Smart control of energy systems with PVT

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DTU Compute, Dynamical Systems

WORKSHOP ON PV-THERMAL SYSTEMS

October 9, 2019

CHALLENGES WITH RENEWABLE DRIVEN SYSTEM

- Make the operation “optimal” using available “flexibility”:
    - Adapt to variation in generation and demand in general (e.g. wind)
    - Help the grid (peaks and congestion)

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Solutions

- Shift demand:
  - Dish washer, etc. (usually low demand)
- Store energy:
  - Thermal (hot water tank, DH grids and in building elements)
  - Chemically (batteries)

Problem: When to charge battery? when to run heat pump?

SEVERAL DEMO CASES OF MODEL PREDICTIVE CONTROL (MPC)

- BIPVT-E project in Stenløse, DK:
  - EMPC for optimizing battery charging
- Grundfos test house:
  - EMPC for optimizing heat pump heating with hot water tank
- Swimming pool heating:
  - EMPC for optimizing the heating of swimming pools

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HVAC in buildings, waste-water treatment, water management, ...

ECONOMIC MODEL PREDICTIVE CONTROL (EMPC)

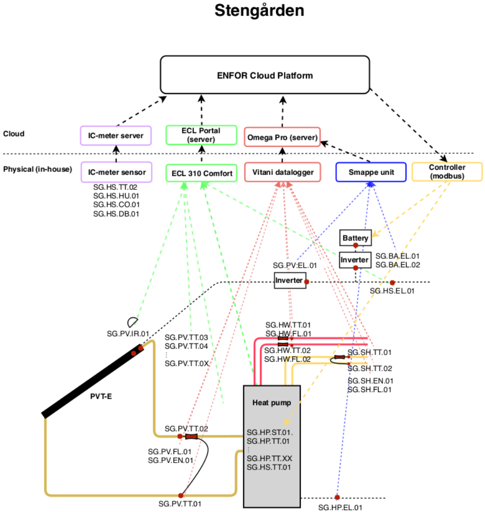
Need to setup:

- A model of the system (keep as simple as needed)
- An objective function with constraints (usually the energy buy and selling costs, but could be any "penalty")
- Forecasts of input variables to the model and objective function

At every time step

1. Calculate forecasts:
    - Weather, generation, demand and price forecasts
2. Optimize the objective function:
    - Find the sequence ahead of control variables (CV) which optimize the objective function, while keeping constraints
3. Implement optimal CV until next step

BIPVT-E system with DTU Byg, COWI, Racell



Stengården

ENFOR Cloud Platform

Cloud

IC-meter server

ECL Portal (server)

Omega Pro (server)

Physical (in-house)

IC-meter sensor

ECL 310 Comfort

Vitani datalogger

Smappe unit

Controller (modbus)

