Different Predictive Control Strategies for Active Load Management in Distributed Power Systems with High Penetration of Renewable Energy Sources

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Abstract

In order to achieve a Danish energy supply based on 100% renewable energy from combinations of wind, biomass, wave and solar power in 2050 and to cover 50% of the Danish electricity consumption by wind power in 2020, it requires more renewable energy in buildings and industries (e.g. cold stores, greenhouses, etc.), and to coordinate the management of large numbers of distributed energy resources with the smart grid solution. This paper presents different predictive control (Genetic Algorithm-based and Model Predictive Control-based) strategies that schedule controlled loads in the industrial and residential sectors, based on dynamic power price and weather forecast, considering users’ comfort settings to meet an optimization objective, such as maximum profit or minimum energy consumption. Some field tests were carried out on a facility for intelligent, active and distributed power systems, which is built around a small power grid with renewable power generations (two wind turbines and solar panels), a vanadium battery for storage, EV-charging infrastructure for EVs, and an intelligent office building. The simulation and field tests demonstrated that GA-based and MPC-based predictive control strategies are able to achieve load shifting and enable end users to participate in market-based power systems, and thus profit from optimal consumption of energy in relation to price and supply of ancillary services in the power system, as well as improve grids with integration of high penetration of renewable energy sources, which could lead to reducing reinforcements in the future power systems.

Introduction

With the increasing demand, rising fossil-fuel prices and the mission of reducing CO₂ emissions, all the countries are devoting to integrating as much Renewable Energy Sources (RESs) as possible. The Danish government pays much attention to reducing CO₂ emission and energy consumption. It aims for Denmark’s greenhouse gas emissions in 2020 to be reduced by 40% compared to 1990 levels. Approximately 50% of traditional electricity supply must come from wind power by 2020, and 100% renewable energy will be used in energy and transport sectors by 2050 [1].

When introducing renewable generation based on wind and photo voltaic, variations in the grid are increasing. The balancing to meet demand with production should be answered by
even more flexible power generation. Moreover, the introduction of electrical cars and heat pumps can lead to an even more fluctuating electricity demand. Therefore, the additional operational flexibility is required to ensure the stability of the grid. Only depending on the generation side to fulfill the system balancing needs for future Danish power system is insufficient. We need the Distributed Energy Resources (DER), like household, electric vehicles, and industry consumers, to participate in the provision of ancillary services. The introduction of DER, together with the introduction of more information and communication technology in the electricity system provides novel and active load management opportunities at the end user level [2]. There is a large potential for additional flexibility in the control of power systems by enabling active load management. It can modify the demand profile to reduce the losses in the grid, maximize consumption while RESs are available, decrease congestions, and save energy [3], [4].

The goal of our research is to implement different predictive control strategies to realize load shifting, using Demand Response (DR) potential to support the introduction of a high penetration of renewables. In this paper, we will present two different scenarios: 1) A Genetic Algorithm (GA)-based control strategy was used to set the temperature in cold storage warehouses to a level, which was determined by the balance between estimated wind energy production and electricity demand. 2) A Model Predictive Control (MPC) strategy was implemented for electric space heaters’ predictive power consumption including maximizing the use of local renewable generation (e.g. solar power) in an intelligent building, based on weather forecast information and dynamic power price signal.

Scenario 1: Genetic algorithm-based temperature controller in cold storage warehouses

**Scenario description**

Cold storage warehouses are major consumers of electrical energy. Electricity is converted by the refrigeration installation into thermal energy in refrigerated or frozen products. When the temperature of stored frozen products in the EU is allowed to vary by 1°C, the warehouses can act as a 50,000 MWh battery on the grid i.e. store over twice the projected 2010 EU average hourly wind power production. In times of high wind supply the temperature in cold storage warehouses can be lowered, using the “excess energy” and, additionally, decreasing future cooling demand. When wind power availability is low, the storage can be “discharged” by allowing the temperature to rise. This has the effect of adding a “virtual battery” to the power system with relatively little investment in new hardware. That is, what the EU “Night Wind” project proposes to demonstrate [5].

