ENCOURAGE

Embedded iNtelligent COntrols for bUildings with Renewable generAtion and storaGE

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1. Executive Summary

This report will focus on strategies for energy management as well at the building level and at the microgrid level. The designed energy management controller will manage energy flow such that generated power in the microgrid is mainly consumed by local consumers and the power trade between the microgrid and the grid is shrunk to minimum. Buildings' role is to provide flexibility to the energy management controller so that this controller can use this flexibility to enhance the local use of the local produced energy and by that mean lower the energy bill for each house in the microgrid. The Optimization of building loads are based on electricity price signal and shedding, shifting or rescheduling the power consumption pattern. The main *shiftable* loads are the HVAC systems. This system will be the primary controllable load for the energy management controller but also curtailable load and non-controllable loads will be taken into account when designing the controller. The flexibility, with respect to the HVAC system, is based on the heat capacity of the house and a thermal tolerance that users give permission for. The wider the thermal tolerance is, the more flexibility will be provided to the energy management controller. Load management strategies will be devised such that thermal comfort and other user-predefined preferences will be satisfied.

This deliverable reports strategies for energy management in the microgrid, designated energy management controller for the buildings load management and results of simulation studies.

1.1. WP5 Objectives

Embedded intelligent controls for buildings with renewable generation and storage (ENCOURAGE) aims to develop embedded intelligence and integration technologies that will directly optimize energy use in buildings and enable active participation in the future smart grid. The target energy saving for a network of buildings composed of distributed energy consumption, production and storage units is 20% via design of supervisory control schemes that coordinates among interplaying energy devices and buildings (Arne Skou, 2012)

A part of ENCOURAGE is to design a supervisory controller, that integrate and manage all energy units in the microgrid. The objectives are as follows:

- Energy needs of the microgrid are, as much as possible, to be provided by local generation units. The purpose is to minimize dependency to the grid power.
- The other objective is to minimize electricity consumption costs of individual households.
- The energy manger i.e. a supervisory controller is supposed to work with the existing single loop controllers in the building for instance heating thermostats.

However, the first two objectives might be conflicting, in which case priority would be with individuals' benefit. For example, there might be time intervals, during which power demand of a house exceeds its production. Assuming that power is provided by the grid at a lower price rate than the neighbouring production units in the island, power would be purchased from the grid. On the other hand, policies could be enacted to promote trade of power mostly within the microgrid in order to minimize dependency to the grid. For instance, price of the locally produced power could be kept always lower than the grid electricity price.

The above mentioned objectives are to be fulfilled via design of a hierarchical control structure that is shown in figure 1. The hierarchy is explained later in the report in more details.

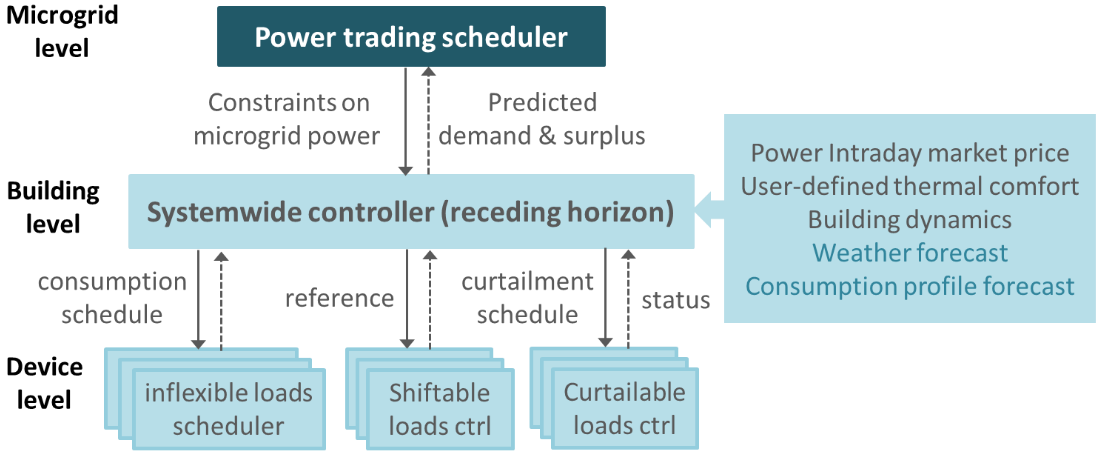

Figure 1. Supervisory controller hierarchy

1.2. WP5 Subtasks

According to ENCOURAGE project proposal, WP5 Task 5.3 will develop energy management strategies for optimal operation of energy generation, consumption, and storage devices connected in a network. This is based on:

Task 5.1: which address the supply side of the system by developing appropriate monitoring and control concepts for local generation elements based either on conventional or renewable energy sources.

Task 5.2: which will develop optimized control strategies for management of internal loads in the building (demand side). This will include shifting and/or shedding of specific loads.

Task 5.3: (this work) will take care of system optimization strategies integrating both supply and demand sides.

These optimization strategies will calculate optimal schedules (e.g. start/stop times and set points of individual pieces of equipment). The most typical solution interval will be one day, but the solution will be scalable to both shorter and longer intervals.

WP5 Timelines and Milestones

The versions of deliverables together with their title are listed in the following. The last report is the presented document. The number of month of delivery is mentioned.

D5.4.01	Initial Draft - Task Roles	M17
D5.4.02	Internal structure and function description	M24
D5.4.03	Development of control strategies for the microgrid energy management	M30

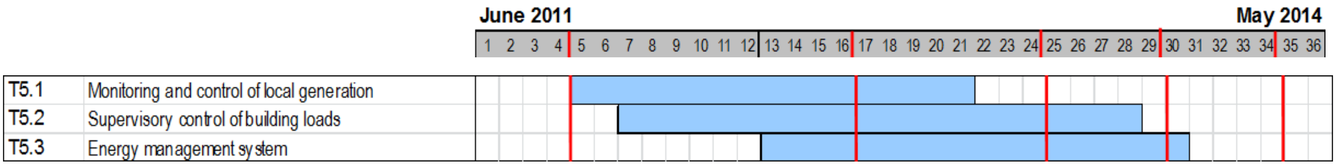

Figure 2. Timelines for WP5 subtasks (based on ENCOURAGE proposal)

2. Introduction

The global movement is toward power production mostly using renewable energy resources rather than using fossil fuels which are environmentally polluting and are being depleted very fast. These renewable energy resources, for instance solar, wind, biomass and geothermal are, by their nature, highly distributed compared to large concentrated nuclear and fossil-fuel power stations. Regaining power balance and allocation of resources in such a diverse and distributed energy market will be two big challenges. Smart grid as a newly emerging concept to be built upon the existing infrastructure of power grid is to facilitate the coordination among all the contributing production, consumption and storage units. In this scheme, a single small-scale power consumer will be no longer an inactive component, but potentially will contribute to energy management of the smart grid by providing flexibility. Making use of local power generation units and storage devices increase flexibility of the grid nodes.

Several world-wide studies have been conducted recently to propose new market, communication, and control layouts for the emerging large scale distributed energy system. ENCOURAGE, NeogridEU, iPower and FlexPower are examples of many ongoing European and national projects that are going to develop methodologies with different approaches to overcome imbalances of the future smart grid.

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2.1. WP5 in ENCOURAGE Architecture

ENCOURAGE aims to develop embedded controls, intelligent hardware devices, and open service-oriented platform that will allow end-users to achieve energy savings by orchestrating various energy generation, consumption, and storage devices in non-residential buildings, campuses, and neighbourhoods, and also enabling the possibility of exchanging energy surplus with other entities. The project has been structured into 8 work packages in order to achieve this main goal.

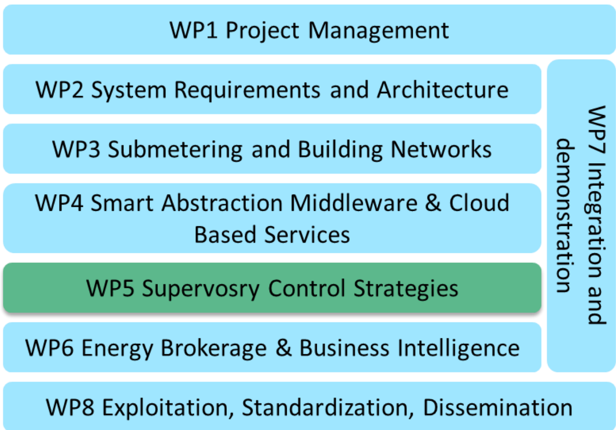

Figure 3. ENCOURAGE structure

WP5 will develop control strategies for optimal operation of energy generation, consumption, and storage devices connected in a network. In order to ensure integration between work packages, WP7 is dedicated to integrate the developed strategies by the other work packages. WP7 conducts tests on a number of microgrid case studies under real conditions. Interactions between WP5 and the rest of system setup are via exchange of information through middleware layer as shown in Figure 4.

