Application of Model Predictive Control for Active Load Management in a Distributed Power System With High Wind Penetration

Yi Zong, Daniel Kullmann, Anders Thavlov, Oliver Gehrke, and Henrik W. Bindner

***Abstract*—This paper introduces an experimental platform (SYSLAB) for the research on advanced control and power system communication in distributed power systems and one of its components-an intelligent office building (PowerFlexHouse), which is used to investigate the technical potential for active load management. It also presents in detail how to implement a thermal model predictive controller (MPC) for the heaters' power consumption prediction in the PowerFlexHouse. It demonstrates that this MPC strategy can realize load shifting, and using good predictions in MPC-based control, a better matching of demand and supply can be achieved. With this demand side control study, it is expected that MPC strategy for active load management can dramatically raise energy efficiency and improve grid reliability, when there is a high penetration of intermittent energy resources in the power system.**

***Index Terms*—Active load management, distributed power system, flexible consumption, model predictive control, wind power penetration.**

Nomenclature

CHP	Combined heat and power.
$C_{(k)}$	Dynamic price signal at sample time k.
CTSM	Continuous time stochastic modelling.
DERs	Distributed energy resources.
DGs	Distributed generators.
DR	Demand response.
H_p	Prediction horizon.
MPC	Model predictive control.
RMI	Remote method invocation.
$P_{heat-max}$	Maximum permitted electrical power consumption of heating units.
T_a	Ambient (outdoor) temperature.
T_i	Indoor air temperature.
T_{i-max}	Set-point of the maximum indoor air temperature.
T_{i-min}	Set-point of the minimum indoor air temperature.
T_{im}	Temperature of the heat accumulating layer in the inner walls and floor.
T_i^k	Predictive indoor temperatures at each sample time k over the prediction horizon H_p.
$T_i^{(k/k)}$	Actual indoor temperature at sample time k.
$T_i^{(k/k-1)}$	Previous (at last sample time $k-1$) predictive indoor temperature (at next sample time k).
$T_i^{(k+H_P/k)}$	Predictive indoor temperature at the end of the predictive horizon.
T_{om}	Temperature of the heat accumulating layer in the building envelope.
T_{ref}	Reference indoor temperature.
Φ_s	Solar irradiation.
Φ_h	Energy input from the electrical heaters.
$\boldsymbol{u}_{(k)}$	Optimized heat input sequence at sample time k.

Manuscript received December 03, 2010; revised June 20, 2011; accepted November 12, 2011. Date of publication February 10, 2012; date of current version May 21, 2012. This work was supported by Interreg IV A program, project "Wind in Oresund" with Lund University, Technical University of Denmark-department IMM & CET, DTU and Risø DTU. Paper no. TSG-00391-2010.

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Digital Object Identifier 10.1109/TSG.2011.2177282

I. Introduction

THE REDUCTION of CO_2 emissions and the introduction of generation based on renewable sources become important topics at present. Wind power will cover 50% of the Danish electricity consumption in 2025 according to Energinet.dk [1], and the Danish government has set a long term target of achieving a Danish energy supply based on 100% renewable energy from combinations of wind, biomass, wave and solar power in 2050 [2]. The electric power system of Denmark exhibits some unique characteristics. Since 1980s, the Danish power system has been evolving from a centralized to a very much distributed system, due to increased penetration of wind turbines and distributed generators (DGs), such as combined heat and power (CHP). Most of these DGs are connected to the network at the distribution level. However, as most of the renewable sources (wind and solar) of electricity are intermittent, their contribution to the grid is limited, unless the grid is flexible enough to absorb the variations from these sources.

To integrate such a high share of intermittent resources into the energy system, especially the electricity supply, it places

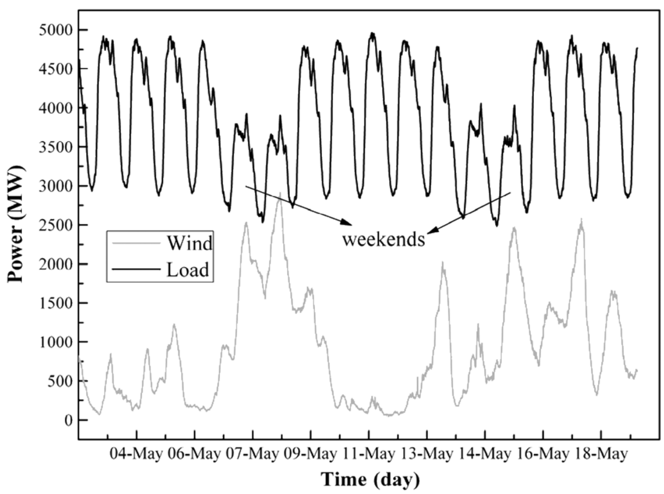

Fig. 1. Load and wind power variations (data source: Energinet.dk).

