Abstract—Heat pump based heating systems are increasingly becoming an economic and efficient alternative for domestic gas heating systems. Concentrations of heat pump installations do consume large amounts of electricity, causing significant grid distribution and stability issues when the diversity factor is low. In this work, the three step control methodology TRIANA is extended to support the control of a heat pump fleet in order to improve diversity. Simulations show that TRIANA can reduce the peak load by at least 25% and improve \( \sigma \) by 33% for a representative soil-water scenario. Mathematical optimization shows that further improvement is possible.

Index Terms—Computer simulation, energy efficiency, energy management, geothermal energy, heat pumps, heating, hierarchical systems, load management, power system modeling, TRIANA.

I. INTRODUCTION

E\(\text{N\text{VIRONMENTAL}}\) constraints and fuel scarcity drive an increasing demand for energy efficient systems in general and a more efficient use of energy in particular. Instigated by these driving factors and anticipating the economic depletion of fossil fuel reserves, an increasing share of the electricity supply is based on renewable energy sources. Combined with distributed generation, energy balancing becomes more and more of a local challenge and the stress on the grid and generation resources increases.

Since 27% of total energy consumption can be attributed to households and 90% of this is used for heat applications [1], [2], heating is of particular interest. Investments in local gas distribution infrastructure in newly developed neighborhoods becomes unattractive due to lower penetration of gas applications [3] and higher insulation standards [4]. Therefore, heat pumps are increasingly regarded as an attractive option for domestic heating. Heat pumps can provide competitive efficiency and costs for heating compared to gas-fired heating systems. A large scale introduction of heat pumps will however result in even more stress on the grid and generation resources, as the heating systems will then become electricity fed.

Electricity fired heating has been used for decades. Not accounting for power plant efficiency, standard resistive heating elements have already a near 100% efficiency. Heat pumps can reach a much higher (electrical) efficiency by extracting heat from the environment, typically attaining an efficiency between 200–600%, depending on the system design and conditions. Furthermore, the heat pump installation can often also be used to efficiently cool the house. For a significant part of the world, this is the dominant mode of operation.

A large penetration rate of heat pumps can however significantly affect the design requirements for the electricity grid. While heat pumps have a high efficiency, heat demand is also high in comparison with other electric demand, increasing the electricity usage of a neighborhood substantially. Furthermore, the standard, naive control strategy within the heat pump in combination with locality-induced similar circumstances in every house results in similar behavior of heat pumps and therefore high common grid usage peaks (low diversity factor). At last, heat pumps have a limited heating capacity which may lead to heat shortages and therefore uncomfortably low temperatures in the houses.

At the University of Twente, a three step control methodology for smart grids TRIANA is developed (Section II-B). This control strategy is able to optimize the runtime of individual devices for a large group of houses to work towards both local and global objectives. In this paper we will show that it is possible and relatively easy to incorporate heat pumps in the TRIANA control strategy and that it is possible to optimize the electricity demand profile of a group of heat pumps.

The remainder of this paper is structured as follows. First, we will provide background on heat pumps (Section II-A) and the three step methodology TRIANA (Section II-B) as well as related work (Section III). Subsequently, we will present the heat pump model for TRIANA (Section IV), followed by our application scenario (Section V). We will show the (mathematically) optimal solution for the control problem (Section V-A) before TRIANA is applied (Section VI). The paper is closed with conclusions (Section VII) and future work (Section VII-A).

II. BACKGROUND

A. Device characteristics

For this paper, we will focus on heat pumps which are based on a condensation/evaporation-based refrigeration cycle. These heat pumps work similar to a fridge and can be used for both heating and cooling. In particular, the thermodynamic cycle runs with the same principles and directions in both applications [5]. Utilization however differs since heat pumps exploit the ‘hot side’ of the process for heating.

The operating medium goes through different phases to be raised from a lower to a higher temperature level using drive
energy (usually electricity). The operating medium withdraws heat from the heat source by evaporation through compression, transfers the energy to the heating circuits and liquefies in the cooling phase, exploiting the latent heat properties of the operating medium [6]. The most common heat sources are soil, air and water. Soil-water heat pumps work with horizontal collectors or geothermal probes. Air-water heat pumps use the outside air, whereas water-water heat pumps work with the temperature of surface water and ground water [5].

