

Central Model Predictive Control of a Group of Domestic Heat Pumps Case Study for a Small District

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Abstract: In this paper we investigate optimal control of a group of heat pumps. Each heat pump provides space heating and domestic hot water to a single household. Besides a heat pump, each house has a buffer for domestic hot water and a floor heating system for space heating. The paper describes models and algorithms used for the prediction and planning steps in order to obtain a planning for the heat pumps. The optimization algorithm minimizes the maximum peak electricity demand of the district. Simulated results demonstrate the resulting aggregated electricity demand, the obtained thermal comfort and the state of charge of the domestic hot water storage for an example house. Our results show that a model predictive control outperforms conventional control of individual heat pumps based on feedback control principles.

1 INTRODUCTION

In the Netherlands, approximately 40% of the total domestic energy consumption is related to space heating and domestic hot water (ECN, 2014). To this date, most Dutch houses rely on natural gas supply and gas boilers. Heat pumps powered by renewable electric energy are a possible way to make the transition towards integration of renewable energy in the building environment (Janssen-Visschers and Lee, 2013), (Scheepers et al., 2007). In the small city Meppel, a new district is under construction with an almost 100% renewable energy supply (Meppelenergie, ND). A biogas CHP provides heat for houses connected to district heating and electric power for other houses with a heat pump. Imports and exports of electric energy from and to the national grid are possible, but the heat pumps should use the electricity from the CHP as much as possible. Development of a smart grid control system is the joined task of a project group formed by University of Twente, University of Delft, the utility Rendo, Meppel city council and system integrator i-NRG.

The Meppel case explores local sustainability, not only due to the employed energy system, but also due to the legal aspects. The entire district heating and cooling system including the heat pumps which are

placed at some of the houses, are owned by a utility company which is founded specifically for this district. Only the supply of hot water for space heating and domestic hot water is sold by the utility company to the households, either delivered by the district heating system, or the heat pumps. The utility company is not allowed to supply households electricity for domestic appliances, e.g. TV's and washing machines. Hence, electric power supply to the heat pumps is through a separated cable. As a consequence, it is possible that the utility company controls starting and stopping of each heat pump on a central level.

Our previous paper (Fink et al., 2014) was aimed at developing a mathematical approach to solve the large scale central optimization problem in an efficient way. In that paper solving one big instance of MILP (Mixed Integer Linear Program) for every time step of 15 minutes is compared with a more efficient method called time scale MILP. However, a pre-calculated data table is used for the prediction of heat demand of 100 households. With this table, the relation between the heat pump planning and the achieved thermal comfort within the households cannot be investigated. In this paper, model predictive control replaces the pre-calculated data table.

Main contributions of this paper are: describing a method for model predictive control for planning

of heat pumps in a district, demonstrating the quality of the heat pump planning for minimizing the peak electricity consumption and demonstrating the achievable thermal comfort within the households. Furthermore, comparing this result with conventional feedback control of individual heat pumps.

The paper is structured as follows. Section 2 considers related work to heat pump planning in smart micro grids and model predictive control. In Section 3, models are formulated for prediction of space heating and domestic hot water demand and input data for the Meppel case is described. Section 4 formulates the general control and optimization problem. Section 5 shows results on the achievable aggregated energy consumption profile of the heat pumps. Also, the resulting thermal comfort of the households is shown. Finally, conclusions are given in Section 6, including a discussion on future work.

2 RELATED WORK

Planning of electric devices in micro-grids is a recent investigation area. In this paper, Triana, a multi-commodity and optimization tool is employed. Different forms of energy (e.g. electricity, heat, biogas) can be simulated in relation to a single optimization objective. Triana is developed at the University of Twente, the Netherlands.

To obtain flexibility within a smart grid, it is required that (a) devices are controllable or (b) the function of the device can be shifted in time without unacceptable consequences for the customer. Such devices are batteries, (dish)washing machines, dryers, fridges and heat pumps. (Bosman, 2012) developed specific planning algorithms for smart micro grids, while (Bakker, 2011) and (Molderink et al., 2010) investigate various case applications like the planning of a group of fridges in relation to varying electricity price schemes, due to renewable energy production by solar PV. (Claessen et al., 2014) compare two smart grid control approaches, i.e. Triana and Intelligator. The Triana approach contains three steps to control devices: prediction on the device level, planning based on price signals from the aggregator and real time control by the device controller. The Intelligator approach is based on the Powermatcher concept (Kok et al., 2005) which uses a multi-agent electricity market. Device agents send bids to a central auctioneer agent. The price signal from the auctioneer clears the market with the purpose to adjust the bids in such a way that the market equilibrium (and consumption) is steered towards the optimization objective. Claessen demonstrates that both approaches are

able to reach certain objectives but also demonstrates the improvement which is possible when predictions are part of the approach.

In this paper, the Triana approach without market based steering principles is applied. In the Meppel case it is possible to simplify the control method and let a central controller directly determine the planning of the heat pumps based on heat demand predictions for each household. Hence, the planning and real time control steps are basically the same. The planning step considers planning of the heat pumps from 2 up to 24 hours ahead, whereas the real time control step considers planning of the heat pumps for the actual time up to 1 or 2 hours ahead. This approach leads to a method called "time scale MILP" in (Fink et al., 2014). The central controller has to solve one large optimization problem every time step of 15 minutes with a time window of 24 hours ahead. However, the size of the problem is reduced by considering larger time steps for moments further in time. In this way, the planning is more and more approximated, the further it looks into the future.

