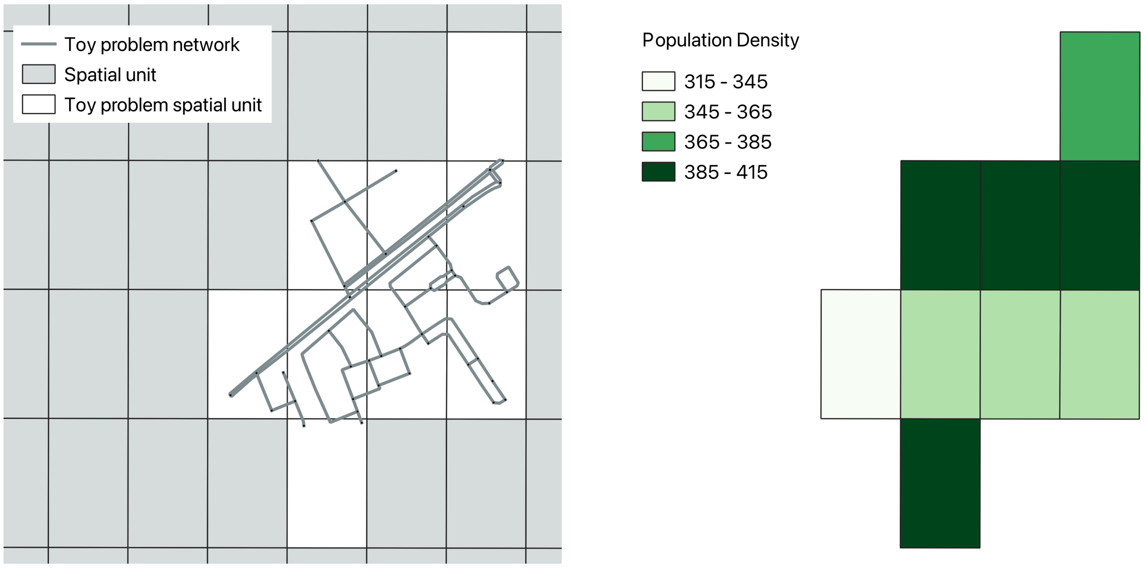
The raster layer is clipped to the municipality boundary of The Hague (raster extraction → clip raster by the mask layer) and then converted to a vector layer by polygonization (conversion → polygonize). Given the conversion may not perfectly create polygons of equal size as the original population density raster grid, manual correction is needed to ensure every newly created polygon represents a single raster grid (toggle editing → split features). The tediousness and time required for manual correction depend on the goodness of conversion. The output is a vector layer composed of 0.077km^2 polygons with population density ranging from 0 to 416 (Figure 5.5a).



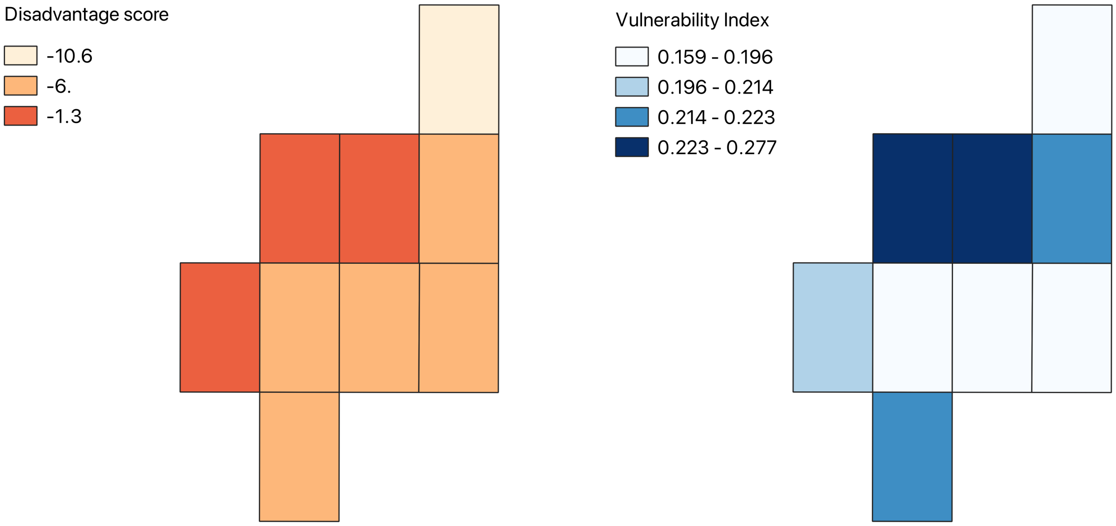
(a) Population density. **(b)** Disadvantage score. **(c)** Vulnerability Index.

Figure 5.5. Processing of population density (a) and disadvantage score data (b) into the composite indicator - vulnerability index (c) for The Hague, The Netherlands. (a) The population density data has a spatial resolution of 0.077km^2, which this research uses as spatial units. (b) The disadvantage score data comes at the neighborhood ('buurten') resolution. (c) The two datasets are spatially joined and the disadvantage score data is attributed to the spatial units. Then, vulnerability index is calculated for every spatial unit given its scaled population density and disadvantage score values.

Next, the disadvantage score data of The Hague is imported into QGIS as a vector layer, each polygon represents a neighborhood in the city and its score (Figure 5.5b). The disadvantage score ranges from -25.1 to 17.4, in which a score of 0 is average, a negative score denotes no or low disadvantage, and a high positive score means the neighborhood is disadvantaged [64]. The disadvantage score layer is spatially joined to the spatial unit layer with population density data (processing toolbox → vector general → join attributes by location). This process transfers the disadvantage score of neighborhoods to the spatial units based on the spatial intersection and each spatial unit will take the disadvantage attribute of the neighborhood it overlaps the most with if it intersects with multiple. This produces a new vector layer in which every spatial unit stores a population density value and a disadvantage score. The inputs for calculating the vulnerability index are all prepared. Following the vulnerability index calculation in Chapter 4, the population density and disadvantage scores are first scaled according to Equation 4.1, then the vulnerability index is calculated for all spatial units with Equation 4.2 (Figure 5.5c). The vector layer of the vulnerability index is cropped to the area of the toy problem and exported as a comma-separated values (CSV) file. Figure 5.6 displays all properties of spatial units in the toy problem.



(a) Spatial units in the toy problem. **(b)** Population density of toy problem spatial units.



(c) Disadvantage score of toy problem spatial units. **(d)** Vulnerability index of toy problem spatial units.

Figure 5.6. Visualizing demographic and socioeconomic data of the spatial units located within the toy problem, an area of 0,09km^2 in The Hague. (a) A map showing the nine spatial units located in the toy problem; (b) visualizing the population density, (c) the disadvantage score, and (d) and the vulnerability index (composed of the former two variables) of toy problem spatial units.

The next step is to assign vertices to spatial units based on shard spatial reference so that the vertices can inherit the vulnerability index as an attribute. The CSV file is loaded in Jupyter Notebook to execute the following mathematical process of transforming the vulnerability index of spatial units to vertex property:

$$\boldsymbol{v'} = \boldsymbol{B}\boldsymbol{v}. \tag{5.5}$$

Given:

$$\boldsymbol{v'} := [v'_{\mathrm{i}}]_{n\times 1}, \tag{5.6}$$

$$\boldsymbol{v} := [v_{\mathrm{i}}]_{v\times 1}, \tag{5.7}$$

$$\boldsymbol{B} := [B_{\mathrm{ij}}]_{n\times s}, \tag{5.8}$$

where:

n the number of vertices in the toy problem,
s the number of spatial units in the toy problem.

The QGIS vector layer of the vulnerability index is loaded into Jupyter Notebook and arranged into array $\boldsymbol{v}$, an array with which each element stores the vulnerability index of a spatial unit (Equation 5.7). Assignment matrix $\boldsymbol{B}$ assigns each vertex to a spatial unit based on intersection (Equation 5.8). The multiplication product of $\boldsymbol{B}$ and $\boldsymbol{v}$ is array $\boldsymbol{v'}$, the final output of this section, which is an array that stores the vulnerability index of the spatial unit each vertex represents (Equation 5.6). $\boldsymbol{v'}$ is visualized in Figure 5.7.

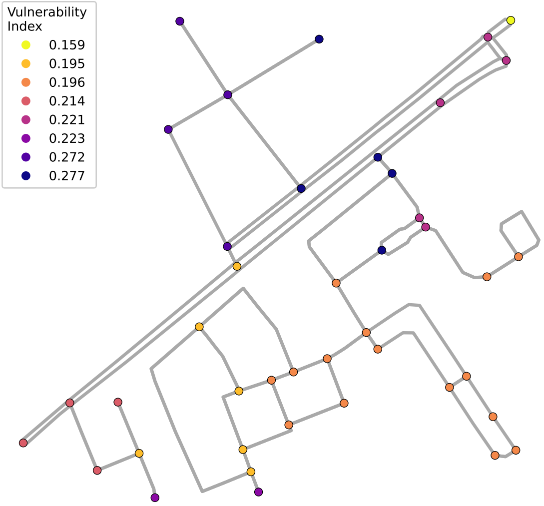


Figure 5.7. Toy problem vulnerability index.

Chapter 6

Model

This chapter introduces the Generative Design (GD) model of the SDSS. Firstly, the design space and fixed variables (σ_{fixed} and σ_{unit}) are defined and initial accessibility for G_{start} without intervention is calculated. Then, the chapter will walk readers through the GD model in detail.

6.1 Model Input Preparation

6.1.1 Define design space

To define the design space, the process takes the graph G_{base} and G_{start} and searches for and stores the indices of the edges absent in the latter but present in the former. This set of a number of non-existing edges in G_{start} specifies the decision variable $\boldsymbol{x}$, which is a a x 1 binary vector. Each element in vector $\boldsymbol{x}$ represents a non-existing edge. The lengths (meter) of the non-existing edges are extracted from G_{base} and stored in vector $\boldsymbol{l}$. There are six edges from G_{base} that are non-existing in the pedestrian G_{start} of the toy problem (Figure 6.1). Thus, $a = 6$ and the decision variable is:

$$\boldsymbol{x} = [x_{\text{i}}]_{6\times 1} \in \{0, 1\}^{6\times 1}. \tag{6.1}$$

Figure 6.1. Map of toy problem's pedestrian G_{start} including the decision variable edges (colored edges). The number of colored edges is less than a as some of them are of the same two-way street but represent different directions.

6.1.2 Calculate accessibility

After defining the decision variable, accessibility is calculated for G_{start}. This is the initial accessibility of the network before an intervention. In the objective function, it is accessibility $\boldsymbol{\alpha}$ at time step t of discrete time iteration when $\boldsymbol{x}$ does not impose an intervention ($\boldsymbol{\alpha}(\boldsymbol{x}^{(t)})$). To calculate accessibility, Dijkstra's algorithm is employed for shortest path calculation [75]. The complete steps to calculating accessibility in this research are explained in this section and Figure 6.2 is a flowchart of the method.

Firstly, given the G_{start} of the toy problem, the weighted shortest path from all n number of vertices to all o_{k} number of POI vertices of a given category c is calculated with Dijkstra's algorithm. POI vertex refers to those in G_{start} that represent a POI category, as informed by two-dimensional array $\boldsymbol{P'}$. The outputs are stored as elements in the two-dimensional array $\boldsymbol{D}_{\text{c}}$:

$$\boldsymbol{D}_{\text{c}} := [Dc_{\text{ij}}]_{n \times o_{\text{k}}} \tag{6.2}$$

This array stores the smallest travel distances to reach every POIs in category c from all vertices. Two particular observations could be made here: some elements in $\boldsymbol{D}_{\text{c}}$ may be zero or not a number (NaN). A vertex's shortest path to a POI will be zero if the vertex represents the POI itself, the method assumes a travel distance of zero. On the other hand, a vertex's shortest path will turn out NaN, if there exists no possible path in the network for the vertex to reach the POI. The latter situation could occur if a network consists of disconnected graphs, i.e. an edge is non-existing because it has been classified as inaccessible to pedestrians or cyclists, thus leading to a part of the graph being disconnected, which is the case for the pedestrian G_{start} of the toy problem (see Figure 5.3a). In reality, everything is connected and such complete disconnection is not possible as an individual can still travel through a street even if it is not designated for walking or biking. Therefore, the method replaces the NaN values by a large number - in this research, 10,000 is used - to simultaneously expresses (i) real-life connectivity that is unrepresented by the graph and (ii) high inaccessibility for the transport mode under study. This problem is less likely to arise when this method of calculating accessibility is applied on a larger graph, such as a city's network, where the shortest paths could still be identified amongst the large sets of edges. Whereas the toy problem consists of a comparably small number of edges, thus a single non-existing edge has a higher importance in the connectivity of the graph. Lastly, it is to be noted that theoretically, the shortest path distances in $\boldsymbol{D}_{\mathrm{c}}$ should be considered 'inaccessibility' instead of 'accessibility', since the larger the number (distance), the more inaccessible a POI is to a vertex. Thus, the reciprocal of the elements in $\boldsymbol{D}_{\mathrm{c}}$ is calculated to convert the values from inaccessibility to accessibility.

