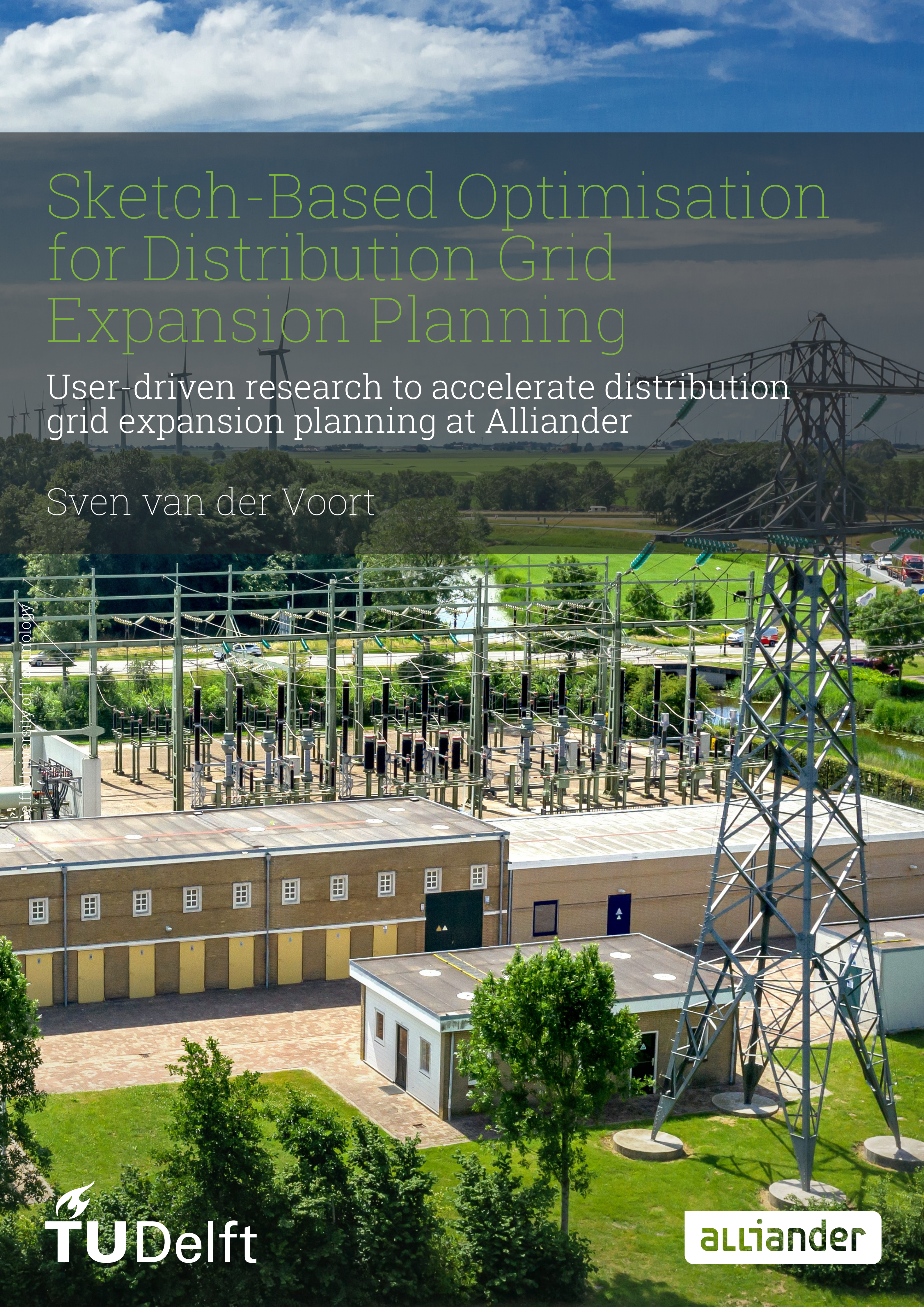
Sketch-Based Optimisation for Distribution Grid Expansion Planning

User-driven research to accelerate distribution grid expansion planning at Alliander

Sven van der Voort



Delft University of Technology

Sketch-Based Optimisation for Distribution Grid Expansion Planning

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by

Sven van der Voort

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Cover: Alliander electrical substation in Bolsward, Friesland. Public domain.

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TU Delft

Preface

Starting this nine-month research project, I did not anticipate the diverse themes that I would touch upon in this thesis. Contrary to technical design and abstract thinking, artistic work like drawing has never been my strong suit. It was therefore surprising to work on a technical topic completely based on sketching. This also applies to the UI designs I had to create to communicate my ideas for improving the user experience. And the same is true for the qualitative user study validating what I had built actually matched with the user's expectations. Reflecting on this journey, I realise I have learned a lot over the course of this project, not in the least through the internship at Alliander. It also uncovers something I firmly believe in; that the purpose of an engineer is to *solve problems for people*, and that people should be at the core of any engineering effort.

As with most things, this thesis is not an individual effort and has come about with the help of many people. I would like to extend my gratitude to them here.

First I would like to thank my thesis committee for their supervision, advice and feedback. To my thesis advisor Neil Yorke-Smith; thank you for your advice and helping me maintain high academic quality and always listening my ideas and concerns during our meetings. To my daily supervisor at Alliander Jaap Schouten; thanks for the countless meetings, often initiated that same morning on my request to 'catch up' ('even bijpraten'). You helped me dig through a complex codebase of over 15.000 lines of code and let me make my own decisions throughout the project, making this thesis something I am truly proud of.

Then I would like to thank my colleagues of team Systeemoptimalisatie at Alliander. You are a major reason why the internship has taught me so much; all of you are experts in your respective fields and I got many new insights because of your diverse backgrounds. I would also like to thank the key users of Holonet and the other participants of the user study for their participation, feedback and ideas to further improve the algorithm.

Finally and foremost I want to thank my family and friends, who have been my biggest supporters for as long as I can remember. Without you this journey towards my engineering degree would not have been possible.

Sven van der Voort
Delft, May 2024

Contents

1 Introduction

Global climate change is driving a rapid energy transition from fossil fuels to renewable energy. Distribution Network Operators (DNOs) are an important stakeholder in the energy transition because their energy grids have to undergo radical changes. These changes are driven by the exponential growth of volatile energy sources such photovoltaic (PV) and wind energy and the increased demand for electricity as a replacement for fossil fuels, for example the introduction of electric vehicles (EV). The energy transition means a change from the traditional model of centralised power generation to decentralised power generation and demand. Moreover the maximum peaks in demand and supply for electricity will increase. As such the current energy infrastructure does not suffice to facilitate the rapidly accelerating energy transition.

Alliander is the largest DNO in the Netherlands with almost 6 million connections, supplying both households and businesses with electricity and gas. As a DNO, Alliander manages the medium- and low-voltage distribution grid (operated on 10kV-20kV and 400V respectively) which is connected to the high-voltage transport grid (operated on 150kV-380kV) through transformers at distribution substations (see Figure 1.1a). From a substation the medium-voltage distribution grid supplies the neighbouring area through underground cables that connect so-called ‘middenspanningsruimtes’ (MSRs) acting as nodes in the medium-voltage distribution grid (see Figure 1.1b). From a MSR medium-voltage power is either transformed to low-voltage power to be distributed to households or supplied to a bulk customer.

(a) Substation that transforms high-voltage power from the transport grid to medium-voltage power to be distributed on the distribution grid. (Onderstation Bolsward)

(b) ‘Middenspanningsruimte’ (MSR) acting as network node by connecting underground cables on the medium-voltage distribution grid. (As seen in a residential area)

Figure 1.1: Examples of an Alliander substation and a ‘middenspanningsruimte’ (MSR).

1.1. Motivation

To facilitate the energy transition Alliander is simultaneously working on multiple strategies to increase grid capacity. One important strategy is expanding the existing electrical distribution grid with new cables and MSRs to add capacity where it is needed now and in the future. The problem of grid expansion planning however is notoriously difficult [1]. Not only are building materials and skilled personnel scarce, but the construction of new electricity infrastructure also has significant societal impact. Available public space is limited and geographical factors such as waterways or highways can affect the feasibility of grid expansion in a certain region. Grid expansion planning of the medium-voltage distribution grid is considered the most complex design problem due to the high number of possibilities and non-convex solution space. Therefore in this research we focus on grid expansion of the medium-voltage grid and consider the design criteria of the Netherlands. Other countries will have different regulations, requirements and constraints for distribution grid design.

At Alliander a group of 'grid architects' is responsible for designing grid expansion plans, where each grid architect is responsible for a particular region. Because of the energy transition there is much more work to be done, however it is hard to recruit new grid architects due to the specialised skill set required. One solution for accelerating the grid expansion design process is using an automated decision support tool. At Alliander such a tool has been developed in the form of a genetic algorithm that optimises the topology of a new grid expansion. The use of such an algorithm should reduce the time needed for particular time-intensive steps in the grid design process. Even though the algorithm is available to the grid architects, it is not yet used for production level projects. Why that is the case and how to solve this misalignment with users' wishes is the main topic of this thesis.

Existing research on the grid expansion planning problem has focused on optimisation methods such as harmony search [2], simulated annealing [3] and genetic algorithms [4, 5]. These methods typically take grid load forecasts, material costs and topological constraints as input and attempt to optimise investments costs and/or operational costs. This gives users little control to express their preferences for a particular grid structure or topological configuration. On the other hand, sketch-based optimisation has been demonstrated as a promising mechanism for user control in other domains such as floor plan optimisation [6], fashion design [7] and quadrotor trajectory planning [8]. To our knowledge sketch-based optimisation has not yet been applied to the domain of distribution grid expansion planning and forms a gap in the existing academic literature to be explored with this thesis.

The main contribution of this research is twofold: First the introduction of a novel sketch similarity measure that can be used for sketch-based optimisation of electrical grids. Second an analysis of the potential impact of sketch-based optimisation to accelerate distribution grid expansion planning.

1.2. Research aim and setup

The main goal of this research is to investigate how to accelerate distribution grid expansion planning through the use of an optimisation algorithm. First we wanted to identify the problems of the algorithm that is currently used. Based on our analysis we introduced sketch-based optimisation into a genetic algorithm for automated distribution expansion planning. Then we investigated both its behaviour and the interaction with users through a case study and a qualitative user validation study respectively.

We formulated the main research questions as follows:

1. How can the user adoption of decision support tools for distribution grid expansion planning be improved?
2. How has sketch-based optimisation been applied in other domains and how can those learnings be applied to distribution grid expansion planning?
3. How to implement sketch-based optimisation for automated distribution grid expansion planning with a genetic algorithm?
4. What would be the impact of sketch-based optimisation be on the distribution grid expansion planning process?

Based on our research aim and research questions this thesis can be split up in roughly three parts: problem identification and exploring potential solutions based on literature review and user interviews, the technical implementation of a novel sketch similarity measure, and a user validation study to evaluate the solution. The chapters of this thesis are structured accordingly. Chapter 2 gives an overview of the related work including the existing genetic algorithm. Chapter 4 discusses how sketch-based optimisation was integrated into the existing genetic algorithm using a novel shape similarity measure. Chapter 5 establishes the experimental setup used to acquire the results. Chapter 6 then presents the results from both the case study as well as the user validation study. Finally, in chapter 7 we discuss our conclusions and present our recommendations for future work on sketch-based optimisation for distribution grid expansion planning.

2
Related work

This chapter will discuss existing work related to this thesis and establish a background for our research. We start with earlier research related to the problem of grid expansion planning and the introduction of important considerations for designing distribution grids. Next, we look at previous research on sketch-based optimisation in other domains. We then cover two past thesis project at Alliander that are closely related to our problem. Finally, we give an overview of the existing Holonet genetic algorithm for grid expansion planning that is currently in use at Alliander.

2.1. Grid Expansion Planning

Grid Expansion Planning covers a wide range of challenges faced by energy grid operators. Examples are Generation Expansion Planning, Substation Expansion Planning or Reactive Power Planning [9]. However, since Alliander is by law not allowed to generate or trade in energy and tools for Substation Expansion Planning already exist at Alliander, the scope of this research is limited to Distribution Network Expansion Planning.

Distribution Network Expansion Planning (DNEP) involves designing expansions to an existing energy distribution network to facilitate increasing demand for energy distribution considering various technical, social and economic constraints. Vahidinasab *et al.* [1] provides an overview of different methods and algorithms for DNEP and introduces a framework for classifying types of DNEP models which can be seen in Figure 2.1.

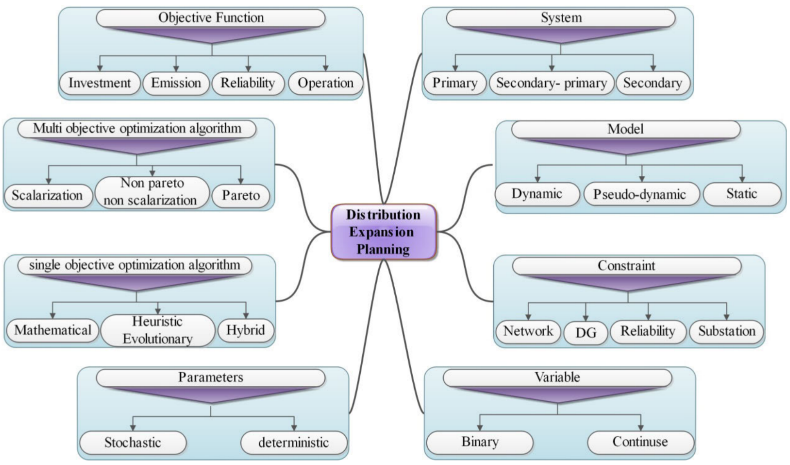


Figure 2.1: A framework for classifying Distribution Network Expansion Planning models [1].

Distribution grid design constraints The book "Netten voor distributie van elektriciteit" by PhaseToPhase [10] gives a complete and up-to-date overview of constraints and best practices for electrical distribution grid design in the Netherlands. We will discuss its most important guidelines and notions. The central element of each distribution grid are one or more substations. Substations transform high voltage power from the transportation grid (e.g. 150kV up to 380kV) to medium voltage power suitable for the distribution grid (e.g. 10kV or 20kV). The distribution grid is then comprised of a connected network of underground cables and nodes distributing power to all clients in that area. These nodes are either a "MiddenSpanningsRuimte" (MSR) or a "DistributieRuimte" (DR) working on 10kV and 20kV power respectively. The nodes typically also contain transformers that convert medium voltage power to low voltage power suitable for end-users of power. Low-voltage distribution grids distributing power to households and small businesses are considered less complex to design and are therefore not the scope for this research.

For distribution grid design two considerations are important: radial operation and redundancy. First, radial operation requires that every node is only actively connected to the substation by a single unique path. Second, redundancy in case of single cable or node failure is a grid design requirement, also known as 'n minus 1 redundancy'. Therefore extra inactive cables between nodes are necessary. A cable that is inactive by design cable is called a Normally Open Point (NOP) and can be activated (closed) in case of a failure elsewhere in the network (after the failing cable has been disconnected to maintain radial operation). For a grid design to feasible all its components must not exceed their rated currents or voltages in case of any single cable failure in the network. An illustrative example of a meshed grid that is operated radially using NOPs can be seen in Figure 2.2.

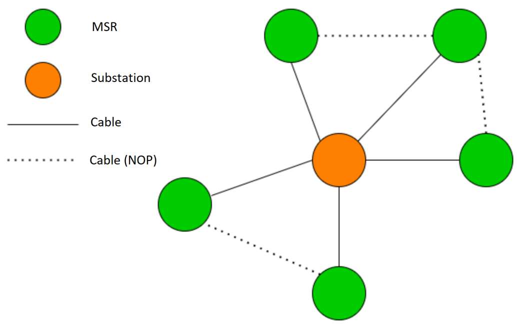


Figure 2.2: Illustrative example of a radially operated meshed grid. Normally Open Points (NOPs) are cables that are normally not connected but guarantee redundancy in case of single cable failure ('n minus 1 redundancy'). (Adapted from [11].)

Genetic algorithms for distribution grid design There has been previous research into using genetic algorithms to optimise Distribution Network Expansion Planning. For example Mendoza *et al.* [4] used the NSGA and SPEA multi-objective genetic algorithms to optimise cost and reliability of a power distribution system design as two separate objectives. The model included cost for building new nodes and cables and technical constraints related to power system such as capacity and voltage drop constraints. However radial operation or redundancy were not included as hard constraints.

In experiments both the NSGA and the SPEA algorithm successfully manage to generate a Pareto front approximation consisting of a diverse set of solutions. The diverse set of solutions allows the user to easily make a trade-off between two opposing objectives cost and reliability. Although redundant operation is not a hard constraint, a redundant solution can be found on the Pareto front where reliability is maximal. However the number of nodes (42) and the number of new cable options (73) is significantly less than the representative network used in our case study with 122 nodes and 3271 new cable options. Our model also includes more free variables such as node locations and reinforcements for existing cables. Finally our problem includes more objectives e.g. grid load in case of cable failure, meaning our problem is overall more complex.

The application of genetic algorithms in distribution grid design is not new and has shown promising results before. Our research will further expand on this by allowing users to exercise control over the optimisation using rough sketches of the desired network shape.

2.2. Sketch-based optimisation

Although sketch-based optimisation has not yet been applied to electrical grid design, it has been applied in other domains to allow intuitive user control over the optimisation. Examples include domains such as floor plan optimisation, fashion design and quadrotor trajectory planning [6–8]. In case of the floor plan optimisation paper shows how the optimisation problem is defined by the user's sketch and then processed by a multi-objective genetic algorithm (NSGA-II). The other two papers first model the problem using one or more objective functions and also hard constraints that limit the solution space. Then the problem model is modified to take into account a user provided sketch as guideline for the optimisation but not as hard constraint.

The Airways paper on quadrotor trajectory generation is a good example of sketch-based optimisation. The goal is to create aesthetically pleasing quadrotor trajectories that can be used for example in aerial videography or light painting [8]. Input to the optimisation is a hand-drawn 3D sketch by the user consisting of waypoints and a set of trajectory requirements. The main objective of the optimisation is to generate a feasible trajectory through all waypoints based on a physics model of the quadrotor control. Additional objectives and constraints can be introduced such as improving trajectory smoothness (by minimising so-called 'jerk'), minimising camera angle error or limiting camera motion between waypoints. The resulting sparse quadratic program can be in real-time, allowing the user to quickly iterate on different sketches and constraint settings.

Our work applies the learnings from other domains to the problem of automated grid expansion planning by introducing sketch-based controls for users when optimising of electrical grid investment plans. To the best our knowledge sketch-based optimisation has not yet been applied in this domain and therefore illustrates the novelty of our work.

2.3. Previous thesis work

At Alliander some earlier research has already been done into automated grid expansion planning for the medium-voltage distribution grid. Two previous thesis projects are especially relevant for our research, since they are at the root of our problem context. Both works are discussed below.

A Decision Support Tool for the Medium Voltage Networks Expansion Problem The idea of automatically generating grid expansion plans originates from the work of Jurriëns [3] in 2019. They formulated a constrained optimisation model for the problem that Alliander is facing when designing expansions to its distribution networks. The Alliander/Netherlands-specific constraints lead to a complex problem that requires a meta-heuristic for efficient solving. Simulated annealing was used to optimise grid expansion plans that resolve predicted distribution grid congestions at minimal cost. The basic constrains for medium-voltage distribution grid design were introduced and two algorithm variants were tested experimentally. The first variant only includes the ability to change which cables are used for redundancy in the network by moving so-called Normally Open Points (NOPs). No new cables, transformers or reinforcement can be placed. The second variant does allow creating new cables between nodes. It was found that both algorithm variants produce expansion plans that reduced the total overload in the grid significantly at minimal costs.

