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Data-driven optimisation framework for assessing energy and emission saving potentials in foundation industries

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Project details

- Project title: **Data-driven optimisation framework for assessing energy and emission saving potentials in foundation industries**
- Industry Project Partner: **Palm Paper Limited**
- Project duration: **6 months**

- Aim: **Quantifying the potentials for energy and emission savings optimising energy performance**
- Objectives:
  - **O1: Data analysis and processing**
  - **O2: Identification of benchmark representative production activities**
  - **O3: Development of a data-driven modelling framework**
  - **O4: Formulation of the optimisation problem**

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Net-Zero and industrial energy

- Industry energy consumption represents almost 40% of current global total final consumption and is still dominated by fossil fuels
- The IEA predicts that efficiency increases will prevent 1Gt of carbon emissions by 2030 alone
- Foundation industries provide a large potential to improve both energy use and production efficiency
- Concerns over climate change are likely to make inefficiency and high emissions increasingly serious business liabilities

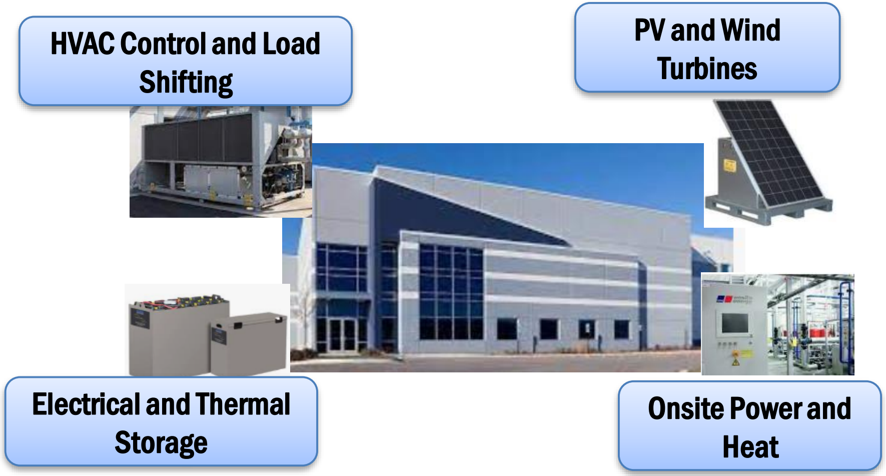
Optimised and energy-efficient production can give energy savings from 10% to 50%

- International energy Agency (IEA), *World Energy Outlook 2021*
- J. Rissman, et al., *Technologies and policies to decarbonize global industry: Review and assessment of mitigation drivers through 2070*, Applied Energy, 2020
- W. Cai et al., A review on methods of energy performance improvement towards sustainable manufacturing from perspectives of energy monitoring, evaluation, optimization and benchmarking, Renewable and Sustainable Energy Reviews, 2022

Energy management in future industry

- Combining energy management with all-important production targets requires new research into systematic, decision-making frameworks
- This becomes more important as
  - ✓ factories install renewable generation
  - ✓ rewards for grid support are available

Intelligent industries



Challenges and contributions

- Unavailable, inaccurate model, high-order highly nonlinear dynamics
- Handling energy resources along with standard operational constraints and objectives
- Multiple non-production objectives:

✓ Costs and emissions minimization
✓ Energy efficiency improvement
✓ Effective service provision

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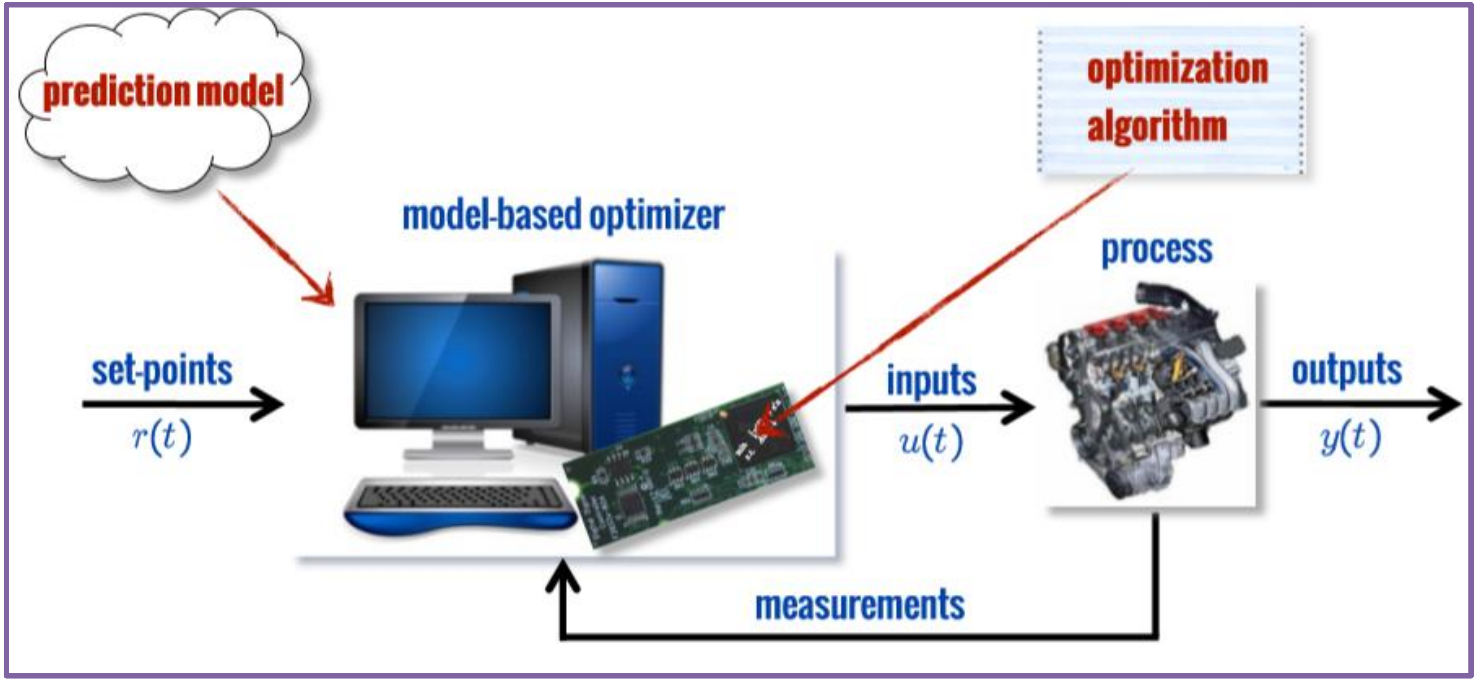
- **Advanced optimisation framework as decision-support system**
- **Data-driven modelling**

