Linear programming control of a group of heat pumps*

Jiří Fink, Richard P. van Leeuwen, Johann L. Hurink, Gerard J.M. Smit

Abstract

For the new Meppel district Nieuwveense landen a hybrid energy concept is developed based on biogas cogeneration. The generated electricity is used to power domestic heat pumps which supply thermal energy for domestic hot water and space heating demand of households. In this paper we investigate scheduling of a group of heat pumps in order to minimize the maximum peak of the total electricity consumption. Results of two different control methods are presented to balance the electric power demand for the group of heat pumps. The paper addresses specific issues like computational hardness and the difficulty of prediction of energy demand. We show that the control method which uses a scaling time gives equal results to an exact approach but requires less computational effort.

1 Introduction

In modern society, a significant amount of energy is consumed for heating water for tap water and space heating [5]. Almost every building is connected to a district heating system or equipped with appliances for heating water locally. Typical appliances for heating water are electrical and gas heating systems, heat pumps and Combined Heat and Power units (microCHP). The heated water is stored in buffers to be prepared for the demand of inhabitants. In our model, a house consists of two local heating systems, one for space heating and the other for tap. A schematic overview of the model is presented in Figure 1. It consists of:

- a supply which represents some source of energy (e.g. electricity, gas),
- a converter which converts the energy into heat (hot water),
- a buffer which stores heat for later usage and

*University of Twente, Department of Computer Science, Mathematics and Electrical Engineering, P.O. Box 217, 7500 AE, Enschede, The Netherlands. This research is conducted within the iCare project (11854) supported by STW. E-mail: fink@kam.mff.cuni.cz, r.p.vanleeuwen@saxion.nl, j.l.hurink@utwente.nl, g.j.m.smit@utwente.nl

- a demand which represents the consumption profile of heat.

A more formal definition of the used model for local heating and the used parameters and variables is given in Section 2. In principle, the presented model can consider arbitrary types of energy but in this paper we use *electricity* and *heat* to distinguish consumed and produced energy. This simple model of a local heating system can not only be applied for heating water but has many other applications in Smart Grids (e.g. control of fridges and freezers) and Inventory Management (Section 2 presents more details about those applications).

The considered problems originate from a project called *MeppelEnergie* [3, 1] where the plan is to build a group of houses and a biogas station in Meppel, a small city in the Netherlands [2]. In this project, part of the houses will have a heat pump for space heating and tap water demands. In the MeppelEnergie project, the electrical production of the biogas station will only be used by the heat pumps. Therefore, the heat pumps should be scheduled in such a way that they only consume, if possible, the electricity produced by the biogas station. If this is not possible, the remaining energy has to be bought on the electricity market at minimal cost.

The planning of a group of heating systems may have many objectives in practice. In the MeppelEnergy project, energy is transported by electrical networks or gas pipes and converted by heating supply systems. Generators and transport equipment have to be dimensioned for the maximal consumption peak. Thus, the main objective is minimizing the maximal consumption which may decrease investments in the system. The mathematical background of this problem is presented in [11] which proves that problem of minimizing peak is NP-complete [11].

A somewhat similar problem was considered by Bosman et al.[7, 9] who studied a microCHP planning problem and proved that minimizing peak is NP-complete in their model [8]. Bosman et al.[6] also present a dynamic programming algorithm for the microCHP planning problem whose time complexity is $O(T^{3C+1})$ where T is the number of time intervals and C is the number of microCHPs.

Although minimizing peak is algorithmically a hard problem, this paper presents its practical importance based on the application to the MeppelEnergie case. Section 2 gives a more detailed problem formulation which leads to an algorithm called global MILP control. As this algorithm requires a lot of computational power, we develop an algorithm called time scale MILP control in Section 3. The simulation results of these two algorithms are presented in Section 5 based on the case MeppelEnergie which is explained in Section 4.

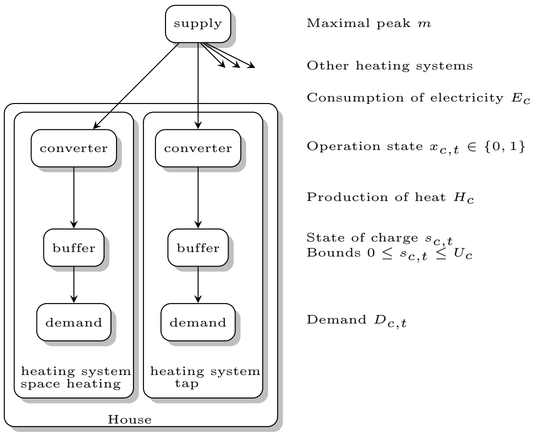

Figure 1: Schematic picture of a house with two separated heating systems for space heating and tap.