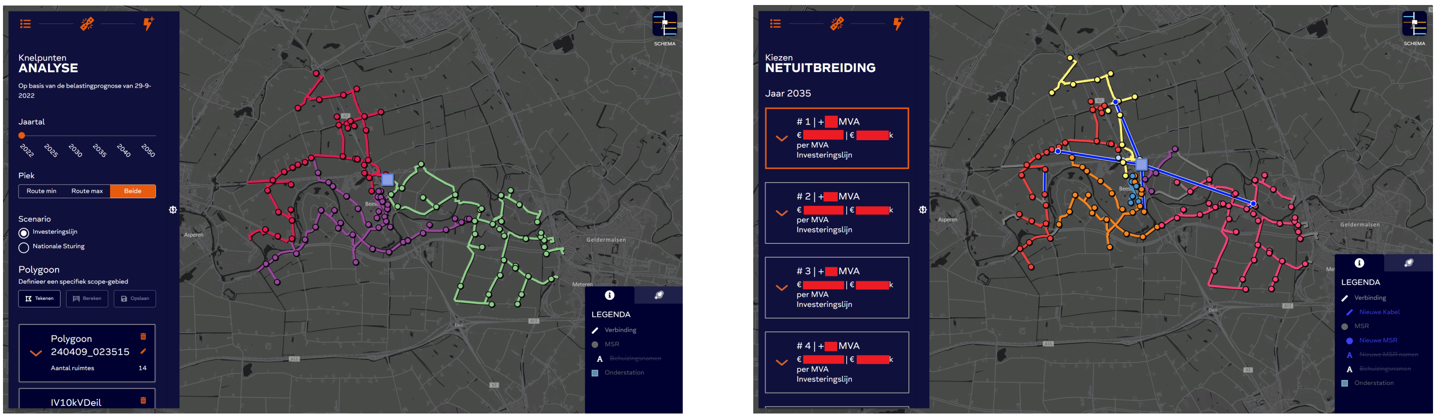
Based on the findings of Jurriëns the Holonet tool was created at Alliander for visualising network congestions and evaluating distribution grid expansion plans. Predictions of future grid load (produced by another team) are used to compute future grid congestions and evaluate investment proposals created by Holonet's main users; distribution grid architects. Figure 2.3 shows the primary user interface of Holonet. In addition to visualisation and evaluation functionality Holonet also contains an algorithm for automated generation of grid expansion plans like proposed in the original research by Jurriëns. However the simulated annealing optimisation algorithm was exchanged for a genetic optimisation algorithm that can output multiple different expansion plans giving the users freedom to choose between solutions. More details about the Holonet genetic algorithm can be found in section 2.4.

The constraints and objectives of the optimisation model proposed by Jurriëns form the foundation of our grid expansion planning model. Rather than simulated annealing we use a genetic algorithm to optimise the model. Moreover, investments generated by our algorithm are typically larger since load scenarios further into the future are used. Our research primarily focuses on adding more user control to the optimisation where this was lacking in the original algorithm.

Evolutionary Multi-Objective Optimisation Algorithm for grid expansion More recently in 2023 Böhmer [11] investigated a multi-objective extension of the Holonet genetic algorithm. Each sub-objective in the optimisation used different grid load scenarios (based on load predictions) closer or further into the future. The motivation for such a multi-objective optimisation is to give grid designers insight into possible trade-offs regarding how future-proof the generated grid expansion plans are. The research uses the NSGA-III algorithm for evolutionary multi-objective optimisation. For each grid load scenario sub-objective the original objective function from the Holonet algorithm was used which combines the investment costs, the reduced grid overload and penalties for grid structure in a single value.

Experiments were executed with both generated toy networks and a single real case study based on an existing electrical grid managed by Alliander. These experiments show that the multi-objective algorithm generates feasible grid expansion plans with lower objective values in some cases than solutions generated by the single-objective algorithm. The multi-objective algorithm was also measured to be up to 40% faster than running the single-objective algorithm multiple times. Another experiment tested running the multi-objective algorithm for much more iterations (1000 instead of 200). The final population of this experiment contained more unique non-dominated solutions with lower objective values on the approximated Pareto front. However it is not clear if this leads to more diversity in the expansion plans themselves, as the study only compares the values of sub-objectives and not the generated expansion plans themselves.

One could argue that the sub-objectives are different moments in time of the same prediction to not have conflicting interests. An optimal solution far into the future will also solve all congestions earlier in time, albeit not at the optimal cost for the early scenario. Our method of multi-objective optimisation does not consider different load scenario as sub-objectives, but rather properties of the solution such as investment costs, grid overload reduction, grid redundancy and sketch similarity. These sub-objectives are much more of conflicting interest and a much better candidate for multi-objective optimisation.



(a) Congestion view; Load scenarios of different years can be selected, red/yellow circles and lines indicate overloaded assets (not shown here due to confidentiality).

(b) Solution view; Solutions from the final population of the genetic algorithm optimisation can be displayed. Blue cables and dots represent proposed cable and MSR investments respectively.

Figure 2.3: Holonet user interface. Colored lines are cables, circles are MSRs and the central square is the substation sourcing the network.

2.4. Holonet Genetic Algorithm

The Alliander application Holonet for analysing predicted medium-voltage grid congestion (see Figure 2.3) already contains a genetic algorithm for automatically generating grid expansion plans. To use the algorithm users select which substation and MSRs should be included in the optimisation and which load scenario is to be used (close or far into the future). The input to the algorithm consists of the current geographical and electrical topology of the grid and the predicted load for each node in the selected load scenario. Since no variance data is available (yet) for the load predictions, the predicted values are treated as deterministic although in practice the predictions have considerable variability. The genetic optimisation algorithm then optimises an objective function by applying mutation, cross-over and selection operators iteratively on a population of solutions (see example population in Figure 2.5). The genetic operators are carefully designed to only generate feasible electrical grids that are connected, contain no cycles and have single voltage for connected components. On top of this Holonet implements a dynamic island model to increase diversity between solutions in the final population. Details about the objective function, the genetic operators and the dynamic island model are given below.

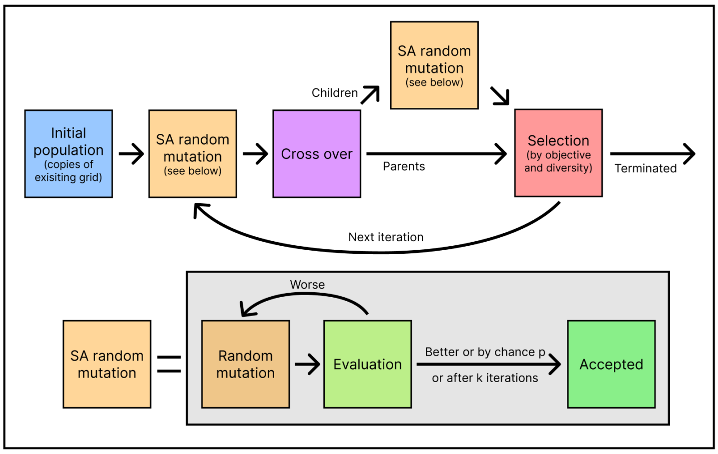


Figure 2.4: Overview of the Holonet genetic algorithm. The mutation step is an integrated Simulated Annealing (SA) procedure that tries to find a mutation that improves the objective. With chance p it also accepts mutations that degrade the objective.

Figure 2.4 shows a flow chart of the execution of the Holonet genetic algorithm. The initial population contains copies of the existing grid with no investments applied. Then all solutions in the population are mutated using a special Simulated Annealing (SA) procedure. The SA procedure attempts to find a mutation that improves the objective value for that solution; only with chance p or after k iterations a worse mutation is chosen. After mutating all solutions, new solutions are created in the cross-over step by combining investments of two parent solutions. These new solutions are then once again mutated using the SA procedure and then added to the population. Finally the selection step selects a subset of solutions from the population to remain in the population. Selection is done according to best objective values and diversity between solutions in the population. This process is repeated until the algorithm has converged or the maximum number of iterations has been reached.

2.4.1. Mutations

The genetic mutation operator changes a single aspect of the solution by for example creating a new cable, removing a previously added cable or changing the voltage of a route. The type of mutation is chosen uniformally at random during the SA mutation procedure. All mutations are designed such that mutated grids always meet the following strict constraints for electrical grid design listed below.

- Connectedness; All cables are connected to exactly two nodes and all nodes are connected to one or more substations by active cables.
- Radial operation; The network does not contain any active cycles, combined with the first constraint this implies that all active cables form a tree with the substation node as root. Cables can also be non-active when marked as a Normally Open Point (NOP). The complete network of both active and non-active cables is allowed to contain cycles (this is actually required for grid redundancy as we will see later).
- Single voltage on connected components; All components that are connected should operate on the same voltage, except for transformers that convert voltages between their two connections.

The Holonet genetic algorithm contains the following mutations operators to create grid expansion plans [5]. These mutations were chosen because they represent the atomic parts that a grid expansion design consists of, like new cables, reinforced cables and NOPs. The exceptions are the backbone mutations which were included because backbone structure are often used in grid designs and they

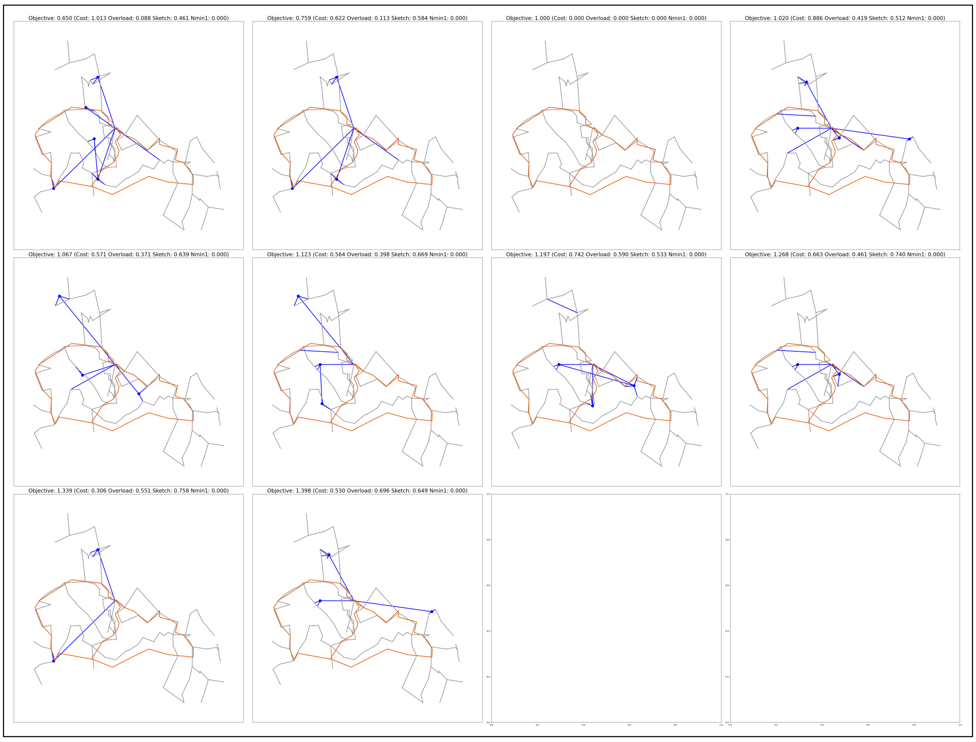


Figure 2.5: Example population from an optimisation, containing 10 solutions. Grey lines are the existing grid, blue lines are new cables and blue dots are new MSRs, orange lines are the user's sketch. The objective values of a solution are printed above each solution respectively.

are too scarcely distributed in the solution space to find during an optimisation.

1. **Move NOP** Change one cable from non-active to active and another cable from active to non-active. Two cables are randomly selected such that connectedness and no active cycles is maintained.
2. **Add cable** Add a new cable between the substation and a MSR or between a MSR and a MSR. The thickness of the cable is randomly chosen to be either 240Al or 630Al.
   For OS-MSR cables the maximum length is [confidential, higher] meters and for MSR-MSR this is [confidential, lower] meters. The cable length is approximated by multiplying the distance by $\sqrt{2}$ to account for variations in the actual cable trace. Initially new cables are placed randomly, later during algorithm execution new cables that worked well are more likely to be placed again.
3. **Reinforce cable** Replace existing cables by higher capacity cables that have a higher capacity. A cable is selected randomly from the currently overloaded cables in the network.
4. **Create backbone** A new backbone will create a new ring-like structure from the substation to an area with insufficient grid capacity. Using new MSRs on this ring the backbone is connected to the existing grid to feed its remaining capacity.
   To create a new backbone two locations for new MSRs are randomly selected from a pre-computed list of MSR locations. Then the MSRs are connected to the substation in a circular fashion, using a NOP to prevent an active ring. Figure 2.6 illustrates this concept.
5. **Modify new backbone** Once a backbone is created other mtuations can modify its structure. For example add or remove a new MSR from the backbone or create a connection from a backbone MSR to the existing grid.

2.4.2. Objective function

The genetic algorithm uses an objective function to evaluate the population of grid expansion plans; its goal is minimize the solution objective values while maintaining a diverse set of solutions. The objective value of a solution is a combination of four sub-objectives: reduce grid overload in the given

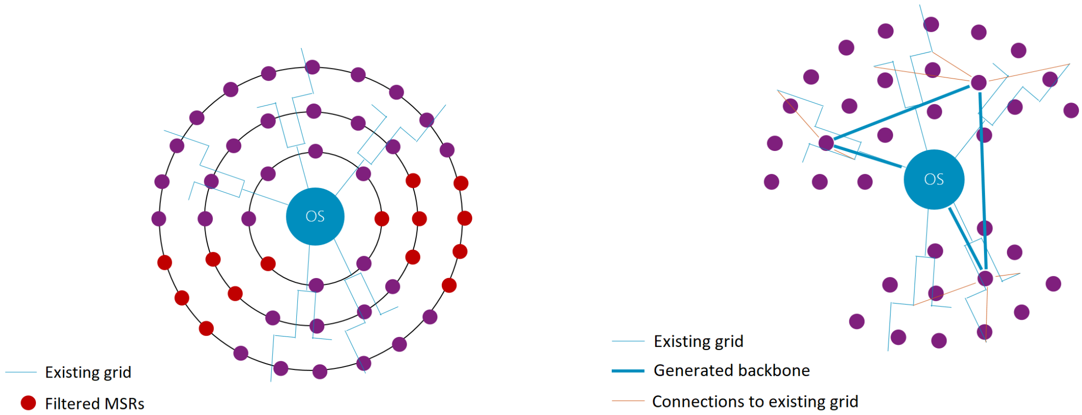


Figure 2.6: Example of backbone creation: The central substation is surrounded by potential new MSR locations in purple. First potential locations are filtered out if they are too far away from existing grid infrastructure. Then a new backbone and its connections to the existing grid are randomly created. (Figures adapted from Alliander [5].)

load scenario, reduce grid overload in case of failure, minimize investment costs and soft constraints related to grid structure.

Equations 2.1, 2.2, 2.3 contain the mathematical definition of the objective function. This definition was extracted from the source code of the algorithm to check it for correctness and analyse its properties. $f(E, I)$ is the main objective function where E is the topology of the existing distribution grid and I is a set of investments from the evaluated expansion plan. The objective function is normalized by the objective function of the original grid with no investments $f(E, \emptyset)$.

For every evaluated grid a load flow simulation is done using a standardised grid simulation library [1]. Based on the load flow simulation the overload in the new network $O(E, I)$ is determined by summing the voltage overload in Volts and current overload in Ampères. $C(I)$ are the financial costs of the investments. $P_{n_min_1}(E, I)$ is the n minus 1 redundancy score of the solution, which measures the worst case grid overload for a single failure in the network. Other $P_*(E, I)$ are penalties given to encourage desired structures (such as support cables) and discourage breaking particular soft constraints (such as the maximum amount of fields available at a substation). Finally $|modified\_support\_cables|$ is the amount of support cables ('steunkabels') from the existing grid that is no longer a support cable in the new solution.

$$f(E, I) = \frac{e^{|modified\_support\_cables|}}{f(E, \emptyset)} \Bigg(\frac{O(E, I) + C(I)}{P_{fields\_balanced}(E, I)} + C_{fields}(I) + P_{max\_fields}(E, I) + P_{n\_min\_1}(E, I) - P_{PSC}(E, I) \Bigg) \quad (2.1)$$

$$C(I) = C_{reinforcements}(I) + C_{edges}(I) + C_{nodes}(I) + C_{switches}(I) \quad \text{(Costs of investments)} \quad (2.2)$$

$$P_{PSC}(E, I) = O(E, I) + O_{fields}(E, I) - \frac{O(E, I) + O_{fields}(E, I)}{1 + P_{score\_support\_cables}(E, I)} \quad \text{(Stimulate support cables penalty)} \quad (2.3)$$

When we analyse the objective function as it is implemented in the Holonet algorithm several things stand out. For example the costs and overload on substation field are added later than other costs and overload and thus are weighted differently. Furthermore Volts and Ampères are simply added together in the overload objective value, while they operate a different scale. Also the use of the

[1] LF Energy Power Grid Model

natural exponential function e^x in the objective is not documented and seems arbitrary. Finally it is not clear how overload, costs and penalties are scaled relative to each other. All this makes it harder to interpret what components the objective function is comprised of and leads to unfair scaling between equivalent components of the objective function.

Together with the implementation of sketch-based optimisation we also propose a restructuring of the objective function to decouple the different embedded sub-objectives. This enables multi-objective optimisation through scalarisation. A detailed description of the proposed changes can be found in section 4.2.

2.4.3. Dynamic island model

To stimulate diversity between solutions in the final population a dynamic island model is used during the genetic optimisation. The population is split over different 'islands' such that solutions can only cross-over with other solutions that 'live' on the same island. The islands can be configured to only allow particular mutations (e.g. backbone creation) or have different selection criteria per island. Solutions can migrate between islands according to a migration map that can be configured beforehand. Similar methods have shown to increase population diversity and avoiding local minima in earlier studies [12].

3 Problem description

The problem central to our research is the increased demand for distribution grid expansion at grid operators like Alliander. The energy transition means the electrical grid is moving away from central power generation and decentral power consumption to both decentral generation and decentral consumption with much higher and frequent peaks [13, 14]. The current electricity grid is unable to transport and distribute the future peaks in power generation and consumption leading to grid congestion. Alliander uses multiple strategies to prevent congestion on the electricity grid now and in the future. One important strategy is expanding the medium-voltage distribution grid by adding more cables, transformers and junctions to the distribution grid. This requires careful planning to take into account economical, societal and environmental factors.

The problem of Distribution Network Expansion Planning (DNEP) is notably hard, therefore Vahidinasab *et al.* [1] has devised a classification framework for DNEP models (see Figure 2.1). The model used at Alliander was introduced by Jurriëns [3] and can be classified as scalarised multi-objective (investment costs, reliability, operational) with deterministic parameters, network and reliability constraints and binary variables. The genetic optimisation algorithm is an evolutionary metaheuristic.

Distribution grid expansion planning is traditionally done by a group of 'grid architects' at Alliander. Their expert knowledge of both electrical grids and the environmental and political restrictions of the concerned area is crucial to create feasible and financially responsible grid expansion plans. However, because of the energy transition, the demand for new plans is increasing while hiring new grid architects is very difficult due to the special skill-set required. By automating part of the grid expansion design process we attempt to accelerate the process and by extension the energy transition.

The Holonet tool already supports grid architects in their design process by providing readily available insights about future grid congestions when designing new grid expansions. To accelerate the process even further, an optimisation algorithm for automated generation of expansion plans was developed. The optimisation algorithm is aimed at supporting grid architects with their decision making process as was proposed in earlier work by Jurriëns [3].

3.1. Problem identification

Although the algorithm has been available to users for some time, it is not actively used by grid architects for designing new grid expansion plans. Therefore the central goal of this thesis is to find out what is holding back user adoption of the existing optimisation algorithm and implement a solution, since the use of the algorithm poses opportunities for accelerating the design process as we just established. To improve the user adaption of the algorithm we need to improve alignment with user requirements so it can effectively be used by grid architects to accelerate their design process.

Through interviews with two grid architects we have attempted to establish why the algorithm is not yet used and what could be improved to make the algorithm a useful part of the grid architect's workflow. The two grid architects who were interviewed are Holonet 'key users' who are representative for the larger user group and frequently consulted for feedback on the application and the algorithm. They are therefore already familiar with the tool and the challenges posed by automating distribution grid expansion design.

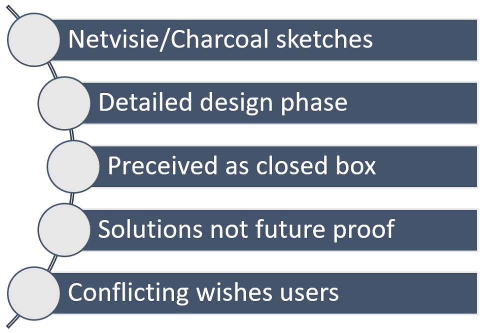


Figure 3.1: Summarised findings from the interviews with Holonet key users for the problem identification.

The interviews resulted in five findings related to the usability of the current Holonet algorithm (summarised in Figure 3.1):

1. **Netvisie/Charcoal sketches** Before any design for a specific local distribution grid starts, a broader grid expansion plan is established for the bigger region called a 'netvisie'. Besides information on areas of interest for distribution grid expansion, the netvisie also contains expansion plans for to the high-voltage transport grid such as new substations. Starting from the overarching plan presented in a netvisie, the first step of distribution grid design is referred to a 'houtskoolschetsen' (charcoal sketches). During this phase grid architects create rough sketches of the geographical and electrical layout of the new grid and use this as a starting point for more detailed designs.

   Holonet key user: *"[The design process of distribution grid expansion] starts with charcoal sketches. This process is mainly based on knowledge, expertise and experience of the grid architects."*

2. **Detailed design phase** After establishing the initial overall strategy and charcoal sketch the detailed design for a specific area has to be made. During the detailed design phase users spend a lot of time on designing and reiterating on details of the grid expansion design, such as on what locations to connect the new grid to the existing grid. Through earlier research by User Experience expert Joep Houterman-Timmers it became clear that this detailed design phase is a time-intensive task that can frustrating to work on [15]. Furthermore, this process typically needs to be done a number of times for each investment proposal, since alternative solutions should also have been considered and electrically analysed before a proposal can be submitted.