A heat pump is an electric appliance with a low temperature thermal input and higher temperature thermal output which is used for space heating or domestic hot water (Mitchel and Braun, 2013), (Hepbasli and Kalinci, 2009). Model predictive control (MPC) of heat pumps in the building environment is a recent investigation area. MPC is investigated either for building climate control to minimize energy consumption, or for power balancing of smart micro grids. Early work on MPC for building climate control is performed by Madsen et al (Madsen and Holst, 1995). Recent investigations which include experimental results are carried out by (Oldewurtel et al., 2012), (Široký et al., 2011) and (Prívvara et al., 2011). (Halvgaard et al., 2012) investigates the use of MPC for the control of a domestic heat pump in relation to minimizing energy costs for heating a house, for which Nordic spot market electricity prices are taken as input data. (Dar et al., 2014) demonstrates how a domestic heat pump can be controlled by MPC such that self consumption of PV-generated electricity is increased.

The previously mentioned research on MPC considers climate control of single buildings with emphasis on the quality of model predictions and the quality of reaching the objectives, i.e. minimizing costs or energy consumption. Based on this work, the conclusion is justified that MPC is a promising control method which outperforms conventional feedback control methods when the control system has more objectives than room temperature control. Our main interest, however, is not on the optimal control

of a single building or heat pump, but the application of MPC to control many houses with heat pumps in a district. The main goal and contribution of this paper is to demonstrate the quality of reaching multiple objectives for a smart micro grid with MPC controlled heat pumps, i.e. minimizing peak loads on the electric network, maintaining thermal comfort in the houses and adequate charge states of domestic hot water storages.

3 PREDICTIVE MODELS

3.1 Model of the Energy System

In Figure 1, a schematic overview of the energy system is given. The picture shows a range of houses (labeled 1 to n , in which n is the number of houses). Each house has a heat pump (HP) which is connected to two types of thermal buffers: (a) a floor heating system and (b) a hot water storage for domestic hot water (DHW). The ability of the floor heating to store thermal energy and possible consequences on thermal comfort and costs is demonstrated in (Leeuwen et al., 2014). The energy inputs to the heat pumps are: (a) low temperature source energy from an underground thermal storage and (b) electric energy from a biogas Combined Heat and Power system (CHP), which due to the constant biogas flow runs continuously. The CHP is also connected to the main electricity grid. Heat produced by the CHP is distributed via a large, centrally located thermal storage to a district heating network which involves much more houses than the number of houses with a heat pump.

This energy system is a combination and further development of two common types of local renewable energy systems: district heating based on biogas co-generation and heat pumps combined with underground thermal storage. In the Netherlands, Germany and Denmark there are numerous regional areas where biogas from waste water treatment plants is used as a source for co-generation of heat and power which is distributed to local consumers through a district heating network and a local electricity grid which has a connection to the larger grid. A large scale example of this is Apeldoorn Zuidbroek (Dreijerink and Uitzinger, 2013) where 2500 houses are heated in this way.

An aquifer underground thermal storage is used as a source for cooling and for heat pumps. An aquifer is an underground groundwater reservoir at a depth of around 60-120 meters. The temperature of the water is around 15°C, which is used as source energy for heat pump evaporators during the heating sea-

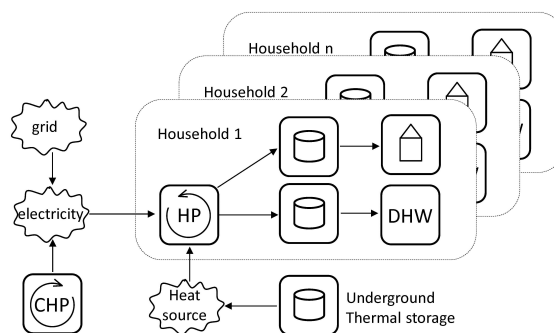


Figure 1: Schematic picture of the energy system.

son. During the summer, the groundwater is used to cool the houses, which also regenerates the reservoir temperature after the heat pumps have cooled the reservoir down during the heating season. In recent years, this type of storage is commonly applied for new larger buildings and urban areas in North Western Europe. The increasing use of heat pumps in new building projects combined with suitable soil conditions and existence of large underground aquifers almost anywhere in the Netherlands, result in increasing applications of this type of storage.

In general, the purpose of the energy system is to provide the new district with almost 100% renewable energy for heating and cooling of houses. As the energy system is a combination of existing options which are proven in practice, more cases with a similar energy system are expected to be developed in the future.