2 Problem statement and global MILP control

In this section we present a mathematical description of the studied model and possible applications of this model.

First of all, we consider a discrete time model for the considered problem, meaning that we split the planning period into T time intervals of the same length. We consider a set $\mathcal{C} = \{1, \ldots, C\}$ of C heating systems and a set $\mathcal{T} = \{1, \ldots, T\}$ of T time intervals. Note that the heating of a house is split into two independent heating systems (see Figure 1). In this paper, the letter c is always an index of a heating system (either space heating or tap) and t is an index of a time interval. For mathematical purposes, we separate a heating system into a converter, a buffer and demand; see Figure 1. We say "a converter c" or "a buffer c" or "a demand c" to refer to the devices of the heating system $c \in \mathcal{C}$.

We consider a simple converter which has only two states: In every time interval the converter is either turned on or turned off. The amount of consumed electricity is E_c and the amount of produced heat (or any other form of energy) is H_c during one time interval in which the converter $c \in \mathcal{C}$ is turned on. If the converter is turned off, then it consumes and produces no energy. Let $x_{c,t} \in \{0, 1\}$ be the variable indicating whether the converter $c \in \mathcal{C}$ is running in time interval $t \in \mathcal{T}$.

The state of charge of a buffer $c \in \mathcal{C}$ at the beginning of time interval $t \in \mathcal{T}$ is denoted by $s_{c,t}$ which represents the amount of heat in the buffer. Note that $s_{c,T+1}$ is the state of charge at the end of planning period. The state of charge $s_{c,t}$ is limited by an upper bound U_c.

The amount of consumed heat by the inhabitants of the house from heating system $c \in \mathcal{C}$ during time interval $t \in \mathcal{T}$ is denoted by $D_{c,t}$. This amount is assumed to be given and is called the demand of heating system c. In this paper, we study off-line problems, so we assume that demands $D_{c,t}$ are given for the whole planning period.

The operational variables of the converters $x_{c,t}$ and the states of charge of buffers $s_{c,t}$ are restricted by the following constraints.

$$s_{c,t+1} = s_{c,t} + H_c x_{c,t} - D_{c,t} \quad \text{for} \quad c \in \mathcal{C},\, t \in \mathcal{T} \tag{1}$$

$$0 \leq s_{c,t} \leq U_c \quad \text{for} \quad c \in \mathcal{C},\, t \in \{1, \ldots, T+1\} \tag{2}$$

$$x_{c,t} \in \{0, 1\} \quad \text{for} \quad c \in \mathcal{C},\, t \in \mathcal{T} \tag{3}$$

Equation (1) is the charging equation of the buffer. During time interval $t \in \mathcal{T}$, the state of charge $s_{c,t}$ of a buffer $c \in \mathcal{C}$ is increased by the production of the converter which is $H_c x_{c,t}$ and it is decreased by the demand $D_{c,t}$. Equations (2) and (3) ensure that the domains of variables $s_{c,t}$ and $x_{c,t}$, respectively, are taken into account. Note that the initial state of charge $s_{c,1}$ can be fixed (e.g. by setting $s_{c,1} = \frac{U_c}{2}$).

In this paper, we consider the objective function of minimizing the peak:

$$\begin{aligned} \text{minimize} \quad & m \\ \text{where} \quad & m \geq \textstyle\sum_{c \in \mathcal{C}} E_c x_{c,t} \text{ for } t \in \mathcal{T} \end{aligned} \tag{4}$$

Since $E_c x_{c,t}$ is the amount of consumed electricity by a converter c in time interval t, the sum $\sum_{c \in \mathcal{C}} E_c x_{c,t}$ is the amount of electricity consumed by all converters in time interval t. Furthermore, the inequality and the objective function (4) guarantees that the value of the variable m is the maximal consumption of electricity during one time period within the whole planning period.

In the following we give some other possible applications of this model.

Fridges and freezers: A fridge essentially works in the opposite way than heating, so it may be modelled similarly. However, we have to be careful with the correct interpretation of all parameters. The state of charge of the buffer again represents the temperature inside the fridge, but a higher state of charge means a lower temperature. The converter does not produce heat to the fridge but it decreases the temperature inside the fridge, so the converter increases the state of charge of the buffer (fridge). The demand decreases the state of charge of the fridge due to thermal loss and usage of the fridge by humans.

Inventory: The considered heating problem is also related to Inventory control problems [14]. A buffer may represent an inventory and a converter may represent orders. However, this leads to a situation, where only a limited capacity of inventory is given and it is only possible to order a fix amount of goods which is not a typical situation in inventory management.

