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Active Load Management in an Intelligent Building Using Model Predictive Control Strategy

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

Abstract--**This paper introduces PowerFlexHouse, a research facility for exploring the technical potential of active load management in a distributed power system (SYSLAB) with a high penetration of renewable energy and presents in detail on how to implement a thermal model predictive controller for load shifting in PowerFlexHouse heaters' power consumption scheme. With this demand side control study, it is expected that this method of demand response can dramatically raise energy efficiencies 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**

I. Introduction

Wind power will cover 50% of the Danish electricity consumption in 2025 according to Energinet.dk [1], and the Danish government has expressed 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]. However, as most of the renewable sources 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 strong demands on flexibility elsewhere in the system. 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. 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. Nowadays the production of electricity system follows the load. In the intelligent energy system (Smart Grid) the production controls the consumption. For example, when the wind blows or the sun shines, consumption will automatically be adjusted, and consumption and consumers will go from being passive participants to be active players in the electricity system.

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 become 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. A widely body of literature states that how to activate the potential of ancillary services from DERs, thereby exploiting their ability to contribute to power system operation [3]-[8].

Developing the smart grid and linking it to smart appliances and other products having DR capabilities will reliably and predictably reduce appliance electricity consumption in real time [8]. This will create the opportunity for significant increases in energy efficiency and conservation and meaningful reductions in greenhouse-gas emissions. 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 will have to be integrated with the rest of the power grid's control system – probably by means of a market for system services and an aggregation mechanism. In order to gain acceptance, the user's needs would need to be met without much noticeable compromise on perceived comfort. Ideally, the user would stay in control while providing flexibility to the grid. The goal of our research is to implement a control methodology to use 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

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Predictive Control (MPC) strategy applied on an experimental facility (SYSLAB) to exploit technical potential of active load management.

MPC refers to a class of control algorithms that compute a sequence of manipulated variable adjustments by utilizing a process model to optimize forecasts of process behavior based on a linear or quadratic open-loop performance objective, subject to equality or inequality constraints over a future time horizon [9]. Here MPC-based control strategy is used to implement a controller for load shifting in an intelligent office building-PowerFlexHouse heaters' power consumption scheme.

This paper is organized as follows. In Section II we shortly introduce Risø's new experimental facility (SYSLAB) for 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, followed by some results and analysis of running the MPC controller on SYSLAB platform are shown in Section IV. Finally, Section V offers the conclusion and the 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 [10]. Currently components on the SYSLAB platform are listed as following (See Fig. 1):

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

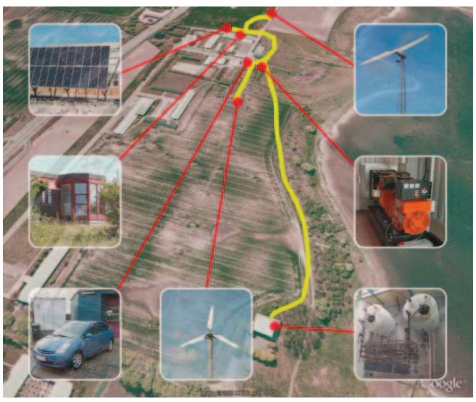

Fig. 1. Components in SYSLAB

The SYSLAB facility is spread across multiple locations at Risø DTU and its backbone is formed by a 400V grid with several busbars and substations (See Fig. 2). 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 automates 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 [11].

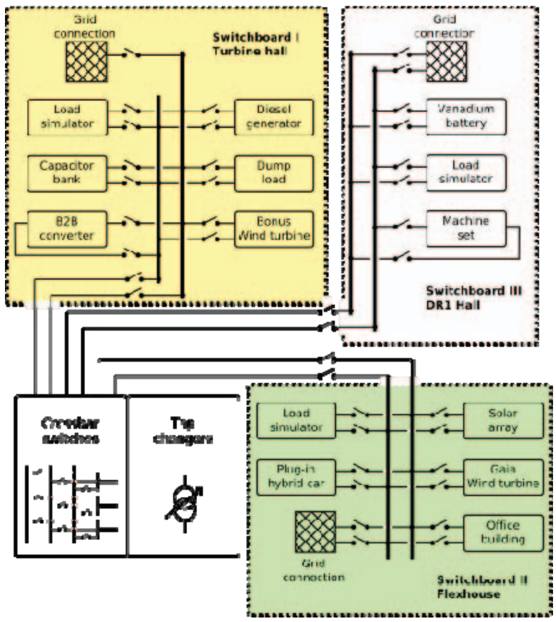

Fig. 2. Layout of SYSLAB

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 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 20kW. All individual loads in the building are remote-controllable from a central building controller. This controller is able to communicate with the SYSLAB grid through its own node computer (See Fig. 3). The controller can access different services to obtain power system information, e.g. dynamic power price, available power and grid frequency signal. 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.