The energy system is configured in such a way that the average electric production of the CHP equals the average required electric input by all heat pumps on the coldest possible day. Furthermore, there are only two energy prices, arranged by contract with the grid operator. A low price for selling electricity from the CHP to the grid and a high price for buying electricity from the grid. Hence, the objectives for the heat pump control are:

- maintain thermal comfort for space heating within each house
- maintain sufficient state of charge of the hot water buffer to cover DHW demand of each house
- use electricity of the CHP as much as possible locally for the heat pumps and avoid buying electricity from the grid. This objective can be reached when the electric demand is flattened towards the average. Also, investments in electricity cables throughout the district and transformers at the energy house are minimal when the peak electric demand is as low as possible. Therefore, the control objective is formulated as: minimize

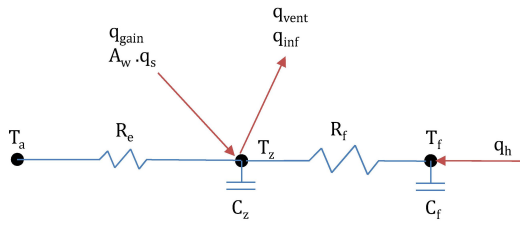


Figure 2: 2R2C model.

peaks of the aggregated heat pump electricity demand.

Following the area plan of the Meppel building project, 104 houses with a heat pump are studied. At this stage, the houses involved are not yet built and hence, the study involves simulations based on specific models which are discussed in the following subsections.

3.2 Household Space Heating Demand Model

In (Fink et al., 2014), a data table per house is used as predictive information for the space heating demand. However, a data table should be based on relevant relations between space heating demand and influences such as weather conditions or occupancy. For this, a simulation model can be used or an online model which learns relations from measurement data. Without a model as integral part of the control system, it is impossible to estimate the consequences on the thermal comfort when storage flexibility of the house structure (thermal mass) is exploited to optimize the control. Applying a model instead of a data table has the advantage that temperatures which are relevant for people's comfort are pre-calculated during the planning phase and deviations with real-time measurements can be corrected during an online real-time control phase. Therefore, a model is used to predict space heating demand for each house in this paper.

For the model of space heating demand in relation to ambient conditions, the following general 2R2C thermal network model shown in Figure 2 is adopted which contains a thermal mass term (C_f) for the floor heating and internal zone of the house (C_z). The model contains the following parameters (Table 1):

The generalized model equation is given by:

$$\frac{dT}{dt} = \mathbf{A}T + \mathbf{B}q \quad (1)$$

In which the vector T contains the thermal mass and ambient temperatures and vector q contains direct heat gains to or loss terms from the thermal masses,

Table 1: Model parameters.

R_f	resistance between floor heating and zone
C_f	capacitance of floor heating
R_e	thermal resistance of house envelope
C_z	capacitance of the zone
A_w	window area on each side of the building
q_s	solar energy on building planes with windows
q_h	heating energy injected into floor heating
q_{gain}	thermal gains by occupants and appliances
q_{vent}	heat loss by ventilation air flow
q_{inf}	heat loss by infiltration air flow

i.e. heating input to the floor heating and solar energy gains to the zone. Matrix \mathbf{A} characterizes system dynamics and contains thermal capacitance and resistance parameters. Matrix \mathbf{B} specifies how the direct heat gains and losses enter the respective thermal masses.

Model parameters are estimated for 4 types of reference houses (AgentschapNL, 2013) for which simulated response data is generated in TRNSYS (TESS, ND). The accuracy of this approach is investigated in detail in (Leeuwen et al., 2015). The parameters for the 4 house types are given in Table 2 in which: TH-Terraced House, CH-Corner House, SDH-Semi Detached House, DH-Detached House.

Table 2: Estimated 2R2C model parameters.

	unit	TH	CH	SDH	DH
R_f	K/kW	3.26	2.81	1.69	1.66
C_f	kWh/K	3.61	3.61	4.56	5.08
R_e	K/kW	11.01	8.23	8.67	7.17
C_z	kWh/K	10.62	16.74	20.34	22.48

The window areas for each building plane are given in (AgentschapNL, 2013). Effective solar transmission through the window into the house is calculated by multiplying the window area of each building plane with the incident total radiation on the plane and a transmission factor. The houses are oriented according to the district area plan into the 4 major wind directions. Incident total solar radiation on each building plane is calculated from measured horizontal total radiation, i.e. from weather station Hoogeveen of the Royal Dutch weather institute, which is near to the city of Meppel. The calculation of diffuse and beam radiation is based on theory outlined in (Duffie and Beckman, 1980). To calculate the amount of diffuse radiation from total horizontal radiation measurements, a correlation proposed in (Erbs et al., 1982) is used.

In total, there are 104 houses. At present, the possible types of occupancy (families, couples, etc.) in relation to the types of houses is not known. Based on a comparative study of a recent built district in

the Netherlands (Blokker and Poortema, 2007), the following 3 types of occupancy and distribution over 104 households are defined: young family (52%), elder couple (15%) and young couple (33%). For the house orientation, indicated by the facing direction of the front facade, and the distribution of occupant types over the different house types, the following is listed, in which the relation between occupant type and house orientation is assumed to be random:

- 41 terraced houses with the following number of houses in combination with the front plane direction: 20-North/4-East/7-South/10-West. Number of households in combination with occupant-type: 12-young family/2-elder couple/27-young couple.
- 20 corner houses: 10-North/2-East/4-South/4-West. Households and occupant-type: 18-young family/0-elder couple/2-young couple.
- 26 semi detached houses: 0-North/10-East/4-South/12-West. Households and occupant-type: 16-young family/6-elder couple/4-young couple.
- 17 detached houses: 0-North/8-East/8-South/1-West. Households and occupant-type: 8-young family/8-elder couple/1-young couple.