Note that the objective function and all constrains are linear and operational state variables are binary, so constraints and the objective (1)–(4) form an instance of Mix Integer Linear Programming (MILP). This instance can be solved by any MILP solver (see e.g. [10]) and we call this approach *global MILP control*. However, as the number of binary variables may get too large for planning many houses over a long planning horizon, this method may get computationally expensive. Therefore, in the following sections an algorithm which significantly reduces the number of variables is given.

3 Time scale MILP control

The method presented in the previous section creates one large instance of MILP and solves it by an MILP solver. This method gives us an optimal solution for the whole planning period but it may not be suitable for practical purposes. First, finding an optimal solution requires a lot of computational power. Next, the prediction of demand for the distant future may be very inaccurate.

Therefore, we consider an on-line control in which the decision which converters will be running is made only for the coming time interval. On the other hand, we cannot ignore the future completely. Indeed, we should take more care about the near future time intervals than the distant ones because the current decision has stronger impact on the near future and the prediction is in general more accurate for the near future.

As the general formal notation of Time scale control may be hard to understand, we use an example to present the approach. Assume that the up-coming time interval has index 1. The decision which converters $c \in \mathcal{C}$ will be running during the coming time interval 1 needs to be made, meaning that the values of variables $x_{c,1}$ need to be decided. Since also the influence of the very near future needs to be detailed, we also consider binary variables e.g. for the next two time intervals i.e. variables $x_{c,2}$ and $x_{c,3}$. For the further future, the plan does not need to be so precise, so for e.g. another two time intervals, we relax the integral constraints, meaning that we require $0 \leq x_{c,4}, x_{c,5} \leq 1$. The reason for relaxing these variables is to decrease the number of integral variables which has the dominating effect on the computational time required to solve an MILP instance. From the practical point of view, these relaxed variables (e.g. $x_{c,4}$) can signify the probability that a converter c will run in time interval 4, and so $\sum_{c\in\mathcal{C}} H_c x_{c,4}$ is the expected demand of electricity.

Following this, for the even more distant future, we only need a rough planning. In order to explain the idea of rough planning, let us consider the state of charge equation e.g. for time intervals $t = 8, 9$ and 10.

$$\begin{aligned} s_{c,9} &= s_{c,8} + H_c x_{c,8} - D_{c,8} \\ s_{c,10} &= s_{c,9} + H_c x_{c,9} - D_{c,9} \\ s_{c,11} &= s_{c,10} + H_c x_{c,10} - D_{c,10} \end{aligned}$$

We sum these equations and after simplification we obtain

$$s_{c,11} = s_{c,8} + H_c(x_{c,8} + x_{c,9} + x_{c,10}) - (D_{c,8} + D_{c,9} + D_{c,10}).$$

The rough plan for converter c for time intervals $t, t+1, \ldots, t'$ is now defined by $x_{c,t..t'} = \sum_{i=t}^{t'} x_{c,i}$, that is we replace time intervals $t, t+1, \ldots, t'$ by one block of time intervals $t..t'$. During this block, converter c consumes $E_c x_{c,t..t'}$ electricity and produces $H_c x_{c,t..t'}$ heat. Using this notation, the state of charge equation for a block 8..10 of time intervals $t = 8, 9$ and 10 is

$$s_{c,11} = s_{c,8} + H_c x_{c,8..10} - D_{c,8..10}$$

where $D_{c,8..10} = D_{c,8} + D_{c,9} + D_{c,10}$ is the cumulative demand for time intervals $8, 9$ and 10. In this example, we replace the three variables $x_{c,8}$, $x_{c,9}$ and $x_{c,10}$ by one aggregated variable $x_{c,8..10}$ which is constrained by bounds $0 \leq x_{c,8..10} \leq 3$. In this way, we can cover a longer planning horizon without requiring too many variables in an MILP instance. Furthermore, note that only the sum of demands $D_{c,8..10}$ for distant future time intervals is important. The practical consequence is that the time where a significant demand occurs does not have to be predicted precisely, e.g. in the morning it is sufficient to predict the amount of hot water demand for evening showers but the exact time when inhabitants will take a shower can be approximated.

In our example, we consider rough planning variables $x_{c,6..7}$, $x_{c,8..10}$, and $x_{11..15}$. In summary, all state of charge equations are

$$\begin{aligned} s_{c,t+1} &= s_{c,t} + H_c x_{c,t} - D_{c,t} \text{ for } t = 1, \ldots, 5 \\ s_{c,8} &= s_{c,6} + H_c x_{c,6..7} - D_{c,6..7} \\ s_{c,11} &= s_{c,8} + H_c x_{c,8..10} - D_{c,8..10} \\ s_{c,16} &= s_{c,11} + H_c x_{c,11..15} - D_{c,11..15} \end{aligned}$$

for every $c \in \mathcal{C}$.

