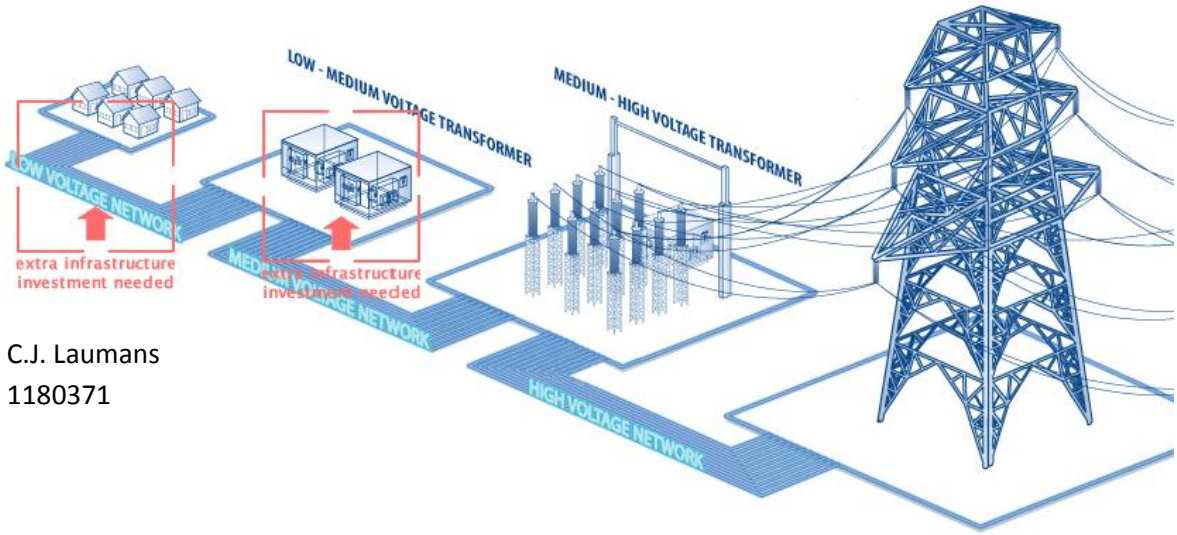
Flexibility of future energy scenarios

Investigating the flexibility of future energy scenarios to limit impact on the Dutch low voltage electricity grid



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Preface

"A journey of a thousand miles begins with a single step." - Confucius

The transition to a sustainable energy future is without a doubt a journey of millions of steps, one which we have already started. Hopefully this thesis can contribute by being one of those steps.

This thesis is about 'flexibility' and I believe that this word also characterizes the journey that it has been. I'm thankful for everyone who has helped me along the way, without them I would have never made it this far. My thanks go out to Quintel Intelligence for offering me the opportunity to do my thesis at the company and giving me the flexibility of picking a topic that interested me. I look forward to next phasese of this project. Thanks to Else Veldman from Enexis for helping me decide on a topic. Thank you to Justin Au-Yeung from Alliander for helping me with data to validate and complete my project. Thanks to Michiel van Lumig van Laborelec for providing me with electricity network configurations. Thank you to Berto Jansen from Phase to Phase for providing me with the Gaia software. And finally special thanks go to my supervisors: Alexander Wirtz from Quintel and Madeleine Gibescu from the TU Delft; although we did not meet much they helped me sort out my thoughts and kept me on track.

Chris Laumans

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A, B	Coefficients in modified Strand-Axelsson equation	(-)
a_{so}	Coefficient in Skartveit and Olseth model	(-)
C	Constant defining spread of stochastic loads	(-)
Cap	Hot water boiler storage capacity	(L)
c_o, c_1, d_{sol}	Terms in Skartveit and Olseth model	(-)
COP	Coefficient of performance	(-)
c_p	Specific heat capacity of air	(J/kg/K)
dT_i, dT_w	Change in indoor and wall temperature	(°C)
E_1	Average yearly electricity demand for one user	(W_eh)
E_{dir}, E_{diff}	Direct and diffuse components of solar irradiation	(W/m^2)
E_{et}	Global extraterrestrial irradiation	(W/m^2)
E_{horz}	Measured global terrestrial irradiation	(W/m^2)
E_{req}	Electric vehicle energy required for charging	(kWh)
E_{sc}	Solar constant	(W/m^2)
E_{sur}	Total radiation incident on surface	(W/m^2)
h	Solar elevation	(°)
H_v	Ventilation heat loss	(W)
$I_{1\Phi}$	Single-phase current	(A)
I_{max}	Current carrying capacity of a network component	(A)
K_w, K_v, K_i, K_o	Thermal conductances in thermal equivalent circuit	(W_{th}/K)
m	Maximum water flow in hot water boiler	(L/s)
n	Number of users	(-)
n_{air}	Number of ventilation air shifts	(1/s)
n_{day}	Day of the year	(-)
$P_{1\Phi,tot}$	Single-phase total power	(W_e)
$P_{avg,1}$	Average power demand of a single user	(W_e)
P_{batt}	Electric vehicle battery capacity	(W_e)
P_{boiler}	Hot water boiler electric power	(W_e)
P_{charge}	Electric vehicle charging power	(W_e)
P_{loss}	Hot water boiler heat loss	(W_{th})
$P_{max,1}$, $P_{max,n}$, $P_{max,inf}$	Peak power demand of 1, n, and an infinite number of users	(W_e)
P_{out}	Hot water boiler thermal output power	(W_{th})
P_{tot}	Total power demand at any point in a electricity network	(W_e)
q	Heat gain in thermal equivalent circuit	(W_{th})
$S_{3\Phi}$	Three-phase complex power	(W_e)
t_{arr}, t_{dept}	Electric vehicle arrival and departure times	(-)
t_{charge}	Electric vehicle charging time required	(-)
T_i, T_o, T_w	Indoor, outdoor and wall temperature	(°C)
T_{in}	Hot water boiler entering water temperature	(°C)
T_{min}, T_{max}	Hot water boiler min and max storage temperature	(°C)
t_{stop}	Electric vehicle charging stop time	(-)
V_{l-g}	Line to ground voltage	(V)
V_{nom}	Nominal line to ground voltage	(V)
Vol	Volume	(m^3)
α, β	Coefficients in Strand-Axelsson equation	(-)
α_{so}	Coefficient in Skartveit and Olseth model	(-)
β_{sur}	Tilt angle of slope of surface from horizontal	(°)
η	Electric vehicle energy use per kilometer	(W_eh/km)
θ_{horz}	Zenith angle	(°)
Θ_{sur}	Angle of incidence of the direct radiation on the surface	(°)
ρ	Density of air	(kg/m^3)
ρ_g	Ground reflectance	(-)
σ_1	Standard deviation of one user	(-)

Abstract

If the Netherlands wishes to achieve an 80% CO_2 reduction by the year 2050, technologies such as heat pumps and electric vehicles will be required to replace their fossil fuel burning counterparts. These technologies however have large consequences for electricity networks; not only will the amount of electricity transported over the networks increase, but so will the peak loads, pushing transformers and cables to their operating limits. This is a challenge that network operators are currently facing, and new methods are required to help them prepare for the future.

In this thesis the flexibility of future energy technologies with the goal of limiting network loads in the Dutch low voltage electricity grid is investigated. 'Flexibility' refers to different variations, control strategies, and combinations of technologies that exist. Focus is placed on eight electric vehicle charging strategies and five types of electric heat pumps. Solar photovoltaics, electric hot water boilers, micro CHPs, and electric heaters as well as the effect of household insulation and thermostat setting are also investigated.

The impact on the electricity grid is quantified by creating a testing environment in which the load of transformers and cables can be easily determined for any combination of market penetrations of the above technologies. Three representative low voltage networks are considered: A city, a village, and a countryside neighborhood. Calculations are carried out for a typical summer and winter day with 15 minute intervals. The technologies are modeled as Strand-Axelsson loads to take into account simultaneousness and accurately be able to predict the peak load of any number of users. The testing environment is validated by comparing the results to those obtained by Gaia, a software package specifically designed for carrying out electricity network calculations.

Power demand profiles for all technologies are created using different modeling strategies. The electric vehicles are modeled based on mobility data of 50.000 Dutch citizens. Eight control strategies are modeled, examples are: uncontrolled charging, night time charging, and vehicle to grid. To model space heating technologies a Matlab model has been constructed that accurately predicts the heat demand of a household taking into account factors such as household type, insulation, thermostat setting, and outdoor temperature. With the model the power demand profiles of heat pumps and other heaters are created by modeling their control strategies. The electric vehicle and heat pump profiles are verified by comparing the results to measured data obtained from Alliander.

The power demand profiles are entered into the testing environment and simulations are carried out. The impact of each technology on transformer and cable loads is quantified and the effects of flexibility are investigated. It is found that uncontrolled use of heat pumps and electric vehicles present problems for the electricity network: market penetrations as low as 20% could cause transformer loads to reach values above 100%. Flexibility options however do exist and can be used effectively to limit network loads.

Electric vehicles offer the most flexibility since the charging times are the easiest to control. Heating technologies have limited flexibility but improving household insulation and using the right thermostat settings can reduce network loads. Micro CHPs combine very well with other technologies and can be very effective at limiting the loads caused by both electric vehicles and heat pumps.

1 Introduction

Energy transition is a hot topic. Every day more and more people are confronted with the importance of sustainability and are becoming aware of the necessity to transition from a fossil fuel economy to a more sustainable one. The word, "Sustainability" is being used at all levels of communication and politics: From the EU goals to reduce CO_2 by 80% in 2050 down to even the household level. Energy transition and sustainability however are not simple matters; they are relatively new and complex topics. Achieving a sustainable future is not simply fixing a problem but rather creating a solution.

Managing Partner of Quintel Intelligence, John Kerkhoven, is currently in the process of building a self-sufficient house. His goal is to go 'off-grid' and become independent of the electricity and gas networks. In other words, this house will need to provide its own electricity and generate its own heat all the while creating a comfortable living environment for the household members. The house will have heat pumps, solar panels, thick wall insulation, well orientated windows for natural ventilation, and a very intelligent control system.

The house that John Kerkhoven is building is an excellent example of the possibilities as well as the challenges of energy transition. Building a regular house is a trivial matter: An architect draws up the plans, a mason lays the bricks, and an electrician places the cables. Building a self-sufficient house however is a whole new ball game. Not only is the concept of such a house rare; the work and cooperation required to achieve it is unprecedented. The architect, mason and electrician now need to work in unison creating innovative solutions to achieve the technical marvel.

Much like building a sustainable house, achieving a sustainable future requires innovation and team work. No longer will it be possible for energy producers, distributors, and consumers to work separately from each other. Sustainability implies that the practices of the past are no longer acceptable and innovation is required.

1.1 Relevant trends in the energy world

It is impossible to predict the future; however when it comes to energy transition four important trends can be identified that will most likely play an important role in shaping the future energy landscape in countries such as the Netherlands:

CO_2 emissions need to decrease dramatically

Global CO_2 emissions have increased sharply over the past 30 years leading to an increase in global temperature and rises in the sea level. With continuous discussions taking place, such as the Climate Conferences of 2009 and 2010 in Copenhagen Mexico, it can be understood that this is a relevant topic for almost all nations of the world.

In an effort to curb the effects of increasing CO_2 emissions the European Union has set the goal of achieving an 80% reduction in CO_2 emissions with respect to 1990 levels by the year 2050. To achieve these goals a severe step in electrification is required (IPCC, 2007 and EC, 2011). An 80% reduction in CO_2 emissions in a country such as the Netherlands would imply that the entire household energy demand (including transport) will need to be electric (Netbeheer Nederland, 2011).

Fossil fuels are being replaced

The second trend that is being observed is that fossil fuels are running out and/or are being replaced. Although no one can say for certain when peak oil will be achieved (or if it has happened already), many are in agreement that the fuels used to power vehicles and to warm homes are becoming scarcer (DOE, 2007). To deal with fossil fuel scarcity and to take advantage of the increase in decentralized production, fossil fuel technologies are being replaced by their electric versions (IEA, 2009 and 2011b).

Decentralized electricity production is increasing

Electricity production is clearly becoming more decentralized implying electricity consumers are starting to become electricity producers. This trend is evening being observed down at the household level. Since the year 2000 the annual growth rate of solar PV capacity has been more than 40%. The IEA predicts that in 2050 solar PV will provide 11% of global electricity production corresponding to 3000GW of installed capacity (IEA, 2010). Not only will solar panels play an important role in decentralized electricity production, also technologies such as micro CHP are expected to have a large market penetration in the coming decade (Werkgroep decentrale gastoepassingen, 2008a).

Household electricity demand is continually increasing

Not only is the number of households that have appliances such as televisions, computers, and washing machines increasing but also the number and size of these appliances per household is increasing. Because of this the household electricity demand has increased approximately 1% per year over the past thirty years and it is expected that this trend will continue (CBS, 2011a and 2011b).

1.2 Limitations of current network impact calculations and studies

Because of the four trends that are being observed it is clear that the electricity landscape is changing. All of these trends will have an effect on the electricity networks, and it is the job of network operators to deal with this; they are the link between supply and demand.

In the past network operators always maintained this link by simply predicting the effect of the growth of electricity demand and possibly adding a bit of extra capacity to deal with technologies such as electric stoves or electric boilers (VDEN, 1986). Now however, the network operators are being faced with new challenges due to the introduction of multiple technologies designed to mitigate CO_2 emissions, replace fossil fuels, and/or produce electricity. The ways of the past are no longer applicable and new research and calculation methods are required to facilitate network operators in carrying out their network planning tasks.

Network operator's dilemma

Because of the numerous technologies and possibilities that exist for future energy scenarios network operators are facing a dilemma. Their options are either speculate about the future and attempt to prepare for it, possibly investing more than is required, or wait for the future to arrive and only then take steps to deal with it, resulting in late action and possibly the inability to meet demand. Either way, the networks are at a loss (Netbeheer Nederland, 2011).

In an attempt to deal with the network operator's dilemma explained in many studies are being carried out to determine the impact of future scenarios on the electricity grid. There are however some limitations in the work that is being done.

Current methods are no longer valid due to the introduction of new technologies

The first thing that needs to be understood is that the current method of network dimensioning is no longer valid. In the past network operators have been able to successfully predict future loads by simply considering the yearly electricity demand of different user groups and adjusting for growth. The method used by network operators is called the Strand-Axelsson equation which is an empirically determined equation correlating the peak load to the yearly electricity demand (VDEN, 1986). However, due to the electrification that is taking place and the emergence of technologies such as electric vehicles and heat pumps the old method is no longer acceptable because these technologies can have a significant impact on the electricity demand of a user group. New methods to predict network peak loads are required.

Not only will the *value*s of the peak loads change significantly due to the introduction of certain technologies, it is also likely that the *time* at which the peak loads occur will change. Therefore, for accurate network planning, operators need to take into account more than just the peak load values; they should consider the entire load profile (Veldman, 2010).

Studies focus often on the effects of a large penetration of a single technology

In a search for a new method to predict network loads many studies are being carried out to determine the impact of new technologies on the electricity network. Studies such as Pruissen and Kamphuis (2010), Papdopoulos (2010), and Stifter and Kathan (2010), all focus on the effect of a single technology on the electricity networks; heat pumps, electric vehicles, and solar panels, respectively. Studies such as these are necessary however they have the limitation that they do not accurately sketch the future scenarios. Although it is impossible to predict the future, it is reasonable to assume that there will be a combination of technologies impacting the electricity network rather than a single technology. These studies therefore do not take into account the effect of the combinations of technologies.

Accurate power demand profiles for future energy technologies are rare

Above it was stated that network operators should carry out their calculations using the power demand profiles instead of just peak load values. If network operators do decide to do this however, they face the limitation that there is limited information available about these technologies. The technologies that are expected to have the largest impact on the low voltage electricity grid are relatively new and hence information is scarce. Some network operators have created simple electricity demand profiles of these technologies and used them in their load flow calculations (Oirsouw, 2010; Veldman, 2010) however more accurate profiles are desirable. Examples of the some of the limitations of these overly simplified power demand profiles are:

- Inaccurately predicting the peak load of the technology and not taking into account differences that might exist due to type of neighborhood, size of the household, behavior of the users.

- Not taking into account different flexibilities of the technology (such as choice for charging strategy or the type of heat pump).
- Not having correct values for the coincidence factors and using a simplistic approach and assuming these are 100%, and hence over predicting the peak load when aggregating multiple loads.

Simulations for a variety of possible future scenarios are not easy to carry out using existing tools

Network operators currently carry out their network dimensioning calculations using software tools such as Power Factory, Vision, Gaia, and PSS/E. These software programs have powerful calculation engines that can accurately calculate the voltages and currents in electricity networks, however they have limited flexibility and executing multiple simulations with varying degrees of market penetration of technologies in succession is not possible without writing elaborate macro scripts (Phase to Phase, 2010).

Furthermore, network operators often carry out their simulations with these tools only using the peak loads values, however if entire power demand profiles are to be used the number of calculations required increases significantly and the calculations take too long to carry out. This is not necessarily a limitation, however it is a desirable that calculations can be carried out quickly and easily when interested in predicting future network loads for multiple possible scenarios.

Innovative solutions to reduce network loads are overlooked or not considered

Assuming then that the network operators do have access to detailed information about the technologies and are able to carry out the desired load flow calculations successfully, they are faced with yet another problem: The operators will quickly come to the realization that in many scenarios costly and time consuming investments will be required to expand the electricity networks to be able to meet the demand (Rooijers and Leguijt, 2010). To deal with this network expansion is often seen as the only solution, “the networks need more copper”. The disadvantage of this is that more innovative solutions are overlooked. Some examples of innovative solutions that could be considered are: Carefully selecting combinations of technologies that could improve network utilization or decrease peak loads, working together with consumers to adjust behavior, and investigating different ways of using the technologies in question.

1.3 Problem definition

From the trends described in Section 1.1 it can be concluded that the means by which households power their homes and vehicles is becoming increasingly electric. This implies that not only will the electricity demand increase significantly, but also the loads experienced by the network will increase. To deal with the increasing loads network operators need to anticipate the future and be able to prepare the electricity networks for this transition, however from Section 1.2 it can be understood that the current body of knowledge is not adequate for determining the loads for future energy scenarios. A new method to determine peak loads in electricity networks is required. Three requirements can be described based on the trends and limitations described in Sections 1.1 and 1.2:

Realistic power demand profiles of the technologies in question are required

To be able to predict the loads of transformers and cables for different type of low voltage distribution networks it is necessary to have realistic power demand profiles of technologies such as electric vehicles and heat pumps. This implies that a few things may not be overlooked: the behavior of individuals (home hours, commute distance, thermostat settings, etc.), the behavior of groups of individuals (how multiple loads need to be aggregated), the type of household (detached, semi-detached, etc.) and the type of neighborhood (countryside, village, and city).

A means to test future energy scenarios with multiple technologies is required

It is likely that in the future the world will have a mix of different energy technologies, each with varying degrees of market penetration. Because of this is necessary to be able to easily design and test a scenario with any combination of possible technologies. Furthermore, because the future is impossible to predict the number of possibilities are endless. It is therefore necessary to be able to quickly and easily modify a scenario and again carry out network load calculations.

A stronger focus should be placed on innovative solutions that can decrease network load

Besides simply determining the load of networks and cables it is interesting to investigate if means exist by which network load can be reduced and/or networks can better be utilized. To do this, it is necessary to focus more on the technologies involved and flexibility of these technologies rather than on the consequences for the network.

1.3.2 Research question

From the requirements stated in the previous section the main research question of this thesis is formulated as:

> To what extent do future energy technologies present a problem for low voltage electricity distribution networks and can these problems be mitigated by the use of flexibility and/or by favorable combinations of technologies?

To answer the above question two sub questions are formulated which first need to be addressed:

> Can a testing environment be created that can easily and accurately determine the load of electricity network components for any given future energy scenario with various technologies and varying degrees of market penetration?

> Can the power demand profiles of energy technologies such as electric vehicles, space heating systems, solar panels, and hot water boilers accurately be modeled, taking into account factors such as user type and behavior?

1.3.3 Scope definition

To answer the questions listed in Section 1.3.2 it is necessary to define the framework of the thesis. The following scope is defined:

- The research will be limited to residential low voltage networks. Three electricity networks are considered: Countryside, village, and city. All loads in the considered networks are from household users; industry or office users are not taken into consideration.
- In the networks considered only the load of the transformer and the load of the cables at the exit of the transformers are calculated. Load is defined as the current divided by the current carrying capacities of the network components.
- In addition to the regular household load due to common appliances, the following technologies are considered in this thesis: Solar PV, electric vehicles, electric water boilers, micro CHP, electric heaters, heat pumps, and air conditioners.
- The thesis will focus in particular on electric vehicles and heat pumps. Eight electric vehicle charging strategies and five types of heat pumps are considered. Additionally, for the heating technologies the effect of household insulation and thermostat settings is also taken into account as well as differences due to household/neighborhood type.
- The investigation is conducted by considering power demand profiles of the technologies mentioned for a typical summer and a typical winter day. Power demand profiles consisting of 15 minute data will be modeled for all the technologies mentioned.

1.4 Outline of the thesis

To answer the research question identified in the previous section, three steps will be carried out.

This research project is carried out for Quintel Intelligence, the makers of the Energy Transition Model (ETM). A very short introduction to the ETM is given in Chapter 0.

In Chapter 3 the first sub question of the research question will be answered. It will be explained how a testing environment is created in which simulations can easily be carried out and the how load of cables or transformers are calculated. The testing environment is verified by comparing the results obtained to those obtained by Gaia, a software tool specifically designed for network calculations.

In Chapters 4-6 the second sub question will be answered by explaining how the various power demand profiles used as input in the testing environment are created. In Chapter 4 it is explained how the power demand profiles for electric vehicles have been created by using mobility data from more than 50.000 Dutch citizens. In Chapter 5 the power demand profiles for space heating technologies are created. This has been done by first creating a Matlab model that accurately predicts household heat demand with consideration for factors such as insulation, house type, and indoor and outdoor temperatures. In Chapter 6 it is explained how the power demand profiles of the remaining technologies are modeled (solar panels, electric boilers, and household appliances). The power demand profiles for electric vehicles and heat pumps are verified by comparing the modeled profiles to measured data obtained from network operators.

In Chapter 7 the results of Chapters 3 through 6 are combined by inserting the power demand profiles into the testing environment. In this chapter the research question is answered. Simulations

are carried out to determine the impact of future energy technologies in the three neighborhoods considered. The investigation is carried out in three parts: First the impact of the base technologies is determined. Then a comparison of the different flexibility options is given and it is determined which are the most beneficial for the electricity network. Finally, combinations of technologies are also simulated to determine what synergies exist between the various technologies and how utilization of the electricity grid can better be optimized.

The results presented in Chapter 7 are more theoretical of nature; therefore in Chapter 8 a discussion of these results is presented by giving consideration to the expected developments of the relevant energy technologies in the Netherlands. Based on the expected developments the implications for the network operators will be discussed.

In Chapter 9 conclusions are drawn. And finally, in Chapter 0 recommendations are given. Recommendations are given for further research, network operators, and for Quintel Intelligence.

2 Introduction to the Energy Transition Model

This thesis project is carried out for Quintel Intelligence, developers of the Energy Transition Model (ETM). In this section a short introduction is given to the ETM.

The ETM is a free to use energy scenario building tool available at www.energytransitionmodel.com. The first version of the ETM was launched in April 2009 and the model is continually being developed by Quintel Intelligence. The model was first created because Quintel noticed a lack of knowledge about the subject of energy transition among politicians, students, consumers, and even among the management of large energy companies. Although some people are knowledgeable about energy their knowledge often does not extend beyond their own field and hence they do not fully grasp the scope and/or the complexity of the problem. With this in mind Quintel Intelligence created the ETM to help communicate the problem of energy transition to the various stakeholders and to promote knowledge development on the subject.

The ETM has been created by working in close cooperation with various partners all involved with energy. A few examples of the numerous partners are: GasTerra, Netbeheer Nederland, Alliander, Enexis, Stedin, Tennet, Essent, Eneco, Shell, and the Municipality of Amsterdam. By working together with these partners Quintel has been able to create an independent, comprehensive, and fact-based model which can be used to communicate issues of energy transition to any audience.

Workings of the model

The Energy Transition Model is a scenario building tool which differentiates itself from other energy scenario tools such as the IEA World Energy Outlook (IEA, 2011a) and Primes (NTUA, 2008). Unlike these models, the ETM does not make predictions about the future, such as what the oil price will be in 2040; instead, these are left to the users. The ETM is therefore not a black box.

With the ETM, users can make their own predictions about what will happen in the future and the model will calculate the effect of these predictions on parameters such as: Energy dependence, CO_2 emissions, cost of energy, and share of renewable energy. A few examples of predictions that the user can make are:

- How will the price of fossil fuels change in the future?
- How will the country supply its electricity? How many coal power plants will we have? How many wind turbines will we have?
- Will the investment costs of technologies such as solar panels decrease? By how much?
- What type of heating systems will be used in households?
- What percent of vehicles will be electric vehicles?

One of the advantages of the ETM is that the model works in real time. This means that after every prediction the user is immediately provided with feedback on this decision. With this users can immediately and quickly compare the effect of different decisions; for example, what is the effect of replacing half of all lights with more efficient versions such as LEDs vs. replacing all lights with LEDs?

Further development of the model

The ETM is continually being developed in both scope and breadth. In addition to creating versions of the model for different countries, provinces, and cities the model is also continually being expanded by including new calculations providing its users with more information about their scenarios.

One of the projects recently conducted was in cooperation with Netbeheer Nederland and network operators Tennet, Alliander, Enexis, and Stedin to determine the impact of future energy scenarios on the Dutch electricity grid. During this project calculations were created that determine how much additional network capacity is required in the various levels of the electricity network for different future energy scenarios. The result of this project was a module in the ETM in which users are provided with feedback about the investment required in the electricity network depending on the scenario they have created.

This thesis work is a continuation of the above project in which methods to reduce the investment required in the electricity network through use of smart combinations of technologies or through use of flexibility are investigated.

3 Creation of a scenario testing environment

The first step in determining the impact of future energy technologies on the low voltage electricity grid is creating a testing environment in which the load of cables and transformers can easily be determined for different future energy scenarios. In this Chapter the testing environment created for this project will be introduced in three sections. In Section 3.1 the requirements of the model will be explained by considering the current methods used to dimension electricity networks. Based on these requirements the testing environment created will be described in Section 3.2. Finally, in Section 3.3 the testing environment will be verified by comparing the results of the testing environment to those obtained by Gaia, a software tool used by network operators for, among other things, low voltage network dimensioning.

3.1 Current methods of network dimensioning

To determine the sizes of and required equipment for an electricity network, network operators carry out load flow calculations using predicted future loads to determine the load of critical parts of the network (usually the transformers and the first section of the feeders). Based on this network operators can conclude whether it is necessary to add additional capacity to certain networks. In this section the basics of network dimensioning will be explained followed by the limitations of the current method.

3.1.1 Network models

Typical low voltage distribution networks consist of a transformer with 3-8 three-phase feeders providing electricity to 50-400 households (VDEN, 1986). Figure 3.1 shows a model of a low voltage distribution network created in Gaia. As can be seen each household is represented as a load (shown as an arrow) and is attached to a node. Between the nodes are cables, for which the cable type is defined. The cables shown Figure 3.1 are three-phase cables. The slack bus is the bus to the left of the transformer with the voltage source.

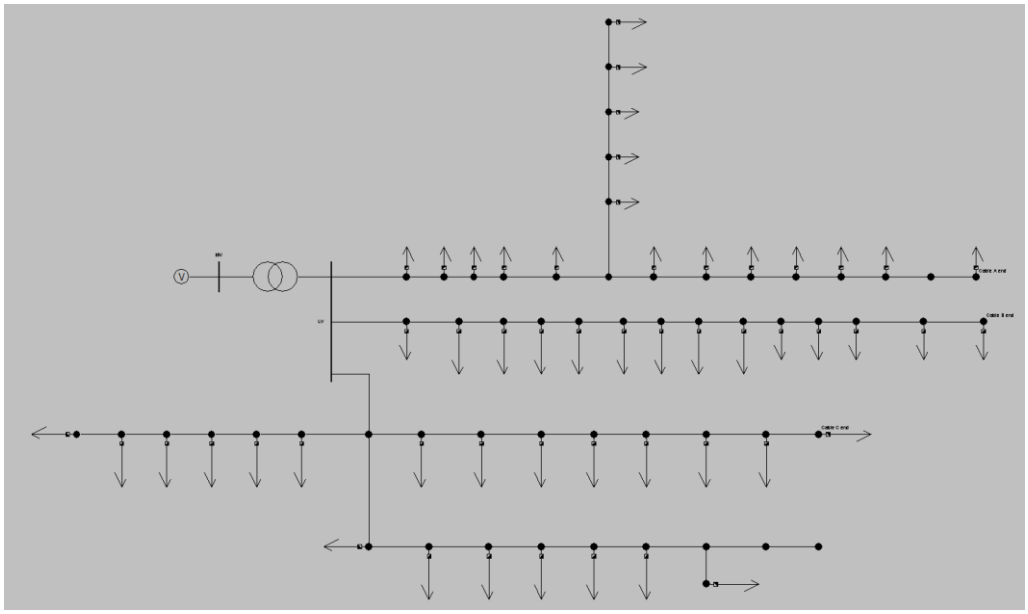

Figure 3.1: Configuration of a countryside low voltage residential distribution network constructed in Gaia

With models such as the one shown in Figure 3.1 it is possible to carry out load flow calculations by assigning each household a load. In such calculations, network operators assign each load a single value, the measured peak power. Software such as Gaia can carry out the calculations automatically and generate reports showing any parameters of interest such as the load of the transformer or any cable part.

3.1.2 Strand-Axelsson model

A limitation of the network model shown in Figure 3.1 is that each household is represented separately and the calculation time to solve the load flow is high. To simplify this, network operators use the Strand-Axelsson equation. The Strand-Axelsson equation is used to determine the peak power demand of multiple users, meaning that similar users can be grouped together into a single load. The equation takes into account that the coincidence factor decreases as the number of users increases (Phase to Phase, 2006). The Strand-Axelsson equation describes a correlation between the peak power of n users of the same type and the yearly electricity demand of those users. The Strand-Axelsson equation to calculate the peak power demand of n users is:

$$P_{max,n} = \alpha E_1 n + \beta\sqrt{E_1 n} \tag{3.1}$$

With:

$P_{max,n}$ – Peak power demand of n users [kW]
n – Number of users
α and β – Empirically determined coefficients depending on the type of user
E_1 – Average yearly electricity of a single user [kWh]

By using the equation described above it is possible to create a simpler model of the electricity network considered. Figure 3.2 shows a simplified version of the network in Figure 3.1 with Strand-Axelsson loads instead of individual loads. For each Strand-Axelsson load the number and type of user is defined, this is seen in captions next to the loads. For the most common user types values for α and β are available in literature or in software programs such as Gaia.

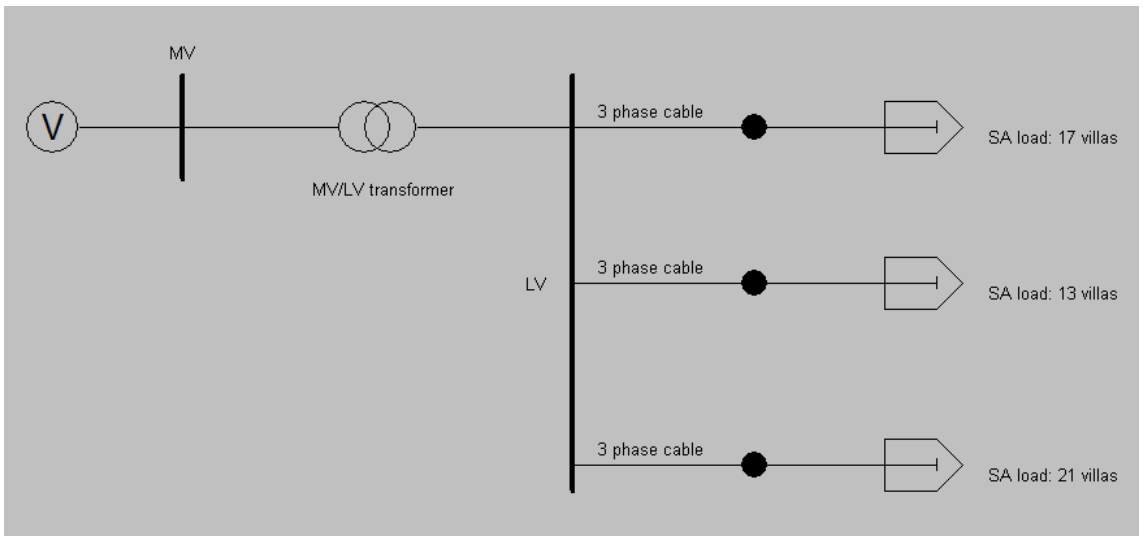

Figure 3.2: Simplified countryside low voltage network using Strand-Axelsson loads

3.1.3 Determining network load

Once the network model is created and the loads are defined it is possible to carry out load flow calculations. When dimensioning electricity networks, two values of interest are the maximum load of the cables and the load of the transformer. The method for determining each is described here.

Cable load

The load that a cable can carry is limited by its current carrying capacity, also called its ampacity. The current carrying capacity is the electric current which a cable can continuously carry while remaining in a safe temperature range. As the current increases the temperature of the cable increases due to the resistance of the cable. When operating at high temperatures due to high currents, cables age quicker, shortening the life time of the cable. At certain temperatures parts of the cable can melt and cause deformations increasing the chance of a failure occurring. The current rating of a cable is dependent on several factors such as the insulation temperature rating, the conductor electric properties, the environment and the environment's ability to transport heat (Slootweg et al., 2007; VDEN, 1986).

In low voltage networks the most common cables are aluminum or copper, with PVC being the most common insulation material used for cables in the Netherlands. The diameters vary from 6mm^2 to 150mm^2 in the low voltage network. The larger diameter cables are found in city areas (VDEN, 1986).

The load of the cable is calculated by dividing the current in the cable by its current carrying capacity. Cable manufacturers provide the nominal current carrying capacity for their cables, and these values can be used to determine the load. It is however important to note that factors such as the thermal diffusivity can affect a cable's current carrying capacity (Slootweg, 2007). In three-phase cables the load can differ per phase, in such cases the maximum current of the three-phases is used to determine the load of the cable (Phase to phase, 2006).

Transformer load

A transformer's capacity is limited by the allowable temperature of the insulation material. At high temperatures the insulation will degrade quicker, shortening the lifetime of the transformer. Above a certain temperature the transformer will become irreversibly damaged. This temperature is dependent on the type of transformer and the chosen insulation material (VDEN, 1986).

Similar to cables, transformers also have a current carrying capacity. Transformer capacity is often expressed in complex power, however the current carrying capacity can be found by dividing the capacity by the nominal voltage.

$$I_{max} = \frac{S_{3\phi}}{3V_{l-g}} \tag{3.2}$$

With:

$S_{3\Phi}$ – Three-phase complex power of the transformer [kVA]
$V_{l\text{-}g}$ – Line to ground voltage [V]
I_{max} – Single-phase current carrying capacity of the transformer [A]

For medium/low voltage transformers the three-phase capacities range from about 160kVA to 630kVA (for small to large networks). The single-phase current carrying capacity of a 160kVA transformer assuming nominal voltage at the exit of the transformer is therefore calculated to be 232A.

In general it is the case that the current carrying capacity of the cables is higher than that of the transformers; the reason for this is that cables are often over dimensioned because of the high costs associated with installing underground distribution cables in urban areas (Lampropoulos, 2009; Hooijmans, 2010). The transformer load can be calculated by dividing the largest current of the three-phases by the transformers ampacity.

3.2 Scenario testing environment to predict network loads

In this section the testing environment will be explained. Currently the testing environment is an Excel document, however in the future the model will be integrated into the Energy Transition Model and it will be an online tool. In this section the essentials of testing environment are given, more information about the structure of the testing environment as well as screenshots can be found in Appendix A.

3.2.1 Assumptions

The testing environment that will be described in the next sections has a few assumptions:

- Only low voltage radial networks are considered. The testing environment created is only valid for low voltage distribution networks that are radially fed. This is an important requirement when using Strand-Axelsson loads (Phase to Phase, 2006).
- Only three typical low voltage residential distribution networks are considered. These networks have been obtained from Laborelec (2009).
- Only the load of the transformer and the load of the cables at the exit of the transformer are calculated. The load is calculated by considering the current and the current carrying capacities in the network components. Only these parts are considered because they experience the highest currents in radial networks and because the Strand-Axelsson equation loses validity at low values of n which occur toward the end of feeders (Laborelec, 2010).
- Loses in the cables and transformer are ignored.
- Nominal voltage is assumed at any point in the feeder and at the transformer.
- A power factor of 0,9 is used (Kersting, 2002; VDEN, 1986).
- Variations in ground temperature, soil type, etc. are ignored. The ground thermal resistivity is assumed to be 1km/W. The current carrying capacities of the cables are taken from Gaia, which were provided by cable manufacturers (Phase to Phase, 2006).
- Every technology can be described as a Strand-Axelsson load with its own set of coefficients.
- Every Strand-Axelsson load type is considered independent of each other. This implies that the peak loads of individual Strand-Axelsson loads can be added to determine the total load.
- Each household is connected to a single-phase and the neutral. Houses with three-phase connections are not considered.
- The households are evenly distributed over the phases.

3.2.2 The three electricity networks considered

Three representative low voltage residential distribution networks are considered: A countryside network with detached houses, a village network with semi-detached houses, and a city network with row houses. Table 3.1 describes the three networks.

Table 3.1: Characteristics of the three low voltage networks considered (Laborelec, 2009)

Parameter	Units	Countryside	Village	City
Number of houses	#	51	181	138
Type of houses	-	Detached	Semi-detached	Row houses
Transformer capacity	kVA	160	400	315
Feeder ampacity	A	185	240	240
Number of feeders	#	3	5	5
Number of houses on feeder A	#	17	28	32
Number of houses on feeder B	#	13	40	42
Number of houses on feeder C	#	21	55	18
Number of houses on feeder D	#	-	23	40
Number of houses on feeder E	#	-	35	6

It is assumed that each household is attached to a separate phase and that the households are evenly distributed over the phases. In the figures in the following sections this assumption is not depicted.

3.2.3 Calculation method

In this section the calculation method of the testing environment is described. The load of the transformer and the cables is calculated by first modeling the energy technologies as Strand-Axelsson loads and then determining the currents in the cables and the transformers.

Strand-Axelsson equation for new technologies

The Strand-Axelsson equation describes the relation between yearly electricity demand and peak power demand for different types of users. Examples of user types identified by Strand-Axelsson are: Villas, flat apartments, mixed households, etc. (VDEN, 1986). For each user type the coefficients α and β are determined. These coefficients remain valid as long as the power demand profiles of the user type remains approximately the same. However, due to the introduction of high energy consumption technologies such as electric vehicles not only does the total electricity demand change, but so does the shape of the profiles. The coefficients determined for each user group therefore lose validity when attempting to take into consideration technologies such as heat pumps and electric vehicles (Laborelec, 2010).

To deal with the above stated problem, each technology with a different power demand profile is given its own set of Strand-Axelsson coefficients. In this manner the original Strand-Axelsson equations can still be used to predict the peak power of a collection of households and new Strand-Axelsson equations are created to describe the new technologies. For households the original Strand-Axelsson equation described in Equation (3.1) is used. For technologies such as heat pumps or electric vehicles the equation is slightly modified:

$$P_{max,n} = An + B\sqrt{n} \tag{3.3}$$

In the modified Strand-Axelsson equation αE_1 is replaced with A and $\beta\sqrt{E_1}$ is replaced with B, eliminating the electricity demand. With the above equation it is possible to describe the relation between the number of users and the peak power demand of said users for any technology.

The coefficients A and B of Equation (3.3) can be determined using simultaneous equations since there are only two unknowns in the equation. Solving the equation requires knowing values of $P_{max,n}$ and n. $P_{max,n}$ can be described in terms of $P_{max,1}$ and $P_{max,inf}$:

$$P_{max,n} = P_{max,inf}n + (P_{max,1} - P_{max,inf})\sqrt{n} \tag{3.4}$$

With:

$P_{max,inf}$ – Average peak power demand per user for an infinite number of users [kW]
$P_{max,1}$ – Peak power demand of a single user [kW]

Equation (3.4) is derived from the models of Rusck and Strand-Axelsson (Phase to Phase, 2008). The equation states that the peak power demand of n users approaches $P_{max,inf}$ as the number of users increases. Comparing equations (3.3) and (3.4) it can be concluded that:

$$A = P_{max,inf} \tag{3.5}$$

$$B = P_{max,1} - P_{max,inf} \tag{3.6}$$

The values for $P_{max,inf}$ and $P_{max,1}$ are obtained from knowledge of the power demand profiles of the technologies considered. $P_{max,1}$ is the maximum capacity of an individual unit and $P_{max,inf}$ is the maximum value obtained after averaging sufficient individual profiles. In this thesis 1.000-15.000 individual power demand profiles are used to determine $P_{max,inf}$ for each technology.