3.3 Occupancy Related Thermal Losses or Gains

For each type of occupancy, hourly schedules are defined for working days and days of the weekend for relevant thermal events. The schedules are related to common behavioral patterns of working people. For this paper, statistical backgrounds of schedules are not investigated. For each occupancy type, basic schedules are defined including randomization of some of the time points at which thermal events occur. In the following, the basic approach for the programming involved is explained. For the occupancy type: young family, a working weekday schedule is shown in Figure 3. Further in the paper, a young family is also considered when discussing the results. The figure shows relative to a defined maximum, the following thermal events:

- Occupancy: thermal gains by occupants present in the house. Schedules consist of a number of time points at which the number of occupants which are present in the house are defined. Based on (Mitchel and Braun, 2013) the thermal gain by people is on average 40 W per person during sleeping hours and 110 W per person during day and evening hours. Figure 3 shows the number of occupants present in the house.

- Ventilation rates: typically, ventilation schedules depend on: (a) the time of the day, (b) the number of occupants present in the house, (c) cooking events which require higher ventilation rates, (d) shower or bath events in the bathroom which require higher ventilation rates. The ventilation system has 4 states for the ventilation rate: (1) cooking, (2) high, (3) medium, (4) low. This relates to typical existing Dutch house ventilation systems. Figure 3 shows ventilation rates for each hour.
- Appliance thermal gains: Four appliance classes are defined: (1) computers/television, (2) lighting, (3) fridge/freezer, (4) background appliances like pumps, fans and standby electronic equipment. The total yearly electricity consumption of the schedule in Figure 3 is approximately equivalent to Dutch average consumption figures published by (Milieucentraal, ND).
- DHW (Domestic Hot Water) demand: for a single household this is determined by several events at certain timepoints each day. In total, 6 possible events are defined, each with a specific amount of required water of 40°C: (1) shower, (2) bath, (3) hand cleaning, (4) small dish wash, (5) large dish wash and (6) body washing. Figure 3 shows the water amounts for a number of events. The amount of water per event and the time points are slightly randomized.

In the same way, schedules are worked out for other occupancy types, both for working days and weekend days.

3.4 Heat Pump Model

Heat pump performance is approximated as a constant relation between electric input and thermal output of the heat pump for two operational modes: space heating mode with an output temperature of 35°C and thermal storage mode with an output temperature of 65°C. Hence, the heat pump has 3 operational states: (1) off, (2) space heating, (3) thermal storage. The relation is given in table 3 which is based on supplier data (Alpha-Innotec, 2014).

Table 3: Heat pump energy specification.

state	unit	input	output
off	kW	0.0	0.0
space heating	kW	1.3	6.0
thermal storage	kW	1.8	5.0

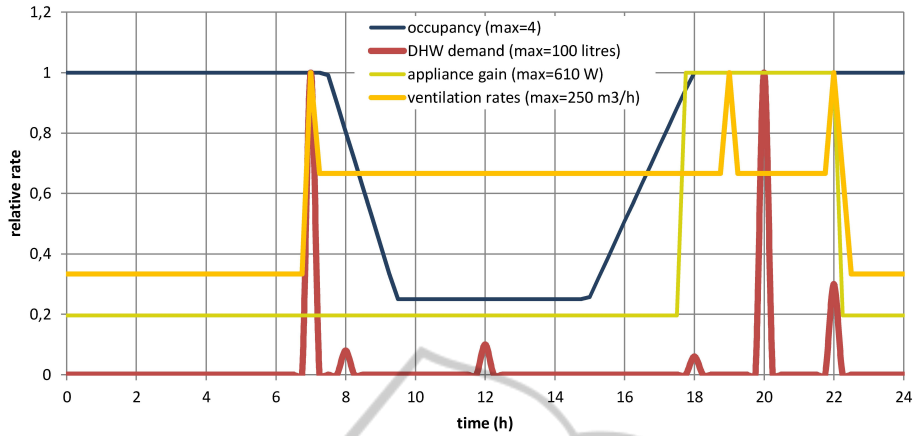


Figure 3: Example weekday thermal event schedule.

4 CONTROL ALGORITHMS

In (Fink et al., 2014) a general approach for off-line and on-line heat pump central control problems is introduced. This paper concerns an off-line problem because the weather and occupancy related data are known beforehand as forecasts. The optimization process is explained in more detail in (Fink and Hurink, 2015). For the simulation, the predictive models, house type definitions, occupant related schedules, weather calculation module, reference and optimization control algorithms are defined as Python script files. The Triana simulation environment, developed at the University of Twente is written in C++. MILP instances are solved by the CPLEX solver package.

4.1 Optimized Control

Following the Triana smart grid method, planning of the heat pumps is determined in two calculation steps: a prediction step and a planning step. The Triana method also contains a third step: real time control, but for this type of off-line problem, this step is irrelevant: it is assumed for now that there is no deviation between the prediction and the simulated reality. On the other hand, if an on-line control problem is studied, the real time control step involves a comparison between measurements in real time and predictions for the short term, resulting in adjustment of the short term heat pump control planning to reduce possible deviations.

