MASTER

Redundancy optimization in power distribution networks

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II. Preface

I hereby present my graduation thesis which is written to finish the master program Construction Management and Engineering at Eindhoven University of Technology. After completing my BSc in Mechanical Engineering I started this master track full of enthusiasm. With completing this master program I'm looking forward to new challenges the future will bring.

Due to a project in my second year about optimization with mathematical programming my interest in optimization technologies grew. The project lead to intensive contact with Wiet Mazairac who offered me the opportunity to work on this graduation project. In combination with my general interest in (sustainable) energy and my background in mechanical engineering this graduation project offered me the challenge I was looking for.

I would like to thank Wiet for his continues constructive support and guidance throughout the project. As my 1st supervisor we had numerous meetings and discussions which helped me a lot. I also would like to thank my 2nd supervisor Bauke for his feedback and advice so I was able to complete this project. Furthermore I would like to thank Saleh for his enthusiasm in the subject and his flexibility to fulfil the task of 3rd supervisor on a short notice. Last but not least I would like to thank my close friends, family and my girlfriend Nicole for their continues support and faith which kept my morale high. Without you I wouldn't been able to complete the project.

Gijs Klein Heerenbrink

III. Summary

Currently an energy transition is going on towards a sustainable energy system. This transition is put in motion due to the global warming issues, the depletion of fossil fuels and political strategies. These political strategies include the national, european and global agreements to fight climate change and use sustainable energy. The transition goes from classic power plants (centralized generation) towards renewable energy sources (distributed generation) like PV panels or wind turbines. Energy storage and conversion are of crucial importance in a sustainable energy system because they can resolve discrepancies between energy supply and demand caused by the intermittent power output of renewable sources. Conventional power distribution grids are not optimized to cope with distributed generation and possibly need to be redesigned to maximize its potential.

Component failure can occur in energy networks which can cause energy demands not being met. Undelivered energy will result in a certain amount of discomfort depending on the building category. Households are an other category then businesses or hospitals. Adding redundancy to a distribution network can make sure that component failure won't lead to undelivered energy. This research presents a stochastic optimization program for the topology of a power distribution network based on redundancy optimization. The optimization is done from an ideologic point of costs minimization since both consumer and network operator (government) could need to make investments for the optimized network.

Research questions

The objective of this research is to develop and use a mathematical model that is able to optimize the redundancy in a power distribution network. From these objectives the following three research questions can be drafted:

1. Can mathematical programming be used to optimize the redundancy in a power distribution network?
2. Which method of mathematical modelling suits this problem best?
3. What is the effect of redundancy optimization in an existing Dutch power distribution grid?

Literature review

From the literature study it can be concluded that mathematical programming is a widely accepted and used method to optimize energy networks. This research contributes in network optimizations by adding penalty costs to undelivered energy and thereby optimize the redundancy in a network based on cost minimization. From the current literature it appears that optimization from this angle is underexposed in most researches. The research will focus on the demand of a single carrier, just like most researches in this field. However via an converter system the first steps of an multi carrier network are included.

Method

Mathematical programming is used to find the optimal network configuration. The goal of mathematical programming is to find an optimal value for an objective variable with respect to the given constraints. In this case a minimization of the costs. There are three different costs to distinguish in the network. The investment costs, the operational costs and the penalty costs. The discomfort will be represented by costs via a penalty factor which depends on the building category. This

results into penalty costs. adding redundancy will keep penalty costs low, only investment costs and operational costs will rise. Finding the right relation between these costs will lead to an overall minimization of the total costs. Because there are both integer as well as continues variables Mixed integer linear programming is used. Two stage stochastic programming is used because of the data uncertainty concerning component failure. In the first stage all the investment decisions are made, which influence the investment costs. After this stage the unknown parameter becomes known and the second stage decisions can be made. These decisions influence the operational and penalty costs.

Model

The model is built in the software package AIMMS, which is specifically designed for modelling and solving large-scale optimization problems. To give an AIMMS model dimension and depth sets and indices are used. The use of sets helps to describe large models in a concise and understandable way. With the parameters the user can fill in all the data which is known in advance. The variables are adjusted by the model to determine the optimized solution. The relations between the parameters and the variables are defined by the constraints. To make the model stochastic extra sets and parameters are added. The model is able to pick three components to built redundancy into the network. The redundant options are a redundant line, a local converter system and a local renewable storage system. The objective variable of the stochastic program is given in equation 1 and 2:

$$z = \max\left(X_n * C_n^{inv} + \sum_{s=1}^{S}(p_s * Q_s(X_n, f_n) + C_s^{pen})\right) \tag{1}$$

$$\text{With: } Q_s(X_n, f_n) = Xw_{s,n} * Y_{s,n} * c_{s,n}^{op} \tag{2}$$

Case study

Two case studies are conducted to show the possibilities of the model. A fictive case and an real case. To conduct the case studies data is needed. This includes energy demands of a building type, investment costs and operational costs of network subsystems, penalty factors, failure probability and last but not least the topology of the current network.

Conclusion

It can be concluded from the literature study that mathematical programming is an excellent resource for this optimization problem, which answers research question 1. Because of the both integer as continues decision variables Mixed Integer Linear Programming (MILP) is used. Two stage stochastic programming is used to find the optimization with data uncertainty. The Two stage stochastic MILP method therefore appeared to be the most suitable solution for this optimization problem which answers research question 2. For research question 3 the case studies are conducted. From the case studies it can be concluded that the penalty factor is very important for the outcome of the model. Since this parameter is arbitrary it can be adjusted by the user at his or hers own discretion. However it can be concluded that for the Dutch power network, for low demand buildings, redundancy is not feasible. Only at an extreme penalty factor local conversion should be used. If PV-panels are already present local renewable storage appears to be the best solution. For low demand buildings building redundant lines is not a feasible option. However when looking at higher demand buildings like commercial or industrial buildings, the redundant lines appear to be the most feasible solution. For an industrial area redundant lines are used at a penalty factor of around 20 which is assumed to be a very reasonable. Purely based on redundancy optimization, only at high demands possibly extra redundant lines should be considered according to the case studies. When a sustainable energy solution is required and a penalty is given for non sustainable energy usage, eventually every optimized network will shift towards renewable storage systems. By answering the research questions it can be concluded that the two main objectives (developing and using an redundancy optimization model) for this research are achieved.

IV. Samenvatting

Momenteel is er een energie transitie gaande naar een duurzaam energy systeem. Deze transitie komt voort uit de zorgen voor de opwarming van de aarde, het opraken van de fossiele brandstoffen en politieke maatregelen. Deze maatregelen behelsen onder meer de nationale, europese en wereldwijde afspraken die overheden met elkaar maken om de opwarming van de aarde tegen te gaan en duurzame energie te gebruiken. De transitie gaat van de conventionele energie centrale (gecentralizeerde opwekking) naar duurzame energie bronnen (gedistribueerde opwekking) zoals zonnepanelen en wind turbines. Energie opslag en energie conversie zijn van cruciaal belang in een duurzaam energie systeem omdat het de discrepantie tussen energie aanbod en vraag kan oplossen. Deze discrepantie ontstaat door de periodieke energie opwekking van zonnepanelen en wind turbines. De huidige elektriciteits distributie netwerken zijn niet geoptimaliseerd voor gedistribueerde energie opwekking. Mogelijk moeten deze netwerken dan ook opnieuw worden ontworpen om het maximale potentieel van gedistribueerde energie opwekking te benutten.

Het falen van netwerk onderdelen kan er voor zorgen dat er op sommige momenten niet aan de energievraag kan worden voldaan. Niet geleverde energie zorgt voor een bepaalde mate van ongemak afhankelijk van het soort gebouw. De mate van ongemak is in woningen minder hoog dan bij bedrijven of in een ziekenhuis. Het toevoegen van redundancy aan een bestaand netwerk kan er voor zorgen dat het falen van een onderdeel niet lijdt tot het niet leveren van energie. Dit onderzoek presenteert een stochastisch optimalisatie model voor de topologie van een elektriciteits netwerk gebaseerd op redundancy optimalisatie. De optimalisatie is gedaan vanuit een ideologisch oogpunt van kosten minimalisatie. Zo kunnen zowel de gebruiker van energie als de netwerk beheerder (overheid) investeringen moeten maken voor het optimale netwerk.

Onderzoeksvragen

De doelstellingen van dit onderzoek zijn het ontwikkelen en gebruiken van een mathematisch model dat geschikt is om de redundancy in een elektriciteits netwerk te optimaliseren. Vanuit deze doelstellingen volgen de volgende 3 onderzoeksvragen.

1. Kan mathematisch programmeren worden gebruikt om redundancy in elektriciteitsnetwerken te optimaliseren?
2. Welke mathematische methode is het meest geschikt voor dit probleem?
3. Wat is het effect van redundancy optimalisatie op bestaande Nederlandse elektriciteitsnetwerken?

Literatuur

Uit de bestaande literatuur kan het geconcludeerd worden dat mathematisch programmeren breedt gedragen wordt als methode om energie netwerken te optimaliseren. Dit onderzoek draagt bij aan netwerk optimalisaties door het toevoegen van penalty kosten wanneer energie niet geleverd wordt. Uit de huidige literatuur blijkt dat optimalisatie vanuit dit oogpunt nog onderbelicht is gebleven. Het onderzoek focussed zich op elektriciteit, maar via het conversie systeem worden hybride netwerken ook behandeld.

Methode

Mathematisch programmeren wordt gebruikt om de optimale netwerk configuratie te vinden. Het doel van mathematisch programmeren is het vinden van een optimale waarde voor een variabele

terwijl er aan alle randvoorwaarden wordt voldaan. In dit geval is die variable het minimaliseren van de kosten. Er wordt onderscheid gemaakt tussen drie verschillende kosten. Dit zijn de investeringskosten, de operationele kosten en de penalty kosten. Via een penalty factor voor het niet leveren van energie zal ongemak worden omgezet in penalty kosten. het toevoegen van redundancy zorgt voor lage penalty kosten maar aan de andere kant zullen de investeringskosten en operationele kosten stijgen. Minimaliseren wordt gedaan door de juiste verhouding tussen deze kosten te vinden. Twee fase stochastisch programmeren wordt gebruikt vanwege de data onzekerheid met betrekking tot de falende onderdelen. In de eerste fase worden de investeringsbeslissingen genomen. Na het bekent worden van de falende onderdelen worden in de tweede fase de operationele beslissingen genomen.

Model

Het model is gebouwd in AIMMS. Dit software pakket is ontworpen voor het oplossen van optimalisatie problemen. Het model bestaat uit sets om het model body te geven. De parameters kunnen door de gebruiker worden ingevuld. De variabelen worden door het model berekend. De onderlinge relatie tussen de parameters en de variabelen wordt door de randvoorwaarden beschreven. Het model kan drie redundancy opties in het netwerk zetten te weten een extra leiding, een conversie systeem of een duurzaam opslag systeem. De formule van de kosten variabele van het stochastische programma is te zien in vergelijking 3 en 4:

$$z = \max\left(X_n * C_n^{inv} + \sum_{s=1}^{S}(p_s * Q_s(X_n, f_n) + C_s^{pen})\right) \tag{3}$$

$$\text{With: } Q_s(X_n, f_n) = Xw_{s,n} * Y_{s,n} * c_{s,n}^{op} \tag{4}$$

Case studie

Er zijn twee case studies uitgevoerd om de mogelijkheiden van het model te laten zien. Een fictieve case en een echte case. Om deze studies uit te voeren is er data nodig zoals energie vraag en aanbod. investeringskosten en operationele kosten van componenten, penalty factors, faal kansen en het huidige netwerk.

Conclusie

Uit de literatuurstudie kan het worden geconcludeerd dat mathematisch programmeren een uitstekende manier is voor dit optimalisatie probleem waarmee onderzoeksvraag 1 wordt beantwoord. Omdat er zowel binaire als continue variabelen zijn wordt Mixed Integer Linear Programming (MILP) gebruikt. twee fasen stochastisch programmeren wordt gebruikt vanwege de onzekere data. De meest geschikte methode voor dit probleem is dan ook twee fase stochastisch MILP wat onderzoeksvraag 2 beantwoord. Voor de derde onderzoeksvraag worden de twee case studies uitgevoerd. Uit deze case studies kan geconcludeerd worden dat de penaltie factor erg belangrijk is voor de uitkomtst van het model. Het kan worden geconcludeerd dat voor het Nederlandse elektriciteitsnetwerk bij gebouwen met een lage energievraag redundancy niet haalbaar is. Enkel met een extreme penalty factor zou lokale conversie gebruikt moeten worden. Wanneer er al zonnepanelen aanwezig zijn is de beste oplossing de duurzame opslag methode. Een extra leiding is bij een lage energievraag niet van toepassing. Bij hogere energievragen (winkels en industrie) en een realistische penalty factor blijkt de extra leiding juist wel de beste oplossing. Conclusie van de case studies is dat wanneer men puur kijkt naar redundancy, redundancy in Nederland alleen van toepassing is op gebouwen met een hoge vraag met extra leidingen. Wanneer een duurzame oplossing wordt gevraagd en conventionele energie een extra penalty krijgt dan zal de oplossing op den duur naar de duurzame opslag methode gaan. Het antwoorde van de onderzoeksvragen heeft er toe geleidt dat de doelen van dit onderzoek behaalt zijn.

V. Abstract

In this study a two stage stochastic mixed integer linear programming (MILP) model is developed for the optimized design of a distributed power system, with components that are prone to errors. When a component fails is uncertain. The model will optimize the topology of an network based on costs minimization while dealing with this failure uncertainty. The total costs depend on the investment costs, operational costs as well as penalty costs for not delivering energy. When an energy demand is not met this amount will be multiplied with an penalty factor to determine the penalty costs. The penalty factor depends on the building category and is arbitrary. The height of the penalty factor appears to a very important factor in the optimized network topology. Mathematical programming proved to be an efficient way to optimize energy networks based on redundancy. It can be concluded that in the Dutch distributed power system for low demand buildings redundancy is not feasible. Only at extreme high penalty factors local options (converter or renewable storage) are beneficial. Higher demand buildings (commercial or industrial) can benefit from redundant lines at a reasonable penalty factor according to the model. When a sustainable solution is demanded the optimized network will shift to the renewable storage for any demand.

keywords: Mixed Integer Linear Programming (MILP), Two stage stochastic programming, Network redundancy optimization

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Chapter 1

Introduction

In this chapter the graduation project will be introduced. First some background information about the subject is given. In the second section the problem definition is presented. This section is followed up by the research questions and the research design. After the research design the expected results are discussed. The chapter is concluded with a section about the structure of this report.