strong demands on flexibility elsewhere in the system. Fig. 1 shows power consumption and wind power generation in Denmark over a period of 16 days. It is shown that the load has a daily and weekly pattern with some stochastic variations and the wind power varies stochastically as well, but having no correlation with the load. Both the lack of correlation and the stochastic nature of the wind power put very strong requirements for flexibility on the rest of the system [3]. Traditionally, there has been a separation between the production and consumption of electricity: Consumption has been regarded a passive part of the system with respect to control, and therefore any generation mismatch caused by variations in renewable energy production has had to be compensated by other generating units. Furthermore, the introduction of new, energy-efficient technologies such as electrical cars can result in even more fluctuating electricity consumption. Lowering and shifting the peak loads is desirable to prolong the usage of the available grid capacity. In recent years, it has been realized that there is a large potential for additional flexibility in the control of power systems by enabling the active participation of the consumption side in the balancing of power supply and demand. Therefore, there is a great need to investigate how flexible consumption should be implemented, seen from the perspective of power system control as well as from that of a consumer. Any such system should be integrated with the rest of the power grid's control system—probably by means of an aggregation mechanism and a market for system services.

The introduction of distributed energy resources (DERs) together with the introduction of more information and communication technology in the electricity system provides interesting and novel automated demand response (DR) opportunities at the domestic user level. Household thereby becomes more active end-users of electricity. The two-way communication capability in the smart grid allows widespread deployment of "demand response" technologies and programs thereby allowing the load to adjust to supply variations. In order to gain acceptance, the user's needs should be met without much noticeable compromise on perceived comfort. Ideally, the user would stay in control while providing flexibility to the grid. A wide body of literature states that how to activate the potential of ancillary services from DERs and DR, thereby exploiting their ability to contribute to power system operation [4]–[11], but most of their work was based on the simulation study.

MPC refers to a class of control algorithms that compute a sequence of manipulated variable adjustments over a future time horizon by utilizing a process model to optimize forecasts of process behavior based on a linear or quadratic open-loop performance objective, subjected to equality or inequality constraints [12]. Today many MPC algorithms have been developed to guarantee some fundamental properties, such as the stability of the resulting closed-loop system or its robustness with respect to a wide class of external disturbances and/or model uncertainties. Therefore, MPC is now recognized as a very powerful approach with well established theoretical foundations and proven capability to handle a large number of industrial control problems [13], [14]. MPC for building climate control has been investigated in several papers before [15]–[17], mainly with the purpose of increasing the energy efficiency. The potential of MPC in power management was investigated in [18], but the ambient temperature was assumed to be constant in its simulation scenarios.

The objective of our research is to implement a control methodology, which uses residential optimization potential to support the introduction of a large penetration level of renewable energy (especially wind) and optimize usage of the current distributed power grid capacity. In this work we give a more detailed description of model predictive control (MPC) strategy applied on an experimental facility (SYSLAB) to investigate technical potential of active load management. Compared to the aforementioned literature, the novel contributions of this work are: 1) implementation of a low-complexity MPC scheme which is used to realize the load shifting for the heaters' power consumption in PowerFlexHouse; 2) integration of weather forecast information and dynamic power price in the MPC-based control strategy; and 3) field test the MPC strategy on a real power grid with high penetration of wind power.

The remaining of this paper is organized as follows: in Section II we briefly introduce Risø's new test facility (SYSLAB) for intelligent, active and distributed power systems and one of its components—PowerFlexHouse. How to implement a thermal model predictive controller for the power consumption prediction in PowerFlexHouse is provided in Section III, including the description on a heat dynamic model for temperature prediction. Then, some results and analysis of running the MPC controller on SYSLAB test platform are shown in Section IV. Finally, conclusion is drawn in Section V, followed by the discussion on future research.

II. Experimental Facility-Syslab Description

Risø DTU has established a flexible platform for research in advanced control systems and concepts, power system communication and component technologies for distributed power systems-SYSLAB. It is built around a small power grid with renewable (wind, solar) and conventional (diesel) power generation, battery storage, and various types of consumers [19]. Currently components on the SYSLAB platform are listed as following (see Fig. 2):

- Gaia wind turbine (11 kW);
- Bonus wind turbine (55 kW);
- Diesel generator set (48 kW/60kVA);
- Solar panel (7 kW);

Fig. 2. Components in SYSLAB.

- Vanadium battery (15 kW/120kWh);
- Capacitor bank (46 kVAr);
- Back-to-back converter (30 kW/45kVA);
- Dump load (75kW);
- Office building-PowerFlexHouse (20 kW);
- Plug-in hybrid car (9 kWh).