The control objective to minimize peak electric demand is formulated as:

$$\begin{aligned} \text{Minimize } & \max_{t \in T} \sum_{op} \sum_c E_{op} \cdot X_{c,op,t} \\ & X_{c,op,t} \in \{0, 1\} \end{aligned} \quad (2)$$

In which E_{op} is the electric demand of a heat pump converter. $op \in \{sh, dhw\}$ denotes an operational mode of the heat pump within a set of operational modes, in this case space heating (sh) or domestic hot water (dhw). $X_{c,op,t}$ is the control state for each heat pump converter.

$c \in \{1, 2, \dots, n\}$ denotes a heat pump converter for each house within a set of heat pump converters which totals the number of houses (n). The time interval $t \in T$ denotes that all time intervals t are within the planning period T . Each heat pump is either "on" ($X_{c,op,t} = 1$) or "off" ($X_{c,op,t} = 0$). However, two operational modes for one heat pump cannot be "on" at the same time, that is $\sum_{op} X_{c,op,t} \leq 1$. For this we introduce additional control variables.

Let x , y and z be control states for which: $x, y, z \in X$. Let $x_{c,t}$ be the control variable for space heating during the prediction phase, $y_{c,t}$ be the control variable for space heating during the planning phase and $z_{c,t}$ be the control variable for DHW during the planning phase. The first stage heat pump planning $x_{c,t}$ for space heating is determined in the first phase of the calculation, i.e. the prediction phase optimizes:

$$\begin{aligned} \text{Minimize } & \sum_t X_{c,op,t} \\ & 0 \leq X_{c,op,t} \leq 1 \end{aligned}$$

subject to the following constraints:

- $Tz_t \geq T_{pref,t}$ for all $t \in T$ where $T_{pref,t}$ is the set-point operative temperature.
- the thermal load of a house is modeled with (1) which relates the floor heating temperatures and zone temperatures to heat losses to the ambient and to heat gains and heat input from the heat pumps.
- pre-calculation of occupancy related thermal gains and ventilation losses based on schedules.

- pre-calculation of solar gains.

The output of the prediction phase is a first stage planning of the heat pumps in order to exactly match the space heating demand of each house.

During the second phase of the calculation, i.e. the planning phase, the first stage planning of the space heating converters is re-calculated but now the optimization includes a space heating thermal buffer. Also, calculation of the planning now includes the DHW demand prediction and the State of Charge of the DHW thermal buffer. Equation (2) is now subject to the following constraints:

- $0 \leq \sum_{i=1}^t (y_{c,i} - x_{c,i}) \leq \frac{SH_{max}}{q_{hp,sh}\Delta t}$ in which $y_{c,i}$ signifies the re-planned control states of each converter for space heating and $q_{hp,sh}$ the thermal output of the heat pump for space heating: $q_{hp,sh} = X_{c,sh,t} \cdot \text{output}_{c,sh}$ in which $\text{output}_{c,sh}$ is the thermal output of the heat pump specified in Table 3. Δt signifies the incremental length of the time interval t and SH_{max} the maximum capacity of the space heating buffer. This capacity is determined in (Leeuwen et al., 2014).
- $0 \leq SoC_t \leq DHW_{max}$ in which SoC_t signifies the State of Charge of the DHW buffer and DHW_{max} the maximum capacity of the DHW buffer, i.e. determined by the water volume and fully charged average temperature.
- $SoC_{t+1} = SoC_t + z_{c,t} \cdot q_{hp,dhw} - D_{t,dhw}$ which yields the control states of the heat pump converters $z_{c,t}$ for the DHW operation mode. $q_{hp,dhw}$ signifies the heat pump thermal output and $D_{t,dhw}$ the DHW demand during time period t . Heat loss of the heat buffer is not modeled, but could be incorporated in $D_{t,dhw}$.

4.2 Reference Control

The reference control is based on a simple set of feedback control rules which results in approximately the same behavior as individual PID control of each heat pump. At each time interval, the following is evaluated for each house:

- For space heating, the operative temperature Tz_t is compared with $T_{pref,t}$ which is the minimum allowed temperature defined in schedules. If the operative temperature is below this value, the heat pump is on. If it is above this value plus a positive deadband value, the heat pump is off.
- For DHW, the State of Charge of the buffer SoC_t is compared with a minimum allowed value. If the SoC is below this value, the heat pump is on. If it is above a value close to the maximum SoC, the heat pump is off.

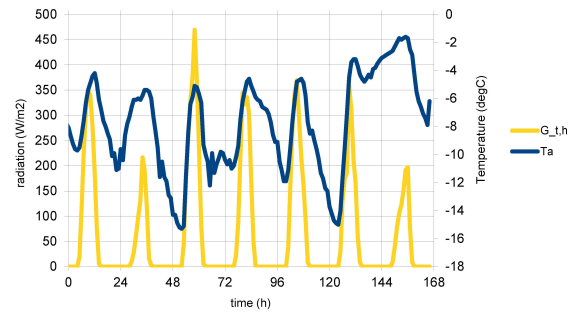


Figure 4: Input weather data.