SG.HS.TT.02
SG.HS.HU.01
SG.HS.CO.01
SG.HS.DB.01

Battery

Inverter

SG.BA.EL.01
SG.BA.EL.02

SG.PV.EL.01

Inverter

SG.HS.EL.01

SG.PV.IR.01

SG.PV.TT.03
SG.PV.TT.04
⋮
SG.PV.TT.0X

SG.HW.TT.01
SG.HW.FL.01
SG.HW.TT.02
SG.HW.FL.02

SG.SH.TT.01
SG.SH.TT.02
SG.SH.EN.01
SG.SH.FL.01

PVT-E

Heat pump

SG.HP.ST.01.
SG.HP.TT.01
⋮
SG.HP.TT.XX
SG.HS.TT.01

SG.PV.TT.02

SG.PV.FL.01
SG.PV.EN.01

SG.PV.TT.01

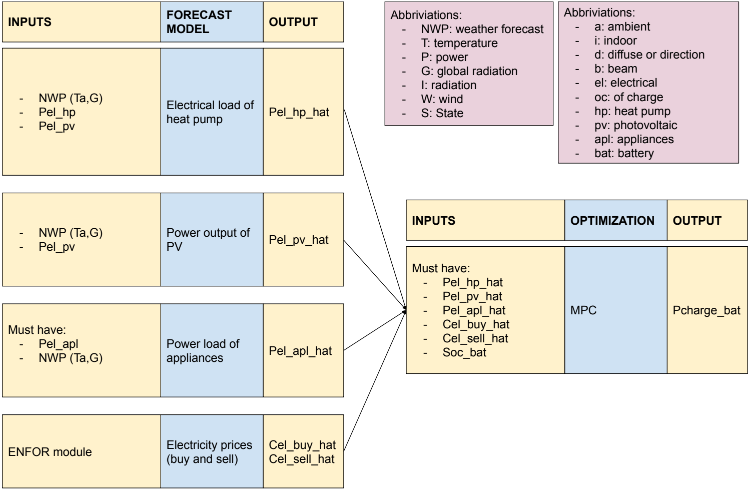
SG.HP.EL.01

PV WITH BATTERY

EMPC objective function and model with constraints:

$$\begin{aligned}
\text{Minimize} \quad & \sum_{k=1}^{N} \left(\lambda_k g_k^- - \tau \lambda_k g_k^+\right) && \text{(cost sell $-$ cost buy)} \\
\text{subject to}_{1\le k\le N} \quad & d_k = p_k + b_k^- - b_k^+ + g_k^- - g_k^+, && \text{(demand)} \\
& b_k = b_{k-1} + c_B b_k^+ - b_k^-, && \text{(Simple battery model)} \\
& 0 \le b_k \le b_{\max}, && \text{(min. \& max. of bat.)} \\
& 0 \le b_k^+ \le b_{\max}^+, && \text{(max. charge rate)} \\
& 0 \le b_k^- \le b_{\max}^-, && \text{(max. discharge rate)} \\
& g_k^-, g_k^+ \ge 0. && \text{(buy \& sell positive)}
\end{aligned}$$

BIPVT-E EMPC FORECASTS



INPUTS	**FORECAST MODEL**	**OUTPUT**
- NWP (Ta,G) - Pel_hp - Pel_pv	Electrical load of heat pump	Pel_hp_hat
- NWP (Ta,G) - Pel_pv	Power output of PV	Pel_pv_hat
Must have: - Pel_apl - NWP (Ta,G)	Power load of appliances	Pel_apl_hat
ENFOR module	Electricity prices (buy and sell)	Cel_buy_hat Cel_sell_hat

Abbriviations:
- NWP: weather forecast
- T: temperature
- P: power
- G: global radiation
- I: radiation
- W: wind
- S: State

Abbriviations:
- a: ambient
- i: indoor
- d: diffuse or direction
- b: beam
- el: electrical
- oc: of charge
- hp: heat pump
- pv: photovoltaic
- apl: appliances
- bat: battery

INPUTS	**OPTIMIZATION**	**OUTPUT**
Must have: - Pel_hp_hat - Pel_pv_hat - Pel_apl_hat - Cel_buy_hat - Cel_sell_hat - Soc_bat	MPC	Pcharge_bat

PV WITH BATTERY (SIMULATIONS)

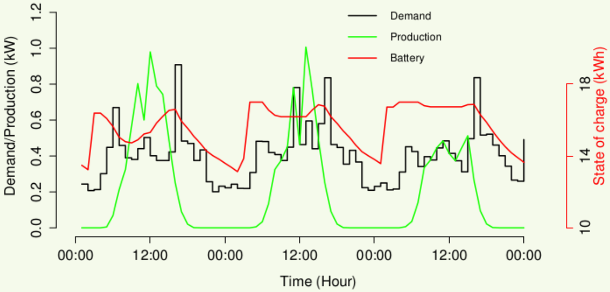


Figure 1: **Demand and own-production with the corresponding state of charge of a battery.**