The objective of the predictive optimal control aspect of this scenario is to minimize electricity consumption costs by optimizing the cooling strategy depending on predicted wind generation and grid electricity prices and continually adjusting the power taken from the grid/from the wind turbines. In some cases, it may actually be profitable to cool during the daytime; in other cases, it may be cheaper to export the electricity produced to the grid and then buy it back as needed.

A GA was used to solve this predictive optimal control problem, which is a search algorithm based on mechanism of natural selection and natural genetics. The reason why use GA is that GA often can be applied to solve various optimization problems that are not well suited for standard optimization algorithms; including problems in which the objective function is discontinuous, non-differentiable, stochastic or highly nonlinear [6].
Problem setup and solution

In order to meet the requirements for keeping the products frozen, there are totally three compressor sets in the cold store. One compressor is always working and the second compressor is on for regulating the air temperature between -21°C and -18°C. If the air temperature is higher than -18°C, then the three compressors are working at the same time. Each compressor set consumes 375kW at maximum cooling capacity. By studying the model of the cold store [7], it is important to note that there is no “continuous” control for the compressors, or for the reference air temperatures. The implemented controller is an ON/OFF controller. At most 36 air temperatures’ reference values were optimized for the next 36 hours.

The GA seeks to maximize the mean fitness of its population, through the iterative application of the genetic operators. The fitness value of a solution in the GA domain corresponded to a cost value in the problem domain. An explicit mapping is made between the two domains. ‘Cost’ is a term commonly associated with traditional optimization problems. It represents a measure of performance: namely, the lower the cost, the better the performance. Optimizers seek to minimize cost. Hence, it is evident that, by maximizing fitness, the GA is effectively minimizing cost. Therefore, the cost/objective function is to minimize the cost on energy consumption for operating the cold store. The number of the optimized variables are less than or equal to 36, because the electricity price is known at 12 o’clock each day for the following day in hours intervals. All the information for the next 36 hours about the wind power prediction, ambient temperature forecasts and electricity buy/sale price were integrated into the controller’s program as input files. The parameters of the cold store (e.g. store volume, product volume, heat capacity of product and product specific mass, etc.) were all defined as constants in the C++ program. A GAlib (A C++ library of genetic algorithm components) was used to obtain the optimized reference temperature in the cold store [8].

The performance of a GA depends on a good combination of all parameters. First of all, the first generation is represented by the reference air temperature and is a random number within the allowed interval of air temperatures (e.g. between -21°C and -18°C). This initial population is selected to ensure sufficient diversity to find the optimum solution efficiently. Secondly, the population size also affects the performance and efficiency of the process. Too small and the result is poor due to insufficient sample size. Too large and the rate of convergence to the global minimum may be too slow. Considering the computational burden due to the heuristic characteristic in GA, the evolution was processed for 100 generations with a population size equal to 73 (2n+1=2×36+1, where n is the number of design variables, i.e. the optimized reference air temperatures in the next 36 hours). Thirdly, in the proposed algorithm, the roulette-wheel selection method was employed. In this selection method, the diversity of population can be maintained and the best individuals can survive in the new generation. A two-points crossover was used with a value of 0.6. It is quicker to get the same results and retain the solutions much longer than one point crossover. Finally, after comparing the computation speed in different experiments, the mutation operator with a probability equal to 0.05 was assigned in the algorithm, the detailed implementation can be found in [9].

Simulation results

Before analysing the results, let us comment some important details. First of all, the initial population is the initial reference temperature in the algorithm for the next 36 hours. Secondly, the tolerant temperature is a threshold value. When the (initial) air temperature in the cold store is higher than it, the compressors are supposed to be always ON, and the GA is
not working. Otherwise, the GA is called to optimize the compressors’ performance. Moreover, in order to avoid any mechanical stress for compressors, which was caused by the fast actuation, a minimum operation time of five minutes for compressors is considered during the simulation experiments. Finally, the range for the optimized air temperature in the cold store is [-21°C, -18°C].