3. **Closed box** The workings of the algorithm are described by its users as a 'closed box' (also known as a 'black box') because it is not clear to them why or how the algorithm decides on investments. This reduces trust in the automated system, particularly when the proposed solutions are unconventional. It was frequently mentioned that if algorithm decision could be explained or understood more easily, the acceptance rate of the algorithm might be higher.

   Holonet key user: *"For example this new cable going all the way to the other side of the grid; why did [the algorithm] do that?"*

4. **Not future proof** The solutions generated by the algorithm are commonly described as 'not future proof'. What is meant by this is that while the solution covers the target load scenario, the load scenario a little more in the future already contains serious network congestions. More so it means that any changes in the uncertain load predictions could still lead to congestions after grid expansion.

5. **Conflicting wishes of users** During the interviews we uncovered an internal conflict that users are experiencing when using the algorithm to generate grid designs. On one hand they want to consult the algorithm's output for 'out-of-the-box' optimal solutions they have not thought of them-

selves. On the other hand they do not typically use unconventional designs when the algorithm generates such designs.

3.2. Proposed solutions

Based on the listed findings from the interviews we proposed four different solutions to improve the existing algorithm for grid expansion planning. Below we briefly summarize the proposed solutions. More details can be found in Appendix A.

1. **Interactive genetic algorithm** To address the perception that the algorithm is a closed box and that solutions are not future proof, users could be given more control during the optimisation process. Interactive genetic algorithms replace one or more steps of the optimisation procedure with user interactions. By integrating interactivity into the genetic algorithm users can exercise control during the optimisation potentially leading to more satisfying solutions. Several steps of the genetic algorithm can be made interactive: population initialization, mutation operations and evaluation/selection [16].
2. **Improve explainability algorithm** One important finding was that users feel that the system is a closed box which does not provide reasoning or explanation for its recommendations. To mitigate these problems methods from Explainable Artificial Intelligence (XAI) could be adopted [17]. Using XAI techniques we can shed light on the decision-making process behind the system's recommendations. For example by visualising the genetic lineage/heritage of solutions or showing which mutations were important for survival of the solutions.
3. **Large language model analysis** Data about existing designs for grid expansion mostly exists in the form of textual documents accompanied by simple images of geographical maps and grid topology. Structuring or indexing this data could provide valuable insights into unknown patterns and constraints governing grid design. Recent advancements in large language models enable analysis and understanding of large amounts of text and image data. These models could be used to process historical investment proposals and transform them into a structured data format suitable for further pattern analysis.
4. **Sketching rough structures** From the interview we concluded that the grid design process has several distinct phases, where the level of detail progressively increases. Creating the final detailed design typically takes much time, while the rough idea and structure of a solution has already been determined. Accommodating this workflow in the algorithm is important for user acceptance. The pre-existing coarse plans could serve as additional prior information for the algorithm, for example in the form of a sketch hard-drawn by the user.

We decided to further develop one of the proposed solutions: sketching rough structures. Sketch-based optimisation for electrical grid design has not been investigated in the scholarly literature and is a promising solution to the business problem Alliander is facing. It addresses the interview finding that the design process has phases with different levels of detail. It also addresses the issue that the existing algorithm often generates solutions that do not align with user's wishes, for example not being future proof.

> Holonet key user: *"[Sketching structures] could serve as an intermediate solution to transition our workflow from only human understanding to new and smart software based intelligence."*

In summary this chapter has identified problems and opportunities related to the increased demand for distribution grid expansion planning. The existing optimisation algorithm for automated generation of expansion plan has the potential to accelerate the grid design process, however it is not yet actively used by grid architects. Through interviews with two grid architects we have formulated issues with the current algorithm implementations and solution proposals to address these issues. We have chosen sketching of rough structures as a solution direction to further develop as it addresses several of the identified issues and has not yet been explored in the context of grid expansion planning.

4

Methods: Sketch-based optimisation

This chapter provides details on how sketch-based optimisation has been integrated into the pre-existing Holonet grid expansion planning algorithm. The existing algorithm and its workings have been described earlier in section 2.4. A new sub-objective was introduced which measures shape similarity between the solution and user drawn sketch. This should incentivise solutions similar in shape to the sketch. Furthermore, some parts of the algorithm were modified or disabled. For example the objective function has been restructured and penalties to stimulate desirable grid structures were disabled. Doing these modifications allows more control over sub-objective prioritisation and to investigate the effects of sketch-based optimisation in isolation without interference from other mechanisms to stimulate grid structures. All implementation details can be found in the subsections below.

4.1. Measure for sketch similarity

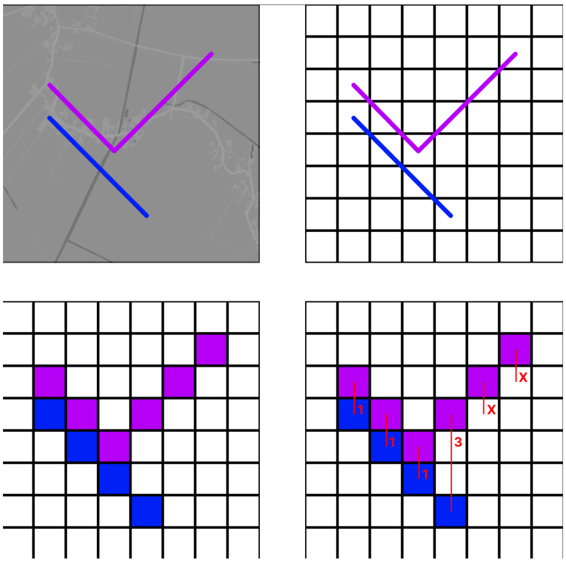
Rather than defining constraints for sketch to solution similarity, a similarity measure was defined to be used as an sub-objective function for the algorithm to minimise. Using a continuous objective function incentives the algorithm to gradually converge to a solution that is close to the user's sketch, while still allowing for (small) deviations if required to optimise other sub-objectives.

The sketch similarity sub-objective function should measure the similarity between the sketch shape and the shape of an investment plan. The similarity measure must satisfy identity ($d(A, A) = 0$) and must allow for partial matching ($d(A, B) = x \implies d(A, B \cup C) \leq x$) for arbitrary sketch or investment shapes A, B, C, such that the algorithm can expand the investment plan beyond the shape of the user's sketch. The measure should also differentiate between similar shapes with a different orientation, e.g. a sketch should not be similar to a rotated version of itself.

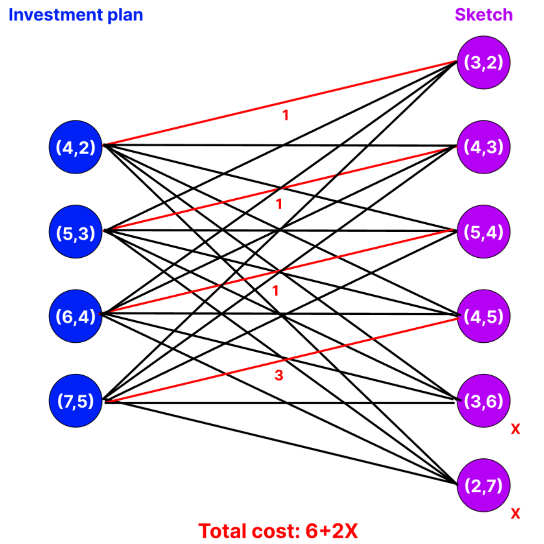
Veltkamp [18] provides a good overview of different similarity measures for shape matching. We considered several of these measures, such as the Fréchet distance which measures the distance between points on two curves while walking along the curves. Alternatively the Turning function computes a descriptive value about the shape of the curve. However both measures do not allow partial matching and the latter also is rotationally invariant, making them not suitable for our application. The directed Hausdorff distance measures the maximum distance to the closest neighbour of points in the sketch and thus allows for partial matching. However the directed Hausdorff distance operates on graph nodes rather than on graph lines, making it also not suitable for our needs (e.g. when a sketch line is broken up into two line segments by an additional node, the similarity should not decrease). Finally the Earth Mover's Distance (EMD) seems to be an applicable measure which we will discuss further.

An intuitive way of understanding EMD is "by thinking of piles of earth spread around in a Euclidean space and holes spread in that same space. Then, EMD measures the least amount of work needed to fill the holes with earth" [19]. We apply this to our problem by converting the investment plan shape to a distribution in two-dimensional space resembling the earth and the sketch shape to resemble the holes. We then find the optimal assignment of piles of earth to holes and use the required amount of work to fill the holes as our shape distance measure. Since not all piles of earth have to be used to fill the holes the measure will allow for partial matching.

Figure 4.1a illustrates the concept of EMD shape matching. It also illustrates how electrical grid shapes can be discretised using rasterisation to allow for efficient computation on vector shapes. The problem of computing EMD can actually be reduced to a linear unbalanced assignment problem in our case, since all sketch shape 'pixels' have the same weight and can be assigned to exactly one investment shape 'pixel'. [1] The cost of each assignment is the distance between the sketch and investment pixels. To penalize incomplete investment plans, every sketch pixel that cannot be assigned an investment pixel will incur an extra constant cost. This can is shown in Figure 4.1b.



(a) The sketch and the investment plan shapes are first discretised. Then the cost of the optimal assignment can be computed. Sketch pixels without assignment incur a constant cost X. In this example the similarity measure is 6+2X.



(b) EMD converted to a linear unbalanced assignment problem. Costs on the edges are Euclidean distances between pixels (not shown). The optimal assignment is highlighted.

Figure 4.1: Illustrating the Earth Mover's Distance (EMD) shape similarity measure considering the shape of an electrical grid.

The final algorithm pseudo code for computing the similarity measure is given in Algorithm 1 for the set of sketch line segments L_s and set of investment line segments L_i. Here we can also see the how the penalty for not assigning a sketch pixel is set to half the maximum distance within the sketch shape S. An example of the similarity measure with real data can be seen in Figure 4.2, where the orange pixels are discretised sketch vectors and blue pixels are discretised investment vectors. Pixels colored pink contain both a sketch and investment pixels and thus are perfectly aligned, incurring no cost for the similarity measure.

When drawing sketches in the Holonet interface, users can distinguish between two types of structures: backbones and independent cables. Case study experiments showed that computing the shape similarity measure on the combination of the two sketch types to undesirable solutions (see subsection 6.1.2). To remediate this we separately compute the shape similarity measure for new backbone cables with the backbone structure sketch and for all other cables with the cable structure sketch. This leads to much more desirable solutions, as can be seen in subsection 6.1.3.

[1] See this StackOverflow answer: `https://stackoverflow.com/a/57563383`

Algorithm 1 EMD Shape Similarity Measure

$D_{ss} \leftarrow$ euclidean_distances(S, S)
$P \leftarrow \max(D_{ss})/2$ ▷ First compute non-assignment penalty P

function EMD_similarity(L_s, L_i)
    $S, I \leftarrow [], []$ ▷ Initialise lists of sketch and investment pixels
    for $l \in L_s$ **do**
        $S \leftarrow S +$ rasterise(l) ▷ Rasterise all sketch lines
    end for
    for $l \in L_i$ **do**
        $I \leftarrow I +$ rasterise(l) ▷ Rasterise all investment lines
    end for
    $D_{si} \leftarrow$ euclidean_distances(S, I)
    $A \leftarrow$ solve_linear_unbalanced(D_{si}) ▷ Compute optimal assignment
    similarity $\leftarrow$ assignment_cost(A)
    for $s \notin A$ **do**
        similarity $\leftarrow$ similarity $+ P$
    end for
    return similarity
end function

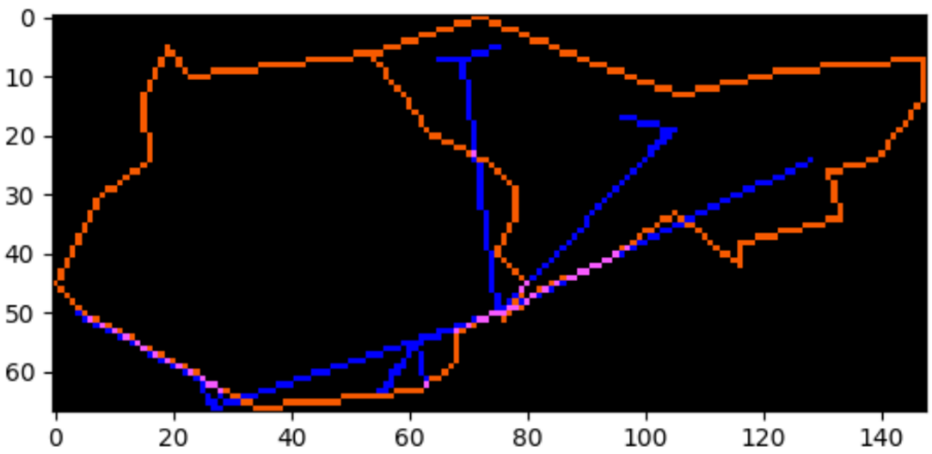


Figure 4.2: Example of discretised sketch and investment vectors used to compute Earth Mover's Distance. Pink pixels are aligned perfectly and incur zero cost when computing EMD.

4.2. Restructured objective function

The objective function used in the existing algorithm is hard to interpret and potentially leads to unfair scaling between the three identified sub-objectives, as we concluded in 2.4. The addition of sketch similarity as a new sub-objective further complicated this and prompted a restructuring of the objective function. By normalising all sub-objectives to a $[0, 1]$ range we prevent hidden scaling differences and therefore hidden prioritisation between sub-objectives. Additionally, with normalised sub-objectives a multi-objective optimisation method 'scalarisation' can be applied which reduces a multi-objective optimisation problem to a single objective problem by minimising a weighted linear sum of the sub-objectives [20, p. 666]. By modifying the weights corresponding to each sub-objectives we can now explicitly control preference between sub-objectives as a hyperparameter of the optimisation.

First we define how to compute the absolute values for the the four sub-objectives: cost ($C(I)$, overload $O(E, I)$, n minus 1 redundancy $R(E, I)$ and sketch similarity $S(I, S)$ (Equations 4.1 - 4.4). Here E is the currently existing grid, I is the proposed investment and S is the sketch drawn by the user. Note how penalties for desirable grid structures found in subsection 2.4.2 are no longer part of the objective functions. As stated earlier this removes interference from other mechanisms that stimulate particular grid structures.

$$C(I) = C_{reinforcements}(I) + C_{edges}(I) + C_{nodes}(I) + C_{switches}(I) \quad \text{(Costs of investments)} \tag{4.1}$$

$$O(E, I) = O_{cables}(E, I) + O_{MSRs\_voltage}(E, I) + O_{MSRs\_delta}(E, I) + O_{fields\_voltage}(E, I) \quad \text{(Overload in network)} \tag{4.2}$$

$$R(E, I) = \sum_{e \in edges(E \cup I)} R_{nminus1}(e) \quad \text{(N minus 1 redundancy)} \tag{4.3}$$

$$S(I, S) = \sum_{s_i \in S} A(s_i, I) \quad \text{(User's sketch soft constraint)} \tag{4.4}$$

To normalise the sub-objective we use the approach suggested by Arora [20, p. 667] as the most robust method for sub-objective normalisation, shown in Equation 4.5. Here $f_i(x)$ is the ith sub-objective function, f_i° is the utopia point (minimum attainable value of $f_i(x)$) and f_i^{max} is the absolute maximum value of $f_i(x)$.

$$f_i^{norm} = \frac{f_i(x) - f_i^\circ}{f_i^{max} - f_i^\circ} \tag{4.5}$$

To determine values for f_i° and f_i^{max} we used a combination of common sense and engineering intuition. This was also validated with the key users introduction in chapter 3. Table 4.1 lists these values per sub-objective including a rationale for selecting these values.

Finally we apply multi-objective scalarisation to combine all sub-objectives into a single objective function $f(x, y, s)$ that can minimised by the genetic algorithm. All sub-objective functions are weighted and then summed using weight vector w where $w_i \in [0, 1] \forall w_i \in w$, as seen in 4.6. The weight vector w is now a hyperparameter of the optimisation which can be tuned according to our needs.

$$f(x, y, s) = \sum_{i=1}^{4} w_i f_i^{norm}(x, y, s) \tag{4.6}$$

	Utopia point f_i°	**Absolute maximum** f_i^{max}
Cost $C(x)$	0 (no costs)	User estimate of total costs (based on early netvisie documents)
Overload $O(x,y)$	0 (no overload in grid)	Predicted overload in target year
Redundancy $R(x,y)$	0 (no overload in case of any single failure)	$\sum_{i \in cables\ checked} P_{n\ minus\ 1}$ (all cables maximum penalty)
Sketch $S(y,s)$	0 (perfect similarity sketch and investment)	$\sum_{i \in sketch\ pixels} P_{sketch}$ (no investment; all sketch pixels maximum penalty)

Table 4.1: Values used for normalisation of sub-objective functions according to Equation 4.5.

4.3. Algorithm parallelisation feature

The existing genetic algorithm includes an optional 'parallelisation' feature that can be enabled for optimisation, for example using 10 processes running in parallel to complete the optimisation. The optimisation computation is not distributed over the different processes but in fact all processes perform their own genetic optimisation with their own set of solutions per generation, much like an ensemble optimisation approach. By exchanging solutions between the different parallel optimisations more diversity is created and the optimisation converges faster. However, in later phase of this research it was discovered that there is no time synchronisation between the processes and solutions from younger or older generations can easily leak into the current population. This behaviour can occur randomly and is not defined.

Earlier research has investigated similar methods of reusing solutions from earlier populations and shows that those methods can improve performance of the genetic algorithm [21, 22]. In general enabling the parallelisation feature leads to better solutions where disabling it can lead to getting stuck in a local minimum and to sub-optimal solutions. In the results chapter it will be clearly indicated if the parallelisation feature has been enabled for each result.

4.4. Other changes to algorithm

Section 2.4 described earlier how the existing genetic algorithm has an island model to stimulate diversity between solutions in the final population. We decided not to use this functionality however, because the focus of this research is to investigate the effect of sketch-based optimisation rather than to create diverse populations. As a result most or all solutions in the final population are very similar to each other, as we will see later.

Other hyperparameters of the algorithm were kept at the default values from the existing algorithm, since they give reasonably good results using the current algorithm. This includes population size (10), number of children per iteration (5) and maximum iterations k of the simulated annealing subprocedure (5).

5 Experimental setup

This chapter discusses the experimental setup used to acquire our results in chapter 6. Two sections discuss the setup of a case study and a user validation study respectively. Both studies are designed to answer the main research questions of this thesis introduced earlier in chapter 1.

5.1. Case study

To see how our technical implementation behaves, we performed several experiments in the controlled setting of a case study. Using a single problem instance we tested the effect of different hyperparameter configurations, for example tuning the prioritisation between the different sub-objectives. From our findings we selected a good hyperparameter configuration to use during the product validation study with actual users.

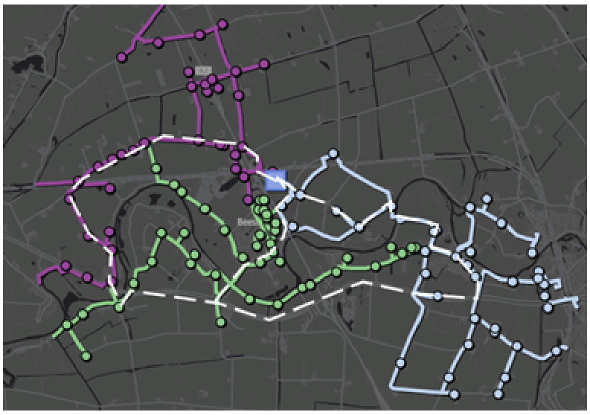
It is important to establish what solutions generated by the algorithm qualify as good solutions. The list below summarises desired properties of good solutions, based on our findings in chapter 3:

1. **No overload** Assuming the target year load forecast, ideally no assets in the network should be overloaded, considering both voltage and current overload.
2. **Sketch sub-objective converges** The sketch shape similarity measure indicates how similar the investment structure of the solution is the the user sketch. Convergence of the sketch sub-objective values shows that the algorithm's optimisation can improve sketch similarity.
3. **Investment visually matches sketch** The investment should visually match the input sketch and capture the user's intent expressed with the sketch. If this is true, our novel sketch shape similarity measure works as expected and can indeed measure the visual correspondence between grid investment and sketch.
4. **Investment assets correctly connected** Two structures sketched by the user which are intended to be connected, should be connected in the solution as well. (e.g. a support cable connecting the center of a backbone to the substation)

The topic of our case study is the Dutch village of Beesd and its surrounding areas. The main reason for choosing this area is the recently approved investment proposal detailing a suitable grid expansion plan for the area. The parameters of the case study are based on this investment proposal. Using assumptions and parameters from an existing and recently approval investment proposal we ensure our case study is representative of real world use cases of our algorithm.