Next, given the shortest paths Dc_{ij} to all POIs in category c, the 'smallest shortest path' (SSP) is selected for each vertex and outputs vector $\boldsymbol{d}$. In doing so, the closest POI in category c for every vertex is identified, and $\boldsymbol{d}$ shows the shortest travel distance that inhabitants represented by a vertex need to travel to reach category c in daily life:

$$\boldsymbol{d} := [d_{\mathrm{i}}]_{n\times 1}\,. \tag{6.3}$$

Given there is k number of POI category, the aforementioned calculation is repeated until there is k number of vector $\boldsymbol{d}$. The set $\mathcal{D} = \{\boldsymbol{d}_0, \boldsymbol{d}_1, \cdots \boldsymbol{d}_{\mathrm{k}-1}\}$, $|\mathcal{D}| = k$. The vectors in set $\mathcal{D}$ are then concatenated to the two-dimensional array $\boldsymbol{D}$. This matrix stores the SSPs for every vertex to reach all POI categories:

$$\boldsymbol{D} := [D_{\mathrm{ij}}]_{n\times k}\,. \tag{6.4}$$

Lastly, the SSPs are averaged and the result is accessibility:

$$\boldsymbol{\alpha} := [\alpha_{\mathrm{i}}]_{n\times 1}\,. \tag{6.5}$$

To calculate accessibility post-intervention, the input graph should be G_{start} and output is $\boldsymbol{\alpha}(\boldsymbol{x}^{(t)})$. But to calculate post-intervention accessibility of generated design, the input graph should be G_{design}

and the output is $\boldsymbol{\alpha}(\boldsymbol{x}^{(t+1)})$.

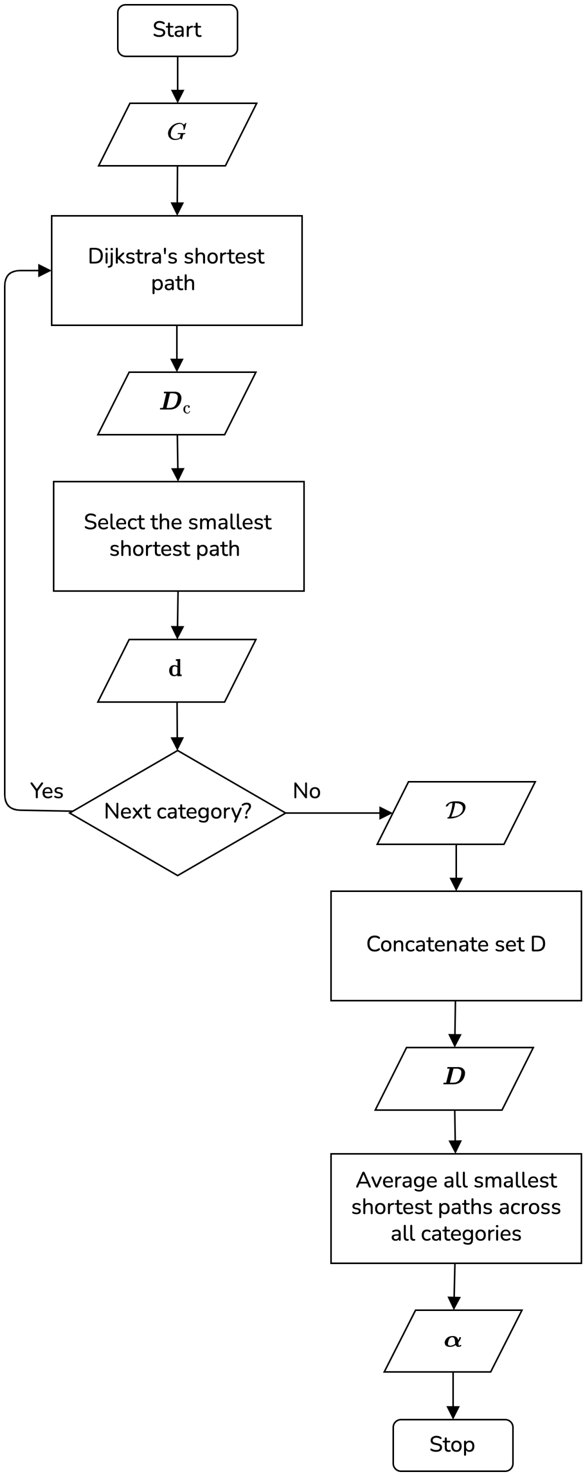


Figure 6.2. Flowchart of accessibility calculation.

6.1.3 Define fixed variables: Fixed and unit cost

The objective function takes two fixed variables: the fixed cost (σ_{fix}) and unit cost (σ_{unit}) of the street enhancement project associated with generated designs. For this research, they are defined as:

$$\sigma_{\text{fix}} = 10,000\,, \tag{6.6}$$

$$\sigma_{\text{unit}} = 1,000\,, \tag{6.7}$$

which are arbitrary values with a non-real monetary unit. For the purpose of testing the GD model, simple fixed variables will suffice and provide ease in the testing process. By now, all inputs required to run the model are prepared.

6.2 Generative Design Model

The goal of the GD model is to determine which edge(s) to add to G_{start} given decision variable $\boldsymbol{x}$, such that the weighted improvement in accessibility relativized by total cost is maximized. The model employs a Genetic Algorithm (GA) for optimizing edge addition. A heuristic approach is necessary because the computational complexity is $O(2^{\text{a}})$. An edge in the decision variable has two possible states: zero or one, so the design space, in other words, the total number of possible combinations, is 2^{a}). The toy problem is comparably small in scale with a total of 64 possible combinations (2^6). However, the number of possible solutions increases exponentially as the problem scales up.

GAs are randomized search algorithms that emulate the process of natural selection to find optimal solutions [76]. Based on the principle of genetics and evolution, GAs operate on a set of randomly generated individuals (population), and through iterative processes of selection, crossover, and mutation, the algorithms proceed by generating successive generations of progressively fitter individuals until the optimal is found [77]. The single-objective GA from the optimization library Pymoo is implemented in this research [78]. Besides GA, this research also solves the problem through exhaustive searches and all possible designs are generated. This is possible due to the small scale of the toy problem but also needed to closely examine the model behaviors.

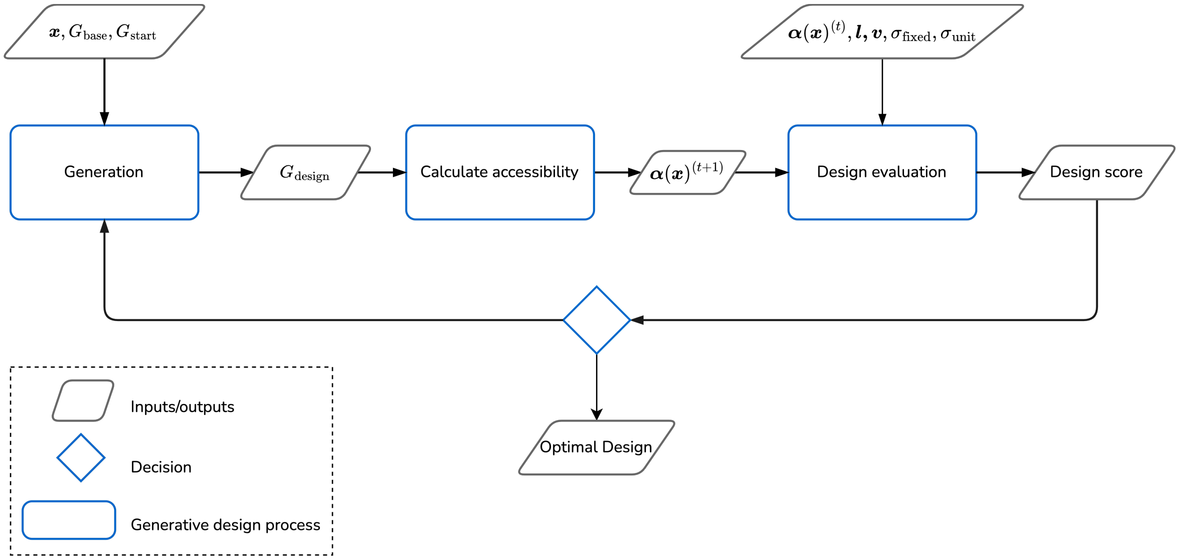


Figure 6.3. Flowchart of Generative Design model.

The processes in the GD model will be explained (see Figure 6.3. **Generation** is a computational process that takes decision variable $\boldsymbol{x}$ at $t{+}1$ time step, representing an intervention (design), and builds a new graph, G_{design}, which is composed of edges of G_{start} and edges added by the intervention. This computational process transforms the intervention from a vector of $\boldsymbol{x}$ to a graph. Next, accessibility ($\boldsymbol{\alpha}(\boldsymbol{x}^{(t+1)})$) is calculated for G_{design} following the method discussed in Section 6.1.2. Lastly, G_{design} is evaluated at the **Design Evaluation** by the objective function and the model outputs a design score. The design score then passes through 'decision'. Decision refers to (i) the GA optimization's search for the optimal by generating successive generations of progressively fitter individuals, and (ii) the engagement and analysis of users, which can immediately feedback to the iterative process until the users find the satisfactory results.

Table 6.1. Parameter settings of Genetic Algorithm for the toy problem [78].

Parameter/operator	Choice
Initial population	50
Sampling	Binary random sampling
Selection	Tournament
Crossover	Half uniform crossover
Mutation	Bit-flip

The GA parameters and operators used in the optimization are listed in Table 6.1. First, an initial population of 50 is generated randomly, every individual represents a design in the design space. Then, the individuals proceed to the generation and accessibility calculation processes. In the performance evaluation process, the design score of each individual is its fitness score, calculated by the objective function. Next, tournament selection is used to select individuals that will propagate.

Tournament selection holds competitions between randomly selected individuals, and the winners with higher fitness are inserted into the mating pool [77]. Half-uniform crossover (HUX) is employed to exchange parental genes for creating new off-springs. HUX calculates the number of bits with non-matching alleles between the parents' genes and swaps half of them during crossover [79]. Crossover enables the exploration of new regions in the design space. Then, the bit-flip mutation, a common operator for optimization problems that involve binary string representations, where a bit in the string is flipped to form a new offspring string [77, 80]. These processes iterate until convergence happens, which in the case of a single-objective problem, an optimal or sub-optimal solution is found.

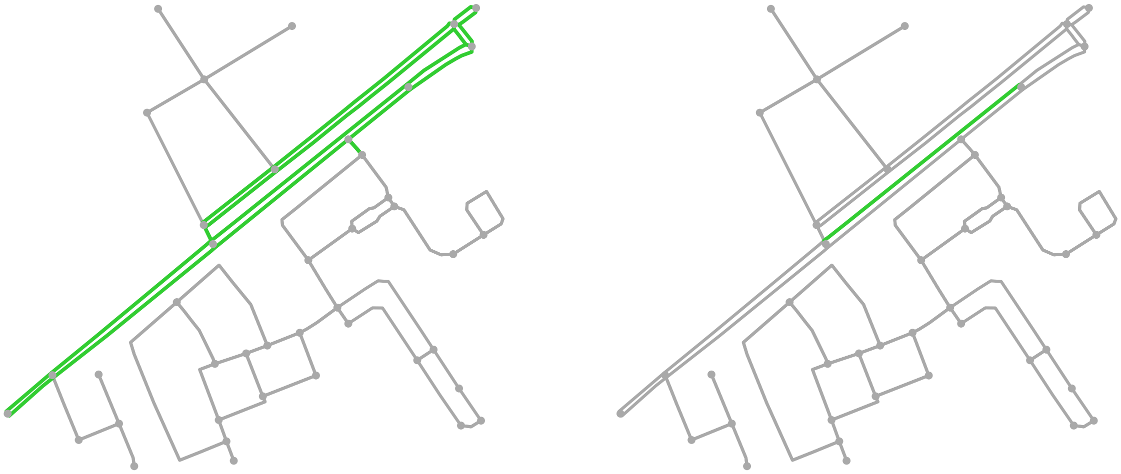
6.3 Define Scenario

A car-dependent city scenario is created to explore how results change if streets are classified differently. As suggested by the name, this scenario is a version of the toy problem but from an imaginary car-dependent city instead of from The Hague. In this scenario, bikeable streets are only those tagged as 'cycleway', 'residential', and 'living street', and walkable streets are streets tagged as 'pedestrian', 'residential', and 'living street' only (Table 6.2).

Table 6.2. List of all relevant enquotehighway key values in the OSM data set on the street network of the car-dependent city scenario and an indication of the transport mode they are accessible to (0 = inaccessible and 1 = accessible).

Key value	**Car**	**Bike**	**Pedestrian**
unclassified	1	0	0
cycleway	0	1	0
tertiary	1	0	0
residential	1	1	1
secondary	1	0	0
pedestrian	0	0	1
primary	1	0	0
living_street	1	1	1
motorway	1	0	0
motorway_link	1	0	0
trunk	1	0	0
trunk_link	1	0	0
primary_link	1	0	0

Based on the street classification system of this scenario, the non-existing streets for the pedestrian and bike network are shown in Figure 6.4. The pedestrian network has a set of 14 non-existing edges as the decision variable $\boldsymbol{x}$. Unlike the toy problem bike network, which shows no difference between its G_{base} and G_{start} and indicates no improvement possible, the bike network of this scenario has one edge in its $\boldsymbol{x}$.



(a) Decision variable of the pedestrian network.

(b) Decision variable of the bike network.

Figure 6.4. Decision variables of the pedestrian and bike network of the car-dependent city scenario.