The values determined for the coefficients A and B for the different technologies are found in Appendix C.

Aggregating multiple Strand-Axelsson loads

Since each technology as well as the base household load are represented as separate Strand-Axelsson loads, a method to aggregate these is required. It is assumed that the Strand-Axelsson loads are independent of each other and therefore the aggregated power demand can be determined by summing the peak power demands determined for each Strand-Axelsson load.

Figure 3.3 visualizes what the electricity networks look like with separate Strand-Axelsson loads. In the figure two technologies are shown in additional to the base household load; it is shown how each Strand-Axelsson load is added separately.

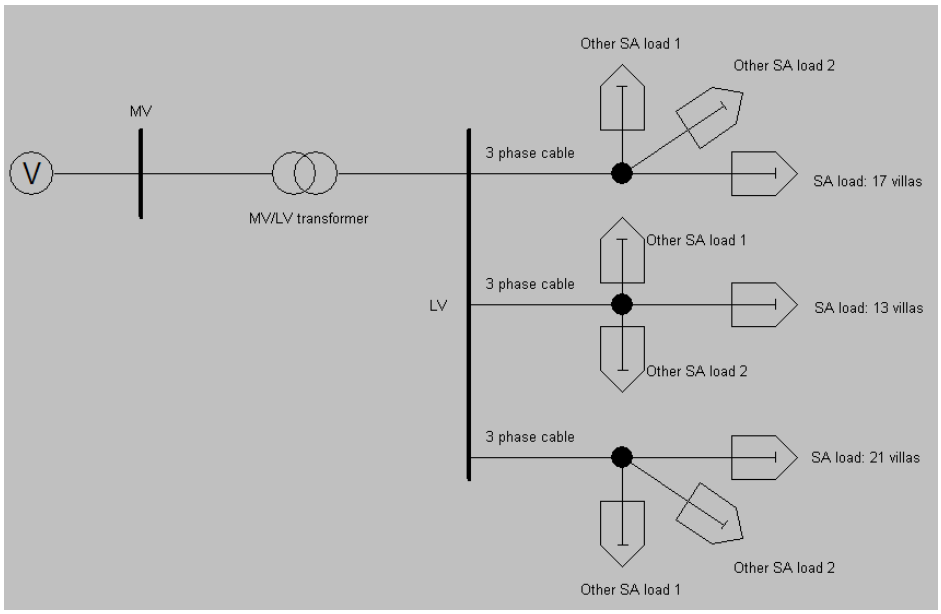

Figure 3.3: Low voltage distribution network with separately represented Strand-Axelsson loads

At each cable the total power demand is determined by summing the Strand Axelsson loads:

$$P_{tot} = P_{SA,house}(n) + \sum P_{SA,technology}(n) \tag{3.7}$$

With:

P_{tot} – Total power demand at any point in the network [kW]
$P_{SA,house}(n)$ – Strand Axelsson load due to n household users [kW]
$P_{SA,technology}(n)$ – Strand Axelsson load for n users of the technology considered [kW]

Calculating transformer and cable loads

The transformer and cable loads are calculated by first determining the maximum currents in the cables and the transformers. It is assumed that the houses are distributed evenly over the phases, and by using the equations described in the previous section the current in each phase can be found. The single-phase currents are estimated with the following calculation:

$$I_{1\phi} = \frac{P_{1\phi,tot}}{0{,}9 \cdot V_{nom}} \tag{3.8}$$

With:

$I_{1\Phi}$ – Single-phase current [A]
$P_{1\Phi,tot}$ – Single-phase total real power [kW]
V_{nom} – Nominal line to ground voltage [V]

A power factor of 0,9 is assumed for the household load and all technologies considered (VDEN, 1986; Verzijlbergh, in press; Kersting, 2002). The voltage decreases over the length of the cable, however nominal voltage is assumed. In Section 3.3 it will be shown that the errors due to this assumption are within reason.

In the testing environment the powers are calculated for each phase separately by considering the number of users on each phase. The largest value is used to determine the maximum current in a single-phase. The power in any point of the network is found by using the Strand-Axelsson equations described in the previous section.

From the maximum current the load of a cable is found with:

$$Load = \frac{I_{1\Phi,cable}}{I_{max}} \cdot 100\% \tag{3.9}$$

$I_{1\Phi,cable}$ is the calculated current in the cable, this depends on the power and hence the number of users on the cable. I_{max} is the current carrying capacity of the cable, which can be obtained from cable manufacturers. The network loads are expressed in percent.

In a similar manner the load for transformers is determined. The current carrying capacity for the transformers is determined using Equation (3.2).

3.3 Verification of the scenario testing environment

In this section the results of the testing environment will be compared to results obtained by Gaia, a software program designed to carry out load flow calculations. A comparison is made between the load profiles of the cables and transformers of a country side neighborhood for a summer and winter day.

The verification consists of three parts. First the voltage drop over the length of a feeder will be shown to determine the error that results from assuming nominal voltage. Then it will be shown that Strand-Axelsson equations can sufficiently accurately model the aggregation of individual loads (this verification is done in Gaia). Once this has been shown it will be shown that the testing environment produces similar results as Gaia. For the verification six scenarios are considered: Only the base household load, only load due to electric vehicles, only load due to heat pumps, base household load plus electric vehicles, base household load plus heat pumps, and base household load plus solar panels.

3.3.1 Effect of assuming nominal voltage

In Equation (3.8) nominal voltage is assumed to calculate the currents at the start of the feeder. In this section this assumption will be tested by considering the loading of a single feeder with 55 loads (the most number of loads in a feeder considered in this thesis, see Table 3.1). The length of the cable is taken as 550, equal to the longest cable considered in this thesis. Note: the longest cable and the most heavily loaded cable are not the same cable, this combination is used however to determine the largest possible error.

The cable type considered is 4x150 VVMvKsas/Alk. The loads are evenly distributed over the cable length and constant power load behavior is assumed. The network is heavily loaded, each load is 2,5kW with a power factor of 0,9. The start of the feeder is strongly overloaded because of this (in

Gaia the calculated load is 97%). Figure 3.4 shows the line to ground voltage over the length of the cable, as calculated by Gaia. The voltage decreases from nominal voltage, 230V to 213,9V.

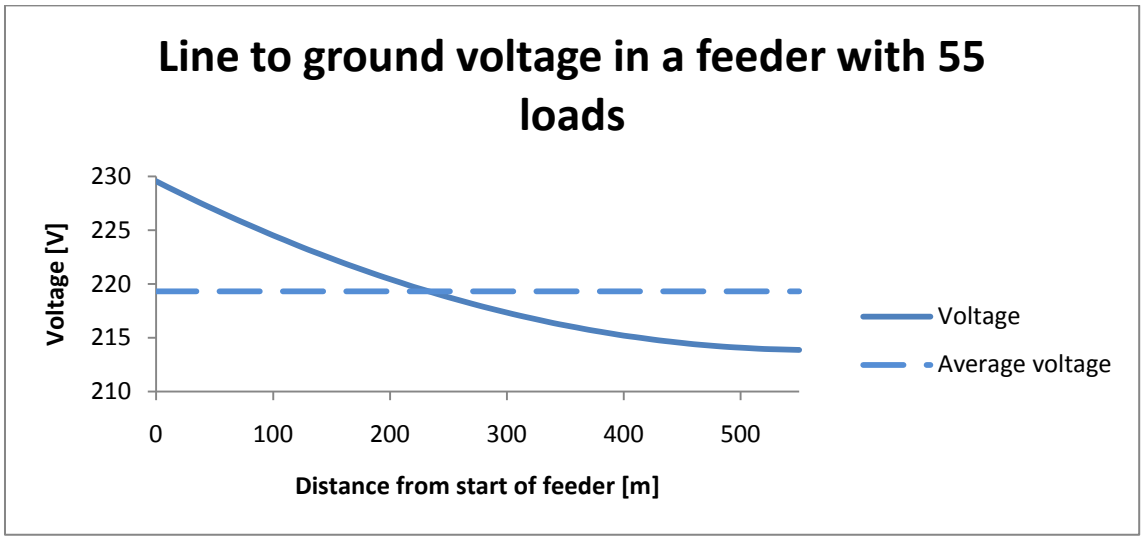

Figure 3.4: Line to ground voltage and current over the length of a cable with 60x2kW loads evenly spaced over 600m calculated in Gaia and the average values

In the testing environment only the voltage at the start of the feeder is calculated, therefore it is not necessary to calculate the voltage at every point in the cable and an average value is suitable. The average voltage in the above figure is 219,3V.

By assuming nominal voltage instead of using this lower average voltage value, the error produced is $1 - \frac{219,3}{230} = 4,78\%$. With larger loads the voltage will drop further, resulting in larger errors, however at this point the loads in the cable are already above 100%. Therefore it can be concluded that for by assuming nominal voltage the largest error that will be obtained in this thesis work will be approximately 5%.

If one wishes to obtain a more accurate value for the average voltage then an option is to use the following estimation suggested by (Kersting, 2002). The equation is an approximation of the voltage drop from the start of a distribution cable to end of the cable, assuming evenly spaced loads over the length of the feeder.

$$V_{drop} = RE\{0,5 \cdot Z \cdot I_{tot}\} \tag{3.10}$$

With, V_{drop} being the voltage drop from the start to the end the cable, Z the total impedance of the cable given by $z \cdot l$, and I_{tot} the total single-phase current. This equation assumes that the loads are evenly distributed along the feeder cable.

Kersting (2002) showed that the error in the above approximation are small, in an example given in Kersting (2002) the error was 0,27%. The above equation can be used to calculate the voltage drop from any point of the feeder to the end, and with it the average value can also be found. Because of time constraints in this thesis the above calculations were not included here and nominal voltage is assumed.

3.3.2 Verification of using Strand-Axelsson equations

The first verification is carried out in Gaia. Two networks are considered, the network shown in Figure 3.1 and a network similar to the one shown in Figure 3.3. In the first network each household is modeled separately and is assigned an individual power demand profile for an electric vehicle (the source of these profiles is described in Chapter 4). In the second network the households and electric vehicles are grouped as Strand-Axelsson loads. The verification is carried out by comparing the resulting load profiles of the cables and the transformers, the following figures show these profiles.

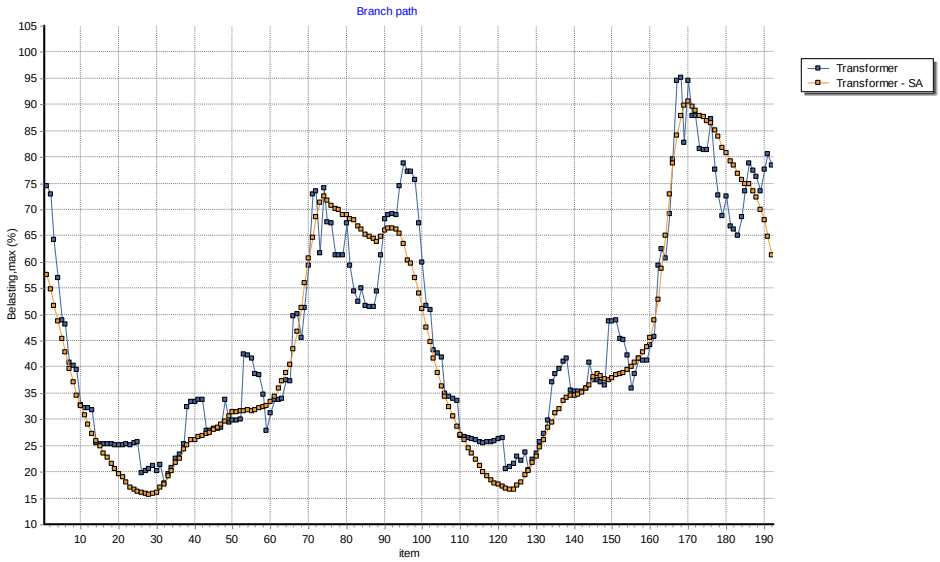

Figure 3.5: Comparison between Strand-Axelsson loads and individual loads, summer and winter day –Transformer load

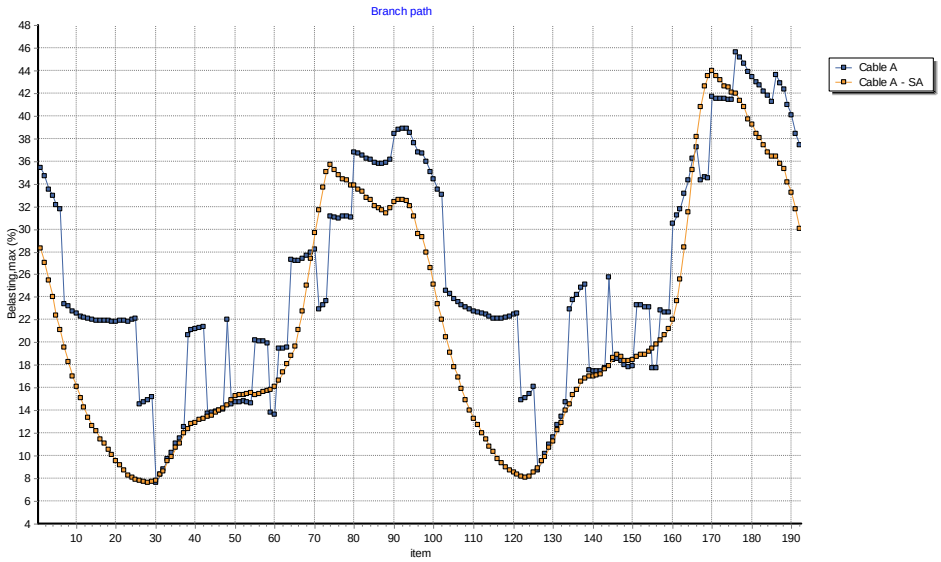

Figure 3.6: Comparison between Strand-Axelsson loads and individual loads, summer and winter day – Load of Cable A

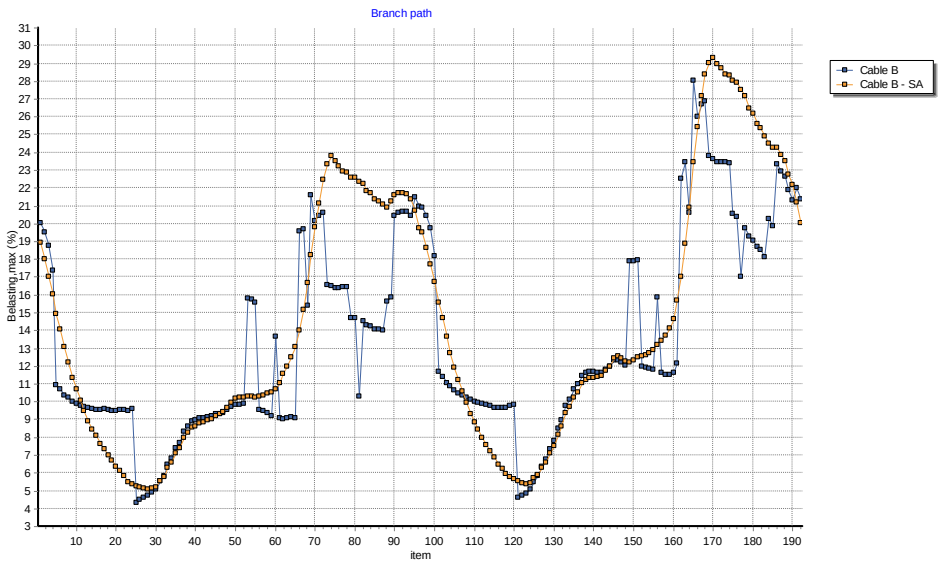

Figure 3.7: Comparison between Strand-Axelsson loads and individual loads, summer and winter day – Load of Cable B

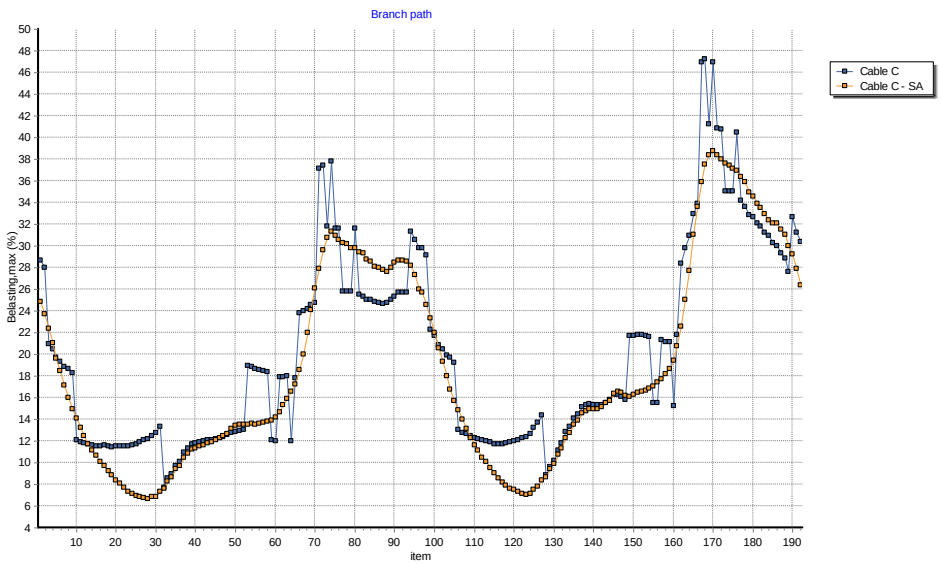

Figure 3.8: Comparison between Strand-Axelsson loads and individual loads, summer and winter day – Load of Cable C

From Figure 3.5 through Figure 3.8 it can be seen that the Strand-Axelsson equations are good at representing the trend of the profiles. Table 3.2 summarizes the calculated peak loads for both networks.

Table 3.2: Peak network loads calculated using individual and Strand-Axelsson loads

Network component	Number of loads	Strand-Axelsson peak load	Individual loads peak load	Difference
Transformer	51	91%	95%	4,2%
Cable A	17	44%	46%	7,7%
Cable B	13	29%	28%	-3,6%
Cable C	21	39%	47%	17%

The difference between the calculation using the Strand-Axelsson loads and using individual loads are moderate. In three of the four cases the peak load of the Strand-Axelsson network are lower, this however is due to the calculation method used by Gaia when adding Strand-Axelsson loads. It will be shown in the next section that testing environment does a better job adding the Strand-Axelsson loads.

It is important to note that when using individual loads the resulting profiles are highly stochastic and the results will vary from simulation to simulation. These differences decrease as the number of loads increase since the individual loads aggregate into the average load profile. However it can be concluded that the Strand-Axelsson equations are representative of what is happening in reality. There are two advantage of using Strand-Axelsson equations over individual loads: Firstly, it is not necessary to assign each load a separate profile, and secondly the calculation time can be reduced dramatically.

3.3.3 Verification of the scenario testing environment results

In this section the results obtained from the testing environment are compared to those obtained by Gaia. Six scenarios will be compared, for each scenario a comparison will be made between the load calculated for cable A and for the transformer in a countryside network. The first three scenarios are a comparison of only individual technologies. The second set of three scenarios are combinations of the base household load plus one additional technology.

In addition to the base household loads the three technologies chosen are electric vehicles, heat pumps, and solar panels. These three technologies are chosen because each has different peak loads and coincidence factors. Electric vehicles have a moderate peak load ($P_{max,inf} = 0,93kW$) and a low coincidence factor (31%). Heat pumps have a high peak load ($P_{max,inf} = 2,60kW$) for a countryside household) and a high coincidence factor (95%). And finally, unlike electric vehicles and heat pumps, solar panels produce electricity and have a moderate peak load ($P_{max,inf} = 1,5kW$) and a high coincidence factor (100%). (The values for $P_{max,inf}$ and the coincidence factors are found in Appendix C).

The following figures show the resulting load profiles for cable A and the transformer as calculated by both Gaia and the testing environment.

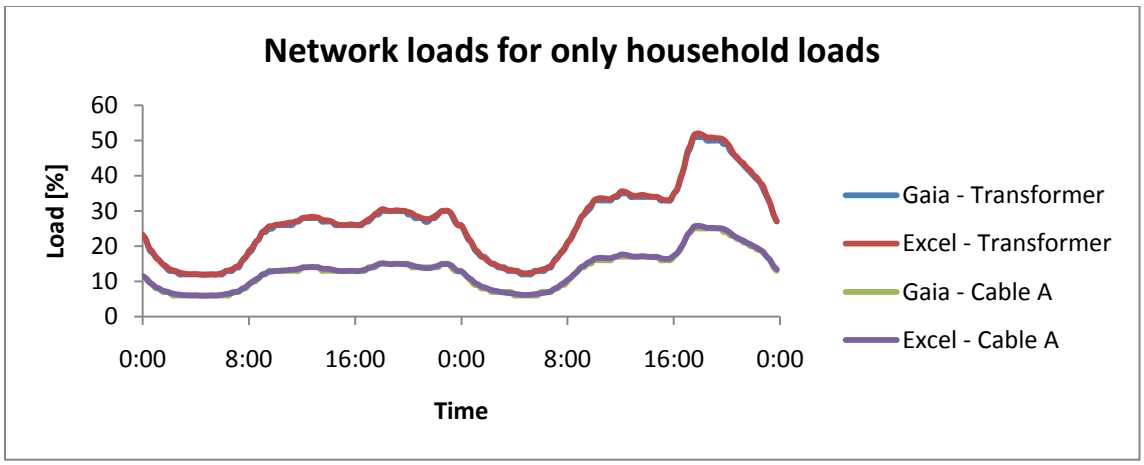

Figure 3.9: Comparison between calculated network loads by testing environment and Gaia, summer and winter day - Household loads only

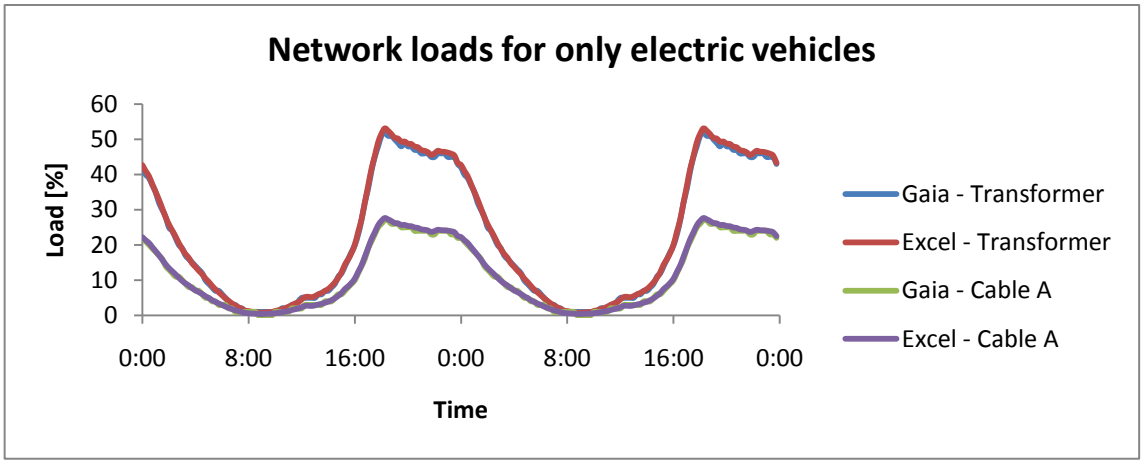

Figure 3.10: Comparison between calculated network loads by testing environment and Gaia, summer and winter day - Electric vehicles only

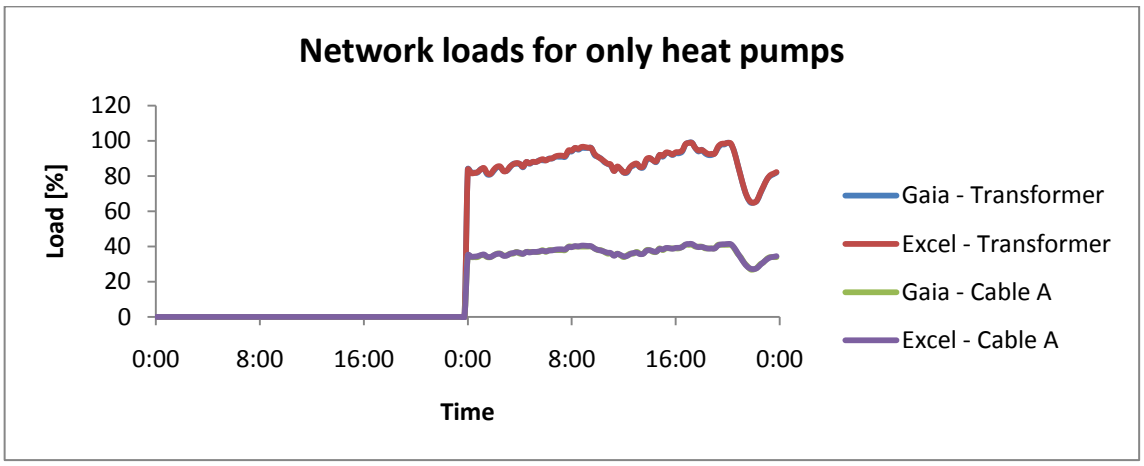

Figure 3.11: Comparison between calculated network loads by testing environment and Gaia, summer and winter day - Heat pumps only

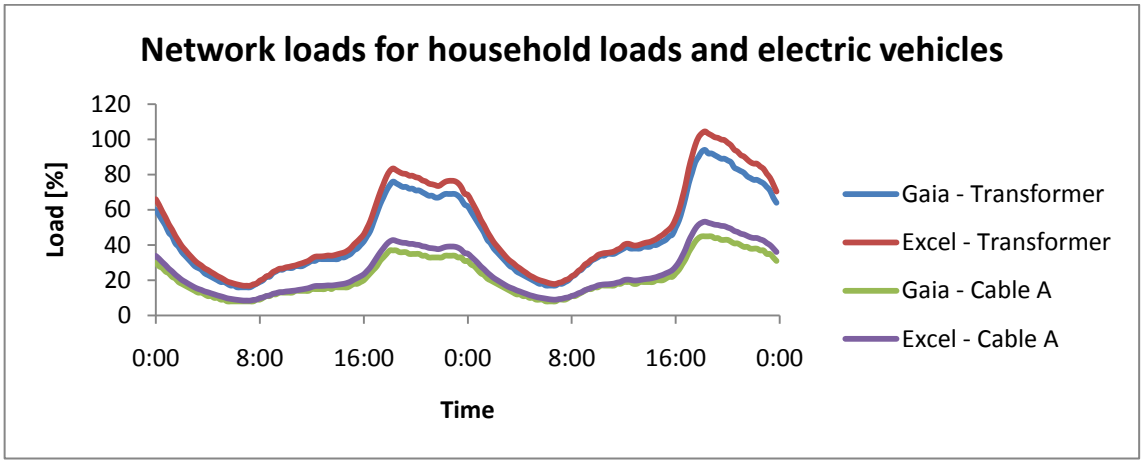

Figure 3.12: Comparison between calculated network loads by testing environment and Gaia, summer and winter day - Household loads and electric vehicles

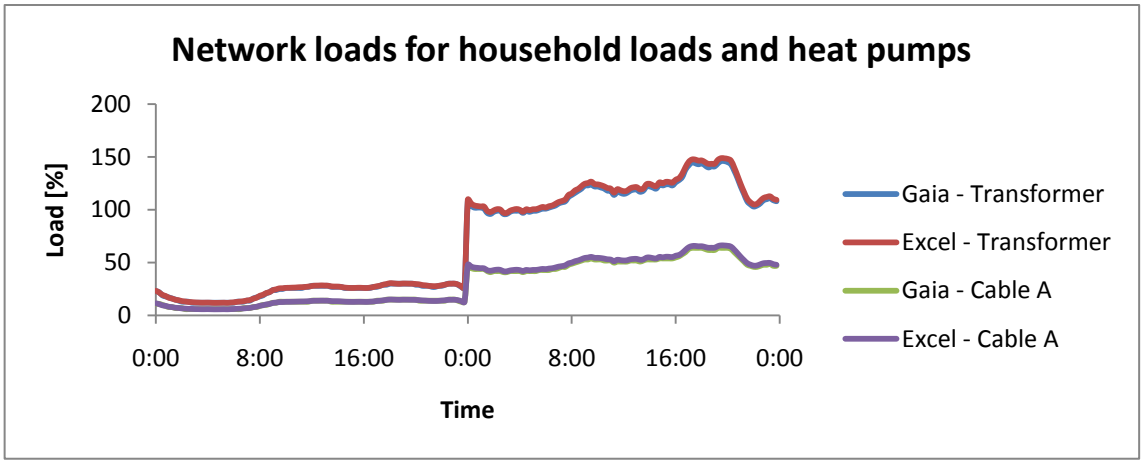

Figure 3.13: Comparison between calculated network loads by testing environment and Gaia, summer and winter day - Household loads and heat pumps

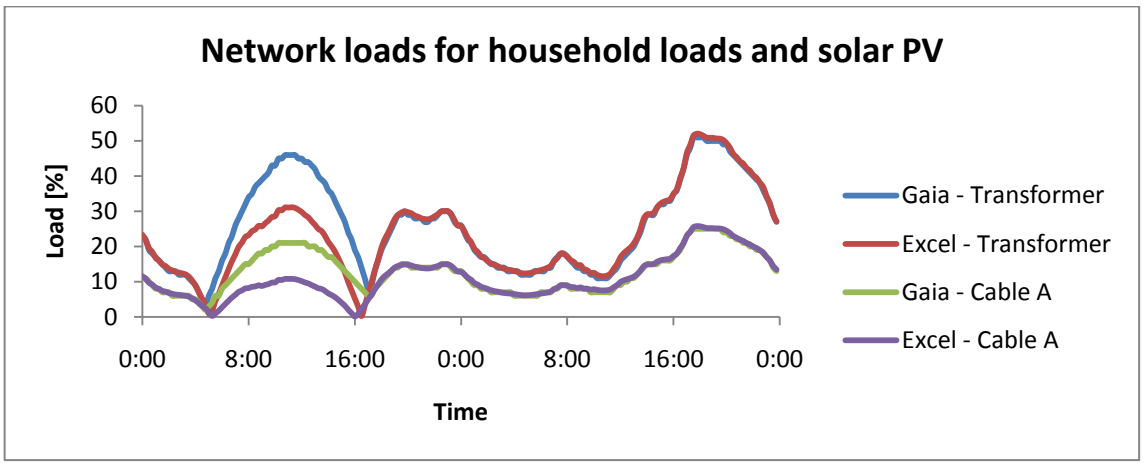

Figure 3.14: Comparison between calculated network loads by testing environment and Gaia, summer and winter day - Household loads and solar PV

As can be seen from Figure 3.9 through Figure 3.14 the testing environment can calculate the same values as the Gaia model. When only an individual technology is compared it is seen that the results are identical. For combinations of technologies the calculated loads deviate slightly; the reason for this deviation can be explained by Gaia's method of aggregating Strand-Axelsson loads.

Gaia uses a procedure called stochastic load flow (Phase to phase, 2008). What this entails is that for each Strand-Axelsson load the maximum power is an average power plus a standard deviation given by:

$$P_{max,1} = P_{avg,1} + C\sigma_1 \tag{3.11}$$

With:

$P_{max,1}$ – Maximum power demand of a single user [kW]
$P_{avg,1}$ – Average power demand of a single user [kW]
C – Constant describing the relation between the maximum load and the stochastic spread
σ_1 – Standard deviation of a single user

This equation is derived from the Strand-Axelsson equation, and hence it can be understood that:

$$P_{avg,1} = \alpha E_1 \tag{3.12}$$

And

$$C\sigma_1 = \beta\sqrt{E_1} \tag{3.13}$$

In other words, Gaia and the testing environment use the same equation to calculate $P_{max,n}$, and therefore the two calculate the same loads when considering only individual technologies. The difference however occurs when combining loads. Combining Strand-Axelsson loads in the testing environment consists of adding the *maximum* powers, $P_{max,n}$, together. In Gaia on the other hand, this process occurs according to stochastic principles in which the *averages* are added together and a new deviation is calculated by adding the variances together for the combined load (Phase to Phase, 2008). The deviation of the combined loads is given by:

$$\sigma_{1+2} = \sqrt{{\sigma_1}^2 + {\sigma_2}^2} \tag{3.14}$$

The above equation implies that when loads are aggregated in Gaia the deviation becomes smaller, and hence the calculated peak loads are smaller than those found in the testing environment, this is best seen in Figure 3.12.

In Figure 3.13 however, almost no difference is seen. This is because heat pumps have a very high coincidence factor and hence a very low variance. Therefore, the deviation of the combined household load with heat pump load is approximately equal to the variance of only the household load:

$$\sigma_{1+2} = \sqrt{{\sigma_1}^2 + {\sigma_2}^2} \approx \sigma_1 \tag{3.15}$$

Solar panels also have a high coincidence factor however in Figure 3.14 a difference *is* observed; this is due to the fact solar panels produce electricity, and again the difference can be explained by how Gaia carries out the calculation. In Gaia the maximum load for multiple Strand-Axelsson loads is calculated by first calculating *average* power using Equation (3.12) then by adding the deviation. This means that when adding a power supply and a power demand technology the maximum load will not be 0% as long as the deviations are non-zero (which is the case for the household load).

3.3.4 Verification conclusions

It can be concluded that the testing environment is capable of producing the same results as the Gaia software. Differences occur when combining Strand-Axelsson loads due to the different calculation method used by Gaia. To determine which method is correct (if any) it is important to understand why Gaia uses the method described above.

Gaia uses stochastic load flows because in general all Strand-Axelsson loads have been of the same type; the loads that they represent consist of the same appliances (dishwashers, televisions, lights, etc.). Therefore, when two Strand-Axelsson loads representing similar technologies are added it is

reasonable that the maximum load should decrease due to the decreasing coincidence factor. Gaia accomplishes this by adjusting the variance when loads are aggregated (Phase to Phase, 2008).

In the testing environment however, the Strand-Axelsson loads are not of the same type, each load represents a different technology. Therefore it is the author's opinion that when adding loads of different sorts, as is the case in the scenarios considered here, the *maximum* loads instead of the *average* loads should be added.

It can be verified that adding the maximum loads is accurate by looking at Figure 3.5 through Figure 3.8. In these figures Gaia calculated in general lower peak loads when using the Strand-Axelsson loads, in the testing environment these peak loads are slightly higher as seen in Figure 3.13 and hence closer to the peak load values found when using individual loads.

4 Creation of electric vehicle power demand profiles

In this chapter it is explained how the electric vehicle power demand profiles are modeled. In Section 4.1 the electric vehicle characteristics and underlying assumptions required to model the charging profiles are given. In Section 4.2 a detailed explanation is given of how the charging profile of a single electric vehicle using uncontrolled charging is modeled. The procedure for modeling the other charging strategies vary only slightly from the uncontrolled charging strategy, therefore detailed explanations of these are omitted. In Section 4.3 it is explained how individual power demand profiles are aggregated to create an average profile (i.e. the profile for a very large number of vehicles). In Section 4.4 the other charging strategies are described and the average profiles are shown. In Section 4.5 the power demand profiles are compared to measurements at charging points.

4.1 Electric vehicle and battery characteristics

To be able to create power demand profiles for electric vehicles it is first necessary to define the characteristics of the electric vehicles and state some assumptions concerning the behavior of the electric vehicle owners.

4.1.1 Electric vehicle and charging characteristics

The following parameters are used for the electric vehicles:

- Battery capacity – $24\mathrm{kWh}$ (Pecas Lopes et al., 2010)
- Efficiency – $0{,}2\mathrm{kWh/km}$ (Verzijlbergh et al., in press; Pecas Lopes et al., 2010)
- Single-phase charging power – $3\mathrm{kW}$ (Verzijlbergh et al., in press; Merge, 2010)
- Three-phase charging power – $10\mathrm{kW}$ (Verzijlbergh et al., in press; Merge, 2010)
- Discharging power (vehicle to grid) – $3\mathrm{kW}$ (Merge, 2010)

These values have been taken from papers but can be verified by looking at the specifications of the Nissan Leaf, Nissan's all electric vehicle. The Leaf has a 24kWh lithium-ion battery and a charging rate of 3,3kW with fast charging possible at up to 50kW. Based on laboratory tests the range is 160km but based on varying driving and climate conditions the rated range is 117km (Nissan, 2010). These values all are in agreement with those listed above.

Two types of charging are considered, single and three-phase AC charging. Single-phase can easily be performed through standard home outlets (Merge, 2010). Three-phase charging often takes place at special electric vehicle charging stations; examples of these can be found in cities such as Amsterdam. These charging stations have 3x16A connections and can therefore charge at rates up to 3,7kW and 11kW for single and three-phase, respectively (Stiching e-laad, 2011). According to Alliander Energy Architect, Justin Au-Yeung, the current method of charging is single-phase; however since 2011 all newly installed charging points are using three-phases (Au-Yeung, 2011).

4.1.2 Assumptions

The following assumptions are used concerning the behavior of electric vehicle owners to model the electric vehicles:

- The behavior of drivers of electric vehicles is the same as drivers of gasoline and diesel vehicles. It is assumed that the ownership of an electric vehicle has no influence on the departure time, arrival time, and distance traveled. In this manner the Mobility Study data can be used simulate electric vehicle trips.
- In approximately 12,5% of the 15.000 recorded trips in the Mobility Study, the traveled distance exceeds the battery capacity of 24kWh. For these cases it is assumed that a range extender is used for the remainder of the trip and that the battery needs to be fully charged upon arrival.
- It is assumed that charging only takes place at home.
- It is assumed that charging only takes place after the last arrival and before the first departure.

4.2 Creation of a single electric vehicle charging profile

In this section it is described how charging profiles are created for a single electric vehicle. A detailed description is given of the simplest charging strategy, uncontrolled charging. The general method to model the other charging strategies are similar; in Section 4.4 it is explained how the modeling of the other charging strategies differ from the method described here.

4.2.1 Data used to model electric vehicle charging profiles

The power demand profiles are created using the database of the Mobility Study 2007 (in Dutch, "Mobiliteitsonderzoek Nederland 2007") (Rijskwaterstaat, 2008). In this study the Dutch government surveyed 52.000 people about the trips that they make, totaling almost 160.000 single way trips. For each trip several parameters are recorded such as transportation type, departure time, distance traveled, arrival time at destination, and endeavor at destination, etc. Of the 160.000 trips, 15.000 round trips with are personal car were recorded. From this data it is possible to create the power demand profiles for electric vehicles.

4.2.2 Calculations used to create electric vehicle charging profiles

To model the power demand profile of a single electric vehicle a Matlab script has been written. The basic steps executed by the Matlab code are explained below:

1. Randomly select a vehicle from the Mobility Study data and read:
   - Departure time, rounded to the nearest 15 minutes, t_{dept}
   - Arrival time, rounded to the nearest 15 minutes, t_{arr}
   - Distance traveled, s
2. Define the following values:
   - Charging power, P_{charge}
   - Charging efficiency, η
   - Battery capacity, P_{batt}
3. Calculate the energy required, E_{req}, based on the distance traveled:

$$E_{req} = \begin{cases} \eta \cdot s & if\ n \cdot s < P_{batt} \\ P_{batt} & otherwise \end{cases} \tag{4.1}$$

4. Calculate time required, t_{charge}, based on the energy required and charging power:

$$t_{charge} = E_{req} \cdot \frac{P_{batt}}{P_{charge}} \tag{4.2}$$

5. Calculate at what time charging stops, t_{stop}, based on time required and arrival and departure information:

$$t_{stop} = \begin{cases} t_{arr} + t_{charge} & if\ t_{arr} + t_{charge} < t_{dept} \\ t_{dept} & otherwise \end{cases} \tag{4.3}$$

6. Loop starting at the arrival time for a full day until either the battery is full or departure time has arrived.

4.2.3 Resulting power demand profile of a single electric vehicle

In this manner the power demand profile of a single electric vehicle is created. An example of such a profile is seen in Figure 4.1.