The shape of the sketch used for this case study can be seen in Figure 5.1b in the dotted white lines, on top of the existing electric distribution grid topology of Beesd. The sketch is directly based on the existing investment proposal, which details a 10kV backbone surrounding the area in need of extra distribution capacity [23]. Additionally, the backbone contains a support cable for redundancy unlocking extra capacity to be used from the backbone. Connections from the backbone to the existing grid are not drawn since that is one of the free variables left to the algorithm to optimise. The total budget

(a) Satellite view of Beesd, the Netherlands. ©Google



(b) Electric distribution grid near Beesd, including sketch of proposed new grid structure (white dotted lines) based on existing and approved investment proposal.

Figure 5.1: Geography and electric distribution grid topology of case study Beesd and surrounding area, including new grid structure from real investment proposal.

listed in the investment proposal € [confidential],- is used as our best estimate of the total costs for normalising the costs sub-objective. The load scenario forecasts for the year [confidential] is selected, based on the most recent forecast data.

During the case study we attempt to answer the following research questions specific to the case study. We will do this by running several optimisations under controlled conditions, then comparing the results and the optimisation meta-data/metrics.

1. What do solutions generated without a sketch look like? (e.g. optimised just based on overload and cost data)
2. What do solutions generated without overload data look like? (e.g. optimised just for sketch similarity and cost) That is, how well can the novel sketch similarity measure approximate the sketch shape?
3. How to generate solutions consisting of a single, connected structure using the novel sketch similarity measure? (e.g. rather than just separate cables that are not connected in a meaningful way)
4. What is the effect of enabling/disabling the n minus 1 redundancy sub-objective for the optimisation?
5. How similar are solutions resulting from different optimisations with the same initial (hyper)parameters? (e.g. how stable is the algorithm output?)

5.2. User validation study

A key part of this thesis is to evaluate the proposed solution with the actual users. This is also reflected in the final research question on the influence of sketch-based optimisation on the workflow of grid architects. To answer this research question we have conducted a qualitative user validation study consisting of interview questions and a think-aloud usability test of the algorithms.

For the user study 6 participants were recruited from the group of roughly 20 distribution grid architects working at Alliander at the time of writing (participants include key users referenced earlier in chapter 3). Given the rather small size of this group a qualitative research was chosen over for example a quantitative survey. The nature of our results is also primarily attitudinal rather than behavioural (evaluating what users say rather than how they behave), since we our study relies on interview questions and a think-aloud usability test [24].

To address the main research question answered with the user study, we introduce more specific research questions to be answered during the user study below. We used these specific research questions to systematically analyse the interview answers and extract relevant findings from the user study.

1. Which aspects of grid design are the most time-consuming time or the most frustrating and could be sped up by sketch-based optimisation?
2. When introduced to the idea and user interface for sketch-based optimisation of grid investment plans, how do users perceive the potential impact on their work designing grid expansions? And would they consider using it in their workflow?
3. To what degree does the new algorithm generate feasible grid investment plans and how close are they to the user's sketch and the user's design intention?
4. After drawing a sketch and being presented with its generated solutions, how do users perceive the potential impact of sketch-based optimisation of grid investment plans on their work? How is this different from their earlier answer?
5. What and how do users think the sketch-based algorithm for grid investment planning could be improved?
6. How do the different sub-objectives behave during optimisation of user drawn sketches?

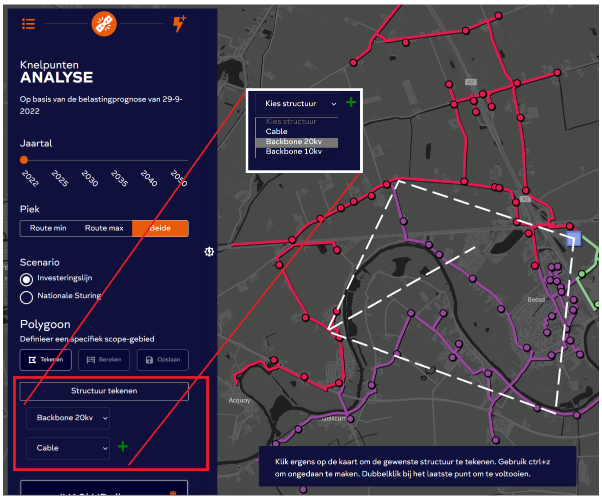


Figure 5.2: Drawing user interface in Holonet used during the user study. Participants were asked to draw a sketch of their desired grid structure.

To answer these research questions a user study was designed consisting of two sessions on the same day for interview questions and the usability test. Both sessions were a one-on-one conversation between the participant and the researcher, either during a meeting at the Alliander offices or an online video call. The study was split into two sessions for each participant because the usability test includes an optimisation run of the algorithm which takes considerable time (one to two hours). The first session consists of introductory questions to get familiar with each other and questions related to their use of Holonet and familiarity with the current optimisation algorithm. Then the idea of sketch-based optimisation for grid expansion planning is introduced to the participant and the participant is asked about what an ideal version of this functionality would look like and how it would impact their work. Thereafter the case study of Beesd is introduced to be used during the usability test. The goal of the usability test is for participants to think of an appropriate grid expansion design that would resolve all congestions in the area as project in the load forecasts for the year 2035 (details on load forecast are confidential). It can assumed that only 10kV supply would be available in the substation in the foreseeable future. The participant is asked to draw their design using a prototype drawing UI directly in Holonet (see Figure 5.2) before answering some questions about their expectations regarding the optimisation results. If time allows, the participant is asked to think of an alternative solution and draw that as well. The time between the two sessions is used to run an optimisation based on the user's sketch. During the second session the resulting investment proposals from the optimisation were shown to the participant. The participants was then asked about their thoughts on the results and how they compared to their expectations. Finally the participant is asked if their opinion about sketch-based optimisation has changed and about any other feedback.

The complete test script with all interview questions and usability test instructions can be found in Appendix B. In the test script all interview questions have been marked with a number corresponding to the user study research questions listed above to indicate a connection between research questions and the user study methodology. The user study methodology was approved by the TU Delft Research Ethics committee.

5.2.1. Interpretation of user study data

To analyse and derive insights from the data gathered with the user study, we use a inductive coding strategy where we identify recurring themes and sentiment. Since the setup of the user study is open-ended and intended to investigate new ideas and concepts we use an inductive coding strategy rather than a deductive coding strategy [25]. With inductive coding the codes and data clustering is developed during data analyse to allow for previously unknown insights.

The data (e.g. feedback, proposed ideas or statements made by participants) clustered by research questions and two extra categories: feedback not on the algorithm but on Holonet and the participant's context. Per clustering category positive and negative sentiment is identified as well as themes that occur in feedback, ideas or suggestions from participants. From the coded data we attempt to extract answers to our research questions and new insights that could be interesting to future work.

5.2.2. Limitations of user study

The user study has some limitations, such as the small participant group size. This limitation has been mitigated to our best ability by recruiting particpants with different backgrounds, for example different types of operational area (urban vs rural) and different levels of experience. Due to the small participant group size we could also not correct for any biases introduced by changing modality (e.g. face-to-face or online video call), however we do not expect the modality of the sessions to affect the results since our study is attitudinal rather than behavioural.

There is also a risk of a social desirability bias where participants feel social pressure to give desirable answers. In particular because from the context of the interview it is clear that the researcher worked on the algorithm that is being evaluated. We attempted to mitigate this risk by taking great care in asking open questions instead of closed or biased questions. The participants were also encouraged to give their honest opinions in light of potential improvement that could be made.

6 Results

This chapter will present the results of our research acquired using the experimental setup described earlier in chapter 5. First we will present the results from the case study where we examined the characteristics of the novel sketch-based optimisation algorithm. Then we present the results of the user validation study where we investigated how users interact with sketch-based optimisation and how it could potentially impact their workflow.

6.1. Case study

The case study is comprised of a series of optimisation runs and their results in order to answer main research question 3. To achieve this section 5.1 introduces new research questions specific to the case study which are listed again below. The optimisation results show the best solution from the final population together with a number of optimisation metrics and the sub-objective weights used. In some cases more configurations were tested than those that presented here. If that is the case, the results of the most relevant or interesting configuration is shown here in accordance with the criteria defined in section 5.1.

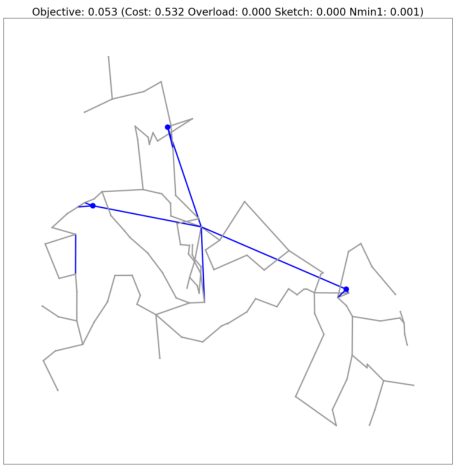
1. What do solutions generated without a sketch look like? (e.g. optimised just based on overload and cost data)
2. What do solutions generated without overload data look like? (e.g. optimised just for sketch similarity and cost) That is, how well can the novel sketch similarity measure approximate the sketch shape?
3. How to generate solutions consisting of a single, connected structure using the novel sketch similarity measure? (e.g. rather than just separate cables that are not connected in a meaningful way)
4. What is the effect of enabling/disabling the n minus 1 redundancy sub-objective for the optimisation?
5. How similar are solutions resulting from different optimisations with the same initial (hyper)- parameters? (e.g. how stable is the algorithm output?)

6.1.1. Baseline: Optimisation without sketch

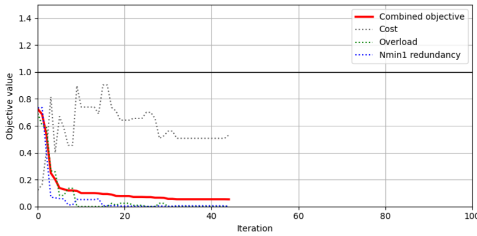
To establish a baseline used for comparison to the existing situation we ran an optimisation with no sketch as input like done in the existing optimisation algorithm. In this baseline configuration the sub-objectives cost, overload and redundancy are enabled. The sub-objectives are summed into the objective function using the weights specified in Figure 6.1d.

The results from the baseline optimisation can be seen in Figure 6.1 where the best solution from the final population is shown together metrics collected during the optimisation. The algorithm has converged to a solution after 44 solutions (rather than the 100 maximum iterations) where all congestions under the predicted 2035 grid load are resolved at reasonable costs (only 53% of the estimated costs).

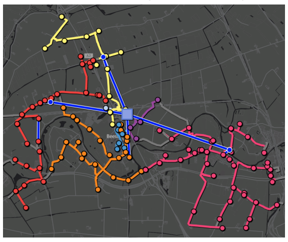
However, upon visual inspection of the solution this is a typical case to be dismissed by users as having ‘no structure’. More specifically; the cables starting from the substation intersect with the densely populated centre of Beesd and with a waterway. Furthermore, using individual cables to feed congested areas rather than using a backbone structure/ring shape does not provide enough flexibility towards the future, according to the key user interviews in chapter 3.



(a) Existing grid (grey), input sketch and new cables (lines) and new MSRs (dots).



(b) Convergence of objective and scaled sub-objectives.



(c) Solution rendered in Holonet.

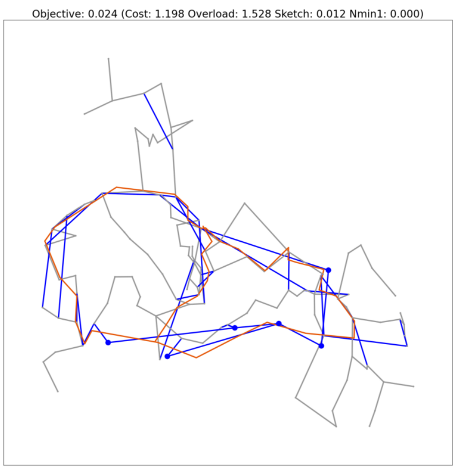
Sub-objective	Weight w_i
Sketch	0.0
Cost	0.1
Overload	0.5
Redundancy	0.5
Parallelisation	Disabled

(d) Sub-objective weights.

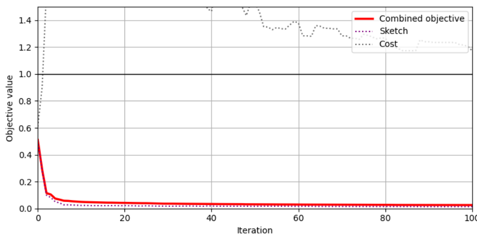
Figure 6.1: Optimisation results without sketch, like in the existing algorithm. Only based on cost, overload and redundancy sub-objectives.

6.1.2. Optimisation with sketch (single structure type), no overload

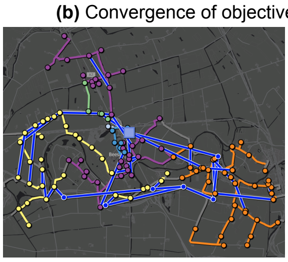
To investigate the behaviour and efficacy of the novel sketch similarity measure, the similarity measure was first tested in isolation from the other sub-objectives. Both grid overload and n minus 1 redundancy were disabled, however the cost sub-objective remained enabled with a small weight for regularisation; to avoid diverging solutions with unlimited amounts of new cables.



(a) Existing grid (grey), input sketch and new cables (lines) and new MSRs (dots).



(b) Convergence of objective and scaled sub-objectives.



(c) Solution rendered in Holonet.

Sub-objective	Weight w_i
Sketch	1.0
Cost	0.01
Overload	0.0
Redundancy	0.0
Parallelisation	Enabled

(d) Sub-objective weights.

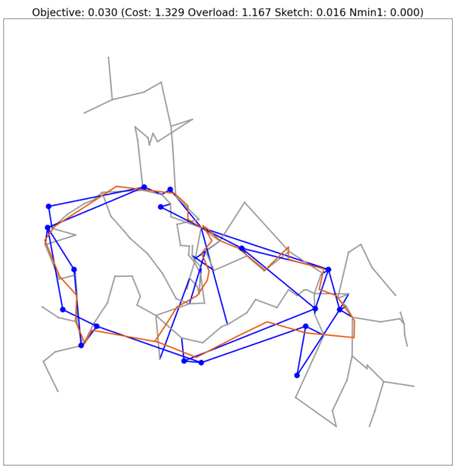
Figure 6.2: Optimisation results with only shape similarity sub-objective (single structure type) With cost sub-objective as regularisation to avoid diverging solutions.

The results of an optimisation based only on sketch similarity can be seen in Figure 6.2. It can be seen that the algorithm approximates the sketch very well with both new backbone structures (blue lines connecting blue dots) as well as separate cables between existing nodes (blue lines connecting grey lines). However, upon close inspection most new cables are not connected to each other or even to the substation, but rather intersecting each other. This is not desirable when we want to recreate familiar grid expansion structures such as backbones.

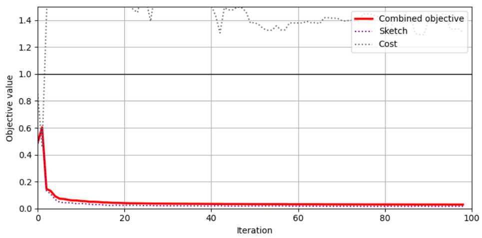
6.1.3. Optimisation with sketch (two structure types), no overload

To remediate the problem of an unconnected grid expansion structure explained above, the sketch similarity measure was changed to measure similarity for backbone and cable sketches separately. When users are drawing a sketch they can select either a backbone structure (which always starts and ends at a substation) or a separate cable (starting and ending anywhere). After drawing sketch lines are saved per structure type and during optimisation a shape similarity measure is computed for each type separately, based on whether new cables are part of a backbone or not. The results of the modified shape similarity measure can be seen in Figure 6.3.

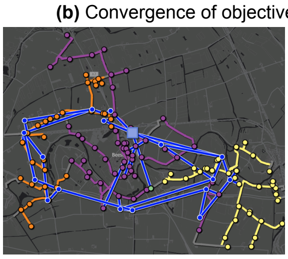
Figure 6.3 shows how the solution improved over the earlier attempt in subsection 6.1.2 when only optimising for sketch similarity. Most of the new cables are now connected into a single structure and cables close to the substation are actually connected to the substation. No feasible or sensible grid topology can be seen yet, since grid connectivity or load distribution was not an objective of this optimisation.



(a) Existing grid (grey), input sketch and new cables (lines) and new MSRs (dots).



(b) Convergence of objective and scaled sub-objectives.



(c) Solution rendered in Holonet.

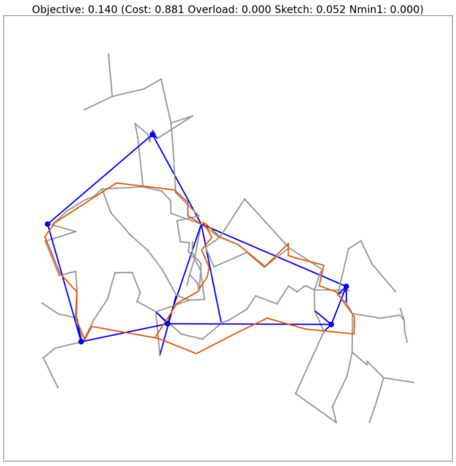
Sub-objective	**Weight w_i**
Sketch	1.0
Cost	0.01
Overload	0.0
Redundancy	0.0
Parallelisation	Enabled

(d) Sub-objective weights.

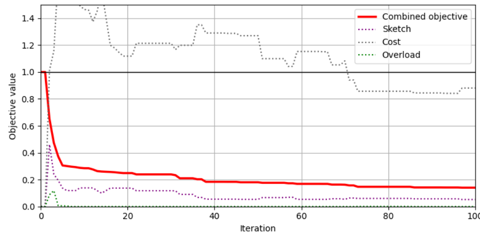
Figure 6.3: Optimisation results with only shape similarity sub-objective (two structure types) With cost sub-objective as regularisation to avoid diverging solutions.

6.1.4. Optimisation with sketch and overload

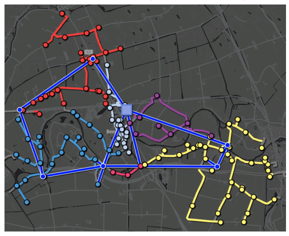
Figure 6.4 shows results when optimising for sketch similarity, future grid overload and costs. The solution contains no congestions anymore for the 2035 predicted load scenario. In addition, a backbone structure has been created surrounding the area, just like the sketch. The separate cables running from north to south across the backbone structure intersect with the backbone cables, however they are not directly connected to the backbone but rather through existing cables. Compared to the sketch-only optimisation from subsection 6.1.3 a lot less new cables are used but the new cables are not as close to the sketch. Both are likely a result from the changed sub-objective weighting (cost from 0.01 to 0.1, overload at 0.1 and sketch similarity remains at 1.0).



(a) Existing grid (grey), input sketch and new cables (lines) and new MSRs (dots).



(b) Convergence of objective and scaled sub-objectives.



(c) Solution rendered in Holonet.

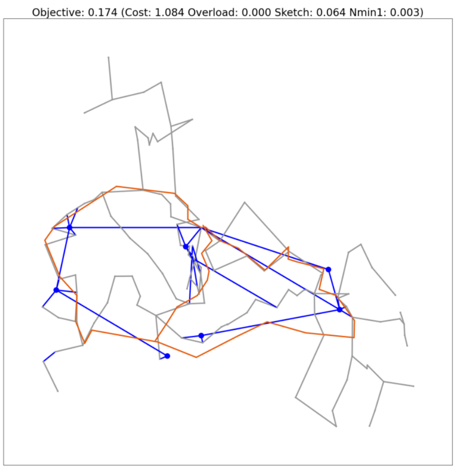
Sub-objective	**Weight w_i**
Sketch	1.0
Cost	0.1
Overload	1.0
Redundancy	0.0
Parallelisation	Disabled

(d) Sub-objective weights.

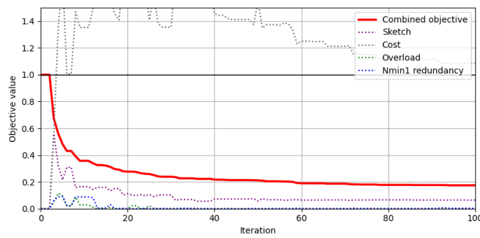
Figure 6.4: Optimisation results when optimising for sketch similarity, cost and overload, but not redundancy.