1.1 Background

The energy challenge is one of the greatest test faced by humanity today. The depletion of fossil fuels as well as the current climate changes require new solutions in the energy sector. This energy sector is one of the pillars of growth, industrial competitiveness and development for modern economies. The overall functioning of modern society depends on safe, secure, sustainable and affordable energy [9]. Our current fossil driven economy and society creates a lot of greenhouse gas emissions which underlie the current climate changes. The consumption of fossil fuels has a major impact on our environment and climate and thus on the habitat of the world population [27]. To fight climate change and reduce our emissions drastically key decisions have to be taken. Therefore, the European Council in 2007 adopted ambitious energy and climate change objectives for 2020 ([10]). These objectives are known as the Energy2020 agreement.

The objectives in the energy2020 agreement consist of a reduction of greenhouse gas emissions by 20 percent, a 20 percent increase in the share of renewable energy and a 20 percent improvement in energy efficiency in the EU. For the EU it is an important task to agree on the tools which will make the necessary shift possible. [8]. To achieve these goals an energy strategy is developed called Energy2020.

This strategy underlies the fact that in the next decades the European energy system is entering a phase of reformation. The 2020 energy strategy therefore encourages grid investments in electricity and gas. Providing a stable supply in energy, gas will play a key role in the coming years and gas can gain importance as the back-up fuel for distributed electricity generation. These so called hybrid (electricity and gas) networks will be of great importance in the EUs energy supply for the upcoming decades [8].

The energy infrastructure needs to be upgraded since the current grid infrastructure is not built to cope with renewable energy. Smart meters and power grids are key to exploit the potential of renewable energy. Also for energy savings and efficiency an upgraded grid is necessary. Besides the short term strategy presented in the Energy2020 the European Commission also looked a bit further on the horizon. With the Energy roadmap 2050 long term objectives and goals are already made.

This 2050 energy strategy is necessary since the many homes, industry and buildings people will use in 2050 as well as the corresponding energy networks are already built now. The fundament of energy production and use in 2050 is already being set. To be well prepared for the future, possible challenges ahead are already explored in the energy roadmap 2050. In this roadmap the EU is committed to reducing greenhouse gas emissions to 80-95 percent below 1990 levels by 2050. Since the energy sector produces the lion's share of human-made greenhouse gas emissions reducing these emissions by 2050 by over 80 percent will put particular pressure on energy systems [9]. Network reformations which are done now already should be able to cope with the objectives set for 2050.

In 2050 it is expected that electricity will play a much greater role than it does now. Studies show that electricity will almost double its share in final energy demand to 36-39 percent in 2050[9]. To achieve this, the power generation system would have to undergo structural change. This emphasizes once again that the share of renewable energy (RES) rises substantially in the upcoming decades. This decentralisation of the power system and heat generation increases due to more renewable energy generation.

The depletion of fossil fuels as well as the European energy strategy all indicate a huge shift to renewable energy for the coming decades. It is for example expected that the biggest share of energy supply in 2050 comes from renewable energy[9]. The energy distribution network therefore needs to adapt as well since the conventional grid cannot cope with the distributed generation. One of the problems of renewable energy is the availability. Wind, hydro and solar power are not always available when needed. These renewable sources cannot control their power output. Daily and seasonal effect as well as the limited predictability result in intermittent generation[17]. To deal with generation from many distributed sources with intermittent generation a Distributed Energy Resource (DER) system is needed [3]. This development of a sustainable energy system which can cope with distributed generation is essential for future energy grids. Energy storage and conversion is of crucial importance in such a system because it can resolve discrepancies between the energy supply and demand.

A conventional energy distribution network like an electric power network, a natural gas network, or a district heating network, operates independently from other carriers. Multi carrier energy networks enable the possibility of conversion between carriers. When one of the carriers suffers from failure, the energy demand can still be provided through conversion of one of the other available forms of energy. When local conversion is possible it is also possible to select a specific form of energy for transportation. At the destination this form can be converted to the form of energy required. Methods which are less failure sensitive can be used for transportation. As mentioned before according to the energy2020 strategy hybrid energy networks will become increasingly important in future energy supply.

Since our economy relies greatly on a safe and reliable grid, improvements are vital. To improve the system reliability for as far as possible several methods exist [7]. For example using a large safety factor when engineering the grid, try reducing the complexity of the grid, use qualitative components, use a planned maintenance and repair schedule and/or structurally add redundancy.

Adding redundancy in an energy grid system basically means using additional components beyond the number required for the system to operate. This results in a system which does not necessarily fail when a component fails because the additional components are used to keep the system function normally [23]. There are two main types of redundancy. These types are known as active and passive redundancy. In active redundancy (parallel redundancy) all redundant components are in operation and share the load with the main component. If one component fails, the remaining components are capable of carrying the load. An example is given in Figure 1.1.

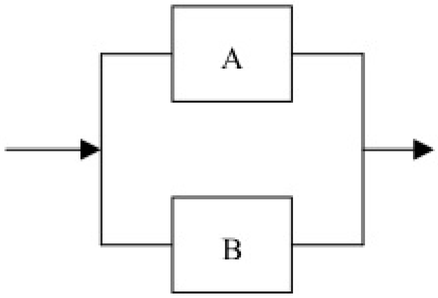


Figure 1.1: Active redundancy

In passive redundancy (standby redundancy) the redundant components only start working when the main component fails. An example is given in Figure 1.2.

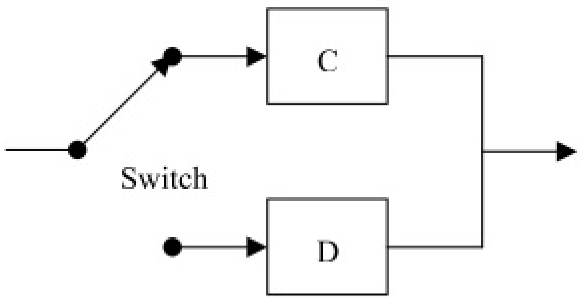


Figure 1.2: Passive redundancy

Adding redundancy to a energy network can make sure that component failure won't lead to undelivered energy.

The Dutch energy grid consists of more than 340.000 km of electricity cables and more than 135.000 km of gas pipes according to [26]. The power grid can be divided into a low, mid, high and extra high voltage network. The high and extra high voltage network are mainly used for transportation over a larger distance. These two voltage levels are in control of the national network operator TenneT. Failure in these voltage levels can have large consequences. Therefore these networks are designed with (n-1) redundancy. The mid voltage network connects heavy industry, combined heat and power (CHP) systems and converter units. The mid voltage network is maintained by regional network operators. Most mid voltage networks are designed in a ring structure. If malfunction occurs the energyflows can be redirected so energy losses are minimized. The low voltage network is also called the distribution network and connects households, shops, businesses and small industry to the grid. Again these networks are maintained by a regional network operator. Low voltage networks are not designed redundant according to [24].

1.2 Problem definition

From the previous section it can be concluded that the energy challenge is one of the most important challenges in the upcoming decades. Burning fossil fuels which emits greenhouse gases into the atmosphere is the primary cause of global warming. On top of that fossil fuels are depleting. A fundamental change in energy supply is needed to cope with the transition to renewable energy sources since the conventional grid is not built to deal with distributed generation. To suit these needs for renewable energy, network reformations are inevitable. Besides these reformations, also a reliable, safe and secure energy network is demanded in modern economies.

Energy networks, however, are prone to errors. As stated by Netbeheer Nederland [26], The

Dutch energy network is very reliable. Despite this high reliability errors are still extremely undesirable and can have a huge financial impact on todays society. To avoid that large areas will be without energy due to a single component failing, redundancy can be applied. This way the energy can still be transported to (a significant part of) the consumers. At the mid and high voltage as well as in the high pressure gas network redundancy is already incorporated in the design. At most local distribution grids, the low voltage power and low pressure gas grids, redundancy is not applied.

This research will focus on optimizing the low voltage power distribution network to determine if redundancy can be an feasible option on this level as well. Costs minimization is used to determine the optimal lay-out of an energy network. The research is distinguished by the penalty factor which is used to add costs when demands are not met due to a failing grid. The penalty factor depends on the building category and is arbitrary. The focus on lower voltage networks is also done because of the energy transition towards renewable energy. This shift leads to a more distributed generation of energy. This means for example that the energy is collected locally and transported to nearby energy demand through the local distribution grid. The importance of a reliable local distribution grid will therefore increase rapidly which may lead to new optimal configurations.

Redundancy can be added in various ways. This research will focus on three different redundancy options, all with their own characteristics. The first redundancy option is adding a redundant distribution line, which can be constructed parallel to an existing line or to make a ring network. The second option is adding a local conversion system which is able to convert natural gas to power. The third and last option is adding a renewable storage system. This system will collect renewable energy via PV-panels and is able to store this energy in a battery until it is needed.

1.3 Research questions

Based on the problem definition two main objectives can be distinguished:

1. Develop a mathematical model that will optimize the redundancy in a power distribution network.
2. Use the model in a case study and find an optimized redundant network based on costs minimization.

These main objectives lead to several research questions. These research questions are listed below:

1. Can mathematical programming be used to optimize the redundancy in a power distribution network?
2. Which method of mathematical modelling suits this problem best?
3. What is the effect of redundancy optimization in an existing Dutch power distribution grid?

1.4 Research design

The research design will describe in more detail the structure of this research and how the research questions described in the previous section will be approached. The basis of this study will be a literature study. For the first research question:

1. Can mathematical programming be used to optimize the redundancy in a power distribution network?

   The literature research will be necessary. The literature study can be found in chapter 3. For the second research question:

2. Which method of mathematical modelling suits this problem best?

   Besides a literature study a deeper insight in the actual optimization problem is necessary. The literature research offers a wide range of solution options for optimization problems. The deeper insight in the optimization problem has to ensure that the most suitable optimization method is chosen. Therefore the parameters, variables and constraints of the optimization problem need to be known.

   To answer the third research question:

3. What is the effect of redundancy optimization in an existing Dutch power distribution grid?

The created model is used in two case studies. The first case study will be fictional, the second case study will focus on an actual existing region. Based on these case studies the effect of redundancy optimization will be determined.

1.5 Expected results

For the expected results the two main objectives stated in the research question section are used.

For the first objective it is expected that a mathematical model is built which is able to determine the optimized power network topology based on redundancy. The penalty factor can be adjusted by the user to influence the possible outcome of the model. The model will return several binary variables which show if a component should be built. These binary variables are made visual with a graph.

For the second objective it is expected that some minor adjustments are needed to optimize the current energy network. It is expected that adding redundant elements in the network can be financially beneficial in some situations. However since the Dutch power grid is already very reliable it is not expected that the optimized network will chance drastically. When or where which type of redundancy should be used will be made clear by the model.

1.6 Structure

This thesis is structured in the following manner: This chapter is used to introduce the problem. In the following chapter the glossery can be found. In the third chapter a literature study will be elaborated. In chapter four the method will be discussed. Chapter five introduces the model. In chapter six the redundancy possibilities of the model will be shown. In chapter seven the model will be used for two case studies in which an fictional and an actual real situation are simulated. In the last chapter the conclusion is presented.

Chapter 2

Glossery

In this chapter an overview is given of important abbreviations, definitions and terminologies.

General

MILP	Mixed Integer Linear Programming
SP	Stochastic Programming
SG	Smart Grid
MG	Micro Grid
DER	Distributed Energy Resource
DG	Distributed Generation
CG	Centralized Generation
PV-panel	Photovoltaic panel (solar panel)
CHP	Combined Heat and Power
kWh	Kilowatt hour
m	Meter

Model

parameters		variables	
ex	existing	X	First stage binary decision
c	costs	Y	Second stage flow decision
f	failure	Xw	Working subsystem
e	energy	C	Costs
cap	capacity		
p	penalty		

subscript		superscript	
no	node	inv	investment
li	distribution line	op	operational
rli	redundant distribution line	pen	penalty
co	converter system	dem	demand
res	renewable storage system	sup	supply
dra	drain		
ns	network supply		
rs	renewable supply		
t	time		
rd	representative day		
tp	time period		
s	scenario		
n	subsystem		

Chapter 3

Literature Study

In this chapter a review of existing literature about network optimization is given. Relevant prior literature is studied to narrow down the theoretical background and determine the scope of the research. The used literature consists of both books from experts in a specific field as well as research reports from scientists. In the first section network optimization will be further elaborated. Secondly the distributed energy resource system is discussed, followed by the third and last section on the reliability and redundancy of networks.

3.1 Network optimization

Network optimization is a core problem domain in many fields like operations research, computer science, applied mathematics and engineering according to Ahuja et al. [1]. Within optimization problems the network flow problems are one of the most important and most frequently encountered classes according to Bertsekas et al. [5]. These network flow problems consist of supply and demand points. The points are connected via one or multiple routes which are used to transfer the transport units from supply to demand. The energy networks will be approached as a network flow problem.

There are many different applications in network optimization. According to Ahuja et al. Bertsekas et al and Liu et al. [1], [5] and [19] the most common class of practical optimization problems are: Shortest paths, maximum flows, minimum cost flows, transportation problem, assignment problems, matchings, minimum spanning trees, convex cost flows, generalized flows, multicommodity flows and traveling salesman problems. Each of these methods cover a basic type of network optimization in an ever expanding spectrum of applications. The redundancy optimization of the energy network will be done based on minimizing the total cost.

Network optimization can be mathematically modelled in terms of graph related notions according to Bertsekas et al. [5]. The basic definitions relating to graphs, paths, flows and other terminology will be introduced here. This terminology originates from graph theory, and is used as a common language in network representation as stated by Posfai et al. [29]. A directed graph, G = (N,A), consist of a set N of nodes and a set A of pairs of distinct nodes from N called arcs. The value of N and A denote the number of nodes and arcs respectively. In general, if (i,j) is an arc, i is the start node and j is the end node of the arc. In the literature of graph theory [29] directed and undirected graphs are distinguished. The transmission lines in a power grid are undirected. A undirected graph is an arc(i,j) in an ordered pair which should be distinguished from arc (j,i). A path P in a directed graph is a sequence of nodes (n1, n2,,nk) with k2 and a corresponding sequence of k-1 arcs. Nodes n1 and nk are called the start node (origin) and the end node (destination). A cycle is a path for which the start and end nodes are the same. The flow of an arc (i,j) is a scalar which is usually denoted by yi,j. The terminology will be used and further elaborated in chapter 5, where the model is introduced.