The efficiency of heat pumps depends on the $\Delta T$; the difference between the temperature of the source and the temperature of the output water. A lower $\Delta T$ gives a higher efficiency since the required temperature increase is lower and therefore also the required compression ratio. For soil-water heat pumps the source temperature is near-constant during the year ($\approx 7^\circ C$), the source temperature of air-water heat pumps can vary widely. The required temperature of the output water depends on its application. Hot tap water requires a temperature of at least $55^\circ C$. High temperature heating (e.g. radiators) also requires a high temperature level to operate ($> 60^\circ C$) whereas low temperature heating demands low temperature water ($\approx 25^\circ C$). In this paper, we assume to have a soil-water heat pump and an output temperature near $25^\circ C$ for a low temperature heating system. Resultingly, we can assume that the efficiency of the heat pump is fixed.

Currently it is not known what the influence of (a large number of) heat pumps on the temperature of the lower layers of the earth is. Therefore, an increasing number of governments and policy makers require a seasonal storage balance: during a year, the same amount of energy should be put into the ground as is extracted. This can be done by heating in winter (pull heat energy out) and cooling in summer (put heat energy back in). Since the simulations in this paper have a horizon of one day, seasonal storage can not be taken into account. However, both in the TRIANA methodology and in the developed model of the heat pump seasonal storage is taken into account.

B. TRIANA — three step methodology

A three step control methodology for smart grids has been developed at the University of Twente over the last half decade. Starting from this paper, we will refer to this methodology as “TRIANA”.

The control strategy exploits the optimization potential of domestic devices in a generic way [7]. The methodology is flexible in both the optimization objective and the technologies available within houses. After all, the objectives as well as the installed technologies are bound to change over time.

This control strategy consists of three steps. In the first step, a system located at the consumer’s premises predicts the production and consumption pattern of all appliances for the upcoming day. For example, in a normal household multiple appliances like a TV, a washing machine and a central heating system are present. For each appliance, based on the historical consumption pattern of the residents and external factors like the weather, a predicted energy profile is generated. Based on the expected energy profile and the characteristics of the devices, the scheduling freedom and optimization potentials are determined. These potentials are aggregated by the local controller and sent to the global controller. The global control is structured as a hierarchical tree, providing a scalable and communication-frugal control infrastructure. The received profiles are aggregated in each node of the tree and sent towards the root node of the tree.

In the second step, these optimization potentials can be used by a central planner to exploit the potential to reach a global objective. The root node determines steering signals based on the received information and the objective. These steering signals are distributed via the tree structure, whereby each node may adjust the steering signals. Adjusted profiles are determined in the houses, based on the (new) steering signals and the predictions. These new profiles are again sent upwards. In this iterative manner, a near-optimal solution can be found within a reasonable computational time. Example objectives are peak shaving or compensating the fluctuation of the production of renewable sources like wind parks. The result of the second step is a planning for each household for the upcoming day and an overall production/consumption profile. In the final step, which is the focus of this paper, a realtime control algorithm decides at which times appliances are switched on/off, when and how much energy flows from or to the buffers and when and which generators are switched on. This realtime control algorithm uses the steering signals from the global planning as input, but preserves the comfort of the residents in conflict situations. The local controller is also able to operate independently without central coordination, for example when the connection with the global controller is lost.

The base of the TRIANA methodology is a general modelling of the energy situation in a domestic environment. This model is used to analyze the energy-streus and optimization potential. The basis of this modelling is the model of a house. Since the behavior of individual devices is optimized, the detail level of the model is on the device level. Houses contain multiple devices and exchange energy with the environment (e.g. gas import, electricity import/export) and multiple houses can be
combined in a grid to analyze their aggregate behavior. Based on this model, a simulator has been developed which can quickly evaluate different scenarios, house configurations and device parameters [8]. An example of a house model is shown in Figure 2.

Multiple types of energy (carriers) can flow through the house (e.g. gas, electricity, heat). These types of energy are modelled as streams transporting one type of energy. These energy-types are converted, buffered and consumed by devices. Furthermore, energy-types can be exchanged with the environment, which is modelled by exchanging devices. Every device can have certain energy-streams flowing in and certain energy-streams flowing out, e.g. a Combined Heat and Power appliance has a gas stream in and an electricity and a heat stream out.

Energy flows between devices: the energy-streams of the devices are connected with each other. Energy may flow directly from one device to another device (e.g. heat from the boiler to the central heating) while in other cases energy can flow from and to multiple devices (e.g. electricity). To accommodate this, pools are introduced. Each device energy-stream is connected to a pool. One or more energy-streams can flow into a pool and one or more energy-streams can flow out of a pool. A discrete simulation approach is used. Therefore the simulation horizon is discretized, resulting in a sequence of consecutive time intervals. For every time interval, the pools in the house need to be in balance: the pool influx and outflux of energy must be equal. A detailed description of the model and the simulator can be found in [8].