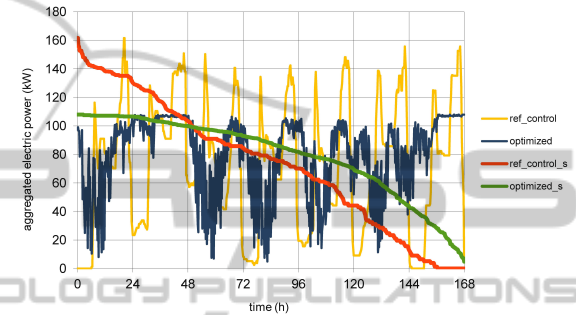


Figure 5: Aggregated electrical energy demand.

- Operation of the heat pump for DHW has priority over space heating: $y_{c,t} = 0$ if $z_{c,t} = 1$.

5 CASE STUDY RESULTS

5.1 Results for a Cold Week

To discuss the quality of the obtained results, the coldest week of the year 2012 is investigated first. This week has the highest average heat demand and therefore the longest peak load duration is expected during this week. The input weather data, i.e. the ambient temperature (T_a) and global horizontal solar radiation ($G_{t,h}$) are shown in Figure 4.

In Figure 5 the electrical energy demand is shown for the reference control (ref_control) and optimized control. The sorted values from high to low (ref_control_s and optimized_s) demonstrate the quality of the peak minimization by the optimized control. The peak for the reference control is 162 kW. This is the peak electric consumption when all heat pumps have their own on/off controlled thermostats. The peak for the optimized control is 108 kW. The average electricity power for the shown period is 74 kW. Compared to this average, the maximum peak of the reference control is 119% higher and of the optimized control 46% higher.

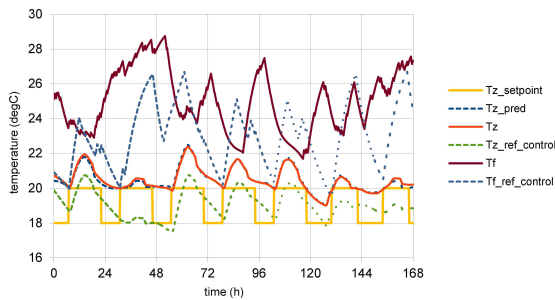


Figure 6: Example indoor operative and floor heating temperatures.

Figure 6 shows an example of the indoor operative and floor heating temperatures for the reference and optimized control. The example concerns a detached house occupied by a young family. Other households show similar results. $Tz_{setpoint}$ relates to the desired setpoint temperature which is set at 18°C during the night and 20°C during the day. $Tz_{ref_control}$ relates to the indoor operative temperature in case of reference control. Tz relates to the optimized control. Notice that the reference control is not able to keep the operative temperatures at the desired daytime setpoints. This is due to the sharp contrast between daylight hours with a relatively high amount of solar gains and nighttime hours with low ambient temperatures. The reference control has no knowledge of the upcoming heat loss during the night. When it reacts, the floor heating system gives a slow response due to its inertia, which is seen on the $Tf_{ref_control}$ line.

In contrast, the optimized control is based on weather forecasts and controls the indoor operative temperatures such that the desired temperatures are reached exactly at the first moment when they are needed, i.e. each morning around 07.00 hours. The average floor heating temperature (Tf) and average operative temperature during this week are thus higher than for the reference control. On some days, the operative temperatures reach 22°C, which is due to solar gains. The optimized control has knowledge of this, but it evaluates the setpoint temperatures as the minimum allowed temperatures and there are no upper limits on the operative temperature during the heating season, to avoid unnecessary cooling.

Figure 6 also shows the operative temperatures which are calculated as result of the prediction step (Tz_{pred}). The result of the planning step (Tz) is only slightly different which is caused by the relatively small size of the space heating buffer, i.e. 12 time periods of 15 minutes continuous charging with the heat pump output for space heating. This equals a storage capacity of $12 \cdot \frac{15}{60} \cdot 6.0 = 18$ kWh. When this buffer is larger (24 time periods instead of 12 time periods) the result is that the electrical energy demand is

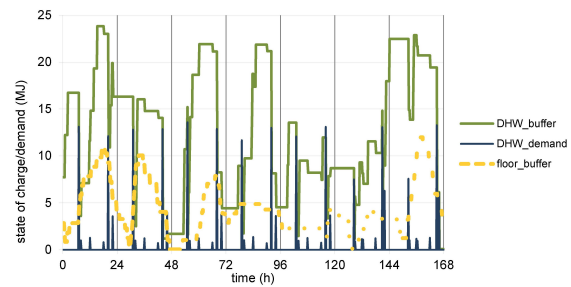


Figure 7: Floor heating and DHW buffer state of charge.

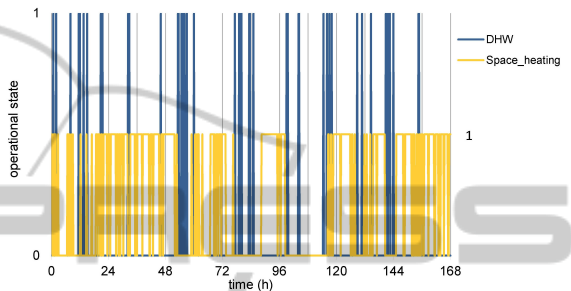


Figure 8: Heat pump operational states.

pushed more towards the average for the whole week, but the real operative temperatures (Tz) differ more from the first stage control which is the result of the prediction step.