Chapter 7

Operational Framework

This research has introduced the Street Allocation Decision Problem (SADP) and the generative design (GD) model of the Spatial Decision Support System (SDSS) insofar. The problem is formulated as such to computationally generate solutions for improving equity of accessibility through GD model. The problem and GD model are built upon the definition of accessibility and equity established in this research: accessibility as the average shortest path distance to all point of interest POI categories and equity as the accessibility maximization for the most vulnerable neighborhoods. They are foundational to SDSS. However, three aspects of the problem are flexible for change. They are namely: (i) the vulnerability index, calculated as the equally weighted geometric mean of disadvantage score and population density; (ii) the street classification system, employing OpenStreetMap (OSM) 'highway' key values to distinguish walkable and bikeable streets; and (iii) the POI used in calculating accessibility, including all urban amenities that fit in the defined seven POI categories. Taking these three aspects as starting points, this chapter will introduce the operational framework developed in this research because delving into the results.

This research develops a framework to guide prospective users in tuning and operating the SDSS for their specific context, problem, and objective. Thereby, is referred to as the operational framework and is presented in Figure 7.1. The framework centers around the three aspects mentioned above, they are referred to as the model 'hyperparameters'. Unlike the hyperparameter in Machine Learning terms, which are parameters that control the learning process, hyperparameters within the context of this research are high-level parameters that determine the social and practical meanings of model results and serve to guide users in understanding the results and the interpretation of their meanings.

As shown in Figure 7.1, the hyperparameters can be adjusted for a given problem and established objective. The process of specifying the hyperparameters is a translation of users' problems into the three aforementioned aspects of SDSS. Ultimately, the data processing computational process takes in data and arranges them for the GD model and the model takes in numbers and outputs numbers. These computational processes are fixed - numbers in and numbers out - but what kind of numbers to input and what outputted values mean, are determined by the hyperparameters. The following section will describe each of the three aspects in detail.

7.1 Vulnerability Index

The vulnerability index ($\boldsymbol{v}$) is a composite indicator aggregated from the equally weighted geometric mean of the disadvantage score and population density in this research. It is, basically, an indicator for grouping the population to identify the group(s) of the population that is of concern with regard to the objective and should be prioritized in the GD model evaluating the goodness of designs. Thus, disadvantage score and population density can be easily replaced by other demographic or socioeconomic indicator(s) to satisfy other objectives, as long as it provides the model a method of approximating which spatial units are more 'in need'. For example, the average household income is an ideal indicator given the objective is to improve the accessibility of lower-income neighborhoods. Whereas for decision-makers that want to expand the walking and cycling networks to improve the accessibility of small and disconnected neighborhoods, population density would have a much smaller weight in the vulnerability index. Given more than one indicator is used in composing the vulnerability index, the decisions on how to combine and weigh the variables also shall reflect the nature of the phenomena being measured and the objective of the study [81]. The nature of the phenomena refers to factors such as the dynamics of the city of interest, context-specific socioeconomic patterns, or specific equity concerns of the decision-makers. The weighting is also a subjective choice that influences the interpretation of what vulnerability embodies in the results.

7.2 Street Classification System

SADP demands a system to classify streets in the network under study in order to identify parts of the network that are deemed unsatisfactory according to a certain criterion. This research uses the OSM data and its 'highway' key values to distinguish walkable and bikeable street network (G_{start}) from the complete street network (G_{base}). The street classification system is a key hyperparameter because it defines the space of possible solutions and gives meaning to edge addition. Edge addition represents a decision to make a street segment accessible to pedestrians and/or cyclists in this research, but it can take on various meanings depending on the problem and objective. For example, given a problem in which low accessibility of vulnerable neighborhoods is due to poor safety of the pedestrian network, crime rate data can be used to classify the streets as safe or unsafe, and edge addition in SADP will represent a decision to make a street segment safe for pedestrians. Safety can also be determined by perceptive safety (e.g. of women) and will require the collection of qualitative data. Edge addition can also take on the meaning of building new bike lanes or expanding walking paths and so forth to demonstrate flexibility.

7.3 Point of Interest

Accessibility in SADP is calculated as the average shortest path distance to seven POI categories, mobility, active living, recreation, food choices, community space, education, and health and well-being. Thereby, the focus is on people's general accessibility to essential services and socioeconomic opportunities. But the selection of POIs can be tuned to one's objective and what is important for the targeted vulnerable population to have good access to. For example, SADP can be applied to improve young people's access to education by calculating accessibility to education-related POIs, such as schools, universities, and libraries. Another possibility is assigning different weights to POIs. For instance, if the goal is to safeguard the accessibility of elders, especially to healthcare facilities, one can use the same POIs as this research but assign a higher weight to healthcare-related POIs.

7.4 Role of Hyperparameters in Result Interpretation

The interpretation of model outputs is the task of the users of the SDSS, with which hyperparameters assist in understanding the social meanings (Who should and are benefiting from the designs? What does improving the accessibility of this neighborhood mean?) and practical meanings (What does edge addition mean for the entire network of the city? Is the total cost acceptable?). The SDSS is flexible for prospective users to integrate their context-specific knowledge and problem when using the tool. This allows the users to participate in the design process and is a useful learning experience for questioning and understanding what is the problem and what are possible solutions. Furthermore, it facilitates and encourages users to reflect on one's idea of what is an equitable distribution while being able to instantly see it manifesting in a network design solution, which should be carefully reflected as equity is more than some data and numbers in reality.

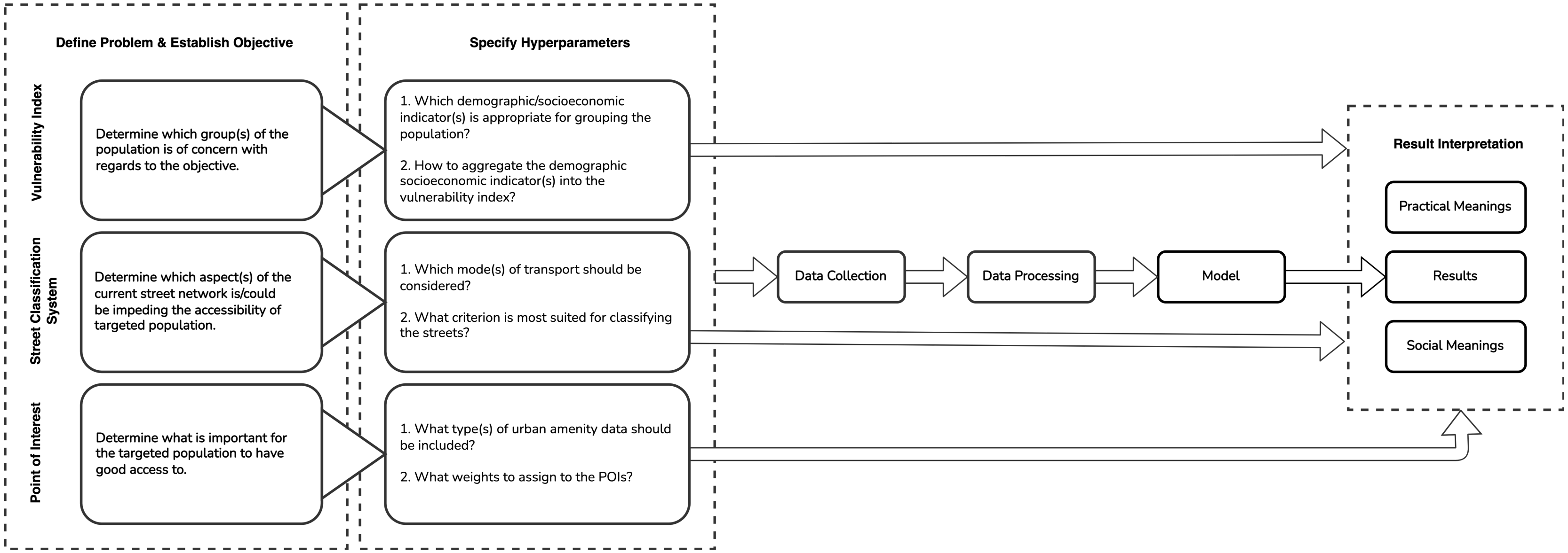


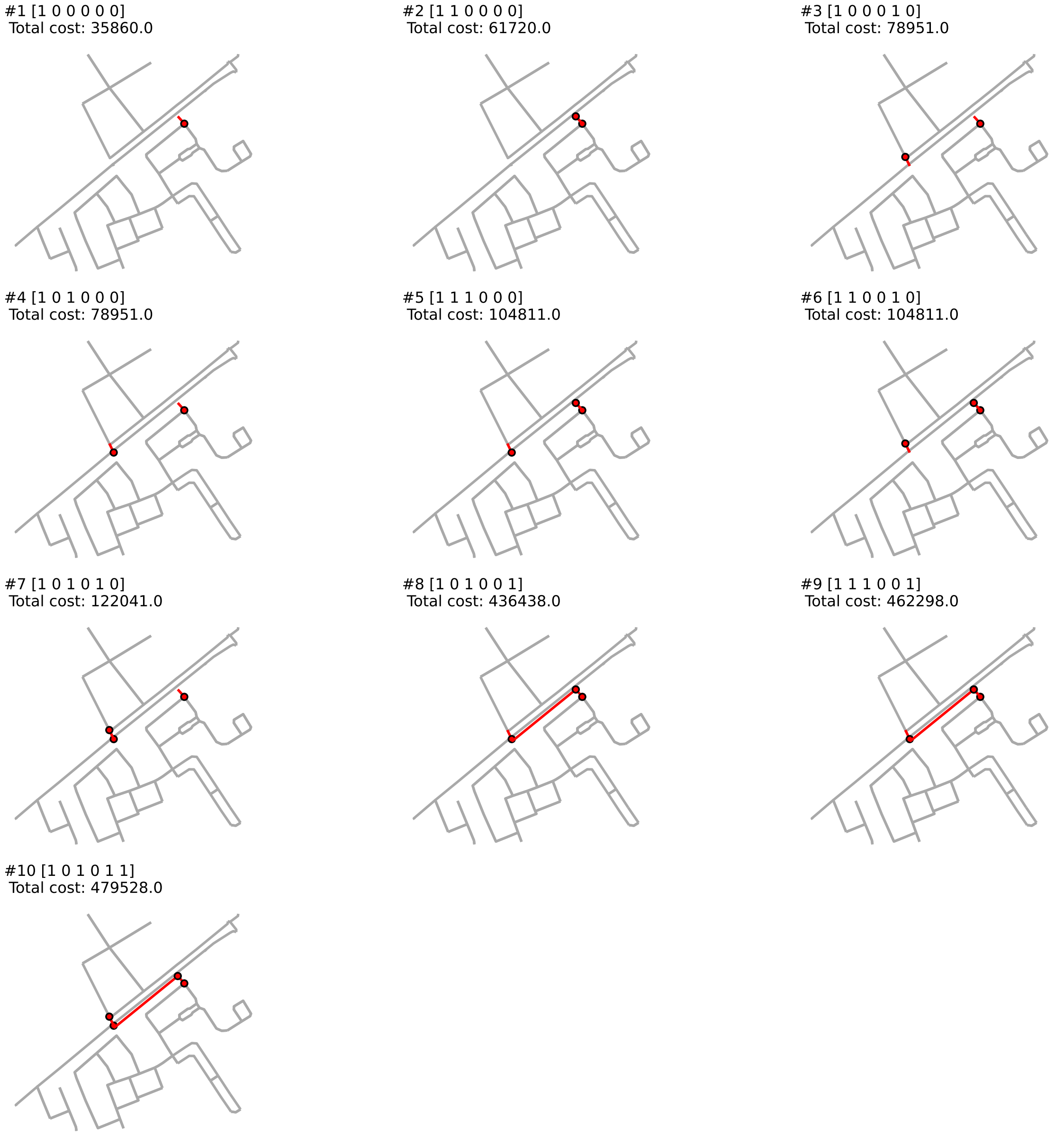
Figure 7.1. Operational framework of the Spatial Decision Support System.

Chapter 8

Results

8.1 Toy Problem Results

This section presents the results of the generated design model for the toy problem pedestrian network. Results include all 64 possible designs generated by an exhaustive search of the solution space for a detailed examination of the model outputs, as well as the optimal design selected by the Genetic Algorithm (GA). The top 10 optimal solutions for the toy problem pedestrian network are presented by Figure 8.1, they represent the various combinations of street segments a decision-maker could select to re-allocate them for pedestrian use. With both the exhaustive search and optimization, Design 1, `[1, 0, 0, 0, 0, 0]`, is the optimal solution with the highest design score of 0.00206. Design 1 improves accessibility by 0.00267 with a total cost of 35,860.


#1 [1 0 0 0 0 0]
Total cost: 35860.0

#2 [1 1 0 0 0 0]
Total cost: 61720.0

#3 [1 0 0 0 1 0]
Total cost: 78951.0

#4 [1 0 1 0 0 0]
Total cost: 78951.0

#5 [1 1 1 0 0 0]
Total cost: 104811.0

#6 [1 1 0 0 1 0]
Total cost: 104811.0

#7 [1 0 1 0 1 0]
Total cost: 122041.0

#8 [1 0 1 0 0 1]
Total cost: 436438.0

#9 [1 1 1 0 0 1]
Total cost: 462298.0

#10 [1 0 1 0 1 1]
Total cost: 479528.0

Figure 8.1. 10 optimal generated designs with the highest design scores of the toy problem pedestrian network. Red edges represent the added edges of generated designs. Some street segments are two-way, and the marker denotes the direction of the added edge. Detailed results in Appendix F.