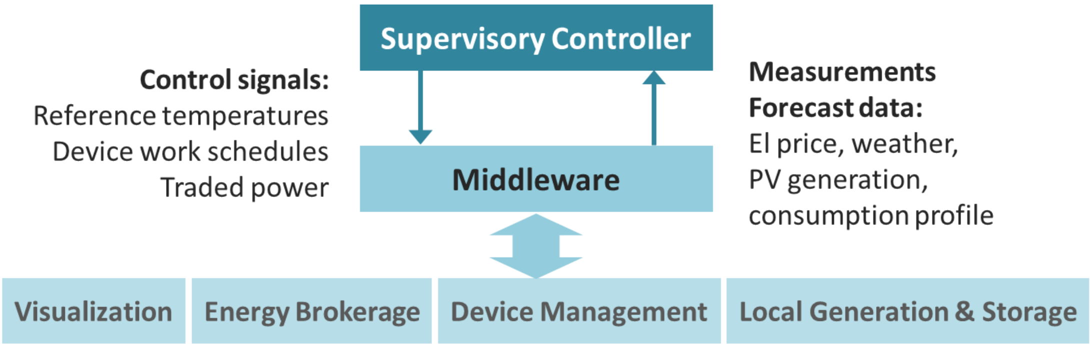

Figure 4. Data exchange between SC and other modules via middleware

2.2. Demonstration Sites

Among different demonstration scenarios of ENCOURAGE project, the focus of work package 5 is dedicated to Denmark demonstration site which is a residential area. However, developed control strategies are general and can be applied to other case studies. In this section we summarize the main characteristics of the concerned microgrid case study.

One of the demonstration sites of the ENCOURAGE project that we focus on in this study is a network of eight residential buildings i.e. detached houses located in Gistrup area, Northern Denmark. Each house is equipped with Photo Voltaic (PV) cells with capacity of producing 4kW of electricity. Thus, electricity need of an individual house is provided partly by solar cells and the remainder could be purchased from both other producers in the microgrid or from the electricity grid. That depends on the energy price provided by each energy source. Indoor air is heated by electrical floor heating in the houses. Measurements show that electrical space heater, electric water heater, appliances, and lighting respectively account for highest to lowest power consumption in a building. A satellite view of the houses taken from Google map is depicted in figure: 5.

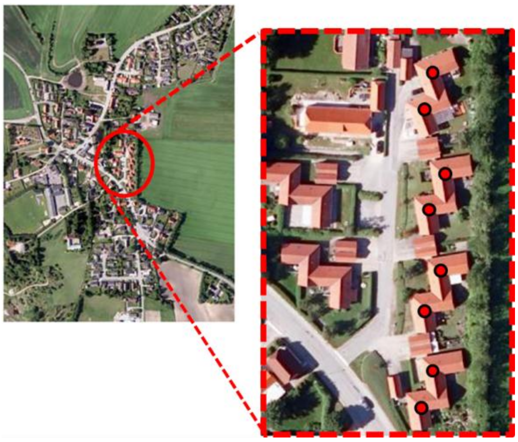

Figure 5. Aalborg demonstration site. Houses denoted with red circles are equipped with PV cells

All the houses are similar and very well insulated. The houses are occupied by different types of families' i.e. young couples, families with children and pensioners who are couple or single. The chosen occupancy diversity allows testing different consumption profiles for load control and energy exchange between the houses which is the normal case in a medium to large scale power island. Some houses are occupied mostly in evenings and weekends, while the others consume power often times during a week.

The microgrid is always connected to the grid. Therefore the islanded-mode is never imposed to the microgrid physically. However, the strategies should be enacted in order to make it as independent as possible from the grid. Therefore, it can purchase and sell electricity from/to the grid at any time. However, the objective is to make the trade flow in only one direction at a time, meaning that as long as there is a power demand in the microgrid, no power will be sold to the grid.

The microgrid local power generators are renewable, non-dispatchable sources. There is no specific energy storage device to store energy for a later use. However, the building thermal mass is a dynamic energy buffer which can be charged in a controlled way, but the discharge is not controllable, although is predictable. The stored energy naturally is in thermal form. Thus, this storage capacity makes the heating and cooling loads flexible to a certain degree determined by the building dynamics.

2.3. Literature Survey

There are two mainstream approaches for energy consumption/production management toward a smarter electric grid i.e. indirect and direct control. In the indirect approach, price incentives are sent to distributed energy resources in order to encourage individual units for example detached houses, residential or office buildings to consume electricity when energy surpluses in the grid by shifting their power demands, and use local energy resources or the stored energy when there is power congestion or deficit in the grid. The direct approach relates to a set-up where an aggregator gives direct commands to an energy node in the grid concerning production or consumption. The node informs the aggregator of its potential flexibility on consumption or production. A further classification of load control policies for demand-side management in smart buildings is proposed in (Anna Magdalena Kosek, 2013) based on the reaction to external signals, participation in markets, topology, decision making mechanisms and fault handling.

Early work on operation of the grid by price was presented in (F. Schweppe, 1995). Alvarado and co-workers studied feasibility and stability issues in (Alvarado F. , 1999) , (Alvarado F. , 2003), and (Alvarado F. , 2001).

(Borenstein, Jaske, & Rosenfeld, 2002) presented an analysis of approaches for real time pricing and advocated wider use of dynamic retail pricing. Experience with real time pricing was presented in (Barbose, Goldman, & Neenan, 2004), (Hammerstrom, 2007) and which indicate that peak load can be reduced with this approach. Recent work in (Roozbehani, Dahleh, & Mitter, On the Stability of Wholesale Electricity Markets under Real-Time Pricing, 2010) and (Roozbehani, Dahleh, & Mitter, Volatility of Power Grids Under Real-Time Pricing, 2012) and (Juelsgaard, Andersen, & Wisniewski, 2013) conclude that passing on the real-time wholesale electricity prices to the end consumers can lead to increased volatility, lack of robustness and instability. In (Dorini, Pinson, & Madsen, 2013) a methodology is described allowing estimating in advance the potential response of flexible end-consumers to price variations. This response is subsequently embedded in an optimal price-signal generator, and prices are estimated and broadcast once a day for the following one, for households to optimally schedule their consumption. (Jokic, Lazar, & Bosch, 2009) and (Annaswamy & Kiani, 2011) suggest price based schemes which ensure economically optimal operation while also respecting grid constraints. Examples of schemes allowing a consumer to optimally exploit real-time prices can be found in (Poulsen, Madsen, & Jørgensen, 2012), (Parisio & Glielmo, 2011), (Oldewurtel, Ulbig, Parisio, Andersson, & Morari, 2010), (Mohsenian-Rad & Leon-Garcia, 2010), (Hovgaard, Larsen, Edlund, & Jørgensen, 2011).

The direct control concept is inspired from method for optimal use of a power plant portfolio; see for instance (Edlund, J.D.Bendtsen, & Jørgensen, 2011). This is also reflected in the terminology where an aggregator is assumed to control a group of consumers as a Virtual Power Plant, (Ruiz, Cobelo, & Oyarzaba, 2009), (Gomes, Antunes, & Martins, 2007), (Gong, Xie, Jiang, & Zhang, 2011). Optimal operation of a portfolio of consumers often involves solving a non-convex optimization problem, for which many approaches may be taken, (Gomes, Antunes, & Martins, 2007) uses evolutionary algorithms, (Parisio & Glielmo, 2011) use Mixed Integer Linear Programming (MILP). A agent based solution is used in PowerMatcher, (Hommelberg, Warmer, Kamphuis, Kok, & Schaeffer, 2007), (Kok, et al., 2012), while a sorting algorithm, which match a certain formulation of the problem has been discussed in (Trangbæk, Bendtsen, & Stoustrup, 2011), and a similar method is used in (Biegel, Andersen, Pedersen, Nielsen, Stoustrup, & Hansen, 2013), (Ramanathan & Vittal, 2008).

The load flexibility is to be provided by means of some storage facilities. In return, the aggregator controls the unit based on the predicted flexibility within the limits and costs agreed upon in advance (Biegel, Andersen, Stoustrup, Hansen, & Victor Tackie, 2013), (Petersen, 2013) propose a taxonomy which divides flexible loads in the three distinct categories described by the names buckets, batteries and bakeries, each with characteristics which can be quantified. Indirect Energy Management Strategy

The focus in this report will be on indirect control strategy of household's energy consumption. We formulated a model predictive controller that systematically finds the energy consumption pattern of flexible loads provided that knowledge about other loads and productions and the building dynamics are available. A cost is formulated based on power consumption and its price which is minimized by the designed controller. In the proposed scheme electricity can also be sold to the grid and consumption can be curtailed if convenient. In contrary to the available literature, we proposed a hierarchical controller rather than a centralized one. The first advantage is that we exploited the existing stand-alone single-loop controllers which are usually available in the buildings. The new integrating and optimizing layer connects to the lowest layer by commanding a general reference signal to the single loop controllers. The system-wide controller is designed in a receding horizon fashion in order to incorporate building energy flexibilities based on a dynamical model, future preferences and disturbances.

The controller outputs are actuation signals to the HVAC, hot water tank, lighting, etc…, and consumption profile to the appliances and other non-critical inflexible loads in the building. Its inputs are measurements like indoor temperature, hot water tank temperature, etc… and forecasts of power consumption in the building, weather, electricity intraday market price in and outside the microgrid, and electricity generation of PVs. In the sequel we describe the controller structure in more details.

2.4. Hierarchical Supervisory Controller for Microgrid Energy Management

The control hierarchy as shown in Figure 2 composes three different layers. The task of each layer and the connection between the layers are described in the following.

- Device layer at the bottom of hierarchy comprises single loop controllers for controllable (shiftable and curtailable) loads, controllable generation units (not available) and storage devices (not available). It is responsible for maintaining a set point, light adjustment, etc. using an on/off or proportional integral (PI) control action.
- Building level at the middle of hierarchy includes a system-wide controller that keeps the economy and comfort in balance. It minimizes the cost of electricity consumption while maintaining the comfort levels determined by the user. A priori knowledge about building dynamics, comfort preferences, weather changes, power generation and price of electricity are needed as inputs to the controller at this level. This layer receives measured status data from device-level controllers i.e. heating/cooling thermostats and provides them with reference signals.
- Microgrid level at the top is responsible for distribution of locally generated energy among households with energy demands. It receives predictions of power surplus profile (for sale) and power needs profile (to be purchased) from the system-wide controllers in the middle. Based on these inputs, it predictively assigns surplus power in the microgrid among the demanding houses. The system-wide controller is designed such that the power produced by PVs is consumed by the producing house at the first place. The excess is distributed by the power trading/scheduler among the other houses with power deficit. It predictively determines

the constraints on the amount of buying energy and selling energy for each house in the microgrid.