PV WITH BATTERY

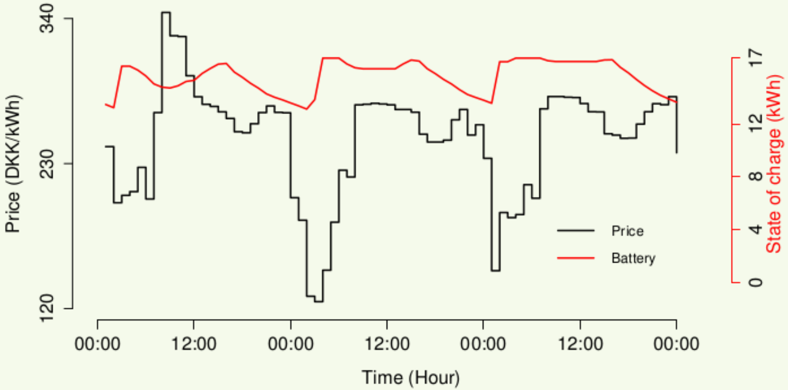
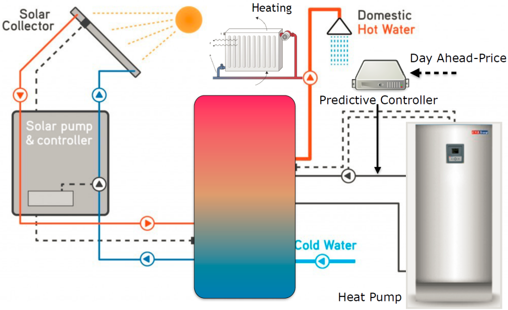


Figure 2: Electricity price and the corresponding state of charge of a battery.

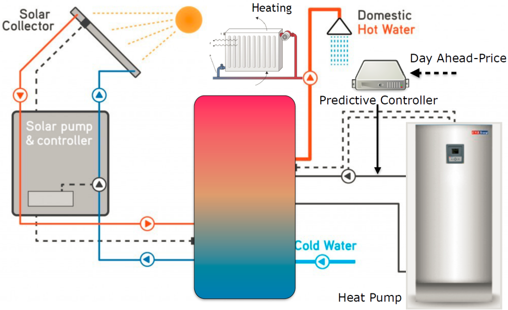
IPower og CITIES projektet (Jacopo Parvizi): Grundfos Test Facility, the heating system is composed of the following elements:

- 600 l Stratified Hot Water Tank
- 7.2 m^2 Solar Thermal Collector
- Heat Pump - $7kW$ with Variable Speed Compressor
- Domestic Hot Water Grundfos Fresh Water Module
- District Heating Backup
- Local Weather Station
- Kamstrup Multical Heat Meters



Necessary forecasts as input to Economic Model Predictive Control (EMPC):

- Heat demand in the building
- Solar heating
- Electricity price



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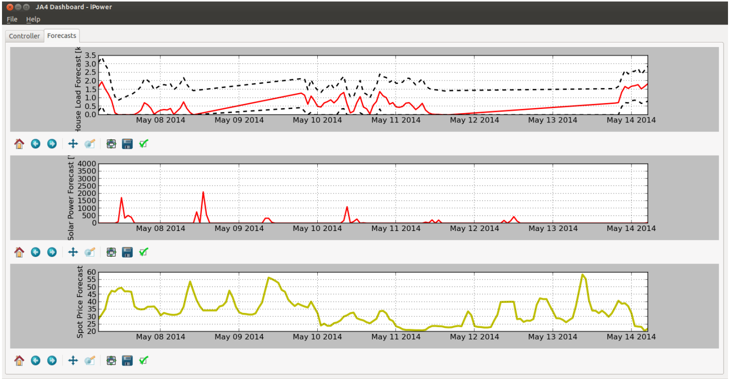