The SYSLAB facility is spread across multiple locations at Risø DTU and its backbone is formed by a 400 V grid with several busbars and substations (see Fig. 3). A central crossbar switch with tap-changing transformers enables meshed operation and power flow control. All components on the grid—generators, loads, storage systems, switchgear—are automated and remote-controllable. Each component is supervised locally by a dedicated controller node. The node design combines an industrial PC, data storage, measurement and I/O interfaces, backup power, and an Ethernet switch inside a compact, portable container. All nodes are interconnected via redundant high speed Ethernet, in a flexible setup permitting on-line changes of topology and the simulation of communication faults. The whole system can be run centrally from any point on the network, or serve as a platform for fully decentralized control [20]. All SYSLAB controller nodes run the SYSLAB software stack, which is a modular framework for developing distributed control systems for power systems. It is written in the Java (TM) programming language. Each physical SYSLAB component is controlled by a software module designing on one of the SYSLAB nodes. Distributed controllers can control these components by using one of the supported types of communication. The one most used is the Java RMI (Remote Method Invocation) system.

One of the components on the SYSLAB grid is a small, intelligent office building, PowerFlexHouse. It contains seven offices, a meeting room, and a kitchen. Each room is equipped with a motion detector, temperature sensors, light switches, window and door contacts, and actuators. A meteorology mast outside of the building supplies local environmental measurements of ambient temperature, wind speed, wind direction, and solar irradiation. The electrical load of the building consists of heating, lighting, air-conditioning, a hot-water supply, and various household appliances, such as a refrigerator and a coffee machine. The combined peak load of the building is close to 20 kW. All individual loads in the building are remote-controllable

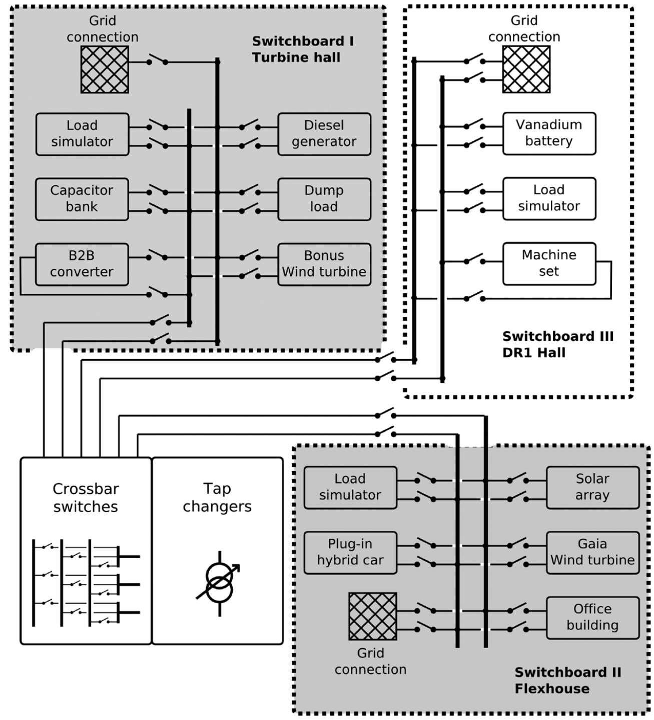

Fig. 3. Layout of SYSLAB.

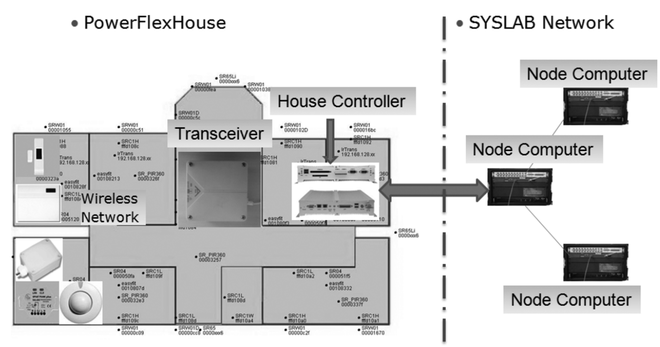

Fig. 4. Communication between PowerFlexHouse and SYSLAB.

from a central building controller. The controller software runs on a Linux-based PC. It is written in Java (TM) and is based on the SYSLAB software stack. The controller software consists of several modules working together. The hardware module collects data from the sensors and sends commands to the actuators. It does this via serial port (communication with the meteorology mast), modbus (switchboard instruments), and wireless transceivers (Enocean and infrared). The database module collects all sensor measurements and all commands sent to the actuators for further analysis. Another module collects data from external sources: the Nord Pool power price, the local weather forecast data, and some state information from the Danish power system. Finally, the controller module supports the development of any kind of controller algorithm for the PowerFlexHouse. The controller is able to communicate with the SYSLAB grid through its own node computer (See Fig. 4). Information can also flow in the other direction, for example providing the power system controller with the expected near-future behavior of the building loads.