The capacity constraints of buffers remain the same, so

$$L_{c,t} \leq s_{c,t} \leq U_{c,t} \text{ for } t \in \{1, 2, 3, 4, 5, 6, 8, 11, 16\}.$$

The operational constraints of converters now are

$$\begin{aligned} & x_{c,t} && \in \{0, 1\} && \text{for } t \in \{1, 2, 3\} \\ 0 \leq\ & x_{c,t} && \leq 1 && \text{for } t \in \{4, 5\} \\ 0 \leq\ & x_{c,6..7} && \leq 2 \\ 0 \leq\ & x_{c,8..10} && \leq 3 \\ 0 \leq\ & x_{c,11..15} && \leq 5 \end{aligned}$$

and the objective is

$$\begin{aligned} \text{minimize} \quad & m \\ \text{where} \quad & m \geq \textstyle\sum_{c \in \mathcal{C}} E_c x_{c,t} \quad \text{for } t \in \{1, 2, 3, 4, 5\} \\ & 2m \geq \textstyle\sum_{c \in \mathcal{C}} E_c x_{c,6..7} \\ & 3m \geq \textstyle\sum_{c \in \mathcal{C}} E_c x_{c,8..10} \\ & 5m \geq \textstyle\sum_{c \in \mathcal{C}} E_c x_{c,11..15} \end{aligned}$$

This instance of MILP problem can be solved by any MILP solver. The values of variables $x_{c,1}$ of an optimal solution are used to determine which converters $c \in \mathcal{C}$ should run in the coming time interval 1. For the next time interval 2, a similar instance of an MILP problem is created by shifting indices of time intervals by one and refining the predicted demands $D_{c,t}$. There is no general rule how time intervals should be split into blocks since it is strongly influenced by the particular case studies. In this study, we use one specific choice to study the potential of this approach.

4 Case application

Both methods of control (Global and Time scale MILP control) are applied to a specific case which involves the final building phase of the Meppel project of 135 houses, where each house is equiped with a separate heat pump for domestic hot water and one for space heating. The applied energy system in Meppel is explained in detail in [17]. The purpose of this paper is to investigate the quality of the power balancing for heat pump electricity demand with both types of control and to compare them with a reference case where each heat pump determines the control by itself (using PI control). To generate heat demand profiles, the following approach is followed:

- develop a thermal model to determine house space heating demand
- apply measured weather data (we investigate one week with a high space heating demand)
- define various typical house and household profiles to generate a variety of space heating and domestic hot water demand profiles
- simulate space heating demands of the various households
- determine reference control results
- input domestic hot water and space heating demands into the Global and Time scale MILP control algorithms and determine results

In the next sections, the individual steps of the approach are explained in more details.

4.1 Space heating thermal model

The purpose of the case application is to investigate whether the MILP control methods outlined in the previous sections give a satisfactory result for practical heat demand profiles or not. Suitable methods to determine space heating demand are listed in [12] and include modelling of thermal network, radiant time series and transfer function methods. Accuracy differences between these methods are small, and largely depend on the accuracy of the input data. We choose to adopt the thermal network modelling approach because it is relatively easy to integrate physical characteristics of buildings into the model. Thermal networks also may be quite suitable to be integrated into smart grid control algorithms at a later stage of our research.

To validate the accuracy of the thermal network approach, we compare the results of our model with simulations of the whole building using TRNSYS and measured data in future work. For the present paper we apply the thermal network shown in Figure 2. The model equations are derived

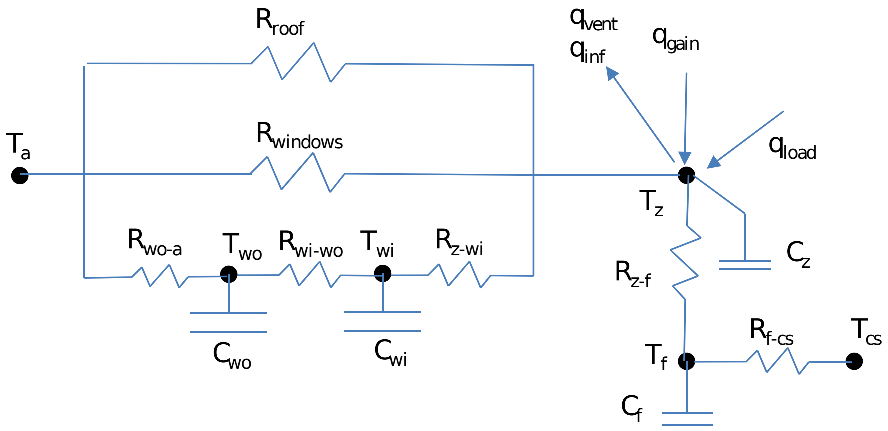

Figure 2: Applied thermal network model

as follows:

