Model Predictive Controller for Active Demand Side Management with PV Self-consumption in an Intelligent Building

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***Abstract*—This paper presents a Model Predictive Controller (MPC) for electrical heaters' predictive power consumption including maximizing the use of local generation (e.g. solar power) in an intelligent building. The MPC is based on dynamic power price and weather forecast, considering users' comfort settings to meet an optimization objective such as minimum cost and minimum reference temperature error. It demonstrates that this MPC strategy can realize load shifting, and maximize the PV self-consumption in the residential sector. With this demand side control study, it is expected that MPC strategy for Active Demand Side Management (ADSM) can dramatically save energy and improve grid reliability, when there is a high penetration of Renewable Energy Sources (RESs) in the power system.**

***Index Terms*— Active demand side management; load shifting; model predictive control; solar/wind power penetration**

NOMENCLATURE

Abbreviation:

ADSM Active demand side management.
CPS Conventional power supply.
DERs Distributed energy resources.
DG Distributed generation.
DSM Demand side management
DTU Technical university of Denmark.
MPC Model predictive control.
RESs Renewable Energy Sources.
RMI Remote method invocation.
RPS Renewable power supply.

Variables & Parameters:

FF Fill factor.
G_a Solar irradiation.
H_p Prediction horizon.
I_o Open-circuit currents.
I_{sc} Short-circuit currents.
n_s Number of cells in the panel connected in series.
n_{ps} Number of panels in series.
n_{sp} Number of strings in parallel.
$P_{C(k)}$ Dynamic power price signal of CPS at control step k.
$P_{heat-max}$ Maximum permitted electrical power consumption of heating units.
P_{max} Maximum power point of a solar cell.
$P_{R(k)}$ Dynamic power price signal of RPS at control step k.
R_s Cell series resistance.
T_a Ambient (outdoor) temperature.
T_c Cell temperature.
T_i Indoor air temperature.
T_i^k Predictive indoor temperatures at each control step k over the prediction horizon H_p.
T_{im} Temperature of the heat accumulating layer in the inner walls and floor.
T_{om} Temperature of the heat accumulating layer in the building envelope.
T_{ref} Reference indoor air temperature.
V_{oc} Open circuit voltage.
V_T Junction thermal voltage.
W_s Wind speed.
Φ_h Energy input from the electrical heaters.
β_I Correction coefficients for current.
χ Correction coefficients for voltage.
$\boldsymbol{u}_{(k)}$ Optimized heat input sequence at control step k.
$\boldsymbol{u}_{s(k)}$ Predictive solar power at control step k.
ΔT Absolute temperature.

I. INTRODUCTION

TO MEET the rapidly increasing demand of the energy consumption, and to achieve a significant reduction in CO_2 emissions, more Renewable Energy Sources (RESs), and other low-carbon energy sources will become major contributors to the future electricity system. The Danish government has adopted a long term goal that the Danish energy system (including transport) can be completely independent of fossil fuels by 2050 without using nuclear energy, based on 100% renewable energy from combinations of wind, biomass, solar power and wave [1], and wind power will cover 50% of the Danish electricity consumption in 2025 [2].

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Due to an increased contribution of fluctuating RESs to the energy system, there are many concerns about the flexibility, variability, non-controllability of these sources, and they have the impact on the ability to keep the balance between supply and demand. Currently, the main method to regulate the supply-demand imbalance is a set of supply-side generation reserves, known as ancillary services, which operate on various scales of time and frequency. The rising share of RESs decreases the controllability of the supply side. The rise in needed balancing power can be fulfilled by utilizing the flexibility potential in demand and Distributed Generation (DG). The introduction of Distributed Energy Resources (DERs) (e.g. household, industrial consumers and electric vehicles), together with the introduction of more information and communication technology in the electricity system provides interesting and novel automated Demand Side Management (DSM) opportunities at the end user level. The combination of DSM with an automatic control of the DERs demand can be called as Active Demand Side Management (ADSM) [3, 4]. ADSM can modify the demand profile to reduce the losses in the grid, maximize consumption while RESs are available, decrease congestions, and save energy [5, 6].