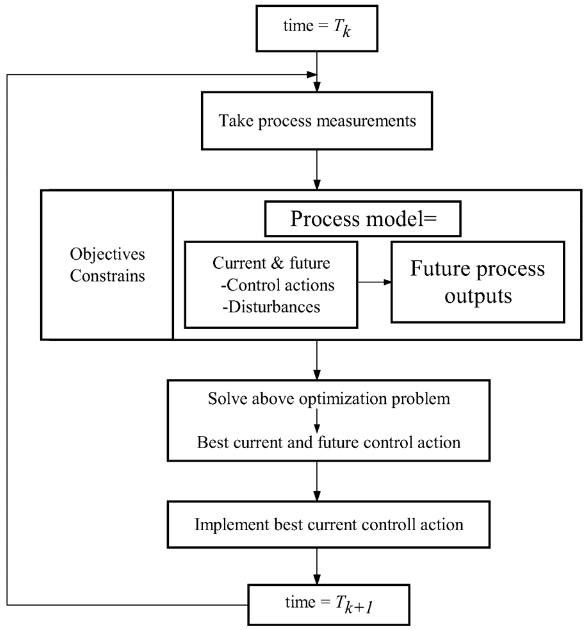

Fig. 5. Model predictive control scheme.

III. MPC Controller For Load Shifting In PowerFlexHouse Heating Strategy

One of the main energy consumption in northern Europe is the electrical heating in the long winter. Heaters are designated as one of the most obvious areas of flexible consumption or demand response. Due to the prediction horizon, an MPC controller can take benefit of knowledge over the future, such as predictive energy demand and it was selected to realize the load shifting for heating in PowerFlexHouse. The objective of this project is to minimize the daily operational cost of heating and provide ancillary services for the power system. Fig. 5 presents the model predictive control scheme.

The main principle of MPC is to transform the control problem into an optimization one and solve this optimization problem over a prediction horizon at each sample time, subjected to system dynamics, an objective function (linear or quadratic), and constraints on states, actions and inputs. At each control step the optimization obtains a sequence of actions optimizing expected system behavior over the prediction horizon. Only the first step of the sequence of control actions is executed by the controller on the system until the next sample time, after which the procedure is repeated with new process measurements [21]. The following subsections describe in detail the prediction model, objective function and control law, which are three important components for MPC algorithm.

A. Thermal Predictive Model For PowerFlexHouse

The indoor temperature model of PowerFlexHouse is given as a stochastic discrete-time linear state-space model, which was directly obtained from [22]. The heat flow in PowerFlexHouse is modeled by a gray-box approach, using physical knowledge about heat transfer together with statistical methods to estimate model parameters. To reduce the complexity, the model of heat dynamics of the PowerFlexHouse is formulated as one large room exchanging heat with an ambient environment. That is to say, we regard the 8 rooms in PowerFlexHouse building as one large room. Heat transfer due to conduction, convection and ventilation is assumed linear with the temperature difference on each side of the medium. When assuming these properties, the heat model can be formulated as an equivalent electric circuit with resistors and capacitors (an RC-circuit), where potential differences are equal to temperature differences and flow of charge equals heat flow. In such a circuit, the resistors can be regarded as resistance to transfer heat and the capacitors as heat storage. The equivalent RC-circuit for the heat dynamic model is shown in Fig. 6. In Fig. 6 the parameter p means a percentage of the solar irradiation, which is absorbed by the inner walls and the rest is absorbed by the indoor air. Based on four time series collected in PowerFlexHouse in the first quarter of 2008, the parameters in Fig. 6 were estimated using maximum likelihood estimation. The estimator was continuous time stochastic modelling (CTSM), which is an estimation tool developed at IMM DTU [23].

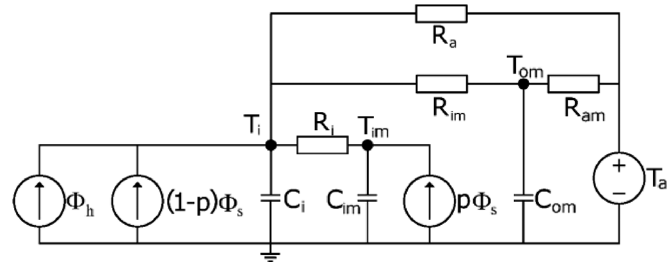

Fig. 6. Equivalent RC-circuit for the heat dynamic model.