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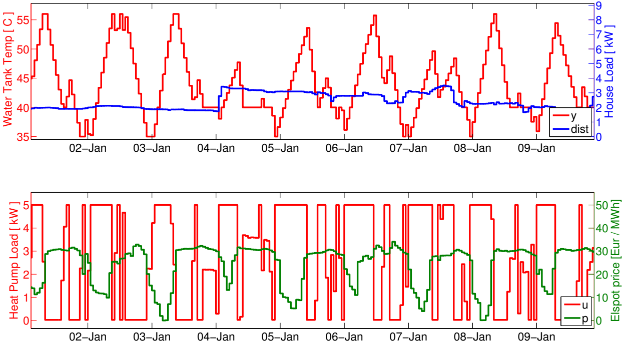
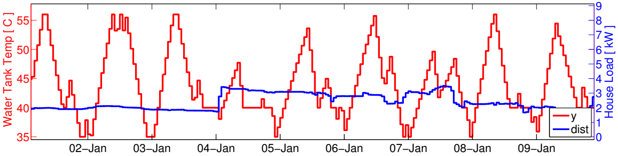
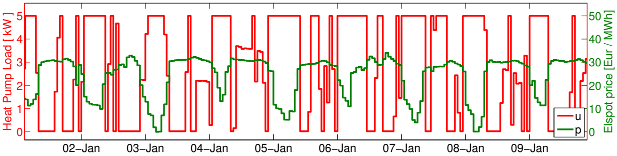


Savings achieved with EMPC (two scenarios: varying price and flat price)

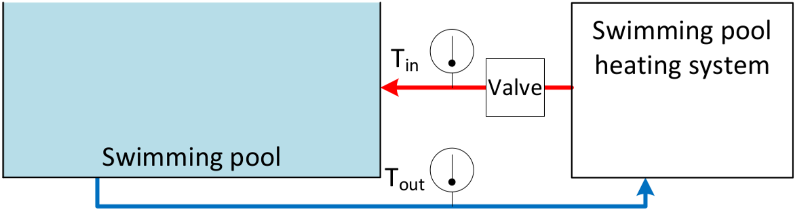
	2013	2014
EMPC var. tariff	11%	16%
EMPC flat tariff	3%	8%





POOL SUMMERHOUSES FROM THE PROJECT SMARTNET

Control of heating of swimming pools in summer houses, using the pool as the heat storage:



POOLSOMMERHUSE FRA PROJEKTET SMARTNET

The EMPC buy electricity when the price is low:

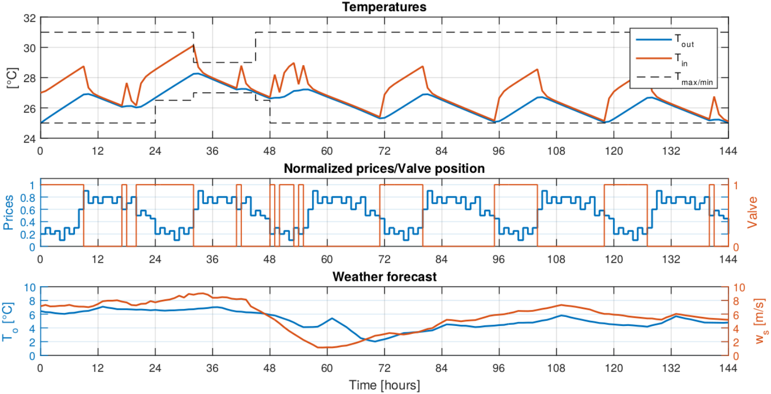


Fig. 3. Simulation results.