The balance in the pools can be reached, as well in the simulation as in real-world scenarios, by using the flexibility of devices: some devices can vary the amount of energy flowing in and/or out. For example, a boiler can be switched on or off, the amount of electricity imported from the grid can vary, a certain amount of energy can be cached or supplied by a buffering device and the operation of some consuming devices can be postponed. The decisions influence the energy efficiency, electricity import profile, etc. and therefore some decisions may be preferable. The goal of the local controller is to make good decisions given a certain objective (e.g. peak shaving or following a global objective). The local controller can work independently or cooperate in the global three step methodology.

The steering signals from the global controller are incorporated as energy import/export prices. When a local optimization strategy is used, the objective is also incorporated by adjusting the energy import/export prices. The control algorithm used for this model is based on the control algorithm described in [9]. A detailed description of the algorithm for the heat pump is given in Section IV.

III. RELATED WORK

In literature, a lot of heat pump related papers are available. However, these papers mainly discuss the organization, operating characteristics and analysis of heat pump systems, pertaining to efficiency and externalities (costs and environmental impact) [10]. Several works improve on their (electrical) efficiency by employing auxiliary (typically renewable) energy sources, e.g. using solar assisted evaporators [11]. In contrast to these works, we assume the COP (or an estimate thereof) to be provided in advance, i.e. it is not the optimization criterion. This paper focuses on improving the consumption profiles of a fleet of heat pumps where the characteristics are given, whereas the above mentioned papers focus on improving the heat pump itself.

Demand side management has attracted substantial research and commercial interest and is part of the smart grid paradigm. Many publications exist on groups of 'smart' devices which can be controlled in concert to attain a desirable power profile while maintaining user acceptance. Typically, heat-oriented devices and applications (freezers, washing machines, heating [12]) are considered due to high energy demands and leniency towards temporary intermissions. Several control policies have been defined, including manual control by a grid operator, automated grid stability protection [12] and cost-based steering approaches [13]. In [14] the triana methodology is extensively compared with other approaches. Most of the researchers propose a hierarchical structured, agent based solution. The hierarchical structure ensures the scalability of the solution. The similarities between the described approaches and our approach are the control up to an appliance level and the hierarchical structure with aggregation on each level (local and global control). The main differences are the prediction/planning steps and the lack of an agent-based approach. The latter substantially affects the design of a control strategy: agents are greedy and try to optimize their own profit whereas our optimization methodology tries to reach a global objective for the whole fleet. As observed in [15], global optimization algorithms generally lead to better results.

The POWERMATCHER approach has been applied to a heat pump scenario, where it manages to curtail heat pump and auxiliary resistive heating demand to prevent grid overload in simulation [16]. In their scenario, electricity demand issues are caused in particular by the use of the resistive heating facility. In practice, however, economics dictate that the heating rod is only to be used when the heat pump is defective as the heating load of a highly insulated house can be met solely with the heat pump.
IV. HEAT PUMP MODEL

The heat pump is classified as a converting device: it appears to convert electricity to heat. The device has four energy-streams: the drive power supply (electricity in), the heat source (heat in), the heat sink (heat out) and loss (heat out). The electrical energy used to power the device is siphoned to the loss port.

The efficiency of a heat pump depends on the temperature difference between the source and the sink element ($\Delta T$). The Coefficient of Performance (COP) of the heat pump is defined as the ratio of the heat displacement from the source to the sink stream to the supplied heat pump work. At each instance in time, the device enforces this fixed conversion ratio between inputs and outputs. For now we may assume that the efficiency of the heat pump is fixed (Section II-A).

The performance of a heat pump is bounded, which we model by limiting the electricity consumption. In our heat pump device model, the heat pump has a number of different modulation levels. The modulation level determines the amount of electricity consumed by the pump and therefore also the heat production of the pump. A heat pump with one modulation point corresponds to a type which does not support modulation.

Many heat pumps can in heating mode recover a large part of the drive energy and contribute this to the heat sink. Whether this is possible can be configured by connecting the loss either to the heat sink pool or to a loss consuming device. The loss is not modeled as part of the COP, because that does not properly represent the energy transfer between the heat source and the sink. This becomes particularly important when the heat source is fed from a finite or billed resource.