The control object is the indoor air temperature T_i. The state-space equations were expressed in (1) and (2):

$$T(\mathrm{t}+1) = \Phi T(\mathrm{t}) + \Gamma U(\mathrm{t}) \quad (1)$$

$$\mathrm{Output}: \mathrm{y}(t) = CT(\mathrm{t}) = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} T_i(t) \\ T_{im}(t) \\ T_{om}(t) \end{bmatrix}. \quad (2)$$

Φ is the system matrix [3 × 3]. Γ is the control matrix [3 × 3]. $T = [T_i, T_{im}, T_{om}]$ is the state vector and $U = [T_a, \Phi_s, \Phi_h]$ is the input vector to the system. Here, $T_i(t)$ is the indoor air temperature; $T_{im}(t)$, and $T_{om}(t)$, which are the temperature of the heat accumulating layer in the inner walls and floor, and the temperature of the heat accumulating layer in the building envelope. T_a is the ambient (outdoor) temperature; Φ_s is the solar irradiation; and Φ_h is the energy input from the electrical heaters. Among them, $T_{im}(t)$ and $T_{om}(t)$ cannot be measured and state estimator-Kalman filter can be used to estimate these two states.

B. MPC Objective Function

The goal of the MPC control strategy for the electrical space heaters in PowerFlexHouse is to minimize the total cost of the energy used in heating over a prediction horizon (H_p). At the same time, it should keep the indoor air temperature close to the given reference temperature T_{ref}. The objective function can be formulated as

$$J = \min \left[\sum_{k=0}^{H_p-1} C_{(k)} \times u_{(k)} + \sum_{k=0}^{H_p-1} w \times \left| T_i^k - T_{\mathrm{ref}} \right| \right] \quad (3)$$

Subject to: $u_{(k)} \in int[0,1,2,3,4,5,6,7,8,9,10]$ in kW, which means the heat input that the MPC controller determines by using a mixed integer optimization approach. There are totally

10 heaters in the PowerFlexHouse. Each of them has a power of 1 kW. Therefore the maximum permitted electrical power consumption of heating units is $P_{\text{heat}-\max} = 10 \times 1\ \text{kW} = 10\ \text{kW}$. The weight coefficient w in (3) is used to tune performance of the MPC controller. In (3), $C_{(k)}$ is the dynamic power price signal obtained from the Nord Pool spot market [24]. The Nordic electricity market is well-known for its efficient market function. The central market is the Nord Pool spot market, which is owned by the four Nordic Transmission System Operators (Statnett SF, Svenska Kraftnätt, Fingrid, and Energinet.dk) and where a daily competitive auction establishes a price for each hour of the next day. The trading horizon is 12–36 h ahead and is done for the next day's 24-h period. That is to say, the minimum prediction horizon is at least 12 h and the actual maximal prediction horizon can reach 36 h. In the Nordic system, during the night, there is a large production by wind turbine. It can be expected that sometime the price variation reflects the level of wind power penetration.

C. MPC Control Strategy

For the purpose of flexible consumption, there is a temperature set-point margin for the consumer to choose via a user interface. For example, when the wind energy production is low, the heaters will work at the lower temperature limit, otherwise, they will be set up to the upper limit. Only when the indoor air temperature is in the range of $[T_{\text{i}-\min} T_{\text{i}-\max}]$, the MPC control algorithm is executed. In addition, the local forecast data of the ambient (outdoor) temperature T_a and the solar irradiation Φ_s are updated twice a day for the next 48 h, which are provided by the meteorology group in Wind Energy Division at Risø DTU. The maximum relative error between the actual weather measurement and the weather forecast data is $\pm 5\%$ on test. Therefore, we concluded that the local weather forecast data are available to be integrated into the MPC-based control strategy.

First, the controller output is initialized by the vector of dimension $1 \times H_p$, $\boldsymbol{u}_0 = [u_0, \ldots, u_{Hp-1}]$, containing the input variables of the plant which are optimized. However, the initialization of the algorithm assumes that the heating units are switched off, $\boldsymbol{u}_0 = [0, \ldots, 0]$. By this way, the search direction is always positive and the optimization speed can be accelerated. Second, the difference between the predictive indoor air temperature at the end of the predictive horizon and the desired T_{ref} is evaluated at each control step. If this difference is small enough to be acceptable: $|T_i^{(k+H_P/k)} - T_{\text{ref}}| \le \varepsilon$, an optimal solution is achieved and only the first element of the controller output sequence (u_0) is used to control the process. At the next sample $(k+1)$, the whole procedure is repeated. Otherwise, the first element of the controller output sequence with the maximum or minimum power consumption of the heating units is used to control the process ($u_0 = P_{\text{heat}-\max}$ or $u_0 = 0$). Finally, to overcome the model's error, here we use the process's real-time output and model's (previous) predictive output to structure one model output feedback correction (see Fig. 7). [25].

The detailed MPC control law is described as follows:

Step 1: Initialization step. $\boldsymbol{u}_0 = [u_0, \ldots, u_{Hp-1}]$, where H_p is the prediction horizon, $\boldsymbol{u}_0 = 0$.

Step 2: At current time k, measure the current indoor air temperature $T_i^{(k/k)}$ and compare it with the previous predictive value $T_i^{(k/k-1)}$ to obtain the predictive error $e = T_i^{(k/k)} - T_i^{(k/k-1)}$.