In Figure 7 the state of charge (SoC) of the buffers for space heating (floor_buffer, dimensionless) and DHW (DHW_buffer, MJ) with the DHW demand (DHW_demand, MJ) for the example household are shown. The space heating SoC has a relation with the floor heating temperature and operative zone temperature shown in Figure 6. In general, the SoC increases when the zone temperatures are higher than the setpoint and decreases when the zone temperatures approach the setpoint values.

Figure 7 also shows the relation between the SoC of the DHW buffer and the DHW demand. The SoC increases due to heat input from the heat pump. Corresponding operational states of the heat pump are shown in Figure 8. In this case, the DHW buffer is large enough to supply the largest short time demand peaks, i.e. for filling a bath. The states of the heat pump are indicated as 0 (off) or 1 (on). For improved visibility, the heat pump state for space heating is scaled different than for DHW in Figure 8.

5.2 Broader Analyses of Results

Heat Pump On/off Switching Behavior

As Figure 8 shows, the heat pump switches on and off frequently, which is undesirable for the service life of the heat pump. Therefore two possibilities to reduce

the amount of switching are considered:

1. defining a minimum running time constraint for the heat pump control, like half an hour or charge until the domestic hot water storage is fully charged. However, this limits the amount of feasible solutions considerably and increases the time to solve the optimization problem.
2. increasing the time interval of the simulation to half an hour. This decreases the number of variables and decreases the time to solve the optimization problem. Therefore we prefer this method.

When the latter method is applied, the load duration curves are similar to the results which are shown in Figure 5. The interior temperatures have a minor difference, which is shown in Figure 9. In this Figure, the subscripts ₁₅ and ₃₀ indicate a 15 minute and 30 minute time interval during simulation respectively. The advantage of the 30 minute time interval is shown in Figure 10, which shows the amount of on/off switches in relation to the amount of uninterrupted running time intervals of the heat pump. For the investigated week, the total amount of switches reduces from 92 to 53. A further reduction can be expected when an additional charging constraint is included for the domestic hot water storage, as most of the heat pump switches are related to short charging periods of this storage.

By comparison, the reference control switches only 11 times. This is perhaps an advantage for the service life of the heat pump, but Figure 6 demonstrates drawbacks on the experienced comfort. The on/off thermostats programmed for reference control of the space heating and the domestic hot water storage, cause too much cooling down of the house and of the hot water storage, which results in long periods of heating demand afterwards. This is observed from the high number of intervals of uninterrupted operation of the heat pump in case of reference control in Figure 10. For the reference control the longest period is 65 time intervals of 15 minutes or 16.25 hours, for the optimized control this is 19 time intervals of 30 minutes or 9.5 hours. In practice, a PID controller to control the space heating demand would probably perform better than the on/off reference control and result in less cooling down of the house and more frequent switching of the heat pumps. This should also result in shorter operating times and possibly some reduction of the aggregated peak electrical loads compared to the reference control.

Results for Periods with Less Heat Demand

As shown in Figure 5 and discussed on Section 5.1, the peak electrical load is reduced significantly for the

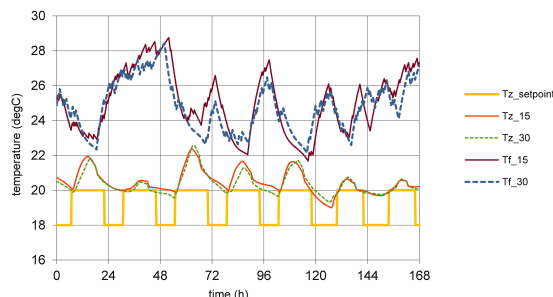


Figure 9: Temperature response for 15 and 30 minute time intervals.

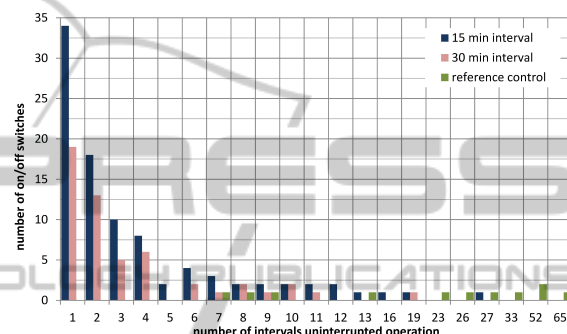


Figure 10: Amount of heat pump on/off switches related to uninterrupted operation time intervals.

optimized control. It is interesting to verify if a similar result is found for periods with less heat demand. In Figure 11, weather data of a different week for the same location and climatic year is shown. The aggregated electrical energy demand for the optimized and reference control is shown in Figure 12. The indoor temperatures (floor heating temperature T_f and interior zone temperature T_z) for the same detached house are shown in Figure 13.

During this week, the domestic hot water demand dominates the aggregated electrical energy demand, while the space heating demand is largely concentrated on one day between 72 and 96 hours. Due to approximately 80% simultaneity in the operation of the heat pumps for domestic hot water, the reference control shows a high peak electrical demand of 145 kW. The optimized control reduces this to 45 kW.