MPC is a control algorithm that optimizes a sequence of manipulated variable adjustments over a prediction horizon by utilizing a process model to optimize forecasts of process behavior based on a linear or quadratic objective, which is subjected to equality or inequality constraints. In MPC, the optimization is performed repeatedly *on-line*. This is the meaning of receding horizon, and the intrinsic difference between MPC and the traditional optimal control. The limitation of this finite-horizon optimization is that, under ideal situations only the suboptimal solution for the global solution can be obtained. However, the receding horizon optimization can effectively incorporate the uncertainties incurred by model-plant mismatch, time-varying behavior and disturbances [7]. 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 [8]. The building sector is one of the largest energy consumptions. Based on the vision of the future electricity system, building controls design becomes challenging since it is necessary to move beyond standard controls approaches and to integrate predictions of weather, occupancy, renewable energy availability, and dynamic power price signals. MPC naturally enters the picture as a control algorithm that can systematically incorporate all the aforementioned predictions to improve building thermal comfort, decrease peak load, and reduce energy costs [9]. MPC for building climate control has been investigated in several papers before [9]-[13], mainly with the purpose of increasing the energy efficiency. The potential of MPC in power management was investigated in [14]-[18], but the weather forecast information (e.g. the ambient temperature) was assumed to be constant in their simulation scenarios.

The goal of our research is to implement an MPC-based control strategy for ADSM, using DERs' predictive optimization potential to support the introduction of a large penetration level of renewable energy. In this paper, an MPC controller was implemented for load shifting in an intelligent office building's heating power consumption scheme, with a maximization of the PV self-consumption. The term "self-consumption" focuses on the usage of the own generated energy, while the energy provided by the grid remains an optional generator. The original contributions of this work are: 1) building an easy, fast to implement model for PV installed at an intelligent building (called PowerFlexHouse), and a stochastic discrete-time linear state-space model for this building; 2) implementing a low-complexity MPC-based scheme which is used to realize the load shifting for the heaters' power consumption, including PV maximum self-consumption in PowerFlexHouse; 3) integrating weather forecast information and dynamic power price into the MPC-based control strategy; and 4) simulating and testing an MPC controller on a real power grid with high penetration of RESs.

The remaining of this paper is organized as follows: in Section II, we present a test platform for intelligent, active and distributed power systems at the Technical University of Denmark (DTU), Risø campus. How to implement a thermal MPC controller for the power consumption prediction in an intelligent building-PowerFlexHouse is provided in Section III, including a simple PV model for solar power prediction, a heat dynamic model for PowerFlexHouse's inside temperature prediction, and formulated MPC objective functions. Some field test results will be shown in Section IV. Finally, conclusion is drawn in Section V, followed by the discussion on future research.

II. Test Platform Description

SYSLAB is a laboratory for intelligent distributed power systems [19] in DTU Elektro, Risø campus. It is built around a small power grid with renewable (wind (11+10kW), solar (7kWp)) and conventional (diesel) power generation, battery storage, and various types of consumers (See Fig. 1). The whole system can be run centrally from any point on the network, or serve as a platform for fully decentralized control. 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. Distributed controllers can control these components by using one of the supported types of communication, for example, the Java Remote Method Invocation (RMI).

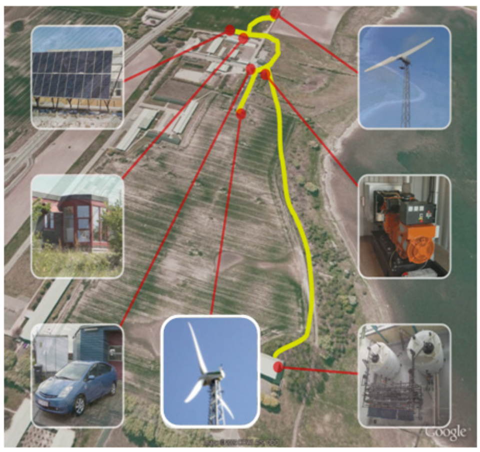

Fig. 1. Components on SYSLAB.

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 weather station 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 20kW. All individual loads in the building are remote-controllable from a central building controller. The controller software runs on a Linux-based PC. It is also written in Java (TM) and is based on the SYSLAB software stack. The controller can communicate with the SYSLAB grid through its own node computer (See Fig. 2). Information can also flow in the other direction, for example providing the power system supervisor controller with the expected near-future behavior of the building loads.