V. APPLICATION SCENARIO

To demonstrate the validity of our heat pump model and to demonstrate the ability of TRIANA to exploit (some of) the optimization potential, we will present an application scenario which we consider to be sufficiently representative for ground source heat pumps in a moderate climate during winter.

In this scenario, 100 houses are used. The heat demand of these 100 houses is extracted from our heat demand database containing measured heat demand data of a number of households, where 100 days with a heat load between 38 kWh and 75 kWh are extracted. We consider this heat demand a representative heat demand for households with a heat pump installed.

Each house is furnished with a 10 kWh heat store. The heat store to some extent decouples the production and consumption of heat, introducing flexibility regarding when and at which modulation level the heat pump operates. The start level of the heat store is chosen at 7500 Wh (75% full) and is the same for all houses.

The overall model of a house is depicted in Figure 3. Although there can be more devices present in the house, these are considered as non-steerable and will be abstracted away. Therefore, these are not included in the house model. The depicted heat exchange represents the heat extracted from the ground. For now, this source is assumed to be unlimited. The electricity exchange represents the grid connection of the house, which can provide all the electricity required by the heat pump. As described in Section IV, the heat production of the heat pump is determined by its COP and electricity consumption. Since we are using the heat pump for heating, both the heat output and the electrical loss energy-streams are connected to the heat store via a heat pool. The heat demand is subsequently supplied using the heat store.

In this scenario, the heat pump has five modulation modes and a maximum electricity consumption of 2 kW. The modulation modes are divided evenly over the maximum electricity consumption, resulting in the following six heat production modes: 0 W, 400 W, 800 W, 1200 W, 1600 W and 2000 W. For COP, a value of 3.0 is chosen. As we assume that the electrical loss can be fully recycled, an effective COP of 4.0 is attained, a value representative for current soil-water heat pump systems. Therefore, between 0 W and 8000 W of heat can be produced by the heat pump.

A. Optimal solution

To determine the quality of the steering, the optimal solution is determined using the following ILP formulation. First the simulated time period of one day is evenly divided into $T_N$ time intervals. For each time interval $t \in 1, \ldots, T_N$ the heat demand $C_{h,t}$ of house $h \in H$ must be supplied. In our simulation, the heat pump supports six modes, i.e. $M = \{0, \ldots, 5\}$. The variable $z_{h,t} \in M$ is introduced to describe the mode of each heat pump at house $h$ and time interval $t$. Based on $z_{h,t}$ the heat production can be calculated via $P_z \times z_{h,t}$, where $P_z$ is the power of the heat pump.

![Fig. 3. Model of the house with a heat pump](image)

![Fig. 4. Load duration curve of the ILP solution](image)
the heat production capacity of mode \( z \) in one time interval. Similarly, the electricity demand (in W) is determined using \( E_z \) via \( E_z \times z_{h,i} \).

The goal of this use case is to decrease the peaks by flattening the electricity demand profile of the group of houses. In other words, the fluctuation of the electricity demand should be minimized. This results in the following objective function:

\[
\min \sum_{i=2}^{T} \sum_{j=1}^{H} E_z \times z_{j,i} - \sum_{j=1}^{H} E_z \times z_{j,i-1}.
\]

Since the heat is supplied from the heat buffer, the buffer level must always be maintained between a lower limit \( b_{\min} \) and an upper limit \( b_{\max} \). The heat buffer is depleted as a result of supplying the heat demand and can be filled by generating heat using the heat pump. Therefore, the following constraint is added:

\[
b_{\min} \leq b_{\text{start}} + \sum_{i=1}^{T} P_z \times z_{h,i} - \sum_{i=1}^{T} C_{h,i} \leq b_{\max} \forall t \in T, h \in H,
\]

where \( b_{\text{start}} \) is the begin level of the heat store (in Wh).

In the optimization as well as the simulation, a time interval length of six minutes is used. The maximum electricity consumption of the heat pump is 2000 W. Since an effective COP value of 4.0 is used, a maximum of 8000 W of heat can be produced, which is 8000/5 = 1600 W per modulation level. Each time interval is six minutes, therefore \( P_z = 1600 \times 5 = 8000 \text{ W} \) and \( E_z = 400 \text{ W} \).

The performance of our approach is quantified using multiple metrics. The first metric is the diversity factor, which is the ratio of the sum of the individual maximum demands to the maximum real demand of the system. In our case, this is 2000/1600, where \( E_{\max} \) is the highest peak in the demand.

The second metric is \( 3\sigma \), where \( \sigma \) is the standard deviation of the electricity consumption, expressing the variation of the load. A lower variation means less fluctuations, meaning that the demand can be supplied more efficiently. Furthermore, load duration curves are used to visualize the capacity utilization.