The solution space is shown by Figure 8.2. Improvement in accessibility refers to the total improvement in accessibility across all vertices in toy problem (sum of all elements in $\boldsymbol{\alpha}\left(\left(\boldsymbol{x}^{(t+1)}\right)-\boldsymbol{\alpha}\left(\boldsymbol{x}^{(t)}\right)\right)$); weighted improvement is the sum of improvement occurring at every vertex relativized by its vulnerability index value (sum of all elements in $\left(\boldsymbol{v}^{T}\boldsymbol{\alpha}\left(\boldsymbol{x}^{(t+1)}\right)-\boldsymbol{\alpha}\left(\boldsymbol{x}^{(t)}\right)\right)$); total cost consists of fixed cost and unit cost; lastly, design score is the weighted improvement relativized by the total cost, which represents the amount of weighted improvement a design could create per unit of its associated cost.

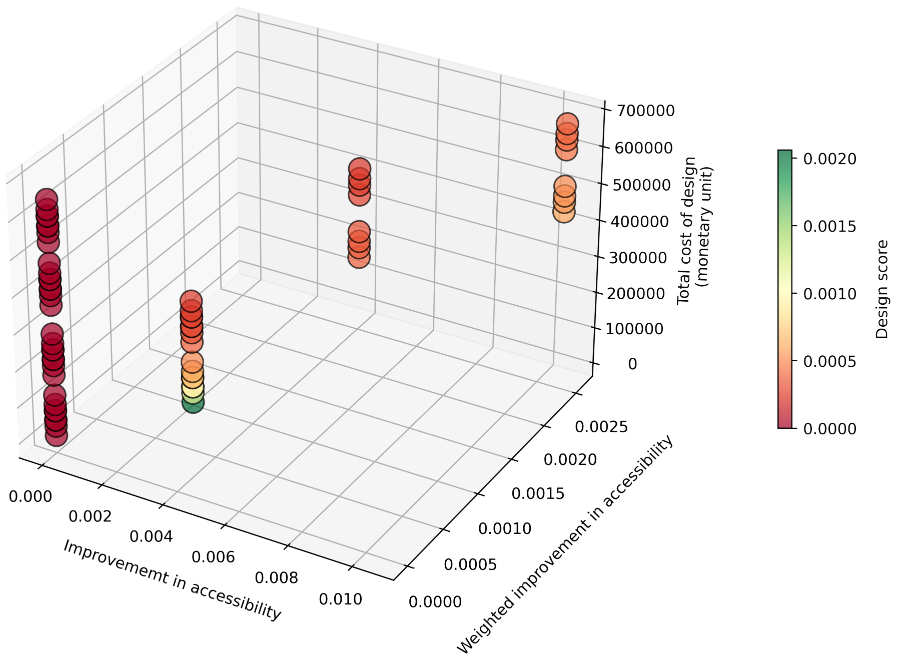


Figure 8.2. 3D scatter plot showing the relationships between improvement in accessibility, weighted improvement in accessibility, and total cost of generated designs by exhaustive search of solution space for toy problem pedestrian network. Markers represent solutions.

Several observations are made with regard to the characteristics of the possible solutions to the problem at hand. Firstly, the bottom left cluster in Figure 8.2 represents a significant number of designs that do not cause improvement in accessibility at all, thus receiving a design score of zero. Secondly, one can see a cluster next to the aforementioned cluster at the right, which improves accessibility slightly but their design scores vary depending on the associated total cost. Next, the upper middle cluster represents a few designs with similar design scores that improve accessibility moderately, induced a relatively high weighted improvement, and are all more expensive than the previous cluster. Lastly, in the upper right cluster are a few designs that increase the overall and weighted improvement significantly but are all costly. Interestingly, each cluster corresponds to a single weighted improvement value, meaning all designs in every cluster lead to the same weighted improvement in accessibility. This can also be seen in Figure 8.3. There is a fixed pattern of combinations between solutions' total and weighted improvement in accessibility: (i) a design with a total improvement of 0.00267 always has a weighted improvement of 0.00074; (ii) a total of 0.00631 always corresponds to a weighted of 0.0015; (iii) a total of 0.01051 always corresponds to a weighted of 0.00258. This means the improvement in accessibility in each combination occurs at the same vertex/vertices, thus improvement values are relativized by the same vulnerability index value and result in the same weighted improvement. The combinatorial pattern likely occurs due to the small scale of the toy problem and the non-existing edges concentrating around a few vertices.

From Figure 8.3, it is worth noting the negative relationship between total costs and design scores as the higher a design's total cost is, the lower its design score tends to be. Also, by observing the distribution of design scores in the diagonal histogram in Figure 8.3, one can argue that there is a clear optimal solution in the toy problem pedestrian network, in which not only it scores the highest but the second highest is nowhere close to it. This is somewhat supported by the color of markers in Figure 8.2, in which most markers (vertices) are red, very few are of the transition color of light orange or yellow, and there is a single marker with green, which represents the distinct optimal.

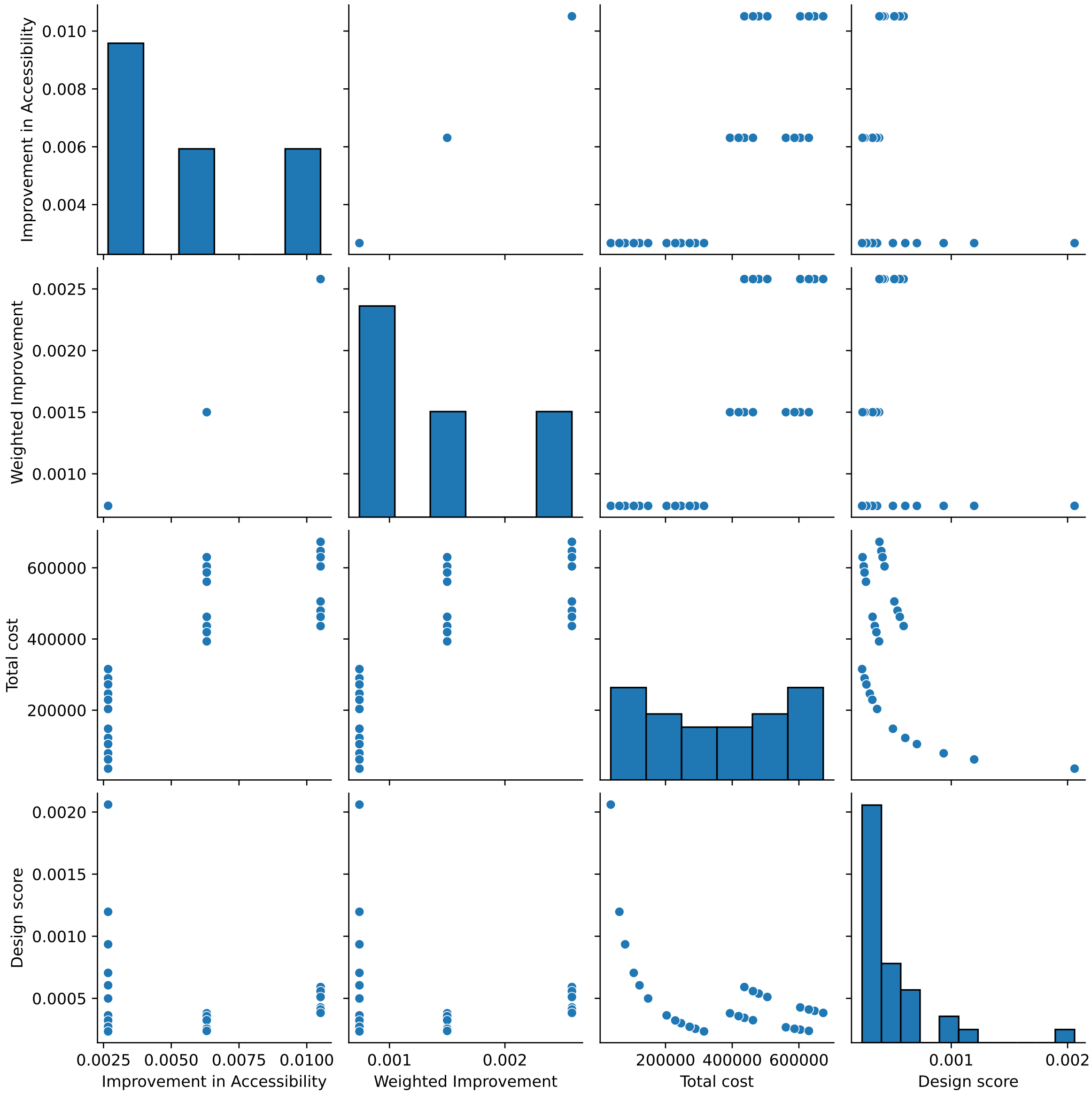
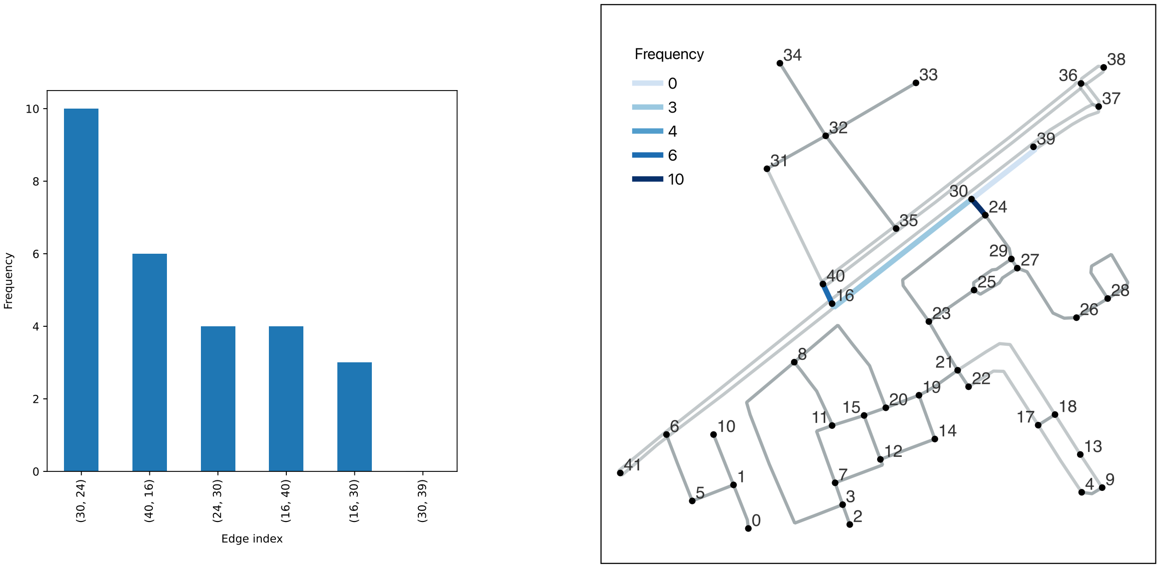


Figure 8.3. Pair-plot showing the pairwise relationships between improvement in accessibility, weighted improvement in accessibility, total cost, and design score of generated designs. Designs with a design score of 0 are excluded.

The decision variable of the toy problem pedestrian network is a set of 6 edges and Figure 8.4 shows the number of times each edge occurs in the 10 optimal designs and their location in the network. Edge [30, 24] is part of all 10 optimal designs and seems to be influential in improving the accessibility of vulnerable vertices. Note that, edge [30, 24] is the single added edge in the optimal Design 1. Next is edge [40, 16], which takes part in 6 designs, edge [24, 30] and [16, 40] in 4 designs, edge [16, 30] in 3, and edge [30, 39] does not appear at all in the optimal designs. This provides some understanding of the significance of non-existing edges in improving current accessibility. As discussed in Chapter 6, the G_{start} of the pedestrian network consists of two disconnected graphs, in which edge [30, 24] is the non-existing edge that connects the disconnected graphs. Thus, it appears reasonable that edge [30, 24] is influential as it connects vertices from the disconnected graphs and enables the shortest paths to POI vertices that were initially inaccessible.



(a) Bar chart showing the frequency of an edge involved in the 10 optimal designs.

(b) Bar chart visualized on a map.

Figure 8.4. Bar chart showing the number of times that an edge in the decision variable is involved in the 10 optimal designs of the toy problem pedestrian network and a corresponding map showing their locations. Edges in the network could be two-way streets, thereby a single edge could have two different values of frequency. The map displays the largest count in such instances.

8.1.1 Disaggregated Results

This section shows the results discussed in the previous section but disaggregated to orient the result presentation for serving decision-support purposes. Figure 8.5 presents (i) on the left, the spatial units of the toy problem and their vulnerability index, (ii) on the right, the spatial units and the improvement in accessibility that they benefit from the 10 optimal generated design. Figure 8.5 enables a side-by-side comparison between spatial units' level of vulnerability and how much the generated design improves their accessibility. Optimal Design 1 to 7 induce the same improvement in accessibility in a single highly vulnerable spatial unit, likewise for Design 8 to 10 but the latter improve accessibility in 7 spatial units. Such a pattern may be explained by Figure 8.1, in which Design 1 to 7 add similar edges to the pedestrian network and Design 8 to 10 too but involve a larger number of edges, which likely leads to a more extensive impact on accessibility. The differentiation in ranking between designs with unified effects on the same spatial units is caused by their varying total cost. Design 1 and Design 2 both benefit the same spatial unit to the same degree, but the former is cheaper, thus it creates higher improvement per unit of cost and ends up with a higher design score.