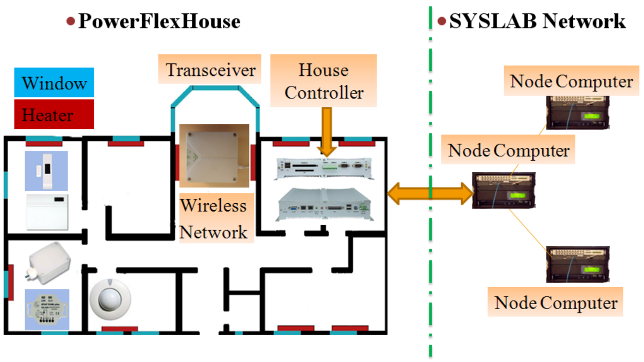

Fig. 2. Communication between PowerFlexHouse and SYSLAB.

III. MPC FOR ADSM IN AN INTELLIGENT BUILDING'S HEATING POWER CONSUMPTION

As described in Section II, the hybrid power supply system (SYSLAB) presented in this paper consists of two parts: a Conventional Power Supply (CPS), and a Renewable Power Supply (RPS). To use the power system efficiently, one of the good ways is to take the advantage of renewable power supply in a maximum degree. Therefore, home appliances primarily use RPS, and CPS is used when RPS is not enough to support the power required by the home appliances. We suppose that RPS has a low cost of power than CPS, considering its generation and CO_2 impact, etc. We denote the dynamic power prices of CPS and RPS by P_C and P_R, respectively. In this paper, to realize the load shifting, we use an MPC control strategy to minimize the daily operational cost of heating in PowerFlexHouse, at the same time to ensure the maximum self-consumption of solar power produced at PowerFlexHouse, and to guarantee users' comfort. There are three important components in MPC, such as the prediction model, the objective function, and the control law, which are present as following.

A. PV Model

We use a single diode equivalent circuit for the PV model described by a simple exponential equation:

$$i = I_{sc} - I_o \cdot \left(e^{(v + i \cdot R_s)/n_s \cdot V_T} - 1 \right) \qquad (1)$$

where I_{sc} and I_o are the short-circuit and open-circuit currents, R_s is the cell series resistance, n_s is the number of cells in the panel connected in series, and V_T represents the junction thermal voltage, which includes the diode quality factor, the Boltzmann's constant, the temperature at standard condition and the charge of the electron.

A solar cell can be characterized by the following fundamental parameters: the short circuit current I_{sc}, the open circuit voltage V_{oc}, the maximum power point P_{max} and the fill factor FF, which is the ratio of the maximum power that can be delivered to the load and the product of I_{sc} and V_{oc} ($FF = \frac{P_{\max}}{V_{oc} I_{sc}} = \frac{V_{\max} I_{\max}}{V_{oc} I_{sc}}$). The fill factor can be taken from the manufactures' data. Then it can be used to obtain P_{max} ($P_{\max} = FF \times V_{oc} I_{sc}$) under non-standard conditions.

Equations for I_{sc} and V_{oc} as a function of absolute temperature ΔT including temperature coefficients (β_I, χ: correction coefficients for current and voltage) that provide the rate of change with respect to temperature of the PV performance parameters, can be expressed as:

$$\begin{aligned} I_{sc} &= I_{sc25} \cdot (1 + \beta_I \cdot \Delta T) \\ V_{oc} &= V_{oc25} \cdot (1 + \chi \cdot \Delta T) \\ \Delta T &= T_c - T_a \end{aligned} \qquad (2)$$

To complete the model it is also necessary to take into account the variation of the parameters with respect to irradiance:

$$I_{sc} = I_{sc25} \cdot (G_a / 1000) \qquad (3)$$

Using a four-parameters model of a single diode equivalent circuit, the v-i characteristics for a solar panel string depending on irradiance and temperature has the following expressions:

$$v = n_{ps} \cdot V_{oc} + n_{ps} \cdot n_s \cdot V_T \cdot \ln\left(1 - i/(n_{sp} \cdot I_{sc25} \cdot G_a / 1000)\right) \quad (4)$$

$$i = n_{sp} \cdot I_{sc} \cdot \left(1 - e^{(v - n_{ps} \cdot V_{oc} + R_s \cdot i)/(n_{ps} \cdot n_s \cdot v)} \right) \qquad (5)$$

where n_{ps} and n_{sp} represent the number of panels in series and the number of strings in parallel, respectively. The equations (4) and (5) can be used to calculate the voltage and current over a string of panels [20][21].