The device layer and building level are described in D5.3. In this document there are some additional investigations concerning the stability and robustness of the building level controller because this work depend on these features.

3. Stability and robustness of the building Level Controller

Block diagram of the hierarchical supervisory controller at the building level is depicted in Figure 6. It is chosen to use a Model Predictive Controller (MPC) as the system-wide controller (Maciejowski, 2012). The reason for this choice is that, all the system disturbances and future references can systematically be incorporated into the MPC. On the other hand, the middle layer has to provide a foreseen estimate of surplus and demand power to the power scheduler at the top layer. This feature would already be embedded in the system-wide controller if we choose a receding horizon controller. At the bottom layer we have designed Proportional Integral (PI) controller for heating loads. Light curtailment is done based on inputs from sensors measuring light or detecting motion.

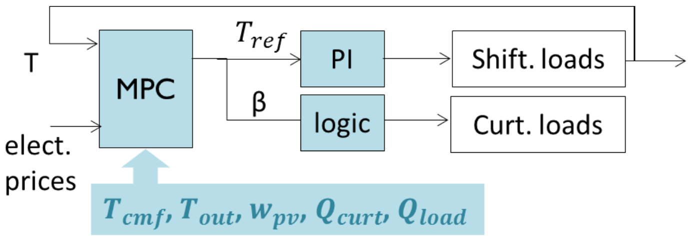

Figure 6. Block diagram of the hierarchical supervisory controller

Inputs to the MPC are: intraday market price of electricity, pre-set user-defined comfort temperature T_{cmf}, forecast of outdoor temperature T_{out}, Prediction of electricity generation by PVs W_{PV}, Predicted consumption profile of curtailable Q_{curt} and non-flexible loads Q_{load}. Output control signals are: a reference temperature T_{ref} to HVAC system controller and a coefficient of curtailment β to the lighting system controller.

A more detailed description can be found in D5.3.

To secure easy deployment of this MPC controller, it is required that the MPC controller is stabile and robust with respect to variations in the dynamic of the houses. The next two chapters will try to explain that this stability and robustness is fulfilled with the chosen configuration.

3.1. Stability of Model Predictive Controller

The discussion on stability is in rather general terms and relies on the general properties of model predictive control schemes. Stability of model predictive control can be established using the value functions as a Lyapunov function. Stability can be ensured by using a sufficiently long horizon or with the application of a terminal constraint or a terminal cost function which should be the cost function extended to infinite horizon (Mayne, Rawlings, Rao, & Scokaert, 2000), (Limon, Alamo, Salas, & Camacho, 2006).

Here the consideration is on the stability of the local predictive controllers. This is to be achieved by requiring that the temperature constraints of the house are fulfilled at every time instant. The feasibility of the control problem will be connected to the power which the heating system is available to deliver to the house and depend on whether the heating system is designed properly for the house. Obviously if the house hasn't both heating and cooling installed there will be periods in the summer or winter time where this system will not be able to keep the temperature below or about the temperature constraints

Stability is of course depending on that the prediction model describes the dynamics of the system sufficiently well. The test that shows that the system has some robustness towards parameter variations is done by simulation. The next section describes this robustness study.

3.2. Robustness of Model Predictive Controller

Robustness or Robust control deals with uncertainty in the controller design. A controller is robust if it performs well as long as uncertain parameters or disturbances are within some (typically compact) set. The primary uncertainties, of a house with respect to the heat control system, are the heat loss and the heat capacity of the house. Deployment of the energy management controller, described in this document, is based on the local house controller. The stability of this local controller has to be relative unaffected of changes in heating dynamic from house to house otherwise the deployment will require a re-tuning of the controller for each house. This chapter will analyse the robustness for the, in D5.3 describe house MPC controller. Firstly the house model will be defined and the uncertain parameters will be found. Secondly the robustness with respect to these parameters will be analysed.

3.2.1 System Modelling

Dynamics of a house and its heat loss can be described by the first order model. This model is accurate enough to describe the main properties of the system and thereby suitable for controller design.

$$C\dot{T} = UA(T_{out} - T) + Q_{heat}$$

Where:

- C: Thermal capacitance $[kJ/\ ^{\circ}C]$

- U: Thermal transmittance [$kW/m^2\ ^{\circ}C$]
- A: Surface area [m^2]

T is the room temperature and T_{out} is the outdoor temperature. C is the heat capacity of the floor material and the houses air, envelope, and furniture. Q_{heat} is dissipated heat from the floor heating system or any other system to the room's air. It is assumed that the Heat flow from the floor heating system is controlled by a PI controller. See figure: 7.

The PI controller in state space form is given by:

$$\dot{\xi} = \frac{K_p}{T_{int}}(T_{ref} - T)$$
$$Q_{heat} = K_p(T_{ref} - T) + \xi$$

Where:

- K_p: Are the proportion gain.
- T_{int}: Are the integration time.
- T_{ref}: Are the reference temperature. [$^{\circ}C$].
- ξ: Are the integral state.

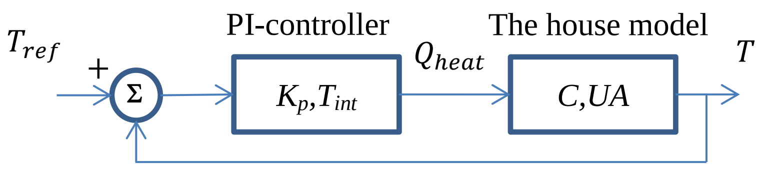

Figure 7: The local heat control system

Figure 7 shows the structure of the local heat control system. It is assumed that the local PI-controller is stable and running on some kind of local control system. The tuning of the PI controller and thereby setting of K_p, T_{int} are not part of this project. For simulation purpose K_p, T_{int} is set to:

- $K_p = UA$:
- $T_{int} = C/UA$

Assuming this means that the local close loop heating system only are a function of C and UA. The design of the MPC-controller depends of these two parameters. The heat loss coefficient UA is relatively simple to estimate. It can be found as the mean heat inlet divided by the difference between the inside temperature and the outside temperature. The heat capacity of the house C is more difficult to estimate. This estimation requires some form of dynamic measurement e.g. a step response or other forms of dynamic data suitable for system identification.

3.3. Robustness of the MPC controllers

Based on the building level MPC controller described in D5.3 the sensibility for variations in the two parameters C and UA will be analysed. The MPC controller design is based on a nominal model given by:

- $C = 4000$ [kJ/C] and $UA = 0.08$ [kW/C]

The question is: will the MPC-controller work if used in a house, with dynamic behaviours different from the nominal model, or in other words how robust are the MPC-controller witch respect to variations in C and UA.

The analysis is based on simulations. Firstly variations in C are analyzed by running a number of test with $C \in [2000{,}6000]$, and secundly variations in UA are analyzed by running a number of test with $UA \in [0.04{,}0.12]$.

Figure 8 shows the electricity prices used in the simulations. These prices are taken from the Nordpool database for a period of one week in February 2013. The selling prices are set to the half of the buying prices.

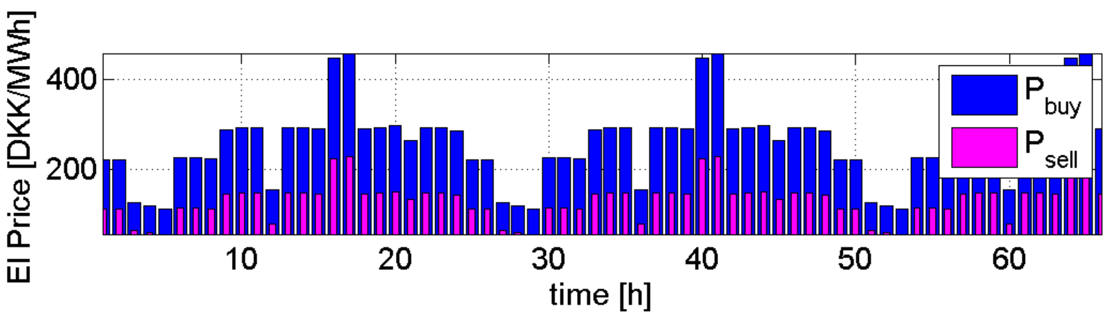

Figure 8: The selling and buying price from the utility

Figure 9, 10 and 11 shows the simulations with the house heat capacity of: $C = 4000$ (figure 9), $C = 2000$ (figure 10) and $C = 6000$ (figure 11). All three figures shows that the MPC controller are stable and act as expected. In all three cases, the controller try to use the electricity when it is cheap and avoid using it when it is expensive without violating the constraints.