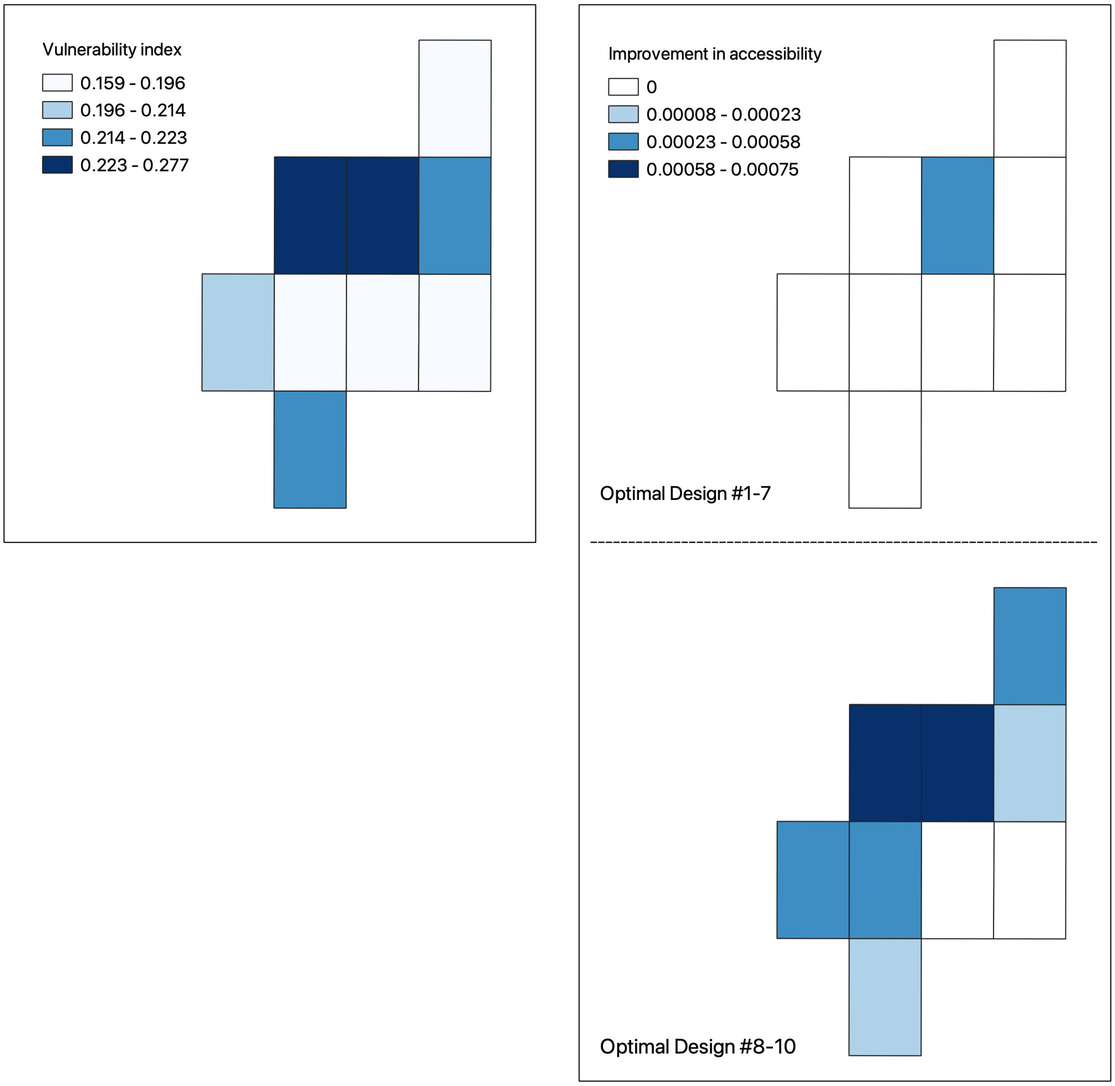


Figure 8.5. Visualization of disaggregated results. The improvements in accessibility induced by 10 optimal generated designs with the highest design scores of the toy problem pedestrian network are disaggregated over the spatial units.

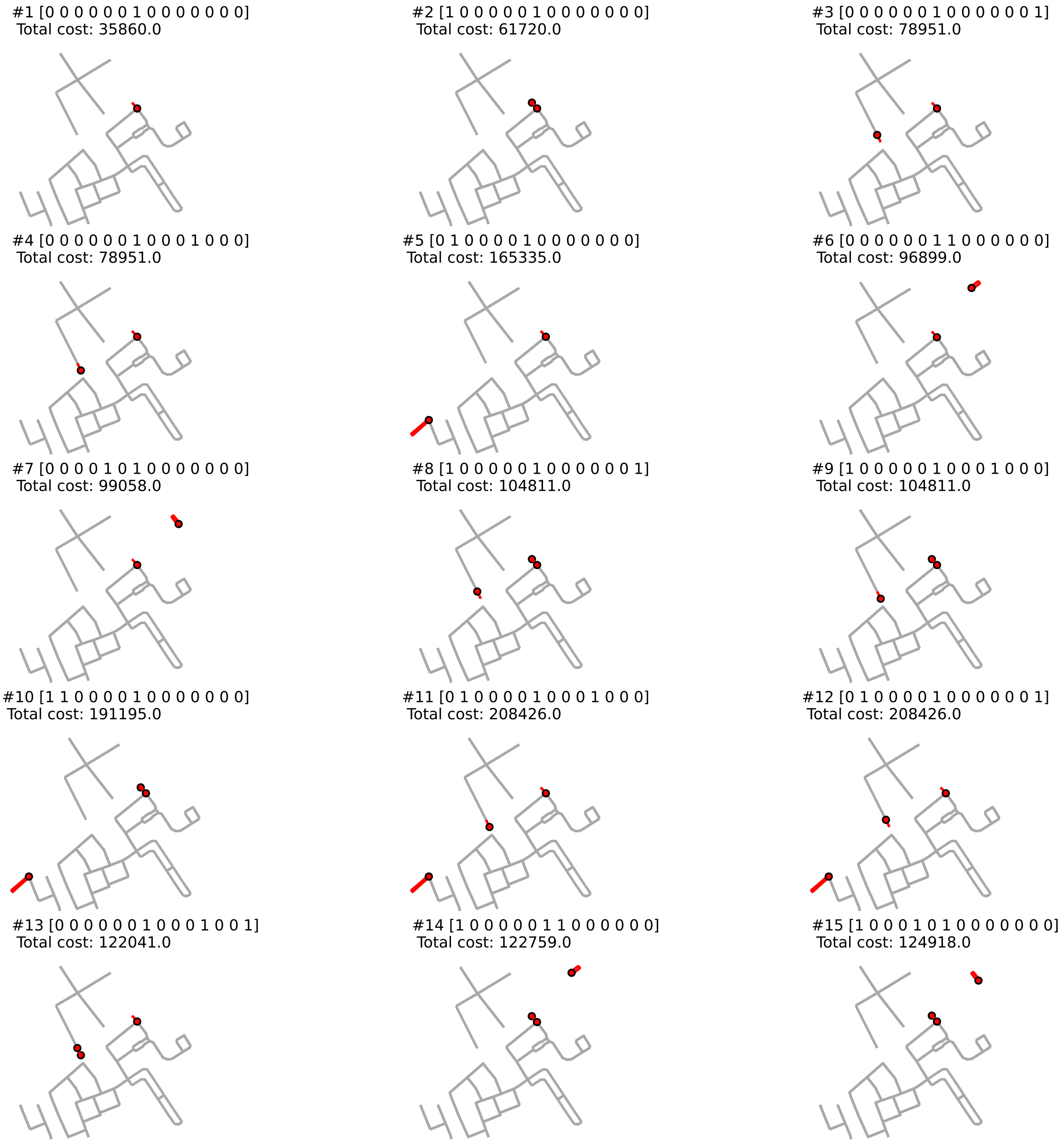
8.2 Car-dependent City Scenario Results

This section presents the car-dependent city scenario results by an exhaustive search of the design space and optimization with GA for the bike and pedestrian networks. The bike network decision variable is a set of a single edge and outputs two possible designs (Table 8.1). Since the solution space is very small, only an exhaustive search is done for the bike network. Both possible solution do not improve accessibility. This suggests the redundancy for a decision-maker to designate the currently non-bikeable street segment for biking in the car-dependent scenario since it does not create a positive impact on accessibility.

Table 8.1. Possible solutions (G_{design}) to the bike network of car-dependent city scenario with exhaustive search.

G_{design}	Added Edge Index	Improvement in Accessibility	Weighted Improvement	Total Cost	Design Score
[0]	[]	0.00313	0.01306	10000.0	0.03127
[1]	[(16, 39)]	0.00313	0.01306	531758.0	0.00059

The exhaustive search for the pedestrian network produces a solution space containing 16,384 possible designs, which is significantly larger than the toy problem with 64 possible designs. The increase in computational complexity can be observed when running the model for the pedestrian network, which took 2.45 minutes to run. One-fourth of the generated design (4,097) have design scores of zeros. Figure 8.6 displays 15 generated designs with the highest design scores. The optimal solution is design `[0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0]`, adding the edge [30, 24]. This is the same edge added by Design 1 of the toy problem. Figure 8.6 shows that the optimal solutions for the car-dependent city scenario are designs with which added edges may be disconnected from other edges and the rest of the network. This was not observed in the toy problem considering the decision variable is a set of six edges only, thus the number of non-existing edges is smaller and the G_{start} of the toy problem is less disconnected than the scenarios. The objective function evaluates designs solely based on the weighted improvement and total cost, and it is unable to/not designed to consider disconnectedness in the evaluation process.


#1 [0 0 0 0 0 0 1 0 0 0 0 0 0 0]
Total cost: 35860.0

#2 [1 0 0 0 0 0 1 0 0 0 0 0 0 0]
Total cost: 61720.0

#3 [0 0 0 0 0 0 1 0 0 0 0 0 0 1]
Total cost: 78951.0

#4 [0 0 0 0 0 0 1 0 0 0 1 0 0 0]
Total cost: 78951.0

#5 [0 1 0 0 0 0 1 0 0 0 0 0 0 0]
Total cost: 165335.0

#6 [0 0 0 0 0 0 1 1 0 0 0 0 0 0]
Total cost: 96899.0

#7 [0 0 0 0 1 0 1 0 0 0 0 0 0 0]
Total cost: 99058.0

#8 [1 0 0 0 0 0 1 0 0 0 0 0 0 1]
Total cost: 104811.0

#9 [1 0 0 0 0 0 1 0 0 0 1 0 0 0]
Total cost: 104811.0

#10 [1 1 0 0 0 0 1 0 0 0 0 0 0 0]
Total cost: 191195.0

#11 [0 1 0 0 0 0 1 0 0 0 1 0 0 0]
Total cost: 208426.0

#12 [0 1 0 0 0 0 1 0 0 0 0 0 0 1]
Total cost: 208426.0

#13 [0 0 0 0 0 0 1 0 0 0 1 0 0 1]
Total cost: 122041.0

#14 [1 0 0 0 0 0 1 1 0 0 0 0 0 0]
Total cost: 122759.0

#15 [1 0 0 0 1 0 1 0 0 0 0 0 0 0]
Total cost: 124918.0

Figure 8.6. 15 optimal generated designs with the highest design scores of the car-dependent city scenario pedestrian network. Red edges represent the added edges of designs. Some street segments are two-way, and the marker denotes the direction of the added edge.

In this scenario, the optimal solution is also distinct with a much higher design score than the rest, even though its impact on the accessibility is on the lower end (see Figure 8.7). Figure 8.7 also shows that the design score is highly sensitive to the total cost of design, in which interventions that create the same degree of improvement in accessibility score drastically differ due to their total costs.