$$
\begin{aligned}
C_{wo} \cdot \frac{dT_{wo}}{dt} &= \frac{(T_a - T_{wo}) \cdot A_{wall}}{R_{wo-a}} + \frac{(T_{wi} - T_{wo}) \cdot A_{wall}}{R_{wi-wo}} \\
C_{wi} \cdot \frac{dT_{wi}}{dt} &= \frac{(T_{wo} - T_{wi}) \cdot A_{wall}}{R_{wi-wo}} + \frac{(T_z - T_{wi}) \cdot A_{wall}}{R_{z-wi}} \\
C_f \cdot \frac{dT_f}{dt} &= \frac{(T_z - T_f) \cdot A_f}{R_{z-f}} + \frac{(T_{cs} - T_f) \cdot A_f}{R_{f-cs}} \\
C_z \cdot \frac{dT_z}{dt} &= D_{c,t} + q_{vent} + q_{inf} + q_{gain} + \frac{(T_f - T_z) \cdot A_f}{R_{z-f}} + \\
&\quad + \frac{(T_{wi} - T_z) \cdot A_{wall}}{R_{wall}} + \frac{(T_a - T_z) \cdot A_{windows}}{R_{windows}} + \frac{(T_a - T_z) \cdot A_{roof}}{R_{roof}}
\end{aligned}
$$

The terms in these equations are explained in Table 1. Scheduled values for heat gains (q_{gain}) due to resident and electric appliance dissipations are given in Section 4.3. Infiltration and ventilation associated heat losses (q_{inf} and q_{vent}) are determined by the following equations:

$$q_{inf} = \phi_{air,inf} \cdot \rho_{air} \cdot c_{p,air} \cdot (T_a - T_z)$$

$$q_{vent} = \phi_{air,vent} \cdot \rho_{air} \cdot c_{p,air} \cdot (T_a - T_z)$$

The used terms are also explained in Table 1. Ventilation air flow values $\phi_{air,vent}$ in m^3/h are defined by schedules given in Section 4.3. Infiltration air flows $\phi_{air,inf}$ are related to leakages of

Term	Signification
T_a	Ambient temperature
T_z, C_z	Zone (room) temperature and thermal capacity
T_{wo}, C_{wo}	Outside wall temperature and thermal capacity
T_{wi}, C_{wi}	Inside wall temperature and thermal capacity
T_f, C_f	Zone floor temperature and thermal capacity
T_{cs}	Cellar or creeping space temperature
R_{roof}	Thermal resistance of roof
R_{window}	Thermal resistance of windows
R_{wo-a}	Thermal resistance between outside wall and ambient
R_{wi-wo}	Thermal resistance between outside and inside wall
R_{z-wi}	Thermal resistance between zone and inside wall
R_{z-f}	Thermal resistance between zone and floor
R_{f-cs}	Thermal resistance between floor and concrete structure
q_{vent}	Ventilation heat flow
q_{inf}	Infiltration heat flow
q_{gain}	Internal gain heat flow
$D_{c,t}$	Heating load flow (heating Demand)
$\phi_{air,inf}$	Infiltration air flow $[m^3/h]$
$\phi_{air,vent}$	Ventilation air flow $[m^3/h]$
ρ_{air}	Air density
$c_{p,air}$	Specific heat capacity of air

Table 1: Nomenclature energy system characterization

the building and assumed as constant values. We defined some variations including heat recovery ventilation.

In the following we give some notes about the complexity of the thermal model. The thermal network model is a simplified version of the model we used in [16] to study the effects of thermal storage in a living room floor heating system. That model included solar gains and more thermal capacitance terms for the interior to study the effects on operative temperature as a measure of thermal comfort. In the present paper we did not include solar gains in order to reduce complexity. Solar gains have the effect that real daytime space heating demands will be lower than our calculation results, but for the purpose of the present investigation this is not relevant.

A setpoint is the zone temperature preferred by inhabitants. Setpoints schedules are defined in Section 4.3. The demand $D_{c,t}$ for every house c and time interval t is determined by the following rules:

- If the zone temperature T_z equals the setpoint, then the demand $D_{c,t}$ is the amount of energy which the heating system has to generate to keep the zone temperature constant.

- If the setpoint is increased, then the demand $D_{c,t}$ is increased to raise the zone temperature in a given warmup speed $\frac{dT_z}{dt}$.