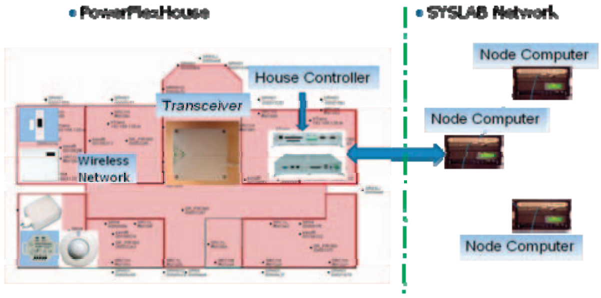

Fig. 3. Communication between PowerFlexHouse and SYSLAB

III. MPC Controller for Load Shifting in PowerFlexHouse Heating Strategy

One of the main electricity consumptions in the northern Europe is the heating in the long winter. Heaters are designated as one of the most obvious areas of demand response. The objective of MPC controller is to minimize the daily operational cost of heating use and provide ancillary services for power system. Fig. 4 presents the model predictive control scheme. It is to solve an optimization problem over a prediction horizon at each control step subjected to system dynamics, an objective function (linear or quadratic), and constrains on states, actions and inputs. At each control step the optimization can obtain a sequence of actions optimizing expected system behavior over the prediction horizon. Only the first step of the sequence of control actions is implemented by controller on the system until the next control step, after which the procedure is repeated with new process measurements.

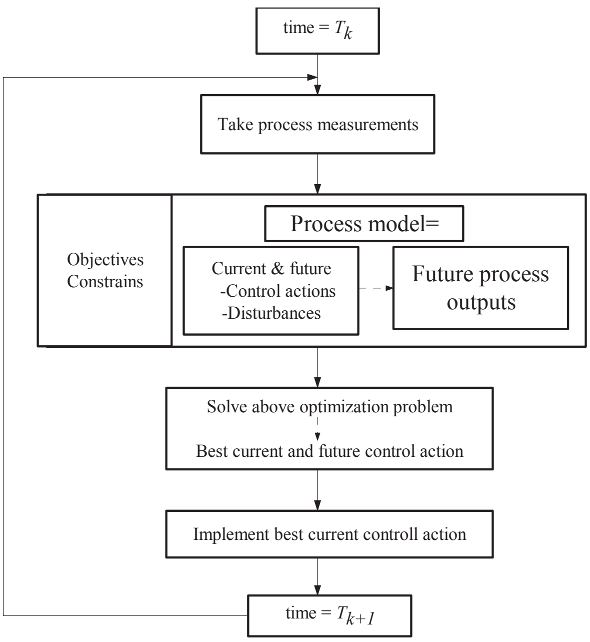

Fig. 4. Model predictive control scheme

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 [12]. To reduce the complexity, the model of heat dynamics of PowerFlexHouse is formulated as one large room exchanging heat with an ambient environment. That is to say, we regard 8 rooms in PowerFlexHouse building as a large room. The control object is the one representing indoor temperature T_{in}. The states space equations were expressed in (1) and (2):

$$T(t+1) = \Phi T(t) + \Gamma U(t) \qquad (1)$$

$$\text{Output: } y(t) = C\,T(t) = \begin{bmatrix}1 & 0 & 0\end{bmatrix}\begin{bmatrix}T_{in}(t)\\ T_{im}(t)\\ T_{om}(t)\end{bmatrix} \qquad (2)$$

Φ is the system matrix. Γ is the control matrix. $T = [T_{in}, T_{im}, T_{om}]$ is the state vector and $U = [T_a, \Phi_s, \Phi_h]$ is the input vector to the system. Here, $T_{in}(t)$ 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.