<table>
<thead>
<tr>
<th>No. of case</th>
<th>Initial air temperature[°C]</th>
<th>Best generation</th>
<th>Profit [€]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-19.1</td>
<td>97</td>
<td>1918.79</td>
</tr>
<tr>
<td>2</td>
<td>-18.4</td>
<td>30</td>
<td>1209.71</td>
</tr>
<tr>
<td>3</td>
<td>-18</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

The results are described for the three different cases. The initial air temperature in these three cases is different. The number of generation for the genetic algorithm is all defined as 100. The control and GA parameters are shown in Table I. The optimized reference air temperature in the different cases equals the lower reference temperature plus the margin or the upper reference temperature minus the margin, where the margin is 0.1 °C. The Figs.1-2 show the results of the first case. They present the variation of optimized reference temperatures, power consumption of compressors (Number of working compressors×375kW) & the predicted inside air temperature by the GA controller, respectively. In the same way, Figs.3-4 describe the results of the second case and the unique difference is that the optimized time (as the x axis shown in Figs. 3-4). For the first case, the optimized time is 36 hours (2160 minutes) and the second one; the optimized time is 25 hours (1500 minutes).

In case 1, the initial air temperature is set to -19.1°C, and it is 0.1°C lower than the tolerant temperature (-19°C). From the beginning, the compressors are switching on and off continually, based on the optimized reference temperature’s variation in the next 36 hours. The results of the GA optimization are shown in Fig.1, and it shows the variation of reference temperature over the 36 hour period of optimization. The pattern of compressor activity and variation of the inside air temperature can be seen in Fig.2. The compressor changes its energy consumption in four different sets of time. In this way, the best fitness function is negative (-1918.79€, obtained in the 97th generation), which means that the owner can sell the energy and make profit.

In case 2, the initial air temperature is set to -18.4°C, which is 0.6 °C above the tolerant temperature (-19°C). Comparing with the case 1, it is logical that from the beginning, 11 hours are needed for the compressors to be operated in the range of the tolerant temperature, and the genetic algorithm is not called. Then, the compressors are switching on and off continually, based on the air temperature’s variation in the next 25 hours (see Fig. 3). The compressor consumes the energy in two different sets of time (see Fig. 4). In this way, the best fitness function is negative (-1209.71€, obtained in the 30th generation), which means that grid can also obtain some economical benefits, but not as much as in the case 1.

In case 3, the initial air temperature is set to -18°C, and it is 1°C higher than the tolerant temperature (-19°C). Comparing with the case 2, it is logical that from the beginning, more hours (here more than 36 hours) are needed for the compressor to be ON to make the air temperature be less than or equal to the tolerant temperature. Finally, in the next 36 hours the control based on the GA is not executed.
Discussion

In the beginning, when we designed the GA-based controller, a GA toolbox in MATLAB was used. It is well known that MATLAB is a powerful tool for theory analysis and algorithm simulation prior to programming. But, the drawback of MATLAB is its runtime. It probably takes hundred times of an equivalent C++ programme. This is because MATLAB has an interpreter, which is much slower than C++. However, for RT application, the processing delay is a critical issue. In this case, we switched over to C++ after some initial testing of the algorithm in MATLAB. Finally, it proved that C++ is more efficient. For example, in the first case, running the programme on the same computer, if it was realized using MATLAB, the whole algorithm process took at least 2.5 hours; while in C++, it only needs no more than 2 minutes.
It is clearly demonstrated that a GA approach is feasible for active load management in cold storage warehouses in a power system with wind power penetration. It can provide the owner of cold storage warehouses with a set of time-ordered investment decisions which is not obtained from static optimizations, but directly from considering the discrete, non-linear and stochastic nature of the wind energy.