- If the zone temperature T_z is above the setpoint (e.g. due to decreasing the setpoint or natural heating by internal gains), the demand $D_{c,t}$ is the minimal non-negative amount of energy which keeps the zone temperature above the setpoint.

The output of the model is the required heating demand for this type of control. Part of our future work is to use heat pump schedules obtained from the MILP control methods as heating input to the zone to investigate whether the obtained heat pump control results in acceptable zone temperature control or not.

4.2 Application of weather data

As we explained in the previous paragraph, we only include heat loss due to temperature differences between the zone temperature and ambient temperatures into the case investigation. Effects of solar gains and wind speeds on the heat demand are excluded. Weather data containing hourly average ambient temperatures are obtained from the website of the Dutch national weather institute ([4]). We choose data of weather station Hoogeveen which is close to Meppel. We investigate the coldest week of 2012 as this week results in a relatively high heat demand for space heating.

4.3 House and household case information

We consider a total of 135 households and we define three types of households (see Table 2) living in semi-detached and detached houses. Houses will be built in three phases and later phases will have higher standard of thermal insulation due to tightening regulations. In this study we assume that in each phase, 30 semi-detached and 15 detached houses will be built. Rc-values of semi-detached houses in the phases are 3.5, 5.0 and 7.5 m^2K/W and the Rc value of detached houses are 5.0, 7.5 and 10.0 m^2K/W.

We consider a temperature lower set point ($18°C$) during working hours and night and a higher temperature set point ($20°C$) otherwise. We also define domestic hot water demand for morning, afternoon and evening peaks. See Table 2 for schedules of the temperature set points and energy demands for hot water.

4.4 Simulation results of heating demand

The model equations of Section 4.1 are solved using a 15 minute time step which is required as a minimum time step for controlling the thermal storage and to estimate related heat pump running times. To obtain 15 minute heat demand data, we applied linear interpolation of the one hour

Type of household		Young couple	Young family	Elderly people
Number of persons in a household		2	4	2
Number of houses	semi-detached	27	54	9
	detached	12	27	6
Higher setpoint	weekdays	17–22	8–22	10–23
	weekend	9–23	9–23	10–23
Hot water on weekdays	morning	15 MJ	8 MJ	4 MJ
	afternoon	0 MJ	4 MJ	4 MJ
	evening	20 MJ	24 MJ	20 MJ
Hot water on weekend	morning	8 MJ	4 MJ	4 MJ
	afternoon	4 MJ	4 MJ	4 MJ
	evening	24 MJ	32 MJ	24 MJ

Table 2: Types of households, the number of household types in both types of houses, schedules of higher temperature setting and hot water demands.

heat demand data. This is performed for all the houses of a different layout (semi detached or detached), different Rc-values and different household types.

As result we show the sum of the heating demand for the 135 houses in Figure 3. The sum of

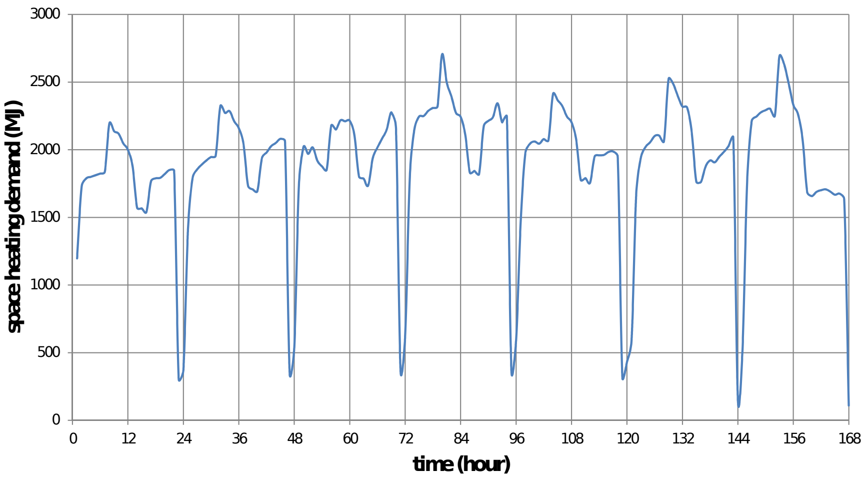

Figure 3: Simulated total space heating demand of 135 households for the coldest week in 2012

the heating demand for domestic hot water is obtained by addition of domestic hot water demand of each household, which is shown in Figure 4.

In our analysis we assume a heat pump coefficient of performance (COP) of 4.5 for space heating and 2.5 for domestic hot water generation for the coldest week in 2012, we find as average electricity input 116.4 kW for space heating and 19.3 kW for domestic hot water, leading to 135.7 kW total average electricity demand. If the MILP control performs well on minimizing peaks, we expect control schedules for the heat pumps to give results close to this average electricity demand.