6.1.5. Optimisation with sketch, overload and redundancy measure

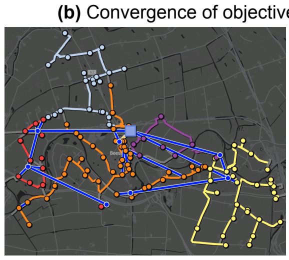
Figure 6.5 shows the results of an optimisation with all sub-objectives enabled including the n minus 1 redundancy measure. The resulting expanded grid has no congestions and nearly no redundancy issues for the 2035 predicted load scenario. The resulting expanded grid has a backbone structure, however with a ‘missing’ bit of cable where instead the existing grid is used to connect the backbone ring. This occurs more frequently for solutions generated during the case study which are not all shown in here. Compared to the solution generated without redundancy sub-objective in subsection 6.1.4 this solution is more expensive (from 88% to 108% of estimated costs). This can be explained by the extra grid components needed to reach grid redundancy rather than just no grid overload. The hyperparameters of this optimisation run were later used for the optimisations of the usability test of the user study.



(a) Existing grid (grey), input sketch and new cables (lines) and new MSRs (dots).



(b) Convergence of objective and scaled sub-objectives.



(c) Solution rendered in Holonet.

Sub-objective	**Weight w_i**
Sketch	1.0
Cost	0.1
Overload	0.5
Redundancy	0.5
Parallelisation	Disabled

(d) Sub-objective weights.

Figure 6.5: Optimisation results when optimising for all sub-objectives sketch similarity, costs, grid overload and grid redundancy.

6.1.6. Stability of solutions

Finally the stability of the algorithm in terms of resulting solutions was investigated. To assess this stability five optimisation runs were done all with the same (hyper)parameters (the parameters from subsection 6.1.5) with parallelisation disabled and enabled (see section 4.3). The results can be seen in Figure 6.7 and Figure 6.8 respectively. From the results some optimisations converged earlier and therefore terminated earlier than the maximum of 100 iterations. In both cases with parallelisation disabled or enabled the optimisation runs converge in a similar fashion as can be seen in the sub-objectives graph. Nevertheless in both cases the resulting solutions vary a lot in structure, shape, etc. This can simply be traced back to the random nature of genetic algorithms, however it also shows that the algorithm can get stuck in (semi-optimal) local optima rather than always finding the global optimum. Figure 6.6 shows the spread objective and sketch sub-objectives values compared between parallelisation disabled or enabled. This shows that solutions generated with parallelisation enabled generally have lower and less variance in objectives values (is better), meaning enabling the parallelisation could contribute to more stable solutions between optimisations.

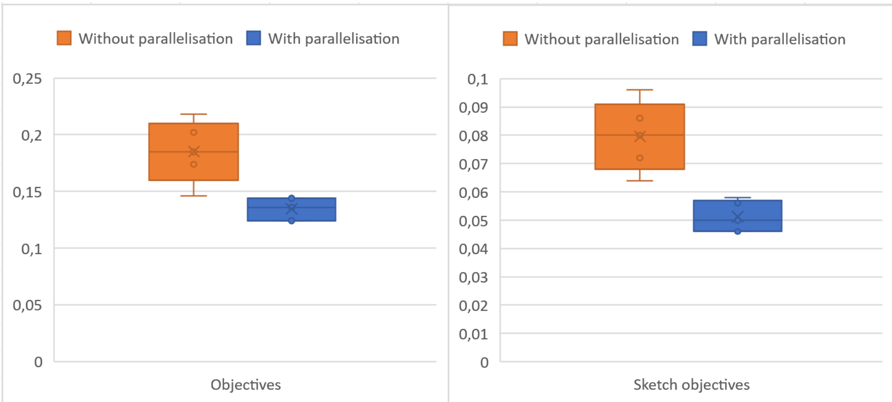
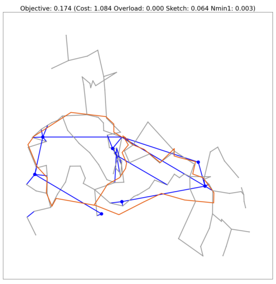
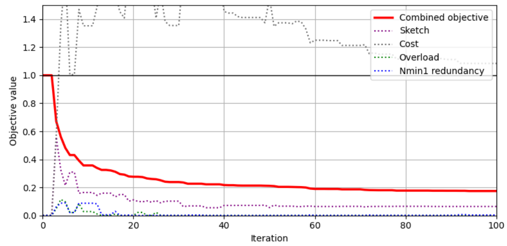


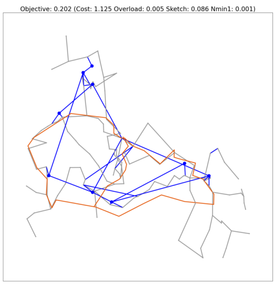
Figure 6.6: Spread of objective and sketch sub-objective values of five optimisations with the same (hyper)parameters with parallelisation disabled and enabled respectively. Objective values of optimisations with parallelisation enabled are generally lower and have less spread.



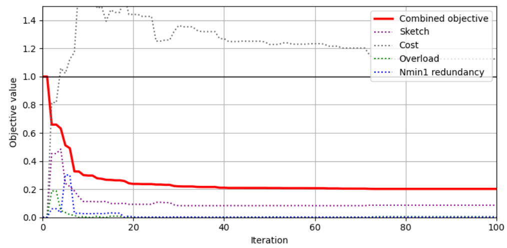
(a) Solution run 1.



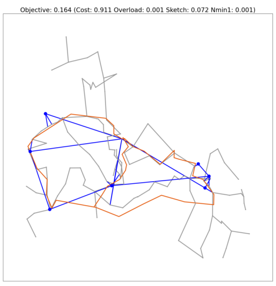
(b) Sub-objectives run 1.



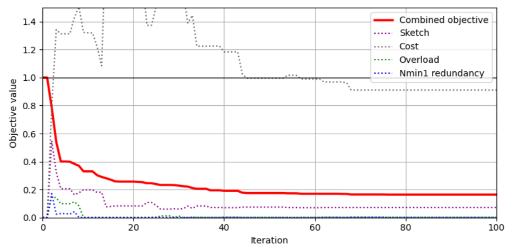
(c) Solution run 2.



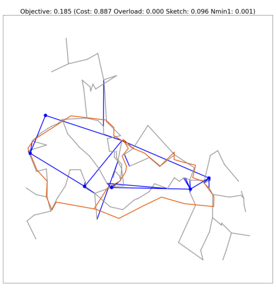
(d) Sub-objectives run 2.



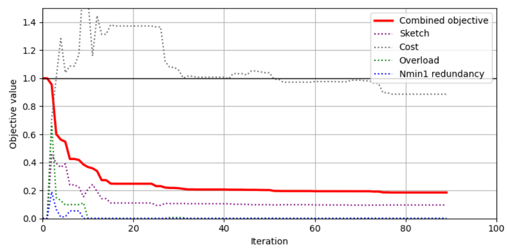
(e) Solution run 3.



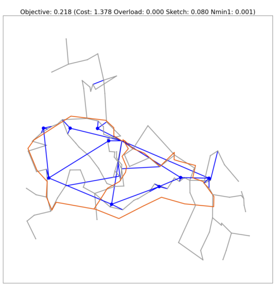
(f) Sub-objectives run 3.



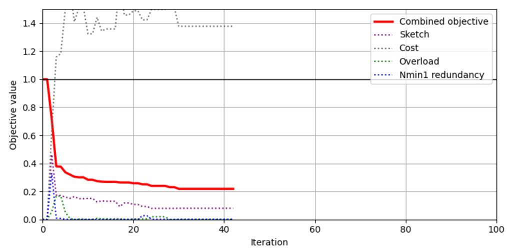
(g) Solution run 4.



(h) Sub-objectives run 4.

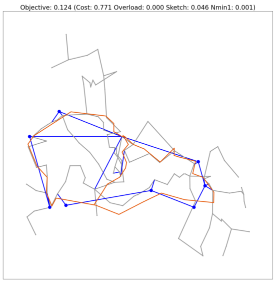


(i) Solution run 5.

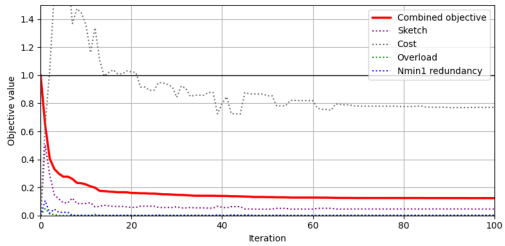


(j) Sub-objectives run 5.

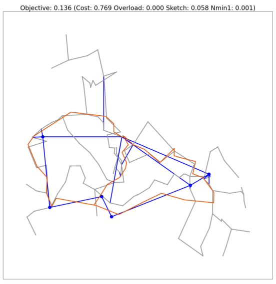
Figure 6.7: Results of five optimisation runs started with the same (hyper)parameters with **parallelisation disabled** to analyse the stability of generated solutions. There are major differences between the shape of structures in the solutions.



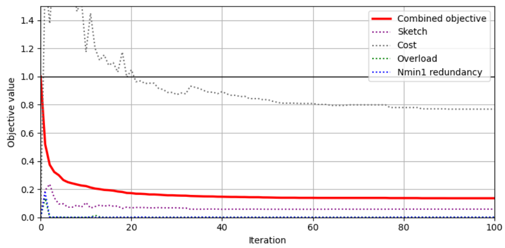
(a) Solution run 1.



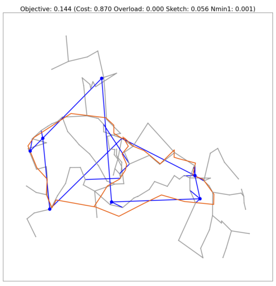
(b) Sub-objectives run 1.



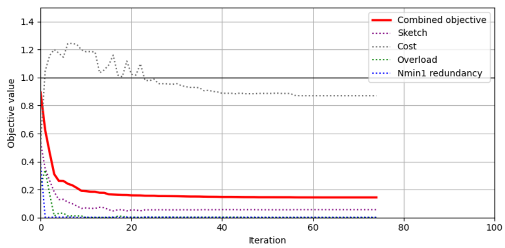
(c) Solution run 2.



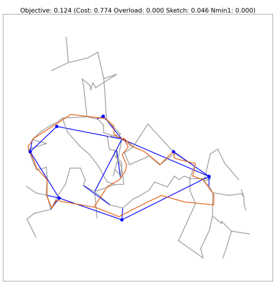
(d) Sub-objectives run 2.



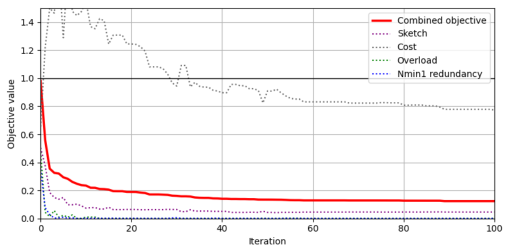
(e) Solution run 3.



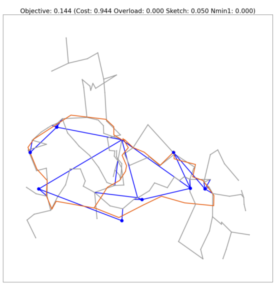
(f) Sub-objectives run 3.



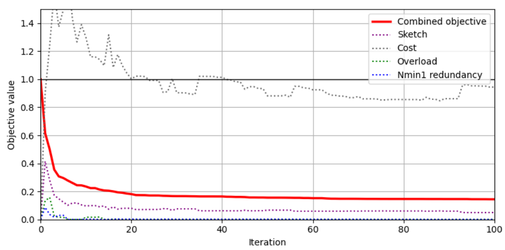
(g) Solution run 4.



(h) Sub-objectives run 4.



(i) Solution run 5.



(j) Sub-objectives run 5.

Figure 6.8: Results of five optimisation runs started with the same (hyper)parameters with **parallelisation enabled** to analyse the stability of generated solutions. There are major differences between the shape of structures in the solutions.

6.2. User validation study

The user study was conducted with 6 distribution grid architects who are currently working with Alliander and are potential users of the sketch-based optimisation algorithm. A thematic analysis was done on the qualitative interview data using inductive coding to identify sentiment and recurring themes per category. The categories used for clustering the interview data are the user study research questions from section 5.2 and two additional categories: participant context and feedback on the Holonet application rather than on the sketch-based optimisation algorithm. The last category is not included in the results because feedback not related to the algorithm is not relevant for this research. Figure 6.9 and Figure 6.10 show an aggregated overview of participant contexts and of sentiment per research question respectively. In the subsections that follow recurring themes per category and other points of interest are presented.

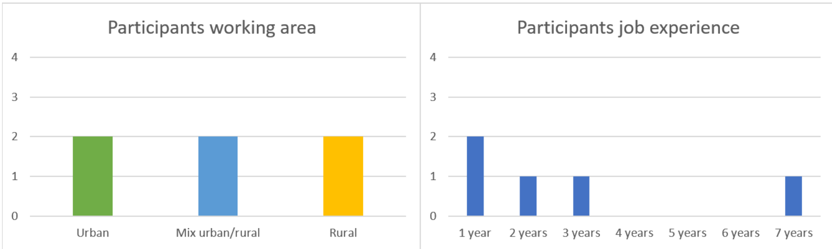


Figure 6.9: Aggregated overview of participants contexts; the type of area they operate in and the number of years experience as distribution grid architect.

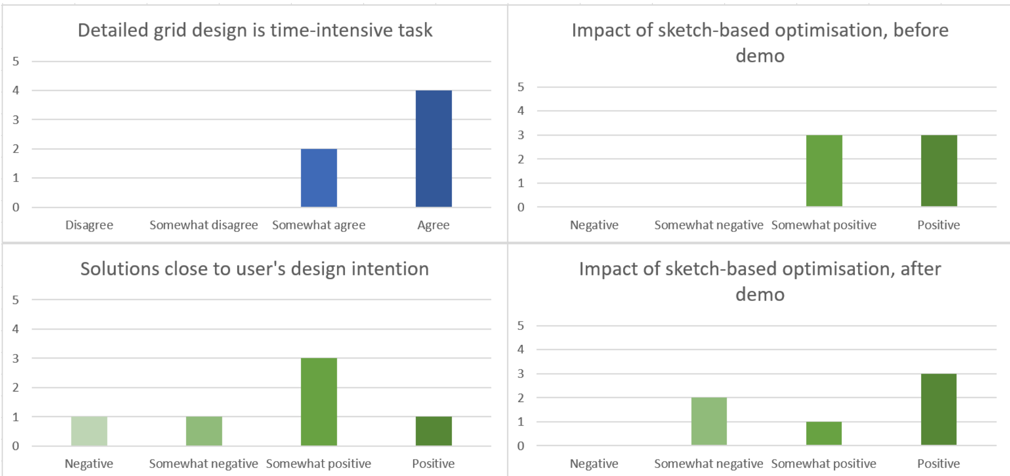


Figure 6.10: Aggregated overview of sentiment per research question/category (where applicable). Analysis and themes extracted from the qualitative data are discussed in the subsections below.

6.2.1. Which aspects of grid design are the most time-consuming?

Most participants indicated that three tasks take up roughly equal time when designing a new grid expansion: gathering and validating information, designing the new grid structure and writing the proposal and getting it approved. It was mentioned that the existing Holonet tool for visualising grid congestion greatly reduced the time needed for gathering and validating information. When zooming in on the grid design task all participants agreed that the rough design, also called 'netvisie' (see chapter 3), takes much less time than the detailed design that is created later (sometimes much later). Determining how to connect the new structure to the existing grid was frequently mentioned as a time-consuming challenge. Since there are usually more ways to approach the problem with no clear best solution, the detailed design task can take considerable time. However, this task was also referred to as a challenge or puzzle and fun to do.

> Participating grid architect: *"I think that 80% of the work can be automated and that the other 20% should remain with [humans with] expert knowledge."*

> Participating grid architect: *“Moving the design process to a single tool (Holonet) could save me a lot of time.”*

Apart from designing grid expansions, participants indicated that they also spend much time on already approved grid expansion proposals, for example writing detailed work instructions and answering questions and communicating about the realisation of the plans.

6.2.2. How is impact of sketch-based optimisation perceived?

Participants were first introduced to the idea of sketch-based optimisation before being shown the actual implementation to gather their thoughts on the impact it could have on their work. The potential impact of using such a tool is overall perceived as positive and 3 out of 6 participants mention time savings as major benefit when asked in an open question format. The (time saving) value of sketch-based optimisation would be to use it as an initial design, which then can be modified and improved by the user. The latter requirement of changing a generated solution was mentioned as a condition to work with the tool effectively.

6.2.3. How close are the solutions to the user's design intention?

Figure 6.11 shows an overview of the sketches drawn by participants during the usability test and the corresponding solutions computed using the same hyperparameters as subsection 6.1.5. Only the best solution from the final population is shown. For some participants time allowed to discuss and sketch an alternative grid design; for others time only allowed for one design. In all cases the algorithm managed to resolve all congestions from the 2035 load forecasts. To illustrate the link between the generated solution and a participant's judgement of the solution, Figure 6.11 also lists the sentiment of each participant regarding how close the solutions are to their sketch and design intention. For participants with two sketches the combined sentiment from the two solutions is recorded.

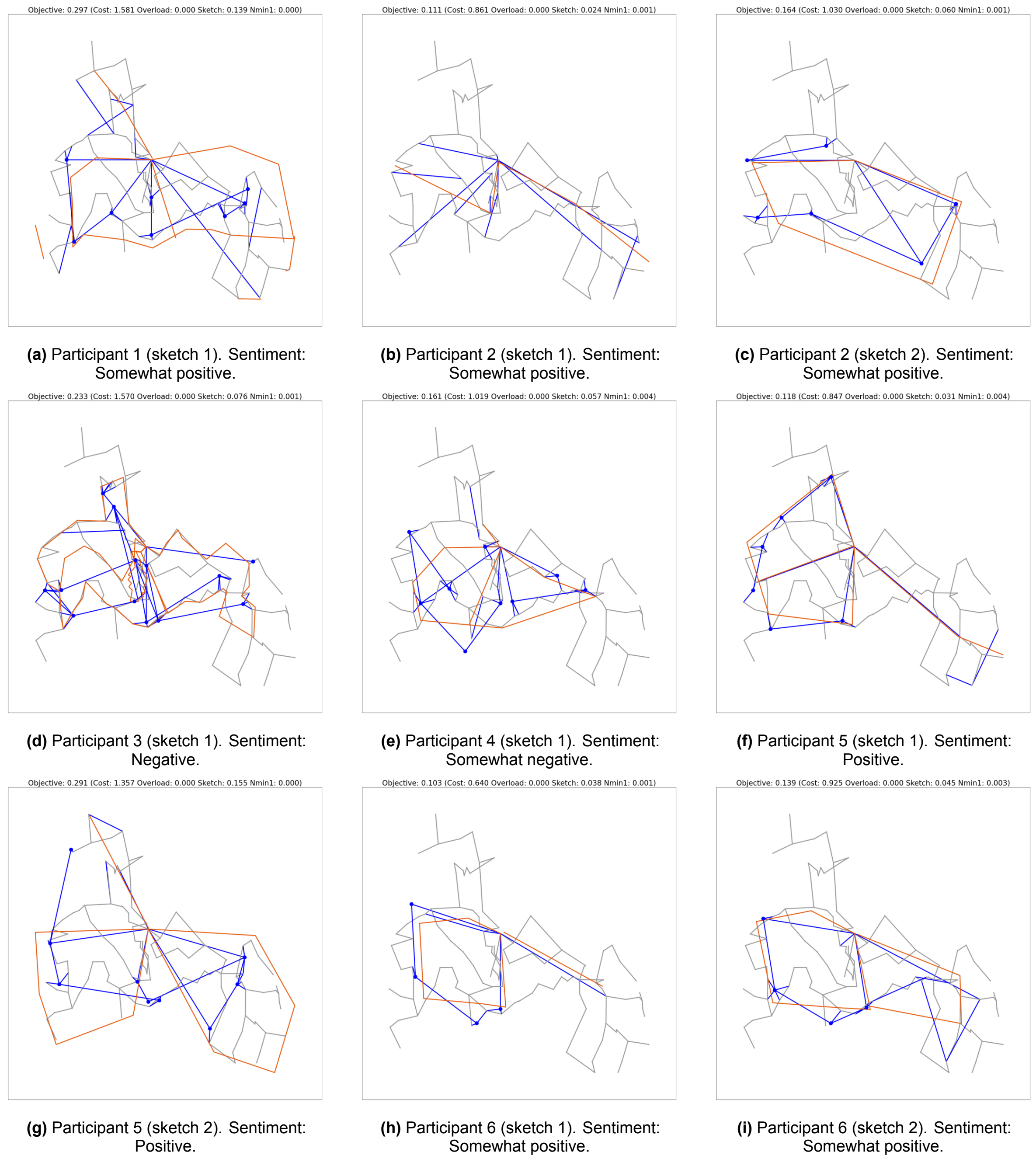
From the qualitative data we extracted several recurring themes. Participants were happy to see that no future congestions remain given the solution. The automatically generated connections from the new structure to the existing grid were generally perceived as most positive aspect of the solution. Also the fact that familiar structures such as a backbone are used in the solutions was perceived as an improvement over the current Holonet algorithm. However, another commonly occurring theme was that the type of cables not matching the users' expectations. For example in practice a backbone typically only contains 630Al cables, however the algorithm often used 240Al cables for backbones. A backbone structure created in the western part of the area often was not completely closed, but rather existing cables were used to connect two ‘arms’ of the backbone. Overall it seemed that generating a solution close to the sketch of a backbone was more often successful (e.g. see Figure 6.11f and Figure 6.11h) than recreating the sketch of separate cables and connecting those separate cables to the intended component in the grid (e.g. see Figure 6.11b).