The temperature and irradiance play a central role in PV conversion process since it affects basic electrical parameters, such as the voltage and the current of the PV generator. If the PV panels are mounted in a region with high wind potential (as in our case), the wind speed must also be considered because it has a large influence [22].

The model was developed in MATLAB, using the equations presented above, and has the solar irradiation G_a and the cell temperature T_c as inputs on the panel, and it sweeps the voltage range of the PV panel in order to calculate the output current and power.

For the model input values, the measurements from the weather station had to be translated via additional function that were implemented, in order to reproduce the values on the actual PV panel conditions. The three ambient measurements: ambient temperature, horizontal solar irradiation and wind speed are fed to an additional simulation module that calculates the cell temperature of the PV panel and the solar radiation on it, as can be seen in Fig. 3.

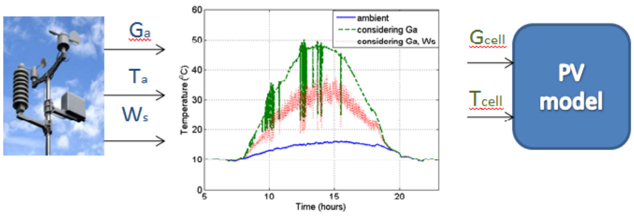

Fig. 3. Description of the PV model input values.

In Fig. 4 is shown a comparison between measured and simulated output power of the PV panel considering the influence of solar irradiance and wind speed on the cell temperature. Comparison with experimental data, acquired by SCADA system and processed by MATLAB, and with the characteristics of the PV panels [22], provided by manufacturers, has shown that this PV model implemented in MATLAB can be an accurate simulation tool to study and analyze the characteristics of individual units and for the prediction of energy production within MPC controller and active loads.

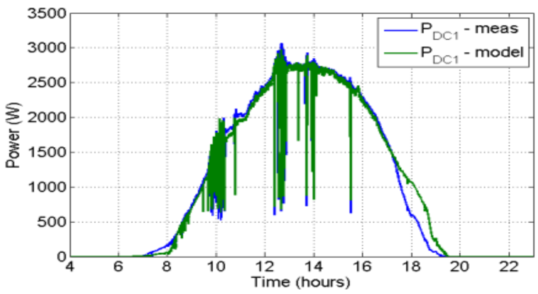

Fig. 4. Comparison between simulations (green) and measurements (blue) of the PV panel output power.

B. *Simple Thermal 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 the reference [23]. To reduce the complexity, the model of heat dynamics of the PowerFlexHouse is formulated as one large room exchanging heat with an ambient environment. The heat flow in PowerFlexHouse is modelled by a grey-box approach, using physical knowledge about heat transfer together with statistical methods to estimate model parameters. The heat transfer due to conduction, convection and ventilation is assumed linear with the temperature difference on each side of the medium. The estimator was Continuous Time Stochastic Modelling (CTSM), which is an estimation tool developed at the department of Informatics and Mathematical Modeling DTU [24]. The model's states space equations are described by (6) and (7):

$$\boldsymbol{T}(t+1) = \Phi \boldsymbol{T}(t) + \Gamma \boldsymbol{U}(t) \tag{6}$$

$$\text{Output: } y(t) = \boldsymbol{C}\,\boldsymbol{T}(t) = [1\ 0\ 0]\begin{bmatrix} T_i(t) \\ T_{im}(t) \\ T_{om}(t) \end{bmatrix} \tag{7}$$

where

$$\Phi = \begin{bmatrix} 9.93\times10^{-1} & 1.87\times10^{-4} & 5.64\times10^{-3} \\ 2.74\times10^{-1} & 7.25\times10^{-1} & 8.19\times10^{-4} \\ 1.56\times10^{-4} & 1.55\times10^{-8} & 9.96\times10^{-1} \end{bmatrix}$$

$$\Gamma = \begin{bmatrix} 1.28\times10^{-3} & 3.00\times10^{-2} & 1.02\times10^{-2} \\ 1.86\times10^{-4} & 2.61\times10^{2} & 1.48\times10^{-3} \\ 3.36\times10^{-3} & 1.61\times10^{-6} & 8.04\times10^{-7} \end{bmatrix}$$