Scenario 2: MPC-based temperature controller for heating consumption in an intelligent building

Scenario description

The building sector is one of the largest energy consumptions. Based on the vision of the future electric energy 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 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 (see Fig. 5.) [10] [11]. It 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 [12]. MPC for building climate control has been investigated in several papers before [12]-[17], mainly with the purpose of increasing the energy efficiency. The potential of MPC in power management was investigated in [18]-[21], but the ambient temperature was assumed to be constant in their simulation scenarios.

According to the Danish Energy Agency’s report, in 2011, average energy consumption per household in Denmark was 76.2 GJ, of which 63.6 GJ were used for space heating and hot water [22]. Therefore, space heaters can be regarded as one of the most obvious areas for active load management. An MPC controller was developed to minimize the daily operational cost of electric space heaters in an intelligent building over a prediction horizon (e.g. $H_p=12$-36 hours). It also integrates the weather forecast data (ambient temperature and solar irradiation, etc.) with the prediction models for the house indoor temperature and the solar power generation.

![MPC Controller Diagram](image)

Fig. 5. MPC design for an intelligent building- PowerFlexHouse
Test facility

We tested this MPC controller on SYSLAB platform, which is an experimental facility in DTU Elektro, Risø campus, with the purpose of research in distributed control and smart grids with a high penetration of renewables [23]. It is built around a small power grid with renewable (wind (11+10kW), solar (7+10+10kWp)) and conventional (diesel) power generation, a vanadium battery for storage, and various types of consumers (see Fig. 6). 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).

![Components on SYSLAB](image)

Fig. 6. 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 real-time measurement data for PowerFlexHouse can be visualized in Fig. 7-a. 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. 7-b). Information can also flow in the other direction, for example providing the power system supervisor controller with the expected near-future behaviour of the building loads.
The hybrid power supply system (SYSLAB) presented in this section 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 CO₂ impact, etc. We denote the dynamic power prices of CPS and RPS by $P_C$ and $P_R$, respectively. An MPC-based control strategy was used to realize the load shifting, 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 follows.
**PV model**

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

\[ i = I_{sc} - I_o \cdot \left( e^{(v+iR_s)/n_sV_T} - 1 \right) \]  

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 \( V_{oc} \). Then it can be used to obtain \( P_{max} \) under non-standard conditions.

Equations for \( I_{sc} \) and \( V_{oc} \) as a function of absolute temperature \( \Delta T \) including temperature coefficients (\( \beta_I, \chi \): 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:

\[
I_{sc} = I_{sc25} \cdot (1 + \beta_I \cdot \Delta T) \\
V_{oc} = V_{oc25} \cdot (1 + \chi \cdot \Delta T) \\
\Delta T = T_c - T_a
\]  

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

\[ I_{sc} = I_{sc25} \cdot \left( G_d / 1000 \right) \]  

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:

\[
v = n_{ps} \cdot V_{oc} + n_{ps} \cdot n_s \cdot V_T \cdot \ln \left( 1 - i/n_{sp} \cdot I_{sc25} \cdot G_d / 1000 \right) \\
i = n_{sp} \cdot I_{sc} \cdot \left( 1 - e^{-(v-n_{ps} V_{oc}+R_s i)/(n_{ps} n_v)} \right)
\]

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 [24] [25].

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 [26].

The model was developed in MATLAB, using the equations presented above, and has the solar irradiation \( G_d \) 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 irradiation on it, as can be seen in Fig. 8.

Fig. 8. Description of the PV model input values.

A comparison between measured and simulated output power of the PV panel is shown in Fig. 9. Comparison with experimental data, acquired by Supervisory Control and Data Acquisition (SCADA) system and processed by MATLAB, and with the characteristics of the PV panels [26], 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. 9. Comparison between simulations (green) and measurements (blue) of the PV panel output power.