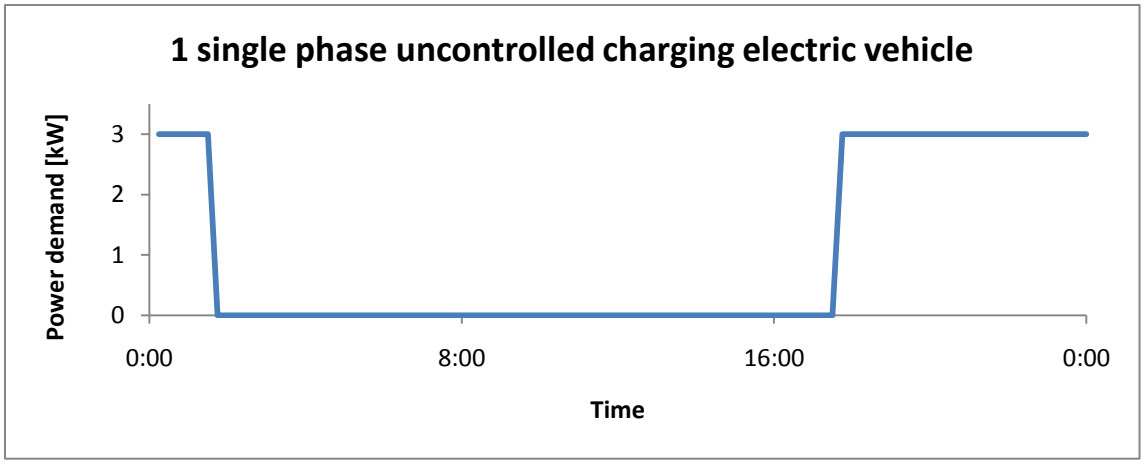

Figure 4.1: Power demand profile – one random electric vehicle single-phase uncontrolled charging

4.3 Creation of average power demand profile by aggregating single profiles

For each vehicle in the Mobility Study it is possible to create a power demand profile similar to the one shown in Figure 4.1. Each profile is different because it has a different arrival time, departure time, and traveled distance. By adding sufficient single profiles together the average profile is obtained. In the following figures the aggregated profiles for 5, 50, and 500 electric vehicles are shown. For each profile the average power per electric vehicle is given.

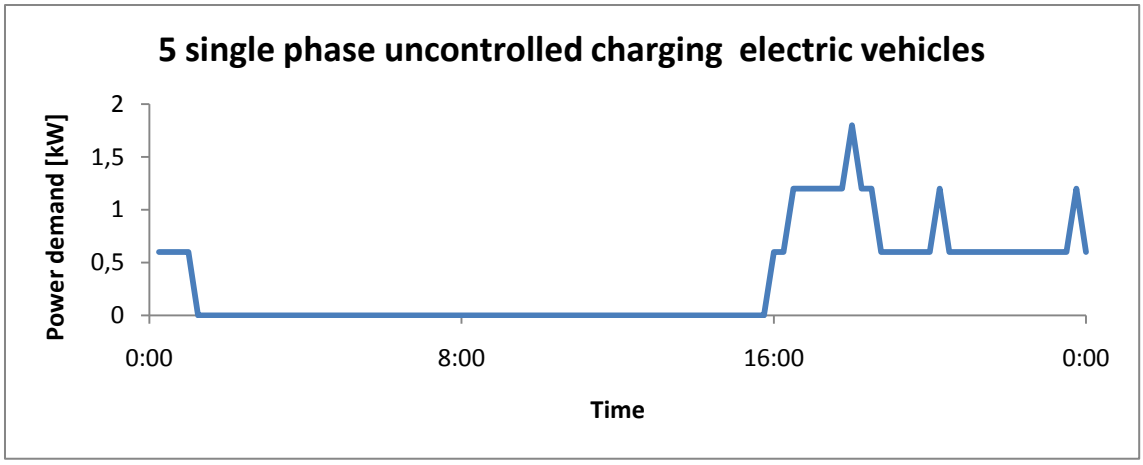

Figure 4.2: Average power demand profile – five electric vehicles single-phase uncontrolled charging

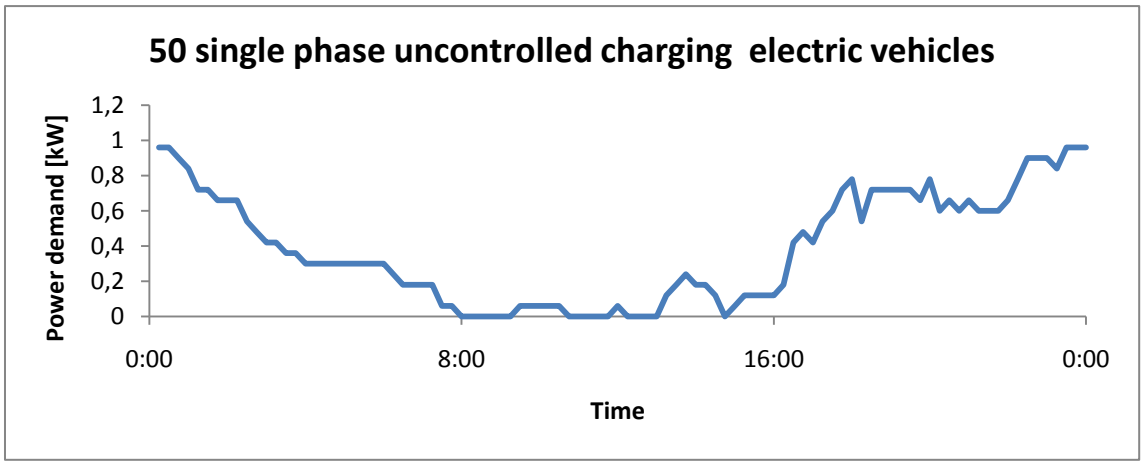

Figure 4.3: Average power demand profile – 50 electric vehicles single-phase uncontrolled charging

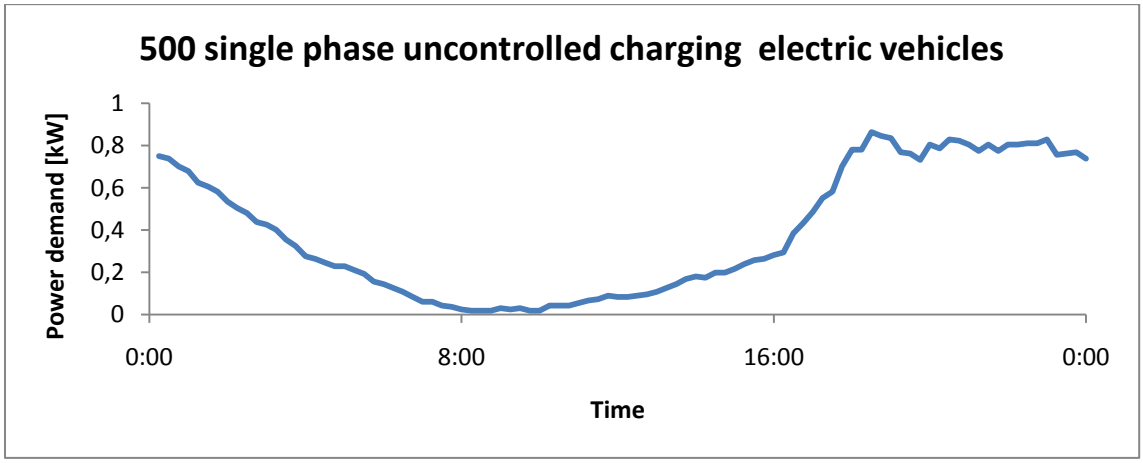

Figure 4.4: Average power demand profile – 500 electric vehicles single-phase uncontrolled charging

This process can be looped for even larger values of n resulting in the average profile shown in Figure 4.5.

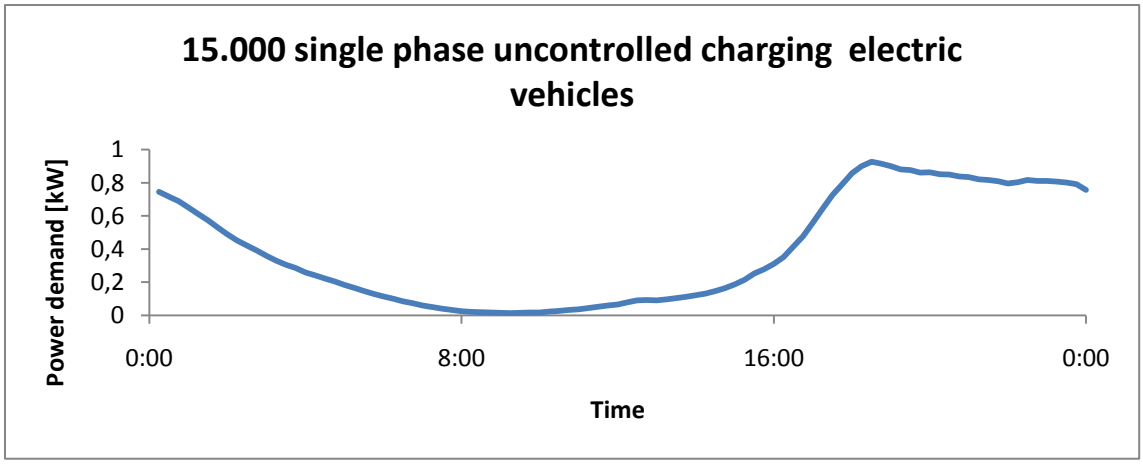

Figure 4.5: Average power demand profile – 15.000 electric vehicles single-phase uncontrolled charging

4.4 Alternative charging strategies and their power demand profiles

Seven different charging strategies are considered. A description of each of these strategies is given below. These seven strategies have been chosen because they are either considered in other studies (Verzijlbergh et al., in press) or because network operators consider them relevant and/or likely (Au-Yeung, 2011). All charging strategies are three-phase, unless stated otherwise.

4.4.1 Single-phase (3kW) and three-phase (10kW) uncontrolled charging

Uncontrolled charging is the simplest charging profile and is the strategy that was described in Section 4.2. Charging takes place at home or via a charging station near the home on a single-phase or on three-phases. The electric vehicles are charged as soon as the owner arrives home and are charged at maximum power until either fully charged or until departure time, whichever comes sooner. The resulting average power demand profiles are shown in Figure 4.12 and Figure 4.13.

4.4.2 Slow charging

The electric vehicles are charged as soon as the owner arrives home similar to the uncontrolled charging; however charging takes place at a slower rate. The charging rate is determined such that the battery is fully charged for the next scheduled departure (Verzijlbergh et al., in press). Instead of using a fixed charging rate of 3kW or 10kW the charging rate is calculated by dividing the required energy, E_{req} by the time available (t_{dept} - t_{arr}). The charging power is capped at 10kW in case the time available is too small. Figure 4.6 shows the power demand profile of the slow charging strategy.

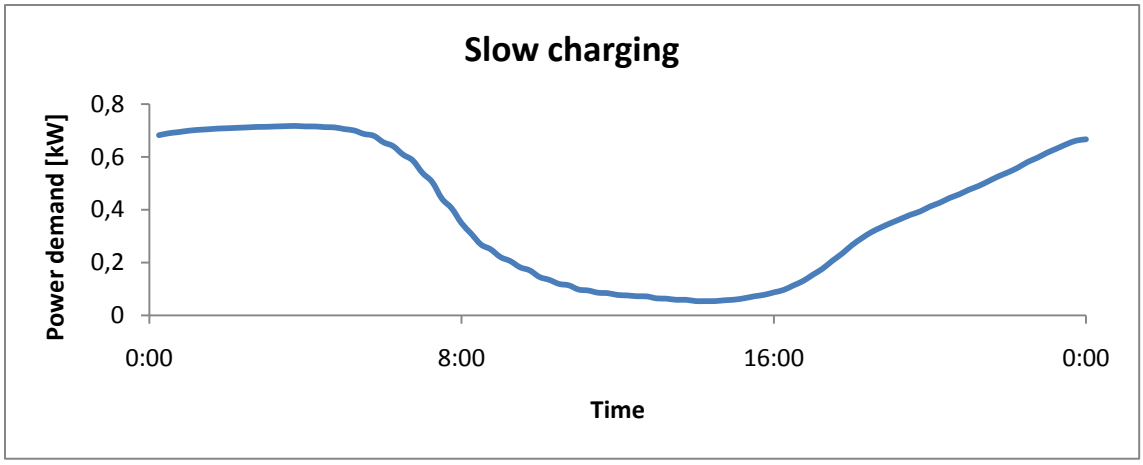

Figure 4.6: Average power demand profile - Slow charging

4.4.3 Economic charging

To save money, electric vehicle owners only start charging their vehicles at 23:00 in the evening, the time at which the night-time electricity tariff goes into effect. This is an unrealistic scenario since it can very easily be mitigated by removing the tariff; however it is used to show the extreme situation in which everyone charges their electric vehicles at exactly the same time.

Economic charging is modeled by first checking if the vehicle is at home at 23:00 and if there is sufficient time to fully charge the battery based on the scheduled departure time. If this is the case, charging only starts at 23:00 and continues until the battery is full. Otherwise charging starts at the arrival time, similar to the uncontrolled charging strategy. In Figure 4.7 shows the power demand profile of the economic charging strategy. There is a very large peak at 23:00 and takes almost entirely place between 23:00 and 02:00.

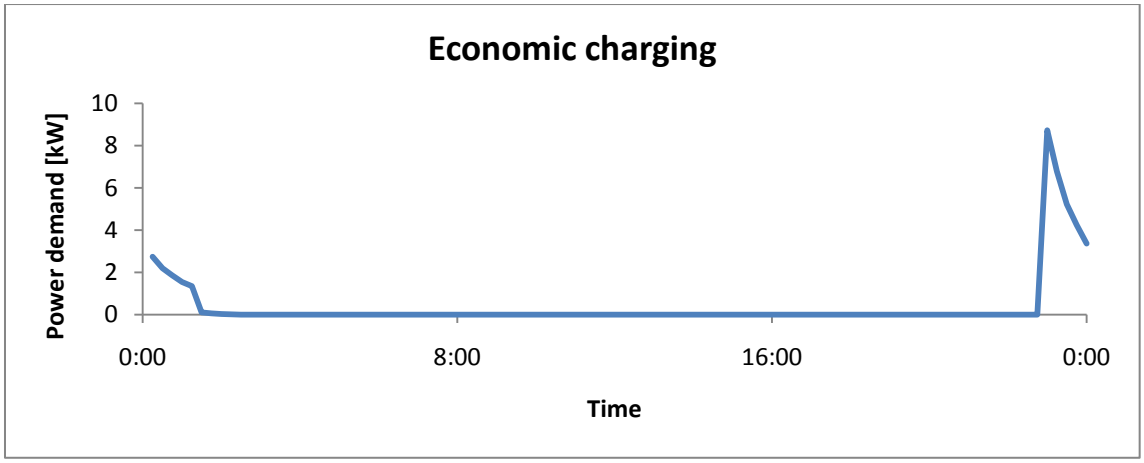

Figure 4.7: Average power demand profile - Economic charging

4.4.4 Charging when battery state of charge is less than 30%

The average round trip distance according to the Mobility Study is 60km (Rijskwaterstaat, 2008). Therefore for many people it is not necessary to charge the battery after every trip. In this charging strategy the electric vehicle battery is only charged if the state of charge is less than 30%.

To model this charging strategy it is assumed that every car in the Mobility Study makes the same trip every day. If the trip distance requires more than 50% of the batteries capacity, then the car battery must be charged otherwise it will not have sufficient range the next day. However if the trip distance requires less than 50% of the battery capacity then it is possible to make a second trip before charging. If this is the case, it is then randomized to determine which trip number it is, and hence whether the state of charge is less than 30% or not (for example, if the trip requires 40% of the battery capacity, it is randomized whether the battery capacity is at 60% or at 20%). If the state of charge is less than 30% charging takes place starting at the time of arrival at maximum power until the battery is full or until the time of departure. Figure 4.8 shows the power demand profile for this charging strategy. As would be expected there is a peak at approximately 17:00, around the time when people get home, similar to the uncontrolled charging strategy. Charging however takes place over a longer duration because of the lower state of charges.

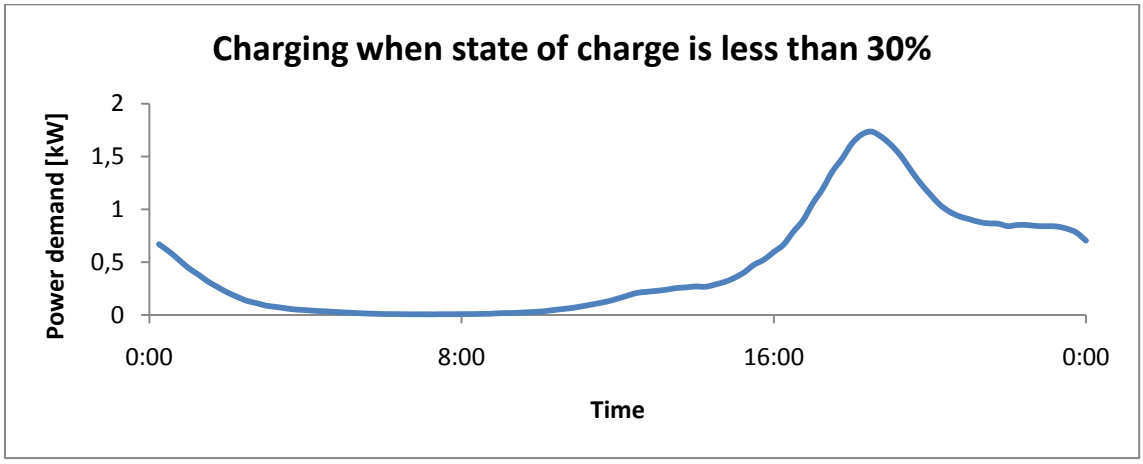

Figure 4.8: Average power demand profile - Charging when battery state of charge is less than 30%

4.4.5 Charging as late as possible

In this strategy charging does not start immediately upon arrival but instead occurs in the hours before departure. The electric vehicle owner enters his scheduled departure time, and based on the current state of charge of the battery it is determined at what time charging needs to start to have a full battery upon departure. This profile is used to avoid the evening peak. Figure 4.9 shows the power demand profile of the charging as late as possible strategy. The peak is at about 7:00.

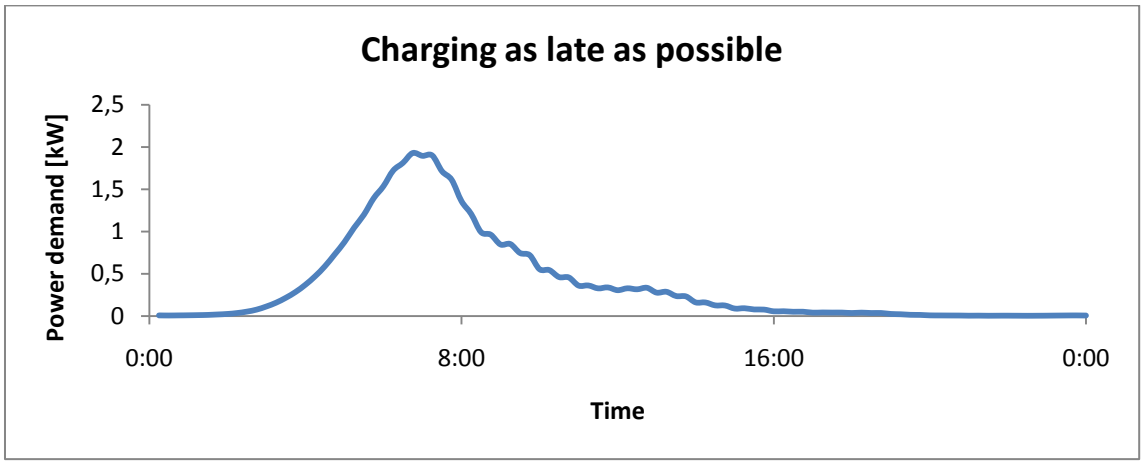

Figure 4.9: Average power demand profile - Charging as late as possible

4.4.6 Night time charging

Charging occurs randomly in the evening hours with the charging peak occurring at approximately 4:00; the time at which household electricity demand is at a minimum. The time to start charging is randomized for each electric vehicle taking into account the scheduled departure time to make sure the vehicles will not have an empty battery upon departure. A normal distribution around 4:00 is used for the creation of this profile. Figure 4.10 shows the night time charging power demand profile.

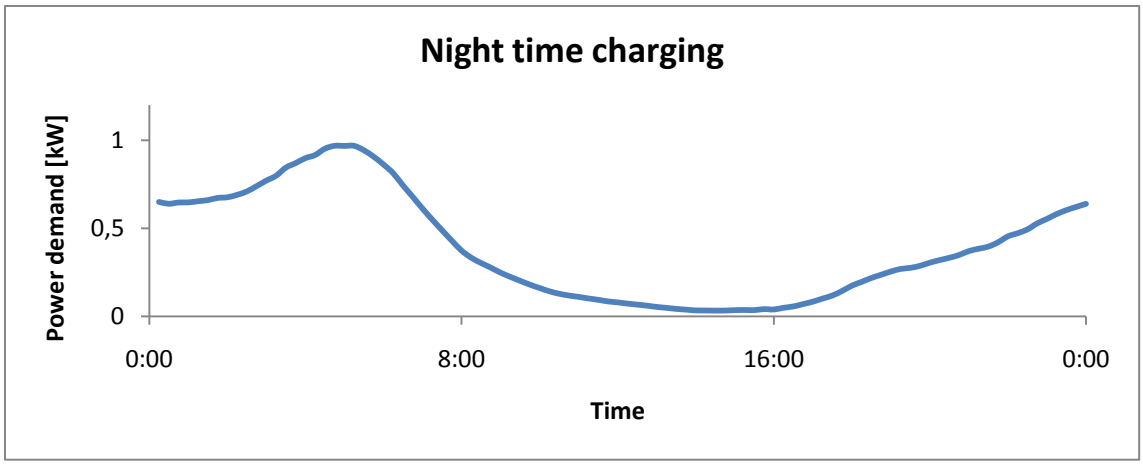

Figure 4.10: Average power demand profile - Night time charging

4.4.7 Vehicle to grid with discharging possibilities

In the vehicle to grid strategy the car battery can also be used as a form of energy storage and can be discharged to provide electricity to households during times of peak demand. The power demand profile of the vehicle to grid strategy is dependent on the demand; however this cannot easily be taken into account. Therefore, it is assumed that discharging takes place in the first hours after arrival (at approximately 17:00 when the household electricity demand is at a peak) and charging takes place in the morning hours before departure (when the electricity demand is at a minimum).

It must be noted that the vehicle to grid profile created here is an extreme case in which the maximum potential of both the discharging and charging are depicted. In reality this is demand driven and peaks might be more moderate. It is assumed that the batteries are constantly discharging at full power until they need to be charged; the power demand profile shows therefore the maximum possible discharge power for every moment of the day besides in the hours before departure. Once charging starts it is assumed that the batteries are at a state of charge of 30%. Figure 4.11 shows the vehicle to grid profile.

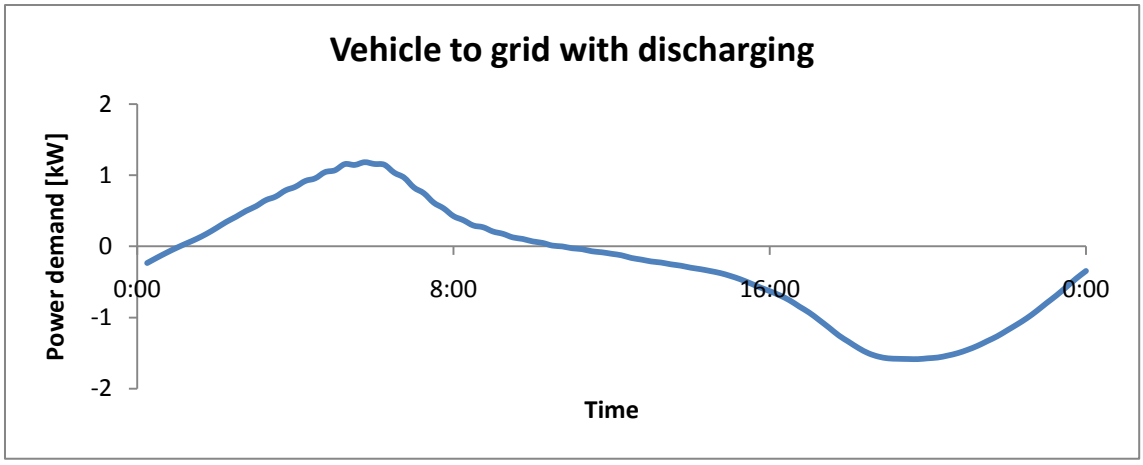

Figure 4.11: Average power demand profile - Vehicle to grid with discharging

4.5 Comparison to measured data

To validate the uncontrolled charging power demand profile a comparison is made to data obtained from Alliander. The data are measurements from 104 electric vehicle charging points in Amsterdam (Au-Yeung, 2011). Figure 4.12 and Figure 4.13 show the comparison.

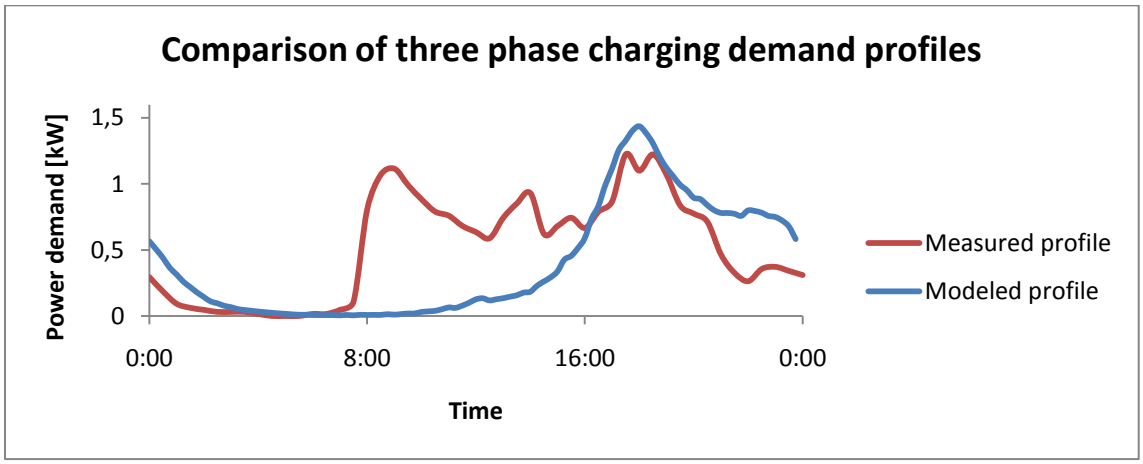

Figure 4.12: Comparison between modeled three-phase uncontrolled charging power demand profiles and measured electric vehicle charging data

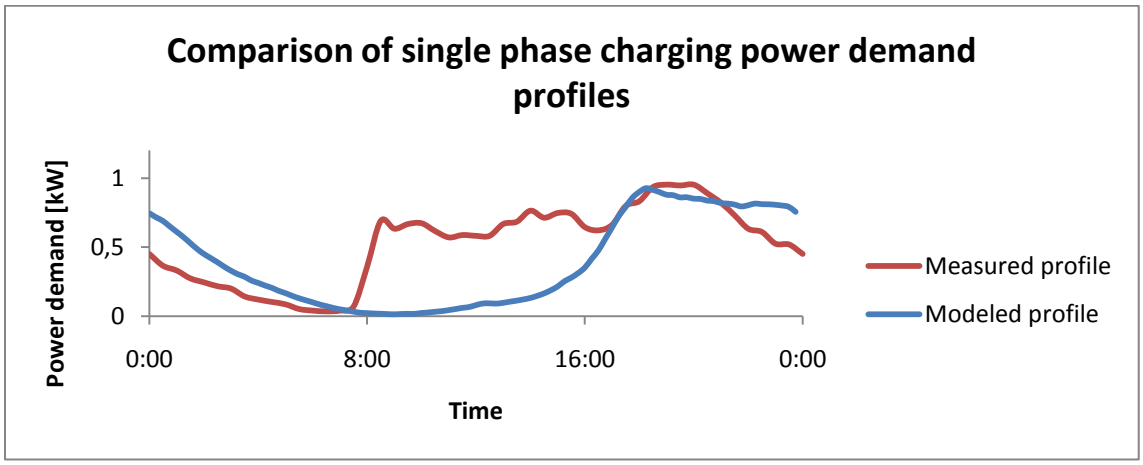

Figure 4.13: Comparison between modeled single-phase uncontrolled charging power demand profiles and measured electric vehicle charging data

From Figure 4.12 and Figure 4.13 it is seen that the modeled profiles accurately predict both the peak value and the time of the peak. The modeled profiles however do not accurately predict the load between 8:00 and 16:00. One possible reason for this is the underlying assumption about where charging takes place; in the modeled profiles it is assumed that charging only takes place after the last trip at home, and hence the profile has a very low load during the day. In the measured data there is no limitation to when or where charging can take place and hence the loads during the day are higher. It is likely that the measured data also contains measurements of vehicles charging while at work, this most likely explains the peaks at approximately 8:30.

5 Creation of heating technology power demand profiles

In this chapter it is explained how the power demand profiles of space heating technologies such as electric heaters, heat pumps and micro CHPs, are created. The profiles have been created by modeling the heat demand of typical Dutch households in Matlab. A lumped-parameter model has been constructed to determine the heating requirements of a household based on its characteristics, such as size, household type, insulation level, year of construction, and thermostat setting. The heat demand model is used to determine the heat demand of a household in fifteen minute intervals for an entire year. Based on the required heat demand the behavior of the heating system can be determined and power demand profiles can be generated for different types of heating systems and households.

In Section 5.1 the heat demand model will be explained along with the parameters used. In Section 5.2 the method of modeling a single power demand profile for an electric heater will be explained, the power demand profiles for other technologies are created in a similar manner. In Section 5.3 it will be explained how individual power demand profiles are aggregated to an average profile. In Section 5.4 the power demand profiles for the other the heating technologies considered are presented. Although the majority of this chapter is dedicated to space heating technologies, the heat demand model can also be used to create power demand profiles for cooling technologies. Therefore in Section 5.4 the profile of air conditioners are also presented. Finally in Section 4.5 a comparison is made between the created heat pump power demand profiles with measured data.

5.1 Household heat demand model

In this section the heat demand model will be introduced. The heat demand of a household is predicted by modeling a household as a thermal equivalent circuit. In this section the thermal equivalent circuit is explained along with the method used to determine all the required parameters. The input values for the model are given at the end of the section.

5.1.1 Thermal equivalent circuit

The heat demand can be determined by modeling the household as an equivalent thermal circuit; heat flow, temperatures, thermal resistances, and thermal capacitances are represented by current, voltages, resistors, and capacitors, respectively (Dewson et al., 1993; Mathews et al., 1994; Pearce, 2001). Figure 5.1 shows the equivalent thermal circuit used, which considers indoor and outdoor temperature and the thermal resistance and capacitance characteristics of the house. In the equivalent thermal circuit heat is produced in the household and it moves along different paths depending on the thermal resistances and the temperature difference. This model can be used to calculate the changes in the indoor and wall temperature.

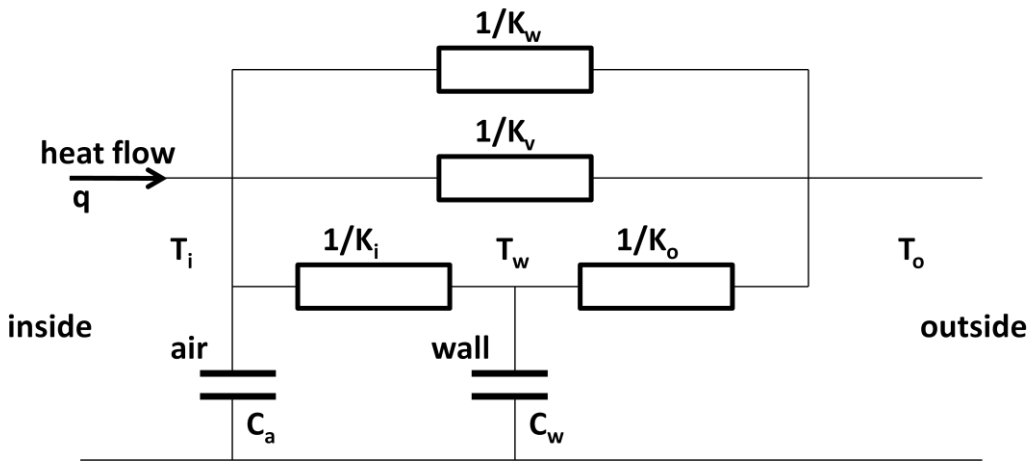

Figure 5.1: Thermal equivalent circuit

The following parameters are used in the thermal equivalent circuit:

q – Heat due to the heating system, solar gain, and appliances and other sources [W]
T_i – Indoor temperature [°C]
T_O – Outdoor temperature [°C]
T_W – Wall temperature [°C]
K_w – Thermal conductance representing heat flow through windows [W/K]
K_V – Thermal conductance representing heat flow due to ventilation and infiltration [W/K]
K_i – Thermal conductance representing heat flow through the building mass [W/K]
K_O – Thermal conductance representing heat between building mass and the outside [W/K]
C_w – Building mass thermal capacitance [J/K]
C_a – Air thermal capacitance [J/K]

Values for the parameters K_w, K_v, K_i, K_o, C_w, C_a depend on the characteristics of the house such as wall material type and dimensions. In Section 5.1.2 it will be explained how these are determined.

From the thermal equivalent circuit the change in indoor and wall temperature is calculated using the equivalent of the current-voltage relation for a capacitor. Instead of current and voltage, heat and temperature are used. The following relationship results:

$$Q(t) = C\frac{dT(t)}{dt} \tag{5.1}$$

The above equation can be used to determine the change in the indoor and wall temperature, dT_w and dT_i. The following two equations result:

$$\begin{pmatrix} \frac{dT_i}{dt} \\ \frac{dT_w}{dt} \end{pmatrix} = \begin{pmatrix} \frac{-K_i - K_v - K_w}{C_a} & \frac{K_i}{C_a} \\ \frac{K_i}{C_w} & \frac{-K_i - K_o}{C_w} \end{pmatrix} \begin{pmatrix} T_i \\ T_w \end{pmatrix} + \begin{pmatrix} \frac{q + (K_v + K_w)T_o}{C_a} \\ \frac{K_o T_o}{C_w} \end{pmatrix} \tag{5.2}$$

Using Equation (5.2) the change in temperature of the indoor air and wall can be calculated numerically for each time interval based on the outdoor temperature, heat supplied, and thermal parameters of the household.

5.1.2 Determining the parameters for the thermal equivalent circuit

In this section it will be explained what values and/or equations are used to determine the input parameters required to model the household heat demand using a thermal equivalent circuit.

Heat flow, q

Three types of heat production are considered:

- Heat production due to lighting, appliances and occupation
- Solar gain
- Heat production from the heating system

Heat production due to lighting, appliances, and occupation

In residential buildings, the internal heat gains due to persons, lighting and appliances can be estimated as 5-6W/m^2 over the day and during the heating season (Wittchen and Aggerholm, 1999; Wepal, 2009). A value of 6W/m^2 is used in the Matlab model.

Solar gain

To calculate the heat gained due to solar radiation through windows the Lui and Jordan model is used. This model determines the radiation incident on a (tilted) surface based on the direct and diffuse components of the solar irradiation (Gouda et al., 2000). The total solar radiation incident on a tilted surface is given by:

$$E_{sur} = E_{dir}cos(\theta_{sur}) + E_{diff}\left(\frac{1 + cos(\beta_{sur})}{2}\right) + (E_{dir} + E_{diff})\rho_g\left(\frac{1 - sin(\beta_{sur})}{2}\right) \quad (5.3)$$

With:

E_{sur} – Total radiation incident on surface [W/m^2]
E_{dir} – Direct component of solar irradiation [W/m^2]
Θ_{sur} – Angle of incidence of the direct irradiation on the surface [°]
E_{diff} – Diffuse component of solar irradiation [W/m^2]
β_{sur} – Tilt angle of slope of surface from horizontal [°]
ρ_g – Ground reflectance [-]

The direct and diffuse components of the global solar irradiation are determined using data from the KNMI and by using the Skarveit and Olseth model (SO model) (Gouda et al., 2000). Equations (5.4) through (5.8) describe this model.

The fraction of diffuse radiation is dependent on the clearness index which is an indication of how cloudy it is. The clearness index is determined by the equation:

$$c = \frac{E_{horz}}{E_{et}} \quad (5.4)$$

With:

E_{horz} – The measured global terrestrial irradiation [W/m^2]

E_{et} – The global extraterrestrial irradiation [W/m^2], given by:

$$E_{et} = E_{sc}\left[1 + 0{,}033\cos\left(\frac{360 n_{day}}{365}\right)\right]\cos(\theta_{horz}) \tag{5.5}$$

With:

E_{sc} – The solar constant, 1.353 W/m^2 [W/m^2]
n_{day} – Day of the year, with 1 being 1 January
θ_{horz} – The zenith angle [°]

Depending on the clearness index the SO model calculates the ratio diffuse to global radiation:

$$\frac{E_{diff}}{E_{horz}} = \begin{cases} 1 & for\ c \le c_0 \\ f_{so}(c) & for\ c_0 \le c \le \alpha_{so} c_1 \\ 1 - \alpha_{so} c_1 \dfrac{1 - f_{so}(\alpha_{so} c_1)}{c} & for\ c \ge \alpha_{so} c_1 \end{cases} \tag{5.6}$$

With:

$$f_{so}(c) = 1 - (1 - d_{sol}) \times [\alpha_{so}\sqrt{K_{so}} + (1 - \alpha_{so}){K_{so}}^2] \tag{5.7}$$

$$K_{so} = 0{,}5\left\{1 + sin\left[\pi\frac{c - c_0}{c_1 - c_0} - 0{,}5\right]\right\} \tag{5.8}$$

The parameters of the above equations are taken from (Skartveit and Olseth, 1986) and are as follows:

c_0 – *0,2*
c_1 – *0,87 – 0,56exp(-0,06h)*
α_{so} – *1,09*
d_{sol} – *0,15 + 0,43exp(-0,06h)*
a_{so} – *0,27*
ρ_g – *0,2*
h – The solar elevation, equal to (1-zenth angle) [°]

From the above equations the incident solar radiation on a window surface is determined in W/m^2. It is important to take the solar gain into account, because even on cold winter days the incident solar radiation can have values of up to 300 W/m^2.

Heat production from the heating system

The heat production from the heating system depends on the heat demand of the household and on the type and size of heating system that is used. The heat demand of the household can be determined by rewriting Equation (5.2) to calculate the total required input heat, q. From q the gain due to appliances and solar gain are subtracted resulting in the heat demand that needs to be supplied by the heating system. Based on this value the heating system is sized accordingly. The sizing of the heating systems is explained in Section 5.2.1.

Outdoor temperature, T_o

Outdoor temperature data in 15 minute intervals for an entire year has been obtained from the KNMI (KNMI, 2011). To model the power demand profiles of the heating systems a very cold day is with a mean average temperature of -7,9°C is considered.

Desired indoor temperature, T_d

The desired indoor temperature is controlled by a thermostat. Two thermostat programs are considered: the average thermostat setting of a Dutch household and a very low temperature thermostat setting. Both of the programs are taken from a study conducted by the Dutch government concerning energy use in households (VROM, 2010). Figure 5.2 shows the two thermostat settings considered. Both have a somewhat similar pattern, temperature is increased in the morning at the time when household members wake up and increases a second time in the evening when everyone is home.

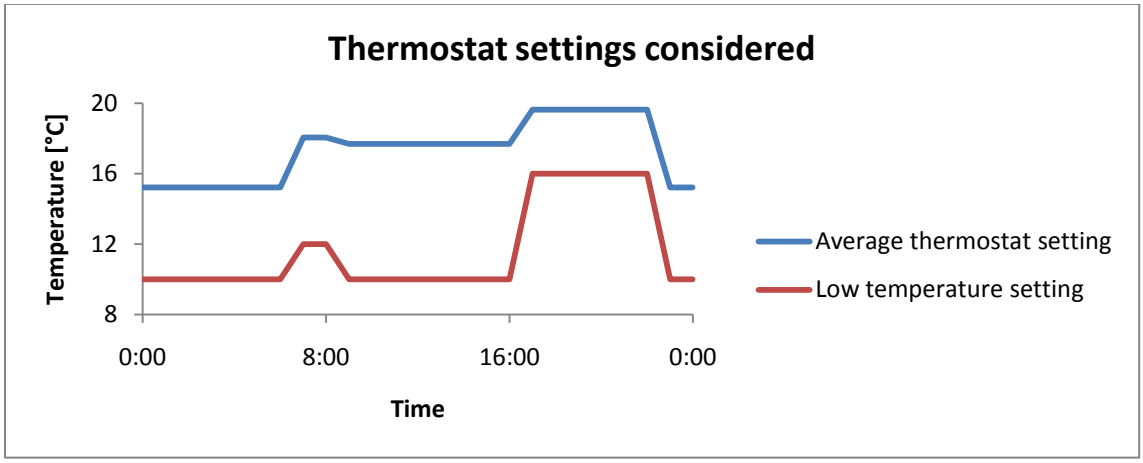

Figure 5.2: Average thermostat and low temperature thermostat settings (VROM, 2010)

The thermostat control has been programmed into the Matlab model to compare the indoor temperature with the desired temperature in 15 minute intervals. To prevent excessive on and off behavior the heater will only turn on if the temperature is 1°C or more below the programmed temperature and will only turn off if the temperature is 1°C or higher than the programmed temperature. This control strategy is based on information available in the manual of a common thermostat (Honeywell, 2001).

Thermal conductance representing direct heat flow between inside and outside, K_v

The thermal resistance given by $1/K_v$ is dependent on the ventilation of a household. Ventilation is the movement of air from outside a building to inside and is required to remove odors and prevent high concentrations of carbon dioxide within households. There are three types of ventilation: Mechanical, natural, and infiltration (ASHRAE, 2001).