3.2 Distributed generation

Farhangi et al.[11] states that the conventional electricity grid has been established through rapid urbanization and infrastructural developments. The grid is a strictly hierarchical system in which power plants at the top of the chain ensure power delivery to customers at the bottom of the chain. Essentially this system is a one-directional pipeline. To withstand maximum anticipated peak demands the grid is over engineered and inherently inefficient. However, as indicated in the introduction, the energy grid system will need a reformation to comply with a distributed generation (DG) of energy. The most common DG technologies include Combined Heat and Power (CHP) generators and micro- turbine gas generators but also the renewable energy sources like solar photovoltaic generators (PV), wind generators and micro-hydro schemes according to Alarcon-Rodriguez et al [4] and Omu et al.[28].

A grid which is able to cope with distributed generation technologies is a Distributed Energy Resource (DER) system according to Omu et al.[28]. This system refers to electric power generation resources that are directly connected to the low and medium voltage distribution system according to Akoredea et al. [2]. It differs from the conventional system of centralised energy generation and long range energy transmission. As stated by Omu et al.[28], this decentralised energy comes partly from renewable energy. DER systems also make use of energy storage technologies as stated by Akordea et al.[2]. Examples are batteries, flywheels or superconducting magnetic energy storage. According to Yang et al.[34], a DER system has elicited an increased amount of interest over the past few years because it is a good option for future energy systems with respect to sustainable development and low-carbon society construction.

Using DG technologies offers four major environmental benefits according to the literature [2]. First of all DG promotes a higher energy efficiency. Secondly it reduces the greenhouse gas emissions since clean energy sources like PV panels and wind generators can be used. Thirdly, as a direct consequence of using clean energy sources, climate changes and health risks reduces. Lastly DG technologies offer a space advantage. For example, PV panels can be integrated into building surfaces.

According to Alanne et al.[3] the energy system of the future is going to be a mixture of centralized and distributed sub-systems, operating parallel to each other. Furthermore [3] states that the main characteristics of a sustainable energy system are (cost-) efficiency, reliability and environmental beneficially. Using DG technologies and utilize local resources is essential for a sustainable energy system. Alanne et al.[3] also allocates the biggest drawback of distributed energy generation which is the fact that distributed systems are fragmented.

Introducing a DER system results in a more complex system to design and manage. To benefit from the economic and environmental potential such systems can offer an optimal design has to be found. In the last decade many studies have been conducted to find the optimal design of a DER system. A number of different decentralized energy models which are used worldwide have been reviewed by Hiremath et al. [15]. It states that energy models are always a simplified representation of real systems. Furthermore Hiremath et al. emphasises the need for decentralized planning approaches. Mainly because current energy planning is focused on fossil fuels and centralized electricity but with the energy transition towards DG this is not applicable any more.

The DER system is commonly referred to as a smart grid (SG). Microgrids (MG) are the building blocks of future smart grids according to Mahmoud et al. [21]. a MG can be defined as the low voltage energy system. MG are able to include generating units and distribute this energy to local loads and will play a key roll in DG. The optimization of the conventional distribution network can therefore be seen as a shift towards a smart grid.

3.3 Optimization techniques

Alarcon-Rodriguez et al.[4] reviews multi-objective DER planning techniques. Hawkes and Leach develop a linear programming cost optimization model for the high level system design [14]. Sderman and Pettersson present a mixed integer linear programming model for structural and operational optimisation in which the production and consumption of power and heat as well as the district heating pipelines are taken into account [32]. A mathematical programming approach for optimal design of distributed energy systems at neighbourhood level is presented by Mehleri et al. in [22]. In this paper MILP is used to find the optimal design of distributed energy generation systems that satisfy the heating and power demand at the level of a small neighbourhood. In this case the optimal solution consists of selecting the candidate technologies (combined heat and power units, photovoltaic arrays, boilers, central power grid) and the distribution lines. Wouters et al. does the same in [33] where an efficient and cost effective local energy system design is presented. A MILP model identifies the optimal solution by minimising the total annualised costs of the system where its yearly demand is still met. Handshin et al. constructed a mathematical model to increase the economic efficiency of distributed generation while considering the existing uncertainties[13]. A two-stage stochastic mixed integer program (SMIP) is developed by Zhu [35] which can be used for multiple applications. uncertainty based design optimization is further elaborated in [12] by Gang et al. where a district cooling system is optimized.

3.4 Reliability and redundancy

According to Sagnell et al.[30], the definition of Reliability is the ability of an item to perform a required function, under given environmental and operational conditions and for a stated period of time. As stated by Kuo et al.[18], In reliability optimization problems exact solutions are often not necessarily desirable.

The configuration of two parallel supply systems allows system redundancy to be obtained. At the same time, parallelism should be minimized as far as possible down to the supplied load to minimize the costs of the system. Ideally, electric power supply of consumers is ensured by at least two redundantly usable, separate power supply units according to SIEMENS[16]. However, this is economical not feasible and therefore optimization is necessary. To find the optimal system reliability by allocation of redundancy components in a system, reliability redundancy allocation is used according to [20]. Also SIEMENS[16] confirms that to cut back on the huge costs of system redundancy, parallel-operating components are used at important places in the network. Not every DG system can automatically be used as a redundant component. For example PV-panels won't work if the central grid fails. However putting an storage unit between the grid and the PV-panels can resolve this problem.

The reliability of the Dutch energy supply is high compared to most of the other European countries. The average yearly power outage is 32,9 minutes per household in 2015 according to [24]. In this year a total of 18.746 interruptions were registered. For the gas network the average yearly interruption duration was 2,1 minutes and a total of 34.968 interruptions were registered according to [25]. The longer interruption duration by power interruptions is caused by the fact that the average power interruption usually affects more people. Yearly digging damage causes more than 10.000 disruptions and is the most important reason for network failure. The total annual turnover in the energy sector is about 40 billion Euro which is 7 percent of the Dutch gross national product. Over 2 billion is yearly invested in expanding, replacing and maintaining the energy network. These numbers again emphasize the size and the importance of the energy transition.

3.5 Conclusion

From the literature study it can be concluded that mathematical programming is a widely accepted and used method to optimize energy networks which answers the first research question.

This research contributes in network optimizations by adding penalty costs to undelivered energy and thereby optimize the redundancy in a network. From the current literature it appears that optimization from this angle is underexposed in most researches. The research will focus on the demand of a single carrier, just like most researches in the field. However via an converter system the first steps of an multi carrier network are included. The exact methodology used in this research is elaborated in chapter 4.

Chapter 4

Method

In this chapter the methodology which is used to solve the optimization problem is described. This research will focus on the optimization of existing distribution networks by adding redundant components based on costs minimization. To solve this costs minimization problem a two stage stochastic MILP model is developed. In the first section of this chapter Mathematical Programming will be discussed followed by a section about cost minimization. In the third section mixed integer linear programming is covered. Parameter uncertainty is discussed in the fourth section and two-stage stochastic programming is covered in the fifth section. The chapter ends with a section about the used software package in which the model will be built. The model will be described in detail in chapter 5.

4.1 Mathematical Programming

Mathematical programming is used to find the optimal network configuration. The goal of mathematical programming is to find an optimal value of a objective variable with respect to the given constraints. Many optimization problems can be modelled as linear programs. A standard linear optimization problem can be written as follows:

$$\begin{aligned} min\ c * x \\ s.t.\ Ax = b \\ x >= 0 \end{aligned} \tag{4.1}$$

where $c * x$ should be minimized while x is subjected to several constraints.

Mathematical programming techniques have been widely utilized for decision making in the optimal design and operation of DER systems according to Yang et al. [34]. In this case it would be minimizing the total cost variable. The model will be able to choose from a variety of redundant network components which are used to deliver energy to the demand point to minimize overall costs.

4.2 Cost minimization

As mentioned in the previous part, the optimal redundant network is based on cost minimization. There are three different costs to distinguish in the network. The investment costs, the operational costs and the penalty costs. These costs all depend on each other. An increase in the investment and operational costs will lead to an increase in network reliability and therefore an decrease in undelivered energy. This results in a decrease in the penalty costs. Penalty costs express the discomfort of not receiving energy in monetary terms. The penalty factor which defines the height of these costs is arbitrary. Finding the right relation between the investment costs, operational costs and penalty costs will lead to an overall minimization of the total costs.

4.3 Mixed integer linear programming

The problem faced in this research can written as a MILP problem. MILP is an extensively used optimization technique in mathematical programming. In this case it is used because of both binary as continues decision variables in the model. The binary decision variables are used for deciding whether or not to built an network component. The continues decision variables decide the flow through each of the available components.

4.4 Parameter uncertainty

Unfortunately it is not known in advance if a component is available or if it fails. Optimization affected by parameter uncertainty has long been a focus of the mathematical programming community as stated by Bertsimas et al. [6]. Two approaches who can deal with this parameter uncertainty are robust optimisation (RO) and stochastic optimization (SO).

According to Bertsimas et al.[6] RO is a more recent approach to optimization under uncertainty. In this approach the uncertainty model is deterministic. The user constructs a solution in a given set that is feasible for any realization of the uncertainty.

In this research the stochastic programming will be used. Stochastic programming is an optimization technique that incorporates random variables as parameters to simulate problems more realistic according to Zhu [35]. In contrast to RO, stochastic optimization starts by assuming the uncertainty has a probabilistic description. Shapiro et al states that the most used stochastic programming models are two-stage linear programs. The basic idea of two-stage stochastic programming is that (optimal) decisions should be based on data available at the time the decisions are made and should not depend on future observations.

4.5 Two-stage stochastic programming

In a two-stage stochastic programming model the decision variables are divided into two groups. The first stage and the second stage decision variables. The first stage variables are decided before the actual observation of the uncertain failure parameter.

The standard two stage stochastic programming problem can be written as follows:

$$\begin{aligned} \min c^T x + EQ(x, w) \\ \text{s.t. } Ax = b \\ x >= 0 \end{aligned} \tag{4.2}$$

Where

$$\begin{aligned} Q(x, w) = \min q^T y \\ \text{s.t. } Wy = h - Tx \\ y >= 0 \end{aligned} \tag{4.3}$$

The first stage decision variable is represented by the x variable. The second stage decision variable is represented by the y variable. Subjected to the given constraints the goal is finding the overall minimum where the first stage variables influence the second stage variables.

In this research the first stage variable is the binary decision if a network subsystem is built. The model is able to pick three components to built redundancy into the network. These so called redundant subsystems of the model are listed below:

1. Redundant distribution line (rli)
2. Local converter system (co)

3. Local renewable storage system (res)

The redundant subsystems are explained in detail in chapter 6. For the three subsystem the investment costs and operational costs are known. In the first stage all investment decisions will be made. The model will focus on a existing distribution network. Because the conventional network is already built in an earlier stage these investment costs won't be taken into account. If the model decides to add one of the redundant subsystems the corresponding investment costs of this subsystem will be added to the total costs.

After the investment stage the unknown failure parameter will be known. The stochastic program uses a scenarios for each component in which it fails. In one scenario all components will work perfectly. The scenario probability decides how often a scenario occurs. With this information the operational costs and penalty costs can be determined in the second stage. The operational costs occur when energy is flowing through a subsystem. The penalty costs variable depends the undelivered energy at a demand node. The height of the given penalty depends on the penalty factor. The optimized network can be found with the two stage stochastic MILP model.

4.6 AIMMS

To develop the two stage stochastic MILP problem introduced in this chapter the software package AIMMS is used. AIMMS is an acronym for Advanced Interactive Multidimensional Modelling System. The software program is specifically designed for modelling and solving large-scale optimization problems. The software consists of an algebraic modelling language as well as the possibility to edit models and create a graphical user interface around it. On top of that it is able to cope with many different mathematical optimization methods like stochastic programming. Last but not least it is available to use for academic purposes. In this research the optimization will be executed using the CPLEX 12.6.3 solver. This solver is developed by IBM and uses a presolve algorithm whereby the problem input is examined for logical reduction opportunities. This high-performance mathematical programming solver is used in complex linear programming and mixed integer programming problems. In the next chapter the model built in AIMMS is described in detail.

Chapter 5

Model

The model in AIMMS will produce an optimized energy distribution network based on costs minimization. The topology of this optimal network depends on many factors. The model will return a set of binary decision variables which describe whether or not to build a certain subsystem. These binary decision variables are also presented in a graph. There are three different subsystems which are described in the previous chapter. In this chapter the model is described in detail. The model consists of sets, parameters, variables and constraints and a stochastic part which will be described in the upcoming paragraphs.

5.1 Sets

To give a AIMMS model dimension and depth sets and indices are used. The use of sets helps to describe large models in a concise and understandable way. The sets in AIMMS are the basis for creating identifiers in the model. Through indices into sets individual values of these identifiers can be accessed. In the model six sets can be distinguished. These set will be declared in the beginning of the model. The sets are nodes, lines, redundant lines, time, timeperiod and representativeday.

5.1.1 Nodes

The set nodes (no,i,j) represent all the nodes in the model. The base model will use a total of 4 nodes. A node has many possibilities. It can serve as a demand point or network supply (ns) point but it can also be used as (multiple) subsystem(s). Nodes can function as a converter (co) or as renewable storage (res).

5.1.2 Lines

The set lines (li) represents the existing energy distribution lines between the nodes. A line can transport energy from node i to node j. The lines are used to show how the conventional distribution network is configured. These lines are failure sensitive. The four nodes are using 6 different lines.

5.1.3 Redundant lines

Next to each line option also a redundant line (rli) option is available. This redundant line is one of the subsystem options for the model to choose from in its search for the optimal network configuration. The distribution lines (black) as well as the redundant distribution lines (curved light blue) can be seen in Figure 5.1.

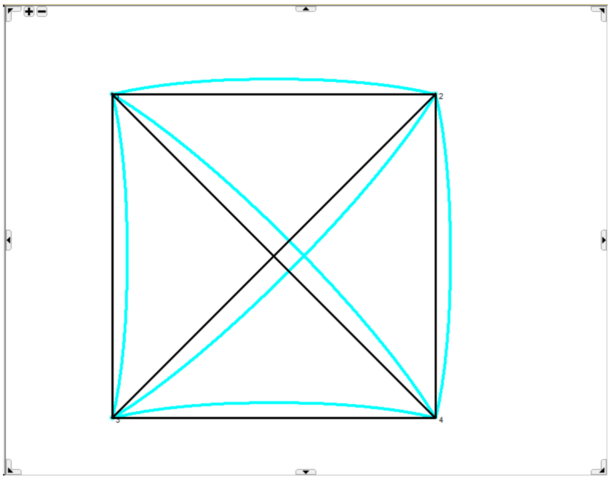


Figure 5.1: (Redundant) line distribution possibilities

5.1.4 Time

The set time(t) represents the overall time period of one year. Its value will therefore be 1. This set will be used for the stochastic program. The first stage will be decided in advance, so prior to t = 1. The second stage will happen during t = 1.