B. MPC Control Strategy

The MPC control strategy for the electrical space heaters in PowerFlexHouse should be found so that the total cost of the energy used in heating is minimized over a time horizon (Hp). At the same time, it should keep the indoor air temperature around the given reference temperature T_{ref}. The objective function can be formulated as:

$$J = \min\left[\sum_{k=0}^{H_p-1} C(k)\times u(k) + \sum_{k=0}^{H_p-1} w\times\left|T_{in}^{k} - T_{ref}\right|\right] \qquad (3)$$

Subject to: $u(k) \in$ *int* [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10], which means the heat input that the MPC controller determines by mixed integer optimization approach. There are totally 10 heaters in the PowerFlexHouse. Each of them has the power of 1kW. Therefore the maximum permitted electrical power consumption of heater units is $P_{heat\text{-}max}$=10×1kW=10kW. In (3), $C(k)$ is the dynamic power price signal obtained from the Nord Pool spot market [13]. The Nordic electricity market is well-known for its efficient market function. The central market is the Nord Pool spot market where a daily competitive auction establishes a price for each hour of the next day. The trading horizon is 12-36 hours ahead and is done for the next day's 24 hours period. That is to say, there is an actual maximal prediction horizon of 36 hours. In the Nordic system at night-hours, there is a large production by wind turbine. It can be expected that sometime the price variation reflects the level of wind power penetration. The weight coefficient w in (3) is used to tune performance of the MPC controller.

For the purpose of the 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 small, the heaters working at the lower temperature limit, otherwise, they will be set up to the upper limit. Only when the indoor temperature is in the range of [T_{in_min} T_{in_max}], the MPC control algorithm is executed. In addition, the forecast data of the ambient (outdoor) temperature T_a and the solar irradiation Φ_s are updated twice a day (10:00 in the morning and 22:00 in the evening) for the next 48 hours, which are provided by the Wind Energy Division, Risø DTU.

Firstly, the controller output is initialized by the vector of dimension $1 \times Hp$, $\boldsymbol{u_0}$ = [u_0, ..., 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, …, 0]. This way, the search direction is always positive. Secondly, the difference between the predicted indoor temperature at the end of the predictive period and the desired T_{ref} is evaluated at each control step. If this difference is small enough to be acceptable: $\left|T_{in}^{k+H_P} - T_{ref}\right| \le \varepsilon$, 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 (hence, at $k+1$), 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=$P_{heat\text{–}max}$ 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. 5.).

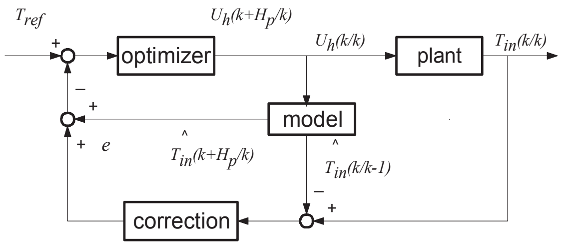

Fig. 5. Block diagram of PowerFlexHouse's MPC

The detailed MPC control law is described as following:

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

Step 2: At current time k, measure $T_{in}(k/k)$ and compare it with the previous predictive value $\hat{T}_{in}^{(k/k-1)}$ to obtain the predictive error $e = T_{in}^{(k/k)} - \hat{T}_{in}^{(k/k-1)}$.

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

{$\boldsymbol{u}(k)$= [u_0, ..., u_{Hp-1}]} = arg

$$J = \min\left[\sum_{k=0}^{H_p-1} C(k) \times u(k) + \sum_{k=0}^{H_p-1} w \times \left|\hat{T}_{in}^{k} - T_{ref}\right|\right]$$

Use the model to predict $\widehat{T_{in}} = \left[\hat{T}_{in}^{k+1}, \ldots, \hat{T}_{in}^{k+Hp}\right]$ and correct the predictive error by $\widehat{T_{in}} + e$.

If $\left|\hat{T}_{in}^{k+Hp} - T_{ref}\right| \le \varepsilon$ and $\forall \hat{T}_{in}^{k+i}, T_{in\_\min} \le \hat{T}_{in}^{k+i} \le T_{in\_\max}$,

where $0 \le i \le H_p$ and ε is a small number.