Step 3: Calculate the optimal control sequence that minimizes the objective function.

$$\left\{\boldsymbol{u}_{(k)} = [u_0, \ldots, u_{Hp-1}]\right\} = \arg$$
$$J = \min \left[\sum_{k=0}^{H_p-1} C_{(k)} \times u_{(k)} + \sum_{k=0}^{H_p-1} w \times \left|T_i^k - T_{\text{ref}}\right| \right].$$

Use the model to predict the indoor air temperature at each sample time k over the prediction horizon H_p.

$$T_i^k = \left[T_i^{(k+1/k)}, \ldots T_i^{(k+i/k)} \ldots, T_i^{(k+H_p/k)}\right],\ 1 \le i \le H_p$$

and correct the predictive value to $T_i^k + e$.

If $|T_i^{(k+Hp/k)} - T_{\text{ref}}| \le \epsilon$ and $\forall T_i^{(k+i/k)}, T_{i-\min} \le T_i^{(k+i/k)} \le T_{i-\max}$, where $1 \le i \le H_p$ and ϵ is a small number.
Go to step 4.
else
if $\forall T_i^{(k+i/k)}, T_i^{(k+i/k)} \ge T_{i-\max}$, where $1 \le i \le H_p$

$$u_o = 0$$

else

$$u_0 = P_{heat-max} = 10$$

end if
end if

Step 4: Apply u_0 to heating units.
Next sample, update $k := k+1$, and repeat from step 2 to step 4.

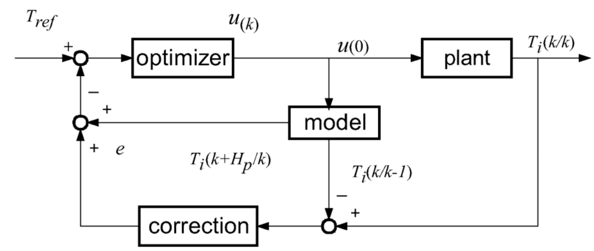

Fig. 7. Block diagram of PowerFlexHouse's MPC.

When we test this MPC controller on the SYSLAB platform, it employs a control step of 10 min. It means that every 10 min, the controller determines which control action to take at the current time. First of all, the MPC controller obtains a measurement of the current state of the house, including the disturbances like the state of doors and windows, and the grid information, such as dynamic power price signal, available power and frequency signal from the test platform SYSLAB. To find the best predicted performance over the prediction horizon, the mixed-integer linear programming problem is solved by GLPK's (GNU Linear Programming Kit) solver with Java native interface [26]. Then it integrates the weather forecast data (ambient temperature and solar irradiation, etc.) with the prediction model for the house indoor temperature, and verifies the predictive values. At

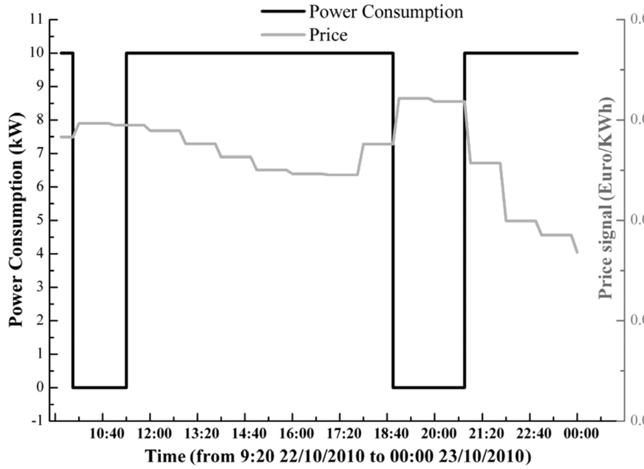

Fig. 8. Optimized predictive power consumption in the next 15 h.

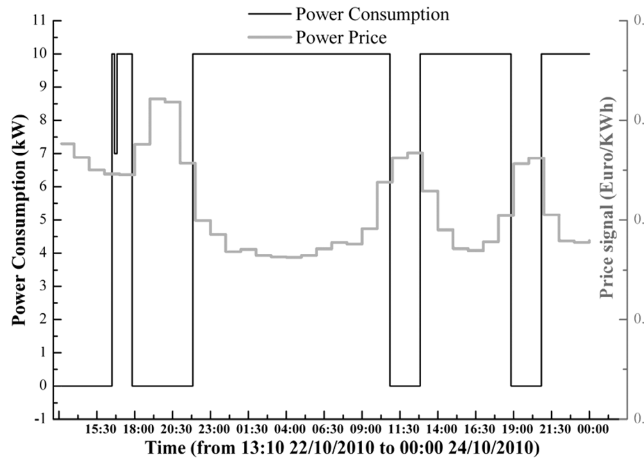

Fig. 10. Optimized predictive power consumption in the next 35 h.