5.1.5 Representative day

The set representative day (rd) is used to simplify the model to save computational time. The user will choose a representative day in the summer and in the winter. These two days will be used to represent a complete year.

5.1.6 Time period

The set time period (tp) does the same as the set representative day. Only this set is used to represent a single day. two time periods are used. One to represent daytime and one to represent the night. Combined these two time periods represent a complete day.

5.2 Parameters

The values of the parameters in the model will be predefined by the user. The model uses several categories of parameters; graph, incidence, existence, investment costs, operational costs, failure, supply and demand, capacity limits and penalty. In the following sections these categories will be discussed.

5.2.1 Graph

The model uses several parameters to construct a graph which shows the optimized network. Therefore the set nodes needs coordinates to place these coordinates on a map. The parameters x(no) and y(no) gives the x-coordinate and y-coordinate for every node. With these coordinates the line length can be calculated for the lines $linelength_{li}$ as well as the redundant lines$linelengthr_{rli}$. An overview of the graph parameters is given in Table 5.1.

Name	**Unit**	**Description**
x(no)	Coordinate	x-coordinate of a node
y(no)	Coordinate	y-coordinate of a node
$linelength_{li,i,j}$	m	line length
$linelengthr_{rli,i,j}$	m	redundant line length

Table 5.1: Graph parameters

5.2.2 Incidence

The binary parameter $nodeincidence_{li,i,j}$ determines if a line (li) from node (i) to node (j) exists. $nodeincidencer_{rli,i,j}$ does the same for redundant distribution line subsystem. In Table 5.2

Name	Unit	Description
$nodeincidence_{li,i,j}$	(0,1)	line possibilities
$nodeincidencer_{li,i,j}$	(0,1)	redundant line possibilities

Table 5.2: Incidence parameters

5.2.3 Existence

The model will analyse existing distribution networks. With the existence parameter the user can model the existing network subsystems. This binary parameter will make use of three existing subsystems. In table 5.3 the parameters are given.

Name	Unit	Description
ex_{li}	(0,1)	existing line subsystems
ex_{ns}	(0,1)	existing network supply subsystems
ex_{rs}	(0,1)	existing renewable supply subsystems

Table 5.3: Existence parameters

5.2.4 Investment costs

The three redundant subsystems which the model can use to find the optimized solution all have their own characteristics. The fixed costs are made only once and can be seen as investment costs. For every subsystems the investment costs are determined. The parameter is shown in Table 5.5.

Name	Unit	Description
c^{inv}_{rli}	€/m	investment costs for subsystem redundant line
c^{inv}_{co}	€/kWh	investment costs for subsystem converter system
c^{inv}_{res}	€/kWh	investment costs for subsystem renewable storage system

Table 5.4: Investment costs parameters

5.2.5 Operational costs

The operational costs are the costs made when using a subsystem. These costs also include the costs of maintenance. The operational costs depends on the amount of energy running through the subsystem. For both the existing as the redundant subsystems the costs are determined.

Name	Unit	Description
c^{op}_{li}	€/m	operational costs for subsystem line
c^{op}_{ns}	€/kWh	operational costs for subsystem network supply
c^{op}_{rs}	€/kWh	operational costs for subsystem renewable supply
c^{op}_{rli}	€/m	operational costs for subsystem redundant line
c^{op}_{co}	€/kWh	operational costs for subsystem converter system
c^{op}_{sto}	€/kWh	operational costs for subsystem renewable storage system

Table 5.5: Costs parameters

5.2.6 Failure

The existing subsystems are sensitive to failure. It is however uncertain when a subsystem will fail. This parameter is made stochastic so this uncertainty can be modelled by using scenarios with a certain probability of occurring. In every scenario one of the components will fail. Only in the last scenario all components will work perfectly. This binary parameter is used to see whether or not an existing component fails in a certain scenario.

Name	Unit	Description
$f_{s,li}$	(0,1)	stochastic binary failure parameter for subsystem line in scenario s
$f_{s,ns}$	(0,1)	stochastic binary failure parameter for subsystem network supply in scenario s
$f_{s,rs}$	(0,1)	stochastic binary failure parameter for subsystem renewable supply in scenario s

Table 5.6: Failure parameters

5.2.7 Supply and Demand

This parameters show at which node and at which time there is a supply or demand in power. The network supply will only come available if the corresponding existing subsystem is present. The renewable energy supply, the storage supply and the renewable storage supply will only become available if the corresponding subsystem is actually built by the model.

Name	Unit	Description
$e^{dem}_{no,tp,rd,t}$	kWh	energy demand per node at a certain time
$e^{sup}_{ns,no,tp,rd,t}$	kWh	network supply per node at a certain time
$e^{sup}_{rs,no,tp,rd,t}$	kWh	renewable energy supply per node at a certrain time
$e^{sup}_{co,no,tp,rd,t}$	kWh	converter supply per node at a certain time
$e^{sup}_{res,no,tp,rd,t}$	kWh	renewable storage supply per node at a certain time

Table 5.7: Supply and demand parameters

5.2.8 Capacity limits

The (redundant) distribution lines and converters are restricted by capacity limits given by this parameter. Because the optimization is focussed on redundancy and not on capacity optimization the capacity limits are made sufficiently high so they won't restrict the flow. An overview is given in Table 5.8.

Name	Unit	Description
cap_{li}	kWh	capacity restriction for subsystem line
cap_{rli}	kWh	capacity restriction for subsystem redundant line
cap_{co}	kWh	capacity restriction for converter system

Table 5.8: Capacity limit parameters

5.2.9 Penalty

When a demand node can't be supplied with the needed energy a penalty factor will determine the actual costs of not delivering. The penalty factor depends on what kind of building category is present at the node. For example commercial buildings will have a higher penalty factor then a normal household. Adjusting this penalty parameter can result in a different optimized network lay-out. Table 5.9 shows the penalty parameter.

Name	Unit	Description
p_{no}		penalty factor per node

Table 5.9: Penalty parameters

5.3 Variables

The variables can be adjusted by the model to determine the optimized solution or are dependent on these decisions. The variables are divided into several categories which are described below.

5.3.1 Total costs

The total costs of the network is given in variable Z. This variable sums up all the investment cost, operational costs and penalty costs made by the model. This variable is the objective variable of the mathematical program. Finding the optimal solution will be done by minimizing this variable. The equation is given in 5.1 and 5.2.

$$z = \max \left(X_n * C_n^{inv} + \sum_{s=1}^{S} (p_s * Q_s(X_n, f_n) + C_s^{pen})\right) \tag{5.1}$$

$$\text{With: } Q_s(X_n, f_n) = Xw_{s,n} * Y_{s,n} * c_{s,n}^{op} \tag{5.2}$$

The first part of formula 5.1 shows the investment costs made in the first stage. The second part shows the operational costs and penalty costs. All variables used to determine the value of Z will be discussed in more detail in the following paragraphs.

5.3.2 Subsystems

The subsystems variable is the first stage binary decision to define whether or not a subsystem is used. When the model decides to use a subsystem the corresponding binary decision variable is set to one. The choices made in the first stage influence the choices in the second stage. The first stage costs of the subsystems are the investment costs of the network. The different subsystems will be indicated by symbol n. The corresponding formula used in the profit calculation is shown in equation 5.3.

$$X_n \tag{5.3}$$

The complete overview is given in Table 5.10.

Name	**Unit**	**Description**
X_{rli}	0,1	First stage decision variable redundant line
X_{co}	0,1	First stage decision variable converter system
X_{sto}	0,1	First stage decision variable renewable storage system

Table 5.10: First stage binary decision variables

5.3.3 Energy flows

The flow in and out of an available subsystem is calculated for every time period. Energy can only flow through subsystems which are chosen by the model in the binary decisions variable. Energy losses in distribution lines are neglected for now since it will increase computational time extensively. Again, the different subsystems will be denoted with symbol n in formula 5.4.

$$Y_n \tag{5.4}$$

The complete overview of the energy flow variable is given in Table 5.11.

The energy flows are chosen by the model in the second stage of the stochastic program. The goal in the second stage is to optimize the profit with the available subsystems chosen in the first stage (binary decision variables).

Name	Unit	Description
Y_{li}	kWh	Second stage decision variable for subsystem line
Y_{ns}	kWh	Second stage decision variable for subsystem network supply
Y_{rs}	kWh	Second stage decision variable for subsystem renewable energy supply
Y_{rli}	kWh	Second stage decision variable for subsystem redundant line
Y_{co}	kWh	Second stage decision variable for subsystem converter system
Y_{res}	kWh	Second stage decision variable for subsystem renewable storage system
Y_{dra}	kWh	Second stage decision variable for subsystem drain connection

Table 5.11: Second stage continues decision variables

5.3.4 Working subsystems

Whether or not an existing subsystem works depends on the binary fail parameter and the binary existence parameter. Multiplying these two parameters results in a new binary variable with working subsystems in the second stage. The available working subsystems are then used in the second stage to determine the energy flows. To multiply binary vectors some extra constraints are used which will be explained in the section binary constraints. The subsystems are indicated with symbol n and the scenarios by symbol s. The working subsystem is calculated with equation 5.5.

$$Xw_{s,n} = ex_n * (1 - f_{s,n}) \tag{5.5}$$

An overview is given in Table 5.12

Name	Unit	Description
$Xw_{s,li}$	0,1	determines if subsystem line works in scenario s
$Xw_{s,ns}$	0,1	determines if subsystem network supply works in scenario s
$Xw_{s,rs}$	0,1	determines if subsystem renewable energy supply works in scenario s

Table 5.12: Working subsystems variable

5.3.5 Investment costs

This variable shows the investment costs of the subsystems in the new network configuration. The costs variables are used in the total costs variable to find the optimized configuration. The investment costs are calculated by multiplying the binary parameter whether or not a redundant subsystem is constructed times the investment costs parameter. For the redundant lines this calculation also is multiplied with the line length. For the converter system and the renewable storage system the calculation is multiplied with the amount of kWh it is able to supply. For the existing subsystem there won't be any investment costs since these costs are already made in a previous stage.

The investment costs of the redundant lines are calculated with equation 5.6,

$$C_{rli}^{inv} = (c_{rli}^{inv} * linelength_{rli} * X_{rli}) \tag{5.6}$$

The investment costs of the converter system is calculated with equation 5.7.

$$C_{co}^{inv} = (c_{co}^{inv} * e_{co}^{sup} * X_{co}) \tag{5.7}$$

And the investment costs of the renewable storage system is calculated with equation 5.8. For this system the investment costs are lower if the renewable source (PV-panels) already are present.

$$C_{res}^{inv} = ((c_{res}^{inv} - ex_{rs}^{sup} * c_{rs}^{inv}) * e_{res}^{sup} * X_{res}) \tag{5.8}$$

An overview of the investment costs variables is given in Table 5.13

Name	Unit	Description
C^{inv}_{rli}	€	redundant line investment costs in the first stage
C^{inv}_{co}	€	converter unit investment costs in the first stage
C^{inv}_{res}	€	renewable storage system investment costs in the first stage

Table 5.13: Total investment costs variables

5.3.6 Operational costs

The operational costs at a certain time is calculated by multiplying the amount of energy what runs through a subsystem and multiply this amount with the operational costs of this subsystem. For the lines this equation is multiplied with the line length. The total operational costs of a subsystem will be the sum of all the time periods.

The operational costs of the subsystems lines and redundant lines are calculated with equation 5.9:

$$C^{op}_n = (c^{op}_n * linelength_n * Y_n) \tag{5.9}$$

The operational costs of the other subsystems are calculated with equation 5.10

$$C^{op}_n = (c^{op}_n * Y_n) \tag{5.10}$$

An overview of the operational costs variables is given in Table 5.14.

Name	Unit	Description
C^{op}_{li}	€	Line operational costs in the second stage
C^{op}_{ns}	€	network supply operational costs in the second stage
C^{op}_{rs}	€	renewable energy supply operational costs in the second stage
C^{op}_{rli}	€	redundant line operational costs in the second stage
C^{op}_{co}	€	converter system operational costs in the second stage
C^{op}_{res}	€	renewable storage system operational costs in the second stage

Table 5.14: Total costs variables

5.3.7 Penalty costs

The penalty costs are costs for not delivering energy in a time period at a demand node. This variable calculates the amount of undelivered energy in a time period with equation 5.11. In this equation the demanded energy is compared to the energy actually supplied.

$$e^{undelivered} = e^{dem} - Y_{dra} \tag{5.11}$$

If there is any energy not delivered this will be multiplied by the penalty factor parameter shown in Table 5.9 according to equation 5.12.

$$C^{pen} = e^{undelivered} * p_{no} \tag{5.12}$$

The total costs variable uses this penalty costs to determine the optimized network. An overview of the undelivered energy variables is given in Table 5.15

Name	Unit	Description
$e^{undelivered}$	kWh	undelivered energy at a node in a certain time period
C^{pen}	€	Penalty costs for not delivering energy at a demand point

Table 5.15: Undelivered energy variables

5.4 Constraints

To define the relations between the subsystems, e.g. the energy should flow from a source node to a demand node constraints are made and energy flows should stay within the capacities. The used constraints in the model will be discussed in this section.

5.4.1 Node constraint

The node constraint defines the relationship between power flowing into and out of a node over a period of time. The node constraint consist of the fact that all the emitted power is equal or less than the absorbed power in that node. The corresponding equation can be found in 5.13.

$$\begin{aligned} Y_{li}out + Y_{rli}out + Y_{dra}out \\ <= \\ Y_{ns}in + Y_{rs}inY_{li}in + Y_{rli}in + Y_{co}in + Y_{res}in \end{aligned} \tag{5.13}$$

The flows are shown in a sankey diagram in Figure 5.2.