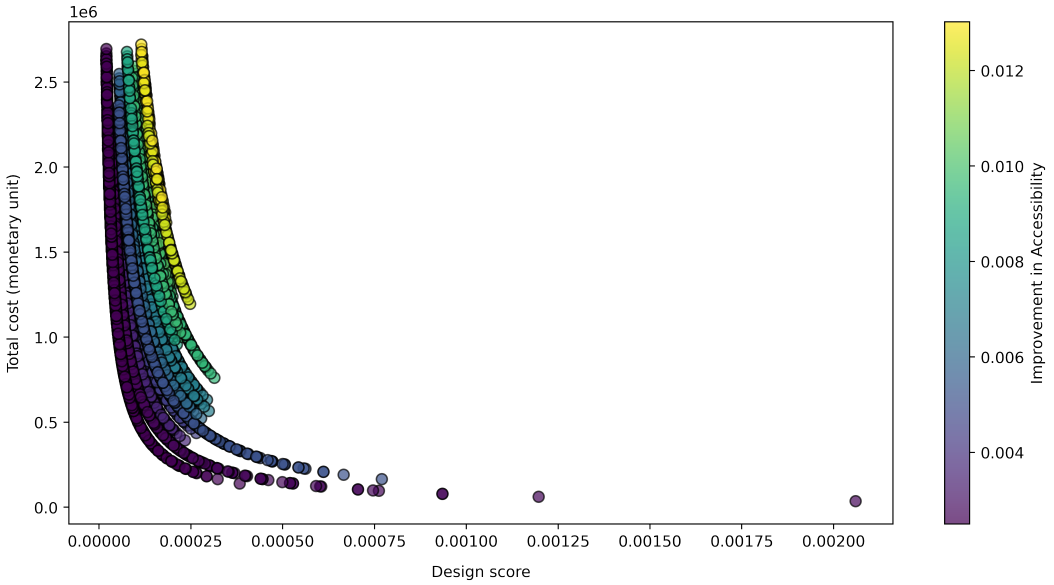
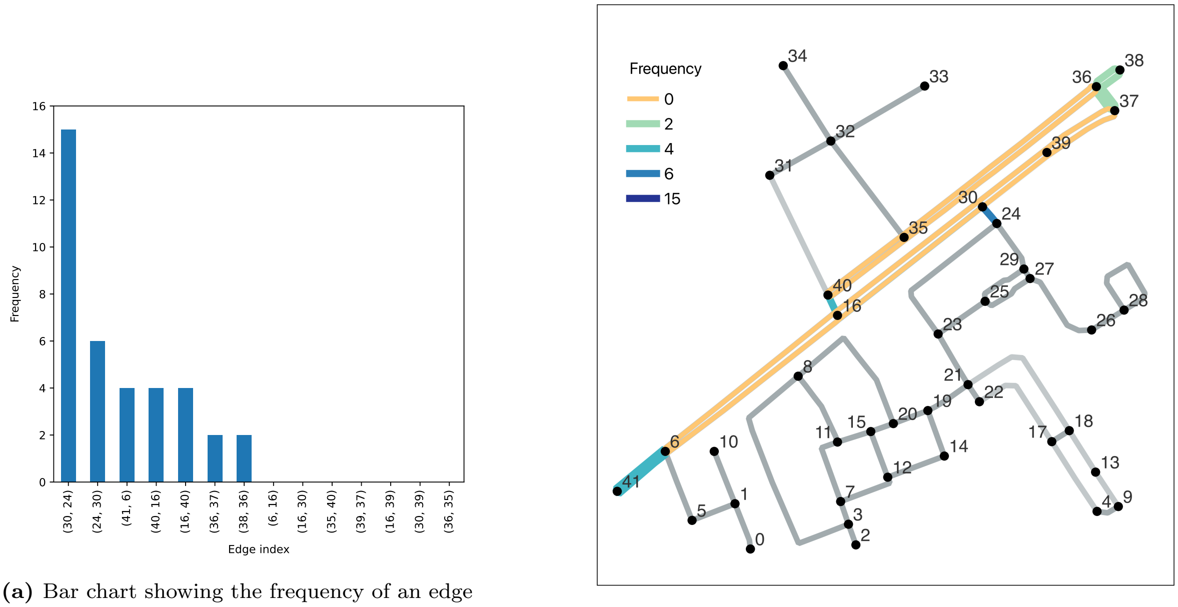


Figure 8.7. Scatter plot that shows all possible solutions to the pedestrian network of car-dependent city scenario with exhaustive search. Designs with a design score of zero are excluded.

Figure 8.8a shows the number of times each edge in the decision variable occurs in the 15 optimal designs and their location in the network. Edge [30, 24] is a part of all 15 optimal designs and seems to be influential in improving the accessibility of vulnerable vertices. This is followed by edge [24, 30], which is in 6 designs. Edge [41, 6], [40, 16], and [16, 40] all appear in 4 designs. Lastly, edge [36, 37] and [38, 36] appear in 2 designs. In the set of 14 edges of the decision variable, half of them do not appear in the 15 optimal designs. This provides some understanding of the significance of decision variable edges in the car-dependent city scenario.



(a) Bar chart showing the frequency of an edge involved in the 15 optimal designs.

(b) Map visualizing the bar chart.

Figure 8.8. Bar chart showing the number of times that an edge in the decision variable is involved in the 15 optimal designs of the car-dependent city scenario pedestrian network and a corresponding map showing their locations. Edges in the network could be two-way streets, thereby a single edge could have two different values of frequency. The map displays the largest count in such instances.

Figure 8.8b shows the location of all decision variable edges with edge color adjusted according to the frequency shown in Figure 8.8a. The G_{start} of this scenario is composed of several disconnected parts. It can be observed in Figure 8.8b that designs, which add edges connecting the disconnected parts to the rest of the graph, appear more frequently in the 10 optimal designs. For example, edge [30, 24], [30, 24] connects the upper part of the graph with the bottom part and edge [41, 6] that connects the disconnected vertex 41 to the network. They are influential edges because they enable the shortest paths to POI vertices that were initially inaccessible and have a higher impact on accessibility.

8.2.1 Disaggregated Results

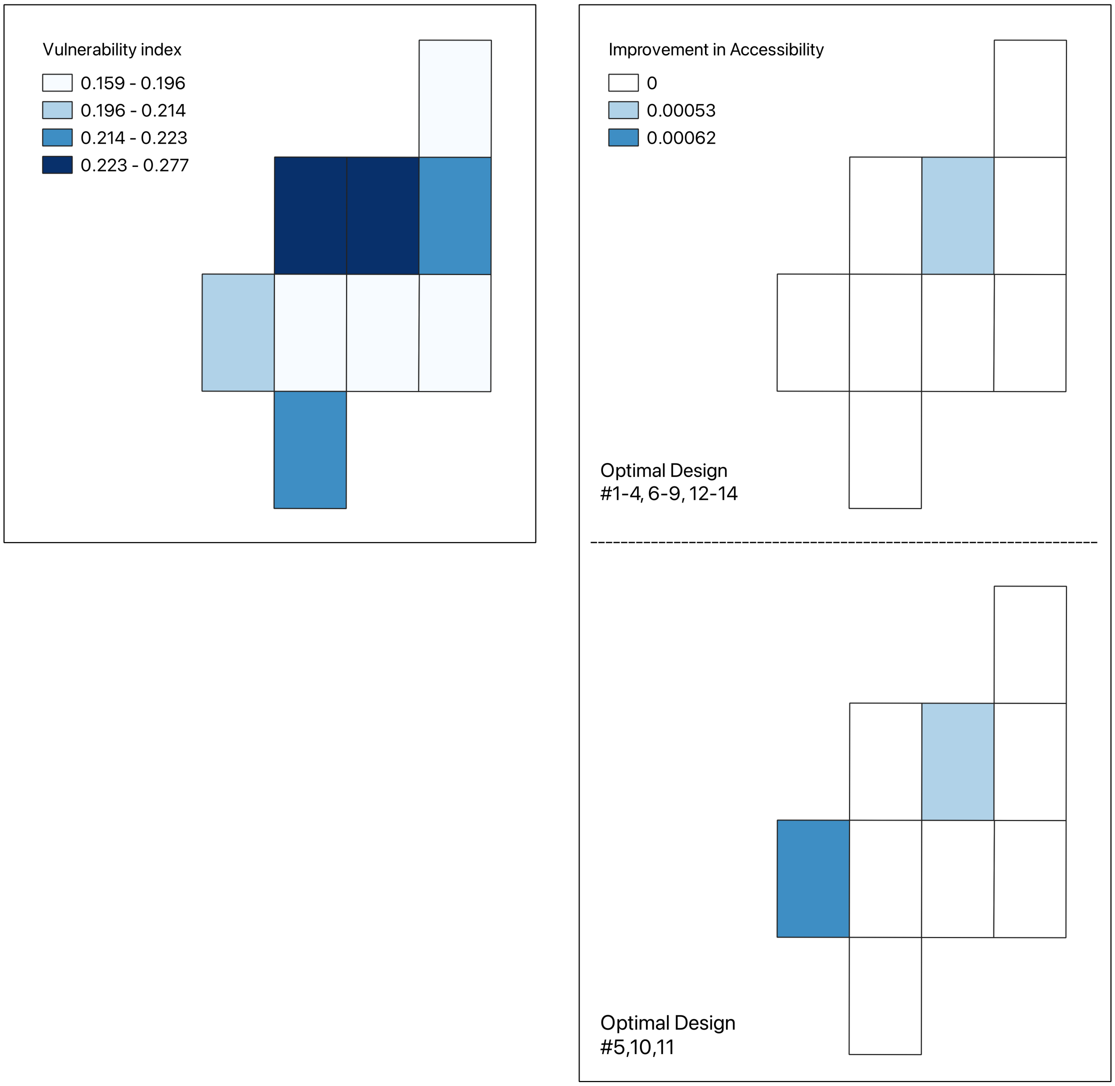


Figure 8.9. Visualization of disaggregated results. The improvements in accessibility induced by 15 optimal generated designs with the highest design scores of the car-dependent city scenario pedestrian network are disaggregated over the spatial units.

The disaggregated results of the car-dependent city scenario pedestrian network are shown in Figure 8.9, which visualizes the vulnerability index of the spatial units next to the improvement in accessibility each spatial unit experience in the 15 optimal designs. Interestingly, there are only two patterns seen in the spatial units' accessibility among these optimal designs. Design 1 to 4, 6 to 9, and 12 to 14 improve the accessibility of a single highly vulnerable spatial unit. Design 5, 10, and 11 improve the accessibility of the same vulnerable spatial unit to the same degree but improve a slightly vulnerable spatial unit more. The differentiation in ranking between designs with the same impacts on identical spatial units is caused by their varying total cost.

Chapter 9

Discussion

This research aims to support decision-making in enhancing equity of accessibility by developing a spatial decision support system (SDSS), which includes a generative design (GD) model and an operational framework for the model, for exploring how re-purposing existing streets for walking and biking could influence the accessibility of vulnerable neighborhoods. The SDSS is a humble attempt to combine Generative Design methodology and Transport Network Design Problems for improving equity of accessibility. It builds on the shoulders of existing literature and utilized well-established definitions and operationalization of the concepts of equity and accessibility. Yet, unlike design generation for products, buildings, or urban blocks, the novelty of this research is its attempt to employ GD on the abstract social criterion of equity as a design objective and formulate equity of accessibility problem into a design problem. The operational framework demonstrates the modularity of the SDSS as it allows the decision-makers' domain, context-specific knowledge to be integrated when operating the SDSS for their specific problems. This is essential as equity and accessibility are highly context-specific.

The GD model was tested on a toy problem and preliminary results were examined. The results demonstrate that the model can successfully generate designs and evaluate them based on the induced weighted improvement in accessibility relativized by their total cost. Results suggest that the toy problem bike network does not need improvement during data processing, as all street segments are considered accessible for biking, based on the street classification system. The optimal design for the pedestrian network generates moderate improvement in accessibility for a single highly vulnerable spatial unit and is deemed optimal as it brings about the highest weighted improvement per unit of cost. In the car-dependent scenario, the model shows no change in accessibility from the single possible intervention and suggests the redundancy for a decision-maker to designate the currently non-bikeable street segment for biking. The pedestrian network has an optimal design identical to that of the toy problem pedestrian network, but the former has less impact on accessibility than the latter. Lastly, it was observed that edge [30, 24] is the most influential in the toy problem network for increasing the accessibility of vulnerable neighborhoods.

Overall, some proof of concepts is gained. The SDSS can process spatial data, generate designs, visualizes the characteristics of problem solutions, and evaluate them based on the degree of impact on accessibility per unit of cost. The operational framework guides prospective users in developing problem definitions and exploring possible directions for solutions. This is a crucial journey for dealing with equity of accessibility through computational means. The model takes in and outputs numbers, it is the users that could give meaning to the numbers. Thereby, users have to develop clear problem definitions to be able to meaningfully interpret the results. This SDSS is ultimately a knowledge-building artifact and the following section will explain its limitations, which bound it as more a tool in experimental settings and explorative aids in early design stages, and the steps future research could take to refine and better the SDSS.

9.1 On Methodology

There are several opportunities for improvement with regard to the method of measuring accessibility. Firstly, it is computationally inefficient and unnecessary to calculate the weighted shortest path from all n number of vertices to all o_k number of POI vertices. Consider a city-scale network, it is computationally intensive to execute the shortest path algorithm between a large set of vertices, only to drop all paths except for the 'smallest shortest path' to be included in the accessibility measure. This is redundant, in the sense that, in reality, a person is unlikely to utilize and would not benefit as much from a distant POI if there is a closer one. Thus, there is a theoretical flaw in this method and it is suitable for a toy problem but troublesome for a larger problem, computational complexity-wise.

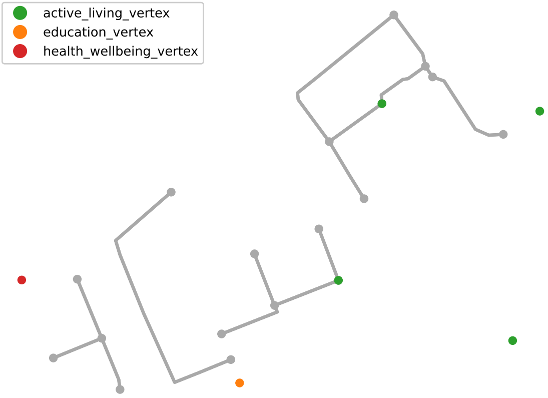


Figure 9.1. Pedestrian G_start with POI as a vertex attribute in the first version of car-dependent city scenario.