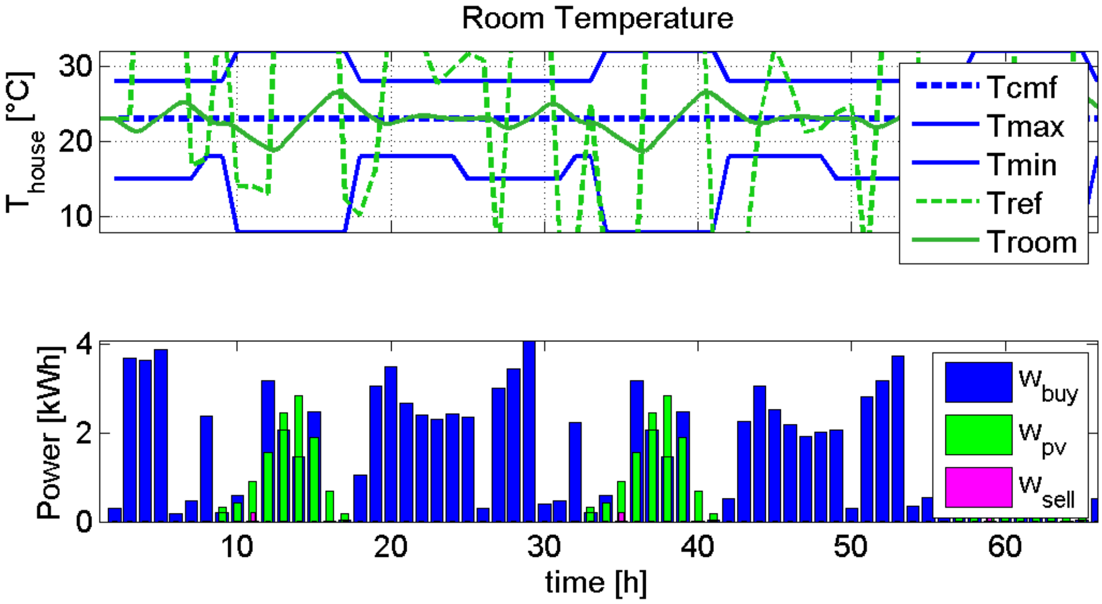

Figure 9: The nominal model C = 4000 [kJ/C], $UA = 0.08$ [kW/C] and simulation model C = 4000 [kJ/C]], $UA = 0.08$ [kW/C]

Figure 9 shows a scenario where the house dynamic is the same as the nominal model used for designing the controller. This is the optimal scenario.

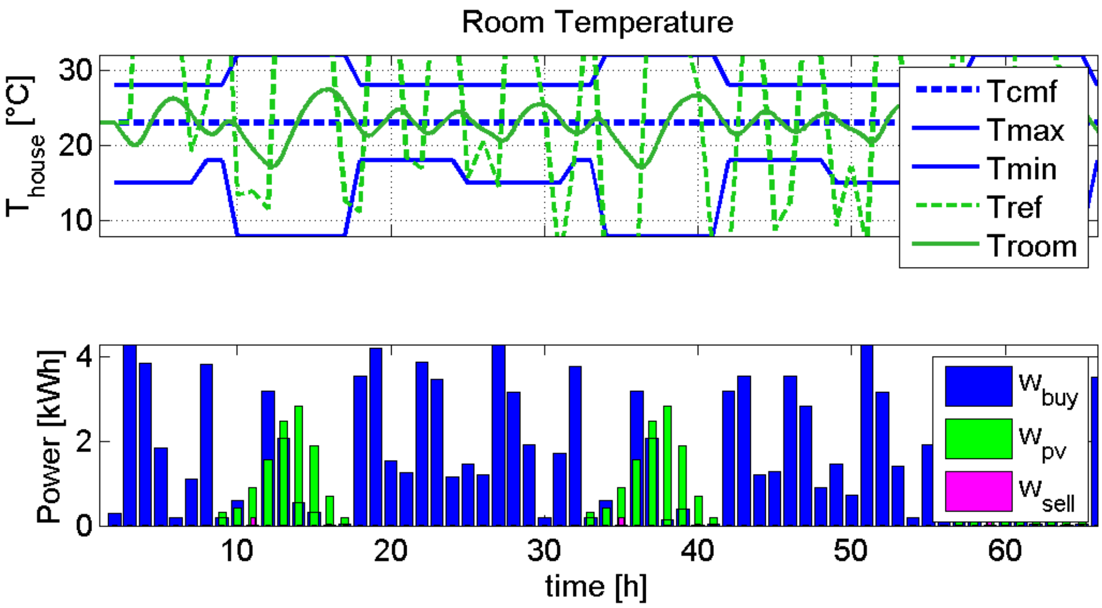

Figure 10: The nominal model C = 4000 [kJ/C] and simulation model C = 2000 [kJ/C]

Figure 10 shows a scenario where the house dynamic is twice as fast as the nominal model used for designing the controller. Here the results show that the room temperature T (Troom) varies more than the nominal example (figure 9). This is due to the lower heat capacity in the house. This again results in lower energy consumption then the nominal example because that the MPC-controller can, relative faster, lower the room temperature and by that mean lower the energy losses from the house. See figure 12.

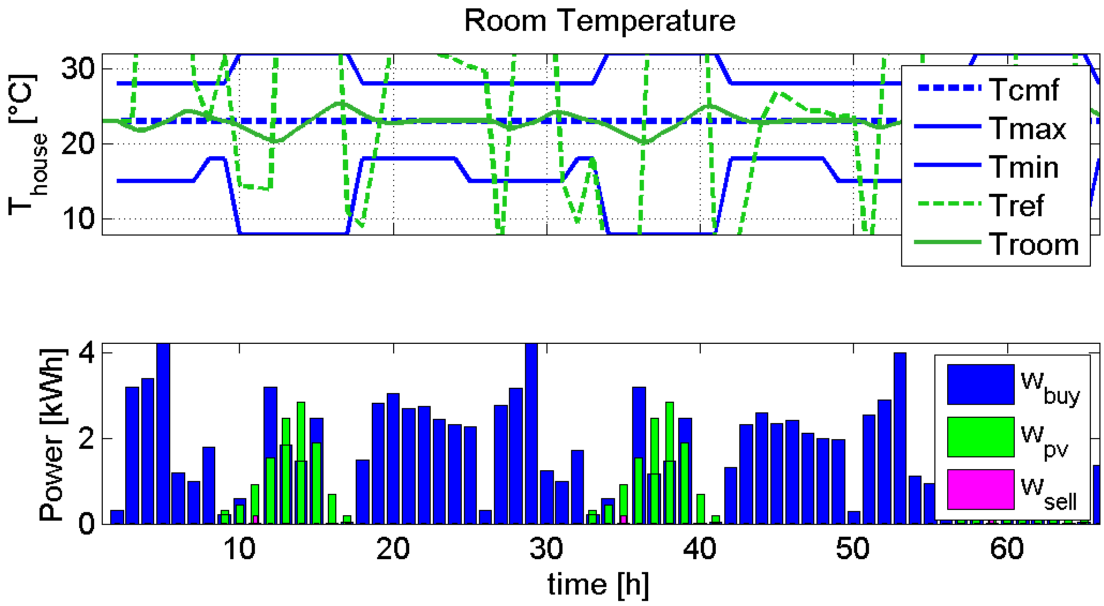

Figure 11: The nominal model C = 4000 [kJ/C] and simulation model C = 6000 [kJ/C]

Figure 11 shows a scenario where the house dynamic is 50% slower than the nominal model used for designing the controller. Here the results show that the room temperature T (Troom) varies less than the nominal example (figure 9). This is because of the higher heat capacity of the house. This again results in a higher total energy price. See figure 12. The reason for that is due to the fact that the MPC-controller not is optimal with respect to this house. Because of that, this controller are not able to move the same amount of energy from the cheap period to the more expensive period compared with the nominal model case.

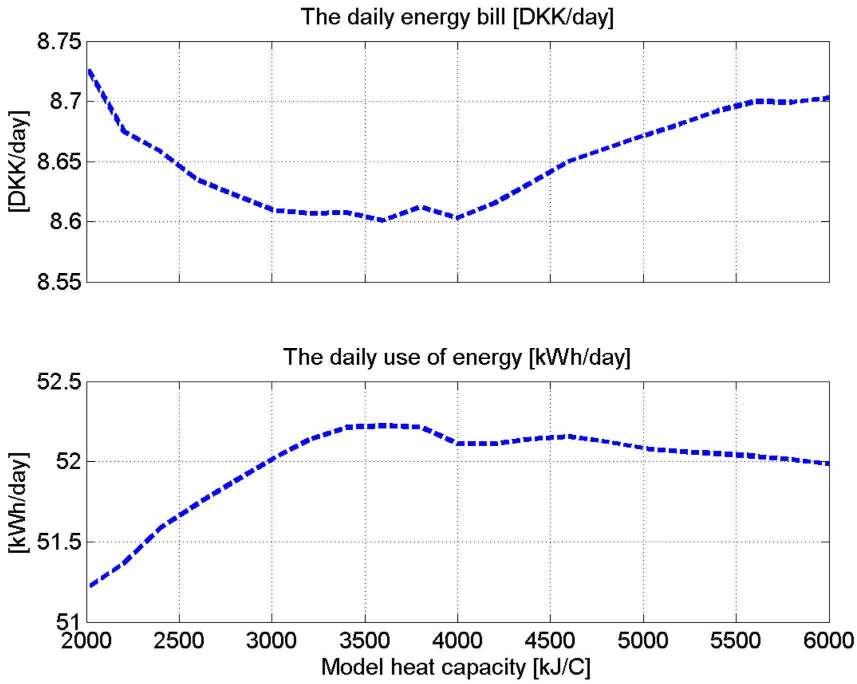

Figure 12: The energy cost and the amount of energy used as function of the mismatch between the nominal model and the house simulation model

Figure 12: shows the daily electricity cost price and the daily amount of electrical energy used. This figure shows that the nominal model (4000 [kJ/C]) gives the best combination of relative low energy consumption and low energy price. It shall be mentioned here that the MPC cost function minimize the energy bill and not the energy consumption. For models different from the nominal model the daily energy bill rises. This is exactly what to expect. On the other hand the energy consumption decreases slightly when using a 'not optimal' controller. For instance, for the 2000 [kJ/C] model, the increase in cost is approximately 1.4 % and the decrease in energy consumption is 1.7%. As mentioned earlier the main reason for that decrease in energy consumption is the fact that the house has a faster rise time, and because of that it is able to lower the temperature in the house faster and by that mean lower the energy consumption.