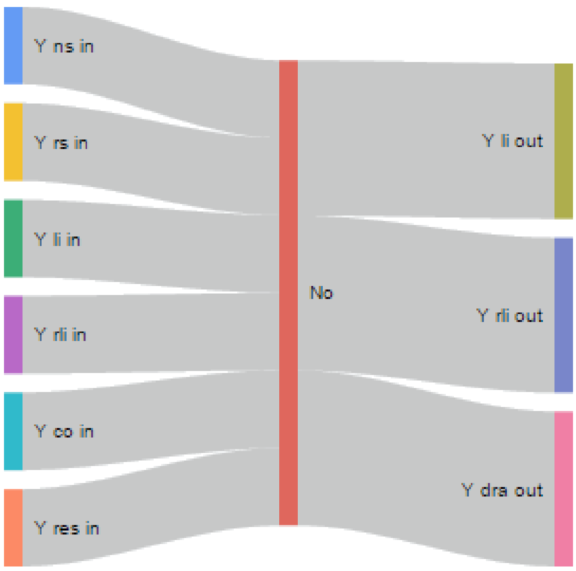


Figure 5.2: Sankey diagram

5.4.2 Flow constraints

This constraint makes sure the flow through a subsystem is not higher then its maximum capacity and only if the subsystem is actually built and not failing at that time period. Therefore the working subsystem variable is used. The line constraint is shown in 5.14. The network supply constraint and the renewable energy supply constraint can be found in resp. 5.15 and 5.16. The redundant line constraint can be seen in 5.17. The converter constraint and the renewable storage constraint are found in 5.18 and 5.19. The drain constraint is shown in 5.20. This constraints makes sure the actual delivered energy in a node is never higher than the demand.

$$Y_{li} <= cap_{li} * Xw_{li} \tag{5.14}$$

$$Y_{ns} <= e_{ns}^{sup} * Xw_{ns} \tag{5.15}$$

$$Y_{rs} <= e_{rs}^{sup} * Xw_{rs} \tag{5.16}$$

$$Y_{rli} <= cap_{rli} * X_{rli} \tag{5.17}$$

$$Y_{co} <= e^{sup}_{co} * X_{co} \tag{5.18}$$

$$Y_{res} <= e^{sup}_{res} * X_{res} \tag{5.19}$$

$$Y_{dra} <= e^{dem} \tag{5.20}$$

5.4.3 Binary multiplication constraints

These constraints are used for the binary multiplications at the working subsytem variable. The working subsystem variable is found after multiplying the binary subsystem variable of the subsystem with the binary parameter fail. The equation can be found in 5.5

To simplify, 5.5 can be written as 5.21:

$$z = x * y \tag{5.21}$$

To multiply two binary variables x and y from 5.21, the three inequalities in 5.22 are used:

$$\begin{aligned} z &<= x \\ z &<= y \\ z &>= x + y - 1 \end{aligned} \tag{5.22}$$

The inequalities shown in 5.22 are used to find the Xw_n subsystem variables.

5.5 Stochastic Program

Two stage stochastic programming is used to show the effect of the uncertainty of failing components in the network. This is done by running several scenarios. For each component in the network there is a scenario in which it fails. The probability of this scenario can be adjusted by the user. In the first stage the investment costs are made. The investment costs are the subsystems fixed costs. In the second stage all working subsystems are determined and based on this info an optimal flow of energy is calculated. This is done for every first stage configuration. At the end the network configuration with the lowest costs is the optimized solution and selected by the model. To make the model stochastic several sets and parameters are added to the model which will be discussed in this section.

5.5.1 Stages

The stochastic program adds two sets to the already existing ones. The first set is $stages_{st}$, which defines the two stages of the program.

5.5.2 Scenarios

The second set is $scenarios_s$. Every failing component is represented by a scenario and one scenario is used to represent a perfectly working system without failure. The amount of scenarios is therefore determined by the amount of available subsystems + one for the scenario without failure.

5.5.3 Scenario probability

With the parameter scenario probability p_s the user can determine how often a scenario occurs. In this model a scenario represents the failure of one single subsystem in the network so the parameter shows the chance the system fails. In one scenario all subsystems work fine. The sum of the scenario probabilities always needs to be 1.

5.5.4 Scenario Treemapping

The element parameter $scenariotreemapping_{s,st}$ defines which scenario occurs during which stage.

5.5.5 Stagemapping

The parameter $stagemapping_t$ defines in which stages stochastic variables are calculated. The parameter is used to make sure that the investment costs are calculated in the first stage and the operational costs and the penalty costs calculated in the second stage of the stochastic program.

Chapter 6

Network Redundancy

The model introduced in the previous chapter offers several redundancy options. The redundant subsystems, as well as the existing network will be discussed in this chapter.

6.1 Redundancy options

Each of the subsystems has their own specific characteristics which makes them suitable in specific situations. The general characteristics are shown in Figure 6.1

Method	**Investment Costs**	**Operational Costs**	**Reliability**
Existing network	None	medium	Low
Redundant line	High	medium	High
Converter system	low	High	High
Renewable storage system	medium	low	High

Table 6.1: Subsystem characteristics

The first option is adding redundant distribution lines to the grid, which can be both to make a ring network or as a double line. Furthermore there are two local redundancy options. Rooftop solar cannot provide usable power when the grid is down. For safety reasons, almost all solar power systems need reference power from the grid to operate. This can be resolved by placing a storage system between the PV-panels and the grid. In general there are two main options for local redundancy: a generator, or a solar system with a battery backup powered inverter. Together with the redundant line these two local redundancy options are used by the model.

6.2 Existing network

In the existing network optimization is done without redundancy. The shortest path is then the optimized configuration since operational costs will then be minimized. This way most distribution networks are designed. The existing network consists of the three existing subsystems. The black line represents the distribution line, the red dot represents the network supply and the blue line represents the demand. An existing network is given in Figure 6.1.

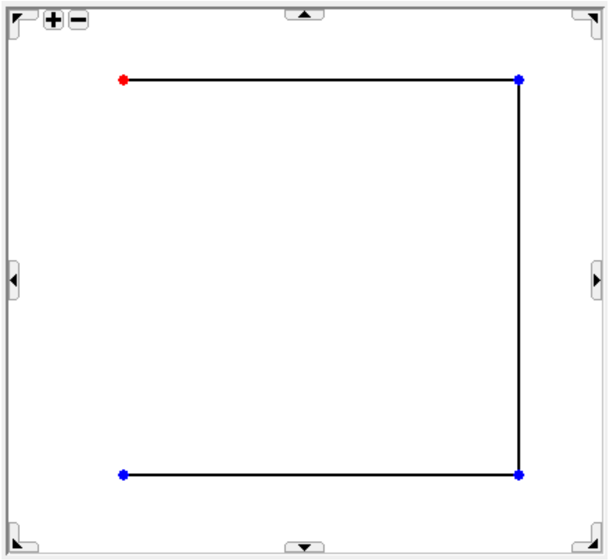


Figure 6.1: Existing network

6.3 The redundant line

The double line solution makes sure that when the conventional line fails, the redundant line will be used to deliver the required amount of energy. In the model a double line is represented by an curved light blue line, see Figure 6.2

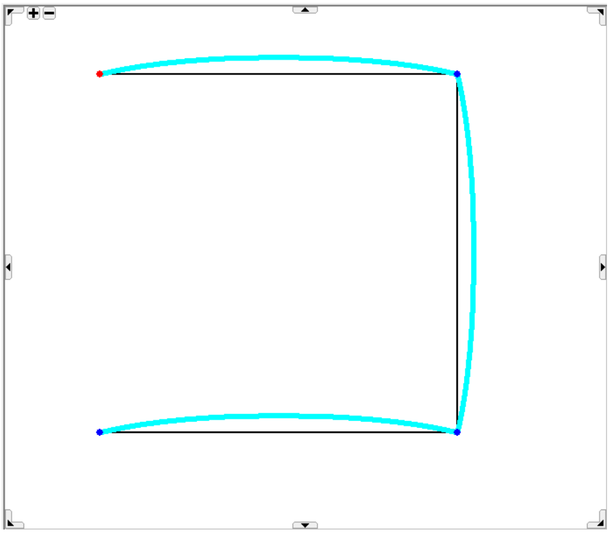


Figure 6.2: Double line

Re-routing the energy through other components is another redundant line possibility. In this case the network delivers the required energy via another path. An example is given in Figure 6.3

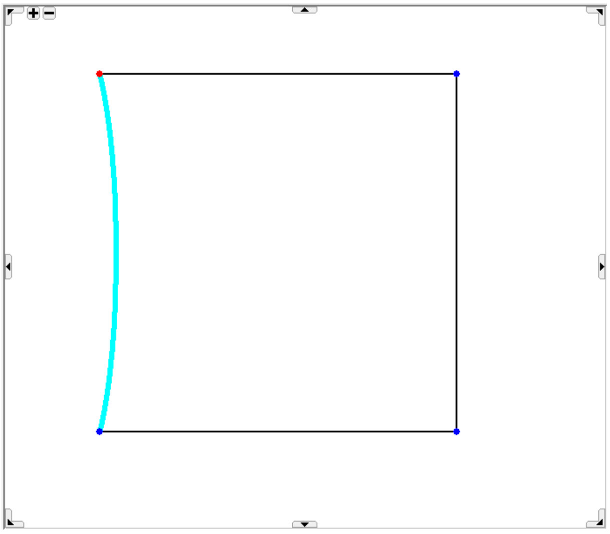


Figure 6.3: Re-routing

6.4 Converter system

When using the converter subsystem the network becomes multi-carrier. The demanded energy is delivered via another carrier through an converter. The idea is the same as when re-routing the energy with an redundant line, only now a second carrier is involved. The pink dot represents a converter. An example is given in Figure 6.4.

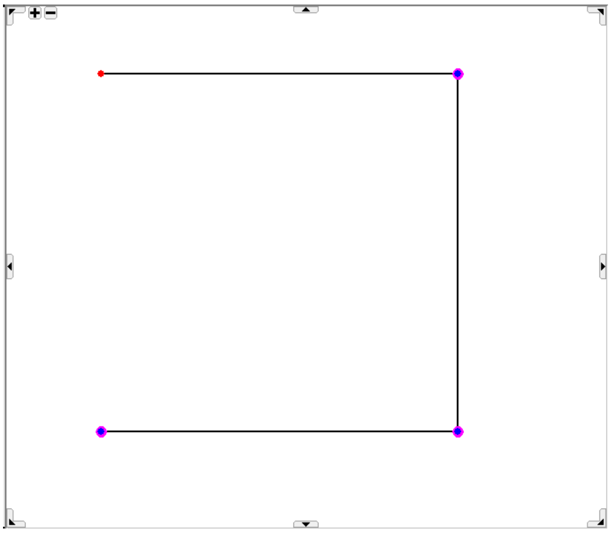


Figure 6.4: Converter system

In this Figure two carriers are shown with the same nodes. In the left figure the energy flows from supply node 1 to converter node 2. In the right picture the energy flows from converter node 2 to demand point 4.

6.5 Renewable storage system

Renewable storage generates energy via PV-panels and is able to store this energy until its needed. The energy is stored when excessive energy is generated and then used when the PV-panels cannot generate the demanded energy. Storing energy is relatively expensive but can secure a constant renewable supply. A renewable storage node is represented by the green dot. An example is given in Figure 6.5.

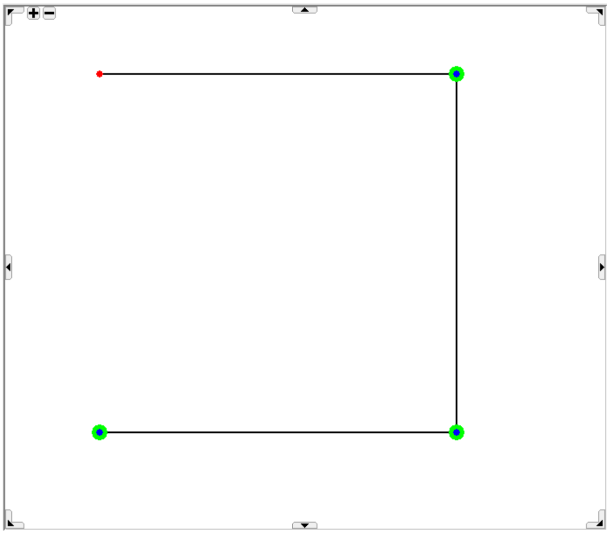


Figure 6.5: Renewable storage system

This chapter is used to show the possibilities of the model. The next chapter will be devoted to a fictional case study followed by a real life case study. In the case studies the data used will be estimated to approximate reality.

Chapter 7

Case Study

This chapter is devoted to two case studies, a fictional case and a real case. These case studies are used to demonstrate the model in actual situations with data estimated to approach reality. The results from the case studies are used to substantiate the conclusions drawn in chapter 8. In the first section the data used in the case studies will be discussed. In the second section a fictive case study will be conducted. In the third section a real situation will be simulated.

7.1 Data

To conduct the case studies data is needed. This includes energy demands of a building type, investment costs and operational costs of network subsystems, energy costs and last but not least the topology of the current network. Additionally the model also uses stochastic data. This data is used to determine whether or not a component fails. In the model the parameters are used to fill in this data. In this first section the parameters and there values will be discussed.

7.1.1 Investment costs

The investment costs of the redundant line are estimated at an average of €100/m including installation. These costs are based on actual power distribution lines prices combined with estimated prices for the installation. It is estimated that the line will work for 50 years and therefore the annual investment costs will be €2/m. The investment costs for a converter system is estimated at €1.8/kWh based on actual natural gas to power converters. With an estimated lifetime of 25 years the annual costs are €0.07/kWh. For the renewable storage combination the investment costs are estimated at €1.5/kWh for the storage system and €2.2/kWh for the PV-panels. Again these prices are based on actual storage systems and PV-panel prices. Both have an estimated life span of 25 years which brings the annual investment costs to €0.15/kWh

An overview of the investment costs are given in Table 7.1.

Method	**Annual investment costs**
Redundant line	€ 2/m
Converter system	€ 0.07/kWh
Renewable storage system	€ 0.15/kWh

Table 7.1: Investment Costs

7.1.2 Operational costs

For the operational costs the price for energy transportation is used. According to the Centraal Bureau voor de Statistiek (CBS) the costs of a kWh are € 0.22/kWh and roughly 10 percent is used for transportation and maintanance of the grid. The operational costs are therefore estimated at € 0.02/kWh. For the converter system the operational costs will be doubled to € 0.04/kWh because of conversion losses and the use of the gas network. The renewable storage combination on the other hand hardly uses any operational costs. These costs are therefore estimated at € 0.005/kWh.