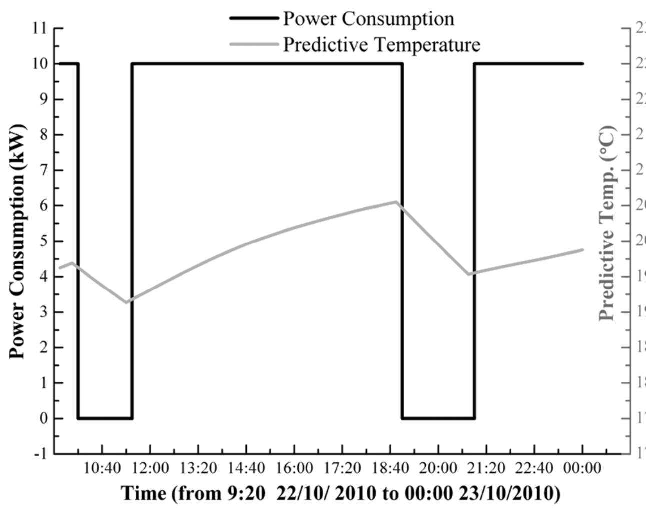

Fig. 9. Predictive indoor air temperature in the next 15 h.

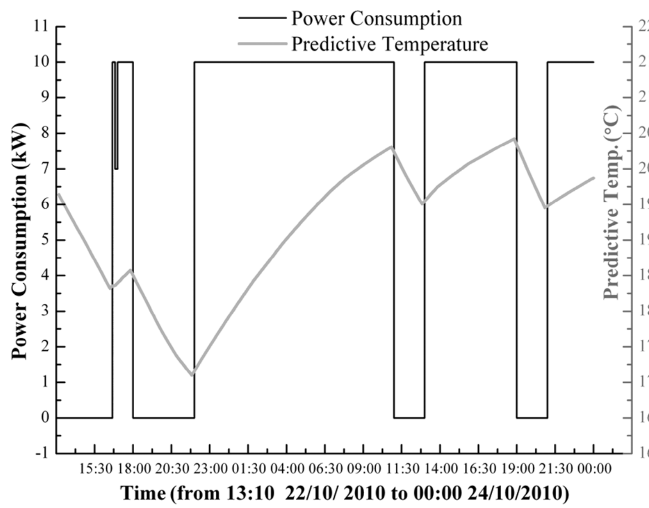

Fig. 11. Predictive indoor air temperature in the next 35 h.

last, only the first step in the found best sequence of actions is executed.

IV. Results

We obtained some results from the field test on October 22-24, 2010. At 9:20 the MPC control algorithm was running on the SYSLAB platform and it provided the optimized profile of the predictive power consumption in the next approximately 15 h for the PowerFlexHouse's heaters, as shown in Fig. 8. Fig. 9 demonstrates the predictive indoor air temperature in the next 15 h according to the optimized switch schedule (the same as in Fig. 8). At 13:10, the MPC produced the results shown in Fig. 10. It presents the optimized profile of the predictive power consumption in the next almost 35 h for the PowerFlexHouse's heaters. At this moment, the prediction horizon could reach 35 h, because the Nord Pool spot market at 13:00 (on the same day) provided next day's 24 h price information for the users. The predictive indoor air temperature in the next 35 h is shown in Fig. 11, according to the optimized switch schedule (the same as in Fig. 10) for heaters in PowerFlexHouse. It can be observed in Fig. 11 that during a few hours the predictive temperature dropped to 17 ^{circ}C. Comparing Fig. 9 with Fig. 11, it can be found that the shorter the prediction horizon the better the predictive control effect. We could tune MPC performance by penalizing this temperature deviation with different weight coefficient values w in (3). Otherwise, users will have some discomfort if they would like to accept a reduced energy bill and allow this deviation on the room temperature. Compared with one thermostat controller, it was observed that the MPC-based controller almost worked within the low price period and it was able to shift the load and reduce the total cost of operating electrical heaters to meet certain indoor temperature requirements.

