

Methodologies for Operating Future Intelligent Energy Systems



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The Danish Wind Power Case

.... balancing of the power system



■ Wind power □ Demand

In 2008 wind power did cover the entire demand of electricity in 200 hours (West DK)



■ Wind power □ Demand

In 2015 more than 42 pct of electricity load was covered by wind power.

For several days the wind power production was more than 100 pct of the power load.

July 10th, 2015 more than 140 pct of the power load was covered by wind power





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From large central plants to Combined Heat and Power (CHP) production

<u>Today</u>



From a few big power plants to many small **combined heat and power** plants – however most of them based on coal



DK has enough excess heat to cover the entire need for heating but ...

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Solar district heating in Denmark



L6

Energy Systems Integration



Energy system integration (ESI) = the process of optimizing energy systems across multiple pathways and scales





Flexible Solutions and CITIES

The *Center for IT-Intelligent Energy Systems in Cities (CITIES)* is aiming at establishing methodologies and solutions for design and operation of integrated electrical, thermal, fuel pathways at all scales.





Smart-Energy OS



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Control and Optimization





In New Wiley Book: Control of Electric Loads in Future Electric Energy Systems, 2015

Day Ahead:

Stoch. Programming based on eg. Scenarios Cost: Related to the market (one or two levels)

Direct Control:

Actuator: Power

Two-way communication

Models for DERs are needed

Constraints for the DERs (calls for state est.)

Contracts are complicated

Indirect Control:

Actuator: Price

Cost: E-MPC at **low (DER) level**, One-way communication

Models for DERs are not needed

Simple 'contracts'



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Direct vs Indirect Control

Level	Direct Control (DC)	Indirect Control (IC)
III	$\min_{x,u} \sum_{k=0}^{N} \sum_{j=1}^{J} \phi_j(x_{j,k}, u_{j,k})$	$ \min_{\hat{z}, p} \sum_{k=0}^{N} \phi(\hat{z}_k, p_k) $ s.t. $\hat{z}_{k+1} = f(p_k) $
IV	$\downarrow_{u_1} \dots \downarrow_{u_J} \uparrow_{x_1} \dots \uparrow_{x_J}$ s.t. $x_{j,k+1} = f_j(x_{j,k}, u_{j,k}) \forall j \in J$	$\min_{u} \sum_{k=0}^{N} \phi_j(p_k, u_k) \forall j \in J$ s.t. $x_{k+1} = f_j(x_k, u_k)$

Table 1: Comparison between direct (DC) and indirect (IC) control methods. (DC) In direct control the optimization is globally solved at level III. Consequently the optimal control signals u_j are sent to all the J DER units at level IV. (IC) In indirect control the optimization at level III computes the optimal prices p which are sent to the J-units at level IV. Hence the J DERs optimize their own energy consumption taking into account p as the actual price of energy.



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Forecast requirements



Day Ahead:

- Forecasts of loads
- Forecast of Grid Capacity (using eg. DLR)
- Forecasts of production (eg. Wind and Solar)

Direct Control: .

- Forecasts of states of DERs
- Forecasts of load

Indirect Control:

- Forecasts of prices
- Forecasts of load







(a) Indirect control



(b) Direct control



Models



Grey-box modelling are used to establish models and methods for real-time operation of future electric energy systems







SE-OS Characteristics

- Bidding clearing activation at higher levels
- Control principles at lower levels
- Cloud based solution for forecasting and control
- Facilitates energy systems integration (power, gas, thermal, ...)
- Allow for new players (specialized aggregators)
- Simple setup for the communication
- Simple (or no) contracts
- Rather simple to implement
- Harvest flexibility at all levels





SE-OS Control loop design – **logical drawing**



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Software solutions

Software for combined physical and statistical modelling

Continuous Time Stochastic Modelling (CTSM) is a software package for modelling and simulation of combined physical and statistical models. You find a technical description and the software at CTSM.info.

Software for Model Predictive Control

HPMPC is a toolbox for High-Performance implementation of solvers for Model Predictive Control (MPC). It contains routines for fast solution of MPC and MHE (Moving Horizon Estimation) problems on embedded hardware. The software is available on GitHub.

MPCR is a toolbox for building Model Predictive Controllers written in R, the free statistical software. It contains several examples for different MPC problems and interfaces to opensource solvers in R. The software is available on GitHub.

Latest news

Summer School at DTU, Lyngby, Denmark – July 4th-8th 2016

Summer School – Granada, Spain, June 19th-24th 2016

Third general consortium meeting – DTU, May 24th-25th 2016

Smart City Challenge in Copenhagen – April 20th 2016

Guest lecture by Pierluigi Mancarella at DTU, April 6th

Lab testing



SN-10 Smart House Prototype





Which type of forecast?