$\boldsymbol{T} = [T_i, T_{im}, T_{om}]$ is the state vector and $\boldsymbol{U} = [T_a, G_a, \Phi_h]$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 heat accumulating layer in the building envelope and the temperature in the heat accumulating layer in the inner walls and floor, can not be measured. State estimator-Kalman filter can be used to estimate these two states; T_a is the ambient (outdoor) temperature; G_a is the solar radiation; and Φ_h is the energy input from the electrical heaters. Using this model, the predicted indoor air temperature was compared with the measured values (See Fig. 5). It was shown that this simple discrete-time linear thermal model for PowerFlexHouse is good enough to be pplicated in MPC.

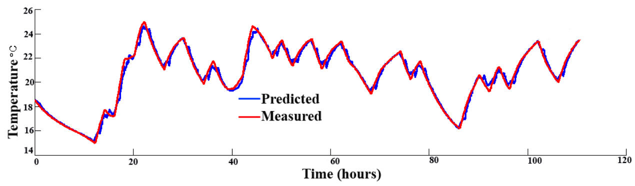

Fig. 5. Predictive (blue) & actual measured (red) indoor air temperature.

C. *MPC Objective Function*

In MPC the control objectives are translated into an optimization problem, which is formulated over a finite prediction horizon. The result of the optimization is a sequence of optimal control moves which drives the system states (or outputs) towards a given reference while respecting system constraints (such as upper and lower limits on the temperature) and minimizing a selected performance criterion (e.g. the reference temperature error, and minimum cost). 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}. In general, the objective function can be formulated as:

$$J = \alpha \sum_{k=0}^{H_p-1} P_{C(k)} \times u_{(k)} + (1-\alpha)[\sum_{k=0}^{H_p-1} P_{R(k)} \times u_{s(k)} + \sum_{k=0}^{H_p-1} P_{C(k)} \times (u_{(k)} - u_{s(k)})] + w \sum_{k=0}^{H_p-1} \left|T_i^k - T_{ref}\right| \quad (8)$$

and

$$\alpha = \begin{cases} 0; & when\, u_{s(k)} \geq min_{(rps)} \\ 1; & when\, u_{s(k)} < min_{(rps)} \end{cases}$$

Subject to: $u_{(k)} \in integer$ [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 1kW. Therefore the maximum permitted electrical power consumption of heating units is $P_{heat\text{-}max}$=10×1kW=10kW. The available solar power at control step k is expressed as $u_{s(k)}$. The minimum solar power supply $Min_{(rps)}$=1kW. To simply the problem, $P_{R(k)}$ are assumed to **[0],** The above formulation provides a means of incorporating both the economic and user's comfort concerns. By assigning different weight coefficient w in (8) to user's comfort term, behaviour on trade-off between economic performance and user's comfort can be studied. In (8), $P_{C(k)}$ is the dynamic power price signal of CPS obtained from the Nord Pool spot market [25]. Its trading horizon is 12-36 hours ahead and it is done for the next day's 24 hours period. That is to say, the minimum prediction horizon is at least 12 hours and the actual maximal prediction horizon can reach 36 hours. In case $u_{s(k)} \geq \min_{(rps)}$, the objective function can be:

$$J = \sum_{k=0}^{H_p-1} P_{C(k)} \times (u_{(k)} - u_{s(k)}) + w \sum_{k=0}^{H_p-1} \left|T_i^k - T_{ref}\right| \quad (9);$$

in case $u_{s(k)} < min_{(rps)}$, the objective function can be expressed as :

$$J = \sum_{k=0}^{H_p-1} P_{C(k)} \times (u_{(k)}) + w \sum_{k=0}^{H_p-1} \left|T_i^k - T_{ref}\right| \quad (10)$$

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].