The heat loss coefficient (*UA*) are given by the Thermal transmittance [kW/m^{2}C] multiplied by the areal of the outside walls and the sealing of the house. The *UA* are set to 0.08 [kW/C] for the nominal house. The nominal model is shown in figure 3.

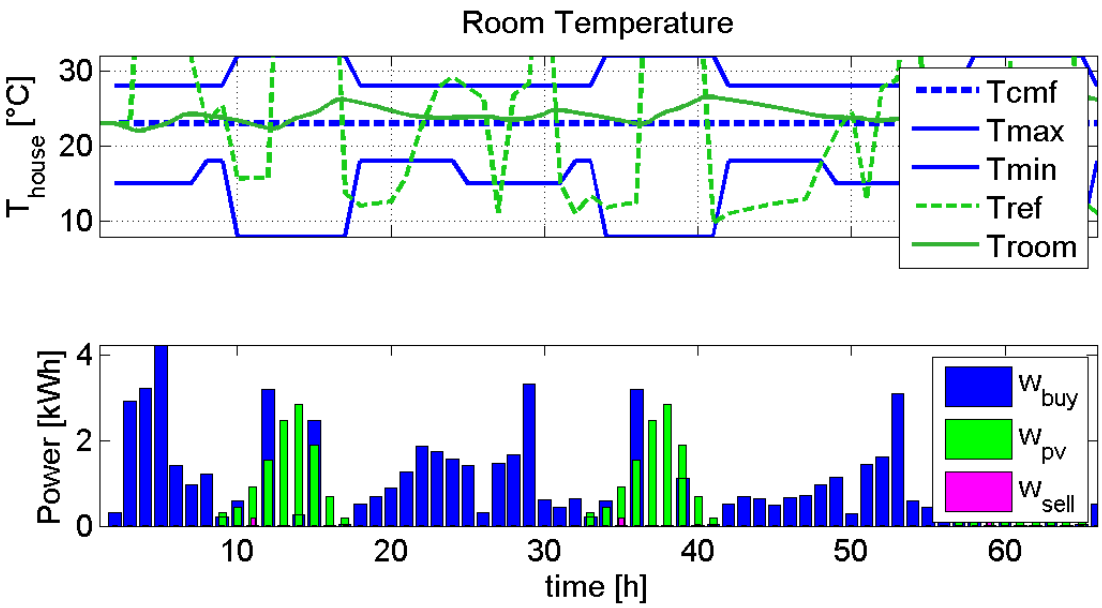

Figure 13: Prediction model heat loss coefficient 0.08 [kW/C] and simulation model heat loss coefficient 0.04 [kW/C]

Figure 13 shows a scenario where the house heat loss is the half of the nominal model used for designing the controller. Here the results show that the room temperature T (Troom) is higher than the nominal example (figure 9). This is due to that the house is better insulated. This again results in relative higher energy consumption then the nominal example. Relative means here the energy consumption divided by UA (the heat loss coefficient).

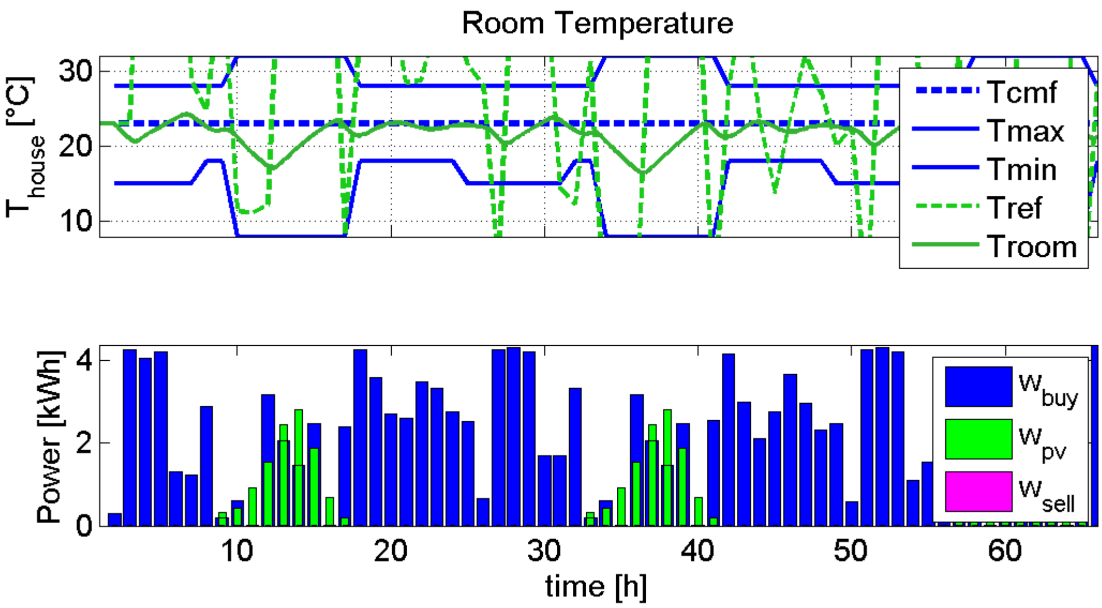

Figure 14: Prediction model heat loss coefficient 0.08 [kW/C] and simulation model heat loss coefficient 0.12[kW/C]

Figure 14 shows a scenario where the house heat loss 50% higher than the nominal model used for designing the controller. Here the results show that the room temperature T (Troom) is lower than the nominal example (figure 9). This is due to the fact that the house is weather insulated than the nominal model. This again results in relative lower energy consumption than the nominal example.

The conclusion on the stability and robustness study is that the MPS controller is insensible with respect to variation in the dynamic of the houses and there by relative easy to deploy in different houses.

4. The Microgrid based Building level MPC controller

4.1. Problem Formulation

In this section we have given formulation of a MPC controller. This controller is placed in each building in a microgrid. A microgrid is a number of buildings working together trying to using as much as possible of the local produced energy as possible, and on the other hand buying as little as possible of energy from the utilities.

4.1.1 System Modelling

Dynamics of a house and its heating loads are, as describe earlier, governed by the following first order model. This model is accurate enough for control design purposes in practice.

$$C\dot{T} = UA(T_{out} - T) + Q_{heat}$$

Heat flow is controlled using a PI controller.

Considering the sampling time, $h = t_{k+1} - t_k$, closed-loop discrete time system is:

$$T(k+1) = a_{11}T_k + a_{12}\xi(k) + b_1T_{ref}(k) + e_1T_{out}(k)$$
$$\xi(k+1) = a_{21}T(k) + a_{22}\xi(k) + b_2T_{ref}(k)$$
$$Q_{heat}(k) = c_1T(k) + c_2\xi(k) + dT_{ref}(k)$$

Where:

- K_p: Proportion gain.
- T_{int}: Integration time.
- T_{ref}: Are the reference temperature. [$^{\circ}C$].
- ξ: Integral state.
- $a_{11} = 1 + \frac{h}{C}UA$
- $a_{12} = \frac{h}{C}$
- $a_{21=} h\frac{K_p}{T_{int}}$
- $a_{22} = 1$
- $b_1 = \frac{h}{C}K_p$:
- $b_2 = h\frac{K_p}{T_{int}}$
- $c_1 = -\frac{h}{C}K_p$
- $c_2 = \frac{h}{C}$:

- $d = \frac{h}{C} K_p$
- h: Sampling time.
- C: thermal capacitance $[kJ/kg\ ^{\circ}C]$

Parameters of the above equation are given in the following matrix form:

$$\begin{bmatrix} T(k+1) \\ \xi(k+1) \end{bmatrix} = \begin{bmatrix} 1+\frac{h}{C}UA & \frac{h}{C} \\ h\frac{K_p}{T_{int}} & 1 \end{bmatrix} \begin{bmatrix} T(k+1) \\ \xi(k+1) \end{bmatrix} + \begin{bmatrix} \frac{h}{C}K_p & \frac{h}{C}UA \\ h\frac{K_p}{T_{int}} & 0 \end{bmatrix} \begin{bmatrix} T_{ref}(k) \\ T_{out}(k) \end{bmatrix}$$
$$Q_{heat} = \begin{bmatrix} -\frac{h}{C}K_p & \frac{h}{C} \end{bmatrix} \begin{bmatrix} T(k+1) \\ \xi(k+1) \end{bmatrix} + \begin{bmatrix} \frac{h}{C}K_p \end{bmatrix} T_{ref}(k)$$

4.1.2. Optimization Problem

Optimization Problem is formulated in a receding horizon framework. An economic solution is achieved by penalizing purchase from the utility grid in the cost function. Also, discomfort i.e. deviation from a comfort temperature profile is penalized. The other term in the cost function is related to curtailment penalty.