- Mechanical ventilation – Air that is exchanged by means of a fan or exhaust.
- Natural ventilation – Air that is intentionally exchanged through open windows or vents.
- Infiltration – Air that is exchanged through cracks in the building envelope, for example around doors and windows.

In this thesis only natural ventilation and infiltration are considered. K_V, the thermal conductance due to the above ventilations can be calculated from the heat loss equations, given below:

$$K_V = \frac{H_V}{T_i - T_O} = c_p \rho n_{air} Vol \tag{5.9}$$

With:

H_V – Ventilation heat loss [W]
c_p – Specific heat capacity of air, 1000 J/kg/K
ρ – Density of air, 1,225kg/m³ at 15°C
n_{air} – Number of air shifts [1/s]
Vol – Volume of room [m³]

Households require a minimum ventilation rate of 0,35 air changes per hour and not less than 7,5L/s per person, this is for safety reasons (ASHRAE, 2001). A value of 0,5 air-changes per hour is chosen for the heat demand model; this value is also often used in other studies and has been verified experimentally (Wittchen and Aggerholm, 1999; Everett et al., 1985).

Thermal conductance between inside air, building mass, and outside air, K_i and K_o

The walls of a household consist of several layers. Each layer has a different thickness, thermal conductivity, and specific heat capacity. These layers can be lumped to form two thermal resistances, $1/K_i$ and $1/K_o$, and one thermal capacity, C_w (Gouda et al., 2002). The thermal conductance from the inside air to the building mass, K_i, is dependent on the first few layers of the wall: An air film, the plaster, brick, and insulation material. The conductance from the building mass to the outside air is dependent on the remaining layers; usually consisting of brick and an external air film.

The values used for K_i and K_o depend on the materials used and therefore vary from building to building. However when detailed information about construction material is unavailable it is possible to consider typical values based on the year of construction of the household (Vabi, 2010). The following thermal resistances for walls are used in the Matlab model and are considered representative for Dutch households:

Table 5.1: Thermal resistance values for buildings walls (Vabi, 2010)

Year of construction	Thermal Resistance of walls, R_c [m²K/W]
<1975	0,44
1975-1979	1,00
1979-1988	1,30
1988-1992	2,00
>1992	2,50

The above values are the thermal resistance of the entire wall, the thermal conductance is found by taking the inverse of the wall resistance and multiplying with the wall and roof area. To determine K_i and K_o an accessibility factor is used (Gouda et al., 2002). The accessibility factor is taken as 0,75 meaning that the inner three-fourths of the wall contribute to K_i and the rest contributes to K_o. The

value 0,75 has been chosen arbitrarily but in such a manner that it is in agreement with values used by Pearce (2001).

Thermal conductance through windows, K_w

The thermal conductance through the windows is based on predefined values given in (Vabi, 2010) for different window types. The following values are used:

Table 5.2: Thermal conductivity values for windows (Vabi, 2010)

Window type	Thermal conductivity, K_w [W/m^{2}K]
Single glass	5,20
Double glass	2,90
HR glass	2,30
HR+ glass	2,00
HR++ glass	1,80
Triple HR glass	1,40

Air thermal capacitance, C_a

The air thermal capacitance, C_a, describes the ability of the indoor air to store internal energy. When the household is heated the energy is stored in the building mass and the air and slowly released over time. The air thermal capacitance can be calculated with the following formula:

$$C_a = 6 \cdot VHC \cdot Vol \tag{5.10}$$

With:

VHC – volumetric heat capacity of air, 1225 J/m^3/K at 15°C [J/m^3/K]
Vol – volume of the air in the household [m^3]

The factor 6 in Equation (5.10) is used to account for the convective inertia of the air (Tindale, 1993) and is an agreement with the household characteristics and air thermal capacitance given in (Pearce, 2001). The volume of the household is calculated from the floor area and the building story height, taken to be 2,7m, an average value for Dutch households (Reed Business, 2011).

Building thermal capacitance, C_w

The building thermal capacitance, C_w, is dependent on the construction material that is used. Schultz and Svendsen (1997) and Wittchen and Aggerholm (1999) give typical values for thermal conductance based on the structure type that range from 30 Wh/m^2°C for extra light structures to 160 Wh/m^2°C for extra heavy structures. Extra light structures consist of wooden skeleton walls and have no heavy elements. Extra heavy structures consist of heavy walls, floors and roofs in concrete (Wittchen and Aggerholm, 1999). In the heat demand model only extra heavy structures are considered since most Dutch households consist of brick. The thermal capacitance, C_w, is found by multiplying the wall and roof area by 160 Wh/m^2°C.

5.1.3 Heat demand model verification

A verification of the heat demand model is found in Appendix B. In this verification a comparison is made between the results obtained by the model and those from a detailed household energy study as well as other experimental results.

5.1.4 Reference houses characteristics for the heat demand model

The model described in the previous two sections is used to determine the heat demand of three reference houses, one for each type of neighborhood: Countryside, village, and city. The characteristics of the houses have been taken from GreenCalc+, a software program used to compare the degree of sustainability of houses and neighborhoods (DGMR Bouw, 2010). In the software program characteristics of typical Dutch houses built in 1990 are given, the values used are given in Table 5.3. From these values given in the table Equations (5.3) through (5.10) can be used to determine the conductances, capacitances, and solar and other heat gains.

Table 5.3: Input parameters for the heat demand model

Parameter	Units	Countryside	Village	City
Type of house	-	Detached	Semi-detached	Row house
Construction year	-	1990	1990	1990
Window type	-	Double glass	Double glass	Double glass
Number of floors	#	2	2	3
Floor area	m^2	141	139	113
External wall area	m^2	113,4	111,9	44,8
Window area	m^2	30,5	26,1	14,5
Roof area	m^2	148	94	63
Shading factor[1]	-	0,9	0,8	0,6

5.2 Creation of a single power demand profile

In Section 5.1 the household heat demand model was explained. In this section it will be explained how this model is used to create the power demand profile for one of the heating technologies. Here a detailed description is given of how the electric heater power demand profile is created. The creation of power demand profiles for the other technologies is similar; a brief explanation of these is given in Section 5.4.

5.2.1 Sizing of the space heating system

The capacities of the space heating systems are dimensioned such that the heat demand of the household can be fulfilled at all times during the year. To size the space heating systems it is therefore first necessary to determine the total heating demand; this is done by rewriting Equation (5.2) and solving for q, assuming a constant indoor temperature of 21°C is maintained. The total heating demand is solved for an entire year in 15 minute intervals. From the total heating demand the heat demand that needs to be provided by the heating system is determined by subtracting the solar gain and the gain due to appliances and persons.

[1] The shading factor is a function of the surroundings and influence the solar gain of the household. The values used are taken from Wittchen and Aggerholm (1999).

The resulting heat demand varies depending on the type of heating system, the type of household and the characteristics of the house (level of insulation, construction year, window type, etc.). Table 5.4 summarizes the capacities determined for the space heating systems considered. These capacities have been determined by taking into account the thermal output of the heating systems during operating conditions. The heating system capacities are rounded up to the nearest 250W.

Table 5.4: Capacities of space heating systems with and without insulation

Parameter	Units	Countryside		Village		City	
Insulation	mm	0	50	0	50	0	50
Peak heat load demand	kW_{th}	6,94	5,70	5,90	4,92	3,43	2,93
Electric heater capacity	kW_e	7,00	5,75	6,00	5,00	3,50	3,00
Monovalent heat pump capacity	kW_e	2,75	2,50	2,50	2,00	1,50	1,25
Bivalent heat pump, sized for 40% of peak heat load	kW_e	5,5	4,5	4,75	4,00	3,00	2,50
Of which heat pump	*kW_e*	*1,25*	*1,00*	*1,00*	*1,00*	*0,75*	*0,50*
Of which booster	*kW_e*	*4,25*	*3,50*	*3,75*	*3,00*	*2,25*	*2,00*
Bivalent heat pump, sized for 60% of peak heat load	kW_e	4,75	4,00	4,00	3,25	2,50	2,00
Of which heat pump	*kW_e*	*1,75*	*1,50*	*1,50*	*1,25*	*1,00*	*0,75*
Of which booster	*kW_e*	*3,00*	*2,50*	*2,50*	*2,00*	*1,50*	*1,25*
Bivalent heat pump, sized for 80% of peak heat load	kW_e	3,75	3,25	3,25	2,75	2,00	1,75
Of which heat pump	*kW_e*	*2,25*	*2,00*	*2,00*	*1,75*	*1,25*	*1,00*
Of which booster	*kW_e*	*1,50*	*1,25*	*1,25*	*1,00*	*0,75*	*0,75*
Ground source heat pump capacity	kW_e	2,00	1,75	1,75	1,50	1,00	1,00
Micro CHP	kW_e	-1,00	-1,00	-1,00	-1,00	-1,00	-1,00

5.2.2 Calculations used to create power demand profiles

After the size of the heating system has been determined it is possible to create the power demand profile. This is done iteratively for in 15 minute intervals:

1. Decide whether to turn the heating system on or off based on the following checks:
    a. Compare the indoor temperature to the desired indoor temperature (based on the thermostat setting). If the indoor temperature is 1°C or lower than the desired temperature turn on the heating system.
    b. If the indoor temperature is 1°C or higher than the desired temperature turn of the heating system.
    c. If criteria a. or b. are not met, keep the heating system in the same state as the last interval
2. Calculate the change in indoor and wall temperature using Equation (5.2)
3. Calculate the new indoor and wall temperature
4. Record whether the heating system was on or off to create the power demand profile

5.2.3 Resulting power demand profile of a single electric heater

Figure 5.3 shows the resulting power demand profile for a single electric heater in a city household. The profile is simply a series of on and off intervals. Because it is a very cold day, the heater is almost continually on however. It is seen that the 'on' periods are slightly longer in the morning and in the evening hours, corresponding with the increase in desired indoor temperature (Figure 5.2).

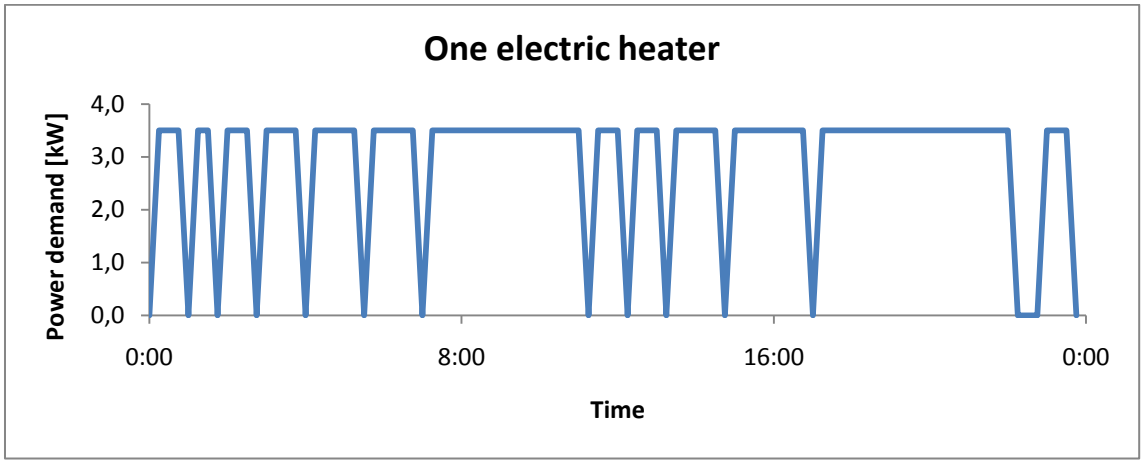

Figure 5.3: Power demand profile of one random electric heater on a very cold day

5.3 Creation of average power demand profile by aggregating single profiles

To aggregate the individual power demand profiles into an average profile assumptions are made about the times at which people wake up in the morning and arrive home in the evening and the duration of the heating. These assumptions are based on information provided in the study conducted by VROM (2010). The following assumptions are made:

- All houses use a thermostat to control the indoor temperatures of their home. The thermostat programs used are shown in Figure 5.2. Characteristic of the programs are a peak in temperature in the morning when everyone wakes up and in the evening when everyone arrives home.
- The desired indoor temperatures of each household are the same, but the exact times at which the thermostats are turned up in the morning and in the evening vary according to the following assumptions:
    - The time at which people increase the desired indoor temperature in the morning is normally distributed with a mean of 7:00 and a deviation of four times 15 minutes.
    - The morning heating period lasts 2 hours.
    - The time at which people arrive home and hence the temperature increases to the evening setting is normally distributed with a mean of 17:00 and a deviation of four times 15 minutes.
    - The evening heating period lasts 5 hours.

From the above assumptions the desired indoor temperature for a random household, and hence the power demand profile of the heating technology, can be created. By creating sufficient of these profiles the average power demand profile for an electric heater on a cold day can be created, Figure 5.4 shows such a profile.

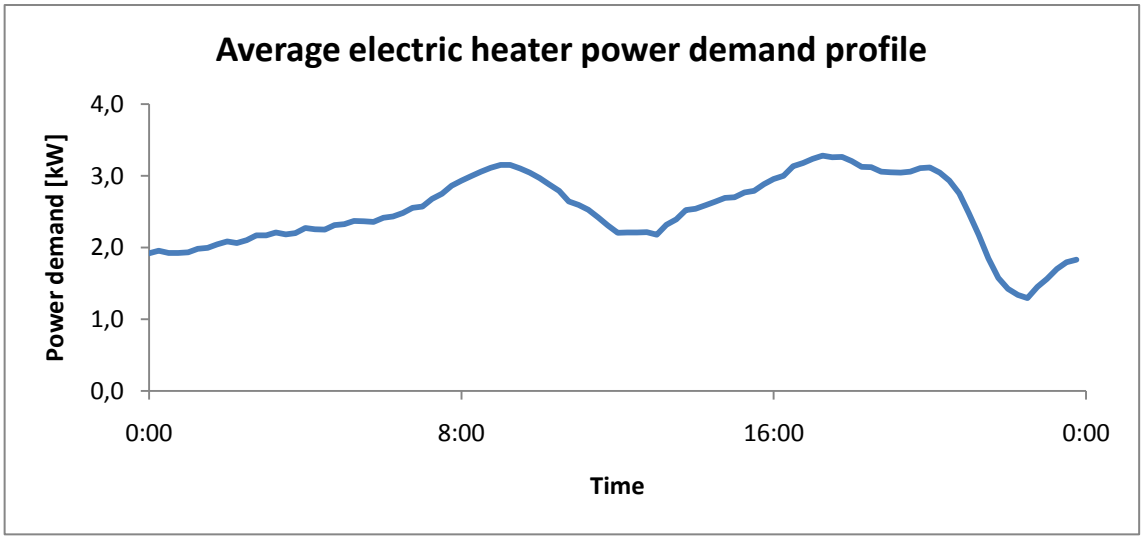

Figure 5.4: Average power demand profile - Electric heater in a city neighborhood

It is seen in the figure that there is a peak in the morning and in the afternoon corresponding with the increase in thermostat temperature settings from Figure 5.2.

5.4 Alternative heating strategies and their power demand profiles

In Sections 5.2 and 5.3 it was explained how the average power demand profile of a heating technology has been created. In these sections the electric heater was used as an example. Four other heating technologies are considered: monovalent heat pumps, bivalent heat pumps with varying capacities of the heat pump and boosters, ground source heat pumps, and micro CHP. In this section the modeling of these technologies and the power demand profiles will be explained.

5.4.1 Electric heater

The electric heater is the simplest technology considered. The electric heater has a 1:1 electricity to heat ratio, therefore the electrical capacity of the heater is equal to the maximum heat load. The power demand profiles of the electric heaters are seen in Figure 5.3 and Figure 5.4. The electric heater profiles for the countryside and village neighborhoods are similar, except with larger values for the power.

5.4.2 Heat pumps

Three different types of heat pumps are considered: Monovalent air-to-air, bivalent air-to-air and ground source heat pumps. Here an explanation is given of these types of heat pumps followed by the power demand profiles of each.

A heat pump uses work (often provided by electricity) to pump heat against the direction of its natural flow. By doing this a heat pump can transfer heat from natural sources such as the outdoor cold air, ground, or water to a building or industrial application (IEA HPC, 2011).

There exist various types of heat pumps; the first way to distinguish them is by their heat source. For household heating applications the most common sources are the ambient air, ground water, and solid ground. In industrial applications exhaust air from industrial processes is also often used (IEA

HPC, 2011). Ambient air heat pumps are most often installed during renovation of existing buildings while ground source heat pumps are more often installed in new buildings (SenterNovem, 2009).

Heat pump performance is often defined according to the coefficient of performance (COP). The COP is the ratio of heat delivered to the electricity supplied to the compressor. The most important factor effecting the COP of a heat pump is the temperature of the heat source; the higher the temperature of the heat source the less work that is required to raise the temperature to the desired temperature (IEA HCP, 2011). Because of the varying outdoor temperatures air heat pumps in particular experience decreasing performance on cold days.

The heat pump capacities are sized depending on the maximum heat load of a household. The power of the heat pump compressor needs to chosen such that it can meet the heat demand at all times. However, since the maximum heat load is expected to occur on a very cold day and the COP of the heat pumps decreases with source temperature, heat pumps are often combined with additional heating elements to meet the maximum demand. Such a heat pump is called a bivalent heat pump. Bivalent heat pumps have a compressor capacity suited to meet 20-60% of the peak heat load, which allows the heat pump to meet 50-95% of the annual heating demand (IEA HCP, 2011). Monovalent heat pumps on the other hand, do not have any extra heating elements and the compressor capacity is designed to be able to meet 100% of the peak heat load.

The power demand profile of a heat pump is created by first determining the electricity supplied to the compressor, this depends on the COP. Values for COP are provided by heat pump manufacturers however these are under ideal conditions, and as was stated above, the COP varies with source temperature. For a heat pump the COP is approximately linear over the temperature range (Morrison, 1983):

$$COP(T_0) = \alpha T_0 + COP(0°C) \tag{5.11}$$

With:

$COP(T_0)$ – The coefficient of performance with source temperature T_0
α – The increase in coefficient of performance per increase in temperature, 0,05 °C^{-1}
$COP(0°C)$ – Coefficient of performance at 0°C

In the Matlab heat demand model the COP of the heat pump is determined for every 15 minute interval during the days considered. Like this, the thermal output is determined and the procedure described in Section 5.2.2 is followed to create the power demand profiles.

In the sections below the different types of heat pumps considered are described and the average power demand profiles are presented.

Monovalent air-to-air heat pump

For air-to-air heat pumps the source temperature, T_o, is taken as the outdoor temperature at any given instant in time. The COP at 0°C is taken as 3,0; this is based on values of commercially available heat pumps.

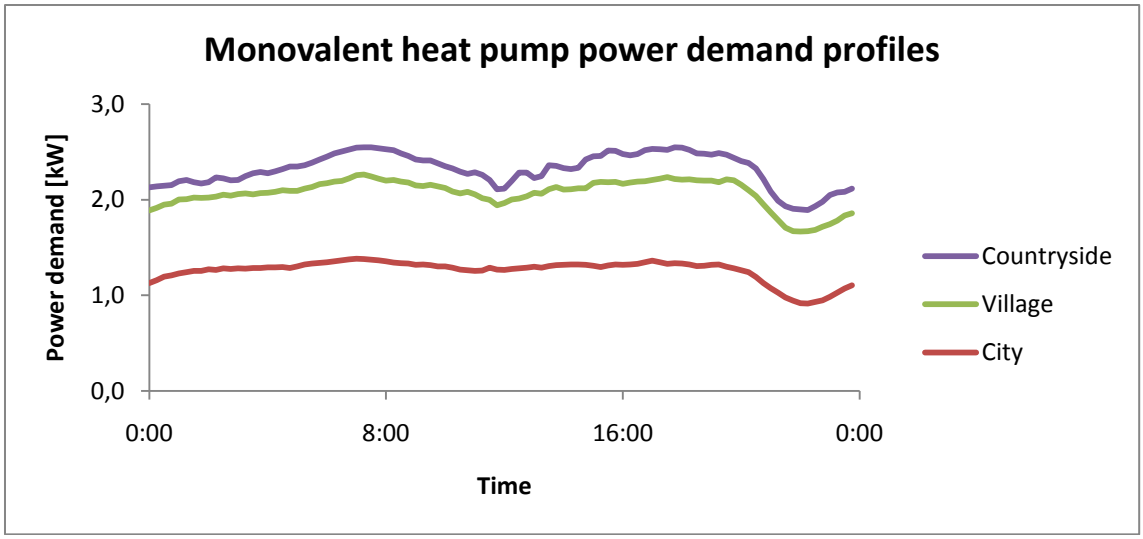

Figure 5.5: Average power demand profiles – monovalent heat pump

The effect of insulation and lowering the thermostat settings have also been taken into account. Figure 5.6 shows the power demand profile of the countryside monovalent heat pumps with and without improved insulation and/or lower thermostat settings. The trends for heat pumps in city and village neighborhoods are similar, figures of these are therefore omitted.

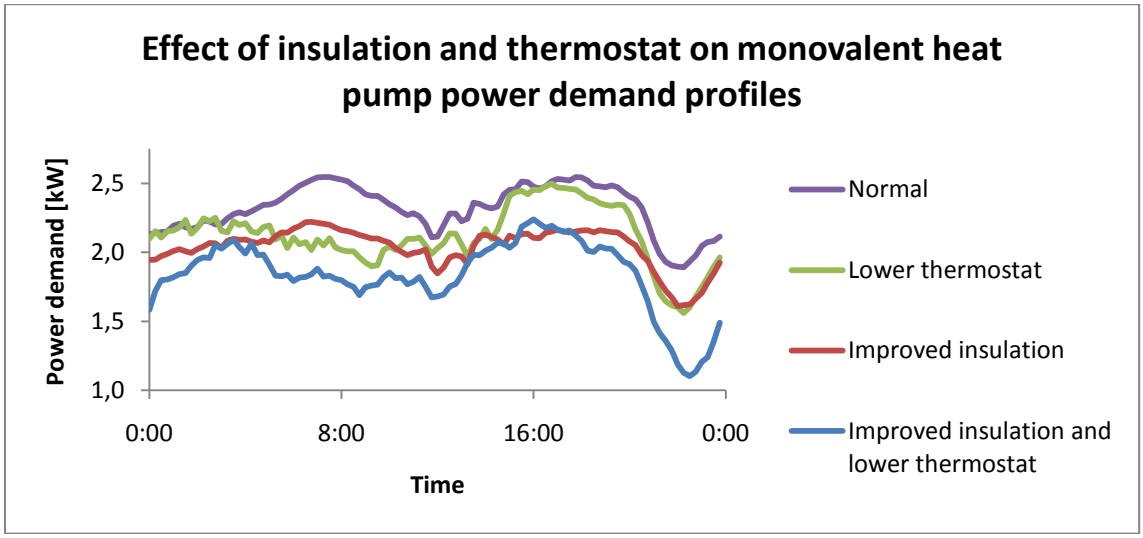

Figure 5.6: Effect of insulation and thermostat setting on the average monovalent heat pump power demand profiles

Bivalent air-to-air heat pump

A bivalent heat pump uses a heat pump as the primary method to provide space heating, however the capacity is not sufficient to meet the heat demand at all times; on very cold days an additional heating element (called a booster) is used in conjunction with the heat pump.

Three bivalent heat pumps with varying capacities are considered. The heat pump capacities are dimensioned to meet 40%, 60%, and 80% of the peak heat load. The boosters are sized to meet the remaining peak heat load demand not met by the heat pump (i.e. 60%, 40%, and 20%, respectively).

For the bivalent heat pumps and additional control strategy is required in addition to the steps described in Section 5.2.2 to determine when the booster needs to be turned on. The control strategy is as follows:

1. Determine whether heat pump needs to be on or off according to procedure described in Section 5.2.2.
2. Calculate the change in indoor temperature, dT_i, using Equation (5.2).
3. If dT_i over a 15 minute interval is less than 0,4°C, turn on the booster.
4. Recalculate dT_i and determine the new indoor temperature.

According to this procedure the heat pump will always turn on before the booster and the booster will only be used if the temperature in the household is not increasing sufficiently rapidly.

Figure 5.7 shows the power demand profiles of the three bivalent heat pumps for a village household. The profiles for the other two neighborhoods are similar with different peaks values. In Figure 5.7 two peaks are observed, one around the time when everyone wakes up and one at the time that everyone arrives home. The size of the peak is larger with small heat pumps, due to the larger booster element required.

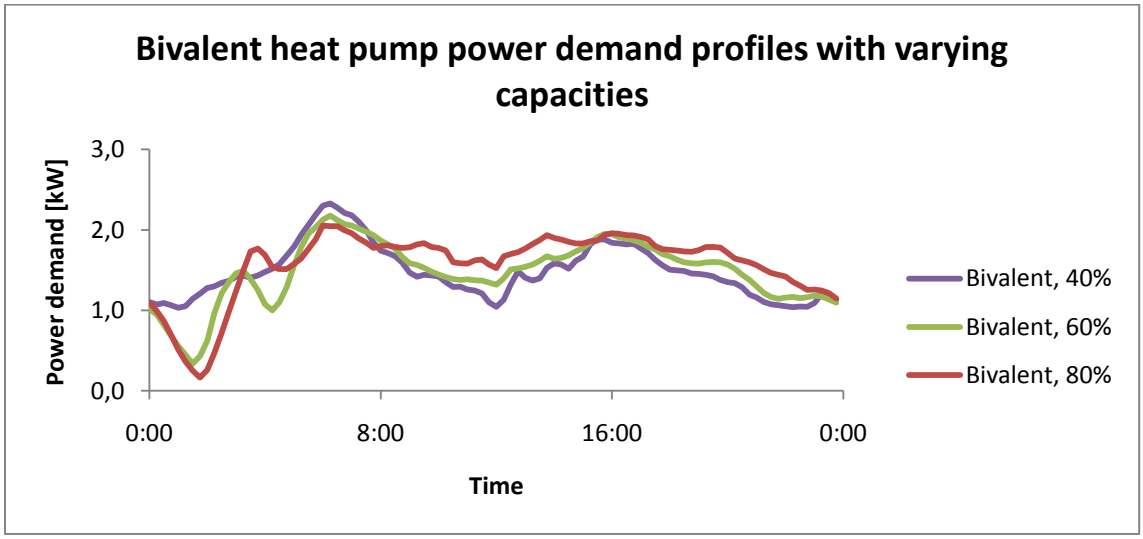

Figure 5.7: Average power demand profiles – bivalent heat pumps in a village neighborhood

Figure 5.8 shows the effect of insulation and/or thermostat setting on the power demand profile of a 60% heat pump in a city neighborhood. It can be seen that when using a lower thermostat setting there is a larger peak in the evening hours, this can be understood by looking at Figure 5.2, it is seen that there is a large rise in temperature at the start of the evening and the booster is required.

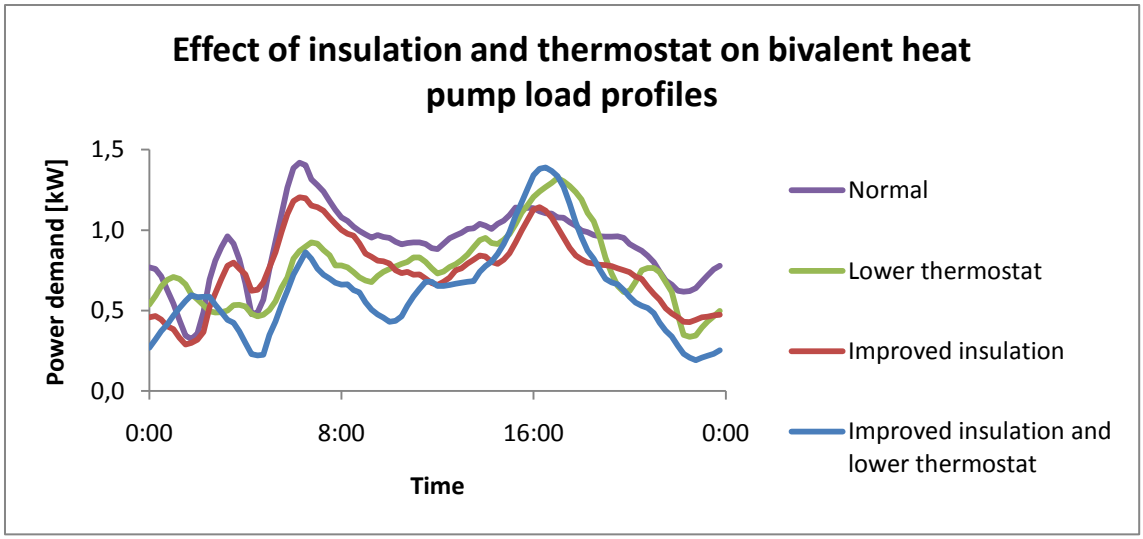

Figure 5.8: Effect of insulation and thermostat setting on the average bivalent heat pump power demadn profiles

Ground source heat pump

For ground source heat pumps the source temperature is not the same as the air temperature. The temperature of the ground source follows the ambient air temperature however the fluctuations are smaller. At depths below approximately 6 meters the temperature is constant and is equal to the year mean temperature (RETScreen International, 2005).
In this study a ground source heat pump with vertical piping is assumed, in which case the depth of the ground source is 45-150 meters deep (RETScreen International, 2005). At depths of 45 meters or deeper the ground source temperature can be taken as equal to the yearly mean temperature, 10°C in the Netherlands (KNMI, 2011a). Based on this, it is determined by Equation (5.11) that the COP for the ground source heat pump is equal to 3,5. This is consistent with values found in (RETScreen International, 2005). Figure 5.9 shows the power demand profile of the ground source heat pumps. Because the COP does not vary, a flatter profile is seen.

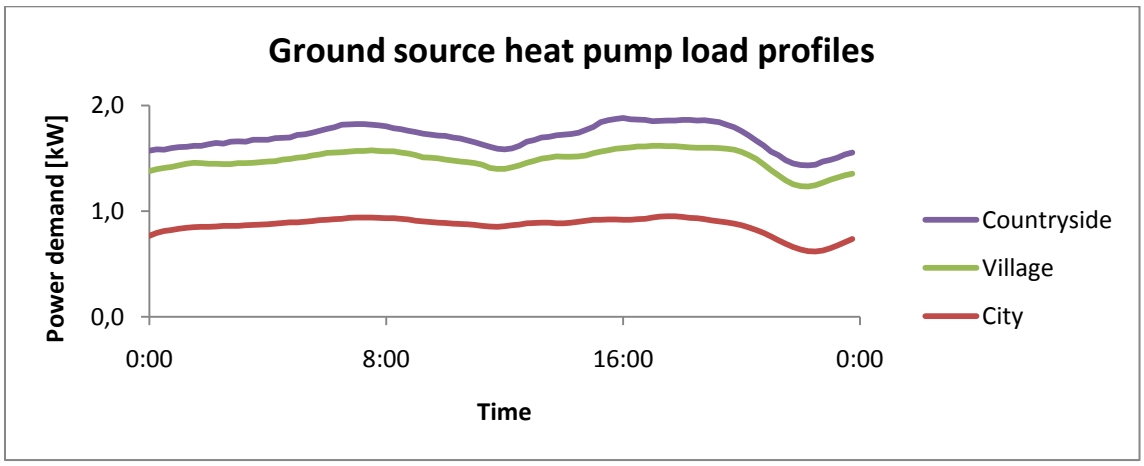

Figure 5.9: Average power demand profiles - Ground source heat pump

5.4.3 Micro CHP

The final heating technology considered is the micro CHP. A micro CHP heating system uses natural gas as fuel and produces both electricity and heat; because of this the control strategies can vary

between being heat demand or power demand driven (Houwing, 2009). In this thesis only a heat driven micro CHP control strategy is considered.

The micro CHP unit has an electrical power output of 1kW and a thermal output of 6,6kW. The heat produced is used to warm a 120L water boiler which in turn is used for space heating and warm water demand. If the heat demand is larger than 6,6kW an auxiliary burner using natural gas is used to provide the remaining demand. The use of the auxiliary burner therefore does not contribute to the power profile of the Micro CHP. The micro CHP cannot be operated in part load and the warm-up and cool-down times are ignored since they are smaller than the 15 minute time steps considered in simulations (Houwing and Bouwmans, 2006).

The power demand profile of the micro CHP system is created by monitoring the temperature of the water boiler. The water boiler temperature drops as heat is provided for either space heating or warm water. If the temperature is below 60°C then the CHP will turn on and heat the water to a maximum temperature of 75°C. If the temperature drops below 58°C the auxiliary boiler will also turn on and heat the boiler to a maximum of 68°C. The heat provided by the auxiliary boiler is between 3kW and 30kW and depends on the required heat demand. This control strategy is based on the work of Houwing and Bouwmans (2006).

Using the above strategy and the household heat demand model the power demand profile of the micro CHP unit can be created by recording the times at which the micro CHP is on. The following figure shows the resulting power demand profiles for the three neighborhoods.

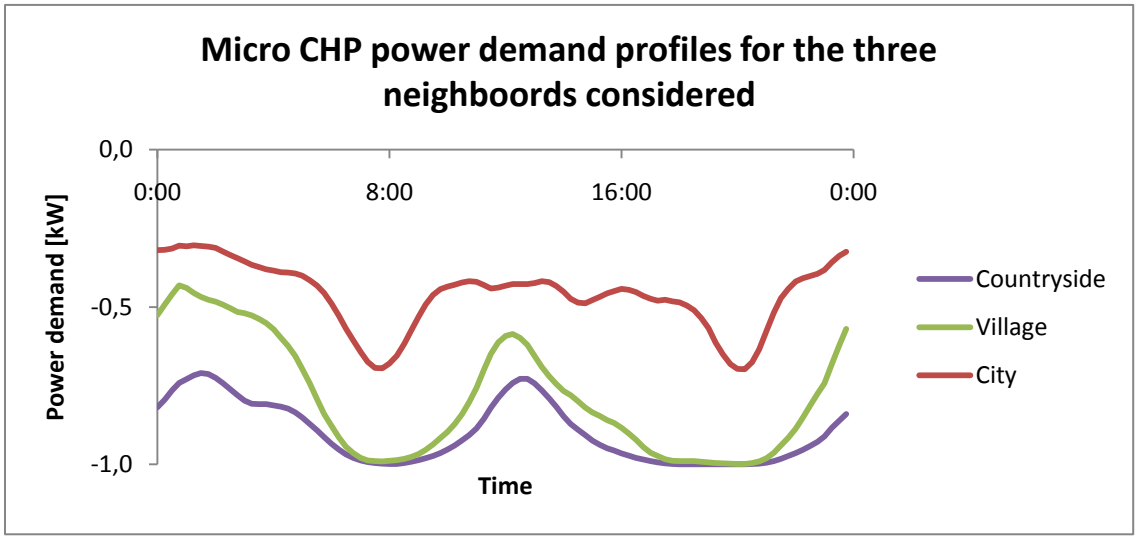

Figure 5.10: Average power demand profiles - Micro CHP power

The power is negative because the micro CHP units provide electricity. It is seen in the figure that in the city neighborhood the load is below 1kW at all times, this is because the row households of city neighborhoods are generally smaller and have lower heat demands. In these cases the auxiliary heater is almost never used. In countryside and village neighborhoods the heat demand reaches a peak in the morning and in the evening and the auxiliary heater is used to provide extra heat.

Because micro CHPs are heat demand driven improving insulation and/or thermostat setting will decrease the power supply. This is seen in Figure 5.11.

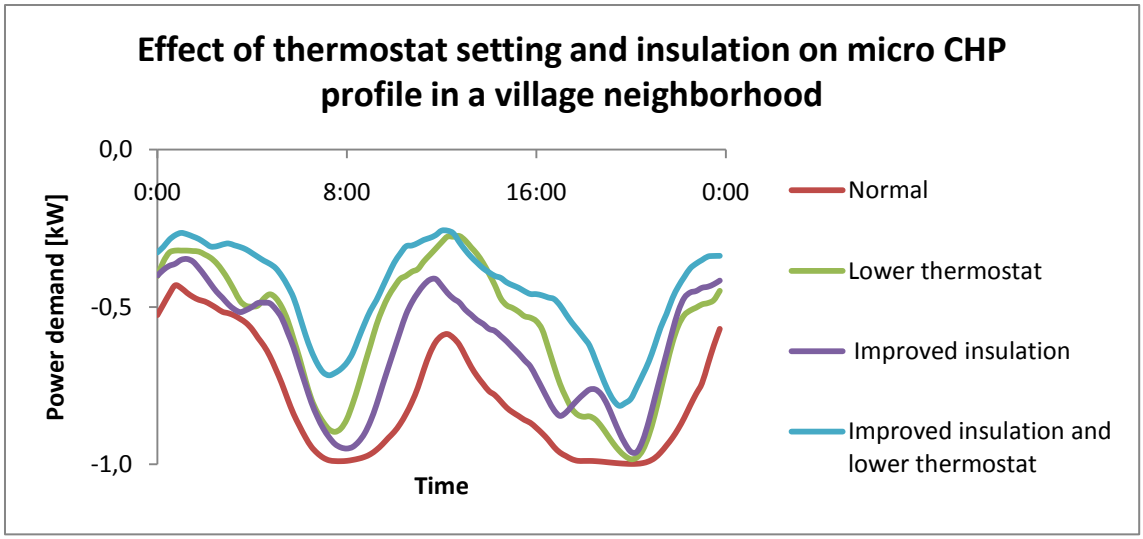

Figure 5.11: Effect of improving insulation and lowering the thermostat on micro CHP power demand profiles for a village neighborhood

5.4.4 Air conditioner

The power demand profile for an air conditioner can also be modeled using the heat demand model described here. An air conditioner functions in a similar manner as a heat pump however it operates in the opposite direction. The coefficient of performance of the air conditioner is taken as 2,75, this is the average value of the commercially available air conditioners of Samsung. The electrical capacities of the air conditioners range between 1kW and 2,05kW, which are similar to the values determined by the heat demand model (Samsung, 2011).

The difference between the heat pump and the air conditioner is that the power demand profiles for the air conditioner are created for a summer day rather than a winter day. To create the profile for an air conditioner the same procedure described in the previous sections is followed, except that instead of considering the heating demand the cooling demand is taken. The cooling demand is the amount of heat that needs to be removed from the household to maintain a 21°C temperature. Figure 5.12 shows the power demand profiles of air conditioners in a city, village, and countryside neighborhood.

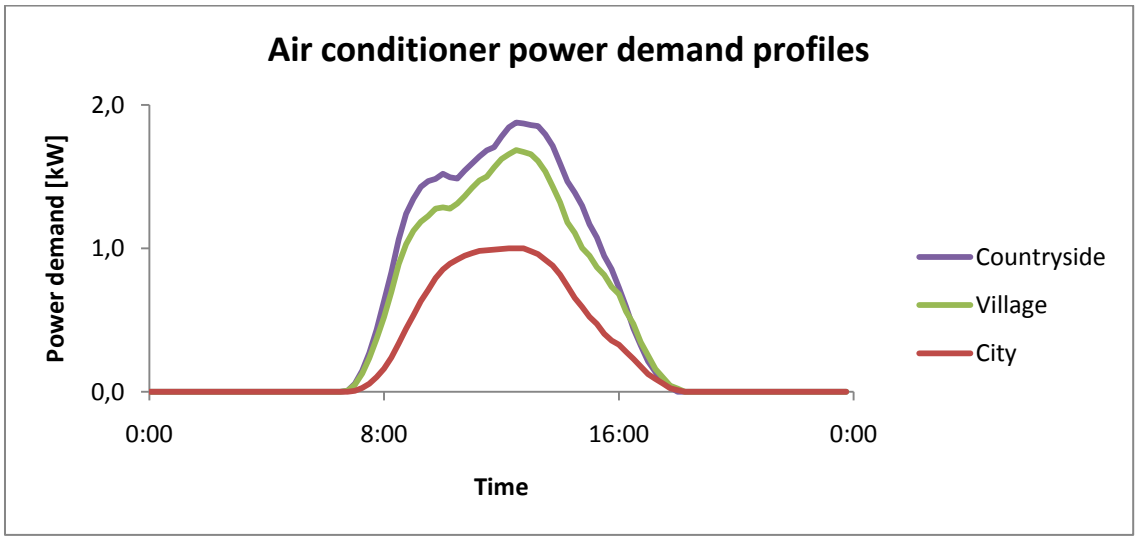

Figure 5.12: Average power demand profiles - Air conditioner

5.5 Comparison to measured data

Measured heat pump compressor power data has been obtained from Alliander (Au-Yeung, 2011). Figure 5.13 shows a comparison between the measured data for eight heat pumps and the average power demand profiles as modeled by the heat demand model. From the figure it is possible to verify that the trends are similar however since limited data is available about the households where the measurements were conducted the comparison has limited value. For this reason three modeled heat pumps are shown.