D. MPC control law

The main principle of MPC is to transform the control problem into an optimization one and solve this optimization problem over a prediction horizon (e.g.12-36 hours) at each control step (e.g. 10 minutes). 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. It also integrates the weather forecast data (ambient temperature and solar irradiation, etc.) with the PV model for the predictive solar power, and with the prediction model for the house indoor temperature. All of them subjected to system dynamics, the objective function (linear or quadratic), constraints on states (e.g. user comfort could be transformed to a set of linear constraints.), and inputs. At each control step the optimization obtains a sequence of actions optimizing expected system behavior over the prediction horizon. But only the first step of the sequence of control actions is executed by the controller on the system until the next control step, after which the procedure is repeated with new process measurements. (See Fig. 6).

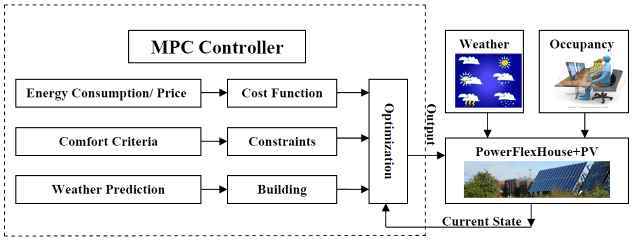

Fig. 6. Basic principle of MPC for building.

IV. Results

We obtained some results from the field test on 18-20, February 2012. The local forecast data of the ambient temperature T_a and the solar irradiation G_a are provided by the meteorology group in DTU Wind Energy at Risø campus. Fig. 7 shows the predictive and the actual measured outside temperature; and in Fig. 8 the predictive and the actual solar irradiation is shown during the test period. The maximum relative error between the actual weather measurement and the weather forecast data is ±5% on test. Therefore, we concluded that the local weather forecast data are accurate in some degree to be integrated into the MPC-based control strategy. Using the PV model described in Section III A together with the local weather forecast data (Fig. 7(red) & Fig. 8(red)), we can obtain the predictive solar power for PowerFlexHouse PV from 8:00 18th to 0:00 20th, February 2012 (See Fig. 9). It was observed that the weather on 18th, February 2012 was bad and there was not solar power to be consumed by heaters. Only during the period of 9:00 to 16:00 on 19th, Feb 2012, there was available solar power supply. In this paper, PV electricity has been used as a local generator, and the concept of self-consumption is meaningful, only when the local generation is available.

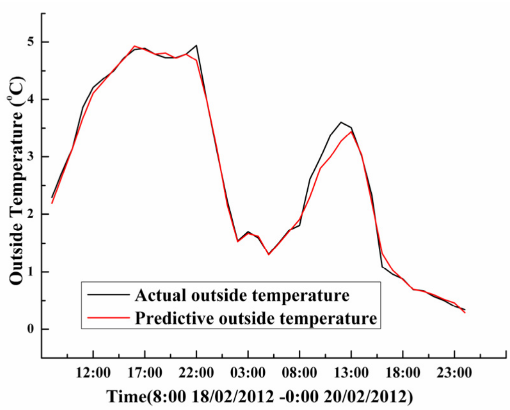

Fig. 7. Predictive (red) and actual measured outside temperature.

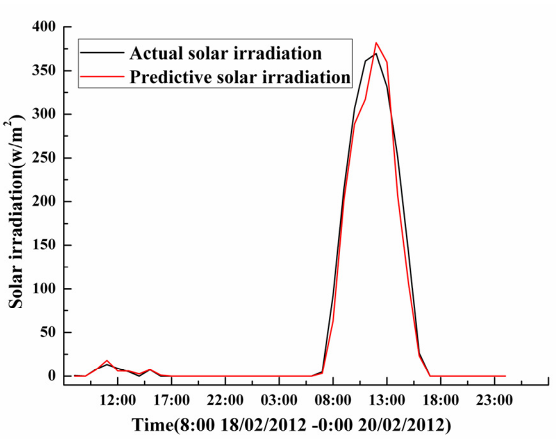

Fig. 8. Predictive (red) and actual measured solar irradiation.