$$\min_{T_{ref},\beta,w_{sell},w_{mg}} \sum_{k=1}^{N} \begin{matrix} \rho_{discmf}\left|T(k)-T_{cmf}(k)\right| + \rho_{buy}(k)w_{buy}(k) - \rho_{sell}(k)w_{sell}(k) \\ +\rho_{mgbuy}(k)w_{mgbuy}(k) - \rho_{mgsell}(k)w_{mgsell}(k) + \rho_{curt}(k)\beta_{curt}(k)Q_{curt}(k) \end{matrix}$$

$$\begin{aligned} s.t. \quad & T(k+1) = a_{11}T_k + a_{12}\xi(k) + b_1T_{ref}(k) + e_1T_{out}(k) \\ & \xi(k+1) = a_{21}T(k) + a_{22}\xi(k) + b_2T_{ref}(k) \\ & Q_{heat}(k) = c_1T(k) + c_2\xi(k) + dT_{ref}(k) \\ & \left|T(k)-T_{cmf}(k)\right| \le T_{tol}(k) \\ & 0 \le Q_{heat}(k) \le Q_{max} \\ & 0 \le \beta_{curt}(k) \le 1 \\ & 0 \le w_{sell}(k) \\ & 0 \le w_{mgbuy}(k) \le w_{mg}^{Max}(k) \\ & w_{mg}^{Min}(k) \le w_{mgsell}(k) \end{aligned}$$

$$w_{mg}(k) + w_{buy}(k) = \\ Q_{heat}(k) + Q_{load}(k) + \left(1-\beta_{curt}(k)\right)Q_{curt}(k) + w_{sell}(k) + w_{mgsell}(k) - w_{pv}(k)$$

in which k is the time instant and N is the prediction horizon. ρ_{discmf} and ρ_{curt} are coefficients of penalty for thermal discomfort and power curtailment of the appertaining curtailable loads, respectively. Control variables are curtailment coefficient $\beta_{curt}(k)$, selling power to the grid

$w_{sell}(k)$ and the reference temperature of the building $T_{ref}(k)$. Predicted signals and system disturbances include comfort temperature profile $T_{cmf}(k)$, buying and selling price between the grid and microgrid $\rho_{buy}(k)$ and $\rho_{sell}(k)$, buying and selling price within the microgrid $\rho_{mgbuy}(k)$ and $\rho_{mgsell}(k)$, discomfort penalty ρ_{discmf}, curtailment penalty ρ_{curt}, curtailable and inflexible loads Q_{curt} and Q_{load}, and electricity generation of PV cells w_{pv}, all for the next 24 hours. Boundaries on building temperature T_{tol} and maximum heat flow Q_{max} are the known parameters.

5. Power Trading Scheduler

Power demand of each house is to be fulfilled by its own PV power generation units at the first place. The excess of generated power will be distributed among the other houses in the microgrid in a fair way. The total power surplus and demand will be predicted for the next N time horizon.

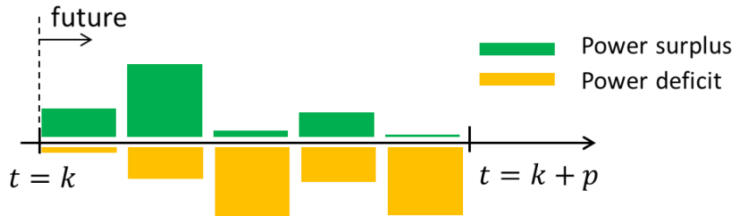

Figure 15. Prediction of power surplus and deficit in the microgrid

For k = 1,…,N, based on the prediction from MPC and for i = 1,…,M total number of houses:

Predicted total power demand: $w_{demand}(k) = \sum_{i=1}^{M} w_{buy}^{i}(k)$

Predicted total power surplus: $w_{surplus}(k) = \sum_{i=1}^{M} w_{sell}^{i}(k)$

Predicted maximum buying power from microgrid for the house #i:

$$w_{mg}^{Max}(i,k) = \frac{w_{buy}^{i}(k)}{w_{demand}(k)} \times w_{sur}(k)$$

Predicted minimum selling power to microgrid:

$$w_{sell}^{Min}(i,k) = \frac{w_{sell}^{i}(k)}{w_{surplus}(k)} \times \min(w_{sur}(k), w_{dem}(k))$$

Buying and selling price from/to microgrid is between sell and buy price from the grid.

$$\rho_{sell} \leq \rho_{mgbuy}, \rho_{mgsell} \leq \rho_{buy}$$

5.1. Algorithm for Power Management in the Microgrid

Step 1 – At t = k, solve the MPC-based optimization problem for each house without considering w_{mg} term and relevant constraints. $w_{buy}, w_{sell}, Q_{heat}$ *and* β will be derived.

Step 2- Calculate constraints on maximum buying power from the microgrid w_{mg}^{Max} and minimum selling power to the microgrid w_{mg}^{Max}, based on formulation in Section 7.
Step 3- Solve the complete optimization problem for each house considering all the constraints on selling and buying power to/from microgrid.

Step 4 – Control variables i.e. T_{ref} *and* β will be applied to the house. Actual selling and buying power is calculated based on actual power consumption:

$$w(t) = w_{pv}(t) - Q_{heat}(t) - (1-\beta)Q_{curt}(t) - Q_{load}(t)$$

$$w = \begin{cases} w_{sell} & if\ w \geq 0 \\ -w_{buy} & if\ w \leq 0 \end{cases}$$

Final calculations: In order to calculate how much power in reality came/went from/to grid or microgrid we do as following:

If $w^i \geq 0$ then selling power to microgrid and grid for individual houses are:

$$w_{sell}^{i,mg}(t) = \frac{w_{sell}^i(t)}{\sum_i w_{sell}^i(t)} \times \min\left(\sum_i w_{sell}^i(t), \sum_i w_{buy}^i(t)\right)$$

Selling power to the grid will be:

$$w_{sell}^{i,g}(t) = w_{sell}^i(t) - w_{sell}^{i,mg}(t)$$

If $w^i \leq 0$ then buying power from microgrid and grid for individual houses are:

$$w_{buy}^{i,mg}(t) = \frac{w_{buy}^i(t)}{\sum_i w_{buy}^i(t)} \times \min\left(\sum_i w_{sell}^i(t), \sum_i w_{buy}^i(t)\right)$$

Buying power from the grid will be:

$$w_{buy}^{i,g}(t) = w_{buy}^i(t) - w_{buy}^{i,mg}(t)$$

6. Simulation Results

This section shows the simulation results of energy management using the proposed algorithm. The simulations will be divided into two parts. The first simulation scenario shows the simulation results for two houses connected in a small microgrid. In the second scenario the Jadevej case study are simulated. This case study consist of 8 houses all equipped with PV cells.

Parameters of the building dynamics are chosen based on data from a low energy building i.e. very similar to the demonstration houses described in Section 2. The sampling time is one hour equal to the time interval of variations in predicted price profile. Predicted signals are assumed to be available one day ahead. This is especially important for the price profile which is settled in an hourly basis a day ahead in the Elspot trading system.

The power price is determined by balance between supply and demand and fixed from 12:45 CET each day to be applied from 00:00 CET the next day Nordpool. Therefor the prediction horizon for MPC is chosen 1 day. Price signals are taken from the Nordpool database for a period of one week in February 2013. Weather data is also taken from Danish Meteorological Institute (DMI). PV cells production data is achieved from Jadevej case study. Power price traded in with the microgrid will be set between grid's power prices, such that it encourages the local produces to sell their power to the local customers and the local customers to buy from local producers.

The formulated MPC is implemented in Matlab using CVX optimization toolkit. In the microgrid, two different power consumption profiles are assigned to the houses.

6.1. Scenario I

In the first simulation scenario the simulation results for two houses which are equipped with electric floor heating, appliances and PV cells are shown. They can trade power with each other and the grid. As discussed earlier, electric floor heating is a flexible automatically controlled load and appliances are manually controllable. However, in this simulation scenario, the supervisory controller only shifts consumption of the floor heating. It does not feed the appliances by advices on consumption pattern.

In ideal condition i.e. perfect forecast of PV production, weather and residents’ behaviour, the results of simulating the algorithm is shown in figure: 16 and figure 17. The two houses have different thermal comfort settings and power consumption profile.

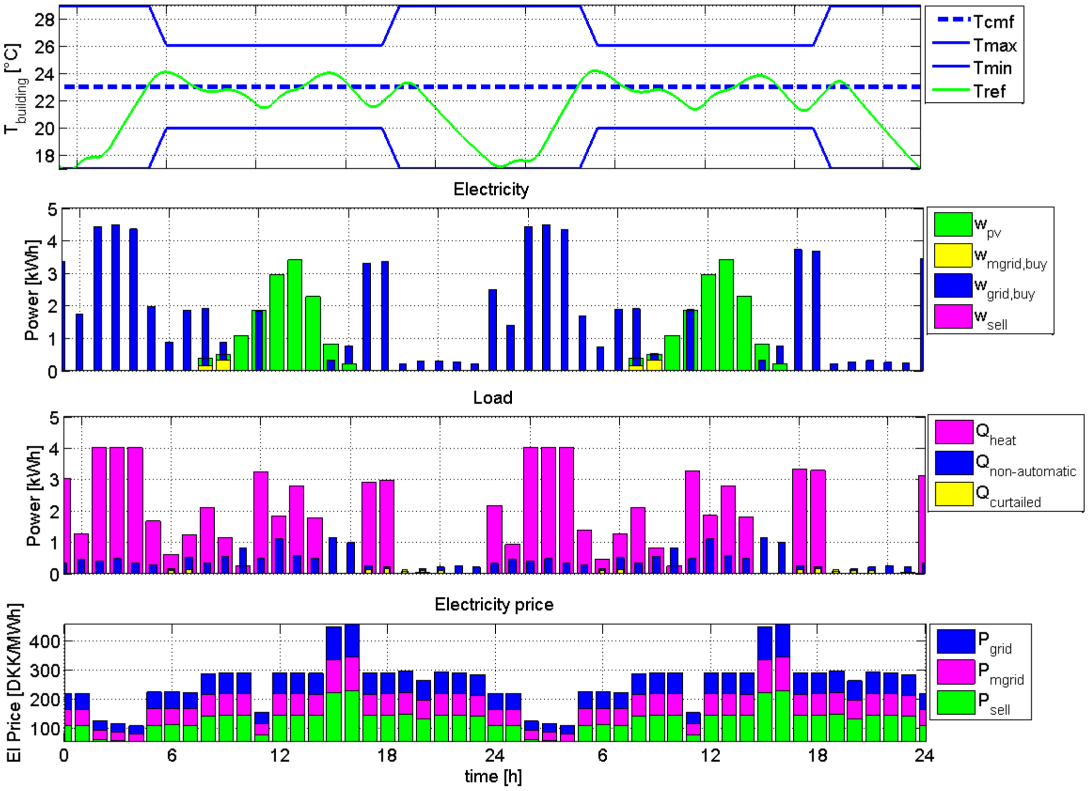

Figure 16. House #1: this house has a tighter thermal comfort requirements compared to House #2