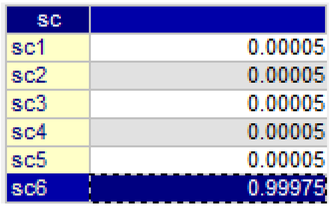
An overview of the operational costs are given in Table 7.2.

Method	Annual investment costs
Redundant line	€ 0.02/kWh
Converter system	€ 0.04/kWh
Renewable storage system	€ 0.005/kWh

Table 7.2: Operational costs

7.1.3 Failure

According to [26] the average power outage in the Netherlands is 28 minutes. This equals a 99,995 percent reliability of the grid. The failure chance for an existing component is therefore estimated on 0,005 percent. Every scenario in the model, which represents a failing component has a 0,005 percent change of occurring. The probability parameter used is shown in Figure 7.1. In this case there are five components used, each with their own failure scenario. The sixth scenario occurs when all components work fine. The summation of the scenario probabilities always has to be 1. Therefore 0,005 percent equals a scenario probability of 0,00005.



sc	
sc1	0.00005
sc2	0.00005
sc3	0.00005
sc4	0.00005
sc5	0.00005
sc6	0.99975

Figure 7.1: Probability parameter

7.1.4 Demand and Supply

According to the Centraal Bureau voor de Statistiek (CBS) the average yearly demand for a household in 2015 was 3.000 kWh. In the same year the average yearly demand for a shop was 35.000 kWh, for an office/school 80.000 kWh and an Industrial building used 150.000 kWh on average. These average yearly demands will be used in the model. Two periods will be distinguished in a year to simulate the seasonal influences. These periods are summer and winter. In the winter demands are higher then in the summer due to the colder temperatures and less daylight. It is assumed that 2/3 of the yearly demand comes from the winter period and 1/3 is demanded in the summer. The corresponding demand profiles are shown in Table 7.3.

Building category	Summer demand	Winter demand
Household	1.000 kWh	2.000 kWh
Shop/commercial	11.667 kWh	23.333 kWh
Office/school	26.667 kWh	53.333 kWh
Industrial	50.000 kWh	100.000 kWh

Table 7.3: Average demand profile

The supply will be equal to the yearly demand. However the supply of the renewable energy system strongly depends on the season and the time of the day. According to Essent the average yearly energy yield for PV panels is 70 percent in the summer and 30 percent in the winter. Also it is assumed that the energy yield only takes places during day time and not during night time. The corresponding supply profile for renewable energy can be found in Table 7.4.

By adding storage to this renewable energy supply the discrepancy between supply and demand can be resolved for at least a short period of time. For this research it is assumed that the renewable storage combination will supply enough energy in both winter and summer. The corresponding supply profiles for the redundant line, converter system and renewable storage combination are shown in Table 7.5.

Building category	Summer supply	Winter supply
Household	2.100 kWh	900 kWh
Shop	24.500 kWh	10.500 kWh
Office/school	56.000 kWh	24.000 kWh
Industrial	105.000 kWh	45.000 kWh

Table 7.4: Renewable energy supply profile

Building category	Summer supply	Winter supply
Household	1.000 kWh	2.000 kWh
Shop	11.667 kWh	23.333 kWh
Office/school	26.667 kWh	53.333 kWh
Industrial	50.000 kWh	100.000 kWh

Table 7.5: Redundant supply profile

7.1.5 Capacity limits

The capacity limits will be sufficiently high that they won't limit the optimization. In real life a line could exist of multiple smaller lines. However in this research these lines are simulated as one large line with enough capacity.

7.2 Fictional case

The fictional case study is conducted to show all the possibilities of the model. Because the case is fictional, some of the parameters like demand profiles or building categories can be adjusted easily. Several scenarios are conducted to show the influence of certain factors. The first scenario will be an residential area. In the second scenario an industrial area are analysed. In the third and last scenario the mix of residential, commercial and industrial buildings is analysed.

7.2.1 Scenario 1: Residential area

In this scenario only buildings with a low demand are taken into account. This will mostly be residential buildings in combination with a couple of commercial buildings. The current network is shown in Figure 7.2.

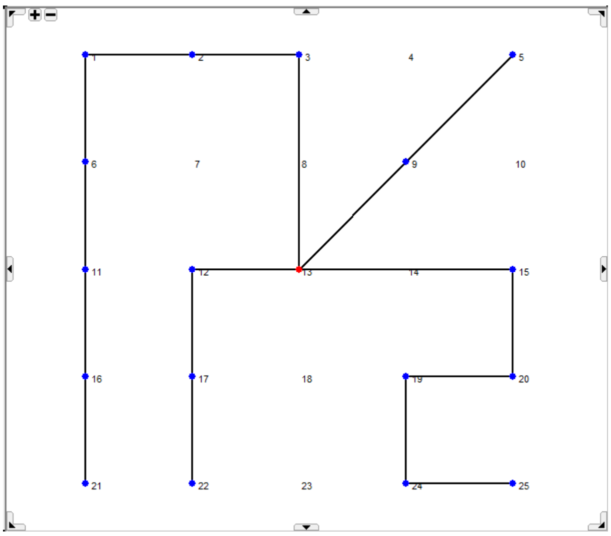


Figure 7.2: Scenario 1 current network

Figure 7.3 shows the redundant network solution. As can be seen the redundancy method used are conversion systems. However this redundancy is only feasible if the penalty factor is 750 or higher. This would mean that missing 1 kWh at a household would be equivalent to a €750,- Therefore it is not likely that in this scenario redundancy will be implemented.

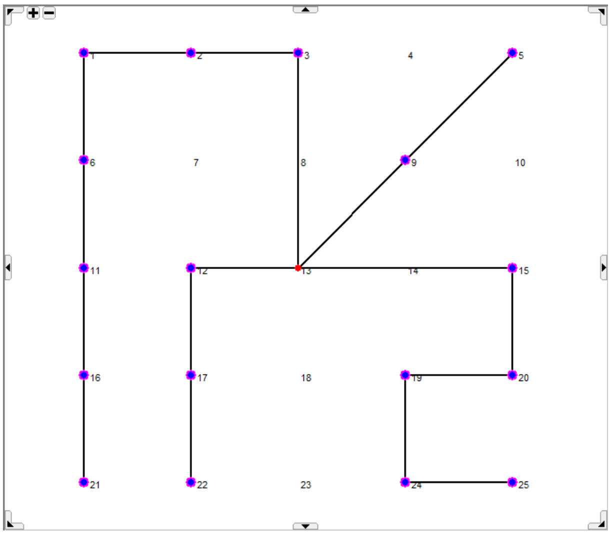


Figure 7.3: Scenario 1 redundant

In residential areas many buildings are already provided with PV-panels. The network including buildings with PV-panels is shown in Figure 7.4.

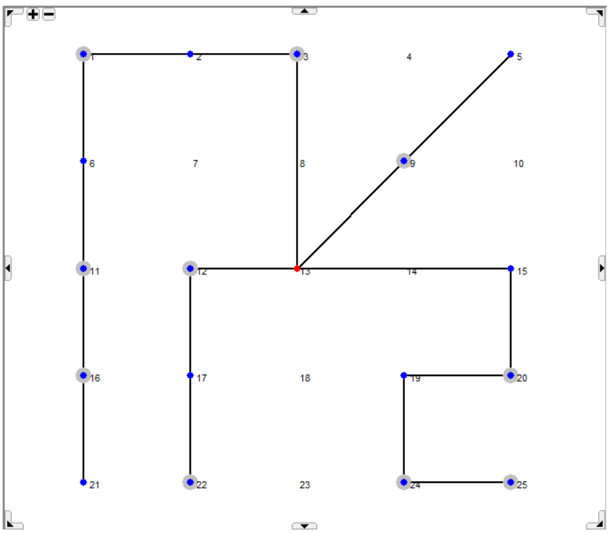


Figure 7.4: Scenario 1 including PV-panels

Because the investment of the renewable energy system is already done, the total investment costs of the renewable storage system will decrease. The redundancy result can be seen in Figure 7.5. This result is reached at a penalty factor of 500. This is lower then the penalty factor in scenario 1 but still extremely high for residential areas.

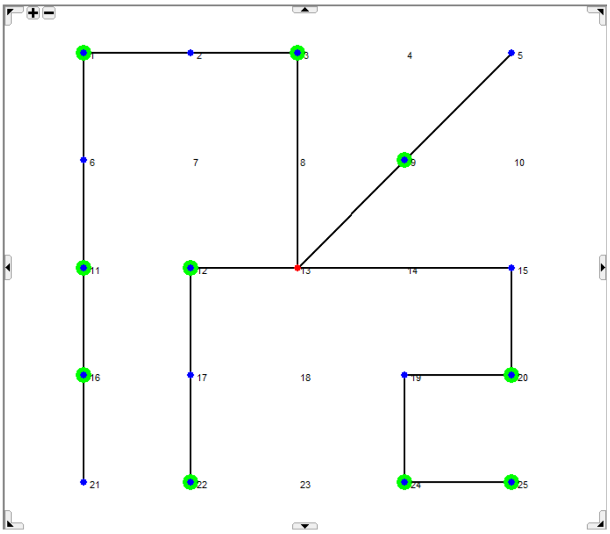


Figure 7.5: Scenario 1 redundancy with penalty factor 500

Using the same penalty parameter as in scenario 1 shows a feasibility for every demand node as can be seen in Figure 7.6. The redundancy options used are now both renewable storage systems as converter systems.

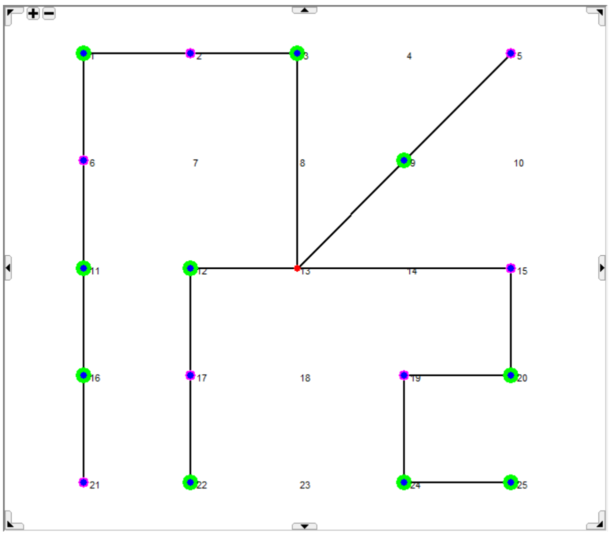


Figure 7.6: Scenario 1 redundancy with penalty factor 750

7.2.2 Scenario 2: Industrial area

The second scenario analyses an industrial area. The demand of these buildings is much higher. The current network can be seen in Figure 7.7.

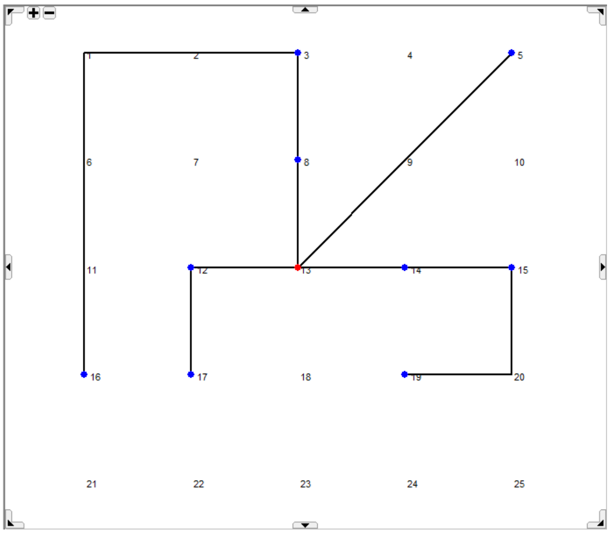


Figure 7.7: Scenario 2 currentnetwork

By running the model it can be seen in Figure 7.8 that there is a need for redundant lines as the most feasible solution. The redundant lines are feasible with a penalty factor of 20 and higher in this scenario.

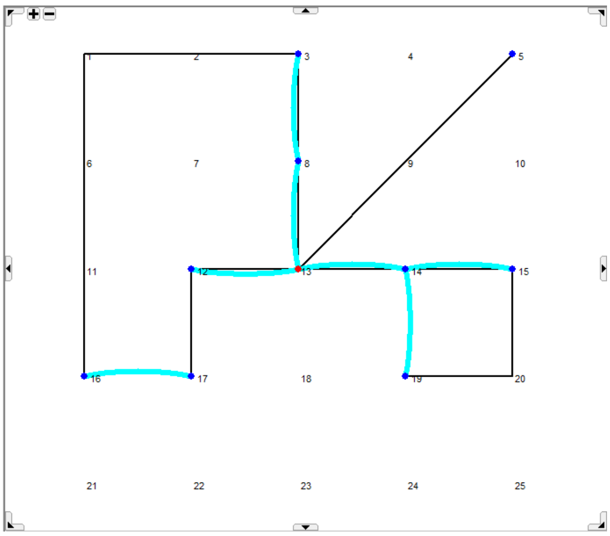


Figure 7.8: Scenario 2 redundancy with penalty factor 20

When the penalty factor is raised more redundant lines will be used. In Figure 7.9 the redundant optimization of the industrial area with a penalty factor of 40 is shown. Adding PV-panels does not influence the redundancy method. As can be seen in the figure no renewable storage system is used.

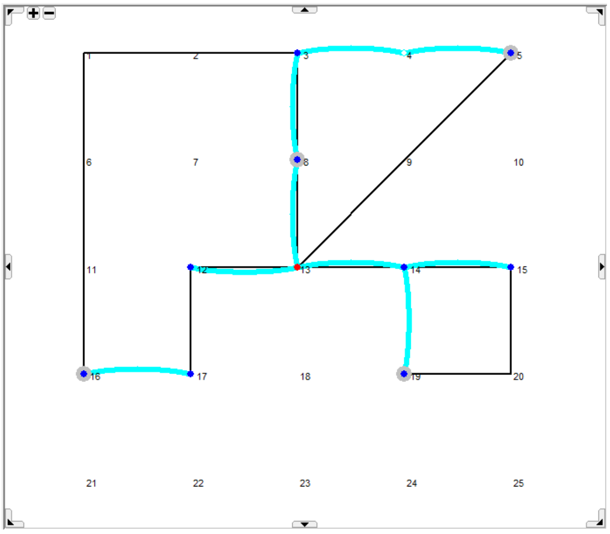


Figure 7.9: Scenario 2 redundancy with penalty factor 40

7.2.3 Scenario 3: Residential, commercial and industrial

In the last scenario of the fictional case the area is provided with a mix of different buildings. The used network can be seen in Figure 7.10. Households are located at node 2, 8, 9, 15, 17, 19, 20, 25. Shops and commercial buildings are located at node 3, 16, 24. Office and school buildings are located at node 6, 11, 14, 22 and industrial buildings are located at node 1, 5, 21. As can be seen in the figure some of the buildings already use PV-panels.