> Participating grid architect: *“Creative solution to use the existing grid as part of the backbone.”*

In some cases the participant indicated that they could not recognise their input sketch in the generated solution. For example participant 3 who created a very detailed sketch (see Figure 6.11d), rather than a rough sketch, later adding that they had expected that the generated cable route would exactly match the sketch. This led to a negative sentiment in this regard coming from a mismatch between expectation and results.

> Participating grid architect: *“There is no orderly structure in this solution, even though I sketched my design before.”*

In general the generated solutions vary a lot between optimisation runs, even though sketches are similarly shaped in most cases. This was also addressed in subsection 6.1.6 where we established that the algorithm is likely to get stuck local minima leading to high diversity between solutions generated in different optimisation runs. This is especially the case when parallelisation is disabled like during these usability tests.



(a) Participant 1 (sketch 1). Sentiment: Somewhat positive.

(b) Participant 2 (sketch 1). Sentiment: Somewhat positive.

(c) Participant 2 (sketch 2). Sentiment: Somewhat positive.

(d) Participant 3 (sketch 1). Sentiment: Negative.

(e) Participant 4 (sketch 1). Sentiment: Somewhat negative.

(f) Participant 5 (sketch 1). Sentiment: Positive.

(g) Participant 5 (sketch 2). Sentiment: Positive.

(h) Participant 6 (sketch 1). Sentiment: Somewhat positive.

(i) Participant 6 (sketch 2). Sentiment: Somewhat positive.

Figure 6.11: The users' sketches and corresponding solutions (best from final population) from the usability study. For some participants there was not enough time to sketch a second solution. For every participant the sentiment is listed regarding how close the solutions are to their sketch and design intention.

6.2.4. After seeing solutions, how is impact perceived?

After discussing the solutions generated by the algorithm in the usability test, the participants were once again asked for their thoughts on the impact that sketch-based optimisation could have on their work. Most participants did not change their positive attitude towards the concept of sketch-based optimisation. Having an initial design to start from was again mentioned as a benefit, as well as quickly testing out different rough designs and having alternative out-of-the-box solutions available. Participants stated that these benefits would result in time-savings or in better design.

> Participating grid architect: *"This workflow could be very useful for eliminating ideas [during the rough design phase] and for determining connections to existing grid."*

2 out of 6 participants changed from an initial positive attitude to a somewhat negative or a negative sentiment towards the idea of sketch-based optimisation. Reasons for the change in attitude are disappointment that the solutions were not close enough to the user's sketch (such as participant 3, discussed above) and that no explanation is provided for the choices made by the algorithm. A recurring theme is that the algorithm (still) behaves like a closed box while the user sometimes wants argumentation for a particular design choice, also given the (societal) responsibility that grid architects have doing their job correctly.

6.2.5. How can the sketch-based algorithm be improved?

Participants were asked for any feedback on the sketch-based optimisation algorithm towards the end of the interviews, but also during initial interview and the usability test plenty of feedback was given. We summarise recurring feedback points as follows:

- Geography is very important in electrical grid design and preferences for behaviour can currently only be expressed through sketching. Adding constraints based on geographical data about for example waterways and highways could improve the usability of the algorithm's solutions.
- Add the functionality to specify the cable type (cable thickness) while drawing. This feedback originated from different two contexts. While drawing the sketch some participants already had an idea of the required cable type. For other participants the cable types in the solutions did not match their expectation and had retrospectively wished to indicate the cable types in their sketch.
- Optimise for equal load distribution over all routes from the substation rather than avoiding overloading any route. To create a distribution grid designed for redundancy and robust to changes in the load predictions, it is smart to distribute the load evenly over routes and not just avoid overloading components.
- Sketch the location of MSRs rather than the location of cables. One participant mentioned that in their urban working area often the location of MSRs is already determined but the location of cables requires complex planning and hence cables could be a good candidate for optimisation rather than to sketch the cables. However, when we validated this idea with participants mainly working in a rural areas they indicated that they often have freedom where to place MSRs but rather have limited options when planning cable routes due to natural obstacles such as highways or waterways. Therefore we conclude that there is no clear consensus between users on this topic.

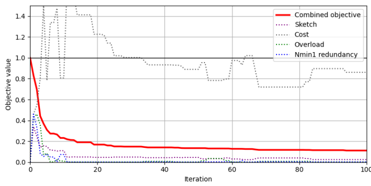
6.2.6. Optimisation metrics

For all optimisation runs done for the usability test with participants' sketches we recorded the sub-objective and objective values while the optimisation progressed. Plots of these values can be seen in Figure 6.12. Unfortunately the data for some optimisation runs is missing due to a technical error in the runtime environment of the algorithm. Rerunning the same optimisation would yield different solutions than those shown to the participants during the interviews (due to the randomised nature of genetic algorithms) and therefore we decided to leave out (sub-)objectives data for these optimisation runs.

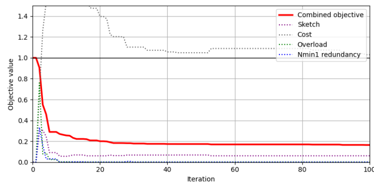
All graphs in Figure 6.12 show a steady convergence of both the objective and the sketch similarity sub-objective. Also the overload and n minus 1 redundancy sub-objectives both converge to a value of zero. This indicates that the algorithm can optimise for our goals well, even when sketches drawn by real users (e.g. the participating grid architects) are used for input. The cost sub-objective takes longer to converge in all cases which is expected, since cost is the least prioritised sub-objective amongst all sub-objectives.

No data available

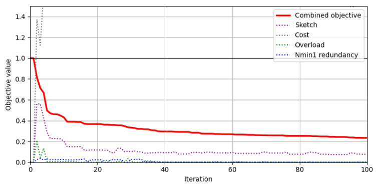
(a) Participant 1 (sketch 1).



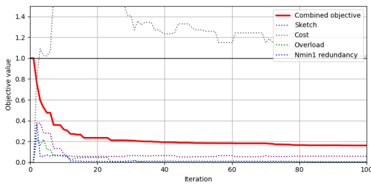
(b) Participant 2 (sketch 1).



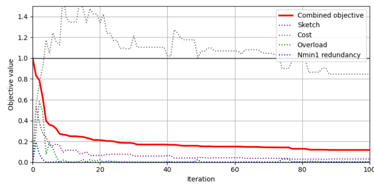
(c) Participant 2 (sketch 2).



(d) Participant 3 (sketch 1).



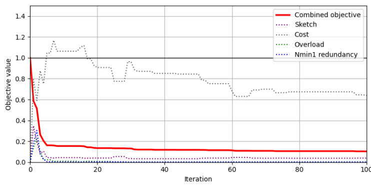
(e) Participant 4 (sketch 1).



(f) Participant 5 (sketch 1).

No data available

(g) Participant 5 (sketch 2).



(h) Participant 6 (sketch 1).

No data available

(i) Participant 6 (sketch 2).

Figure 6.12: Evolution of sub-objective and objective values for each optimisation run of the usability test. A steady convergence of both the objective and the sketch similarity sub-objective can been seen as well as a slower convergence of the least prioritised cost sub-objective. Due to a technical error data for some optimisation runs are missing.

6.3. Discussion

The results of the case study and the user study can be summarised as follows. The case study shows that the shape similarity measure can enable sketch-based optimisation of grid expansion designs using a genetic algorithm. The proposed implementation of sketch-based optimisation generally outperforms the existing optimisation algorithm on the geographical feasibility of its solutions, while also resolving all predicted congestions. Geographical feasibility is improved because known structures such as backbones are used in solutions guided by users' sketches. However new structures in solutions are not always connected with each other as intended by the user. Furthermore the stability between generated solutions is low, meaning that the algorithm is not guaranteed to give a good solution on every use. This is most likely because the genetic algorithm gets stuck in local minima during the optimisation. Enabling the existing parallelisation (see section 4.3) could help overcome this problem, but by itself does not suffice.

The user study provided insights into the potential impact of sketch-based optimisation for accelerating distribution grid expansion planning. In general the impact of sketch-based optimisation is perceived as positive by participants, both before and after using the current implementation. The most frequently mentioned advantages are time savings and the ability to test different designs. Other participants are more critical however, referring to their solutions as infeasible. In these two cases the misalignment between user expectation and results could be a result of a much too detailed sketch (participant 3) or the algorithm getting stuck in a local minimum (participant 4). Further research is needed into these problems or a training for users as part of deployment of this algorithm. Moreover, according to the user study participants the implementation could be improved by having more inputs/controls available while sketching (e.g. selecting the cable type or sketching MSR locations) and by taking into account the underlying geography during sketching.

7 Conclusion

The main goal of this thesis was to investigate how to accelerate distribution grid expansion planning through the use of an optimisation algorithm. The research was done in the context of Alliander, the largest DNO of the Netherlands faced with a big challenge to expand their grids to facilitate the rapidly accelerating energy transition. Earlier research at Alliander has led to the development of a genetic optimisation algorithm for automatically generating optimal grid expansion designs in terms of added capacity and costs. However, in practice this algorithm is not used by its intended users; grid architects. This research first identified reasons why the algorithm is not yet used and proposed several ideas to improve alignment with user requirements. Then a technical implementation of sketch-based optimisation using a novel shape similarity measure was presented and its behaviour is analysed using a realistic case study. Furthermore, a qualitative user study was done to evaluate the potential impact of sketch-based optimisation on user adoption of automated grid expansion planning.

7.1. Answering research questions

How can the user adoption of decision support tools for distribution grid expansion planning be improved?
Based on early interviews with grid architects we attempted to establish why the algorithm is currently not used. This resulted in several new findings regarding the grid expansion design process and regarding how users experience the current algorithm. The process of grid expansion design roughly consists of two phases. First the creation of a 'netvisie': a general plan for a larger region, specifying what type of grid structures are needed but not the exact design. Later during the detailed design phase details like grid structure shape and connections to the existing grid are determined. The user study has confirmed that the detailed design part takes up considerably more time than the earlier netvisie phase.
The current algorithm for automatically generating grid expansion plans is often experienced as a closed box by users because to them arbitrary decisions are proposed without an explanation. They also indicate that generated solutions are often not future proof enough because they do not align with the netvisie due to a lack of control over the (shape of) structures that are used. Finally, users seem to have an internal conflict of what they wish the algorithm would generate: from out-of-the-box designs to designs that confirm with current design practices.
We conclude that control and explainability are crucial to user adoption of decision support tools for grid expansion planning. Both would reduce the feeling of a closed box system and increase trust in solutions generated by the algorithm. We proposed a novel way to introduce more user control to the optimisation: sketch-based optimisation for distribution grid expansion planning.

How has sketch-based optimisation been applied in other domains and how can those learnings be applied to distribution grid expansion planning?
We are not aware of any earlier work that applies sketch-based optimisation to electrical grid design. In other domains sketch-based optimisation has been applied successfully however, such as floor plan optimisation, fashion design and quadrotor trajectory planning [6–8]. Learnings from these previous

studies are the distinction between the use of hard sketch-based constraints or soft constraints in the form of an objective function that can be optimised. The optimisation of quadrotor trajectories by Gebhardt *et al.* [8] uses additional objectives and constraints such as trajectory smoothness or camera motion limitations to create aesthetically pleasing results. This can be applied to our problem model since it consists of multiple constraints and objectives that have to optimised at the same time.

How to implement sketch-based optimisation for automated distribution grid expansion planning with a genetic algorithm?
To enable sketch-based optimisation with the existing genetic algorithm a novel shape similarity measure was developed. The Earth Mover's Distance measure was adapted to form a new sketch similarity sub-objective for the optimisation algorithm, while the formulation of the other sub-objectives was improved. In general the shape similarity measure works well to create feasible and cost-effective grid designs similar to the original sketch. However, it does not always manage to sufficiently capture the user's intent. In particular the creation of backbones works well, while separate cables do not connect to other grid structures as intended by the user. We suspect that these inter-structure connections are not generated correctly because the sketch similarity measure compares the overall investment shape and does not check intra-structure connectivity different investment structures. On the contrary, backbone sketches imply a connection between the different cables that are part of the backbone and the algorithm enforces this. We suspect that this is why creation of backbones generally works better.

What would be the impact of sketch-based optimisation be on the distribution grid expansion planning process?
During the qualitative user we found that a majority of the participants expect sketch-based optimisation to have a positive impact on their work designing distribution grid expansions. Time-savings are mentioned most frequently as a potential advantage, next to the ability to explore several different designs to potentially improve on current design methodology. The algorithm does however need to be further improved to align with all user requirements and expectations. Users wish to have more control over the optimisation, for example by defining specific cables types in the sketch or sketching where MSRs should be placed. Furthermore the visualisation of the generated solutions could display the load of each cable instead of only overloaded cables and there could be an indication of cable type in the map view.

We conclude that sketch-based optimisation indeed has potential to accelerate distribution grid expansion planning at DNOs. The presented novel shape similarity measure enables sketch-based optimisation of electrical grid designs using a meta-heuristic like genetic algorithms. Alliander will integrate our implementation of sketch-based optimisation into the Holonet application over the coming year along with other recommendations from this thesis. Accordingly sketch-based optimisation will become available to distribution grid architects to be used for distribution grid expansion planning.

7.2. Future work

This thesis has shown the opportunities for sketch-based optimisation for planning of electrical grids to accelerate the energy transition, a major global challenge. The research also gives rise to more questions about the technical and process implementation of sketch-based optimisation. Further research is needed in several areas as we discuss below.

First, the technical implementation of sketch-based optimisation could be improved by investigating methods to stimulate correct connections between different structures, which works already works within backbone structures. The case study also showed that solutions generated by the algorithm are unstable between optimisation runs, most likely due to the algorithm getting stuck in local minima. Therefore further research should also focus on avoiding local minima using genetic algorithms or other meta-heuristics for grid expansion planning optimisation. Then regarding load forecasts, currently only deterministic grid load forecasts are available without information on the variance of the predictions while in reality these forecasts can vary a lot. When quantitative data about prediction variance becomes available it would be interesting to see how this can be applied to automated grid expansion planning.

Second, in the broader context of grid expansion design, the solutions generated by the algorithm should be explainable to the users. This would create a better understanding between the algorithm and its user and make it more likely that (insights from) solutions are actually implemented by users. Research into explainable AI for power systems (e.g. Machlev *et al.* [17]) could focus on optimisation of grid expansion planning. In addition to explainability users also desire more control over the optimisation, both when sketching and with other constraints for the grid design.

Third, in this research multi-objective optimisation is implemented through scalarisation, which is a simple weighted prioritisation of sub-objectives. Future work could expand on our implementation by using a multi-objective optimisation algorithm that can approximate the Pareto frontier of the sub-objectives that we have identified. This could lead to more diverse solutions giving users broader insights into possible designs and potentially prevent getting stuck in local minima. It could also improve explainability by presenting users with information on where each solution lies on the Pareto front, indicating to users its strong and weak properties in terms of the defined sub-objectives.

Finally our recommendations to Alliander are to integrate sketch-based optimisation into the existing Holonet algorithm and to investigate other methods of user control and explainability for the algorithm. This can further improve user adoption of the decision support tool. Another interesting line of research could be splitting up the current general optimisation problem into several smaller optimisation problems to further constrain the solution space and increase explainability of individual decisions of the algorithm. For example by first determining the location of MSRs and then using this information determine which cables should be placed.

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A

Proposed solutions

This appendix contains ideas for extensions of the Holonet algorithm to improve alignment with user requirements. These ideas are based on the available documentation and conversations with key users of Holonet (grid architects), the product owner of Holonet and the other members of team Systeemoptimalisatie who work on Holonet.

The following solutions are discussed one by one: interactive genetic algorithm, drawing rough structures, explainability of the algorithm and automated analysis of investment proposals. The first three directions have been worked out using user stories that describe different variants of each solution direction. The descriptions are deliberately not formal or specific because the implementation details will be determined later in the process.

By Sven van der Voort on October 18th, 2023 (automatically translated using Microsoft Word, then manually edited)

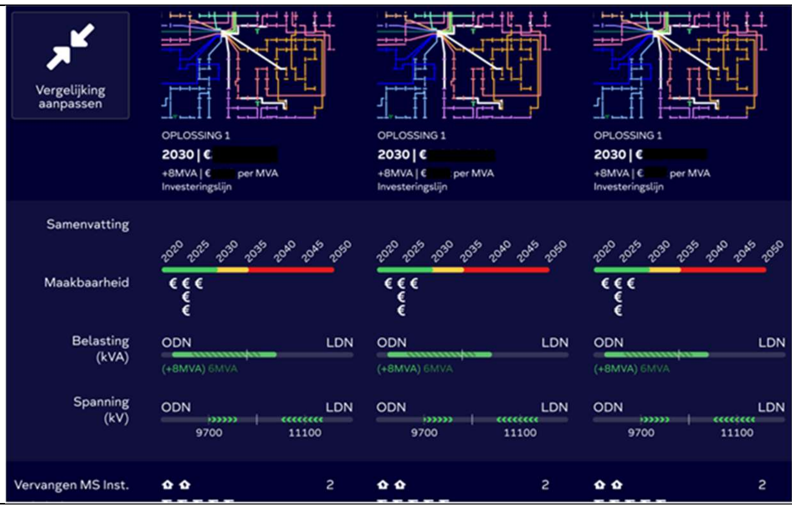
Interactive genetic algorithm

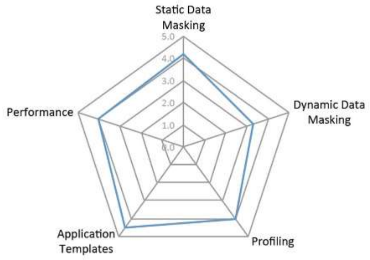
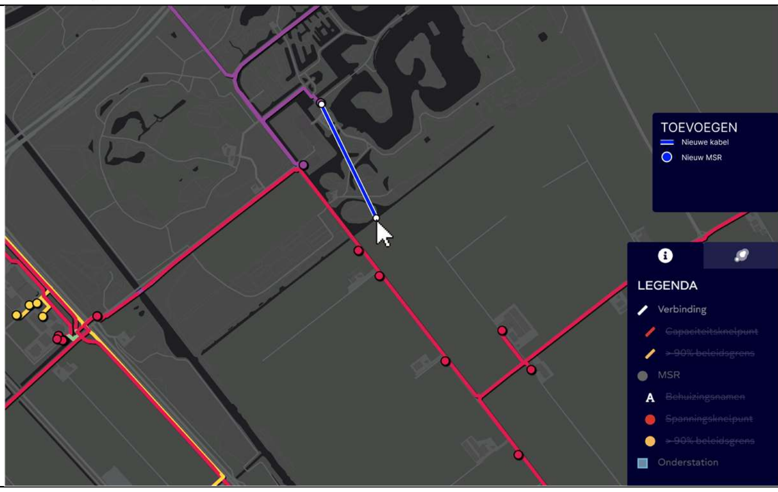
To give users more control over solutions generated by the genetic algorithm, it is possible to make parts of the algorithm interactive. Existing research describes how each component of the genetic algorithm (initialization, mutations and crossovers, and evaluation) can be replaced or supplemented by the user. Below is outlined how that would work in the case of the Holonet algorithm.

User stories (variants)

- [Initial population modification] At the start of the algorithm, all solutions do not yet have mutations. As a user, I apply one or more mutations to the solutions in the population by means of a graphical user interface (laying a cable, weighting cable or laying backbones). Then I activate the calculation and come back later for the result. *(The goal is for solutions to converge faster and/or better meet the expectations of grid architects.)*
- [User-driven mutations] As a user, after x iterations, I apply one or more mutations to the solutions in the population by means of a graphical user interface (laying a cable, reinforce a cable or creating backbones). This can be done for all solutions from the population or only for solutions on a particular island. The process repeats until the algorithm displays the final solutions. *(The goal is for solutions to converge faster and/or better meet the expectations of grid architects.)*
- [Subjective evaluation] As a user, after starting the calculation, I wait until the first x iterations of the genetic algorithm are complete. The solutions in the current population are presented with a schematic/geographical overview of the changes and/or with a valuation of the solution on various aspects (e.g. tax, costs, future-proofing). Then I indicate my preference of all solutions in the population by means of a rating or an ordering of the solutions. This assessment is added to the objective function with which the algorithm calculates further. This process is repeated a number of times until the algorithm displays the final solutions. *(The goal is for solutions to better meet the expectations of grid architects.)*

Sketches interface

<table>
<tr>
<td>Example comparing different solutions based on the properties of the solutions. (Created by Joep Houterman-Timmers)</td>
<td>
</td>
</tr>
</table>

A 'star diagram' in which different properties and qualities of solutions could be visualized.	
Sketch of a graphical interface where the user can enter mutations themselves, for example placing a new cable or MSR.	