Go to step 4.

else if $\left|\hat{T}_{in}^{k+Hp} - T_{ref}\right| > \varepsilon$

if $\forall \hat{T}_{in}^{k+i}, \hat{T}_{in}^{k+i} \ge T_{in\_\max}$, where $0 \le i \le H_p$

u_0= 0

else if $\forall \hat{T}_{in}^{k+i}, \hat{T}_{in}^{k+i} \le T_{in\_\min}$,where $0 \le i \le H_p$

u_0= $P_{heat-max}$

end if

end if

Step 4: Apply u_0 to heating units.

Next sample (hence, at $k+1$), k=$k+1$, and repeat from step 2 to step 4.

IV. Results

The MPC controller employs a control period of 10 minutes, while we test it on the SYSLAB platform. It is meaning that every 10 minutes 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; the grid information e.g. dynamic power price signal, available power and frequency signal. 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) Java native interface. Then it integrates the weather forecast data (ambient temperature, solar irradiation, wind speed and wind direction, etc.) with the prediction model for the house indoor temperature, and verifies the predictive error. At last, only the first step in the found best sequence of actions is implemented.

At 9:20 on October 22, 2010, the MPC control algorithm was running on the SYSLAB platform and it provided the optimized profile of the predictive power consumption in the next approximant 15 hours for the PowerFlexHouse's heaters, as shown in Fig. 6. Fig. 7 demonstrates the predictive indoor temperature in the next 15 hours according to the optimized switch schedule (the same as in Fig. 6). When the current time was 13:10 on October 22, 2010, the MPC produced the results shown in Fig. 8. It presents the optimized profile of the predictive 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 October 22, 2010, provided next day's 24 hours' price information for the users. The predictive indoor temperature in the next 35 hours was shown in Fig. 9, according to the optimized switch schedule (the same as in Fig. 8) for heaters in PowerFlexHouse. It was observed in Fig. 9 that during a few hours the predictive temperature dropped to 17ºC. Comparing Fig. 7 with Fig. 9, it can be found that the shorter the prediction horizon the better the predictive control effect. We probably could tune MPC performance by penalizing this temperature deviation with different weight coefficient value. Otherwise, users will have some discomfort if they would like to accept a reduced energy bill and allow this deviation on the room temperature.