**Simple thermal model for PowerFlexHouse**

The indoor temperature model of PowerFlexHouse was given as a stochastic discrete-time linear state-space model, which was directly obtained from the reference [27]. 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 [28]. The model’s states space equations are described by (6) and (7):

\[
T(t + 1) = \Phi T(t) + \Gamma U(t)
\]

Output: \( y(t) = C \begin{bmatrix} T_i(t) \\ T_{in}(t) \\ T_{cell}(t) \end{bmatrix} \)

where
\[
\Phi = \begin{bmatrix}
9.93 \times 10^{-1} & 1.87 \times 10^{-4} & 5.64 \times 10^{-3} \\
2.74 \times 10^{-1} & 7.25 \times 10^{-4} & 8.19 \times 10^{-3} \\
1.56 \times 10^{-4} & 1.55 \times 10^{-4} & 9.96 \times 10^{-1} \\
\end{bmatrix}
\]

\[
\Gamma = \begin{bmatrix}
1.28 \times 10^{-1} & 3.00 \times 10^{-2} & 1.02 \times 10^{-3} \\
1.86 \times 10^{-1} & 2.61 \times 10^{-2} & 1.48 \times 10^{-3} \\
3.36 \times 10^{-1} & 1.61 \times 10^{-2} & 8.04 \times 10^{-3} \\
\end{bmatrix}
\]

\[T = [T_i, T_{im}, T_{om}]\] is the state vector and \(U = [T_{ap}, G_a, \Phi_h]\) 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 irradiation; and \(\Phi_h\) is the energy input from the electrical heaters. Using this model, the predicted indoor air temperature was compared with the measured values (see Fig. 10). It was shown that this simple discrete-time linear thermal model for PowerFlexHouse is good enough to be applied to MPC.

![Image](image.png)

Fig. 10. Predicted indoor temperature (blue) and the actual measured indoor air temperature (red) with a time step at 5-minute interval.

**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 electric space heaters in PowerFlexHouse is to minimize the total cost of the energy used in heating over a prediction horizon \((H_p)\), including the maximum usage of local PV generation. 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:

\[
J = \alpha \sum_{k=0}^{H_p-1} P_{c(k)} \times u_{(k)} + (1-\alpha) \sum_{k=0}^{H_p-1} P_{r(k)} \times u_{s(k)}
\]

\[
+ \sum_{k=0}^{H_p-1} P_{c(k)} \times (u_{(k)} - u_{s(k)}) + w \sum_{k=0}^{H_p-1} \left| T_k^i - T_{ref}\right|
\]

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

Subject to: \(u_{(k)} \in \text{integer } [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]\) 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 $P_{\text{heat-max}}=10 \times 1\, \text{kW}=10\, \text{kW}$. The available solar power at control step $k$ is expressed as $u_s(k)$. The minimum solar power supply $\min(u_s)\succeq 1\, \text{kW}$. 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), $P_{C(h)}$ is the dynamic power price signal of CPS obtained from the Nord Pool spot market [29]. 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. To simply the problem, the dynamic power price signal of RPS, $P_{R(k)}$ are assumed to [0]. In case $u_s(k)\succeq \min(u_s)$, the objective function can be:

$$J = \sum_{k=0}^{H-1} P_{C(k)} \times (u_s(k) - u_s(k)) + w \sum_{k=0}^{H-1} [T_{k} - T_{ref}]$$

(9)

in case $u_s(k) < \min(u_s)$, the objective function can be expressed as :

$$J = \sum_{k=0}^{H-1} P_{C(k)} \times (u_s(k) - u_s(k)) + w \sum_{k=0}^{H-1} [T_{k} - T_{ref}]$$

(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 [30].

**MPC control law**

The main principle of MPC is to solve the aforementioned 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 RPS and CPS, 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 $u_{(0)}$ 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. 11).

![MPC Controller Diagram](image)

Fig. 11. Block diagram of MPC controller in PowerFlexHouse
Field test 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. 12 shows the predictive and the actual measured outside temperature; and in Fig. 13 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. 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, February 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 PV generation is available.