CONCLUSIONS USING EMPC

Conclusions

- EMPC become attractive when economic incentives are strong enough (especially tax schemes have influence)
- It doesn't need to be a price signal which drives, any "penalty" can be used
- We need robust statistical models and good forecasts
- To be done: hotwater tank, building and battery in one EMPC

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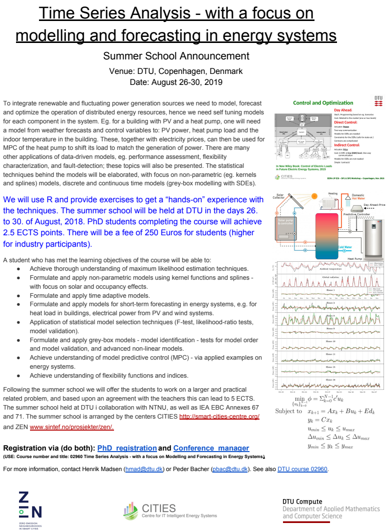
- To be done: hotwater tank, building and battery in one EMPC

- Forecasting software (R package)
- Grey-box modelling (R package (ctsmr: `ctsm.info`)
- Many optimization implementations are available (easy with linear models: linear programming)

SUMMER SCHOOL AT DTU



Time Series Analysis - with a focus on modelling and forecasting in energy systems

Summer School Announcement

Venue: DTU, Copenhagen, Denmark
Date: August 26-30, 2019

To integrate renewable and fluctuating power generation sources we need to model, forecast and optimize the operation of distributed energy resources, hence we need self tuning models for each component in the system. Eg. for a building with PV and a heat pump, one will need a model from weather forecasts and control variables to: PV power, heat pump load and the indoor temperature in the building. These, together with electricity prices, can then be used for MPC of the heat pump to shift its load to match the generation of power. There are many other applications of data-driven models, eg. performance assessment, flexibility characterization, and fault-detection; these topics will also be presented. The statistical techniques behind the models will be elaborated, with focus on non-parametric (eg. kernels and splines) models, discrete and continuous time models (grey-box modelling with SDEs).

We will use R and provide exercises to get a "hands-on" experience with the techniques. The summer school will be held at DTU in the days 26. to 30. of August, 2018. PhD students completing the course will achieve 2.5 ECTS points. There will be a fee of 250 Euros for students (higher for industry participants).

A student who has met the learning objectives of the course will be able to:

- Achieve thorough understanding of maximum likelihood estimation techniques.
- Formulate and apply non-parametric models using kernel functions and splines - with focus on solar and occupancy effects.
- Formulate and apply time adaptive models.
- Formulate and apply models for short-term forecasting in energy systems, e.g. for heat load in buildings, electrical power from PV and wind systems.
- Application of statistical model selection techniques (F-test, likelihood-ratio tests, model validation).
- Formulate and apply grey-box models - model identification - tests for model order and model validation, and advanced non-linear models.
- Achieve understanding of model predictive control (MPC) - via applied examples on energy systems.
- Achieve understanding of flexibility functions and indices.

Following the summer school we will offer the students to work on a larger and practical related problem, and based upon an agreement with the teachers this can lead to 5 ECTS. The summer school held at DTU i collaboration with NTNU, as well as IEA EBC Annexes 67 and 71. The summer school is arranged by the centers CITIES http://smart-cities-centre.org/ and ZEN www.sintef.no/prosjekter/zen/.

$$\min_{\{u_k\}_{k=0}^{N-1}} \phi = \Sigma_{k=0}^{N-1} c' u_k$$

$$\begin{aligned} \text{Subject to} \quad & x_{k+1} = Ax_k + Bu_k + Ed_k \\ & y_k = Cx_k \\ & u_{min} \le u_k \le u_{max} \\ & \Delta u_{min} \le \Delta u_k \le \Delta u_{max} \\ & y_{min} \le y_k \le y_{max} \end{aligned}$$

Registration via (do both): PhD registration and Conference manager
(USE: Course number and title: 02960 Time Series Analysis - with a focus on Modelling and Forecasting in Energy Systems)

For more information, contact Henrik Madsen (hmad@dtu.dk) or Peder Bacher (pbac@dtu.dk). See also DTU course 02960.

ZEN
ZERO EMISSION NEIGHBOURHOODS IN SMART CITIES

CITIES
Centre for IT Intelligent Energy Systems

DTU Compute
Department of Applied Mathematics and Computer Science