The load duration curve after solving the ILP is given in Figure 4. The start level of the heat store \( b_{\text{start}} = 7500 \text{ Wh} \), as in the simulations. As can be observed, the start level of the heat store results in start up effects. For every time interval, there is a heat buffer level which provides the flexibility required for the given objective. However, it takes a while to reach this heat buffer level. The limited heat demand restricts the possible operation modes, resulting in a deviation from the desired profile. After this startup phase, it is possible to achieve a perfect flat electricity consumption profile with a maximum electricity demand of \( 6 \times 10^4 \text{ W} \). The corresponding \( 3\sigma \) value is 5.4 \( \times 10^4 \) and the diversity factor is 3.3.

VI. RESULTS

The simulation results are shown in Figure 5 and Figure 6. In Figure 5, the accumulated electricity consumption profile of the 100 houses is given, both with and without optimization. As can be seen in the figure, using optimization the peaks are lowered and the very low demand periods (0–3 AM) are exploited. Since the heat demand is low during the night and can be satisfied using the initial stored buffer contents, the scenario without steering starts with low electricity demand and increases as the buffers deplete. During the morning heating peak (7–9 AM), all buffers become empty and prefer to be replenished, resulting in an electricity demand peak. In the evening (around 8–9 PM), the day demand plateau is observed. This behavior is flattened by the TRIANA methodology, resulting in 25% lower peaks: the diversity factor increases from 1.79 to 2.37.

Figure 6 shows the load duration curves, with and without optimization. Due to the lower peaks in consumption and the increase during the low demand periods in the case with optimization, the load duration curve is also flattened. This follows from the \( 3\sigma \) values: it decreased from 9.05 \( \times 10^4 \) to 6.10 \( \times 10^4 \), a decrease of 33%.

VII. CONCLUSION

Defining and incorporating the model of the heat pump into the TRIANA methodology was relatively easy. The model is already generic enough to cover most scenarios and future extensions towards other types of heat pumps and/or seasonal storage are taken into account. Without changes to the TRIANA methodology it was able to improve the consumption profile of a large concentration of heat pumps.
The consumption profile improved significantly: the peaks decreased by 25% and the fluctuation with 33%, even when using a rather naïve and straightforward planning method. Exploration of the optimal solution showed that there is even more potential to decrease peaks and fluctuations. Studying the simulation results in more detail showed that the differences between the optimal solution and the simulation using the TRIANA methodology are mainly caused by the planning methodology. Improving this planning methodology by adding optimization on the lowest level is expected to enhance the results significantly. This is left for future work.

A. Future work

The model of the heat pump and the results of this initial version of the control methodology are very promising. Therefore, a number of directions for future work are defined that will be investigated.

1) Improved planning: The planning on the lowest (in house) level is very naïve and straightforward, causing the large disparity between the optimal case and the actual results. Improvements to the planning strategy will improve the results significantly.

2) Real application scenario: The data used for the simulations in this paper are based on real world measurements, but is not acquired from heat pump scenarios. We expect measurements from a neighborhood with heat pumps in Nordhorn, Germany. The simulations should also be performed on this data set.

3) Investments: Advanced energy systems are expensive and need to be amortized over extensive periods of time. Therefore, the model should be extended to accommodate investments with long-term payoff. In this way can be evaluated whether it can be economically justified to refrain from a gas distribution network in a neighborhood and whether it is worthwhile to install the optimization infrastructure and methodology.

4) Temperature dependent efficiency: To be able to also simulate use cases with air-water heat pumps and/or multiple output temperatures, the model should be extended with a $\Delta T$ dependent COP.

5) Seasonal thermal storage: For the situation of seasonal thermal storage, the heat pump model must be extended with cooling capabilities. These are not inversely proportional to heating since the electrical losses (as heat) cannot be exploited. The next step is to extend the control methodology with capabilities to account for seasonal storage, i.e. not only optimize the usage for the current day but also incorporate the net amount of energy extracted from the earth in the optimizations.

VIII. Acknowledgements

This research is conducted within the DREAM project supported by STW.

The authors would like to thank Maurice G.C. Bosman for his efforts to provide the results of the optimal case calculations.

REFERENCES

[10] K. Chua, S. Chou, and W. Yang, “Computational studies on domestic heat pump optimization on the lowest level is expected to enhance the results significantly. This is left for future work.

A. Future work

The model of the heat pump and the results of this initial version of the control methodology are very promising. Therefore, a number of directions for future work are defined that will be investigated.