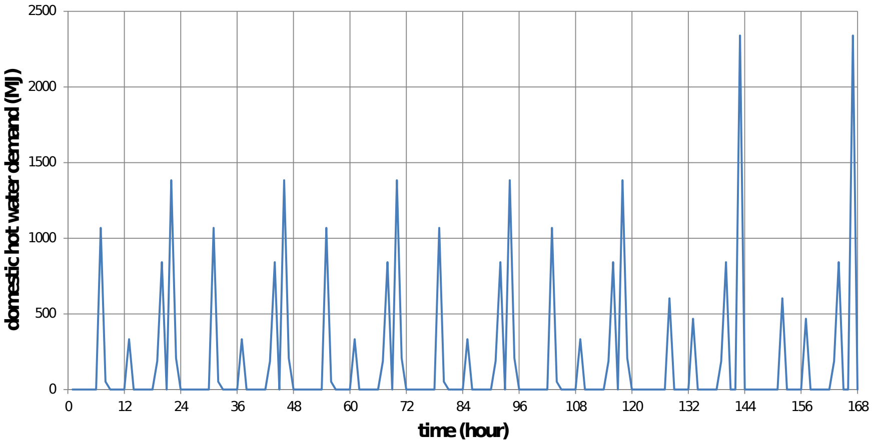

Figure 4: Calculated total domestic hot water demand of 135 households

5 Case results

In Figure 5 we show the electric energy demand (E-demand) and the results achieved with the three methods of control. The E-demand in time intervals t is calculated as the sum of electrical energy needed to produce heat for the space heating demand in time interval t and the average domestic hot water demand over the whole week. For domestic hot water, calculating with the average demand is more appropriate than the real demand because as Figure 4 shows, the real demand is concentrated during several hours each day. It is common practice that heat pumps take hours each day to charge the domestic hot water buffer from which the real demand is supplied, which results in an average heat generation and electricity demand for all the houses together.

The reference control, which resembles PI control, of the zone state of charge and hot water buffer state of charge, results in a dynamic electricity demand with many peak loads on the network, which indicates a high level of simultaneous running heat pumps at those times.

Both methods of MILP control of the heat pumps lead to an improved, almost flat electricity consumption profile. The result of Time scale MILP control is only slightly less flat than Global MILP control. The average for both is 135.6 kW. The standard deviation for Time scale MILP control is 5.9 and for Global MILP control 5.2, but for reference control 45.0. So compared to the reference control, the total improvement of both MILP control methods on peak reduction is approximately 87%. Global MILP control gives 1.6% better peak reduction performance than Time scale MILP control. If we consider this almost equal performance and take into account the reduced computational effort of Time scale MILP control, we prefer this method for future algorithm development.

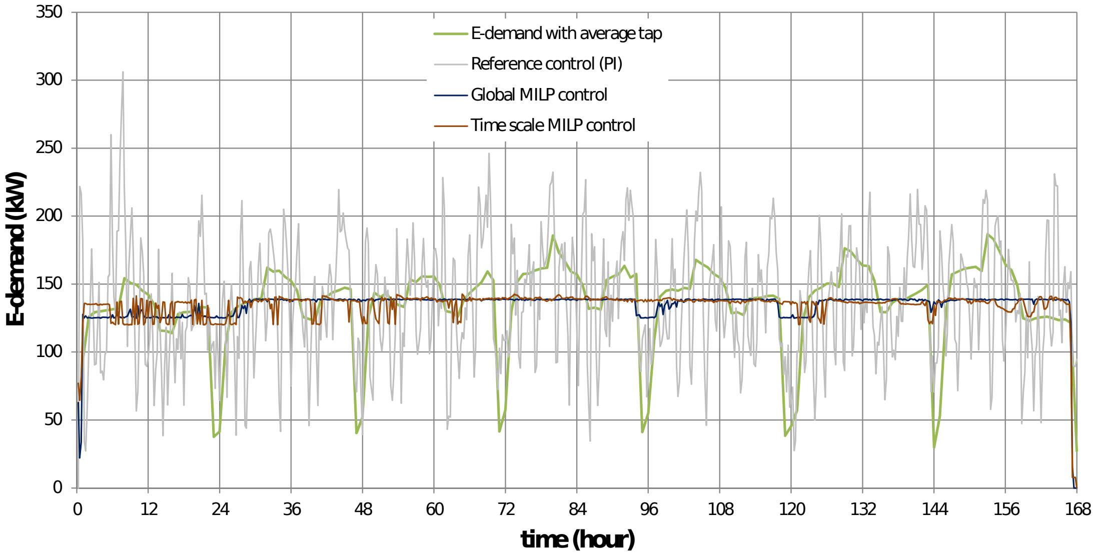

Figure 5: Case results

6 Conclusions

In this paper we investigate scheduling of a group of heat pumps for 135 different households in order to minimize the maximum peak of total electricity consumption. We generate heat demand data for space heating by simulation with a thermal network model of houses with different insulation properties and define domestic hot water demand profiles for three types of households. We compare three control methods: reference (PI) control, Global MILP control and Time scale MILP control.