- Point forecasts
- Conditional mean and covariances
- Conditional quantiles (Prob. forecasts)
- Conditional scenarios
- Conditional densities
- Stochastic differential equations

for IT Intelligent Energy Systems



Wind and Solar Power Forecasting

- Methods for wind power forecasting have been continuously developed and used operationally since 1995 (solar power since 2005).
- Implemented for instance in WPPT, Anemos WPS, AWEFS, ASEFS, ..
- Sold for instance in systems provided by ENFOR (Denmark) and Overspeed GmbH (Germany)
- Today our systems are used worldwide (North America, Europe, Africa, Japan, Middle East, Australia).
- Used by all major players in Denmark (TSO, DSOs, BRPs, ...)





Example

Solar Power Forecasting







Solar Power Forecasting





- Grid connected PV-systems mainly installed on rooftops
- Average of output from 21 PV systems in Brædstrup





Based on MET forecasts and online readings of output

Two-step method:

- 1) Transformation to atmospheric transmittance with statistically clear sky (see above),
- 2) A dynamic model + adaptive quantile regression.







Adaptive correction method







Adaptive correction method





Adaptive correction method (correction function)





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Adaptive correction method







Example

Grey-box Modelling





Grey Box Models for Integration

Energy Systems Integration using data leading to stochastic grey box models for real-time operation of future flexible energy systems.





The grey-box model



Drift term



System equation Observation equation

Diffusion term

Observation noise

Notation:

- X_t : State variables
- u_t: Input variables
- θ : Parameters
- Y_k : Output variables
- t: Time
- ω_t : Standard Wiener process
- e_k : White noise process with N(0, S)





Grey-box modelling concept



- Combines prior physical knowledge with information in data
- Equations and parameters are physically interpretable









Grey-Box Modelling

- Bridges the gap between physical and statistical modelling
- Provides methods for model identification
- Provides methods for model validation
- Provides methods for pinpointing model deficiencies
- Enables methods for a reliable description of the uncertainties, which implies that the same model can be used for k-step forecasting, simulation and control



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Case study

Control of Power Consumption to Summer Houses with a Pool









Services





- The large inertia of pools allows for shift of electricity consumption by several hours.
- Via active coordination of the flexibility below a critical node on the DSO grid.
- Active load management to help finding an optimal routing of the power.





Smart Control of Houses with a Pool





Case study

Control of Power Consumption (DSM) using the Thermal Mass of Buildings





Data from BPA



Olympic Pensinsula project

- 27 houses during one year
- Flexible appliances: HVAC, cloth dryers and water boilers
- 5-min prices, 15-min consumption
- Objective: limit max consumption







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Response on Price Step Change







Control of Power Consumption







Control performance

Considerable reduction in peak consumption





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Case study

Heat Pumps and Local Storage





Grundfos Case Study

Schematic of the heating system



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Modeling Heat Pump and Solar Collector

Simplified System





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Avanced Controller

Economic Model Predictive Control

Formulation

The Economic MPC problem, with the constraints and the model, can be summarized into the following formal formulation:

$$\min_{\{u_k\}_{k=0}^{N-1}} \phi = \sum_{k=0}^{N-1} c' u_k$$
Subject to $x_{k+1} = Ax_k + Bu_k + Ed_k k = 0, 1, \dots, N-1$ (4b)
 $y_k = Cx_k \qquad k = 1, 2, \dots, N - 1$ (4c)
 $u_{min} \le u_k \le u_{max} \qquad k = 0, 1, \dots, N-1$ (4d)
 $\Delta u_{min} \le \Delta u_k \le \Delta u_{max} \qquad k = 0, 1, \dots, N-1$ (4e)
 $y_{min} \le y_k \le y_{max} \qquad k = 0, 1, \dots, N - 1$ (4f)



Heat pump with thermal solar collector and storage (savings up to 35 pct)







Case study

Control of Wastewater Treatment Plants





Waste-2-Energy





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Kolding WWTP





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Energy Flexibility in Wastewater Treatment



Pumps and storage in sewer system

Overall goals:

Cost reduction Minimize effluent concentration Minimize overflow risk





Energy Flexibility in Wastewater Treatment







WWTP Control goal

minimize $p_{fee}Q^TS_N + p_{elspot}^Tu$



Activated Sludge Model (ASM) No. 1

$$\begin{split} \dot{S}_{NH} &= -i_{XB} \left(\rho_1 + \rho_2 \right) - \left(i_{XB} + \frac{1}{Y_A} \right) \rho_3 + k_a S_{ND} X_{B,H} \\ \dot{S}_{NO} &= -\frac{1 - Y_H}{2.68 Y_H} \rho_2 + \frac{1}{Y_A} \rho_3 \\ \dot{S}_O &= -\frac{1 - Y_H}{Y_H} \rho_1 - \frac{4.57 - Y_A}{Y_A} \rho_3 \\ \dot{S}_S &= \rho_7 - \frac{1}{Y_H} \left(\rho_1 + \rho_2 \right) \\ \dot{X}_S &= (1 - f_p) (b_H X_{B,H} + b_A X_{B,A}) - \rho_7 \\ \dot{X}_{B,H} &= \rho_1 + \rho_2 - b_H X_{B,H} \\ \dot{X}_{B,A} &= \rho_3 - b_A X_{B,A} \\ \dot{S}_{ND} &= \rho_8 - k_a S_{ND} X_{B,H} \\ \dot{X}_{ND} &= (i_{XB} - f_p i_{XP}) (b_H X_{B,H} + b_A X_{B,A}) - \rho_8 \\ (S_I, X_I, X_P, \text{ and } S_{ALK}) \end{split}$$

Reaction Rates in ASM No. 1

$$\begin{aligned} \rho_{1} &= \hat{\mu}_{H} \frac{S_{S}}{K_{S} + S_{S}} \frac{S_{O}}{K_{O,H} + S_{O}} X_{B,H} \\ \rho_{2} &= \hat{\mu}_{H} \frac{S_{S}}{K_{S} + S_{S}} \frac{K_{O,H}}{K_{O,H} + S_{O}} \frac{S_{NO}}{K_{NO} + S_{NO}} \eta_{g} X_{B,H} \\ \rho_{3} &= \hat{\mu}_{A} \frac{S_{NH}}{K_{NH} + S_{NH}} \frac{S_{O}}{K_{O,A} + S_{O}} X_{B,A} \\ \rho_{7} &= k_{h} \frac{X_{S} / X_{B,H}}{K_{X} + X_{S} / X_{B,H}} \left(\frac{S_{O}}{K_{O,H} + S_{O}} + \frac{\eta_{h} \frac{K_{O,H}}{K_{O,H} + S_{O}} \frac{S_{NO}}{K_{NO} + S_{NO}} \right) X_{B,H} \\ \rho_{8} &= \rho_{7} \left(X_{ND} / X_{S} \right) \end{aligned}$$



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minimize overflow $+ p_{elspot}^T f(Q)$







Sewer System Annual Elspot Savings



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Energy Flexibility Some Demo Projects in CITIES

- Control of WWTP (ED, Krüger, ..)
- Heat pumps (Grundfos, ENFOR, ..)
- Supermarket cooling (Danfoss, TI, ..)
- Summerhouses (DC, SE, Energinet.dk, ..)
- Green Houses (NeoGrid, Danfoss, F.Fyn,)
- CHP (Dong Energy, FjernvarmeFyn, HOFOR, NEAS, ...)
- Industrial production (DI, ...)
- EV (charging) (Eurisco, ED, ...)









(Virtual) Storage Solutions



Flexibility (or virtual storage) characteristics:

- Supermarket refrigeration can provide storage 0.5-2 hours ahead
- Buildings thermal capacity can provide storage up to, say, 5-10 hours ahead
- Buildings with local water storage can provide storage up to, say, 2-12 hours ahead
- District heating/cooling systems can provide storage up to 1-3 days ahead
- DH systems with thermal solar collectors can often provide seasonal storage solutions
- Gas systems can provide seasonal/long term storage solutions

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Discussion



- IT-Intelligent Energy Systems Integration can provide virtual storage solutions (so maybe we should put less focus on electrical storage solutions)
- District heating (or cooling) systems can provide flexibility on the essential time scale (up to a few days)
- Gas systems can provide seasonal virtual storage solutions
- Smart Cities are just smart elements of a Smart Society
- We see a large potential in Demand Response. Automatic solutions, price based control, and end-user focus are important
 - We see large problems with the tax and tariff structures in many countries (eg. Denmark).
 - Markets and pricing principles need to be reconsidered; we see an advantage of having a physical link to the mechanism (eg. nodal pricing, capacity markets)



Summary



- A Smart-Energy OS for implementing flexibility energy systems in smart cities has been described
- Built on: Big Data Analytics, Cyber Physical systems, Stochastic opt./control, Forecasting, IoT, IoS, Cloud computing, ...
- Modelling: Toolbox CTSM-R for combined physical and statistical modelling (grey-box modelling)
- **Control:** Toolbox MPC-R for Model Predictive Control
- Simulation: Framework for simulating flexible power systems.



Some 'randomly picked' books on modeling