Drawing rough structures

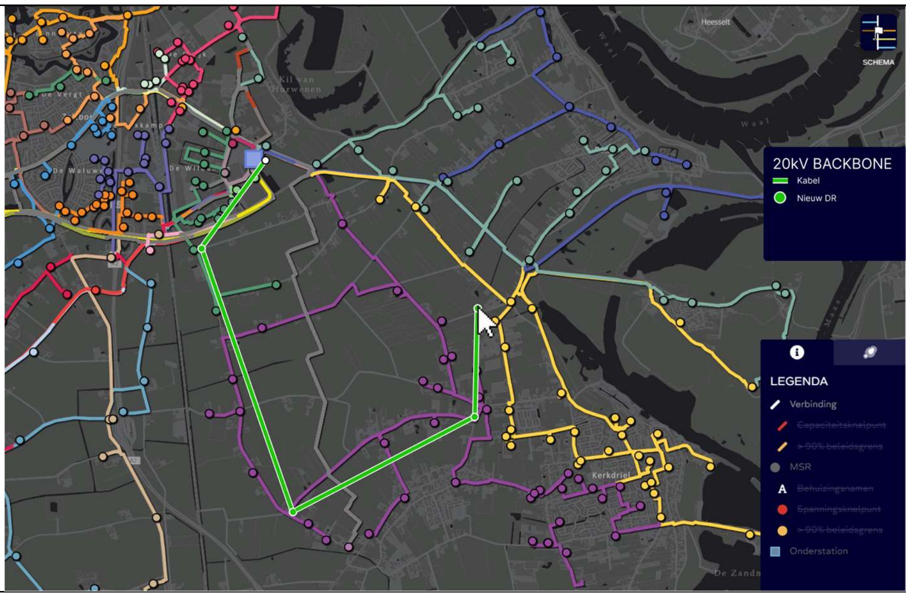
Discussions with key users showed that their investment proposals almost always contain a new (backbone) structure. This is done to make the distribution network more future-proof while solving the congestion. In addition, this limits the disturbance for the local environment because instead of upgrading existing infrastructure, mainly new infrastructure is being built.

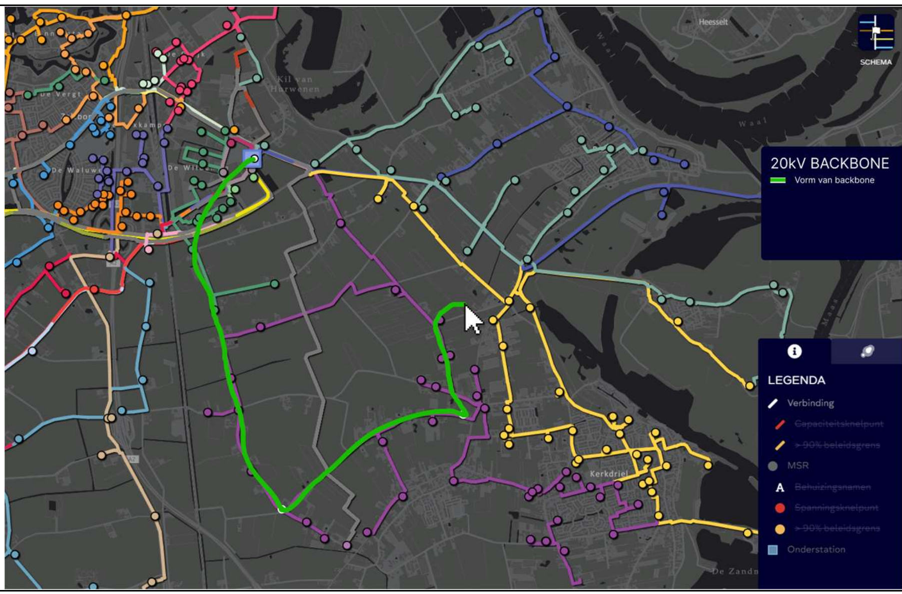
These ideas for the Holonet algorithm implement this by giving grid architects a degree of control over the (rough) shape of the new structure. They draw the shape of a backbone on the map, which is then given to the optimization as (soft) constraint. This should ensure that the generated solutions are more in line with the wishes of the network architect and are therefore more usable.

User stories (variants)

- [Drawing new structures] As a user I use a graphical interface to draw the rough outline of a new mesh structure, for example a new backbone. If I want to calculate multiple scenarios or ideas I repeat this process. Then I start the calculation by the algorithm and come back later to see the results. The algorithm gets the rough contour as (fuzzy) constraint and will optimize the details of the new structure (e.g. where to connect to the old grid). *(The goal is that grid architects can quickly simulate multiple strategies without having to calculate/design details such as the feeding locations, because they are optimized faster by the algorithm.)*
- [Drawing routes] As a user, I select in the graphical interface which MSRs should be linked to a new route. I can also draw new routes and/or backbones. Then I start the algorithm and come back later to see the results. The algorithm will use as mutations or as constraints during optimization. *(The goal is for grid architects to quickly validate a strategy, especially if they have an idea in advance what the design should look like.)*

Sketches interface

Sketch of a graphical interface where the user can draw a backbone structure. When the user clicks, a new DR is 'placed'. This serves as a guide for the algorithm and does not have to be strictly followed.	

Sketch of a graphical interface where the user can draw much coarser lines to guide the algorithm to where a new backbone structure should be build.	

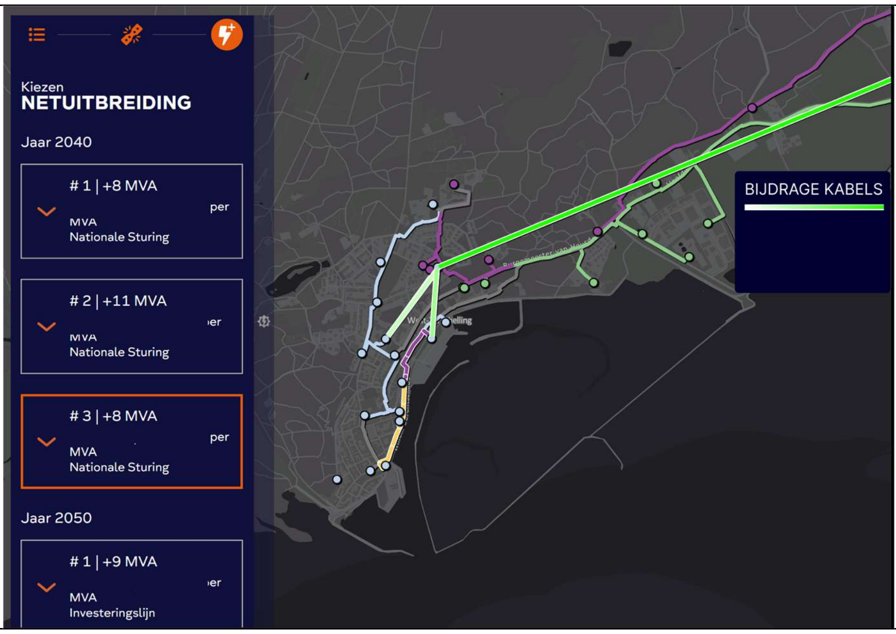
Explainability of the algorithm

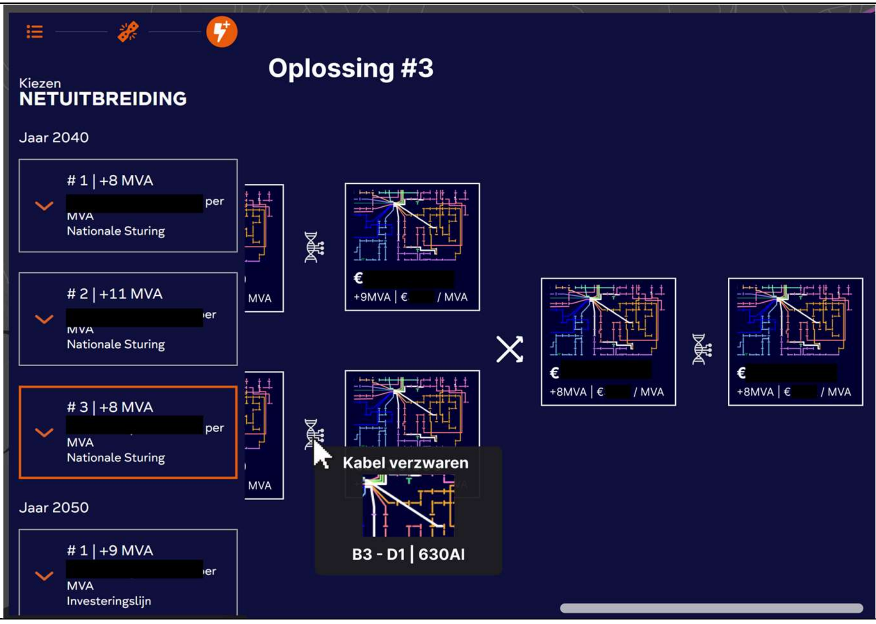
A common remark from users of the Holonet algorithm is that it is unclear to them how the algorithm came up with a particular solution. To give users more insights into this process we can make the algorithm more 'explainable', using the principles of Explainble AI (XAI). Details about the generated solution and the process leading up to the solution are displayed to the user, so that they gain more insight into the operation of the algorithm and can possibly make adjustments.

User stories (variants)

- [Dear mutations] As a user I start the optimization of the active area in the Holonet interface. After the calculation is done I come back to the Holonet interface and can view the different solutions. By clicking on a solution I get to see which mutations gave the biggest improvement for that solution. *(The goal is to give the user more insight into how the algorithm works.)*
- [Grid lineage] As a user I start the optimization of the active area in the Holonet interface. After the calculation is done I come back to the Holonet interface and can view the lineage graph of each. This lineage diagram shows how the solution mutated and which crossovers were important to arrive at the final solution. To do this the complete lineage graph (very large) must be compressed into a clear visualization. *(The goal is to give the user more insight into the operation and decisions of the algorithm.)*
- [Decision Tree] As a user I start optimizing the active area in the Holonet interface. After the calculation is done I come back to the Holonet interface and can view the different solutions. For each solution I can see a decision tree of the mutations that led to this solution. Mutations that have not been further calculated form 'leaves'/ends of the decision tree and can still be calculated by clicking on them. *(The aim is to give the user more insight into the operation of the algorithm and to make adjustments when they disagree with a decision of the algorithm.)*

Sketches interface

Sketch of a graphical interface where the user can see from the color of the cables which cable gives the greatest gain within the selected solution.	

Sketch of a graphical interface where the user can view a compressed version of the lineage diagram of each solution. The details of each mutation and crossover can be seen by moving the mouse over the icon.	

Large Language Models for insight and net design

Investment proposals

At the moment, investment proposals are written manually by net architects and delivered in the form of Word documents. They have a semi-structured form in which the current situation, proposed solution, associated costs, alternatives and risks are described. Additionally figures are added with a geographical and schematic design of the proposed grid expansion.

These investment proposals potentially contain a lot of information of which, if properly structured and/or learned by an (AI) model, can be of value for the Holonet algorithm and for general insights about the work process of the net architects. With the recent developments of Large Language Models it should be possible to analyze the text and even pictures of investment models.

An important limitation is the small amount of training data, especially for learning the complex relationships required for the described functionality. Therefore the success of this direction depends on the generalization ability of the Large Language Model, of which the implementation details often are not available.

Grid-to-text and text-to-grid

A futuristic application of Large Language Models for electricity grid design could be to be able to write automated investment proposals based on a digital grid design (grid-to-text). In addition, you can think of an application in which a new digital grid design is generated based on text from, for example a network vision document and description of the requirements (text-to-grid).

B

User validation study script

The test script shown below was used to conduct the user study interviews and usability tests. Where applicable interview questions are marked with a number in (orange) to link them to user study research questions from section 5.2. The user study sessions were conducted in Dutch but have been translated to English for this thesis report.

Preparation session 1

- Send participant introduction information and informed consent form:
  "Dear [participant], this message contains more information about the user study on [session date]. I have developed new functionality for the existing Holonet algorithm for automated investment proposals. You can now sketch the desired new grid structure (e.g. a backbone, or support cables). For the user study I will ask you to sketch a number of solutions for the area surrounding substation Beesd (RS Beesd). To prepare you could take a look at the area in Holonet, but this can also be done during our meeting. Besides this study has an 'informed consent' form where you give permission to collect and publish anonymised data. If you want to participate in the study, you can sign the form before the session: [form URL] Finally I want to emphasise that participation in the study is completely voluntary. Thanks in advance!"
- Check whether participant submitted informed consent form
- Prepare Holonet by opening RS Beesd

Session 1

- [Introduction researcher and participant]
- Please tell me something about yourself.
- Could you tell me something about the last time you used Holonet? What do you usually use it for?
- What do you usually spend a lot of time on when creating a new investment proposal? (1)
- What do you know about the Holonet algorithm for automatically generating investment proposal? / When did you use for the last time?
- [Introduction of sketch-based optimisation: With sketch-based optimisation you give input to the algorithm about your preferred shape/structure for the solution. The sketch will be used by the algorithm just like grid load and investment cost are used as input. This diagram (Figure B.1) illustrates that as well. Using those inputs the algorithm will try to create a fitting investment proposal/grid design.]
- Let us imagine that this functionality exists and it would work exactly as you want. How would it work and how would you use it? What would be the impact on your work? (2)

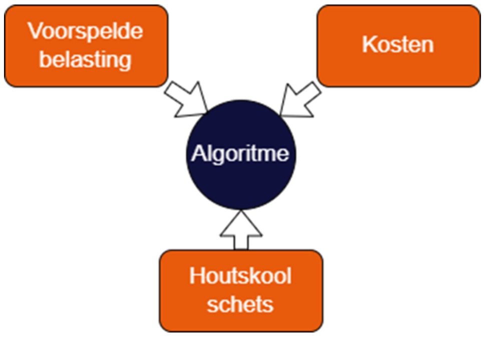


Figure B.1: Diagram shown to participants during the first session to illustrate the concept of sketch-based optimisation.

- [Introduction usability test: A prototype of sketch-based optimisation was built in Holonet. You will test this functionality with the example case of the RS Beesd substation. The goal is prevent any congestions in the 2035 load scenario. You can assume only 10kV will be available at the substation.]
- Think aloud while you take some time to think about solutions to the resolve the congestion. Feel free to use Holonet to get more insights into the problem. (3)
- Now activate the sketching functionality with this button and sketch the solution that have thought of. It can be a really rough sketch; draw how you would connect it electrically rather than the exact cable routing. Take me along in what you are doing. (3)
- How do you experience the sketching?
- What do you think the algorithm will do now? (3)
- [If time allows] Now think of an alternative solution that you would add to your investment proposal. Think aloud while you are using the sketching functionality again to sketch your solution. (3)
- [If time allows] What do you think the algorithm will do now? (3)
- ["I will now use your sketch as input to the algorithm and start a computation. In the afternoon during our second session I will show you the results."]

Preparation session 2

- Start optimisation computation with the following (hyper)parameters:
  Area of RS Beesd, predicted load scenario of 2035
  Estimated costs: [confidential]
  Population size: 10
  Max iterations: 100
  Weights: Costs 0.1, Overload 0.5, Sketch 1.0, Redundancy: 0.5
  Parallelisation: disabled
- Check and open generated solutions in Holonet

Session 2

- Take a look at the resulting solutions, is there something that you notice or something that stands out? (3)
- How do the resulting solutions compare to your earlier expectations? And how do you feel about that? (3)
- To what degree did the algorithm generate a realistic solution? (Follow-up: What would you have done differently and why?) (3)
- How would you use the suggested solutions during your grid expansion design process? How do you feel about that? (4)
- [Repeat first four questions above for the alternative, if time allows]

- What is your current view on the potential impact of sketch-based optimisation on your work? (4)
- What could be improved about the things we just discussed? (5)
- Do you have any remaining questions about what we just discussed or about the research?

C
Academic paper draft

To share our research on sketch-based optimisation for distribution grid expansion planning with a broader audience we intend to submit our findings as an academic paper to the Innovative Applications of Artificial Intelligence (IAAI) ’25 conference. This appendix includes a draft version of the paper which we intend to refine and improve upon before final submission to the conference. Therefore please note that the content in this appendix is subject to change as we make improvements and incorporate feedback.

Sketch-Based Optimisation for Distribution Grid Expansion Planning

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Abstract

Distribution Network Operators (DNOs) have a significant challenge to expand the capacity of the electricity distribution grid to facilitate the energy transition. Designing grid expansions for the distribution grid poses a complex problem with many constraints. Earlier work on optimisation of distribution grid design does not consider user preference and expertise, whereas we argue that this is imperative for user adoption. We present a technical implementation of sketch-based optimisation for distribution grid expansion planning using a novel shape similarity measure to enable user input. We investigate its behaviour through a realistic case study. Furthermore, a qualitative user study is done to evaluate the potential impact of sketch-based optimisation on distribution grid expansion planning. We conclude that the novel shape similarity measure enables sketch-based optimisation of distribution grid expansion planning and that it has potential to accelerate electricity grid design processes. Alliander, the largest DNO of the Netherlands, will implement sketch-based optimisation in their distribution grid design application later this year, making it available to 20+ grid architects to accelerate their design process.

Introduction

Global climate change is driving a rapid energy transition from fossil fuels to renewable energy. The energy distribution grid, operated by Distribution Network Operators (DNOs), will have to undergo radical changes to facilitate the exponential growth of volatile energy sources such photovoltaic (PV) and wind energy and the increased demand for electricity as a replacement for fossil fuels, for example the introduction of electric vehicles (EV) (Afman 2017). In addition, grid expansion planning is a notoriously difficult problem (Vahidinasab et al. 2020). At Alliander, the largest DNO of the Netherlands, a group of 'grid architects' is responsible designing grid expansion plans. As a result of the energy transition the need for grid expansion designs is growing while grid architects with the required expertise are scarce. Therefore Alliander has developed a state-of-the-art genetic algorithm for optimising grid expansion designs on their medium-voltage grids. However, in practice the algorithm does not fully suit the need of its intended users grid architects because they feel the system operates like a closed box and they have little control over the outcomes of the optimisation. Solutions often deviate too much from their current design practices which hinders user adoption. For example because they lack a coherent structure such as a new circular backbone structure or new cables intersect with geographical obstacles such as waterways and highways (van der Voort 2024).

Existing methods for automated grid expansion planning typically only consider grid load forecasts, material costs and grid topology as input. This gives users little control over the generated solutions. This work attempts to bridge this gap. We introduce a sketch-based optimisation algorithm for distribution grid planning. The algorithm optimises multiple sub-objectives: predicted grid overload, investment costs, a grid redundancy measure as well as a novel sketch similarity measure. Solutions generated by the algorithm represent feasible grid expansion plans that provide users with insights they can use when designing grid expansions. We also evaluated the new algorithm in a qualitative user study to assess the potential impact of sketch-based optimisation on the acceleration of grid expansion planning.

Applying sketch-based optimisation to the domain of electricity grid design is the main challenge we address, along with a demonstration of the potential of sketch-based optimisation in this domain.

In summary, our contributions are as follows:

- The introduction of a novel shape similarity measure that enables sketch-based optimisation of electrical grid expansions.
- A functioning prototype of sketch-based optimisation for distribution grid expansion planning.
- Qualitative user study with the prototype to demonstrate the potential of sketch-based optimisation for accelerating distribution grid expansion planning.

Results from this work will be deployed later this year to make it available to distribution grid architects at Alliander.

Background and problem statement

The Dutch electricity grid can be divided into three network layers: the high-voltage (HV) transmission grid (110kV-380kV), the medium-voltage (MV) distribution grid (10kV-20kV) and the low-voltage distribution grid (400V) (Phase-

ToPhase 2024). Each MV distribution grid is sourced from the HV grid by a central substation. Then underground cables distribute power from the sourcing substation to network nodes, forming a graph network. Expansion planning for MV distribution grids in particular is complex for three reasons.

1. Existing infrastructure such as waterways or highway present geographical limitations for constructing new cables.
2. The construction of underground cables is also expensive and has a high societal impact.
3. The grid has to be redundant to any single component failure (also known as 'n minus 1' redundancy). This is achieved by reconfiguring the network in case of a failure.

More design constraints for MV distribution grids, including Alliander-specific constraints, can be found in (Jurriëns 2019).

Existing research on the grid expansion planning problem has focused on optimisation methods such as harmony search (Agajie et al. 2020), simulated annealing (Jurriëns 2019) and genetic algorithms (Mendoza, Bernal-Agustin, and Domínguez-Navarro 2006; Alliander 2022). These methods typically take grid load forecasts, material costs and topological constraints as input and attempt to optimise investments costs and/or operational costs. However this gives users little control to express their preferences for a particular grid structure or topological configuration.