In the defined case of 135 houses, MILP control decreases electricity peaks by 87% compared to reference control. The difference between Global and Time scale MILP control is small. Peak reduction results of Global MILP control are only 1.6% better than Time scale MILP control. But since Time scale MILP control is computationally much more efficient, we propose to use Time scale MILP control. The influence of chosen time scaling on the achieved result may be studied in future research.

In this paper we only investigate the effects on peak reduction and the results look promising. Future work will be dedicated to investigate the resulting thermal comfort as a result of the obtained heat pump planning. For this we will perform 'inverse' simulations, using the heat pump schedules as input for the thermal network model used in this paper. Also part of future work is to investigate methods of reaching a social fairness in heat pump planning and integrating this work into the TRIANA smart grid control method [15].

References

[1] Meppel. http://www.utwente.nl/ctit/energy/projects/meppel.html, 2013.

[2] Meppel, nieuwbouwprojecten. http://www.meppel.nl/Inwoner/Wonen_ver_bouwen/Ver_bouwen_slopen/Nieuwbouwprojecten, 2013.

[3] Meppel woont. http://www.meppelwoont.nl/nieuwveense-landen/, 2013.

[4] Royal Netherlands Meteorological Institute. http://www.knmi.nl, 2014.

[5] C. Aguilar, D. J. White, and D. L. Ryan. Domestic water heating and water heater energy, consumption in canada. *The Canadian Building Energy End-use Data and Analysis Centre*, 2, 2005.

[6] M. Bosman. *Planning in Smart Grids*. PhD thesis, University of Twente, The Netherlands, 2010.

[7] M. G. C. Bosman, V. Bakker, A. Molderink, J. L. Hurink, and G. J. M. Smit. The microCHP scheduling problem. In *Proceedings of the Second Global Conference on Power Control and Optimization, PCO 2009, Bali, Indonesia*, volume 1159 of *AIP Conference Proceedings*, pages 268–275, 2009.

[8] M. G. C. Bosman, V. Bakker, A. Molderink, J .L. Hurink, and G. J. M. Smit. On the microCHP scheduling problem. In *Proceedings of the 3rd Global Conference on Power Control and Optimization PCO, 2010, Gold Coast, Australia*, volume 1239 of *AIP Conference Proceedings*, pages 367–374, 2010.

[9] M. G. C. Bosman, V. Bakker, A. Molderink, J. L. Hurink, and G. J. M. Smit. Controlling a group of microCHPs: planning and realization. In *First International Conference on Smart Grids, Green Communications and IT Energy-aware Technologies, ENERGY 2011, Venice, Italy*, pages 179–184, 2011.

[10] W. J. Cook, W. H. Cunningham, W. R. Pulleyblank, and A. Schrijver. *Combinatorial optimization*, volume 33. Wiley.com, 2011.

[11] J. Fink and J. L. Hurink. Minimizing costs is easier than minimizing peaks. Submitted, 2013.

[12] J. W. Mitchel and J. E. Braun. *Principles of Heating, Ventilation, and Air Conditioning in buildings*. Wiley, 2013.

[13] F-Chart software. Engineering equation solver. http://www.fchart.com/ees/, 2014.

[14] A. Sven. *Inventory control*, volume 90 of *International Series in Operations Research and Management Science*. Springer, 2006.

[15] H. A. Toersche, V. Bakker, A. Molderink, S. Nykamp, J. L. Hurink, and G. J. M. Smit. Controlling the heating mode of heat pumps with the triana three step methodology. In *Innovative Smart Grid Technologies (ISGT), 2012 IEEE PES*, pages 1–7, 2012.

[16] R. P. van Leeuwen, J. Fink, J. B. de Wit, and G. J. M. Smit. Thermal storage in a heat pump heated living room floor for urban district power balancing, effects on thermal comfort, energy loss and costs for residents. In *Smartgreens 2014*, 2014.

[17] R. P. van Leeuwen, J. Fink, J. B. de Wit, and G. J. M. Smit. Upscaling a district heating system based on biogas cogeneration and heat pumps. In *ESEIA conference 2014, University of Twente, the Netherlands*, 2014.