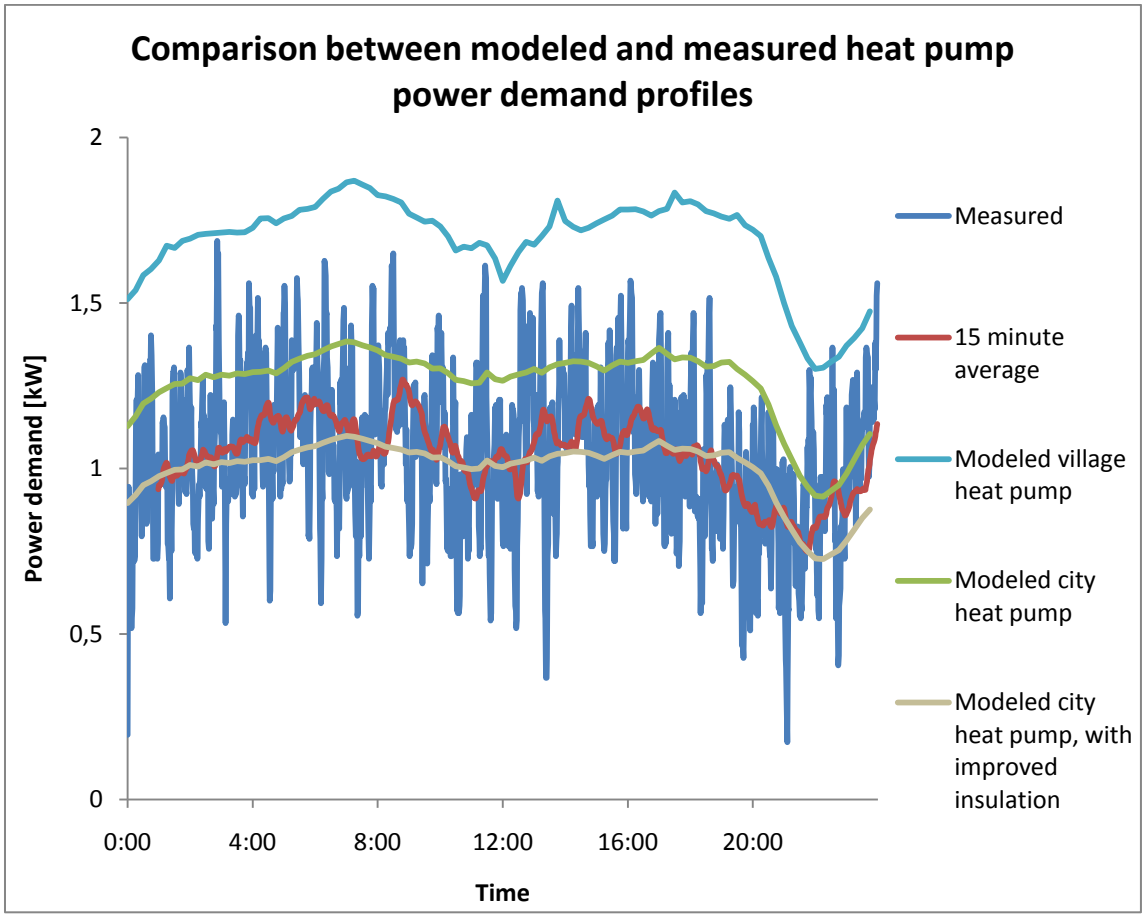

Figure 5.13: Comparison between modeled heat pump power demand profiles and measured heat pump data

The following observations can be made:

- The trend of the modeled data and the running average of the measured data is the same: There is a small peak in the morning and evening with a trough in afternoon. In the evening there is a sharp decrease in the load, this is seen in both profiles.
- The measured data is more stochastic, this is because it contains only data of eight heat pumps.
- No information is available about the characteristics of the households where the data was recorded (such as insulation level, type of household, etc.). Improving the insulation of the household in the heat demand model would shift the profile down, resulting in a better fit. However it is uncertain what the characteristics are of the households where the measurements are taken.

6 Creation of other power demand profiles

In Chapter 4 and Chapter 5 it was explained how the power demand profiles of electric vehicles and the heating technologies were created. In this chapter the creation of the remaining power demand profiles will be explained. The technologies considered in this chapter are each distinct and no flexibility options are considered therefore they have all been grouped together here. In Section 6.1 the creation of the power profile for solar PV panels will be described. In Section 6.2 the power demand profiles for electric boilers and heat pump boilers will be explained. Finally in Section 6.3 the power demand profile of the basic household electricity demand due to common appliances will be described. Within each section it will be explained how an individual profile is created as well as how they are aggregated.

6.1 Solar PV

The solar PV profiles have been created by considering solar irradiation data available from the Royal Dutch Weather Institute (KNMI, 2011b). The data available via the KNMI consists of measured surface irradiation in ten minute intervals for the entire year. From this data the summer and winter days with the largest total irradiation are taken. The surface irradiation is given in the units W/m^2, therefore to calculate the solar panel electricity production the irradiation is multiplied by the solar panel surface area and the efficiency of the solar panel (Sinke, 2009a). Silicon wafer solar panels are considered, these have an efficiency of about 11,5% (Sinke, 2009a). An area of $15m^2$ is assumed per house. Figure 6.1 shows the power demand profiles for the solar panels. The power is negative because it is supplied to the network.

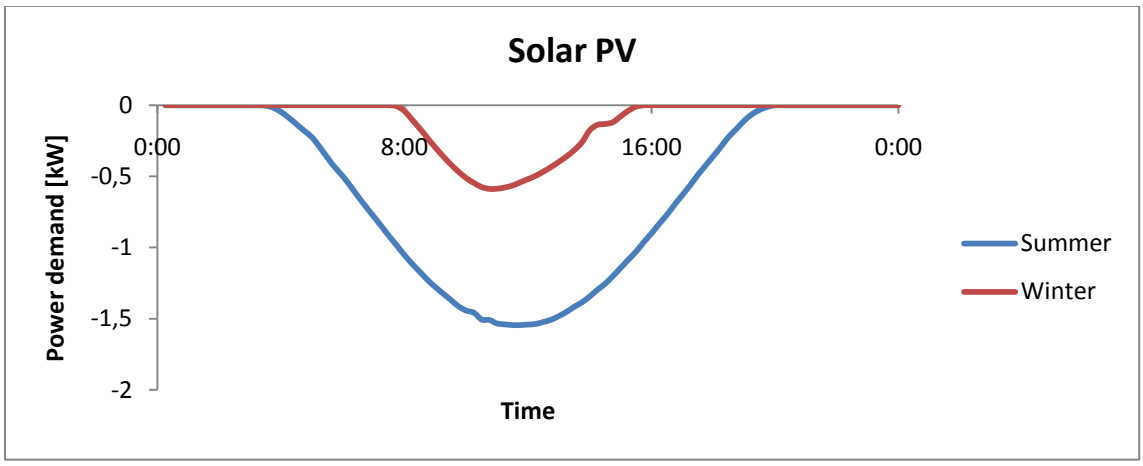

Figure 6.1: Power demand profile – Solar PV

It is assumed that the solar panel power profile does not vary between the various households within one neighborhood; therefore they all have the profile shown in Figure 6.1.

6.2 Electric and heat pump water boiler

The power demand profiles for hot water heating have been created using a Matlab script using hot water consumption data measured by the IEA. In this section the modeling of the profiles is described.

6.2.1 Hot water consumption data

The electric and heat pump water boiler power demand profiles are created by using data from an IEA study on distributed heat and power generation. One of the data files consists of a full year of measurements of the hot water use of households with average consumptions of 100, 200, and 300 liters of water (IEA, 2008). The average Dutch citizen uses 125 liters of water per day and each household has an average of 2,3 people, therefore the 300 liter consumption data is taken (TNS-NIPO, 2008 and CBS, 2011a).

6.2.2 Electric and heat pump water boiler characteristics

The hot water boilers are designed according to specifications of commercially available hot water boilers. Information from (Assos Boilers, 2011) and (Milieu Centraal, 2011) is used for the technical specifications of the boilers. Table 6.1 lists the characteristics of the two types of boilers; the only difference between the two is the coefficient of performance.

Table 6.1: Technical specifications of hot water boilers

Parameter	Symbol	Units	Electric boiler	Heat pump boiler
Entering water temperature	T_{in}	°C	10	10
Boiler capacity	Cap	L	120	120
Minimum storage temperature	T_{min}	°C	60	60
Maximum storage temperature	T_{max}	°C	70	70
Power	P_{boiler}	kW_e	5,7	1,5
Coefficient of performance	COP	-	1,0	3,8
Heat output	P_{out}	kW_{th}	5,7	5,7
Heat loss	P_{loss}	kW_{th}	0,05	0,05
Maximum water flow rate	m	L/s	0,2387	0,2387

6.2.3 Creation of a single power demand profile

A Matlab script has been written to determine the electricity demand profiles of the hot water boilers. The script does the following:

1. Import the hot water consumption data. This is 15 minute data for one year.
2. Define the characteristics of the hot water boiler (Table 6.1).
3. Loop for one year and for every data point do the following:
    a. From the hot water consumption data read how much water is removed from the boiler. An equal amount of cold water enters the boiler to be heated.
    b. Assume the water in the boiler is perfectly stirred and calculate the new temperature of the water:

$$T_s = \frac{T_{in} * water_{out} + T_s * (cap - water_{out})}{cap} - \frac{P_{loss}}{cap * 4{,}186} \qquad (6.1)$$

    c. If the temperature is below the minimum temperature, the water boiler is turned on. The increase in the water temperature is calculated with:

$$dT_s = \frac{Q_{boiler}}{cap * 4{,}186} \tag{6.2}$$

d. If the temperature is above 70°C the water boiler is turned off.
e. The new temperature of the water boiler is calculated.
f. The power output of the boiler is recorded to create the power demand profile.

By carrying out these steps for an entire year the hot water profiles can be created. Figure 6.2 is an example of what one day looks like:

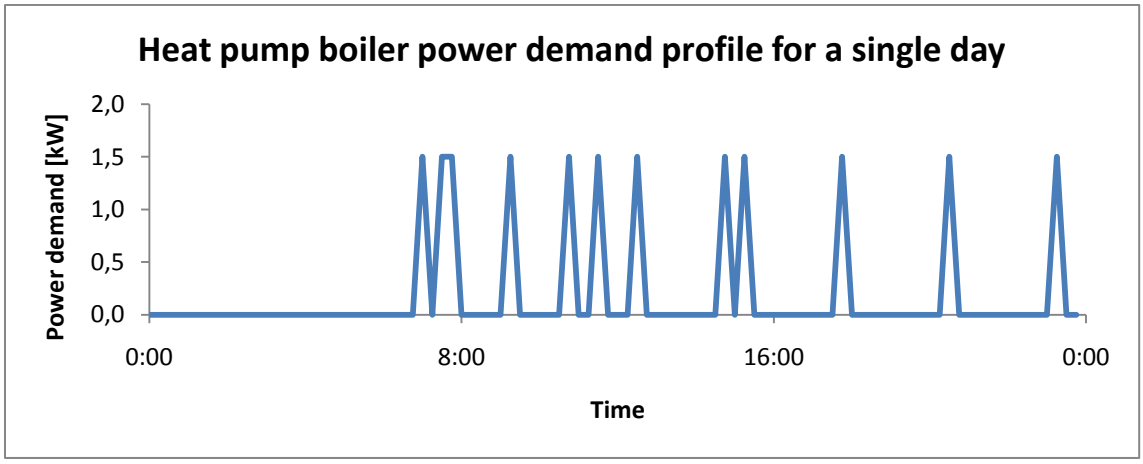

Figure 6.2: Power demand profile – heat pump boiler

6.2.4 Creation of average power demand profiles by aggregating single profiles

In Section 6.2.3 it is explained how the power demand profiles for every day of an entire year are created. To create an average power demand profile for electric boilers and heat pump boilers it is assumed that hot water consumption is independent of day of the year, like this the 365 separate profiles can be aggregated into one average profile. Figure 6.3 shows the average power demand profile of a heat pump boiler. The profile for an electric boiler is the same but scaled by the coefficient of performance, 3,8.

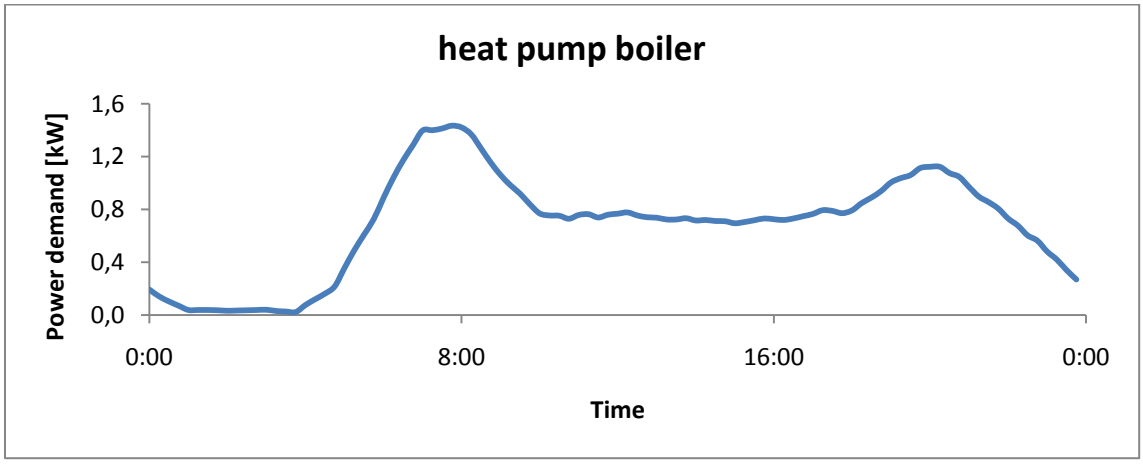

Figure 6.3: Average power demand profile – heat pump boiler

The profile shown in Figure 6.3 is as it would be expected; the peak is in the morning at approximately 7:30, the time at which many people shower. A second peak smaller peak is seen in the evening when people arrive home at the end of the day. For verification the hot water profile can be compared with a profile found in (Abu-Sharkh et. al, 2006).

6.3 Household demand profile

In addition to the power demand profiles of technologies such as heat pumps, electric vehicles, and solar panels it is also necessary to have a power demand profile for the basic household demand. This is the power demand of households due to common appliances such as lights, televisions, computers, washing machines, etc. The power demand profiles of common household appliances have been obtained from network operators. These power demand profiles are based on measured data in 1200 Dutch households over a long period of time (Energiened, 2006). The appliances are not modeled separately but are rather are summed into one profile representing the average electricity demand of a household. Figure 6.4 shows these profiles for a typical summer and winter day.

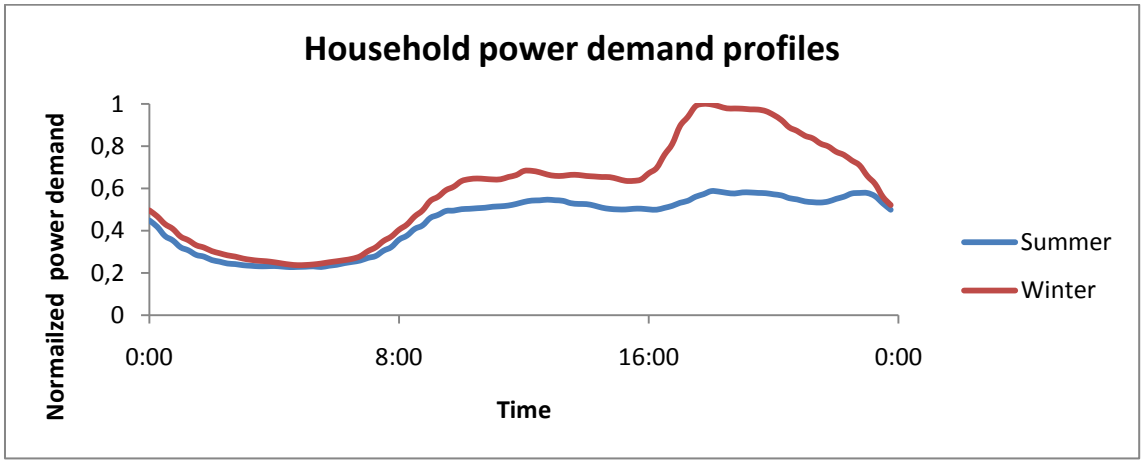

Figure 6.4: Average power demand – Households

As expected the peak in Figure 6.4 is in the evening hours after approximately 17:00. This peak is larger in the winter than it is in the summer. The profile shows the average electricity demand for a Dutch household, and is scaled to per units. Depending on the type of household that is considered the profile is scaled accordingly using the Strand-Axelsson equation, explained in Section 3.1.2. The coefficients for the Strand-Axelsson equation for the three types of households considered in this report are given in the table below; these values have been empirically determined by network operators and are found in sources such as VDEN (1986) and in the Gaia software program (Phase to Phase, 2011).

Table 6.2: Parameters used to calculate scale household power demand profiles

Parameter	Units	Countryside	Village	City
Type of house	-	Detached	Semi-detached	Row houses
α	-	0,0002319	0,0002332	0,000189
β	-	0,0234	0,0159	0,0325
E_1	kWh	5.000	4.000	3.500
$P_{max,1}$	kW	2,81	1,94	2,58

7 Simulations and results

In the previous chapters it was described how a testing environment was created and how the power demand profiles of various technologies have been modeled for a typical summer and winter day in three neighborhoods: City, village, and countryside. It is now possible to carry out simulations and determine the impact of future energy scenarios on the Dutch low voltage electricity grid. In this chapter the results of simulations carried out in the testing environment will be presented. It must be noted that the results presented in this chapter are more theoretical of nature; large market penetrations of the technologies considered are used. In the discussions chapter, Chapter 8, a more practical outlook will be given by considering more realistic market penetrations and mentioning what the implications are of the results presented here.

The results are presented in four sections. In Section 7.1 the business as usual scenario is evaluated, in this scenario the market penetration of all technologies considered is 0% and only the growth of traditional household electricity demand is taken into account. In Section 7.2 the critical market penetrations of a selection of technologies is determined; these are used as a baseline. In Section 7.3 the flexibility options for electric vehicles and heat pumps will be compared to this baseline. The goal of this section is to determine what the most favorable flexibility option is to reduce network impact. Finally in Section 7.4 the impact due to combinations of technologies will be presented to determine how the electricity networks can better be utilized or the impact can be reduced.

7.1 Impact of the business as usual scenario

In the business as usual scenario it is assumed that the market penetrations of technologies such as electric vehicles, heat pumps, electric heaters, and solar panels are insignificant. In this scenario it is assumed that the only trend impacting the electricity network is a steady growth in the electricity demand of 1% per year due to an increase in the number and size of common household appliances. This growth is in accordance with the growth observed between 1990 and 2009 (CBS 2011a and 2011b).

Under the above assumptions it is found that the network problems will not occur in the foreseeable future. In countryside neighborhoods the transformer will reach a peak load of 100% in the year 2073. In village and city neighborhoods it will reach the peak in 2073 and 2098, respectively. The cable loads in these years are all below 80%. Considering that network components have a life time of approximately 40 years (VDEN, 1986), it is safe to assume that in the business as usual scenario no network problems are expected during the life time of the transformers and cables.

In the business as usual scenario the shape of the load curve does not change, it is assumed that the peak will always occur during a winter evening at approximately 18:00. The only difference is the value of the peak load. Figure 7.1 shows the load profiles of a transformer in a countryside neighborhood for the years 2011 and 2030 in the business as usual scenario.

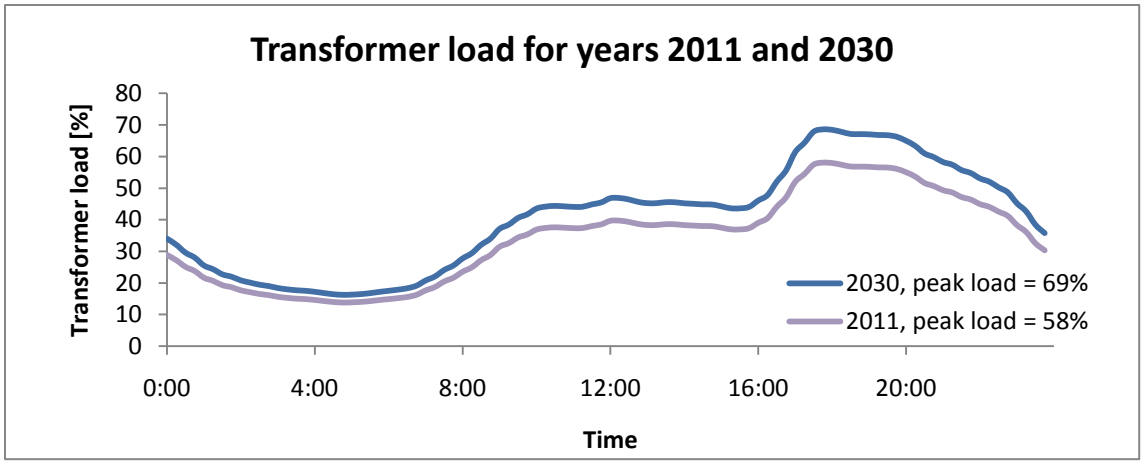

Figure 7.1: Load profile of a countryside transformer on a winter day in 2011 and 2030 assuming 1% per year growth in electricity demand

The load profiles for the other two neighborhoods are similar. In Table 7.1 are summarized the values of the peak loads in the different neighborhoods for the years 2011 and 2030 under different growth scenarios.

Table 7.1: Peak load of cables and transformers for the year 2030 in business as usual scenarios

Year	Electricity demand growth	Countryside		Village		City	
		Transformer	Cable	Transformer	Cable	Transformer	Cable
Present		58%	32%	56%	44%	47%	33%
2030	+2,0% / year	81%	45%	79%	62%	65%	44%
2030	+1,0% / year	69%	38%	66%	53%	55%	38%
2030	+0,5% / year	63%	35%	61%	48%	51%	36%
2030	-0,5% / year	53%	30%	51%	41%	43%	31%
2030	-1,0% / year	49%	28%	47%	37%	40%	28%

The correlation between the electricity demand growth and the transformer load is linear. It can be determined that to achieve 100% transformer load in the year 2030 a electricity growth of approximately 3% per year is required in countryside and village neighborhoods and 4,5% per year for the city neighborhood.

Unless stated otherwise, in the remainder of the report it is assumed that the future year is 2030 and the traditional electricity demand growth is 1% per year.

7.2 Critical market penetrations of the base technologies

Having determined the base loads the first thing that can be determined is which technologies individually present a problem for the electricity grid. In Table 7.2 the market penetrations required to achieve 100% transformer and cable load are presented for a selection of technologies (for electric vehicles and heat pumps the most common flexibility option is used). Technologies that create overload at penetrations under 100% have been highlighted with a red cell.

Table 7.2: Critical market penetrations to cause transformer and cable overload

Technology	Time of peak	Countryside		Village		City	
		Transformer	Cable	Transformer	Cable	Transformer	Cable
Solar PV	Summer 11:15	150%+	150%+	150%+	150%+	150%+	150%+
EV 10kW uncontrolled charging	Winter 18:00	22%	104%	24%	36%	35%	73%
Electric water boiler	Winter 19:45	35%	150%+	38%	65%	52%	120%
Micro CHP	Winter 7:15	150%+	150%+	150%+	150%+	150%+	150%+
Bivalent 60% heat pump,	Winter 17:30	31%	131%	30%	58%	75%	150%+
Air conditioner	Summer 12:30	90%	150%+	72%	110%	140%	150%+

Several observations can be made from the above table:

- In all cases the critical penetration to cause cable overload is higher than the value required for transformer overload. This is an expected result since the ampacity of the cables is very often higher than that of the transformers because of the high costs associated with maintaining low voltage distribution cables.
- The peak loads almost always occur either during the summer day or during the winter evening.
- The times of the peak loads for electric vehicle uncontrolled charging, electric boilers, and bivalent heat pumps approximately coincide with the time of the current peak observed due to household electricity demand (approximately 18:00). These technologies therefore do not combine well with the base household load.
- The neighborhood where network problems occur first varies from technology to technology.
- The most problematic technologies are electric vehicles, electric boilers, and heat pumps.
- Some technologies have critical penetrations of above 100%. This however does not necessarily imply that these technologies will never cause problems; for example by using larger or more efficient solar panels, or larger capacity air conditioners networks could be overloaded at penetrations below 100% (Here a solar panels of 15m^2 with efficiencies of 11,5% are assumed. The air conditioner capacities range between 1kW and 2kW depending on the neighborhood).
- Electricity production technologies, Micro CHP and Solar panels, are quite network friendly; penetrations of above 150% are required to cause network problems since they first need to compensate the demand.
- The cables in countryside and city networks are in almost all cases well dimensioned.

7.3 Comparison of flexibility options

In this section the flexibility options for electric vehicles and heating technologies are compared. In Section 7.3.1 this is done for electric vehicles. In Section 7.3.2 the different heating technologies and

the effect of improving insulation and thermostat settings are considered. The comparisons are made to the reference technologies used in Table 7.2.

7.3.1 Electric vehicles

Figure 7.2 shows the market penetrations required for transformer overload for different electric vehicle charging strategies. The power demand profiles of the different charging strategies are found at the end of Chapter 4.

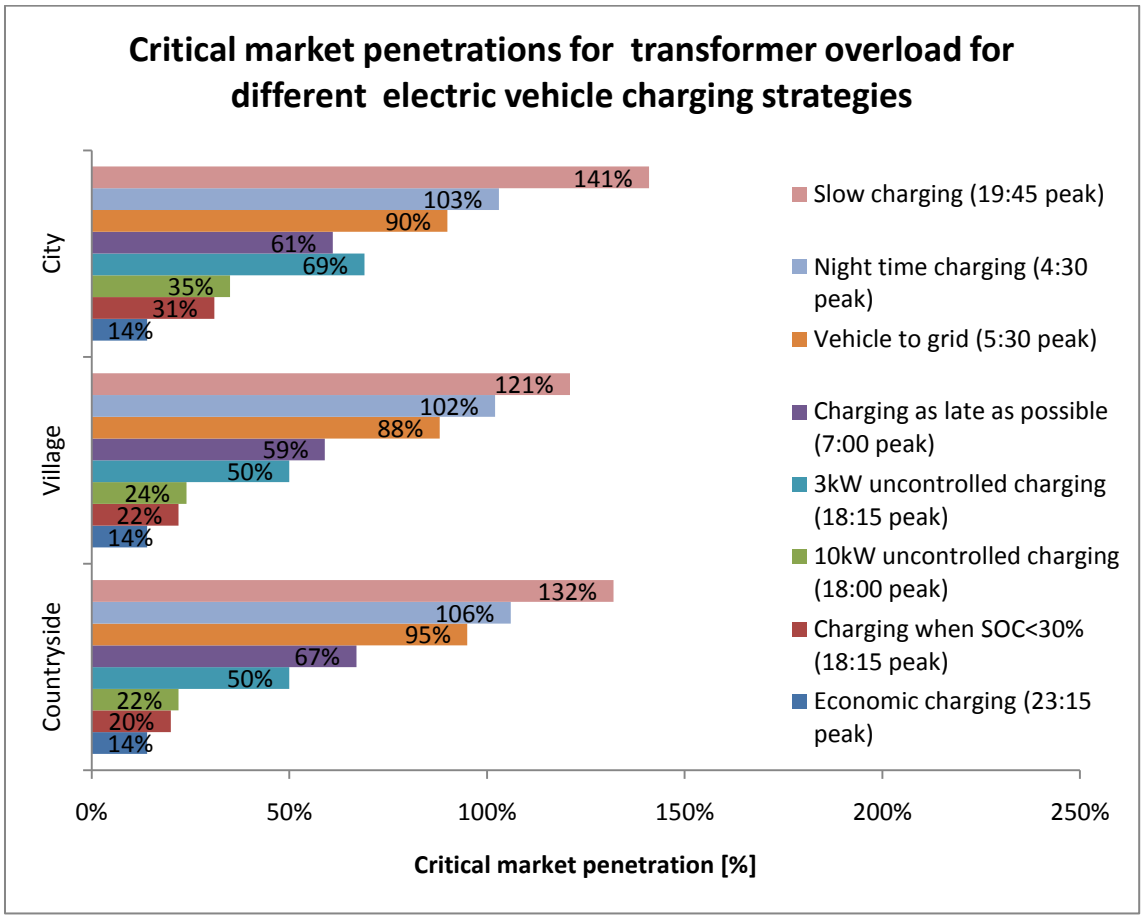

Figure 7.2: Critical market penetrations of electric vehicle charging strategies for transformer overload

From Figure 7.2 a few things can be concluded:

- Compared to the reference technology (10kW uncontrolled charging), many strategies are a more favorable and much larger penetrations of electric vehicles can be supported; a factor 3-6 increase in the critical market penetration is possible.
- There is little distinction between the impacts of electric vehicle among the three types of neighborhoods. Although the networks have different numbers of households, the penetrations required for most charging strategies are almost equal in each of the neighborhoods.
- The least favorable type of charging is economic charging in which everyone charges their vehicles the moment the night-time tariff is applicable. This can fortunately easily be avoided by removing low energy tariffs.

- Charging when electric vehicle battery's state of charge is <30% has a higher impact than the reference case. This is interesting to note because in this strategy the number of electric vehicles charging at a time is less, however the charging time required is greater. It is worth investigating to see how changing the SOC cutoff affects the load profile and whether this could play a role in reducing the total load.
- The most favorable charging strategy is slow charging. As can be seen from Figure 4.6 in the power demand profile of slow charging is favorable because peaks are avoided by spreading charging over the longest possible period of time.
- Other favorable strategies are night time charging and vehicle to grid, in both of these cases the charging peak is found in the mornings at approximately 5:00. Charging as late as possible also has a peak in the morning; however this peak is at 7:00 and coincides too much with the increasing load due to the base household load.
- 10kW uncontrolled charging is one of the least favorable charging strategies because of the high peak occurring around the time that people arrive home.
- The critical market penetration for night time charging is approximately 100%, with this charging strategy investments in the transformers could be avoided. Figure 7.3 shows the transformer and cable loads for a 100% market penetration of electric vehicles with night time charging in a countryside neighborhood; in this case every household has one electric vehicle. Although the peak load is just over 100%, this occurs for a small fraction of time.

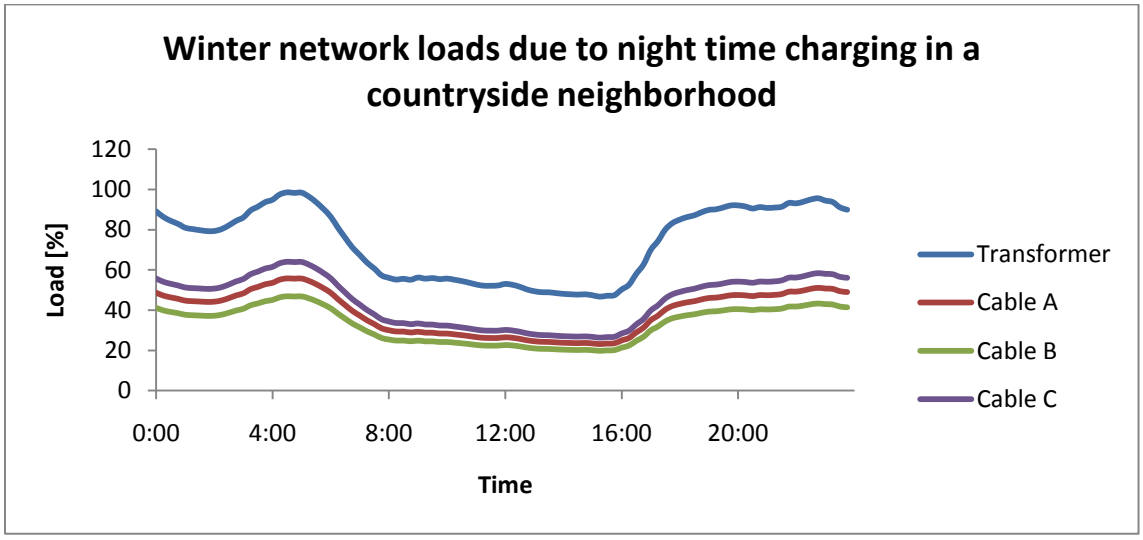

Figure 7.3: Load profiles of network components due to night time charging of electric vehicles

It is also possible to consider the critical market penetrations to overload the cables; this is done in Figure 7.4.

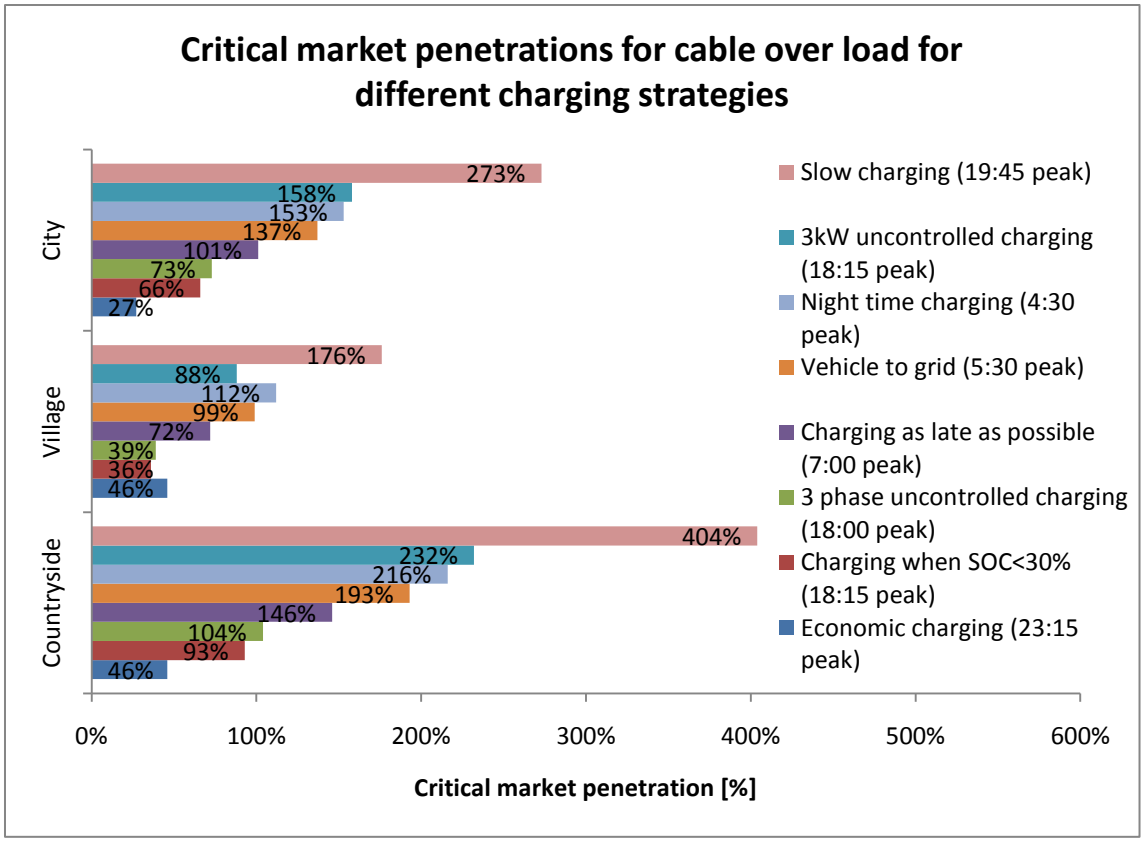

Figure 7.4: Critical market penetrations of electric vehicle charging strategies for cable overload

From Figure 7.4 a few things are concluded:

- At the cable level there is a larger difference between the impacts of the different electric vehicle charging strategies between the three types of neighborhoods. The impact on the cables in the village neighborhood is larger due to this neighborhood having the largest number of users on a single cable (55 compared to 42 in a city neighborhood).
- It is interesting to note that critical market penetration of economic charging in village neighborhoods is *higher* than for a few other strategies. This has to do with the times of the peak loads of the strategies and the traditional household load. Since the village neighborhood is already very highly loaded without electric vehicles the transformer is very easily overload in the winter at 18:00 with the uncontrolled charging strategies. Since economic charging has a peak at 23:15 a slightly higher penetration is required.
- In the countryside and city neighborhoods there are five to six strategies for which the market penetrations of above 100% are required for cable overload. This implies that as long as the uncontrolled and economic charging strategies are avoided it should be possible to fit electric vehicles into the electricity network without investing in additional cables.
- The largest gains are made in switching from three-phase uncontrolled charging to either single-phase charging or to a morning charging strategy.
- Single-phase uncontrolled charging may appear favorable, especially considering that this is the current method of charging, however the peak load coincides with the current peak due to the traditional household load making the network susceptible to overloads. Figure 7.5 shows this. (Figure 7.3 can be considered for comparison, the load in the evening hours is reduced and the peak is found in the morning)

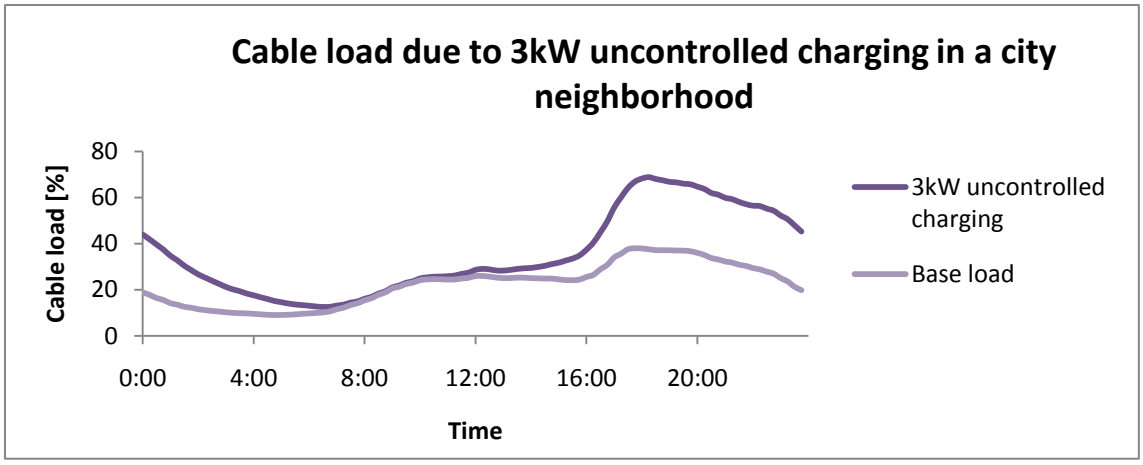

Figure 7.5: Cable load profile due to 3kW uncontrolled charging of electric vehicles

7.3.2 Space heating technologies

In this section a comparison is made between the different types of heating technologies. Also the effect of improving household insulation or using a more energy efficient thermostat setting is investigated. Micro CHPs are disregarded in the comparison between space heating technologies since it is trivial that these are more beneficial for the networks (as was seen in Figure 7.2).

Comparison of the different heating technologies

Figure 7.6 and Figure 7.7 show the critical market penetrations required to overload the transformer and cables for the various heating options, respectively.