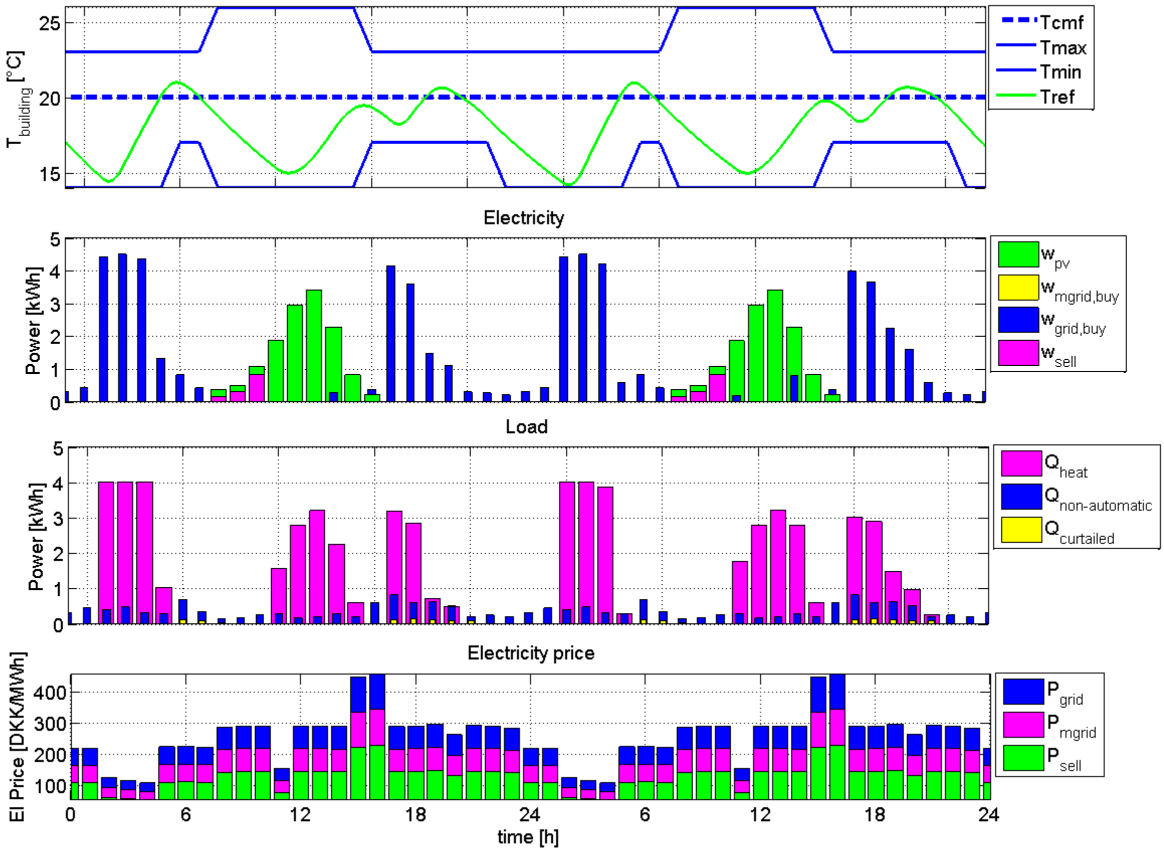

Figure 17. House #2 comfort temperature is less than the other house. It sells power to the grid and the other house during hour 8 to 10

Thermal comfort is more flexible in house #2 compared to the house #1. Power consumption pattern is different in the two houses. As a result, house #2 sells power to the house #1 during hour 8 to 10.

6.2. Scenario II

8 houses in the Jadevej case study are simulated using the designated energy management method. The results are shown in the following for 24 hours. We considered two types of power consumption pattern in the simulations. Examples of the two type's consumption are shown in figure: 18 and figure: 19. The other figures compare the consumption and show energy trading between the houses.

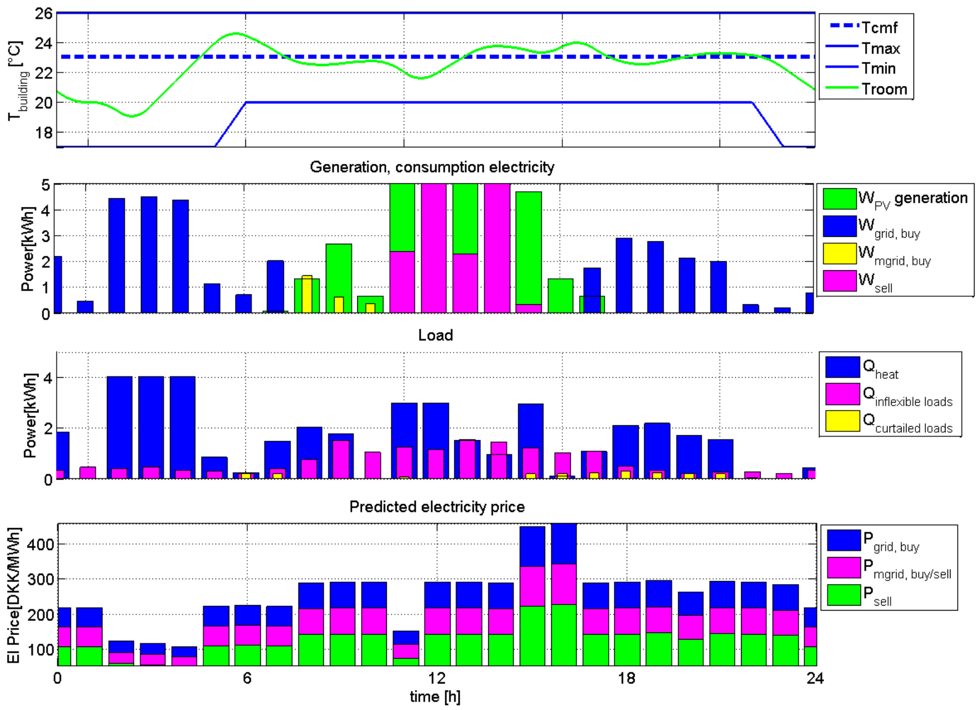

Figure 18. House type 1: comfort temperature is 23 °C and it is limited between 26 °C and 17 °C

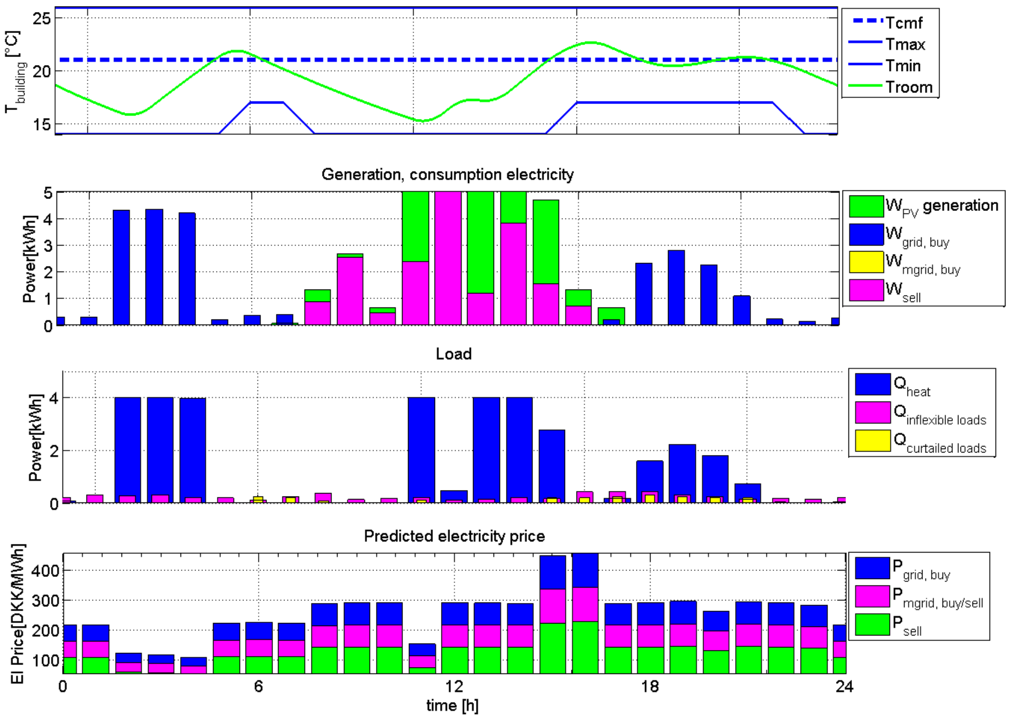

Figure 19. House type 2: comfort temperature is 21 °C and it is limited between 26 °C and 14 °C