![Fig. 12. Predictive (red) and actual measured (black) outside temperature.](image12)

![Fig. 13. Predictive (red) and actual measured (black) solar irradiation.](image13)

![Fig. 14. Optimized heaters’ power consumption (black) & dynamic power price (red) in the next 16 hours.](image14)
At 8:00 (18\textsuperscript{th}, February 2012) the MPC control controller 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. 14. Fig. 15 demonstrates the predictive indoor air temperature in the next 16 hours according to the optimized switch schedule (the same as in Fig. 14). At 13:00 (18\textsuperscript{th}, February 2012), the MPC produced the results shown in Fig. 16. 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. 16 is the solar power consumption, which would be consumed by heaters from 9:00 to 16:00 on 19\textsuperscript{th}, February 2012. The predictive indoor air temperature in the next 35 hours is shown in Fig. 17, according to the optimized switch schedule for heaters supplied with RPS and CPS, shown in Fig. 16. It was observed that the MPC-based controller almost worked within the low price period, including when there was 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.
Discussion

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. In addition, to overcome the model’s error, here we used the process’s real-time output \( T^{(k/k)} \) and model’s (previous) predictive output \( T^{(k/k-1)} \) to structure one model output feedback correction, where the error was expressed as: \( e = T^{(k/k)} - T^{(k/k-1)} \). (see Fig. 18.) [31].

The thermal mass of buildings offers some heat capacity, and it can therefore be used for unidirectional storage of electrical power, where electric space heaters are used. Once many units aggregated intelligently in the distribution grid, this can have a giant impact on power balancing. Unfortunately, PowerFlexHouse is a very light building that does not allow a lot of thermal energy to be stored in the building [32]. The other construction material, for example, a brick building with thick concrete floors can offer a much bigger capacities and can be preferred as active loads. However, for demonstration and proof of concept the PowerFlexHouse has shown good results, and it can be used as an active load.

By analyzing the data of Nord Pool in 2010 and 2011, 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. In the Nordic system at night-hours, there is a large production by wind turbines. This is correlated with the dynamic power price, which is much lower during the period from 21:00 to 7:00. According to [33], it is proved that the spot price, generally decreases when the wind power penetration in the power system increases, using the data from western Denmark market. To some degree, the Nordic Electricity spot prices reflect the amount of wind power in the system. Fig. 14 and Fig. 16 illustrate that space electric heaters are always switched on at midnight and MPC control strategy can achieve energy savings by shifting load from on-peak to off-peak period. In the meantime, it shows that MPC control strategy can be investigated on DR in intelligent houses, which is exploited to stabilize fluctuations in the power grid with a high penetration of wind or other renewables.

Conclusions and future research

In order to enable more use of RESs in the future power system, active load management should be introduced with Smart Grids solution. 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.

To improve the operation of various energy resources, operation efficiency of DERs and controllable loads should be coordinated and optimized. Simulations and experimental results of two scenarios, which are set up respectively in the industrial and residential sector, have shown the effectiveness of the GA-based and MPC-based control scheme, and they are feasible for active load management in a distributed power system with a high RESs penetration. It also demonstrated that the DR potential is mainly dependent on the heat capacity of the thermal mass in cold stores or buildings. The industrial sector (e.g. cold store and manufacturing sites) offers opportunities because it is able to contribute unusually large amounts of load-even from just one plant. Therefore, large industrial sites have been considered the low-hanging fruit by DR providers [34].

The predictive optimal problem for active load management 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.

Integrating dynamic power prices and the weather forecast data, it demonstrates that the GA-based and MPC-based 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 should 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 predictive control strategies, and the robustness of these controllers against uncertainty in measurements and
forecasts. Finally, we will apply the proposed methods to matching the RESs with other controllable loads, for example, hot water supplies and electric vehicles can be used for the purpose of the maximum PV self-consumption.

Acknowledgment

This work was supported by the “Night Wind” project, which was a specific targeted research project under the European Commission 6th Framework Program, the full title is “Grid Architecture for Wind Power Production with Energy Storage through Load Shifting in Refrigerated Warehouses” and Interreg IV A program, project “Vind i Øresund”.

The authors would like to express their appreciation to Andrea N. Hahmann, Senior Scientist, from the Department of Wind Energy, Risø campus, Technical University of Denmark, for providing us with the local weather forecast data.

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