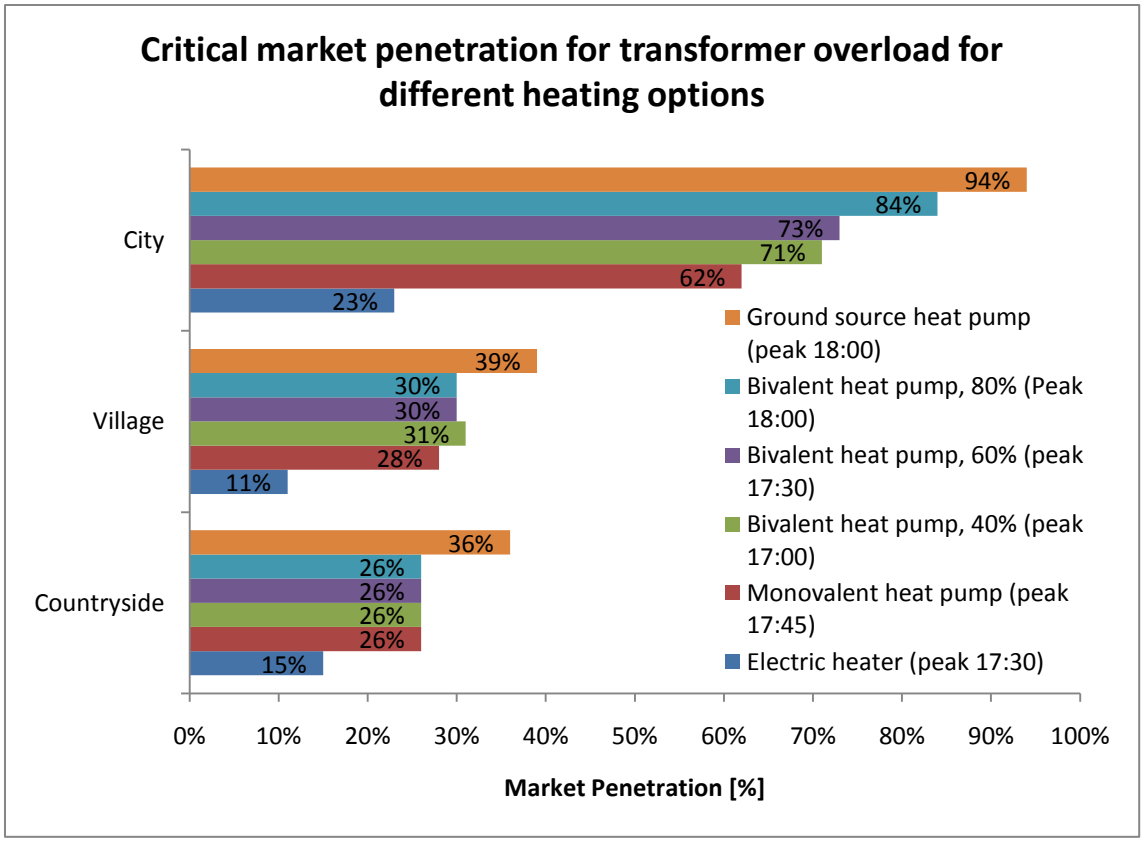

Figure 7.6: Critical market penetrations of heating strategies for transformer overload

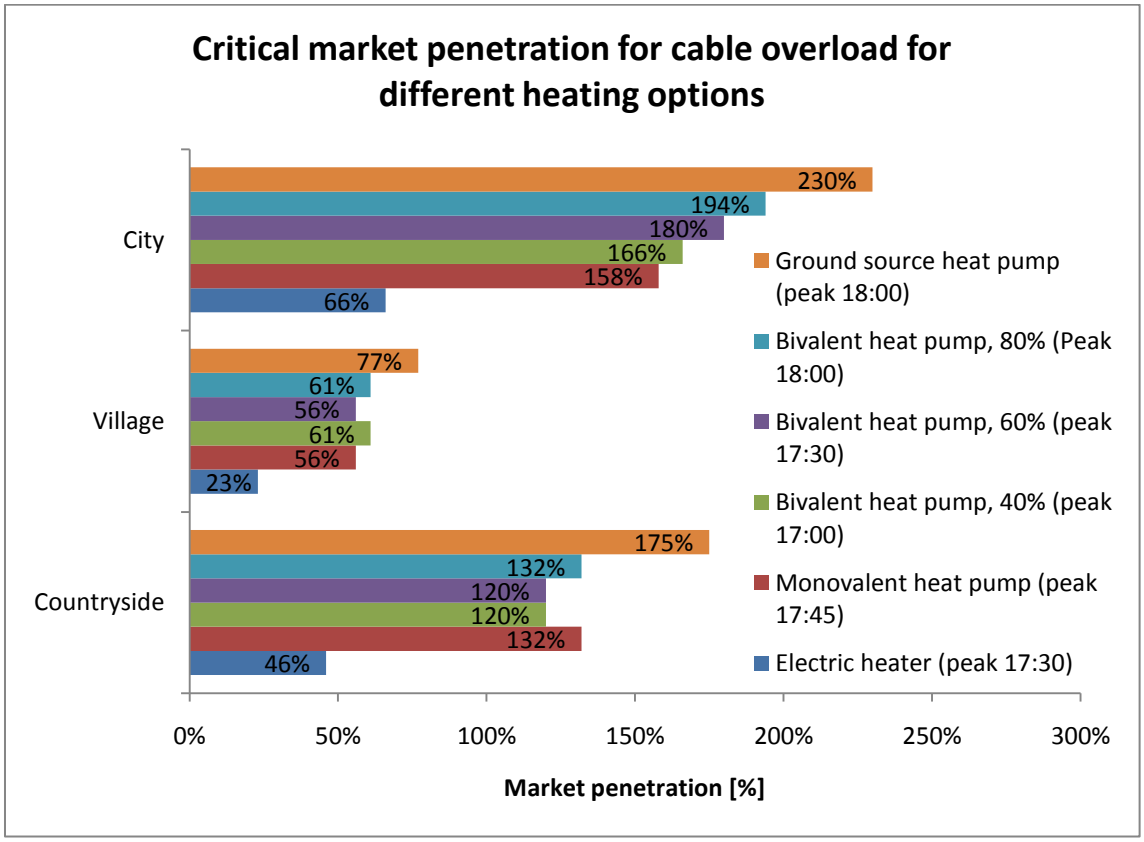

Figure 7.7: Critical market penetrations of heating strategies for transformer overload

From Figure 7.6 and Figure 7.7 the following conclusions can be drawn:

- Very surprisingly, and in contradiction with other studies such as (Rooijers and Leguijt, 2010), monovalent heat pumps have in some cases *lower* critical market penetrations than their bivalent counterparts (The reason for this is further investigated below).
- There is little difference in the network impact due to the three types of bivalent heat pumps considered.
- A ground source heat pump offers moderate savings compared to the air-to-air heat pumps, however this technology has a very large investment cost and requires a large space. It should be investigated whether these costs are worth the savings they provide for reducing the network load.
- Electric heaters should be avoided as the network impact of these is very large, only small penetrations are required to cause high network loads (11-23% to overload the transformers).
- The penetrations required to overload the cables are for all cases except electric heaters above 100%.
- In city networks the penetrations required to overload the network components are very high compared to the other two networks. This is because the city houses are small row houses and hence have lower heat losses and require smaller heat pump capacities. In these types of neighborhoods heat pumps should therefore not result in too many complications for the electricity network.

The most surprising result of Figure 7.6 and Figure 7.7 is that monovalent heat pumps are just as bad as or even worse than bivalent heat pumps for the electricity network. This is in contradiction with results from other studies such as (Rooijers and Leguijt, 2010) and (Veldman, 2010).

To explain the contradicting results it is first important to understand the difference between the assumptions used in the different studies. Rooijers and Leguijt (2010) and Veldman (2010) consider heat pumps with booster electrical heating elements of 6kW; these are oversized. In these studies no considerations are made for the size of the heat demand that cannot be met by the heat pump alone. In this thesis work these considerations are made however and the size of the extra heating element therefore depends on the size of the heat pump (the larger the heat pump capacity the smaller the extra heating element capacity).

Furthermore, the heating element is sized according to the heat demand that cannot be met by the heat pump; from this it is determined that the largest heating element required is 4,25kW for a countryside neighborhood with no additional insulation. In city neighborhoods the heating element has only a capacity of at most 1,5kW. In both cases the extra heating element is smaller than the 6kW used in other reports.

A final difference between the contradicting results is that in this thesis the values for the coincidence factors have been determined. In the study by Rooijer and Leguijt (2010) the coincidence factor for heat pumps has been assumed to be 100%, however the coincidence factors of a bivalent heat pump are not the same as for a monovalent one. Here it has been determined that monovalent heat pumps have a high coincidence factor (approximately 90%) while bivalent heat pumps have

much lower coincidence factors (approximately 60%). (The values for the coincidence factors are found in Appendix C.

Next it is necessary to consider the load profiles of the monovalent and bivalent heat pumps. Figure 7.8 shows the load profile of the heat pumps only (i.e. excluding the traditional household load).

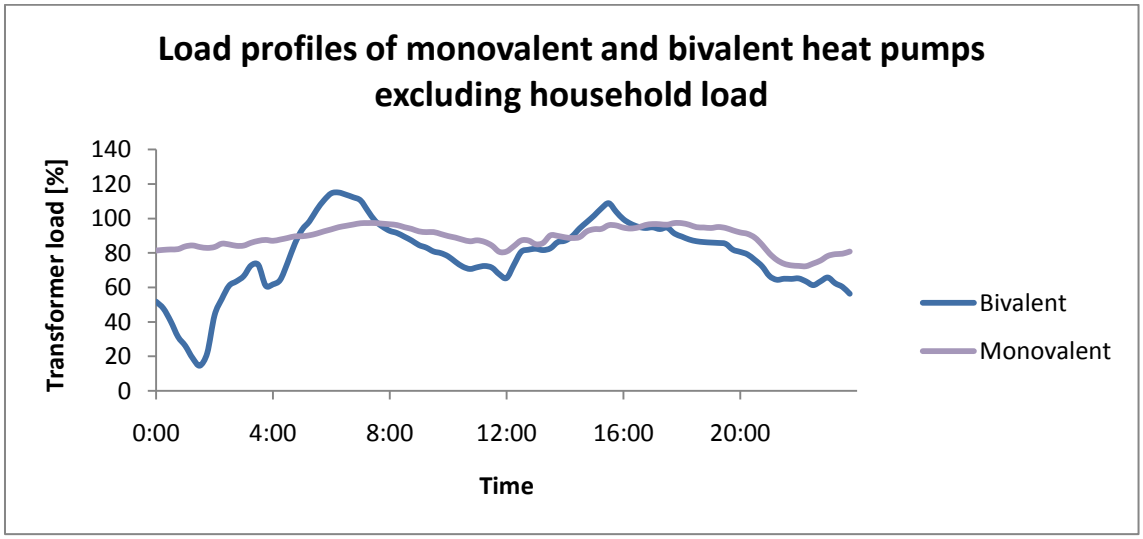

Figure 7.8: Transformer load profiles of monovalent and bivalent heat pump excluding the traditional household load

A few things can be observed:

- The bivalent heat pump has two spikes, one at approximately 6:30 and one at approximately 15:30. At noon the heat demand in households is slightly lower due to heat gain through windows, this however is of short duration and at 15:30 the bivalent heat pump causes a second peak. These peaks depend on the thermostat setting considered (Figure 5.2).
-
- The monovalent heat pump has a more stable load profile over the course of the entire day with very moderate rises in the load in the morning and the afternoon.
- (It is also interesting to note the area under the curves is smaller for the bivalent heat pump, meaning this technology is more energy efficient.)

However, when looking at the load profiles of the same heat pumps with the household load included, no significant difference is seen between the peak loads of the two heat pumps. This is seen in Figure 7.9.

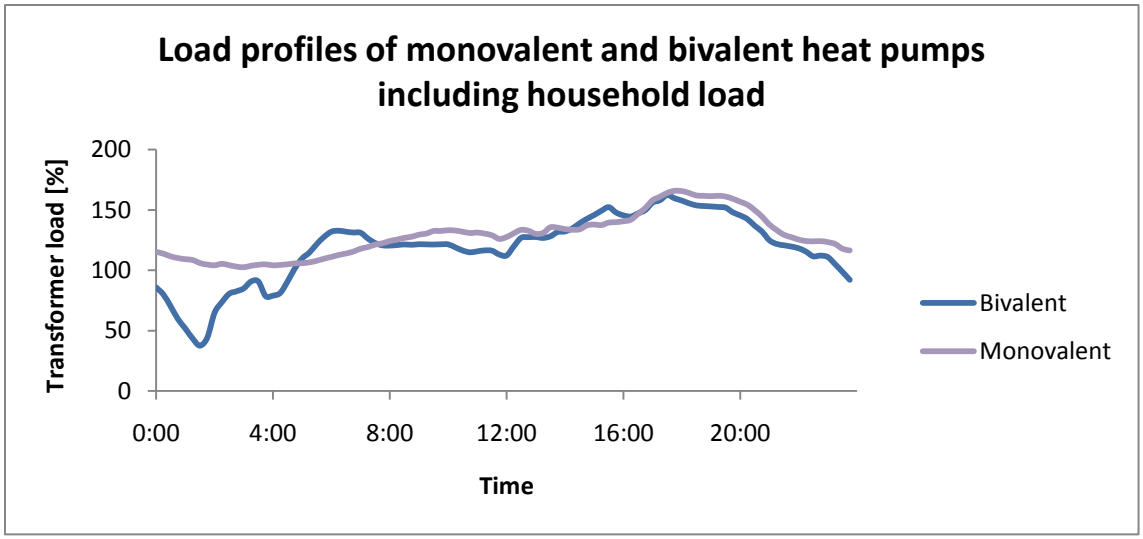

Figure 7.9: Transformer load profiles of monovalent and bivalent heat pump including the traditional household load

The load profiles of the heat pumps shown in Figure 7.8 and Figure 7.9 however are very dependent on the thermostat setting considered. The effect of the thermostat setting will be investigated in the next section.

Effect of insulation and/or thermostat setting

In this section the effect of insulation and/or thermostat setting on the load of the network components is determined. As was explained in Section 4.5 two thermostat settings are considered, Figure 5.2 shows the two thermostat programs considered.

Figure 7.10 shows the critical market penetrations of the space heating technologies with and without improved insulation and a low energy thermostat setting in a village neighborhood. The figures for the load of the cables and for the loads of other networks are found in Appendix D, these are not included here because they are similar to the one presented below. The village network is presented here because it has the largest loads.

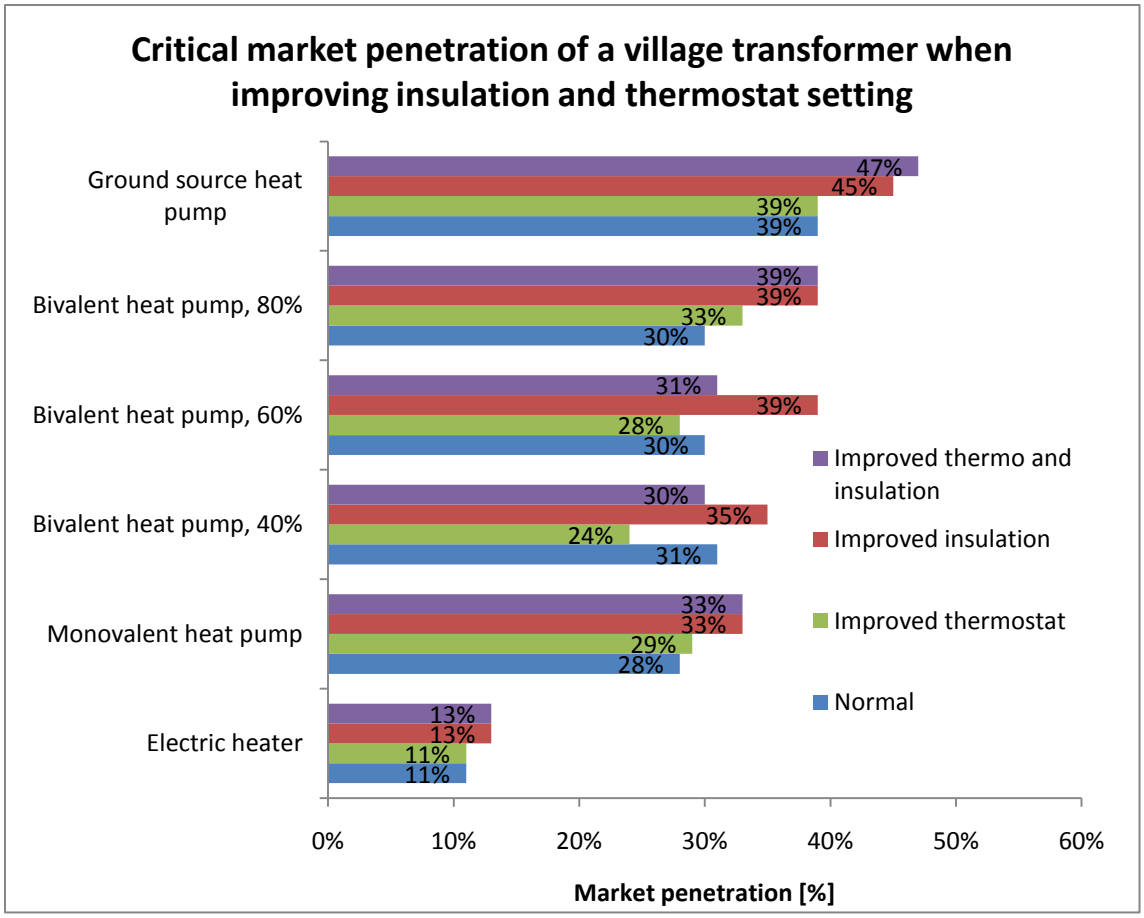

Figure 7.10: Effect of insulation and thermostat setting on the transformer load in a village neighborhood

From Figure 7.10 several things are observed:

- In all cases improving household insulation has a positive effect, however in the village neighborhood only a 2-9% increase in market penetration is possible due to improving insulation. (For the other two neighborhoods the increase is slightly larger, but still moderate.)
- For bivalent heat pumps the effect of using an energy efficient thermostat setting is worse for the network than when not doing this. For monovalent heat pumps this is not the case. (The reason for this effect is explained below).
- For monovalent heat pumps, improving insulation has only a small effect on the network load. This is understandable because on a very cold day the household heat loss is very high and the heating system will most-likely be on during the peak evening hours, regardless of thermostat setting.

The most surprising result is the fact that lowering the thermostat does not always have a positive effect on the load of the network components. This can be understood by taking a look at the load profile of a bivalent heat pump with the low energy thermostat and without, Figure 7.11.

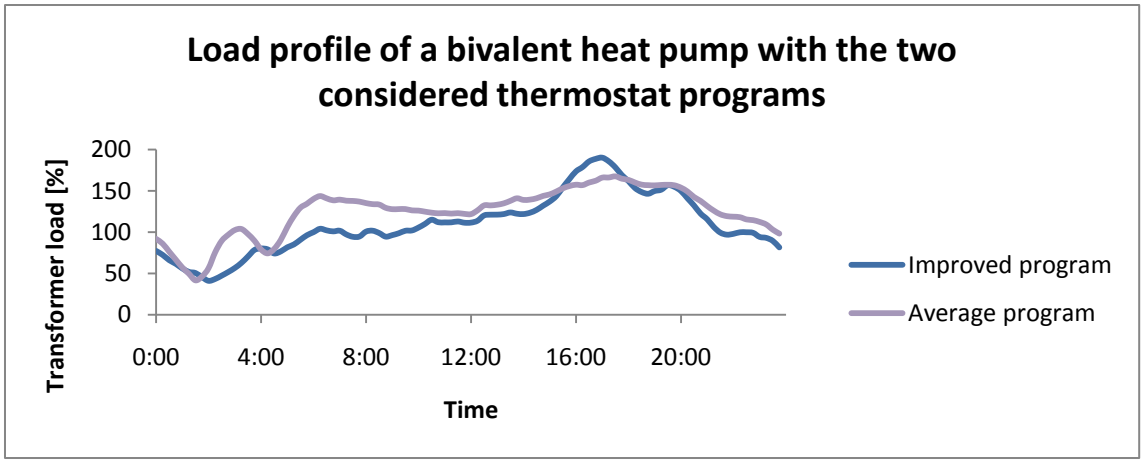

Figure 7.11: Transformer load profiles of bivalent heat pumps with and without low energy thermostat settings

Comparing Figure 7.11 and Figure 5.2 it can be understood why the low energy thermostat setting actually increases the load on the transformer. This occurs because of the large jump in temperature setting in the afternoon in the low energy thermostat program. This is a problem for bivalent heat pumps because all the electrical heating elements turn on at this time to meet the demand. This is also the reason why this effect is not seen with a monovalent heat pump. The "improved" thermostat program considered is energy efficient, which can be seen by comparing the areas under the curves, however the maximum load on the network is higher.

To avoid the high peak in the low energy thermostat setting a recommendation is made for a new thermostat setting; the two previous thermostat settings and new setting are seen in Figure 7.12. The only difference between the new setting (called the low peak setting) is that instead of decreasing the temperature during the day, it is *increased*. This is done to prevent the large jump in temperature occurring after 16:00.

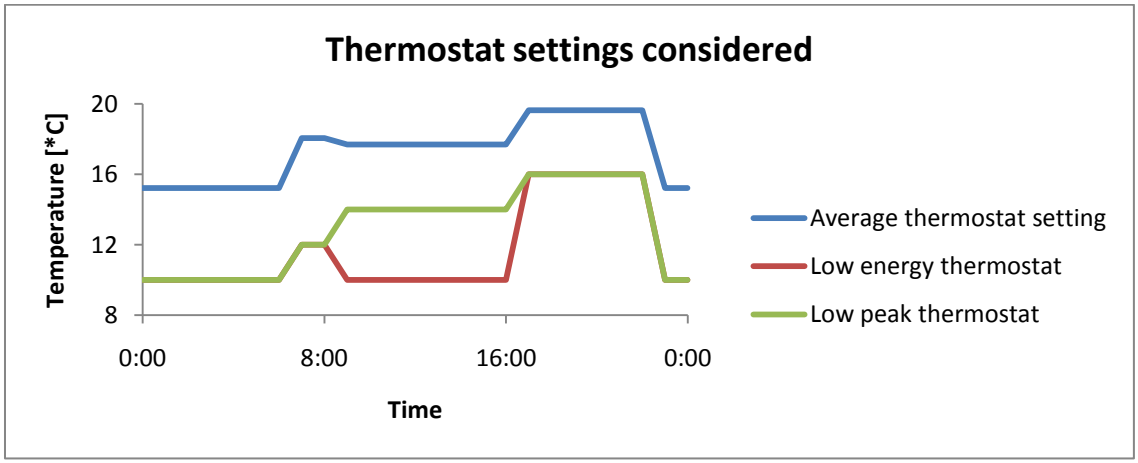

Figure 7.12: A third thermostat setting is added especially for bivalent heat pumps

The next figure shows the power demand profiles of a bivalent heat pump with the three thermostat settings.

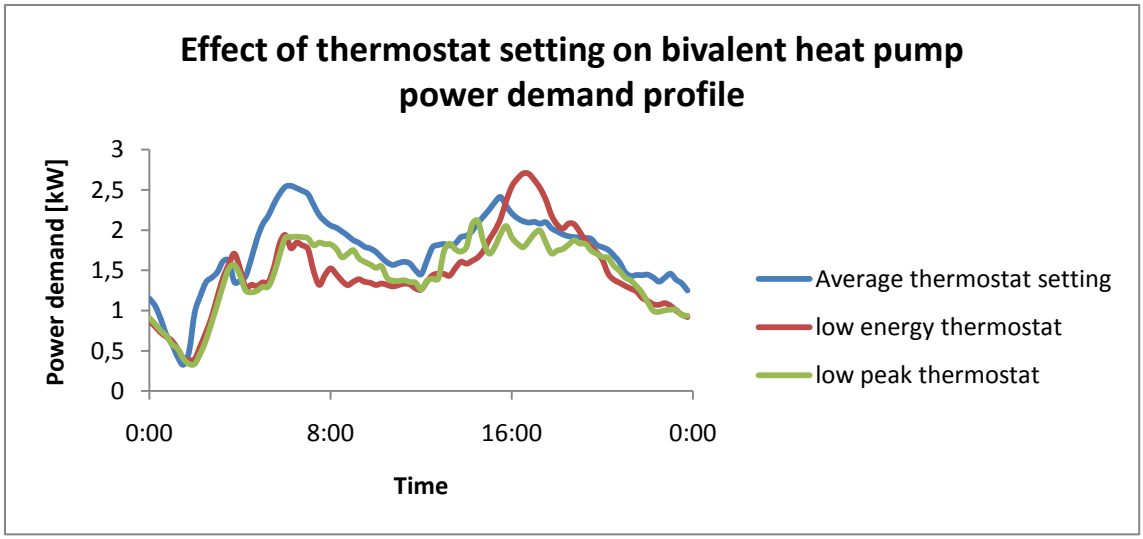

Figure 7.13: A third thermostat setting increases energy use slightly but avoids the peaks in both the morning and evening

Figure 7.13 shows that by avoiding large jumps in thermostat temperature spikes in the power demand profiles can be avoided. It can also be shown that with the "low peak" setting higher critical market penetrations are possible, this is seen in Figure 7.14.

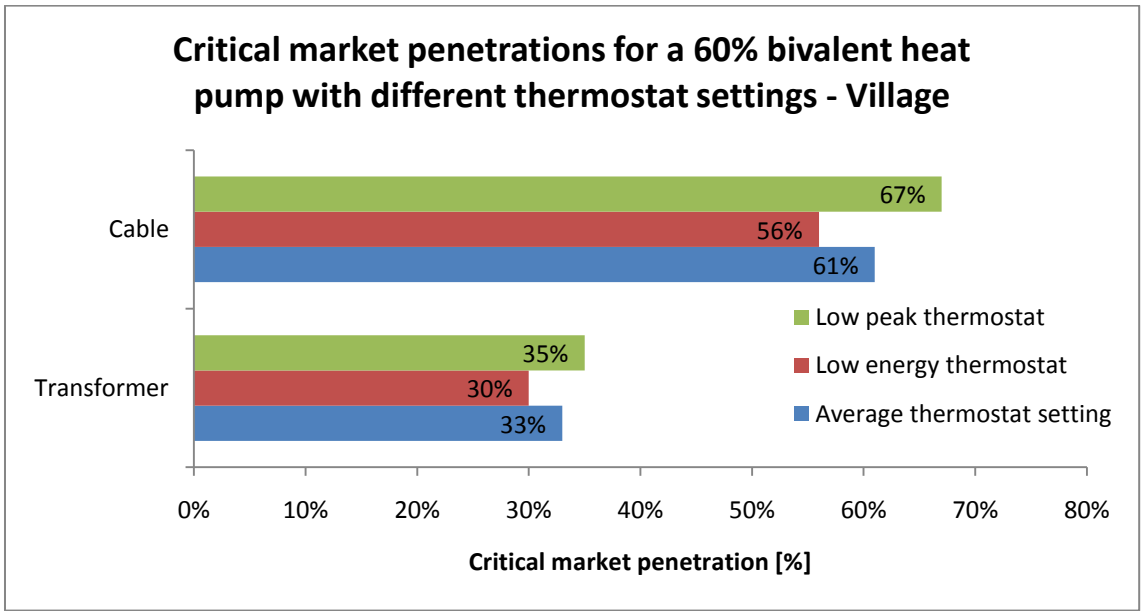

Figure 7.14: Critical market penetrations for a 60% bivalent heat pump in a village neighborhood with three thermostat settings

It remains to be investigated what the effects of the low peak thermostat setting are on the critical market penetrations of the other neighborhoods and the other bivalent heat pumps, however it has been shown above that this is worth further investigation.

Finally, micro CHPs were not considered here because it is trivial that they are beneficial for the electricity network; however it is worth repeating that improving insulation and thermostat settings in households with micro CHPs decrease the electricity production and hence have a *negative* effect on network loads (see Figure 5.11). It can therefore be concluded, from a network perspective, that micro CHPs are best suited for older households with poor insulation while heat pumps are better suited for well insulated households.

7.4 Impact due to combinations of technologies

The final investigation in this chapter is the impact of combinations of technologies. In this section it will be determined to what extent network utilization can be optimized by investigating if any synergies exist between technologies. This investigation is done in two sections: First, only combinations of electricity demand technologies are considered. Then, the potential of decentralized production to reduce low voltage network load in combination with demand technologies will be considered.

To limit the number of combinations that need to be considered the technologies are split into six categories. The power demand profiles of the technologies in each category have similar shapes; therefore only one representative technology of each category is taken. Table 7.3 shows the six identified categories along with the technologies that have been chosen as the representative technology (underlined):

Table 7.3: Technology categories

Category	Electricity supply	Electricity demand
Solar	Solar PV	
Electric vehicles, morning peak		Charging as late as possible Night time charging Vehicle to grid[2]
Electric vehicles, evening peak	Vehicle to grid[1]	3kW uncontrolled charging 10kW uncontrolled charging Economic charging Slow charging Charging when SOC<30%
Hot water	Micro CHP	Electric boiler Heat pump boiler
Heating technologies	Micro CHP	Electric heater Monovalent heat pump Bivalent heat pumps Ground source heat pump
Cooling technologies		Air conditioning Ground source heat pump

By considering only six categories instead of the technologies individually the number of combinations that need to be investigated is reduced significantly.

To quantify the effects of combinations of technologies four types of synergies are identified:

- Positive effect (Color: green) – the impact of the combination of the technologies is less than the impact of the single technology with the largest impact. (This is only expected when considering combinations of electricity demand and production technologies together)
- Zero to very small effect (Color: blue) – the impact of the combination of the technologies is no more than 1,10 times the impact of the single technology with the largest impact.

[2] The vehicle to grid profile considered is an electricity supply technology in the evening and an electricity demand technology in the morning

- Moderate negative effect (Color: yellow) – The impact of the combination of the technologies is at most 1,3 times the impact of the single technology with the largest impact.
- Strong negative effect (Color: orange) – The impact of the combination is greater than 1,3 times the impact of the most impacting single technology.

The investigation in this section is carried out in two parts. First the impact of combinations of electricity demand technologies on the transformer load is determined. This is done to understand to what extent network utilization can be improved by adding technologies. In the second part it is determined to what extent electricity production technologies can be combined with electricity demand technologies to reduce network loads.

7.4.1 Combinations of electricity demand technologies

In Table 7.4 a matrix has been created showing the transformer load for combinations of technologies. In each case a 100% market penetration of the technology is taken. For comparison purposes the impact of a 100% market penetration of a single technology is shown on the main diagonal.

Table 7.4: Transformer load for combinations of 100% market penetration of different electricity demand technologies

	EV morning peak	EV evening peak	Hot water	Heating technologies	Cooling technologies
EV morning peak	96-98%				
EV evening peak	177-187%	160-171%			
Hot water	163-171%	212-228%	133%-145%		
Heating technologies	162-210%	215%-268%	187%-241%	112%-168%	
Cooling technologies	98-130%	160%-171%	135%-180%	112%-168%	80%-125%

By comparing the off diagonal terms with the main diagonal terms it can be seen by how much the transformer load is expected to increase when introducing a second technology. Table 7.5 summarizes this by showing by what factor the transformer load increases with respect to the maximum load of the individual technologies. (For example: combining heat pumps with electric vehicles with an evening peak results in a transformer load of 1,34-1,57 times higher than when considering only electric vehicles or the heating technology separately.)

Table 7.5: Synergies between electricity demand technologies

	EV morning peak	EV evening peak	Hot water	Heating technologies	Cooling technologies
EV morning peak	1,00				
EV evening peak	1,09-1,11	1,00			
Hot water	1,18-1,23	1,31-1,36	1,00		
Heating technologies	1,21-1,45	1,34-1,57	1,35-1,43	1,00	
Cooling technologies	1,00-1,05	1,00	1,02-1,24	1,00	1,00

From Table 7.4 and Table 7.5 a few things are worth noting:

- From Table 7.4 it is seen that a 100% market penetration of cooling technologies, such as air conditioning, result in a transformer load of 80-125%. From the last row in Table 7.5 however, it is seen that when used in combination with another technology the network load does not increase significantly. This is because the air conditioning load occurs at very different times than the other loads.
- Electric vehicles with a morning peak have much better synergies than electric vehicles with evening peaks.
- The worst synergies are found when using heating technologies. From Figure 7.6 it is understood that regardless of heating technology chosen the transformer load is above 100%. This implies that if networks are dimensioned to accommodate electric heating technologies, they should be over dimensioned to accommodate other technologies as well.
- The worst synergy is due to heating technologies in combination with electric vehicles with an evening peak. Both technologies experience peaks in the evening hours therefore the combined peak is considerably large. This peak load of the transformer can be reduced by approximately 12% if a morning charging strategy is used for the electric vehicles.
- There is a very good synergy between charging electric vehicles in the evening and in the morning. What is understood from Table 7.5 is that doubling the number of electric vehicles only increases the transformer load by 9-11% when half of the vehicles are charged at a different time.

7.4.2 Combinations of electricity production and demand technologies

The second set of combinations is electricity production technologies coupled with electricity demand technologies. In this section it is investigated by how much the load of the transformers decreases by including an electricity production technology in combination with electricity demand technologies.

Table 7.6 shows the maximum transformer load due to electricity demand technologies and the minimum achievable transformer loads when adding electricity production technologies. The first column is a reference, in which the transformer load due a 100% market penetration of only the demand technology is given; these are listed as reference values. In the remaining columns the

lowest achievable transformer load is given for the combinations of technologies. A color code is used to show the most favorable combinations, these are shown in green. All other cells either have a negative effect (orange) or minimal to no effect (no color).

Table 7.6: Transformer load for combinations of electricity demand and production technologies

	Only demand technology		Solar PV		Vehicle to grid		Micro CHP	
	Summer	Winter	Summer	Winter	Summer	Winter	Summer	Winter
Baseload	32-40%	55-69%	32-40%	55-69%	28-35%	36-45%	30-37%	25%-31%
EV morning peak	95-98%	96-98%	89%	96-98%	negative effect	negative effect	94-97%	65-77%
EV evening peak	134-143%	160-171%	123-128%	160-171%	70-74%[3]	82-88%[3]	130-138%	119-135%
Hot water	115-126%	133-145%	111-119%	133-145%	negative effect	122-132%	114-124%	92-100%
Heating technologies	32-40%	112-168%	32-40%	112-168%	32-40%	102-156%	32-40%	87-125%
Cooling technologies	80-125%	55-69%	32-55%	55-69%	74-111%	55-69%	80-125%	55-69%

Several things can be concluded from the above table:

- Solar panels are only effective to compensate the network load from cooling technologies. According to the table they do have a positive synergy with electric vehicles and hot water technologies in the summer; however the winter load is larger and hence remains limiting to the network.
- Although solar panels also produce some electricity in the winter they do not in any case reduce the peak load of the networks. The winter peak loads always occur in the evening at times when solar electricity production is zero.
- The vehicle to grid technology has a positive effect on almost all technologies and can be used to reduce the peak significantly. It must be noted however that the combination with other electric vehicles is not as favorable as it seems since it implies that some vehicles are being discharged to charge others.
- Micro CHP is the best technology to reduce the network load of the other technologies. Micro CHPs produce electricity almost constantly throughout the day during the winter, and the production peaks at approximately the same time as the demand technologies have their peak demand.
- Minimizing the transformer load is a balancing act; increasing the share of electricity production technologies reduces the transformer load to a certain extent, but beyond a certain point the time of the peak load changes and the peak load possibly even increases due to an oversupply of electricity. In this sense Micro-CHP is the most favorable since it has the flattest load profile as well as the lowest peak.

[3] Although the transformer load is reduced, vehicle to grid in combination with electric vehicles with an evening peak is not a good synergy because it implies discharging some electric vehicles to charge other vehicles.

8 Discussion and implications for network planning

In Chapter 7 the network impact of different energy technologies has been determined. The results presented in the chapter however are more theoretical of nature; they show the impact of large penetrations of the energy technologies considered, without consideration for if and when problems will arise for a given scenario. In this chapter a more qualitative look is taken at the implications of the results obtained.

This discussion will focus on three things: The impact of decentralized electricity production, the impact of electric heating in households, and the impact of electric vehicles.

8.1 High levels of decentralized electricity production

As was seen in Table 7.2 of Section 7.2 decentralized electricity production technologies such as micro CHP and solar panels pose little problems for the electricity network, mainly because they first need to compensate for the local electricity demand before they can cause any problems at the transformer level. According to Table 7.2 very large market penetrations of micro CHP or solar panels (above 150%) are required to cause transformer overload.

Although these penetration values sound unlikely, they are in theory possible if either of the following occurs: The electricity production of solar panels or micro CHP increases due to improvements in efficiency or due to the use of larger units, or the local electricity demand decreases. In this section it will be determined if and under what conditions decentralized electricity production poses a problem for electricity networks.

Excepted development of micro CHPs

The following two figures show the expected growth in the number of micro CHP units and the expected improvements in electricity and heat production capacities of micro CHPs, respectively.

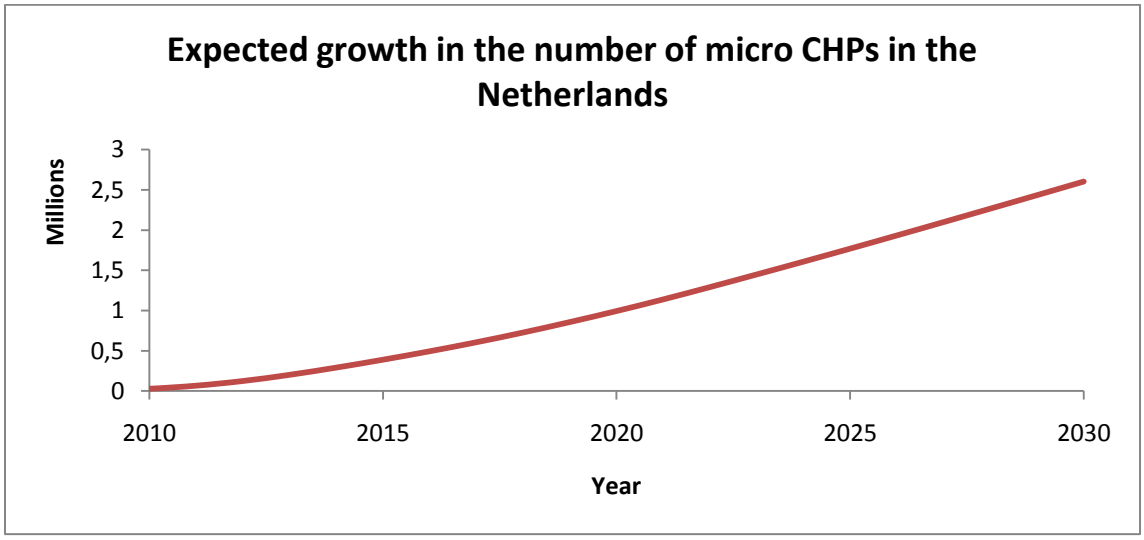

Figure 8.1: Expected growth in the number of micro CHPs in the Netherlands (Werkgroep Decentrale Gastoepassingen, 2008b)

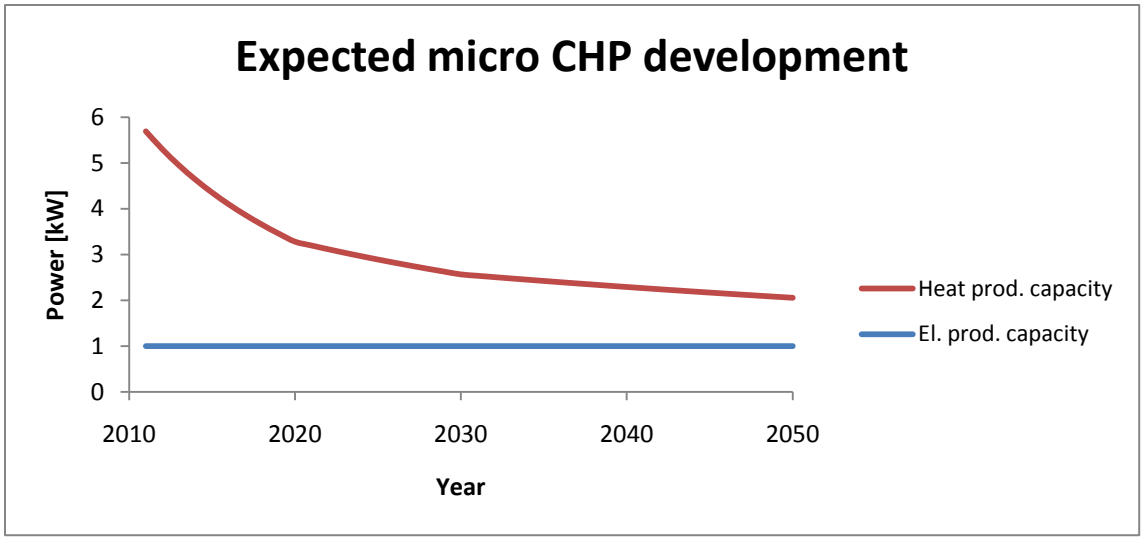

Figure 8.2: Expected micro CHP heat and electricity production development (de Jong, 2010)

Figure 8.1 shows that there will be approximately 2,65 million micro CHPs in the Netherlands in 2030. This is a 36% market penetration if it is assumed that the micro CHPs are evenly distributed and that they are all installed in existing buildings. This is a fair assumption considering the fact that heat pumps are the more often chosen heating technology for new buildings since they can be easily installed during construction and are more difficult to retrofit in existing buildings (SenterNovem, 2009).

Figure 8.2 shows that the heat production capacity of micro CHPs per kilowatt electricity will decrease. The reason for this is because as houses become better insulated the required heat decreases, therefore by increasing the electrical efficiency (i.e. decreasing the heat efficiency) the micro CHP units will be able to operate more as base load power plants. As a result of this the simultaneousness of micro CHPs will increase, but for the networks this has very few consequences: On the coldest days of the year micro CHPs are already acting as base load units.

From the above two figures it can be concluded that micro CHPs will pose little problems both now and in the future for the electricity grid mainly because the high market penetrations required to cause network load problems are near impossible to achieve.

Expected development of solar panels

For solar panels market penetrations of above 100% are required to cause network problems. If the efficiency of the solar panels increase, then penetrations of lower than 100% could in theory cause network problems. The possibilities of this happening are considered here.

According to Sinke (2009b) solar panels will achieve efficiencies of up to 20% in 2020 and 25% in 2030 with a long term potential of up to 40%. The same values are found in the IEA roadmap (2010). Figure 8.3 shows what efficiencies are required to cause transformer overload in different electricity demand growth scenarios assuming a 100% market penetration. It is assumed that each household has 15m^2 of solar panels.