Notice that the interior zone temperatures are approximately similar for the reference and optimized control. The slightly increasing temperatures above the setpoints which is seen on the last two days are due to relatively high solar gains. The short term up and down movement of the floor heating temperatures from 0 up to 84 hours indicates frequent on/off switching of the heat pump. Also in this case, the heat pump switching is more frequent for the optimized control than for the reference control. The total

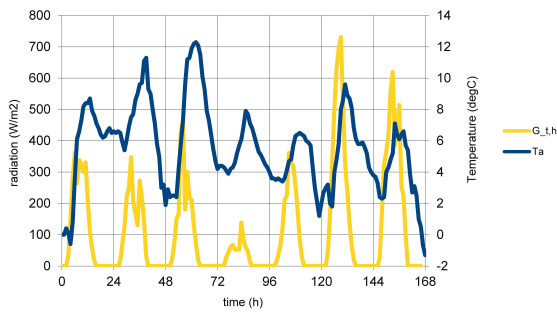


Figure 11: Input weather data for a week with less heat demand.

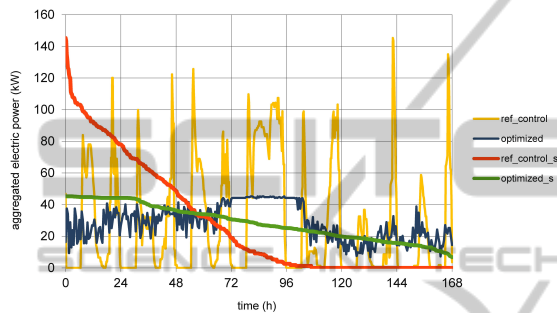


Figure 12: Aggregated electrical energy demand for a week with less heat demand.

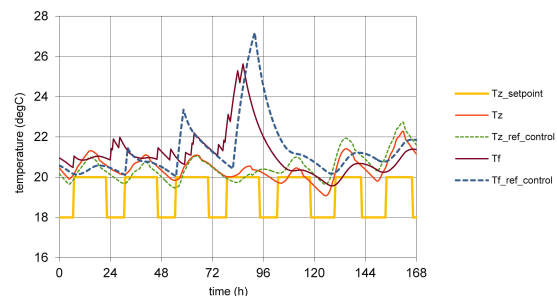


Figure 13: Indoor temperatures for a week with less heat demand.

amount of switches for this week is 32 for the optimized control and 10 for the reference control. However, the longest period of uninterrupted heat pump operation is 3 hours for the optimized control and 10.25 hours for the reference control, which increases the chance for simultaneity and hence explains the high peak electrical load of the reference control. This also has a relation with the schedules shown in Figure 3. As young families and young couples dominate the district’s population and the applied schedules for domestic hot water demand and interior temperature setpoints of these occupancy types are approximately similar, the chance for simultaneity is high. A commonly used hot water storage contains a single temperature sensor. Within the storage, a good degree of

temperature stratification of hot and cold water layers is present. In that case, a PID controller would not perform much better than the simple on/off reference control.

Optimality of the Control

The main objective for the optimization is to minimize peak electricity consumption. Besides this objective, there are some hard constraints on the thermal comfort, i.e. a minimum temperature, maximum size of the flexible space heating storage and minimum hot water storage state of charge. Besides that, a 30 minute time interval is introduced during optimization to avoid excessive on/off switching of the heat pumps. Hence, the definition of what is in this case really “optimum” for the control is not so obvious. As our results show, the peak electricity decreases significantly as the result of the optimized control, but there is a trade off between the quality of this objective, reaching comfort temperatures in the house which are close to the setpoints and limiting the amount of heat pump on/off switches.

6 CONCLUSIONS AND FUTURE WORK

Optimal control on a central or aggregated level of a group of heat pumps used for providing space heating and domestic hot water is investigated. It is demonstrated that model predictive control is required in order to anticipate on changing weather conditions and occupancy related thermal gains and losses. The developed control algorithm is very well capable to reach multiple objectives, i.e. minimize peak electrical demands and maintain adequate thermal comfort levels for each household in terms of comfortable, desired operative temperatures and sufficient charging states of the buffers to supply domestic hot water.

For the simulation case which involves 104 houses, it takes 100 seconds to compute the heat pump planning for 7 days in advance with 15 minute time intervals, on a PC with Intel quad core processor and 8 GB internal memory. Thus acceptable computational effort for this type of control is demonstrated. For larger district scales, the computational time can be limited further by shorter planning horizons, a larger time interval and applying the more efficient time scale MILP algorithm.

A comparison with simulated results using a reference control algorithm which equals existing non-optimized, individual heat pump control, demonstrates for the optimized, central control, a substantial decrease of the aggregated electricity demand

peaks and improved thermal comfort for the residents. However, the optimized control causes a significant increase of the amount of heat pump on/off switches, which can be decreased by increasing the time period of the optimization and by defining additional constraints on charging the domestic hot water storage.

Future work is aimed at developing predictive models for home space heating and domestic hot water demand in which online learning is incorporated and at studying cases which involve cooling during the summer months. We will also apply the developed simulation environment to applications which are more complex and require additional control algorithms. Besides that, we will further compare the quality of central control with individual control where optimization is based on auction principles.

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