The hours when the maximum and minimum spot prices occur in 2010 (data source: Nord Pool) are presented in Fig. 12 and Fig. 13 respectively. There is certain predictability in the occurrence of peak load periods during the day, and this predictability is reflected in the hourly spot price. In Fig. 12, the peak load periods and high spot prices occur mainly in the same hours of the day (morning 8:00-11:00 and afternoon 17:00–20:00), because in the morning the main loads are from the industries and offices; and in the afternoon from 17:00-20:00 it is rush time to cook and amuse at home in Denmark. Fig. 13 illustrates the low spot prices take place in the deep of night, due to industries and domestic users shut down most of their consumption at night while the wind turbines are still producing roughly amount of energy. Fig. 8 and Fig. 10 illustrate that MPC control strategy can achieve energy savings by shifting load from on-peak to off-peak period. According to [27], it is concluded that the spot price, generally decreases when the wind power penetration in the power system increases, that is

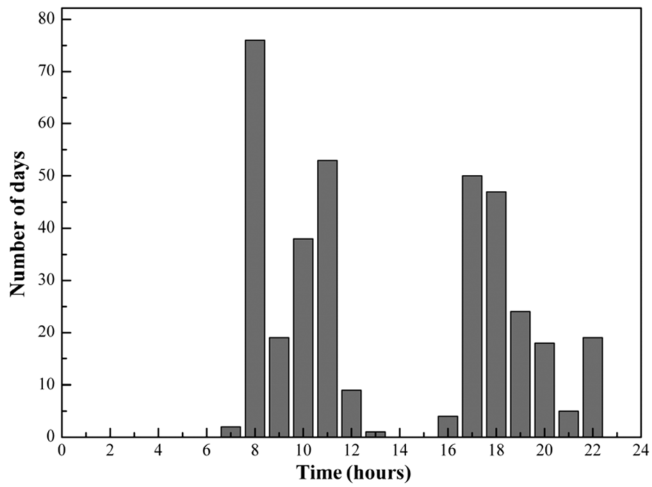

Fig. 12. Histogram of the occurrence of maximum spot prices in 2010 from Nord Pool.

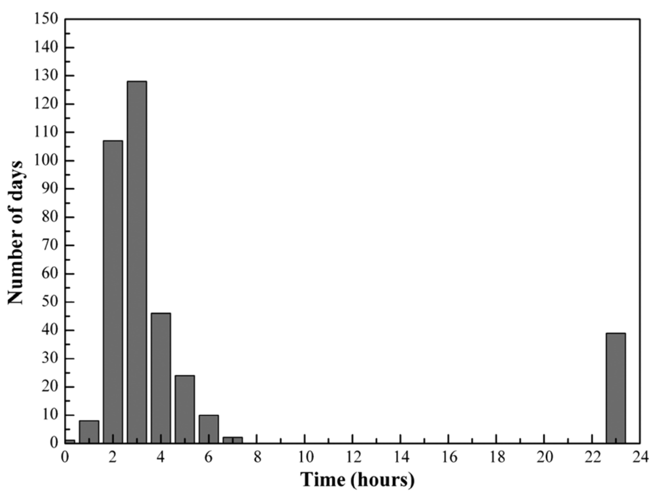

Fig. 13. Histogram of the occurrence of minimum spot prices in 2010 from Nord Pool.

to say, the Nordic Electricity spot prices reflect the amount of wind power in the system. At the same time, it shows that MPC control strategy can be investigated on active load management in this intelligent house, which is used to stabilize fluctuations in the power grid with a high penetration of wind power and other renewable energy.

V. Conclusion And Future Research

Flexible consumption must be established in order to enable more use of renewable energy in power system. The predictive behavior of power consumption for Power FlexHouse's heaters shows that the MPC strategy is feasible for active load management of intelligent houses in a distributed power system with high wind penetration. Using dynamic power prices and integrating the weather forecast data, it demonstrates that the MPC control strategy is able to shift the electrical load to periods with low prices. Residential customers can avoid high electricity price charge at peak time, and the power grid can benefit from load control. It also shows that the local (within the house) MPC controller can result in a generic solution supporting different technologies and houses with different optimization potential, which can provide services for the global controllers (aggregators) in a scope of a group of houses, e.g., a neighborhood (micro grid) or a global scope (virtual power plant). The load in a power grid is widely seen as one of the keys to achieving additional operational flexibility to ensure the stability of the grid as penetration levels rise. However, in comparison with the actual power system presented within the SYSLAB, it shows that the efficient use of load management demands a tight integration with the control system of the power grid.

Future work should be focused on the different optimization methods, analyzing the effect of the predictive horizon length on the performance in the MPC controller, and the robustness of this MPC controller against uncertainty in measurements and prediction. Furthermore, a multiagent MPC should be taken into account to find an acceptable near-optimal solution for the whole distributed power system.

Acknowledgment

The authors would like to express their appreciation to Andrea N. Hahmann, Senior Scientist, from Wind Energy Division, Risø DTU National Laboratory for Sustainable Energy, for her work on providing us with the local weather forecast data.

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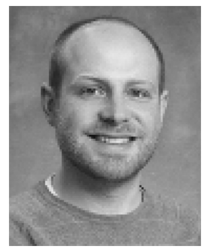

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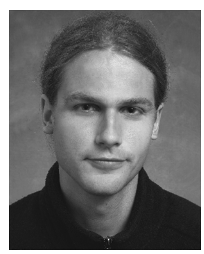

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