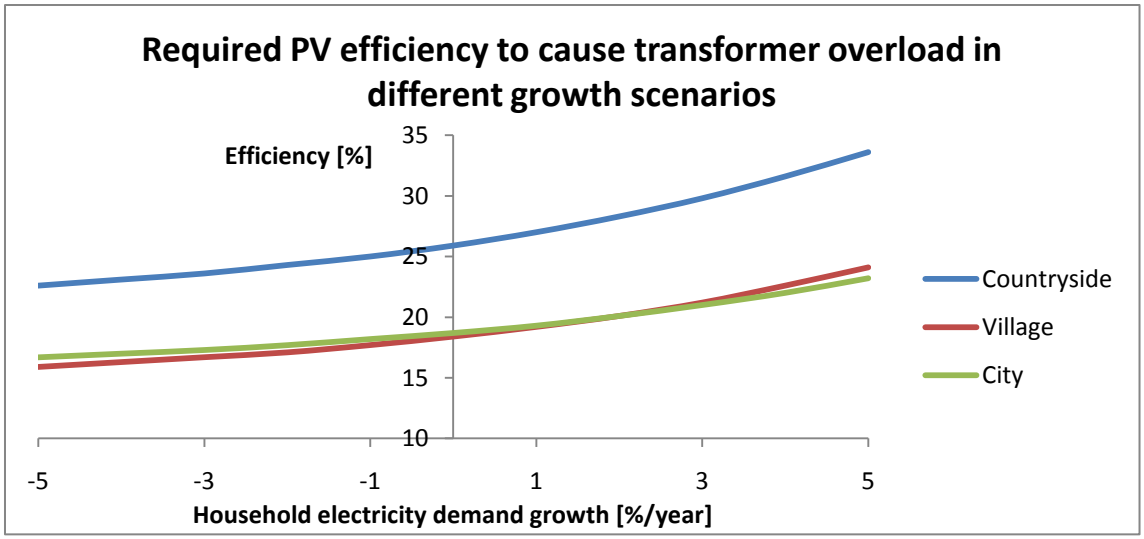

Figure 8.3: Required solar panel efficiency to cause transformer overload in different electricity growth scenarios

With the current electricity demand growth of approximately 1% per year and the expected efficiency of 25% for solar panels in 2030, it is in theory possible that large penetrations of solar panels can cause transformer overloads. This however requires two things: First, all houses must have at least 15m^2 of solar panels; and second, the panels must be start of the art and have high efficiencies.

In theory solar panels could cause network problems when considering the expected efficiency improvements, however large market penetrations are required. According to the Ministry of Economic Affairs (2008) in the most favorable scenario there will be 4GW of solar PV in the year 2030. This is equivalent to approximately 1,5 million 15m^2 solar panel installations with 20% efficiency, resulting in a market penetration of at most 21% (assuming there is no growth in the number of households).

Solar panels therefore do not pose a significant problem for the low voltage electricity network.

8.2 Impact of heat pumps in households

From Chapter 7 it can easily be concluded that electric heaters should be avoided at all costs. Heat pumps on the other hand are much more energy efficient but do in many cases pose a problem for the electricity grid. In Chapter 7 it was found that market penetrations for heat pumps as low as 24% can cause the transformer loads to reach 100%. This is a rather low penetration, and if the other technologies are added to the network the critical penetration could easily drop to under 20%.

Figure 8.4 shows the expected deployment of heat pumps in existing buildings in the Netherlands (Ecofys, 2007). In 2030 a penetration of 17,5% is expected.

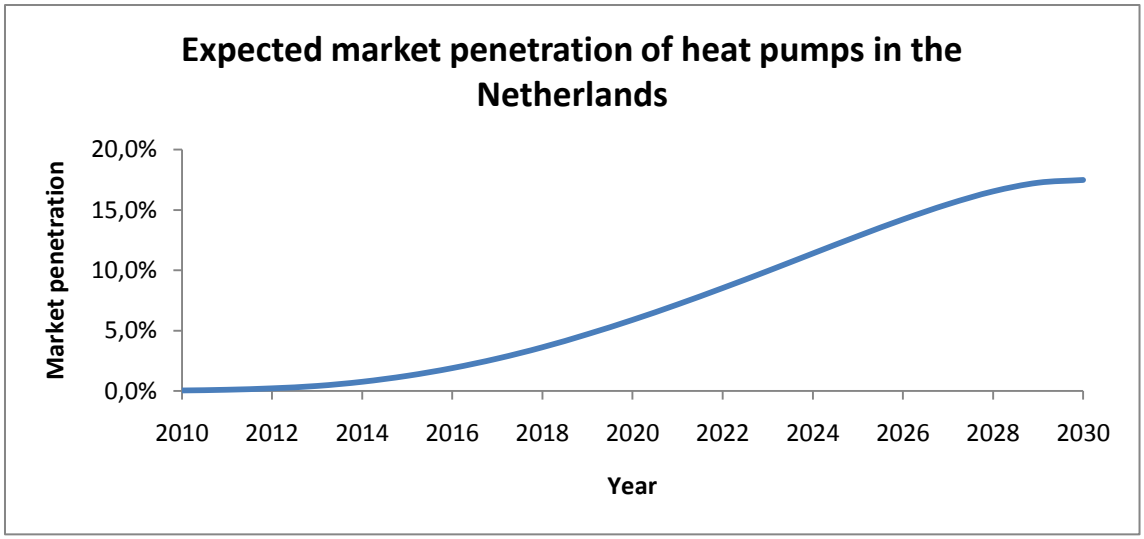

Figure 8.4: Expected market penetration of heat pumps in Netherlands in existing buildings (Ecofys, 2007)

From the figure it can be concluded that heat pumps will very likely be a problem for electricity networks in the future. Although the predicted penetration of 17,5% is less than the critical market penetration of 24%, it is also necessary to take into account market penetrations of other technologies simultaneously. As has been shown in Table 7.4 the heating technologies combine poorly with other technologies, therefore it is very likely that heat pumps will cause network problems before the year 2030 at the transformer level if measures are not taken.

8.3 Impact of electric vehicles

Figure 8.5 lists the number of expected electric vehicles in the Netherlands according to the Dutch government (Ministry of Infrastructure and the Environment, 2009).

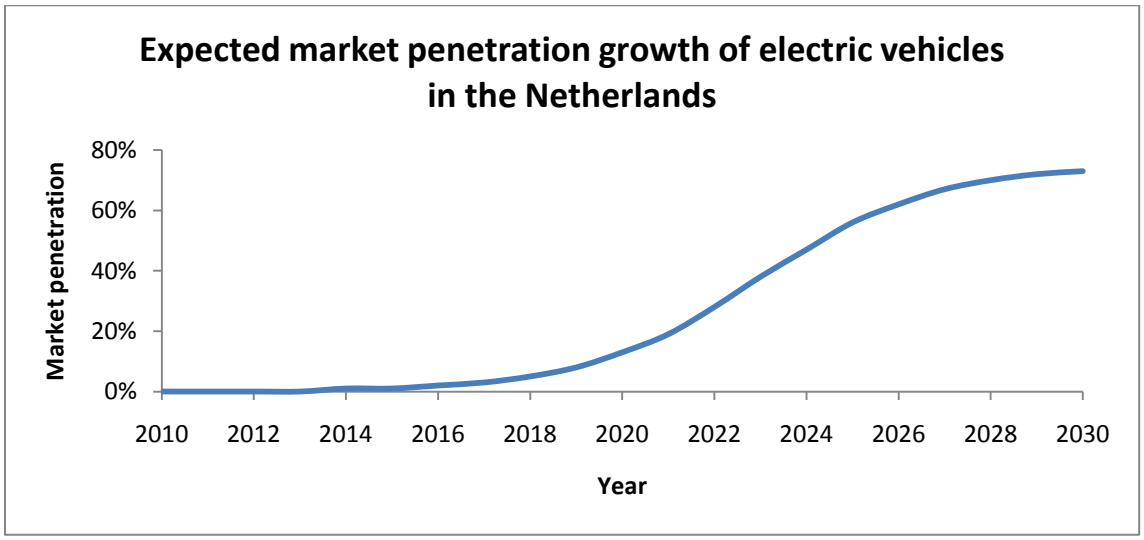

Figure 8.5: Expected market penetration of electric vehicles in Netherlands (Ministry of Infrastructure and the Environment, 2009).

The deployment of electric vehicles expected by the Dutch government is very enthusiastic, in the year 2030 the market penetration will be 73%. This implies that it is very likely that network problems will be expected if measures are not taken. From Figure 7.2 and Figure 7.4 it is seen that if

smarter charging strategies are not used then problems are expected around the year 2021, when the electric vehicle market penetration reaches approximately 20%.

Figure 8.5 shows that the market penetration of electric vehicles is expected to increase very rapidly starting in the year 2020. This means that although problems are not expected for a while, when they do come they will come very fast. Network operators will need to anticipate this.

8.4 A likely 2030 scenario with and without flexibility

In the previous sections the expected market penetrations for solar panels, micro CHPs, heat pumps and electric vehicles have been presented, these are summarized in Table 8.1 for the year 2030.

Table 8.1: Predicted market penetrations for the year 2030

Technology	Market penetration in 2030
Micro CHP	36%
Solar PV	21%
Heat pumps	18%
Electric vehicles	73%

The above market penetrations are entered into the testing environment using uncontrolled charging and a bivalent heat pump. Figure 8.6 shows the resulting load profile for a winter day in a village neighborhood (this neighborhood is chosen because it is the most heavily loaded). The summer day load profile is omitted because the loads are largest during the winter.

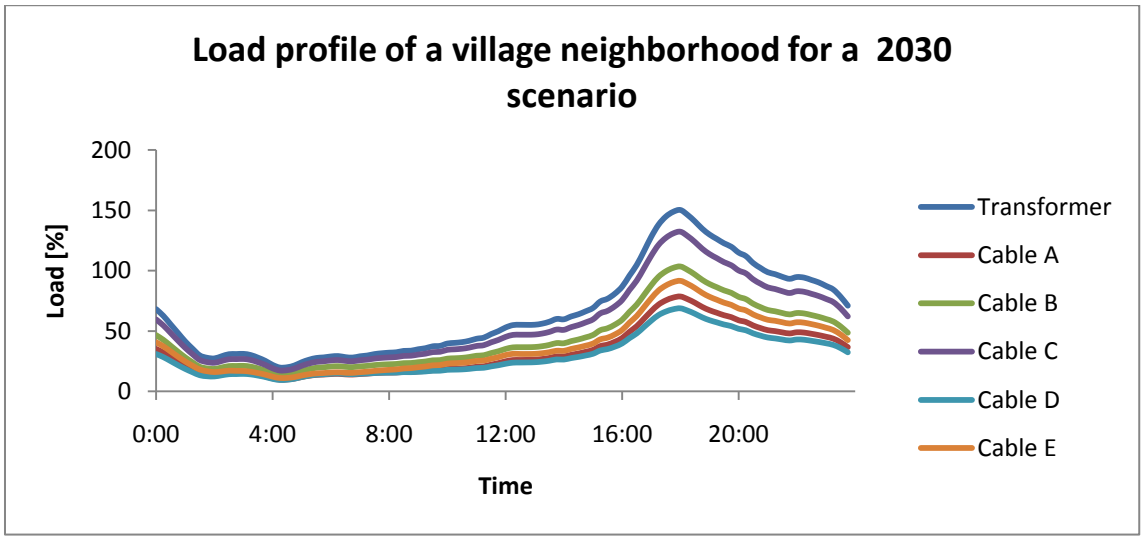

Figure 8.6: Load profiles of network components for a 2030 scenario without use of flexibility

It is seen in Figure 8.6 that the load of the transformer reaches up to 150%. The maximum load of the cables is 132%. The high loads are mainly due to the uncontrolled charging of electric vehicles. In the following figure it is seen how peak loads can be reduced by decreasing the share of uncontrolled charging. In Figure 8.7 only 20% of vehicles use uncontrolled charging, 20% use slow charging, and the remaining 33% use night time charging (these values have been arbitrarily chosen). Here it is seen that the peak load of the transformers has been reduced to 112% and the load of the cables is 101%.

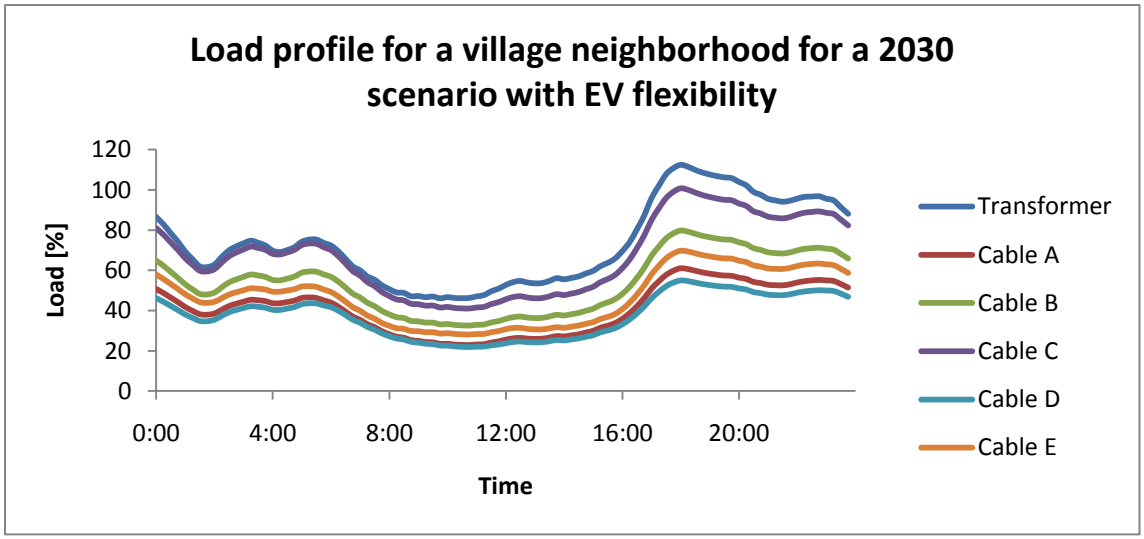

Figure 8.7: Load profiles of network components for a 2030 scenario with improved electric vehicle charging strategies

The load profile of Figure 8.7 can further be reduced by improving insulation and the thermostat setting in these households. Also the share of the share of micro CHPs is increased to compensate the load due to heat pumps (the insulation and thermostat setting of the houses with micro CHP is not improved, since this results in less electricity production, see Figure 5.11). In the following figure these measures have been taken and the number of micro CHPs has been increased from 36% to 45% (the village neighborhood has 181 households, therefore the number of CHPs needs to increase from 65 to 81).

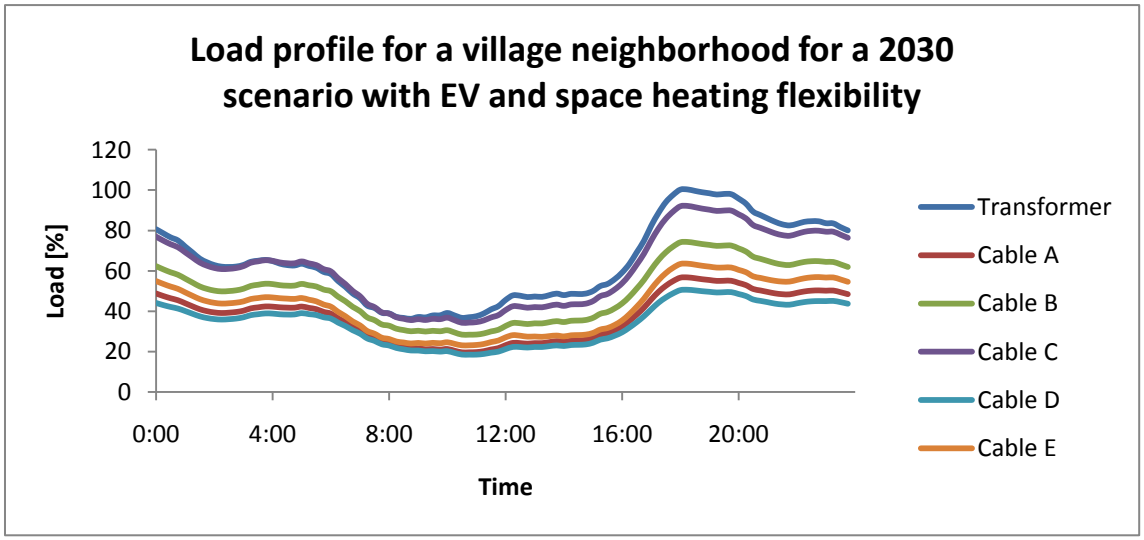

Figure 8.8: Load profiles of network components for a 2030 scenario with improved electric vehicle charging strategies, improved insulation, and additional micro CHPs

The loads of the network have now been reduced to 100% in the transformer and 92% in the cable. Similar results apply to city and countryside neighborhoods.

The above goes to show how combinations of technologies and careful selection of technologies can go a long way to decrease the network loads. The most interesting result is that adding micro CHPs not only decreases the network load but it also promotes improving energy efficiency in households with inefficient heating systems and helps the transition to a sustainable future.

9 Conclusions

In the introduction of this thesis the following research question was identified:

> To what extent do future energy technologies present a problem for low voltage electricity distribution networks and can these problems be mitigated by the use of flexibility and/or by favorable combinations of technologies?

To answer this question four steps have been taken. First, a testing environment was created where future energy scenarios could easily be created and transformer and cable loads could be calculated (Chapter 3). Then, in Chapters 4 through 6 the power demand profiles of future energy technologies such as heat pumps, electric vehicles, and solar panels were created for a warm, sunny summer and a cold winter day. In Chapter 7 the results of the previous chapters were combined by entering the created power demand profiles into the scenario testing environment and simulations were carried out to determine the impact of future energy technologies on the considered electricity networks. Finally, in Chapter 8 a discussion was presented in which the implications of the results for low voltage networks were given by considering the expected development of future energy technologies. In this section the most important conclusions of each chapter are given and it will be determined to what extent the above question has been answered.

In Chapter 3 it was concluded that although software tools such as Gaia and PowerFactory are effective for determining network loads, these programs have the limitation that it is not easy to quickly carry out multiple simulations with varying degrees of market penetration for various technologies. Because of this, a new scenario testing environment has been created. This environment has been created in Excel but will eventually be incorporated into the Energy Transition Model as an online tool and will be made publicly available.

In the testing environment users can easily create scenarios by entering market penetrations for numerous future energy technologies such as heat pumps and electric vehicles. The testing environment then calculates the resulting transformer and cable load profiles in real time for a typical summer and winter day.

The scenario testing environment was verified by comparing the calculated transformer and cable loads to those obtained by Gaia. In the verification it was determined that although losses are ignored and nominal voltage is assumed, the loads calculated are very much similar to those calculated by Gaia; Due to assuming nominal voltage the errors obtained are not larger than 5%. Differences are found when adding multiple Strand-Axelsson loads; however these can be explained due to Gaia's calculation which is incorrect for the Strand-Axelsson loads considered in this thesis.

After creating the testing environment the next step was to create the power demand profiles for the numerous energy technologies considered. This was done in three chapters: First for electric vehicles, then for space heating technologies, and finally for the remaining technologies such as solar panels and electric hot water heaters.

In Chapter 4 the procedure for creating the electric vehicle power demand profiles was explained. The power demand profiles were created based on mobility data of more than 50.000 Dutch citizens. Power demand profiles for seven charging strategies have been created: Single-phase and three-phase uncontrolled charging, economic charging, slow charging, charging when the state of charge is less than 30%, night time charging, charging as late as possible, and vehicle to grid with discharging possibility. The electric vehicle power demand profiles were verified by comparing them to measured data obtained from Alliander. The measured data was compared to the modeled uncontrolled charging strategies and it was determined that the created profiles accurately predict the time and value of the peak loads.

To create the power demand profiles for space heating technologies, a Matlab model was created that accurately predicts the household heat demand at 15 minute intervals for an entire year. In the Matlab model, factors such as house type, construction year, degree of insulation, thermostat setting, window area, heat gain through windows, and outdoor temperature are all taken into account to predict the heat demand. Based on this heat demand, control strategies for different heating systems were written to predict the on and off behavior of a heating system and with this the electric power demand profiles were created. Profiles for the following technologies were created: Monovalent air-to-air heat pumps, bivalent air-to-air heat pumps, ground source heat pumps, electric heaters, and micro CHPs. The power demand profile for air conditioners has also been created using the model. Furthermore, the effect of improving insulation and using a different thermostat program on the power demand profile has been determined for each of the listed technologies. The heat pump profile has been verified by comparing the results to measured data obtained from Alliander.

Electricity power supply and demand have also been created for solar PV panels and electric water boilers. The solar PV profiles were created based on irradiation data at The Bilt, taken from the KNMI (KNMI, 2011b). The water boiler profiles were created using household water consumption data from the IEA (IEA, 2008).

In Chapter 7 the power demand profiles created in Chapters 4 through 6 were inserted into the testing environment created in Chapter 3. Using the testing environment simulations were carried out to determine the cable and transformer loads in different scenarios. The simulations were carried out in three steps: First the market penetrations at which transformer and cable overload occurs were determined for the individual technologies. Next it was determined to what extent the alternative technologies or charging strategies could be used to reduce network loads. It was also investigated what the influence of insulation and thermostat setting are on the network loads due to space heating technologies. Finally, it was investigated to what extent technologies can be combined to improve network utilization or reduce network load.

The most important conclusions of the results chapter are given below.

It was determined that heat pumps and electric vehicles pose the largest problem for the electricity networks. When using three-phase uncontrolled charging, electric vehicles can cause transformer overload problems at market penetrations as low as 23%. Heat pumps also cause significant problems for the electricity network, causing transformer overload at penetrations between 30-75% (depending on the type of network). Fortunately the electricity cables of Dutch low voltage networks

have larger ampacities than the transformers and therefore are more difficult to overload. In most cases few problems are expected in these cables, however at large market penetrations of electric vehicles (40%+) and/or heat pumps (58%+), overloads are possible in the cables as well.

Although electric vehicle charging can cause network problems at low penetrations it was determined that more favorable charging strategies exist. Of the seven alternative strategies considered it was determined that five were more favorable than uncontrolled charging in terms of network load. The most favorable strategy is slow charging, in which electric vehicles are charged at lower rates but over longer durations. Night time charging is also very favorable since the peak load occurs at approximately 4:00, the time at which the normal network load is at a minimum. By using night time charging or slow charging the critical market penetrations of electric vehicles can be increased from 23% to 102% or 121%, respectively. The most favorable options reduce the load by 35-55% compared to uncontrolled charging. It is therefore concluded that choice of a proper charging strategy will offer a lot of opportunities to mitigate network problems.

In a similar manner a comparison has been made between different heating options to determine if more favorable methods exist for space heating. A bivalent air-to-air heat pump sized for 60% of the heat load was taken as the reference technology. It was concluded that there was little difference between the different types of heat pumps in terms of transformer and cable loads. Ground source heat pumps are were found to be the most favorable option, however these only reduced the network load by 8-15% compared to the reference heat pump.

An interesting conclusion contrary to conclusions made in other studies is that monovalent heat pumps are just as problematic as their bivalent counterparts. Studies such as Rooijers and Leguijt (2010) conclude that the booster electric heating elements in bivalent heat pumps cause large loads; however here it was determined that this is not the case. Provided that the heat pumps are properly sized, the monovalent heat pumps have in general a lower peak load, but a higher coincidence factor. When combined with the traditional household electricity demand, the total load of monovalent heat pumps is approximately the same as for bivalent heat pumps. It can therefore be concluded that the type of heat pump used offers little difference for the electricity networks. It must however be stated that it is important that the heat pumps are not oversized, especially when using bivalent heat pumps with booster electric heating elements.

The effect of insulation and thermostat setting on the load profiles of heating technologies has also been investigated. It has been determined that adding 50mm of insulation to households can reduce network loads by approximately 2-14% compared to non-insulated households. This conclusion holds true for all the heating options considered. The potential savings for the network are small, however if consumers plan to renovate their homes they should improve their insulation before adding a heat pump.

Using a lower thermostat setting offers only small benefits in terms of network loads in a few cases. Interestingly however, the lower thermostat setting considered resulted in higher transformer loads when using a bivalent heat pump. This can easily be explained by the large change in temperature seen in the thermostat program, causing all bivalent heat pumps to use their booster electric heating elements resulting in a large spike in the load profiles at the time of the temperature change. The conclusion is therefore that to minimize network loads when using bivalent heat pumps it is essential

that large changes in thermostat temperature be avoided. The suggestion is to either gradually increase the temperature or simply maintain a constant indoor temperature. The effectiveness of gradually increasing the temperature has been shown. Unfortunately this strategy results in a slightly higher energy consumption.

Finally, because it is likely that any future energy scenario will consist of multiple technologies it was also investigated what the effect is of combinations of technologies on the low voltage network loads. The synergies between pairs of technologies have been quantified in terms of transformer load and the most favorable combinations have been determined. This investigation was conducted by first considering only electricity demand technologies to see what options exist for improved network utilization followed by considering combinations of electricity production technologies with demand technologies to see how these can compensate each other and hence reduce transformer and feeder loads.

It has been determined that heating technologies, such as heat pumps, combine particularly poorly with other technologies. When combined with electric vehicles or electric water boilers the network loads increase by a factor 1,21-1,57 with respect to the load with the heating technology only. This implies that if networks are to be dimensioned to support technologies such as electric heat pumps, they should be dimensioned at least 60% larger to also allow room for other technologies such as electric vehicles.

On the other hand, air conditioners when introduced on a large scale are expected to cause network problems; however this technology can easily be combined with other technologies without inducing extra network loads because of the different times at which the peak loads occur. It is therefore suggested that networks be dimensioned based on the predicted winter evening peak loads and if these contain large loads due to technologies such as heat pumps or electric water boilers, then it can safely be assumed that air conditioners will not create additional network problems.

The most interesting, and possibly obvious, synergy is between electric vehicles charging strategies with an evening peak load and those with a morning peak load. It has been determined that the number of electric vehicles can be doubled with only a 9-11% increase in the network loads if half of the vehicles use a different charging strategy than the first group. This suggests that there might not be a single best charging strategy, but that a combination of charging strategies will be optimal for the network.

In the final investigation conducted it was determined to what extent electricity production technologies (solar panels, vehicle to grid, and micro CHP) can be used to reduce the network loads due to electricity demand technologies.

It was found that solar panels offer very little benefit to reducing network loads. Although solar panels do produce some electricity in the winter they only work to reduce the transformer loads during the summer, and in most cases the peak loads are larger in the winter than they are in the summer. Solar panels can therefore only effectively be used to reduce the loads of air conditioning, which they do very well; the network load due to a large market penetration of air conditioners can be reduced by 55-60%.

Using electric vehicles as batteries (the vehicle to grid strategy) can be very effective to reduce the peak network loads. The times at which the vehicles are available for discharging coincide well with the time at which most peak loads occur due to other technologies. This strategy can be ideal for 'peak shaving'; the peak transformer loads can be reduced by 12-24%.

Micro CHPs are by far the best option to reduce peak network loads when combined with other technologies; they are effective at reducing the peak loads for all combinations except cooling technologies. These peak loads can be reduced by a factor of 21-55% by adding large penetrations of micro CHP. Two important things must be mentioned however: First, since micro CHPs are heat demand driven they are best suited for older houses, improving insulation and lowering the thermostat reduces the electricity production of the micro CHP unit. Second, micro CHPs have the disadvantage that they use natural gas, and hence if the Netherlands wishes to achieve 80% CO_2 reduction in 2050 then micro CHPs will not be an option. For the next 10-20 years however micro CHPs are however a very good option for accelerating energy transition.

Finally, in Chapter 8 the research question of this thesis was put to the test. In Chapter 8 a discussion was given regarding the expected market development of the technologies considered. The share of heat pumps and electric vehicles are expected to reach penetrations of 17,5% and 73% in the year 2030, respectively (Ministry of Infrastructure and the Environment, 2009; Ecofys, 2007). If these penetrations are reached without concern for the electricity networks, peak network loads of up to 150% will be achieved. It has been shown however that many options for flexibility exist and by using proper control strategies and by taking advantage of favorable combinations the network loads can be kept under their maximum values.

It can be concluded that favorable combinations and flexibilities do exist and these can be used to reduce the network loads of future energy technologies. However, much like when building a self-sufficient house, team work will be required.

10 Recommendations

Several recommendations can be made based on the thesis work done here. The recommendations are presented in three categories: those for network planners, for further researcher, and for Quintel Intelligence.

10.1 Recommendations for network planners

In the introduction chapter the network operator's dilemma was explained: Network operators need to either anticipate future energy scenarios and preventively invest in the electricity networks, possibly resulting in unnecessary costs, or they need to wait for markets to develop and only then invest in the networks, possibly delaying energy transition. Because of the numerous possible future energy scenarios that exist however, it is difficult to predict what will happen. One clear conclusion of this thesis however is that in their uncontrolled form heat pumps and electric vehicles pose significant problems for the low voltage electricity networks. It also has been shown that there are options available to manage the impact of these technologies. This however requires proper planning, team work, and a proactive role from network operators.

It is therefore recommended that network operators assume a more proactive role in the transition to a sustainable energy future. Network operators need to become involved in the decision making process so that they can voice their opinion for certain preferences, such as choice for charging strategy or the best way to warm a home on a very cold day when using technologies such as heat pumps.

In particular, network operators need to work together with consumers. It has been shown that there are some very unfavorable technologies for the electricity networks: electric heaters and economic charging of electric vehicles. These both can easily be avoided, but they require informing consumers about the effects of their behavior. It has also been shown in the report that bivalent heat pumps are not as problematic as other studies predicted, however this is only under the condition that the heat pumps are not over dimensioned. Network operators should therefore inform consumers about their buying decisions and make clear the impact that over sized heating systems can have on the electricity networks.

Finally, one of the most important recommendations that can be given to network operators is the importance of communication. If network operators become aware of what technologies are causing overload problems in their networks and of the behavior of the consumers in these networks, then they have the information they need to find innovative solutions to dealing with capacity problems. Adding more copper is the not the only solution.

Allowing network operators to play a more proactive role could even speed up the transition to a sustainable energy future. It has been shown that favorable combinations of technologies do exist in terms of network load, and with this in mind network operators could possibly argue that investing *more* in extra technologies such as micro CHPs could reduce loads in the networks and in the long run lower costs that otherwise might be incurred to due blackouts and required additional capacity.

10.2 Recommendations for further research

Several recommendations for further research can be made based on the work that has been done here. These research projects range from improving the testing environment created to expanding the study to other networks and even results here in other studies unrelated to electricity networks.

Adding voltage drop to the calculations

This thesis focuses on the load of low voltage electricity network components. Another important factor for network planners is the voltage; this must always be within a 10% range of nominal voltage for household consumers. An improvement to the testing environment would be to add a voltage drop calculation in which the maximum and minimum expected voltages in a scenario are calculated. The following equation is given in (Kersting, 2002) and can be used to reasonably accurately (Kersting reports an error of 0,27%) calculate the voltage drop in a feeder:

$$V_{drop} = RE\{0{,}5 \cdot Z \cdot I_{tot}\} \tag{10.1}$$

With, V_{drop} being the voltage drop, Z the total impedance of the cable, and I_{tot} the total single-phase current. This equation assumes that the loads are evenly distributed along the feeder cable. Adding a calculation such as this one to the study could be beneficial, especially if the testing environment is to be used for network planning calculations. (Note: this calculation has been added to the testing environment to calculate the minimum and maximum network loads however no results concerning the voltage drop are given in the thesis.)

Continue study for low voltage networks with different user types

This thesis project focused on low voltage distribution networks with only residential users. Most low voltage networks however contain a mix of users: Residential, offices, and industry. To further the study it would be interesting to consider the implications when taking these other user types into account.

To do this two things need to be done: New power demand profiles need to be created for the new user types and information needs to be obtained about the mix of users among low voltage networks. It is the author's opinion that both of these things are not very difficult to do.

The power demand profiles for electric vehicles charged at work can be created in a similar manner as was described in Section 4.2; only different arrival and departure times need to be used, and the purpose for travel needs to be known. This data is available in the Mobility Study data. This information can be used to create the 'charging at work' electric vehicle profiles.

The power demand profiles for space heating technologies can be created using the heat demand model. This requires knowing the characteristics of office and industry buildings (insulation, number of external walls, window area, etc.). The most important requirement is the choice of the thermostat setting, but this probably can be assumed to be 19-21°C during office hours and 10-16°C otherwise.

Finally, information about the mix of users in different low voltage networks is required. This information can be obtained from network operators, they include this information in their 'belasting prognose' (load forecasts).

Continue the study for higher voltage levels

Technologies such as heat pumps and electric vehicles will not only affect low voltage networks but higher voltage levels as well. Since electricity production becomes more decentralized, it is important to also consider the medium and high voltage levels. This study is a good start for future studies to determine the impact at the medium or high voltage levels. The output of this study could be used as input for the next.

The following things need to be taken into consideration when considering higher voltage levels. Firstly, the mix of users is different at higher voltage levels; industrial and agricultural users are found here, therefore the loads of these users will also need to be included. Second, at higher voltage levels the number of technologies that need to be taken into consideration increases. For the medium voltage level technologies such as industrial CHPs, agricultural CHPs, industrial heat pumps, and wind turbines need to be taken into account. At the high voltage level central production technologies such as coal and gas power plants, offshore wind farms, and import and export of electricity need to be considered.

Investigate the costs of network expansion and of the flexibility options

In this thesis no reference has been made to the costs of certain results, this was beyond the scope of the work. However a clear optimization problem can be identified: To what extent does investing in flexibility reduce the required investments in the networks? Clearly controlled electric vehicle charging strategies will require more investments than uncontrolled strategies, but are these investments worth the savings they offer?

Add other power demand profiles

The testing environment has been created in such a manner that it is possible to easily add additional power demand profiles. The study can easily be expanded by adding new power demand profiles for other technologies or for different flexibility options.

Add week profiles

In this thesis the typical load profiles of one summer and winter day were taken. Using seven day profiles might over more insights in how electricity demand varies over time. Seven day profiles could provide more information such as the difference between loading on very cold days vs. less cold days, between sunny days and warm days, and between week and weekend.

Other applications of the research

Although the focus of this thesis was on the impact of certain energy technologies on the electricity grid, the knowledge gained in this report is applicable to other studies besides things involving the electricity networks.

The first possibility is using the testing environment for the dimensioning of energy neutral neighborhoods. The testing environment could easily be modified to change the results to show the total power supply/demand in a certain scenario instead of network load. Based on this users could try to minimize the power demand and/or determine how energy storage technologies could be used to become completely energy neutral.

Another possibility would be using the created Matlab household heat demand model for the sizing of space heating systems. By entering only a few characteristics of any household into the heat demand model an accurate indication is given about what the heating demand of the household is, and hence what capacity is required for the heating system (See Appendix B for a verification of the accuracy of the heat demand model in predicting household yearly heat demand).

An alternative would be to further expand the heat demand model to make it viable for household energy label calculations. Companies such as Wepal (2009) use similar calculations as those used in the heat demand model to determine the energy label of a household. The only difference being that more than space heating alone is taken into account to determine the energy label, all building related energy needs to be considered; for example energy for lighting needs to be included as well.

10.3 Recommendations for Quintel Intelligence and the Energy Transition Model

This thesis project was conducted for Quintel Intelligence and the results are to be integrated into Quintel's online scenario planning tool, the Energy Transition Model (ETM). Recommendations for Quintel Intelligence are given below.

Incorporate power demand and load profiles into the ETM

The ETM does not currently show how energy demand varies over time; instead it only considers year values. Incorporating the load profiles created in this project can add invaluable information to the ETM. The following steps to implementing the profiles are suggested:

1. Start by generalizing the information to the national level. i.e. in the first phase, leave out details such as how the results vary from one type of neighborhood to the next. This generalization step requires conducting a small case study to figure out how the results calculated for the three neighborhoods scale up to the national level.
2. Start by implementing the power demand profiles instead of the load profiles. The load profiles are interesting for network operators, but for most users simply showing how electricity demand varies in different scenarios is more relevant. Furthermore, to calculate the load profiles the power demand profiles must first be included.
3. After implementing the power demand profiles it is possible to add load profiles for the transformers and cables. It is recommended that before doing this, discussions are held with network operators to inquire whether they interested in using this functionality, and if so what things they would like to have included. Ideally network operators could use the ETM to obtain preliminary results to determine what scenarios are the most interesting for further investigation. The following questions should be asked to the network operators:

   a. What things would they like to control? Should the user be able to configure the network, or should the model contain only the three typical neighborhoods?
   b. What results would they like to see?
   c. How will the tool be used?
   d. Are there any calculations that should be included to further improve the tool?
4. Although it is the author's opinion that the network operators are interested in seeing the transformer and cable load profiles, if they are not it is suggested to continue with the power profiles and expand the functionalities of these. A possibility would be to continue to add technologies (larger CHPs, wind turbines, and forms of energy storage) and then create an environment where users can build their own 'energy neutral city'.

Adding gas demand profiles

The results of this thesis make it possible to add electricity demand profiles to the ETM; the next goal should be to add similar profiles for gas demand. Doing this would present users with a nice optimization problem, in which they try to balance and reduce both the gas and electricity loads.

Improve the current network impact calculation and add flexibility feedback

The current network calculation can be improved by adjusting the peak load and simultaneousness values for the energy technologies in the ETM. Since the ETM simply adds peak loads instead of adding the profiles, the effect of combinations of technologies needs to be checked in particular. It should be checked that the values obtained are not significantly higher than those obtained here. An ideal option would be to link the network impact calculation with the load profiles, if implemented.

Furthermore, it is possible to take advantage of the ETM as a communication tool and communicate to users the options that exist for flexibility. Users currently see the network impact of the decisions that they do not have many options to reduce this impact. The results of this thesis should be incorporated into the ETM to show users how smarter charging strategies or improving insulation can be used to reduce the investment required in the electricity network.

Recommendations for internationalization

The focus of this thesis was on Dutch low voltage electricity networks however the results can easily be applied to other countries. It is assumed that there is little distinction between the behavior of electric vehicles and space heating technologies in the Netherlands and abroad, therefore the power demand profiles are immediately applicable to other countries. The only research that needs to be conducted is how the electricity networks differ in other countries and what the current loads are of these networks.

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Appendix A – Screenshots of the testing environment

In this Appendix an explanation is given about the testing environment with screenshots.

Front end of the testing environment

The front end consists of three parts, each which will be described below: Creation of a network, creation of a scenario, and results.

Creation of a network

In the testing environment a network can easily be created by defining a few parameters. The next figure shows a screenshot of how a network is created. In this section a user specifies the type of network, the capacity of the transformer, the voltage being used, the number of households, the number of cables, how the households are distributed over the number the cables, and finally the ampacity of the cables. The ampacity values are provided by cable manufacturers. If these are unknown then typical values can be used.

Network Design

Type of results	Load [%]	
Neighborhood type	Countryside	
Future year	2030	
Electricity growth (% / year)	1,0%	
Transformer capacity (kVA)	160	
Number of cables	3	
	Number of houses	Ampacity (A)
Cable A	17	185
Cable B	13	185
Cable C	21	185
Cable D		
Cable E		
Cable F		
Cable G		
Cable H		
Total	51	

Network design interface in the testing environment

Creation of scenarios

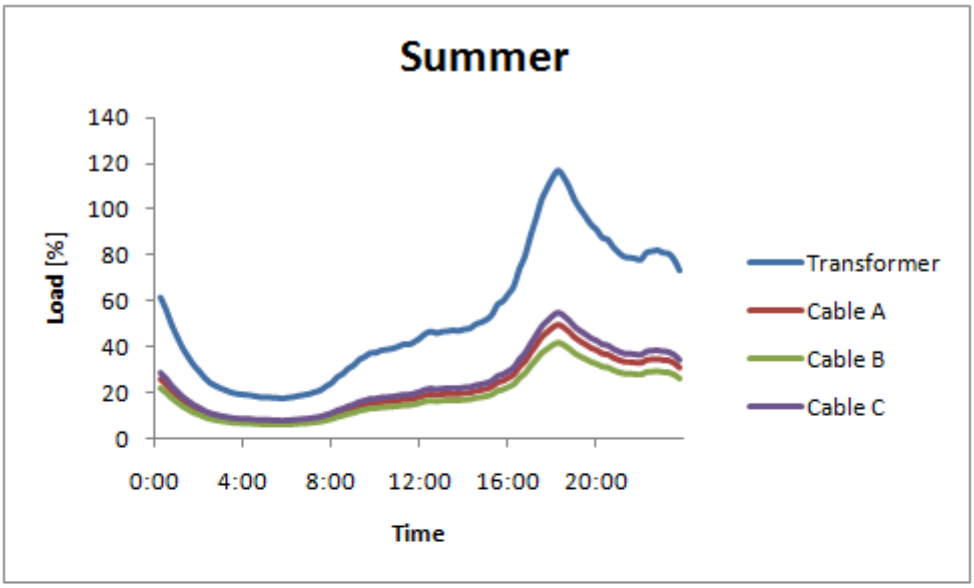
All the load profiles in the model, with the exception of the household demand profile, are connected to a slider. The sliders can be moved to a value between 0 and 100% representing the degree of market penetration of the technology. The next figure shows a screenshot of the slider controls.