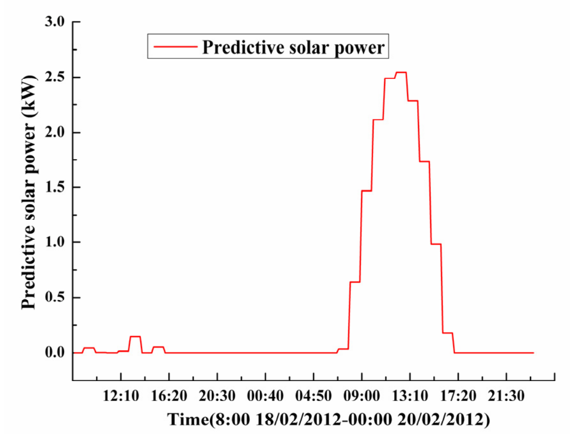

Fig. 9. Predictive solar power.

At 8:00 (18th, February 2012) 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 16 hours for the PowerFlexHouse's heaters, as shown in Fig. 10. Fig. 11 demonstrates the predictive indoor air temperature in the next 16 hours according to the optimized switch schedule (the same as in Fig. 10). At 13:00 (18th, February 2012), the MPC produced the results shown in Fig. 12. It presents the optimized profile of the predictive total power consumption in the next almost 35 hours for the PowerFlexHouse's heaters. At this moment, the prediction horizon could reach 35 hours, because the Nord Pool spot market at 13:00 (on the same day) provided next day's 24 hours' price information for the users. Since the solar power has a high priority to be used, the green area in Fig. 12 is the solar power consumption, which would be consumed by heaters from 9:00 to 16:00 on 19th, Feb 2012. The predictive indoor air temperature in the next 35 hours is shown in Fig. 13, according to the optimized switch schedule for heaters supplied with RPS and CPS, shown in Fig. 12. It was observed that the MPC-based controller almost worked within the low price period, including when there is solar power, and it was able to shift the load and reduce the total cost of operating electrical heaters to meet certain indoor temperature requirements. It is also shown that preheating during the night is a possible way to achieve energy savings.

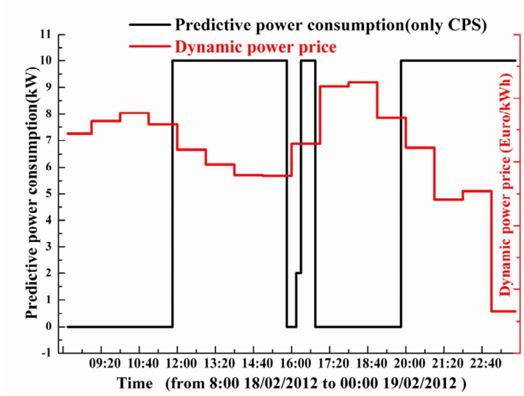

Fig. 10. Optimized heaters' power consumption (black) & dynamic power price (red) in the next 16 hours.

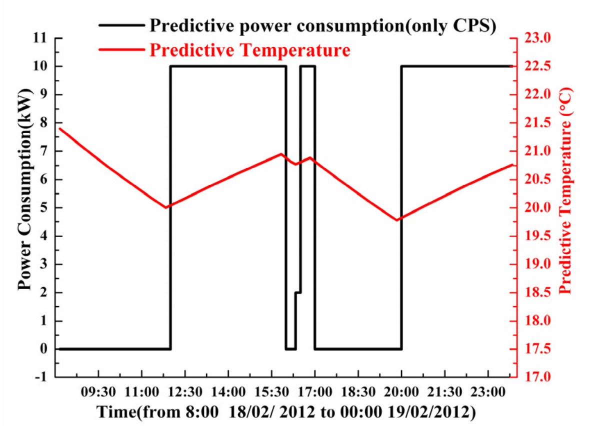

Fig. 11. Predictive indoor air temperature (red) according to the optimized heaters' power consumption (black) in the next 16 hours.

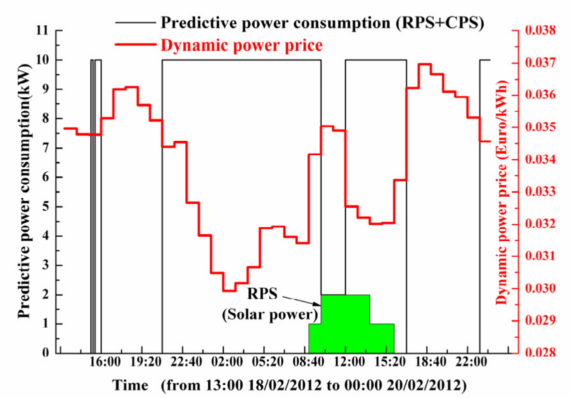

Fig. 12. Optimized heaters' power consumption (black) & dynamic power price (red) in the next 35 hours.