The second opportunity for improvement concerns a theoretical flaw suitable for larger problems but troublesome for the toy problem. The first version of the car-dependent scenario consists of a stricter street classification that only considers ‘cycleway’ and ‘living street’ as bikeable and ‘pedestrian’ and ‘living street’ as walkable edges (see Appendix E). The scenario cannot be analyzed and was subsequently dropped from the research because the initial accessibility ($\boldsymbol{\alpha}\left(\boldsymbol{x}^{(t)}\right)$) cannot be calculated, and the generated designs for this scenario cannot be evaluated by the objective function without it. As shown by Figure 9.1, some vertices have no means to reach POIs in all three categories. The method is limited as every vertex has to be able to reach at least one POI vertex in every category in order for the accessibility to be calculated. This is less of a concern for larger problems, considering the larger number of vertices and edges would most likely guarantee the shortest path to all categories. It can be concluded from preliminary results that the model is more suited for applying on the network with relatively extensive pedestrian and bike infrastructure to avoid this problem. The model can be used to identify important opportunities (missing links) in the network that could improve the accessibility of vulnerable neighborhoods, similar to the work by Vybornova *et al.* (2022) [82].

Lastly, the accessibility calculation of this research is difficult to interpret due to the need to convert from ‘inaccessibility’ to accessibility and replace NaN values with a large number, if the shortest path is zero and (10,000, in the case of this research, see Chapter 6 for details). The multiple data transformation steps in the calculation result in accessibility values ranging from 0.0001 to 0.3351 in the toy problem. This makes interpretation difficult as accessibility lost a graspable real-life measurement, such as distance or time. By solely looking at the generated designs, one can tell it is optimal by design score but the real-life meaning of its impact on accessibility is difficult to comprehend.

It is recommended that future research search for other measures for calculating accessibility that is more computationally efficient to fix the first identified methodological problem, measures that are more robust against the sizes of the network to avoid the second problem, and measures that can present accessibility in distance or time to solve the last problem. The second problem could also be solved by using a continuous instead of a binary street classification system. For example, give a vertex is connected to a POI via a very poor bike lane in reality, a continuous classification system could assign this lane a low score, and traveling through this lane is perhaps penalized in some ways to inform the model that this lane needs improvement. In this example, the vertex will not be disconnected from the POI completely. A street ’scoring’ system that assigns values between 0 to 1 instead of a binary classification used in this research also reflects reality better. In reality, most streets are not ‘black or white’ in terms of the designated modes of transport (of course, with exception such as highways), but‘good or bad’. For example, cities, such as Taipei and Bologna, have bike lanes but they are mostly drawn on the pedestrian paths, which makes the conditions for pedestrians worse (less space to walk and having to walk with bikes) and does not necessarily provide the best infrastructure for biking either (small bike lanes and often with pedestrian obstacles e.g. street bollards). The scoring system will support decision-making in further improving the lanes instead of simply accepting them as bikeable or not and facilitating safer biking in the cities. Although, this will lead to more demanding data requirements and much bigger solution space.

9.2 On Result Quality

A major limitation of the SDSS is that the result quality is highly sensitive to data quality. The result suggests that edge [30, 24] is highly important for the accessibility of vulnerable neighborhoods and it has the highest number of occurrences in the optimal designs. Based on the model result, one can conclude that the street segment represented by edge [30, 24] should be reallocated for pedestrians. However, a reality check disagrees with such a conclusion (Figure 9.2).

Figure 9.2. Image of edge [30,24] in the toy problem in reality, from Google Maps [83].

In reality, edge [30, 24] represents a bridge that is actually accessible for both pedestrians and cyclists. Upon closer examination of the OSM street network data, edge [30, 24] is tagged as 'cycleway', thereby it is classified as bikeable by the model and excluded in the G_{start} of pedestrian network. This highlight two key points that should be considered when processing OSM data. Firstly, the key values denoting the types of roads represented by edges often do not express a clear indication of the transport mode permitted or restricted (Appendix C). Secondly, the edges could be tagged incorrectly. In the case of edge [30, 24], it is tricky to say if it is both or neither of the two highlighted problems. It is a street segment accessible to bikes and can be considered a cycleway, however, it is accessible for pedestrians too, which is not expressed by the ‘cycleway’ tag and misrepresented the reality. This is a major limitation of this research’s methodology, as the quality and usefulness of results greatly depend on the level of precision with which the edges represent reality. In the toy problem, data quality is not of consideration, and problems such as labeling inconsistencies or ’unclassified’ tags are not further investigated, thus the surprise with edge [30,24] should be expected. Future work can improve street network data quality by checking the OSM data with satellite or field examination to provide more precise information on each street segment besides the OSM tags. It is also recommended that key value ‘unclassified’ should be examined closely as it contains additional information on the OSM street data. Furthermore, this could also be an opportunity to collect data from citizens and facilitate participatory design and decision-making.

Another observation from preliminary results that demands additional attention is the disconnectedness of edges in some generated designs. In the car-dependent scenario, added edges in various solutions are disconnected from the rest of the graph. At first, this was not observed in the toy problem due to a smaller number of edges in the decision variable. It seems that disconnected edges in the generated design will occur if there is a larger set of decision variable edges. The problem formulation did not account for connectivity, thereby it is an unexpected limitation of the research. The disconnectedness of added edge can be considered a limitation as it compromises the interpretability and practicality of the solution. Stepping away from the model, in reality terms, an ‘optimal’ design with an added edge that is disconnected from (some parts of) the network represents a decision to allocate a street segment for, e.g. pedestrian, while the adjacent streets are left non-walkable. This may be useful to provide insights into how important different street segments are for the accessibility of vulnerable neighborhoods. However, to solve the problem and improve the SDSS usability, future research could define the decision variable such that it involves designs that always connect to the rest of the network.

Chapter 10

Conclusion

The research question of this project is: **How can optimal improvements of existing street networks be identified to enhance equity of accessibility and decision support be provided?** To answer the question, the research has formulated equity of accessibility as a GD problem, named the Street Allocation Decision Problem (SADP) (first sub-research question), and developed a Spatial Decision Support System (SDSS) (second and third sub-research question) that solves the SADP.

In SADP, *improvement* is defined as a decision to allocate a street segment to be made accessible for walking and/or biking; *accessibility* is defined as the ease with which people can reach seven categories of points of interest (POI) that are essential for quality of life; *equity* is defined as vertical equity and operationalized as providing the most to the under-served. The problem involves a single-objective function that defines optimal solution as generating the maximum weighted improvement in accessibility per unit of its total cost.

The SDSS consists of a generative design (GD) model for solving the SADP and an operational framework. The operational framework guides prospective users in tuning and operating the SDSS for their specific context, problem, and objective. This is important because equity and accessibility are highly context-specific problems. Furthermore, the journey of developing the SADP, including defining problems and objectives and transcribing them into the language of models, was rich in knowledge-building and encourages one to understand the system under study more. Thereby, the framework is written to guide prospective users through the same fruitful, but more structured and easier, journey. Prior to decision-making, decision-makers have to first understand the problem, or his/her perception of the problem.

The GD model was tested on a toy problem, a 0,09km^2 area in The Hague, with a simple single-objective Genetic Algorithm, as well as an exhaustive search to look through the entire solution space to understand the model. The preliminary results have demonstrated the feasibility of the model. On the other hand, limitations have also been observed. The result quality of the model is highly dependent on the precision of street network data. The results also suffer from difficulty in interpretation as they are unitless values, which returns accessibility that cannot be temporally or distance-wise understood. It appears that the model is best for networks with relatively extensive pedestrian and bike infrastructure.

This is the first and a humble attempt at developing an SDSS for enhancing equity of accessibility with a GD model. Although, only a proof of concept at the moment, the SDSS is a valuable starting point due to its advantages, such as transparency, modularity, humane-ness, and flexibility. The world is progressively data-driven so is decision-making. This SDSS is built to involve decision-makers in the design process, which could serve as a useful learning experience for questioning and understanding what is the problem and what are possible solutions. Perhaps this is also valuable as a contribution to equitable decision-making - facilitating and encouraging one to reflect on one's idea of what is the problem and what is an equitable distribution while being able to instantly see it manifesting in a network design solution - in experimental settings or as explorative aids in early design stages. This is the essence of 'decision-support', providing the computational power to support people in knowledge-building instead of solely generation of numbers and best solutions. Before decision there needs understanding, equity is more than some data and numbers in reality, it embodies collective experiences and sufferings

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Appendix A

Code and Model

Code of the Spatial Decision Support System (SDSS) includes:

- OpenStreetMap data extraction
- Data processing
- Generative design model
- Result visualization

GitHub:

- Repository name: ‘Spatial-Decision-Support-System-for-enhancing-equity-of-accessibility’
- Repository owner: ‘springonions-87’

Appendix B

Inequitable Accessibility as a Wicked Problem

Table B.1. The ten properties of 'wicked problem' related to the improvement of equity of accessibility [17]. The comparison is inspired and adapted from [84]

Properties of wicked problems	Example from improving equity of accessibility
1. There is no definitive formulation of a wicked problem.	There is not a single objective definition of equity and any decision on what constitutes a fair distribution of transport resources/accessibility will ultimately be underpinned by normative judgment. Likewise, the definition of accessibility and the scope of the problem is difficult to define (e.g. one can expand the problem by incorporating the land use aspect of accessibility, frame the problem as urban-wide socio-spatial segregation, or shrink the scope as a problem of access to jobs).
2. Wicked problems have no stopping rule.	There is no *the* or *a* solution to the problem. What is considered a 'good enough' or 'better' solution to improve equity of accessibility is situational and continuously transforming.
3. Solutions to wicked problems are not true-or-false, but good or bad.	Solutions will be judged differently depending on the special value sets and ideological predilections of the actors involved. The goodness or badness of solutions also highly depends on the city under study and the context-specific knowledge of decision-makers.

Continued on next page

Properties of wicked problems	Example from improving equity of accessibility
4. There is no immediate and no ultimate test of a solution to a wicked problem.	Any solutions, such as altering street infrastructure and distribution of amenities or providing financial support on commuting, would generate waves of consequences over an extended period of time after implementation. The full consequences cannot be appraised until it has been implemented.
5. Every solution to a wicked problem is a "one-shot operation"; because there is no opportunity to learn by trial-and-error, every attempt counts significantly.	People's lives will likely be irreversibly influenced by the solutions. Undesired consequences, such as indirect segregation, will pose another set of wicked problems.
6. Wicked problems do not have an enumerable (or an exhaustively describable) set of potential solutions, nor is there a well-described set of permissible operations that may be incorporated into the plan	Ill-defined problems have ill-definable solutions. Any new ideas for urban planning to improve equity of accessibility may become a solution candidate. Enlarging the set of solutions as well as choosing which plans of action to pursue relies largely on judgment.
7. Every wicked problem is essentially unique.	The basis for decision-making related to improving equity of accessibility needs to be put into the context of the specific real-world situation (e.g. given a city under study, which groups of the population are considered disadvantaged and why are they disadvantaged; the size of the city will affect what good accessibility means and the set of solutions to consider) and available resources.
8. Every wicked problem can be considered to be a symptom of another problem.	Poor accessibility and differences in accessibility level amongst the population is both a symptom and a cause of other relevant wicked problems. If it is to be formulated as a 'higher-level' problem (e.g. considered as a symptom of urban segregation), the more difficult it becomes to do something about it. But addressing the problem as a symptom on a too-low level (e.g. providing financial support to commute for low-income households could be insufficient in addressing any of the system dynamics that drive the problem.
9. The existence of a discrepancy representing a wicked problem can be explained in numerous ways. The choice of explanation determines the nature of the problem's resolution.	The analysts' 'world view' is the strongest determining factor in explaining if there is and why is there inequity in accessibility. And this explanation is key to specifying the direction of solutions.

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Properties of wicked problems	**Example from improving equity of accessibility**
10. The planner has no right to be wrong.	Decision-makers are held responsible for all the consequences of the actions taken to improve equity of accessibility. Even though it is highly likely with any social policy all strata of the population will benefit greatly and the solutions and their consequences will be judged by increasing pluralism of the contemporary public.

Appendix C

Examine OpenStreetMap Data of The Hague

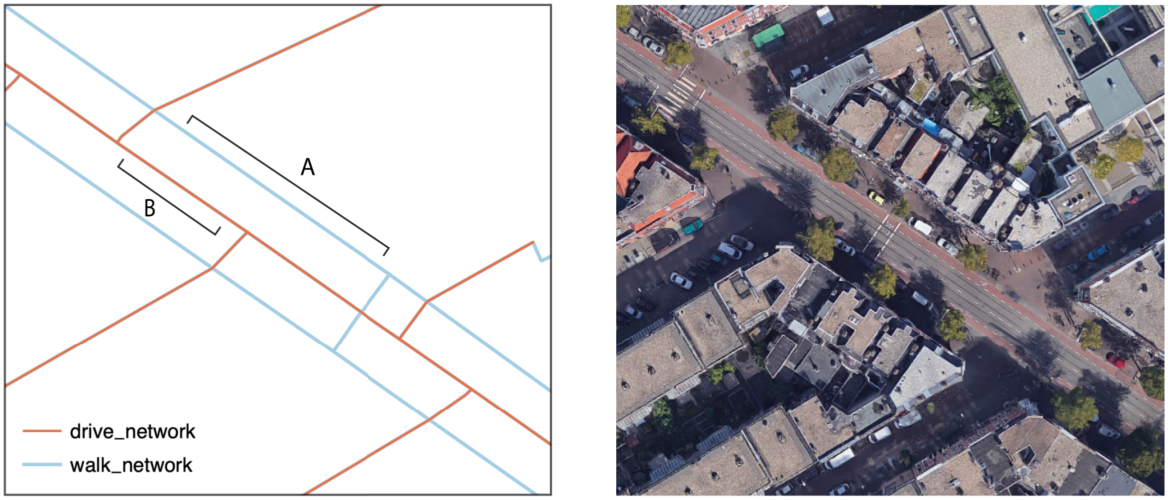

Figure C.1. Closer examination of the OpenStreetMap (OSM) street network data of The Hague to support street segment classification. In the left sub-figure, street segments are classified as drive (red) and walk (blue) networks according to OSM classification of different network types. **A** is tagged ‘footway’ and **B** is tagged ‘residential’. The left sub-figures are a satellite view of the right sub-figure, screen capture from Google Maps [83].