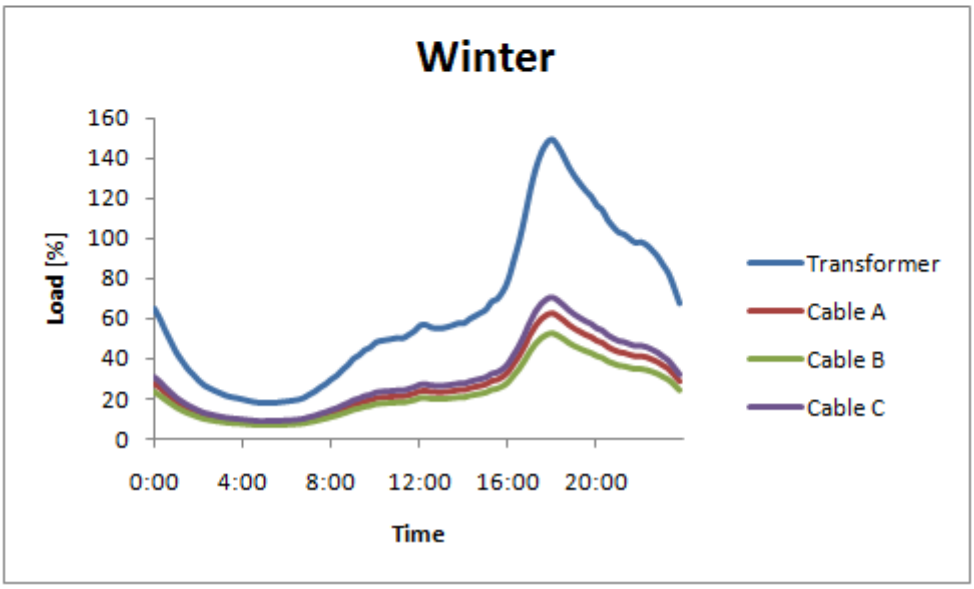
Technologies				
	Market penetration			
Electricity production			efficiency	area [m2]
Solar PV	0%		12%	15
Transportation				
3kW uncontrolled charging	0%			
10kW uncontrolled charging	50%			
3kW economic charging	0%			
10kW economic charging	0%			
3kW Slow charging	0%			
Vehicle to grid	0%			
Transformer controlled char	0%			
Charging only when <30%	0%			
Hot water				
Electric boiler	0%			
Heat pump boiler	0%			
Heating				
Micro CHP	0%			
Electric heater	0%			
Monovalent heat pump	0%			
Bivalent heat pump, 40%	0%			
Bivalent heat pump, 60%	0%			
Bivalent heat pump, 80%	0%			
Ground source heat pump	0%			
Heat pump with thermal sto	0%			
Cooling				
Air conditioning	100%			

Scenario building interface in the testing environment

Results

Once the user has defined his scenario by moving the sliders the results are shown in two graphs, as can be seen in the next figure. Besides showing the results as a graph it is also possible to write the results to a file where values for the peak load are given.





Results in the testing environment

Back end of the testing environment

At the back end of the model all the calculations take place. The back end consists of several sheets each conducting part of the calculation. The calculation consists of the following parts: Distributing the households and the technologies over the cables and phases, compiling the power demand profiles, determining the peak load of each cable, scaling the power demand profiles accordingly, and finally determining the load of the transformer and the cables.

Distribution of households over the cables

Once a user specifies the number of households per feeder the model then automatically assigns the households to separate phases. It is assumed that the houses are evenly distributed over the phases; this is also what happens in reality to keep the networks as balanced as possible (VDEN, 1986).

Distribution of technologies over the households

When a user creates a scenario with for example a 45% market penetration of a given technology, the model calculates how many households receive the technology. The model assumes that the technologies are evenly distributed over the feeders and over the phases and assigns the technologies to the households accordingly.

The figure below shows an example of how the distribution takes place. In the figure it can be seen that multiple technologies have market penetrations varying from 0 to 100%, this is seen in the fact that the total number of each technology (column B) is between 0 and the number of households, 51.

Calculates the number of houses on each phase/cable	Total	A	B	C	Cable A	A	B	C	Cable B	A	B	C	Cable C	A	B	C
Household load	51	16	18	17	17	5	6	6	13	4	5	4	21	7	7	7
Solar PV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Electric boiler	21	6	8	7	7	2	3	2	5	1	2	2	9	3	3	3
Heat pump boiler	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Air conditioning	44	14	15	15	15	5	5	5	11	3	4	4	18	6	6	6
Electric heater	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Micro CHP	6	0	3	3	2	0	1	1	2	0	1	1	2	0	1	1
Bivalent heat pump, 40%	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Bivalent heat pump, 60%	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Bivalent heat pump, 80%	6	0	3	3	2	0	1	1	2	0	1	1	2	0	1	1
Monovalent heat pump	13	3	5	5	5	1	2	2	3	1	1	1	5	1	2	2
Ground source heat pump	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Heat pump with thermal storage	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3kW uncontrolled charging	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10kW uncontrolled charging	9	2	4	3	3	1	1	1	2	0	1	1	4	1	2	1
3kW economic charging	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10kW economic charging	21	6	8	7	7	2	3	2	5	1	2	2	9	3	3	3
3kW Slow charging	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Charging only when <30%	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Vehicle to grid	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Transformer controlled charging	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Distribution of loads over the cables and phases in the testing environment

Inclusion of power demand profiles

The sliders at the front end are each linked to a power demand profile in the back end of the model. Each power demand profile consists of 192 data points, one data point per 15 minutes for two days. These power demand profiles are compiled in the model. Currently in the model the following profiles are available: Household electricity demand, Solar PV, eight electric vehicle charging strategies, electric and heat pump water boilers, micro CHP, electric heater, air conditioning, and five types of heat pumps.

Application of Strand-Axelsson equations to determine load of households

The testing environment calculates the peak loads by reading the slider positions and using the Strand-Axelsson equations taking into account the distribution of the houses over the feeders and phases. An example of this is seen below. Also seen in figure are the values for $P_{max,1}$ and $P_{max,inf}$ of each technology.

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	*Calculates the peak load, Pmax, per cable/phase*			Total	Total 2	A	B	C	Cable A	Cable A 2	A	B	C
2		Pmax,1	Pmax,inf										
3	Household load	2,57	1,07	63,1	25,0	22,5	25,0	23,7	23,7	9,9	8,6	9,9	9,9
4	Solar PV	1,54	1,54	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
5	Electric boiler	5,70	1,43	49,7	23,5	19,1	23,5	21,3	21,3	11,7	8,9	11,7	8,9
6	Heat pump boiler	1,50	0,38	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
7	Air conditioning	2,00	2,00	88,0	30,0	28,0	30,0	30,0	30,0	10,0	10,0	10,0	10,0
8	Electric heater	7,00	6,64	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
9	Micro CHP	1,00	1,00	6,0	3,0	0,0	3,0	3,0	2,0	1,0	0,0	1,0	1,0
10	Bivalent heat pump, 40%	5,50	3,02	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
11	Bivalent heat pump, 60%	4,75	2,91	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
12	Bivalent heat pump, 80%	3,75	2,81	19,2	10,1	0,0	10,1	10,1	6,9	3,8	0,0	3,8	3,8

Calculation of peak loads per cable, phase, and transformer in the testing environment

Once the peak load of each technology is known the resulting load profile is created for the transformers and the cables. This is done by scaling the average power demand profiles according to the required P_{max} determined for each network part. The resulting profiles are compiled in a single sheet as shown

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
1	*Calculates the resulting load profile on each cable and transformer*	0:00	0:15	0:30	0:45	1:00	1:15	1:30	1:45	2:00	2:15	2:30	2:45	3:00	3:15	3:30	3:45	4:00	4:15	4:30	4:45	5:00
22	Power (max per phase)	Single phase																				
23	Total	61	51	44	37	32	14	12	11	10	9	8	8	8	7	7	7	8	8	9	10	12
24	Cable A	28	23	20	17	15	6	5	5	4	4	3	3	3	3	3	3	3	4	4	4	5
25	Cable B	22	19	16	14	12	5	5	4	4	3	3	3	3	3	3	2	3	3	3	3	4
26	Cable C	30	26	22	19	16	7	6	6	5	4	4	4	4	3	3	3	4	4	4	5	6
27	Cable D	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
28	Cable E	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29	Cable F	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Resulting load profiles for cables and transformers in the testing environment

Calculating the load of transformers and cables

Finally, once the power demand profiles have been compiled the load of the transformer and cables is calculated for each of the 192 data points. The loads are calculated according to the methods described in the report.

Appendix B – Heat demand model verification

The heat demand model introduced in Chapter 5 can be used to determine the heat demand of a household based on a limited number of characteristics entered by the user. Here it will be verified that the model can accurately predict the heat demand of a household by comparing the results with expected values and results obtained in various studies.

House K-values and expected heat demand

Often the total insulation value of the building, the K-value, is used to give an indication of the energy use of a house. The K-value is obtained according to the following equation (Borsodchem):

$$K - value = \frac{Inward\ surface\ of\ outward\ walls}{Volume\ of\ the\ building} \times \overline{U}$$

With $\overline{U}$ being the average U-value of the outward walls of the building. The units for the K-value are W/m^3K and the number gives an indication of the energy required to maintain a certain temperature difference. For example, a house with a volume of $400m^3$ and a K-value of 0,45 W/m^3K requires 180W to maintain its temperature 1K above the exterior temperature.

The K-value can therefore be used to validate the model by comparing the results of the heat demand model with the expected heat demand according to the calculated K-value. To do this, first the K-values are found. The average U-value is found by taking a weighted average of K_i, K_o, K_w, and K_v over the areas over which they act:

$$\overline{U} = \frac{\left(\frac{1}{R_{tot}}\right) \times (wall\ area + roof\ area) + U_w \times window\ area + K_v}{wall\ area + roof\ area + window\ area}$$

With:

R_{tot} – The total resistivity of the wall elements including insulation [m^2K/W]
U_w – The thermal conductivity of the windows per square meter [W/m^2K]

The following table shows the K-values obtained for the three reference houses considered:

K-values of the reference houses along with the expected and calculated heat demand to maintain an indoor temperature of 20°C with an outdoor temperature of 0°C

	K-value	Expected heat required to maintain 20°C temperature difference [W]	Heat demand calculated by the model to maintain 20°C temperature difference[W]	Percent difference
Countryside	0,8842	6853	7179	4.8%
Village	0,7906	6041	6298	4.3%
City	0,6512	3873	4009	3.5%

It is seen that the heat demand obtained from the model is at most 5% higher than the expected demand. The values calculated by the model are higher because the model not only takes into

account the thermal conductivities but also considers the capacitances of the indoor air and the building mass.

Comparison to an actual Dutch house

In this section the model is validated by comparing the results of the household heat demand model to the results obtained in a detailed energy study conducted by Wepal (2009) at a Dutch household in Rotterdam used to determine the energy label of the house. In the study conducted by Wepal detailed information about the house was required: area of all windows and external surfaces, type of windows, orientation of windows, and construction type.

Since it is impossible to take into account behavior of inhabitants the Wepal study calculates the standardized energy use of the household which can be used to compare the energy efficiency of households. Some of the assumptions used by Wepal (2009) are unknown; therefore the assumptions used for the heat demand model are stated here:

- The cut off temperature for recording heat loss and heat gain. In the model it is assumed that only if the mean outdoor temperature is below 13°C the heat loss and gain is relevant.
- The indoor temperature. In the model it is assumed that a thermostat is used to maintain an indoor temperature of 21°C.

The following table shows the results from the study compared to the results obtained in the heat demand model:

Comparison of the heat demand calculated by the model and Wepal (2009). Negative values imply a heat gain.

	Values found by Wepal 2009 [MJ]	Values found by the heat demand model [MJ]	Percent difference
Heat loss - transmission	49.971	54.065	-8,2%
Heat loss - ventilation	16.137	14.691	9,0%
Heat production - appliances and occupation	-12.337	-12.924	4,8%
Heat gain - windows	-8.137	-10.385	-27,6%
Resulting heat demand	45.670	45.447	0,5%

The results found in the heat demand model vary at most 28% from the results found by Wepal (2009). The largest difference is found in the heat gain through the windows. This difference is because the heat demand model assumes that all windows have a favorable orientation and hence the resulting heat gain is larger than the value determined in the Wepal study. However, the heat gain through windows is only a fraction (about 16%) of the heat loss due to transmission and ventilation, so although the percent difference of the heat gain through windows is large the total resulting heat demand is accurate.

Comparison to the results obtained in Pearce 2001

In Pearce (2001) a thermal equivalent circuit is used to predict the heat demand of six English households. It is not possible to compare the results of the heat demand used by Pearce and the model created here because the input temperature data is for England rather than the Netherlands and hence the resulting heat demand is different. However Pearce does provide the values for the

thermal conductances and thermal capacitances of the six households and it can be shown here that these values can be obtained using the simplified input of the household heat demand model. This will show that the heat demand model can accurately obtain the values used for the thermal equivalent circuit.

Three of the households considered by Pearce are based on a study conducted by Everett et al. (1985). Everett et al. provide the necessary characteristics of the houses such as dimensions, type of insulation, and year of construction. These characteristics will be used in this section to show that the household heat demand model can determine approximately the same thermal conductances and capacitances as have been determined by Pearce (2001). The table below shows the relevant characteristics that are given for the three households in Pearce (2001) along with $K_{transmission}$ and K_{total} which are the total conductance through the wall and total conductance of the house.

Summary of household characteristics provided in Pearce (2001)

	House 33	House 35	House 36
House-type	Detached	Detached	Detached
Floor area, m^2	72	72	72
Extra insulation	Yes	Yes	Yes
C_a [J/K]	$1{,}63 \times 10^6$	$1{,}63 \times 10^6$	$1{,}63 \times 10^6$
C_w [J/K]	109×10^6	134×10^6	109×10^6
K_v [W/K]	103	103	103
K_i [W/K]	95,1	50,7	95,1
K_o [W/K]	882	625	882
$K_{transmission}$, total conductivity through the walls [W/K]	86	47	86
K_{total} , total conductivity [W/K]	189	150	189

In addition to the characteristics given in the above table, the following characteristics are given by Everett et al. (1985):

- Insulation – 50 to 100mm (the value of 50 is assigned to houses no. 33 and no. 36 and 100 to house no. 35. House no. 35 has lower values for K_i and K_o which are dependent on the insulation)
- Window glazing – Double glazing
- Construction year – 1980
- Number of floors – 2
- Air changes per hour – 1 (in the heat demand model 0,5 is assumed, however in Everett et al. (1985) it is specifically stated that the measured air changes per hour is 1.)

From the above parameters the data is entered as input into the heat demand model. The remaining parameters, such as window area, roof area, and wall area are provided by Everett et al. however these values are not required as input for the heat demand model and are calculated by the model.

Input into the heat demand model

	No. 33	No. 35	No. 36
Insulation level	50mm	100mm	50mm
Window type	1	1	1
Construction year	1980	1980	1980
Area	72	72	72
Number of floors	2	2	2
Number of external sides	4	4	4
Structure type (based on the observation that house no. 35 has a higher wall capacity, C_w, than houses no. 33 and no. 36)	Heavy	Extra heavy	Heavy

The thermal equivalent circuit used here is different than the one used by Pearce, therefore for comparison the conductivity through the windows K_w has been added to the ventilation conductivity K_v, also the total conductivity through the walls, $K_{transmission}$, and the total conductivity of the house, K_{total}, have been calculated for comparison.

Thermal capacitances and conductances calculated by the household heat demand model

	Units	No. 33	No. 35	No. 36
C_a	J/K	$1.45x10^6$	$1.45x10^6$	$1.45x10^6$
C_w	J/K	$92,3x10^6$	$123x10^6$	$92,3x10^6$
K_v	W/K	109,1	109,1	109,1
K_i	W/K	80,4	53,1	80,4
K_o	W/K	723,5	478,1	828,2
$K_{transmission}$, total conductivity through walls	W/K	72,3	47,8	82,8
K_{total} , total conductivity	W/K	181,4	156,9	191,9

The values in the table above vary between 4 and 16% from those given by Pearce (2001), the percent differences are shown in the next table. The individual conductances vary the most, however the difference in the total conductance, K_{total}, are small. It is likely that Pearce uses different calculations and assumptions and therefore the values deviate, however as can be seen in the previous table the error in the total conductances is small.

The error in the capacitances C_a and C_w is larger and is between 8% and 15%. The capacitances calculated by the heat demand model are consistently lower than those calculated by Pearce. There is no information available about the calculations used by Pearce and hence it is difficult to determine what the cause of the differences is. The effect of the error is however negligible; changing the C_a and C_w values to those given by Pearce only changes the required heat demand calculated by the heat demand model by 0,2%.

Percent difference between values found by Pearce (2001) and values calculated by heat demand model

	No. 33	No. 35	No. 36
C_a	9%	9%	9%
C_w	15%	8%	15%
$K_{transmission}$	16%	-2%	16%
K_{total}	4%	-5%	4%

Appendix C - Peak loads and coincidence factors

Determined Strand Axelsson coefficients for technologies not dependent on neighborhood type

Technology	$P_{max,1}$	$P_{max,inf}$	$A = \alpha V$	$B = \beta\sqrt{V}$	coincidence factor
Solar PV	1,54	1,54	1,5437	0,0000	1,00
Electric boiler	5,70	1,43	1,4334	4,2666	0,25
Heat pump boiler	1,50	0,38	0,3772	1,1228	0,25
3kW uncontrolled charging	3,00	0,93	0,9280	2,0720	0,31
10kW uncontrolled charging	10,0	1,44	1,4369	8,5631	0,14
Slow charging	3,00	0,72	0,7172	2,2828	0,24
Charging when SOC <30%	10,0	1,74	1,7356	8,2644	0,17
Charging as late as possible	10,0	1,93	1,9306	8,0694	0,19
Night time charging	10,0	0,97	0,9685	9,0315	0,10
Vehicle to grid	10,0	1,18	1,1812	8,8188	0,12
Economic charging	10,0	8,72	8,7200	1,2800	0,87

Strand Axelsson coefficients for countryside heaters

Technology	$P_{max,1}$	$P_{max,inf}$	$A = \alpha V$	$B = \beta\sqrt{V}$	coincidence factor
Electric heater	7,00	6,65	6,6493	0,3507	0,93
Monovalent heat pump	2,75	2,55	2,5474	0,2026	0,90
Bivalent 40% heat pump	5,50	2,58	2,5827	2,9173	0,60
Bivalent 60% heat pump	4,75	2,55	2,5479	2,2021	0,54
Bivalent 80% heat pump	3,75	2,41	2,4076	1,3424	0,57
Ground source heat pump	2,00	1,88	1,8816	0,1184	0,91
Micro CHP	1,00	1,00	1,0000	0,0000	1,00
Air conditioner	2,00	1,88	1,8816	0,1184	0,94

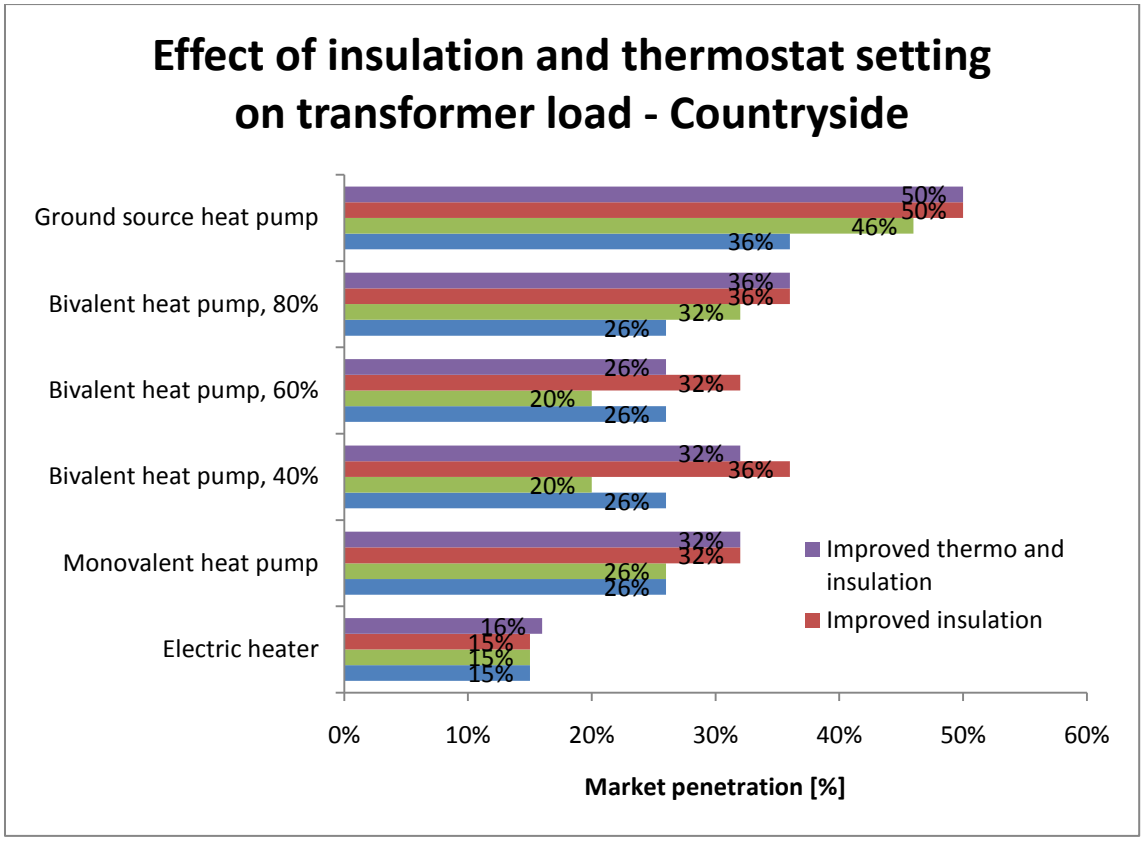
Strand Axelsson coefficients for village heaters

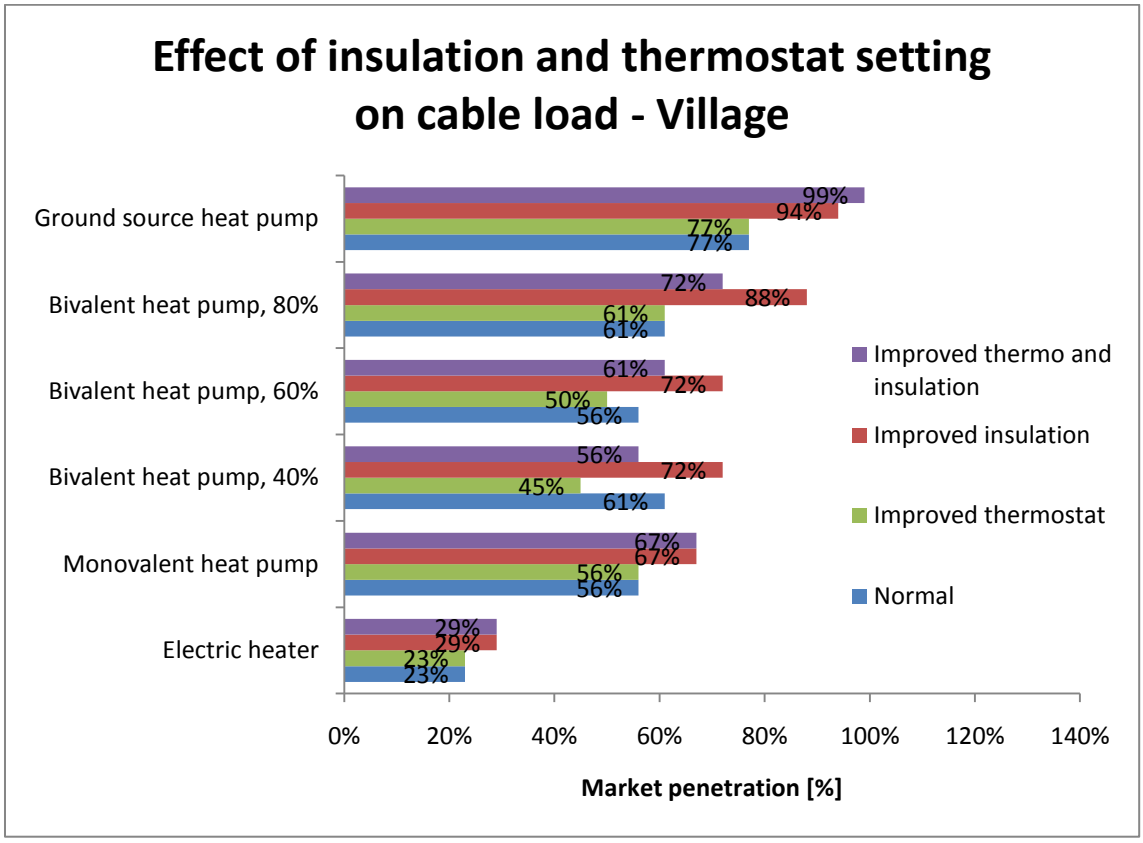
Technology	$P_{max,1}$	$P_{max,inf}$	$A = \alpha V$	$B = \beta\sqrt{V}$	coincidence factor
Electric heater	6,00	5,59	5,5945	0,4055	0,95
Monovalent heat pump	2,50	2,26	2,2640	0,2360	0,90
Bivalent 40% heat pump	4,75	2,33	2,3277	2,4223	0,55
Bivalent 60% heat pump	4,00	2,18	2,1789	1,8211	0,58
Bivalent 80% heat pump	3,25	2,05	2,0540	1,1960	0,61
Ground source heat pump	1,75	1,69	1,6861	0,0639	0,91
Micro CHP	1,00	1,00	0,9989	0,0011	1,00
Air conditioner	1,75	1,69	1,6861	0,0639	0,96

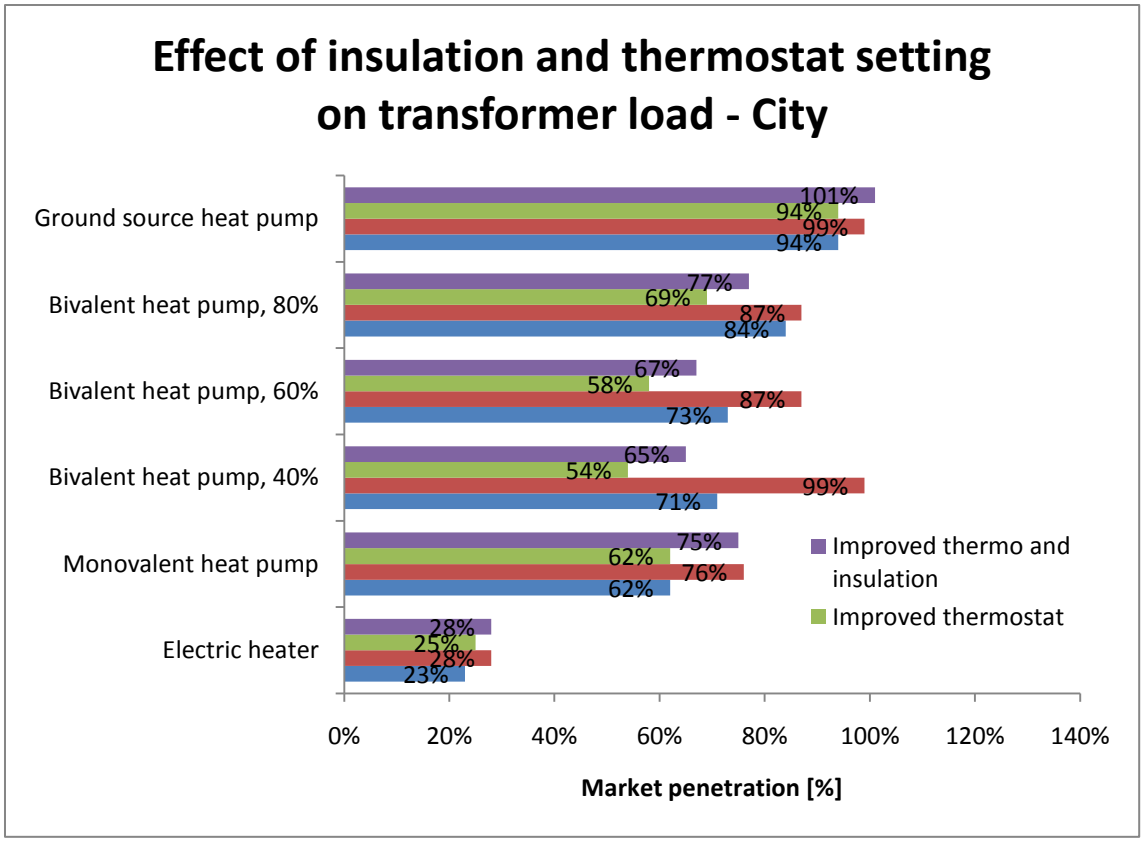
Strand Axelsson coefficients for city heaters

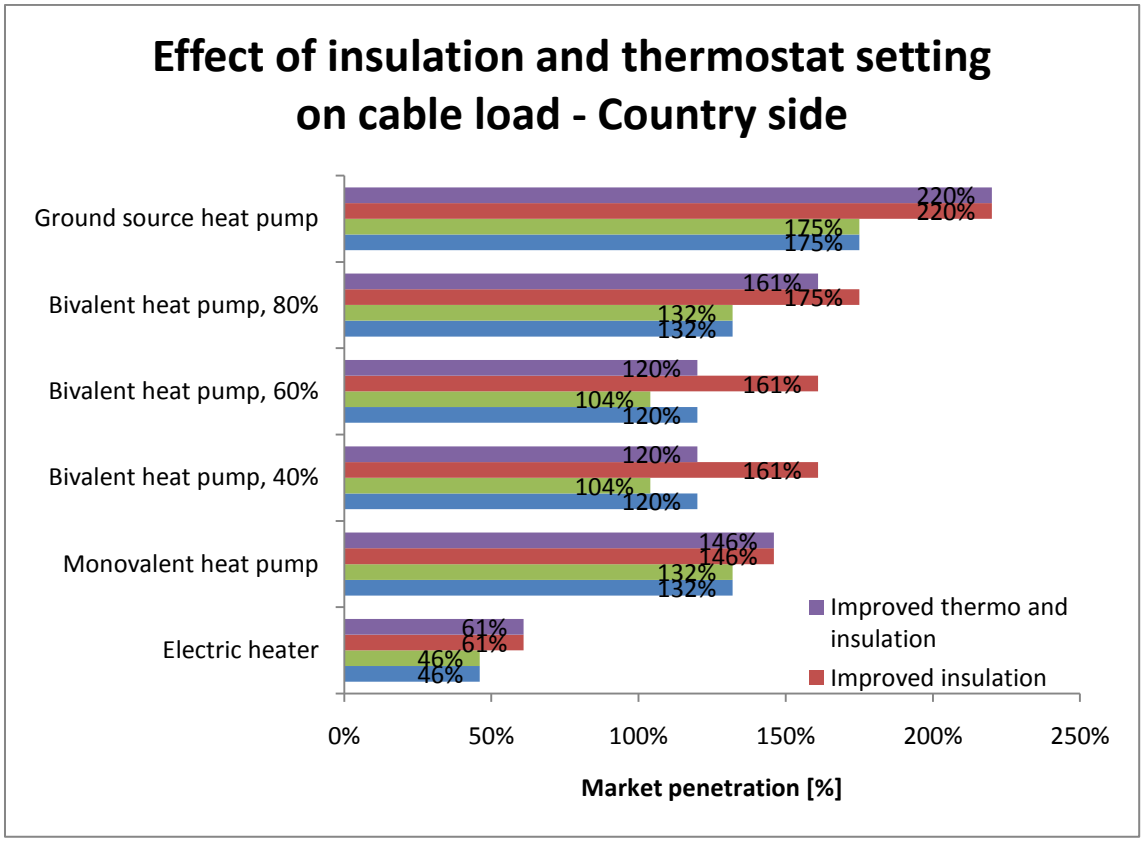
Technology	$P_{max,1}$	$P_{max,inf}$	$A = \alpha V$	$B = \beta\sqrt{V}$	coincidence factor
Electric heater	3,50	3,33	3,3336	0,1664	0,96
Monovalent heat pump	1,50	1,38	1,3836	0,1164	0,94
Bivalent 40% heat pump	3,00	1,42	1,4199	1,5801	0,57
Bivalent 60% heat pump	2,50	1,42	1,4198	1,0802	0,69
Bivalent 80% heat pump	2,00	1,21	1,2111	0,7889	0,60
Ground source heat pump	1,00	1,00	1,0000	0,0000	0,91
Micro CHP	1,00	0,7	0,6974	0,3026	0,70
Air conditioner	1,00	1,00	1,0000	0,0000	1,00

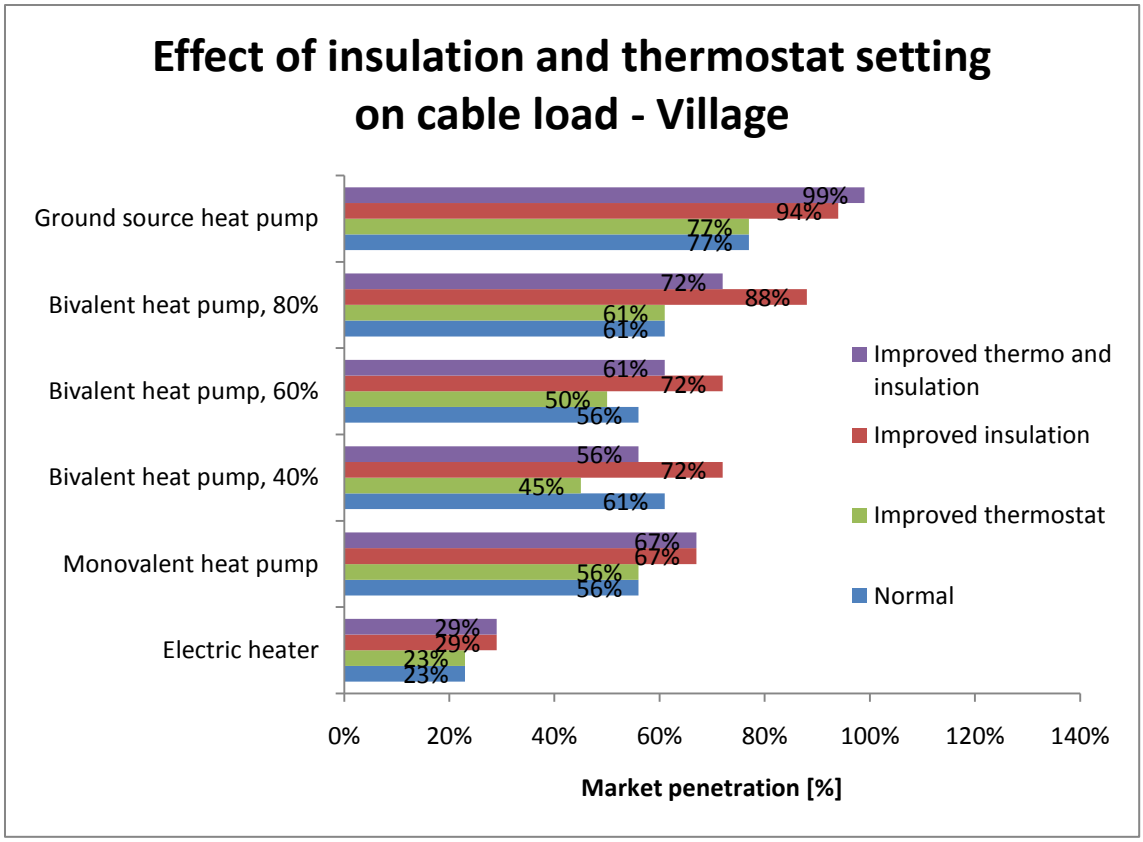
Appendix D – Effect of insulation and thermostat setting

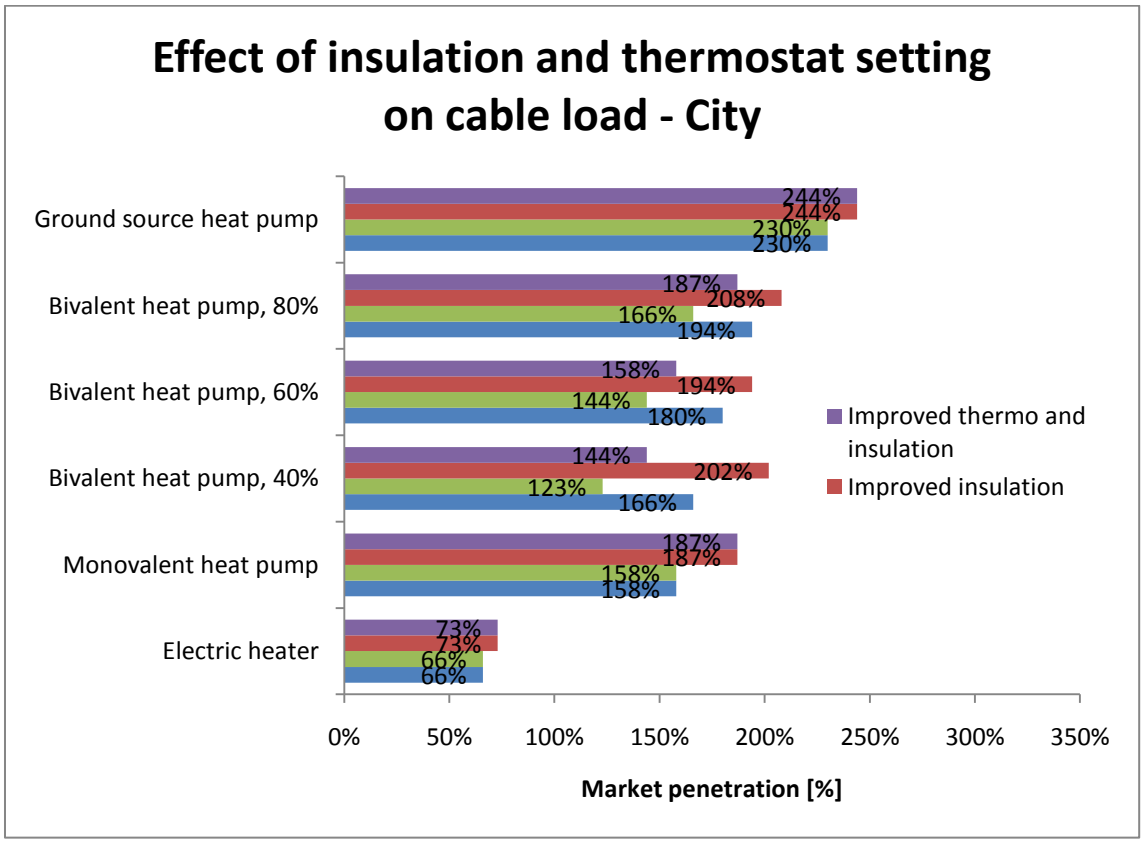





Effect of insulation and thermostat setting on transformer load - City
Ground source heat pump
Bivalent heat pump, 80%
Bivalent heat pump, 60%
Bivalent heat pump, 40%
Monovalent heat pump
Electric heater
101%
94%
99%
94%
77%
69%
87%
84%
67%
58%
87%
73%
65%
54%
99%
71%
75%
62%
76%
62%
28%
25%
28%
23%
Improved thermo and insulation
Improved thermostat
0%
20%
40%
60%
80%
100%
120%
140%
Market penetration [%]


Effect of insulation and thermostat setting on cable load - Country side
Ground source heat pump
Bivalent heat pump, 80%
Bivalent heat pump, 60%
Bivalent heat pump, 40%
Monovalent heat pump
Electric heater
220%
220%
175%
175%
161%
175%
132%
132%
120%
161%
104%
120%
120%
161%
104%
120%
146%
146%
132%
132%
61%
61%
46%
46%
Improved thermo and insulation
Improved insulation
0%
50%
100%
150%
200%
250%
Market penetration [%]


Effect of insulation and thermostat setting on cable load - Village
Ground source heat pump
Bivalent heat pump, 80%
Bivalent heat pump, 60%
Bivalent heat pump, 40%
Monovalent heat pump
Electric heater
99%
94%
77%
77%
72%
88%
61%
61%
61%
72%
50%
56%
56%
72%
45%
61%
67%
67%
56%
56%
29%
29%
23%
23%
Improved thermo and insulation
Improved insulation
Improved thermostat
Normal
0%
20%
40%
60%
80%
100%
120%
140%
Market penetration [%]


Effect of insulation and thermostat setting on cable load - City
Ground source heat pump
Bivalent heat pump, 80%
Bivalent heat pump, 60%
Bivalent heat pump, 40%
Monovalent heat pump
Electric heater
244%
244%
230%
230%
187%
208%
166%
194%
158%
194%
144%
180%
144%
202%
123%
166%
187%
187%
158%
158%
73%
73%
66%
66%
Improved thermo and insulation
Improved insulation
0%
50%
100%
150%
200%
250%
300%
350%
Market penetration [%]