1) Improved planning: The planning on the lowest (in house) level is very naïve and straightforward, causing the large disparity between the optimal case and the actual results. Improvements to the planning strategy will improve the results significantly.

2) Real application scenario: The data used for the simulations in this paper are based on real world measurements, but is not acquired from heat pump scenarios. We expect measurements from a neighborhood with heat pumps in Nordhorn, Germany. The simulations should also be performed on this data set.

3) Investments: Advanced energy systems are expensive and need to be amortized over extensive periods of time. Therefore, the model should be extended to accommodate investments with long-term payoff. In this way can be evaluated whether it can be economically justified to refrain from a gas distribution network in a neighborhood and whether it is worthwhile to install the optimization infrastructure and methodology.

4) Temperature dependent efficiency: To be able to also simulate use cases with air-water heat pumps and/or multiple output temperatures, the model should be extended with a $\Delta T$ dependent COP.

5) Seasonal thermal storage: For the situation of seasonal thermal storage, the heat pump model must be extended with cooling capabilities. These are not inversely proportional to heating since the electrical losses (as heat) cannot be exploited. The next step is to extend the control methodology with capabilities to account for seasonal storage, i.e. not only optimize the usage for the current day but also incorporate the net amount of energy extracted from the earth in the optimizations.

VIII. Acknowledgements

This research is conducted within the DREAM project supported by STW.

The authors would like to thank Maurice G.C. Bosman for his efforts to provide the results of the optimal case calculations.

REFERENCES

Hermen A. Toersche was born in Westerhaar-Vriezenveenewijk, the Netherlands in 1986. He received his M.Sc. degree from the University of Twente, Enschede, the Netherlands in 2010 at the Computer Architecture for Embedded Systems group, where he currently also is a Ph.D. candidate. His research interests include efficient distributed embedded systems.

Vincent Bakker received his M.Sc. degree in Computer Science from the University of Twente in 2007, with a minor certificate in Entrepreneurship. Currently he is working on his Ph.D. thesis researching domestic demand prediction for home optimizations. Currently his interest are: machine learning, optimization modeling and large scale distributed (intelligent) systems.

Albert Molderink received his B.Sc and M.Sc. degree in Computer Science from the University of Twente, Enschede, The Netherlands, in respectively 2004 and 2007. In 2011 he received his PhD degree from the same university. He is working in a research group that investigates the possibilities of increasing energy efficiency using embedded control, mainly via optimization and control algorithms. His research focus is on algorithms to optimize energy streams within a house.

Johann L. Hurink received a Ph.D. degree at the University of Osnabrueck (Germany) in 1992 for a thesis on a scheduling problem occurring in the area of public transport. From 1992 until 1998 he has been an assistant professor at the same university working on local search methods and complex scheduling problems. From 1998 until 2005 he has been an assistant professor and from 2005 until 2009 an associated professor in the group Discrete Mathematics and Mathematical Programming at the department of Applied Mathematics at the University of Twente. Since 2009 he is a full professor of the same group. Current work includes the application of optimization techniques and scheduling models to problems from logistics, health care, and telecommunication.

Stefan Nykamp was born in Nordhorn, Germany in 1983. He received his M.Sc. degree from the University of Muenster and the RWTH Aachen, Germany in 2010 in Energy Economics. Currently, he is a Ph.D. candidate at the University of Twente, Enschede, the Netherlands and works in the distribution network planning with RWE, Germany. His research interests include the technical and economical integration of renewable energy systems and the (appropriate) regulation of (smart) grids.

Gerard J.M. Smit received his M.Sc. degree in electrical engineering from the University of Twente. He then worked for four years in the research and development laboratory of Océ in Venlo. He finished his Ph.D. thesis entitled “the design of Central Switch communication systems for Multimedia Applications” in 1994. He has been a visiting researcher at the Computer Lab of the Cambridge University in 1994, and a visiting researcher at Lucent Technologies Bell Labs Innovations, New Jersey in 1998. Since 1999 he works in the Chameleon project, which investigates new hardware and software architectures for battery-powered hand-held computers. Currently his interests are: low-power communication, wireless multimedia communication, and reconfigurable architectures for energy reduction. Since 2006 he is full professor in the CAES chair (Computer Architectures for Embedded Systems) at the faculty EEMCS of the University of Twente. Prof. Smit has been and still is responsible of a number of research projects sponsored by the EC, industry and Dutch government in the field of multimedia and reconfigurable systems.