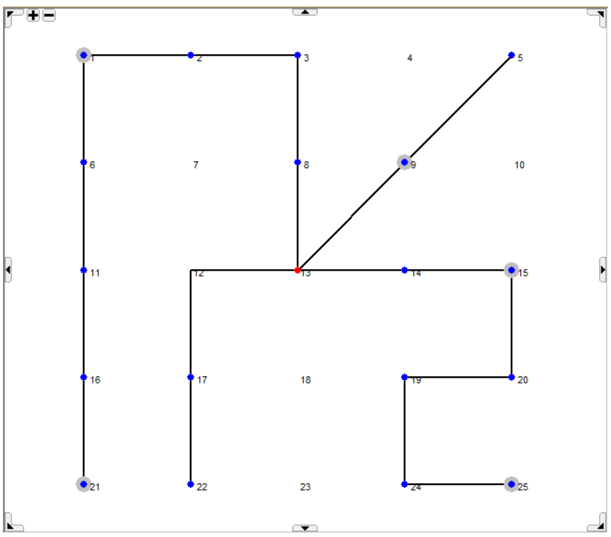


Figure 7.10: Scenario 3 current network

The first redundancy can be found after a penalty factor of 60. The redundant network is shown in Figure 7.11. It can be seen that all the industrial buildings are supplied with redundancy (node 1,5 and 21). Other demand buildings will profit from this redundancy. The redundancy is needed at a higher penalty factor (60) than in a full industrial area, see scenario 2, because of the surrounding buildings with a lower demand.

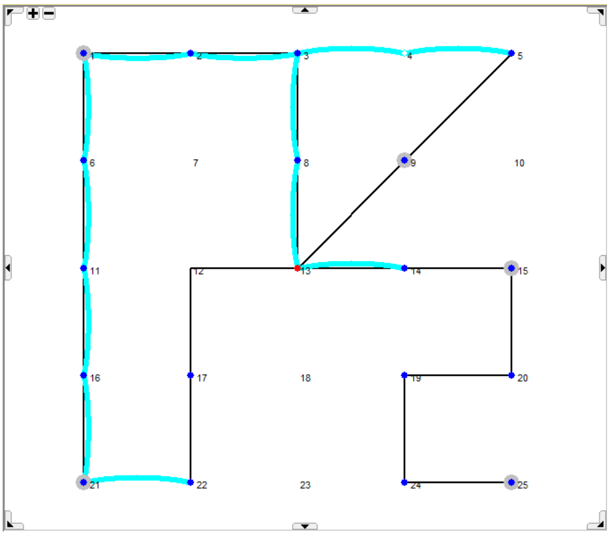


Figure 7.11: Scenario 3 redundant network with penatly factor 60

If the penalty factor rises to around 250 the commercial building at node 24 will also need a redundant line as can be seen in Figure 7.12.

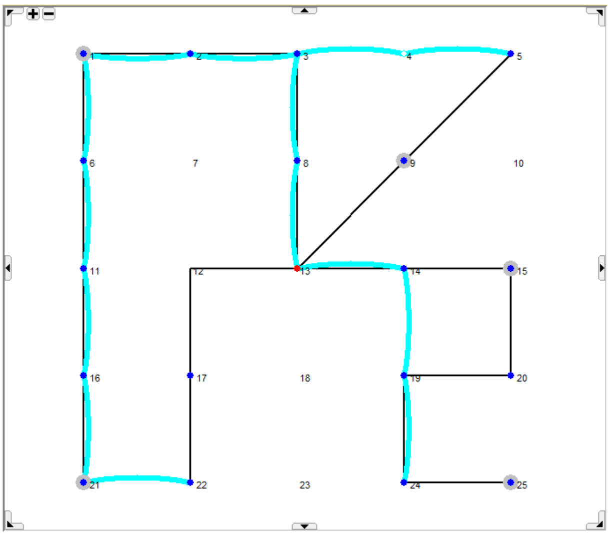


Figure 7.12: Scenario 3 redundant network with penalty factor 250

The nodes where already PV-panels are installed (node 9, 15 and 25) will need a renewable storage system at a penalty factor of 500. This confirms the results from scenario 2 and can be seen in Figure 7.13.

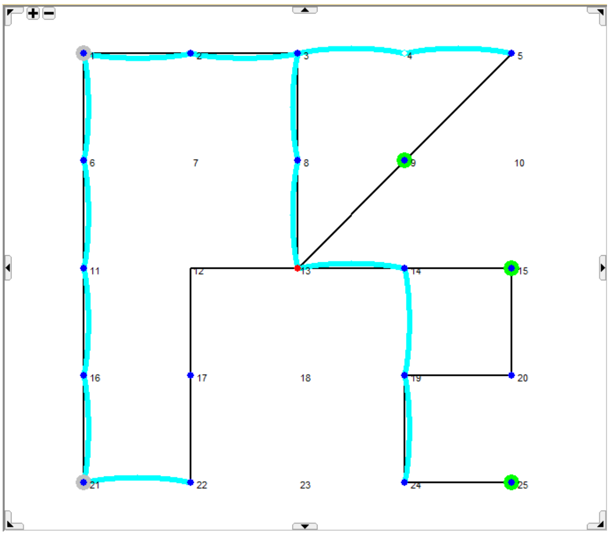


Figure 7.13: Scenario 3 redundant network with penalty factor 500

When looking at scenario 1, it can be seen that the every node will receive redundancy at a penalty factor of 750. The same goes for scenario 4. The buildings which are not yet receiving redundancy will get it at this penalty factor by a converter system. This result can be seen in Figure 7.14.

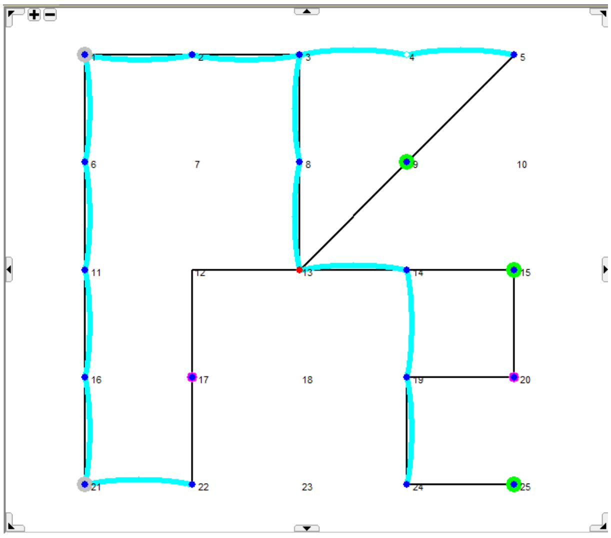


Figure 7.14: Scenario 3 redundant network with penalty factor 750

If sustainable solutions are promoted, for example by adding a penalty for non renewable energy usage the redundant network would change according to Figure 7.15. Converter would not be used anymore and all places where PV-panels where already installed will also use a renewable storage system.

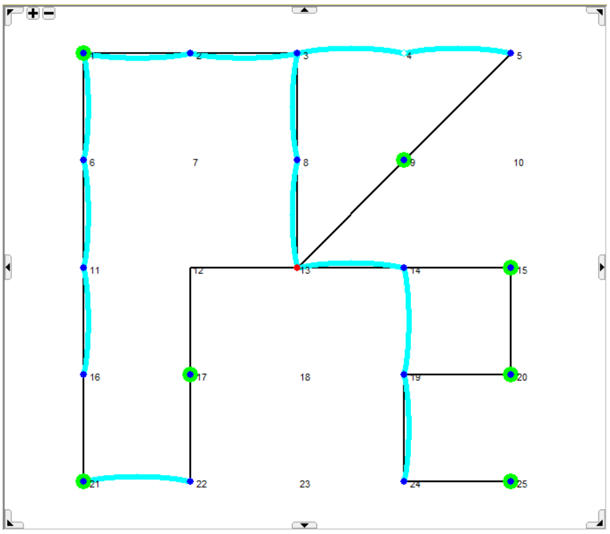


Figure 7.15: Scenario 3 redundant network sustainable

Eventually, if the penalty for non renewable energy would increase, the optimized redundant network would shift to Figure 7.16. The redundant lines would all be replaced by the renewable storage system.

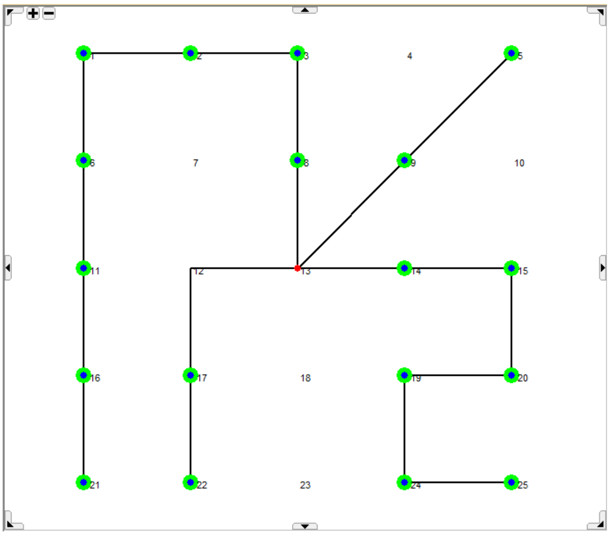


Figure 7.16: Scenario 3 redundant network extra sustainability

7.2.4 Results

For lower demand the first redundancy options used is the converter option. However if a household already has PV-panels the renewable storage options appears to be the best option. These options are only feasible with an penalty factor of 500 and higher. This penalty factor is extremely high and it can therefore be concluded that in the reliable dutch power network no redundancy will be used in residential areas.

For the industrial area the redundant line is the first option which is feasible. In scenario 3 it can be seen that this option is already feasible with a penalty factor of 17. The penalty factor is arbitrary but for a industrial area this factor seems reasonable. Adding redundancy in a industrial area therefore seems feasible according to the model.

In the mixed building scenario it can be seen that higher demand buildings will receive redundancy first by redundant lines. Depending on the topology it can occur that lower demand buildings will get redundancy as well because they are on the same line. Eventually the lower demand buildings will need a local redundancy solution when the penalty parameter is sufficiently high. As seen in the residential scenario the first option then is a converter system. However when PV-panels are already presented or when sustainable solutions are promoted the optimized solution will shift to renewable storage systems. Eventually, if penalties on non renewable energy are sufficiently high, every node will receive redundant energy from the renewable storage option.

7.3 Real case

The second case study will be based on a real situation. First the location of the case study will be discussed. Then the current network which is already there will be presented. Three scenarios will be used with different values for the penalty factor. A realistic scenario, a higher penalty factor scenario and a full redundancy scenario. In the last section the results are shown.

7.3.1 Location

The location of the case study is based on a neighbourhood close to Eindhoven in Geldrop. In this region different types of buildings are present. With the penalty system the costs of not delivering energy can be determined and thereby the need for redundancy. A google maps figure of the location is given in Figure 7.17.

Figure 7.17: Case study location

In the north and north west sport facilities are located and in the north east the beginning of a industrial area can be seen. In the South west a school is located and in the south east some commercial buildings are situated. Between these four different kind of buildings many residential buildings can be found in the neighbourhood.

7.3.2 Current network

The current network is obtained from QGIS combined with PDOK. By using the open data provided by Enexis this software program shows the current components in the low voltage network. This network can be seen in Figure 7.18. The blue lines represent the distribution lines. The dot represents the supply node and the light brown lines represent the demand nodes.

Figure 7.18: Current power network

This network is reproduced in the model and shown in Figure 7.19. In this Figure it can also be seen that four households are equiped with PV-panels. The network consists of 25 distribution lines and one supply node.

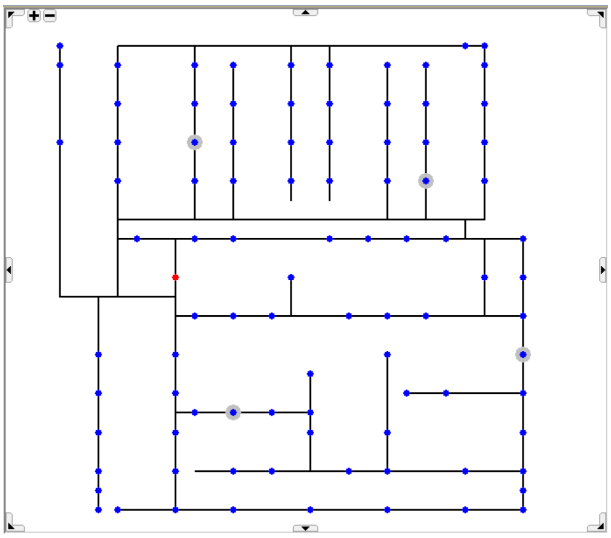


Figure 7.19: Current power network

7.3.3 Scenario 1: Realistic

The penalty factor of the buildings used in the realistic study is 5 for households, 25 for commercial buildings, 25 for offices and 50 for industrial buildings. In Figure 7.20 the results are shown.

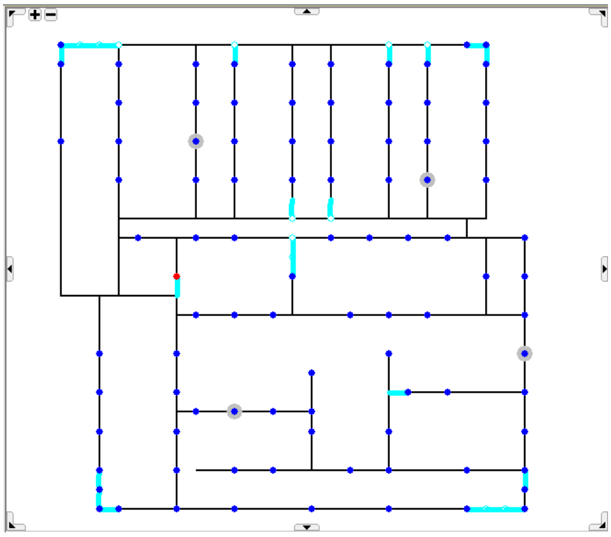


Figure 7.20: Realistic redundancy optimization

In the Figure it can be seen that at all corners redundant lines are used. At these corners there are buildings with a higher demand and higher penalty factor. Furthermore there are some redundant lines which make the total network more meshed.