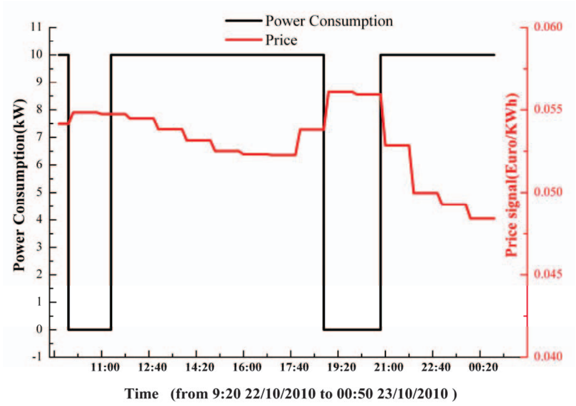

Fig. 6. Optimized predictive power consumption in the next 15 hours

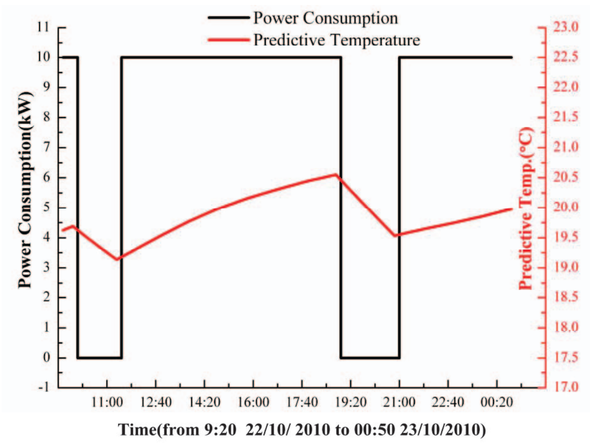

Fig. 7. Predictive indoor temperature in the next 15 hours

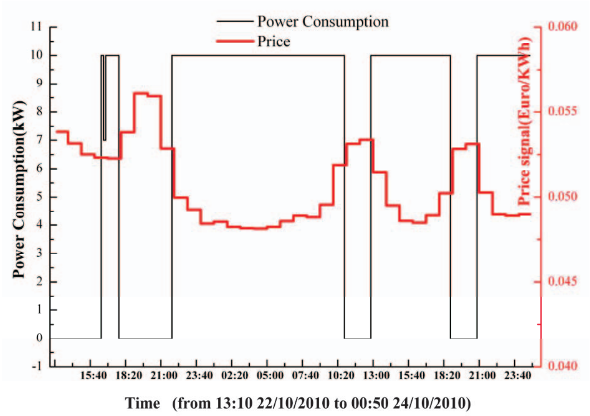

Fig. 8. Optimized predictive power consumption in the next 35 hours

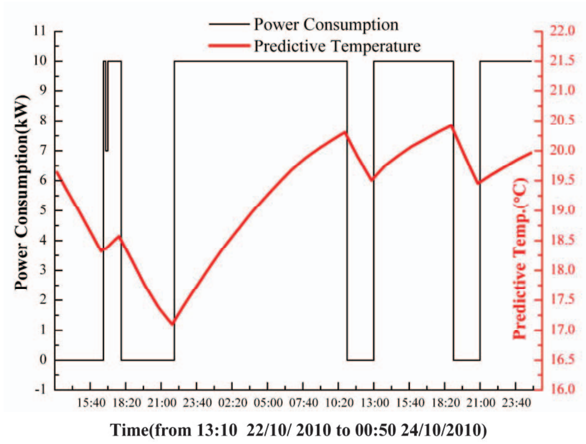

Fig. 9. Predictive indoor temperature in the next 35 hours

V. Conclusion and Future Research

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. 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.

On one side, the future research will focus on analyzing the effect of the predictive horizon length on the performance in MPC controller. On the other side, a multi-agent MPC should be taken into account to find an acceptable near-optimal solution for the whole distributed power system.

VI. 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 the weather forecast data.

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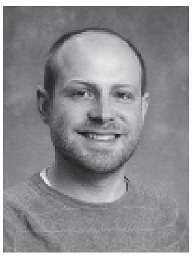
VIII. Biographies

Yi Zong was born in Wuhan, Hubei province, China, on August 21, 1971. She graduated in Control Engineering and Control Theory from Wuhan University of Science and Technology. She got PhD degree on System Engineering and Automation in 2006, at the University Complutense of Madrid, Spain.

Her employment experience included the Wuhan Institute of Technology, China. Since 2006 she had been employed as Post.doc at the Wind Energy Division of Risø DTU National Laboratory for Sustainable Energy. She is currently a Scientist at Intelligent Energy Systems, Risø DTU. Her special fields of interest include advanced and intelligent control for demand side units in households and industry supporting flexible power consumption.

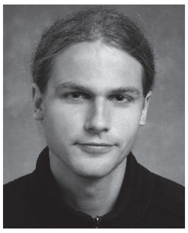
Daniel Kullmann was born in Frankfurt/Main, Germany, on August 15, 1973. He graduated in Computer Science from Darmstadt University of Technology in 2002.

After working for several years in the IT industry, he started in 2008 a PhD degree at Risø National Laboratory in Denmark. His fields of interest are distributed control and communication in power systems.



Anders Thavlov was born in Copenhagen, Denmark, on June 3, 1979. He graduated from Department of Informatics and Mathematical Modeling at Technical University of Denmark in 2008.

He is currently conducting his Ph.D. study at the Intelligent Energy Systems at Risø DTU National Laboratory for Sustainable Energy. His main research interests are energy systems modeling and control.



Oliver Gehrke was born in Frankfurt am Main, Germany, on March 15, 1975. He graduated in Electrical Power Engineering from Darmstadt University of Technology and got his PhD degree at Risø National Laboratory in Denmark. He is currently a Scientist at Risø DTU.

His special fields of interest include the embedded and distributed control of power systems with a high penetration of renewable energy sources.

Henrik Bindner was born on 30 June 1964 in Copenhagen, Denmark. He received his master in electrical engineering from the Technical University of Denmark in 1988. Since 1990 he has been with Risø DTU National Laboratory for Sustainable Energy in the Wind Energy Division, currently as a Senior Scientist.

He has mainly been working on integration of wind energy into power system. The work has included analysis, design and control of small island systems as well as technologies and techniques for integration of wind in large systems. Currently, he is researching how distributed energy resources can be applied to increase penetration of wind energy.