The work by Jurriëns on simulated annealing for grid expansion optimisation introduced a model for Dutch distribution grid constraints and design criteria. The model was found to be too complex to solve with linear optimisation and require a meta-heuristic such as simulated annealing to find feasible solutions. The initial algorithm using simulated annealing is a predecessor of the genetic algorithm that currently is deployed at Alliander. (Alliander 2022)

Sketch-based optimisation has been demonstrated as a promising mechanism for user control in other domains such as floor plan optimisation, fashion design and quadrotor trajectory planning. (Keshavarzi et al. 2021; Zhu et al. 2016; Gebhardt et al. 2016) The latter two studies create a model using (multiple) objective functions and constraints from the original model and then add a new (sub-)objective function that measures sketch to solution similarity. This acts as a soft constraint for the algorithm to approximate the sketched shape. This paper applies a similar approach to the design of electricity network design, which has not yet been explored in literature.

Genetic algorithm

The state-of-the-art genetic algorithm that is currently deployed at Alliander optimises multiple sub-objectives: components overload based on load predictions, n minus 1 redundancy based on load predictions and cost of investments. The algorithm starts with a population of empty solutions containing just the current grid and no investments. The objective function consists of a combination of the sub-objectives and is optimised by iteratively applying genetic

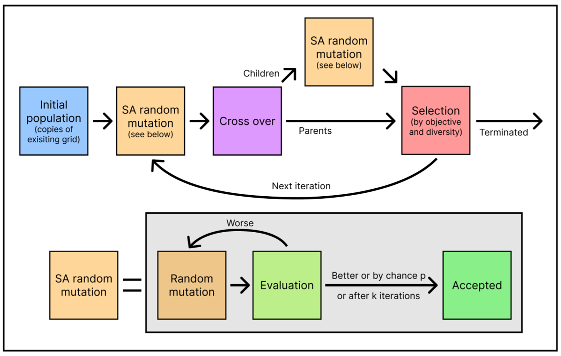


Figure 1: Overview of the genetic algorithm for grid expansion optimisation. The mutation step actually consists of an embedded simulated annealing procedure to improve optimisation convergence.

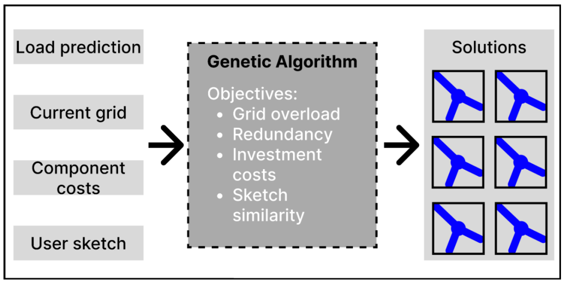


Figure 2: Input and sub-objectives of the modified genetic algorithm for sketch-based optimisation of grid expansion designs.

operators: mutation, cross-over and selection. The mutation step actually consists of an embedded simulated annealing procedure to improve optimisation convergence. An overview of the genetic algorithm can be seen in figure 1. The generic operators mutation and cross-over are designed to be invariant to specific strict grid design constraints: connectedness, radial operation and single voltage on connected components. More details about the objective function, constraints and different mutation operators can be found in (van der Voort 2024).

Methodology and implementation

To enable sketch-based optimisation a fourth sub-objective was added to the genetic algorithm for grid expansion optimisation. The new sub-objective measures the shape similarity between the user sketch and generated solution. Minimising this sub-objective should create solutions that approximate the shape of the user sketch. Scalarisation is used as multi-objective optimisation strategy: all sub-objectives are first normalised and then combined into a single objective function using a weighted sum. The sub-objective weights are hyperparameters used to prioritise specific sub-objectives over others. An overview of the genetic algorithm for sketch-based optimisation can be seen in figure 2.

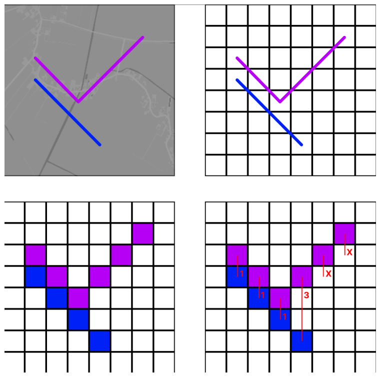


Figure 3: The purple sketch and the blue investment shapes are first discretised. Then the cost of the optimal assignment can be computed. Sketch parts without assignment incur a constant cost X. In this example the similarity measure is 6+2X.

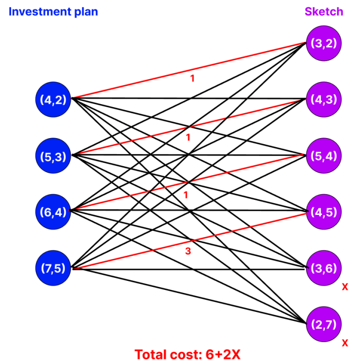


Figure 4: EMD converted to a linear unbalanced assignment problem. Costs on the edges are Euclidean distances between sketch and investment parts (not shown). The optimal assignment is highlighted in red.

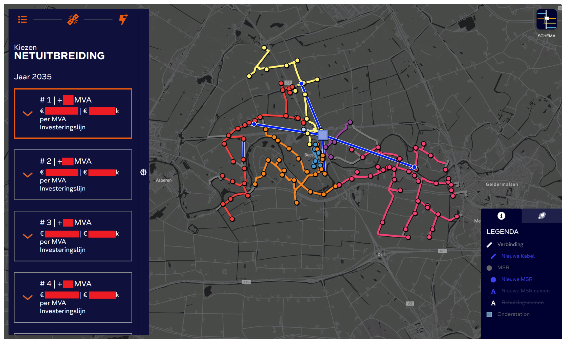


Figure 5: Web interface displaying an optimised solution in blue. The lines are cables, circles are nodes and the central square is the substation sourcing the network.

Shape similarity measure

The novel shape similarity measure uses a two-dimensional and binary version of the Earth Mover's Distance (EMD) as proposed by (Rubner, Tomasi, and Guibas 2000). The Earth Mover's Distance (also known as the Wasserstein metric) is a (dis)similarity measure between two distributions. An intuitive way of understanding EMD is "by thinking of piles of earth spread around in a Euclidean space and holes spread in that same space. Then, EMD measures the least amount of work needed to fill the holes with earth" (Rubner, Tomasi, and Guibas 2000). This can be applied to our problem by converting the investment plan shape and the sketch shape into two two-dimensional distributions resembling the piles of earth and the holes respectively. Then the amount of work done to fill the holes with dirt using the optimal assignment measures the similarity between the two shapes. We allow for partial matching of the investment with the sketch by allowing piles of earth to remain unused.

Computing the EMD optimal assignment of investment cable parts (piles of earth) to user sketch parts (empty holes) can in our case be reduced to the optimal linear assignment problem. In this problem vertices from one part of a bipartite graph have to be assigned to vertices in the other part according to the minimum sum of costs on the edges. This is true because quantities at a location are binary and can therefore not be split or combined to a destination location. Cost represents the Euclidean distance between a investment cable part and a sketch cable part, or a constant penalty if a sketch cable part could not be assigned (a hole could not filled with dirt). See figure 4 for an example.

To apply EMD to our problem in practice we have to discretise the vectors of the solution's investments and the user sketch. An example of this can be seen in figure 3. Algorithm 1 presents the pseudo code for computing the shape similarity measure.

Deployment

The sketch-based optimisation algorithm was deployed on existing infrastructure at Alliander. The system consists of a high-performance analytics database storing load prediction and grid topology data, a Kubernetes environment running short-lived containers with optimisation processes and a web interface for starting optimisation runs and displaying optimisation results. Figure 5 shows a screenshot of the user interface displaying an optimised solution. The chosen architecture allows for completely automated operation of the system and is always available to grid architects after training on the system.

Experimental setup

Our research has two experimental aspects: a demonstration of the sketch-based optimisation implementation using a realistic case study and a qualitative user validation study to assess the potential impact of sketch-based optimisation on grid expansion planning processes.

Both the case study and user study use Beesd as an example case, a medium-sized village in the Netherlands. The distribution grid there has 122 nodes and there are 3271 pos-

Algorithm 1: EMD Shape Similarity Measure

$D_{ss} \leftarrow$ euclidean_distances(S, S)
$P \leftarrow \max(D_{ss})/2$ {First compute non-assignment penalty P}

function EMD_SIMILARITY(L_s, L_i)
$S, I \leftarrow [], []$ {Initialise lists of sketch and investment pixels}
for $l \in L_s$ **do**
  $S \leftarrow S +$ rasterise(l) {Rasterise all sketch lines}
end for
for $l \in L_i$ **do**
  $I \leftarrow I +$ rasterise(l) {Rasterise all investment lines}
end for
$D_{si} \leftarrow$ euclidean_distances(S, I)
$A \leftarrow$ solve_linear_unbalanced(D_{si}) {Compute optimal assignment}
similarity $\leftarrow$ assignment_cost(A)
for $s \notin A$ **do**
  similarity $\leftarrow$ similarity $+ P$
end for
return similarity
end function=0

sible new cable options. The case of Beesd is interesting because a recently approved grid expansion plan is available which indicates the need for grid expansion as well as provides a feasible design that could be used as sketch input during the case study. Figure 6 shows the current grid topology of Beesd and the sketch of the approved grid expansion design, which includes a circular backbone structure and a support cable going across the backbone.

For the user validation study 6 participants were recruited from the group of roughly 20 distribution grid architects currently working at Alliander. Given the small number of participants we adopted a qualitative approach focused on attitudinal interview questions and a usability test (Moran 2019). For each participant the user study consisted of two individual sessions held on the same day. The first session consisted of introductions, interview questions about the participant's work as grid architect and an introduction to the idea of sketch-based optimisation. Then the usability test where the participant was asked to sketch their ideas for a good grid expansion plan. The second session the participant was asked to comment on the results of the usability test. Time between the sessions was used to run the optimisation which typically takes between 1 and 1.5 hours to run. Data analysis was done using an inductive coding strategy to identify recurring sentiment and recurring themes (Thomas 2003).

Results

Here we present and discuss the results of the case study and the user validation study. Used hyperparameters for all experiments can be found in the thesis report this research is based on (van der Voort 2024).

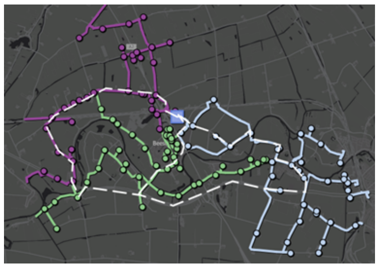


Figure 6: Current grid topology of Beesd (colored lines) and sketch of existing grid expansion plan (white dotted lines).

	Overload	Redun.	Cost	Sketch
Baseline	0.5	0.5	0.1	0.0
Only sketch	0.0	0.0	0.01	1.0
Sketch&Overload	1.0	0.0	0.1	1.0
All	0.5	0.5	0.1	1.0

Table 1: Sub-objective weights for case study optimisation runs shown in figure 7.

Case study

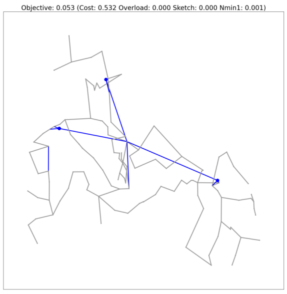
The case study demonstrates the sketch-based optimisation implementation through examples of optimisation runs with an increasing number of sub-objectives enabled. Figure 7 shows the best solutions from the final population of optimisation runs. Table 1 shows the sub-objective weights for each optimisation run.

Starting with figure 7a showing a baseline optimisation run without any sketch input where the overload, redundancy and cost sub-objective were enabled. All congestions were resolved at reasonable costs (53% of the estimated costs), however this is not a feasible solution according to the grid architect's requirements: new cables intersect with a major highway and a waterway and no future proof backbone structure is used.

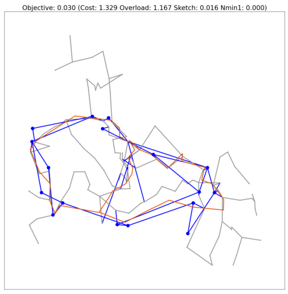
Then figure 7b shows the result of isolating the sketch similarity sub-objective by disabling overload and redundancy sub-objectives. A small weight (0.01) is assigned to the cost sub-objective to act as regulariser to avoid diverging solutions with unlimited new components. The result shows that the algorithm approximates the shape of the sketch well given the finite, discrete set of options it has available.

The overload sub-objective is added together with significantly weighted cost sub-objective for the optimisation in figure 7c. Here the algorithm managed to resolve all predicted congestions and generated a clear circular backbone structure in line with the input sketch. The new support cable going across in a north-south direction is however not directly connected to the new backbone while this was the user's intention based on the input sketch. The algorithm has also generated connections from the new backbone to the existing through new nodes, which is generally seen as a complex and time-consuming task (van der Voort 2024).

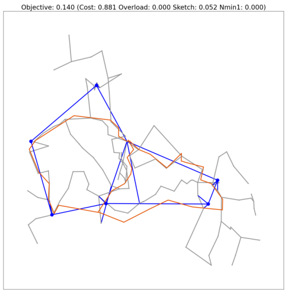
Finally figure 7d shows the result of an optimisation of all sub-objectives, now including n minus 1 redundancy. The resulting expansion design resolves all predicted congestions



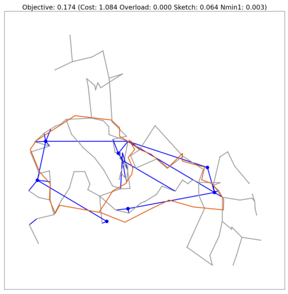
(a) Baseline, no sketch.



(b) Only sketch.



(c) Sketch and overload.



(d) All sub-objectives.

Figure 7: Case study results illustrating the existing grid (grey), the input sketch (orange) and the solution's new cables (blue lines) and new nodes (blue dots).

and 99.7% of predicted redundancy issues. Compared to the solution optimised without redundancy in figure 7c, this solution is more expensive (from 88% to 108% of estimated costs) and chooses a slightly different grid structure while still staying close to the input sketch. Also noteworthy is how the generated backbone is not a complete circle but rather uses the existing grid to create a n minus 1 redundant circle.

Stability of solutions The stability of solutions between optimisation runs was also investigated using five different optimisation runs with the same input parameters. Although the (sub-)objectives converge in a similar fashion for all runs, the resulting solutions vary much in shape, as can be seen from the examples in figure 8. This indicates that the genetic algorithm potentially gets stuck in local minima rather than efficiently explored the solution space. Furthermore, it could hinder user adoption because no apparent reason is given for two varying results.

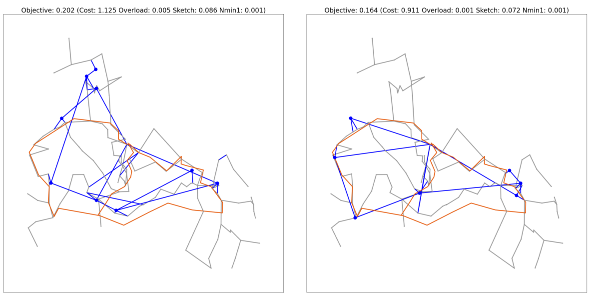


Figure 8: Two solutions generated with the same input parameters. Although both solutions converged, the solution shape differ a lot.

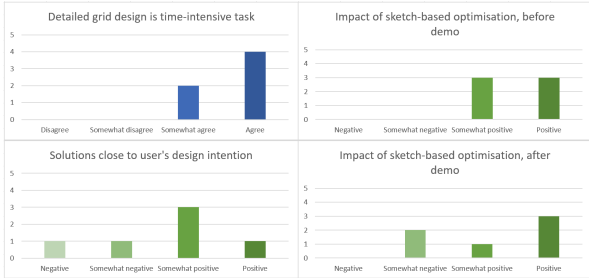


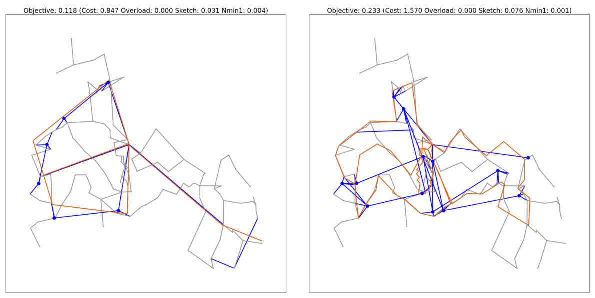
Figure 9: Aggregated participant sentiment from user study.

User study

With the user study we attempt to assess the potential impact of sketch-based optimisation on grid expansion planning processes. An overview of the sentiment per question can also be seen in figure 9. Below we summarise recurring themes from the interviews with participants per interview question category.

How is impact of sketch-based optimisation perceived? All participants indicate that the use of sketch-based optimisation could have a positive impact on the grid expansion design process. 3 out of 6 participants identify time savings as the primary advantage. The results of the optimisation could be used as an initial design which is electrically and geographically feasible. They then could iterate on and validate using their current design processes.

How close are the solutions to the user's design intention 4 out of 6 participants feel that the generated expansion design somewhat or completely resembles their design, while 2 out of 6 participant do not.
An example of a solution with positive participant sentiment can be seen in figure 10a. The design follows the user sketch closely while resolving all congestions and 99.6% of all redundancy issues, at 84.7% of the estimated costs. It is interesting to note that the backbone again is not a completely closed circle, instead the algorithm opted to complete the circle using existing cables. In this case the support cable structure running east-west across the backbone is connected to the backbone structure.
An example of a 'bad' result can be seen in figure 10b. The design does roughly implement the sketch shape and all congestions and redundancy issues are resolved. However, the solution is not a feasible grid design; no clear backbone structure is present in the western sub-grid while the central town centre is cluttered with new cables that intersect with expensive geographical boundaries such a waterway. We hypothesise that in this case the user's sketch was too detailed,



(a) Example 'good' solution. (b) Example 'bad' solution.

Figure 10: Examples of user study solutions showing the existing grid (grey), the input sketch (orange) and the solution's new cables (blue lines) and new nodes (blue dots).

while the algorithm is designed for roughly sketching the electrical layout of the expansion design.

After seeing solutions, how is impact sketch-based optimisation perceived? After discussing the results from the usability test, participants were once again asked about the potential impact of sketch-based optimisation on their grid expansion process. Besides the benefit of having an initial feasible design to iterate on, participants also imagined sketching multiple designs and to quickly compare different design approaches. The participants who did not feel like their solution matched their sketch also changed their opinion about sketch-based optimisation. They still felt like the algorithm did not consider their sketch and that it still behaved like a closed box.

How can the sketch-based optimisation algorithm be improved? Several suggestions were made by the participants for improving the current sketch-based optimisation implementation. Many participants suggested to include user control over the cable type while sketching (cable types have different transport capacities) and to include the possibility to sketch location of MSRs. Another suggestion was to optimise for equal load distribution over the cables routes, instead of merely avoiding overloaded assets. Finally, geography is seen as a very important aspect of grid expansion design. This is partly addressed by sketch-based optimisation, however participants suggested to also incorporate geographical data for the optimisation.

Discussion and future work

This paper presents the innovative application of sketch-based optimisation to electricity distribution grid expansion planning using genetic algorithms. The sketch-based optimisation prototype is driven by a novel shape similarity measure used as an extra sub-objective for the optimisation. The case study shows that the sketch-based optimisation can approximate the sketch shape well while still resolving all congestions and maintaining n minus 1 redundancy.

The qualitative user study has shown the potential of sketch-based optimisation for accelerating grid expansion planning processes. It introduces more user control to a process that is experienced as a 'closed box' which prevented user adoption. Decision support tools can accelerate grid expansion planning and by extension accelerate electricity grid expansion to facilitate the energy transition and combat climate change. Alliander, the largest Distribution Network Operator (DNO) of the Netherlands, intends to deploy the sketch-based optimisation prototype later this year making it available to 20+ distribution grid architects.

We have also identified areas of improvement, mainly further improving control and explainability of decision support systems for grid expansion planning. The stability of solutions generated by the algorithm can also be improved which would further contribute to explainability and trustworthiness of the system. To address both opportunities we suggest expanding the current implementation with multi-objective optimisation methods that can approximate the Pareto front of sub-objectives, such as NSGA-III (Deb and Jain 2013).

For deployment of a decision support tool like the one discussed in this paper having an intuitive user interface is vital. We therefore recommend thorough user experience research preceding deployment of a user interface. Training accompanying the deployment of a decision support tool is also important, as seen from the over-detailed sketch leading to poor results during the user study.

The potential applications of sketch-based optimisation extend beyond distribution grid expansion planning. We believe that our findings for medium-voltage distribution grid expansion can extended to high-voltage and low-voltage grid expansion, since similar planning can arise there. Planning of other civil infrastructure like heat networks, highways or zoning planning are other apparent use cases.

Acknowledgments

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