7.3.4 Scenario 2: Full redundancy

By increasing the penalty factor to 750 every node will receive a redundant options, just like in the fictional case. The result is shown in Figure 7.21

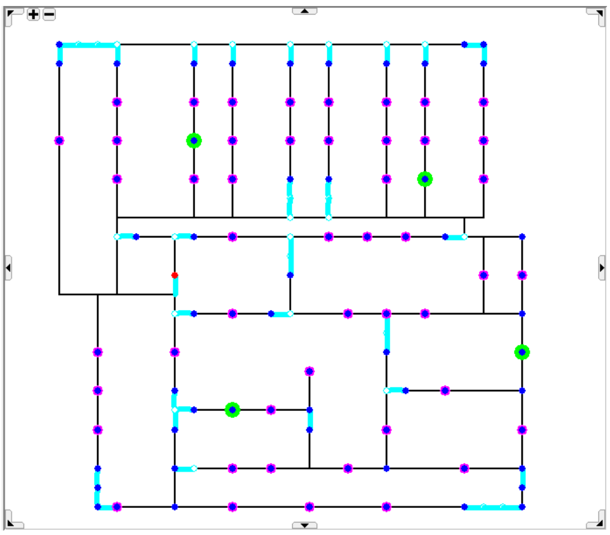


Figure 7.21: Full redundancy with penalty factor 750

Compared to the realistic scenario there are even some more redundant lines added. At the demand points where PV-Panels where present the renewable storage system is used and at the other points where no redundant lines is present the converter system is used.

Just like in the fictional case, when a penalty is added when using non sustainable energy, the optimized redundancy network shifts to the renewable storage system. The results of adding this penalty is shown in figure 7.22

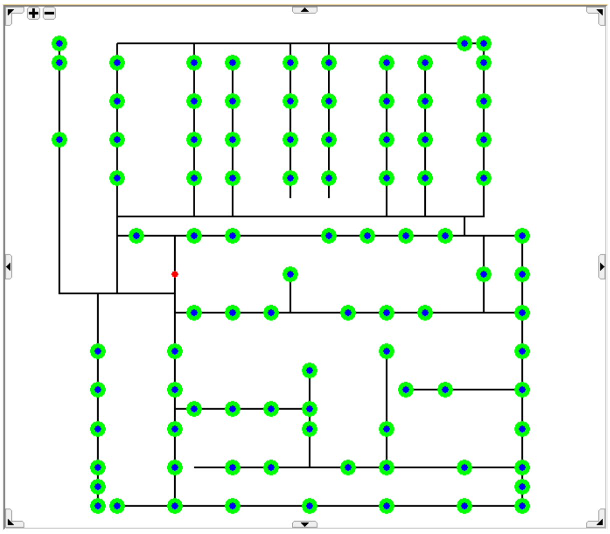


Figure 7.22: Full redundancy with non sustainability penalty

7.3.5 Results

The results from the real case support the results found in the fictional case. Again it shows that in Dutch energy networks local redundancy optimization are not feasible. Only with extremely high unrealistic penalty factors these options will be interesting. The converter system will therefore not be feasible under normal circumstances. The renewable storage system can be used not only for redundancy but also to make renewable energy generation more efficient. It can also be used to make revenues instead of costs.

The redundant line appears to be too expensive for only households. When building demands are in a higher category (commercial or industrial) this option should be considered. With redundant lines the topology of the current network and the location of the buildings is very important.

When a sustainable solution is needed the optimization will shift to renewable storage eventually. The political commitments made by the Dutch government therefore have an influence in the optimized redundant network.

Chapter 8

Conclusion

8.1 Conclusion

In this section the conclusion of this research will be presented. The research questions drafted in chapter 1 will be answered in this chapter.

For the first research question: Can mathematical programming be used to optimize the redundancy in a power distribution network? It can be concluded from the literature study that mathematical programming is an excellent resource for this optimization problem. This is supported by the model in AIMMS

For the second research question: Which method of mathematical modelling suits this problem best? It was possible to write the problem as an linear optimization problem. Because of the both integer as continues decision variables Mixed Integer Linear Programming is used. Two stage stochastic programming is used to find the optimization with data uncertainty. The Two stage stochastic MILP method therefore appeared to be the most suitable solution for this optimization problem.

For the third research question: What is the effect of redundancy optimization in an existing Dutch power distribution grid? This research presents a two stage stochastic mixed integer linear programming model. This model is able to optimize power distribution networks based on costs minimization. These costs consist of investment costs, operational costs and penalty costs. In this optimization the possible failure of network components is taken into account. Penalty costs are added when the network fails to deliver the demanded energy. The height of these costs depend on the penalty factor which can be determined by the user. The model is able to identify locations in an existing network which could possibly use redundancy and is able to deliver a solution based on three different redundancy components.

Two case studies are conducted to demonstrate the model and show the effects of the optimization. From the case studies it can be concluded that the penalty parameter is very important in the outcome of the model. The penalty parameter converts discomfort of not receiving power to a value expressed in money. Since this parameter is arbitrary it can be adjusted by the user at his or hers own discretion. If a penalty factor is set sufficiently high, any demand point will need redundancy at some point.

The case studies show that in the Dutch distribution network redundancy is not feasible for households unless extreme penalty factors (750+) are used. This would mean that missing 1 kWh at a household would be equivalent to a €750,- penalty which is obviously very unlikely for this building category. However, when this penalty factor is used, the first redundancy option for households is the local converter system. When there are renewable energy generators (PV-panels) present the renewable storage options comes out at best. The case studies show that redundant lines are too expensive for households compared to the local redundancy solutions.

At higher demand buildings like commercial, office or industrial buildings the redundant lines are the most feasible solution according to the case studies. Redundant lines are already feasible at a penalty factor of around 20 at an industrial area. This penalty factor is assumed to be very reasonable for industrial buildings. The optimized redundant solution depends on the locations of the buildings and the current topology of the network. Also if a renewable generator is already present the most feasible option was still adding an redundant line when looking at higher demand buildings. When the solution should be more sustainable and a penalty was added to non renewable energy usage all redundant solutions eventually shift to the renewable storage option.

The energy transition towards more renewable energy usage leads to a more distributed generation of energy. In this research this is simulated by adding PV-panels to buildings. When a household is equipped with PV-panels the renewable storage is the most feasible redundancy option. However this is only achieved with an extremely high penalty factor. It can be concluded that for the Dutch energy network local redundancy options are not feasible for low demand buildings and that therefore redundancy optimization won't contribute much in the current energy transition. Adding renewable storage has more advantages then only being a redundant solution. There are environmental, financial and efficiency advantages which can make the choice for renewable storage attractive. By answering the research questions it can be concluded that the two main objectives (developing and using an redundancy optimization model) for this research, drafted in chapter 1, are achieved.

8.2 Recommendations

It should be considered that the results in this research only can be used as an indication where redundant network components could possibly be financial beneficial. This is mainly because for many parameters yearly average values are used. While the model is able to give accurate results based on the given input it is interesting to see how results are influenced with a more detailed input. An extended research is therefore necessary. It is recommended to further develop the model to approach reality. The research merely focuses on cost optimizing based on redundancy. In an actual network other factors like line capacities or peak demands should be taken into account to find the overall optimized network.

In this research the renewable storage option is seen as a method which is always able to deliver the needed energy when the grid is failing, just like the converter system and the redundant line. With the Dutch power grid in mind, this is probably possible in 95 percent of the case since power outages normally don't take very long here. However, in a winter period the renewable storage combination won't be able to deliver all the demanded energy for days where the converter system or redundant line is capable of doing so. This means that for long power outages the converter system or the redundant line is more reliable.

8.2.1 Future work

Based on the given recommendations three suggestions for future work are given to elaborate on the current research.

1. Use this model in other countries where the power grid is less reliable. The Dutch power grid is one of the most reliable grids in the world. In other countries, where component failure occurs more often, results could be different and maybe local redundancy can be feasible as well.

2. Simulate in more detail instead of working with average annual values. Simulate a day in 24 timesteps (hours) instead of two timesteps (day and night). Use the exact demand profiles instead of generalised profiles. Within the same building category large differences in demand can occur since not every household of industrial building is the same.

3. Expand the multi carrier part. Not only use a converter to extract energy from another carrier but actually also comply to the demands of this carrier. Use multiple carriers to satisfy multiple demands. This also gives more redundancy options like for example a micro CHP system which generates both power as heat in a more efficient and sustainable way.

Bibliography

[1] Ravindra K Ahuja, Thomas L Magnanti, James B Orlin, and M R Reddy. Applications of Network Optimization. *Handbooks OR MS*, 7.

[2] Mudathir Funsho Akorede, Hashim Hizam, and Edris Pouresmaeil. Distributed energy resources and benefits to the environment.

[3] Kari Alanne and Arto Saari. Distributed energy generation and sustainable development.

[4] Arturo Alarcon-Rodriguez, Graham Ault, and Stuart Galloway. Multi-objective planning of distributed energy resources: A review of the state-of-the-art. *Renew. Sustain. Energy Rev.*, 14:1353–1366.

[5] Dimitri P Bertsekas. Network Optimization: Continuous and Discrete Models.

[6] Dimitris Bertsimas, David B. Brown, and Constantine Caramanis. Theory and Applications of Robust Optimization. *SIAM Rev.*, 53(3):464–501, 2011.

[7] Fulvio Corno and Maurizio Rebaudengo. Redundancy techniques. *Time*, pages 140–152.

[8] European Commission. Energy 2020. Technical report, 2010.

[9] European Commission. Energy Roadmap 2050. 2015.

[10] European Parliament. Directive 2009/28/EC of the European Parliament and of the Council of 23 April 2009. *Off. J. Eur. Union*, 140(16):16–62, 2009.

[11] Hassan Farhangi. The path of the smart grid. *IEEE Power Energy Mag.*, 8(1):18–28, 2010.

[12] Wenjie Gang, Godfried Augenbroe, Shengwei Wang, Cheng Fan, and Fu Xiao. An uncertainty-based design optimization method for district cooling systems. *Energy*, 102:516–527, 2016.

[13] E Handschin, F Neise, H Neumann, and R Schultz. OPTIMAL OPERATION OF DISPERSED GENERATION UNDER UNCERTAINTY USING MATHEMATICAL PROGRAMMING.

[14] A D Hawkes and M A Leach. Modelling high level system design and unit commitment for a microgrid. *Appl. Energy*, 86:1253–1265, 2008.

[15] R B Hiremath, S Shikha, and N H Ravindranath. Decentralized energy planning; modeling and applicationa review ARTICLE IN PRESS. *Renew. Sustain. Energy Rev.*, 11:729–752, 2007.

[16] Siegbert Hopf, Ulrike Fleischmann, Wolfgang Fruth, Ralf Gluth, Birgitta Grandjean, Jasmin Gruner, Thomas Klimiont, Wolfgang Peter, Frank Scheunert, and Manfred Weiß. Planning of Electric Power Distribution. Technical report, 2015.

[17] M S Hossain, N A Madlool, N A Rahim, J Selvaraj, A K Pandey, and Abdul Faheem Khan. Role of smart grid in renewable energy: An overview. *Renew. Sustain. Energy Rev.*, 60:1168–1184, 2016.

[18] Way Kuo and V. Rajendra Prasad. An annotated overview of system-reliability optimization. *IEEE Trans. Reliab.*, 49(2):176–187, 2000.

[19] Xian Liu. Network optimization with stochastic traffic flows. *Int. J. Netw. Manag.*, 12(4):225–234, 2002.

[20] G. S. Mahapatra. Reliability Optimization of Entropy Based Series-Parallel System Using Global Criterion Method. *Intell. Inf. Manag.*, 01(December):145–149, 2009.

[21] M.S. Mahmoud, S. Azher Hussain, and M.A. Abido. Modeling and control of microgrid: An overview. *J. Franklin Inst.*, 351(5):2822–2859, 2014.

[22] Eugenia D. Mehleri, Haralambos Sarimveis, Nikolaos C. Markatos, and Lazaros G. Papageorgiou. A mathematical programming approach for optimal design of distributed energy systems at the neighbourhood level. *Energy*, 44(1):96–104, 2012.

[23] Reliability Modeling and Prediction B. Reliability Engineering Part 13. *Reliab. Eng.*, pages 1–4.

[24] Netbeheer Nederland NBN. Betrouwbaarheid van elektriciteitsnetten in Nederland Resultaten 2015. 2016.

[25] Netbeheer Nederland NBN. Betrouwbaarheid van gasdistributienetten in Nederland Resultaten 2015. pages 1–39, 2016.

[26] Netbeheer Nederland. Energie in cijfers. pages 1–30, 2013.

[27] Netherlands Ministry of Economic Affairs. Energierapport. 2016.

[28] Akomeno Omu, Ruchi Choudhary, and Adam Boies. Distributed energy resource system optimisation using mixed integer linear programming. *Energy Policy*, 61:249–266, 2013.

[29] Márton Pósfai, Gabriele Musella, Mauro Martino, Roberta Sinatra Acknowledgements, Philipp Hoevel, Sarah Morrison, and Amal Husseini. ALBERT-LÁSZLÓ BARABÁSI NETWORK SCIENCE.

[30] B. Sagnell. *System reliability*, volume 2. 1958.

[31] Alexander Shapiro and Andy Philpott. A tutorial on stochastic programming. *Manuscript. Available www2. isye. gatech. edu* {...}, pages 1–35, 2007.

[32] Jarmo Söderman and Frank Pettersson. Structural and operational optimisation of distributed energy systems. *Appl. Therm. Eng.*, 26(13):1400–1408, 2006.

[33] Carmen Wouters, Eric S. Fraga, and Adrian M. James. An energy integrated, multi-microgrid, MILP (mixed-integer linear programming) approach for residential distributed energy system planning A South Australian case-study. *Energy*, 85:30–44, 2015.

[34] Yun Yang, Shijie Zhang, and Yunhan Xiao. Optimal design of distributed energy resource systems coupled withenergy distribution networks. *Energy*, 85:433–448, 2015.

[35] Xiaomei Zhu, Hanif D Sherali, and Chair K Ebru Bish Kyle Y Lin Subhash C Sarin Antonio A Trani. Discrete Two-Stage Stochastic Mixed-Integer Programs with Applications to Airline Fleet Assignment and Workforce Planning Problems. 2006.