Figure C.1 shows that in OpenStreetMap (OSM) data, street segment **A** is tagged as ‘footway’ and in parallel, street segment **B** is tagged ‘residential’ (*“Roads which serve as an access to housing, without the function of connecting settlements. Often lined with housing.”* [73]). However, as shown by the satellite image in Figure C.2, there is a bike lane sandwiched between the former two street segments. This demonstrates the difficulty in deriving precisely which transport mode can access a street segment simply through the key value of OSM data. In this case, it would have been incorrect to classify **A** as not bikeable. Figure C.2 shows street tagged as ‘primary’ (*“The next most important road in a country’s system. Often link larger towns.”* [73]), which is designated for cars but has walking and biking paths. Thus, it would be incomplete to classify it as a street only for cars.

Figure C.2. Primary street segments. To show that primary streets could be streets that also have pedestrian and cycling paths even though there are non-parallel edges for those two transport modes (unlike Figure C.1). Screen capture from Google Maps [83].

Table C.1. The number of single-direction (one-way) and bi-directional (two-way) street segments in each 'highway' tag in the OSM data set on the street network of The Hague.

	one-way	two-way
residential	4912	12102
cycleway	4502	4230
tertiary	1956	910
secondary	1834	262
unclassified	221	674
primary	205	4
living_street	171	870
busway	169	256
motorway_link	59	0
primary_link	54	0
pedestrian	42	1160
secondary_link	37	2
motorway	20	0
trunk	17	0
trunk_link	12	0
tertiary_link	11	2
(residential, living_street)	3	30
(trunk_link, secondary_link)	3	0
(trunk, primary)	2	0
(residential, pedestrian)	1	44
(residential, tertiary)	1	0
(primary_link, tertiary)	1	0
bridleway	0	190
track	0	124
(residential, cycleway)	0	98
(cycleway, living_street)	0	46
(unclassified, cycleway)	0	14
(residential, busway)	0	4
(unclassified, residential)	0	4
(living_street, track)	0	3
(living_street, pedestrian)	0	2
(residential, cycleway, living_street)	0	2
(residential, track)	0	2
(track, pedestrian)	0	2
(track, living_street)	0	1

Appendix D

Categories of Points of Interest

Table D.1. OpenStreetMap (OSM) key values of key:amenity arranged into seven points of interest (POI) categories.

Amenity Key Values	POI Categories						
	Mobility	Active Living	Recreation	Food Choices	Community	Education	Heath & Wellbeing
transit _stop	X						
bus_stop	X						
bus_station	X						
public_transport	X						
fitness_centre		X					
sports_centre		X					
park		X					
pitch		X					
playground		X					
swimmming_pool		X					
garden		X					
nature_reserve		X					
marina		X					
recreation_ground		X					
fitness_station		X					
skate_park		X					
gym		X					
pub			X				
bar			X				
theatre			X				
cinema			X				
events_venue			X				
arts_center			X				
restaurant				X			
cafe				X			
food_court				X			
marketplace				X			
community_centre					X		
library					X		
social_facility					X		
social_centre					X		
townhall					X		
school						X	
childcare						X	
kindergarten						X	
university						X	
college						X	
pharmacy							X
dentist							X
clinic							X
hospital							X
doctors							X
bank							X
police							X

Appendix E

Car-dependent City Scenario Supplementary Information

Table E.1. List of all relevant 'highway' key values in the OSM data set on the street network of The Hague and indication of the transport mode they are accessible to (0 = non-accessible and 1 = accessible) for the first version of car-dependent city scenario.

Key value	Car	Bike	Pedestrian
unclassified	1	0	0
cycleway	0	1	0
tertiary	1	0	0
residential	1	0	0
secondary	1	0	0
pedestrian	0	0	1
primary	1	0	0
living_street	1	1	1
motorway	1	0	0
motorway_link	1	0	0
trunk	1	0	0
trunk_link	1	0	0
primary_link	1	0	0

Appendix F

Supplementary Results

Table F.1. Possible solutions to the pedestrian network of toy problem with exhaustive search.

Design	Index of added edge	Improvement in accessibility	Weighted improvement in accessibility	Total cost	Design score
[0 0 0 0 0 0]	[]	0.0	0.0	10000.0	0.0
[0 0 0 0 0 1]	[(16, 30)]	0.0	0.0	367487.0	0.0
[0 0 0 0 1 0]	[(16, 40)]	0.0	0.0	53091.0	0.0
[0 0 0 0 1 1]	[(16, 40), (16, 30)]	0.0	0.0	410578.0	0.0
[0 0 0 1 0 0]	[(30, 39)]	0.0	0.0	177576.0	0.0
[0 0 0 1 0 1]	[(30, 39), (16, 30)]	0.0	0.0	535063.0	0.0
[0 0 0 1 1 0]	[(30, 39), (16, 40)]	0.0	0.0	220667.0	0.0
[0 0 0 1 1 1]	[(30, 39), (16, 40), (16, 30)]	0.0	0.0	578154.0	0.0
[0 0 1 0 0 0]	[(40, 16)]	0.0	0.0	53091.0	0.0
[0 0 1 0 0 1]	[(40, 16), (16, 30)]	0.0	0.0	410578.0	0.0
[0 0 1 0 1 0]	[(40, 16), (16, 40)]	0.0	0.0	96181.0	0.0
[0 0 1 0 1 1]	[(40, 16), (16, 40), (16, 30)]	0.0	0.0	453668.0	0.0
[0 0 1 1 0 0]	[(40, 16), (30, 39)]	0.0	0.0	220667.0	0.0
[0 0 1 1 0 1]	[(40, 16), (30, 39), (16, 30)]	0.0	0.0	578154.0	0.0
[0 0 1 1 1 0]	[(40, 16), (30, 39), (16, 40)]	0.0	0.0	263758.0	0.0
[0 0 1 1 1 1]	[(40, 16), (30, 39), (16, 40), (16, 30)]	0.0	0.0	621245.0	0.0
[0 1 0 0 0 0]	[(24, 30)]	0.0	0.0	35860.0	0.0
[0 1 0 0 0 1]	[(24, 30), (16, 30)]	0.0	0.0	393347.0	0.0
[0 1 0 0 1 0]	[(24, 30), (16, 40)]	0.0	0.0	78951.0	0.0
[0 1 0 0 1 1]	[(24, 30), (16, 40), (16, 30)]	0.0	0.0	436438.0	0.0
[0 1 0 1 0 0]	[(24, 30), (30, 39)]	0.0	0.0	203436.0	0.0
[0 1 0 1 0 1]	[(24, 30), (30, 39), (16, 30)]	0.0	0.0	560923.0	0.0
[0 1 0 1 1 0]	[(24, 30), (30, 39), (16, 40)]	0.0	0.0	246527.0	0.0
[0 1 0 1 1 1]	[(24, 30), (30, 39), (16, 40), (16, 30)]	0.0	0.0	604014.0	0.0
[0 1 1 0 0 0]	[(24, 30), (40, 16)]	0.0	0.0	78951.0	0.0
[0 1 1 0 0 1]	[(24, 30), (40, 16), (16, 30)]	0.0	0.0	436438.0	0.0
[0 1 1 0 1 0]	[(24, 30), (40, 16), (16, 40)]	0.0	0.0	122041.0	0.0
[0 1 1 0 1 1]	[(24, 30), (40, 16), (16, 40), (16, 30)]	0.0	0.0	479528.0	0.0
[0 1 1 1 0 0]	[(24, 30), (40, 16), (30, 39)]	0.0	0.0	246527.0	0.0
[0 1 1 1 0 1]	[(24, 30), (40, 16), (30, 39), (16, 30)]	0.0	0.0	604014.0	0.0
[0 1 1 1 1 0]	[(24, 30), (40, 16), (30, 39), (16, 40)]	0.0	0.0	289618.0	0.0
[0 1 1 1 1 1]	[(24, 30), (40, 16), (30, 39), (16, 40), (16, 30)]	0.0	0.0	647105.0	0.0
[1 0 0 0 0 0]	[(30, 24)]	0.00267	0.00074	35860.0	0.00206
[1 0 0 0 0 1]	[(30, 24), (16, 30)]	0.00631	0.0015	393347.0	0.00038
[1 0 0 0 1 0]	[(30, 24), (16, 40)]	0.00267	0.00074	78951.0	0.000935
[1 0 0 0 1 1]	[(30, 24), (16, 40), (16, 30)]	0.00631	0.0015	436438.0	0.000343
[1 0 0 1 0 0]	[(30, 24), (30, 39)]	0.00267	0.00074	203436.0	0.000363
[1 0 0 1 0 1]	[(30, 24), (30, 39), (16, 30)]	0.00631	0.0015	560923.0	0.000267
[1 0 0 1 1 0]	[(30, 24), (30, 39), (16, 40)]	0.00267	0.00074	246527.0	0.0003
[1 0 0 1 1 1]	[(30, 24), (30, 39), (16, 40), (16, 30)]	0.00631	0.0015	604014.0	0.000248
[1 0 1 0 0 0]	[(30, 24), (40, 16)]	0.00267	0.00074	78951.0	0.000935
[1 0 1 0 0 1]	[(30, 24), (40, 16), (16, 30)]	0.01051	0.00258	436438.0	0.000591
[1 0 1 0 1 0]	[(30, 24), (40, 16), (16, 40)]	0.00267	0.00074	122041.0	0.000605
[1 0 1 0 1 1]	[(30, 24), (40, 16), (16, 40), (16, 30)]	0.01051	0.00258	479528.0	0.000538
[1 0 1 1 0 0]	[(30, 24), (40, 16), (30, 39)]	0.00267	0.00074	246527.0	0.0003
[1 0 1 1 0 1]	[(30, 24), (40, 16), (30, 39), (16, 30)]	0.01051	0.00258	604014.0	0.000427
[1 0 1 1 1 0]	[(30, 24), (40, 16), (30, 39), (16, 40)]	0.00267	0.00074	289618.0	0.000255
[1 0 1 1 1 1]	[(30, 24), (40, 16), (30, 39), (16, 40), (16, 30)]	0.01051	0.00258	647105.0	0.000399
[1 1 0 0 0 0]	[(30, 24), (24, 30)]	0.00267	0.00074	61720.0	0.001197
[1 1 0 0 0 1]	[(30, 24), (24, 30), (16, 30)]	0.00631	0.0015	419207.0	0.000357
[1 1 0 0 1 0]	[(30, 24), (24, 30), (16, 40)]	0.00267	0.00074	104811.0	0.000705
[1 1 0 0 1 1]	[(30, 24), (24, 30), (16, 40), (16, 30)]	0.00631	0.0015	462298.0	0.000324
[1 1 0 1 0 0]	[(30, 24), (24, 30), (30, 39)]	0.00267	0.00074	229296.0	0.000322
[1 1 0 1 0 1]	[(30, 24), (24, 30), (30, 39), (16, 30)]	0.00631	0.0015	586783.0	0.000255
[1 1 0 1 1 0]	[(30, 24), (24, 30), (30, 39), (16, 40)]	0.00267	0.00074	272387.0	0.000271
[1 1 0 1 1 1]	[(30, 24), (24, 30), (30, 39), (16, 40), (16, 30)]	0.00631	0.0015	629874.0	0.000238
[1 1 1 0 0 0]	[(30, 24), (24, 30), (40, 16)]	0.00267	0.00074	104811.0	0.000705
[1 1 1 0 0 1]	[(30, 24), (24, 30), (40, 16), (16, 30)]	0.01051	0.00258	462298.0	0.000558
[1 1 1 0 1 0]	[(30, 24), (24, 30), (40, 16), (16, 40)]	0.00267	0.00074	147901.0	0.000499
[1 1 1 0 1 1]	[(30, 24), (24, 30), (40, 16), (16, 40), (16, 30)]	0.01051	0.00258	505388.0	0.000511
[1 1 1 1 0 0]	[(30, 24), (24, 30), (40, 16), (30, 39)]	0.00267	0.00074	272387.0	0.000271
[1 1 1 1 0 1]	[(30, 24), (24, 30), (40, 16), (30, 39), (16, 30)]	0.01051	0.00258	629874.0	0.00041
[1 1 1 1 1 0]	[(30, 24), (24, 30), (40, 16), (30, 39), (16, 40)]	0.00267	0.00074	315478.0	0.000234
[1 1 1 1 1 1]	[(30, 24), (24, 30), (40, 16), (30, 39), (16, 40), (16, 30)]	0.01051	0.00258	672965.0	0.000383