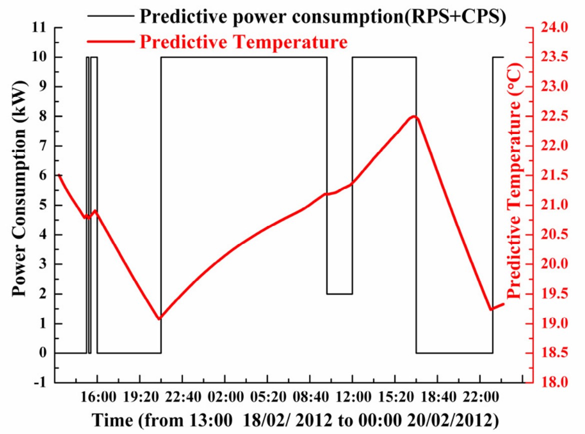

Fig. 13. Predictive indoor air temperature (red) according to the optimized heaters' power consumption (black) in the next 35 hours.

After analyzing the data of Nord Pool in 2010, it is concluded that there is certain predictability in the occurrence of peak load periods during the day in Denmark, and this predictability is reflected in the hourly spot price. 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) and the low spot prices take place in the deep of night [27]. In the Nordic system at night-hours, there is a large production by wind turbine. This is correlated with the dynamic power price, which is much lower during the period from 21:00 to 7:00. According to [28], it is concluded that the spot price, generally decreases when the wind power penetration in the power system increases, that is to say, the Nordic Electricity spot prices reflect the amount of wind power in the system. Fig. 10 and Fig. 12 illustrate that heaters are always switched on late at night and MPC control strategy can achieve energy savings by shifting load from on-peak to off-peak period. At the same time, it shows that MPC control strategy can be investigated on ADSM in this intelligent house, which is used to stabilize fluctuations in the power grid with a high penetration of wind power or other renewable energy, and it can maximize the use of local PV generation.

V. Conclusion and Future Research

In order to enable more use of renewable energy in the future power system, ADSM should be established to encourage consumers to improve energy efficiency, reduce energy cost, change the time of usage, or promote the use of different energy sources. From the control systems view, smart grids are essentially predictive optimal control problems, which can be formulated as optimizing the cost, the use of the storage, the use of the wind/PV source, and to match the production with the consumption in a predictive horizon.

Simulations and experimental results have shown the effectiveness of the MPC-based control scheme. The predictive optimal problem, which is set up a residential sector, can be naturally modeled with discrete time steps, because balance settlement and markets work within discrete periods. Complex models cannot be readily used for control purposes, since the computation time for the optimal load scheduling should be low. Meanwhile in real conditions, efficiency of the predictive schedule depends on accuracy of the forecasts.

To improve the operation of various energy resources, operation efficiency of building energy, and loads should be coordinated and optimized. The predictive behavior of power consumption for residential sectors shows that MPC-based strategies are feasible for active DSM in a distributed power system with high renewable energy penetration. Integrating dynamic power prices and the weather forecast data, it demonstrates that MPC control strategies are able to shift the electrical load to periods with low prices. The end users can avoid high electricity price charge at peak time, and the power grid can benefit from load control.

The future work will focus on the other different optimization methods for predictive controllers and the computation time for their optimal scheduling. Moreover, we need to analyze the effect of the predictive horizon length on the performance in the MPC strategies, and the robustness of these controllers against uncertainty in measurements and forecasts. At the same time, the different home appliances, such as a water heater, can be used for maximum PV self-consumption.

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VIII. BIOGRAPHIES

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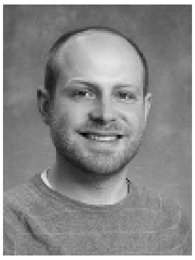

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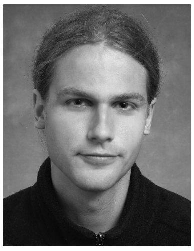

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