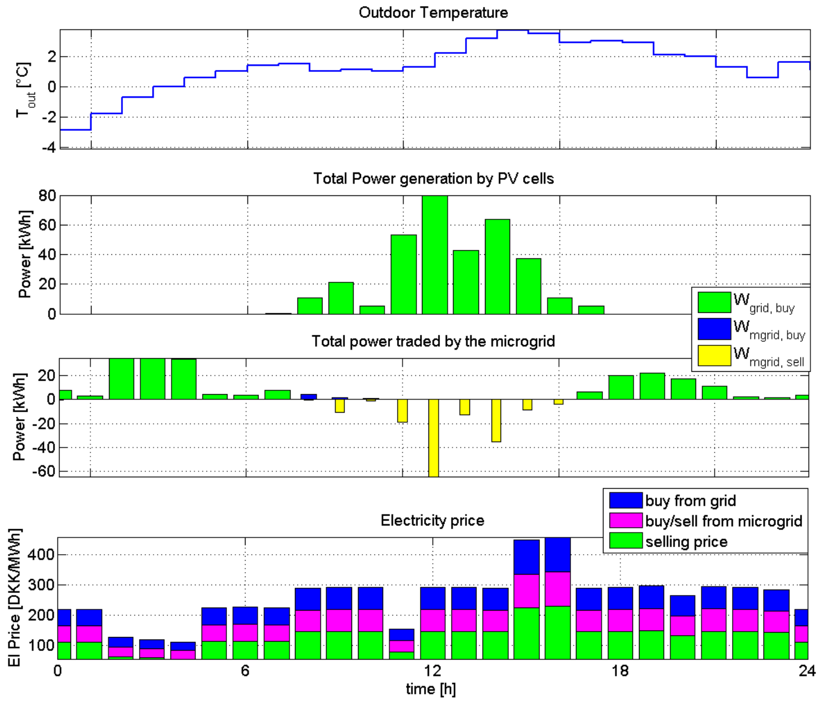

Figure 20. Outdoor temperature, total power generation by PV cells, power consumption and traded power

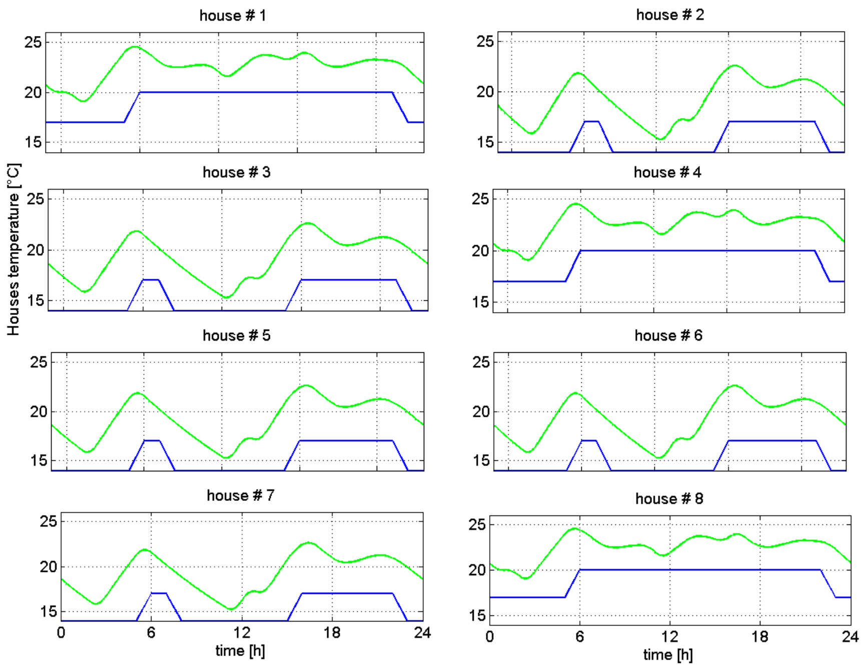

Figure 21. Indoor temperature variations of each house is shown

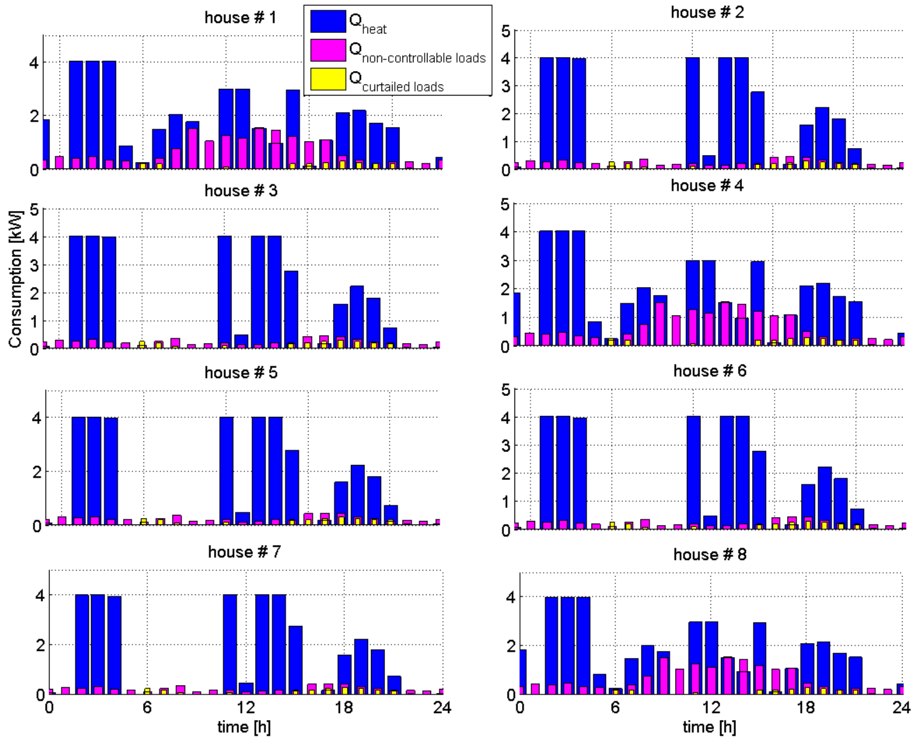

Figure 22. power consumption of houses' loads

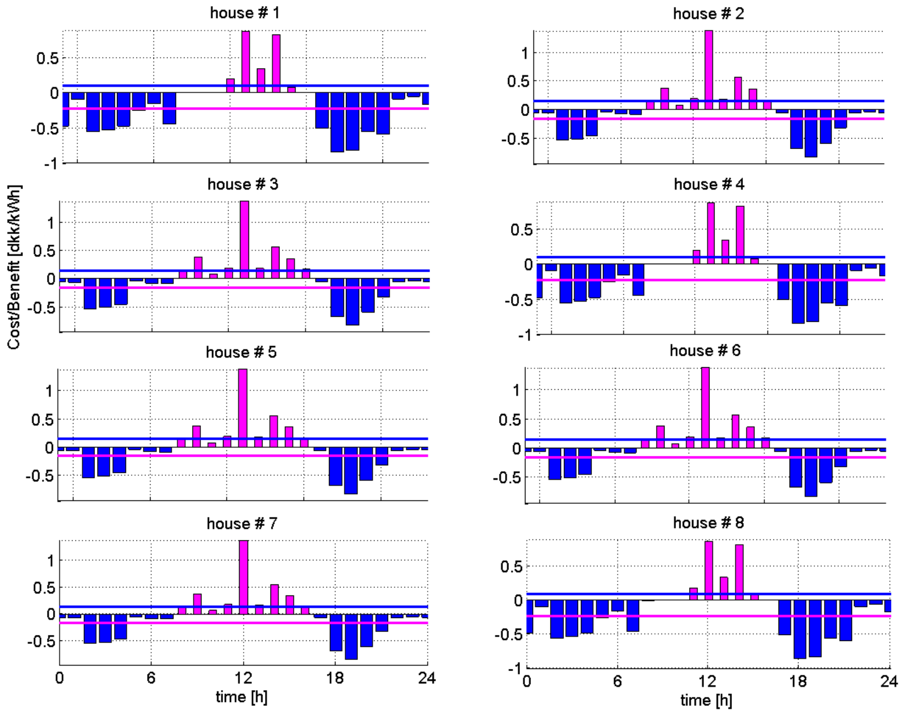

Figure 23. Power traded with the grid and within the microgrid. Average sold and purchased power is shown

Cost of consumption for house type 1 has been 0.88 EUR per day while it is 0.6 EUR per day for the type 2 house. Moreover, the monetary benefit of selling power is 0.30 and 0.45 for type 1 and 2 houses, respectively. In total, the cost benefit of more flexibility in type 2 compared to type 1 was 73% which is considerable. It is worth mentioning that the energy price does not include tax which is in fact a large share of power price in Denmark. Considering 70% tax the monetary benefit due to consumption shift will be negligible. However, in future a high rate of tax might be diminished in order to encourage consumers to be flexible.

7. Conclusion

The deliverable describes a hierarchical control structure as an energy management system of a microgrid. MPC in the building-level works in combination with device layer controllers by supplying them with control references. It is shown that this building-level MPC controller are robust with respect to variation in the dynamic features of the house. Because of that, it should be relative easy to deploy the controller in large set of not equal houses.

The microgrid energy management control strategies have been tested by simulation. The test case it the Jadevej demonstrator. The results show that with reliable price predictions substantial savings in energy costs are obtainable for consumers which implement control strategies. It is shown that the saving depends on the flexibility of the houses. E.g. if the flexibility is increased then the saving increases considerably.

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