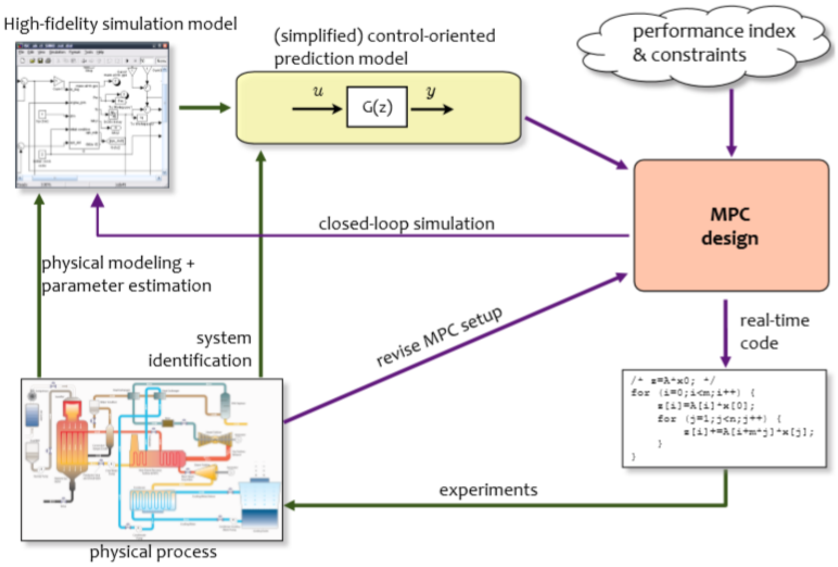
Model Predictive Control (MPC)



MPC uses a dynamical model of the process/system to predict its future evolution and choose the "best" control action

Why Model Predictive Control

- Systematic use of data, forecasts and measurements
- Based on the future behavior of the system
- Handling of constraints
- Use of a feedback mechanism
- Economic, social and environmental objectives
- Mature code and development tools
- Flexible and advanced control design

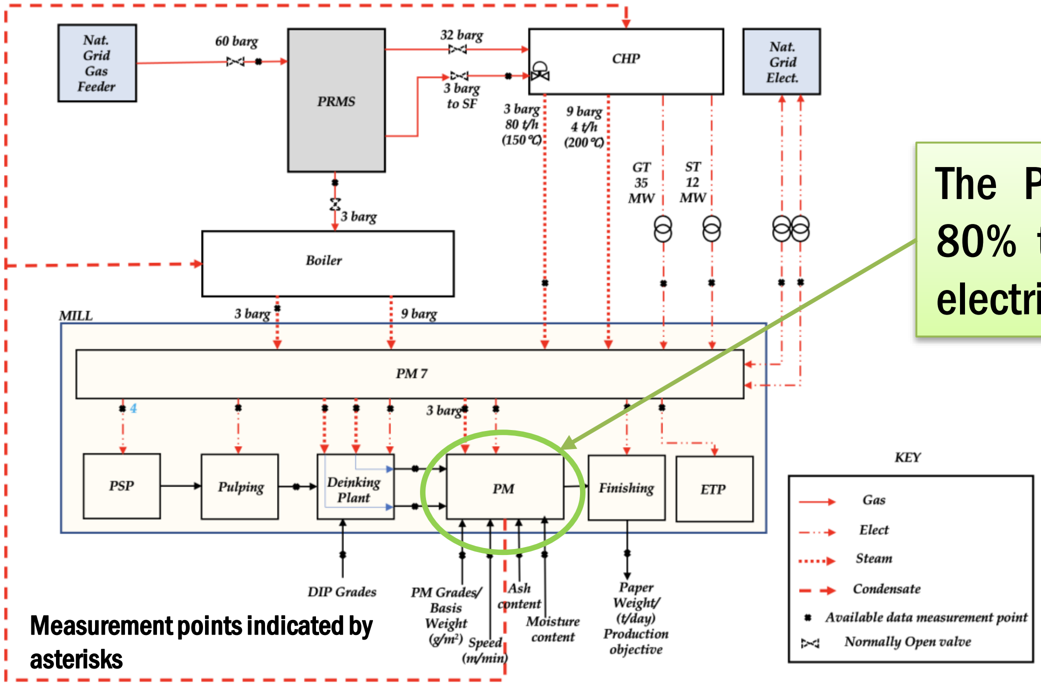


MPC design flow

Part I: Data-driven modelling

Paper industry

- Paper production company producing newsprints and news paper grades from completely recycled materials
- Production relying on natural gas and electricity



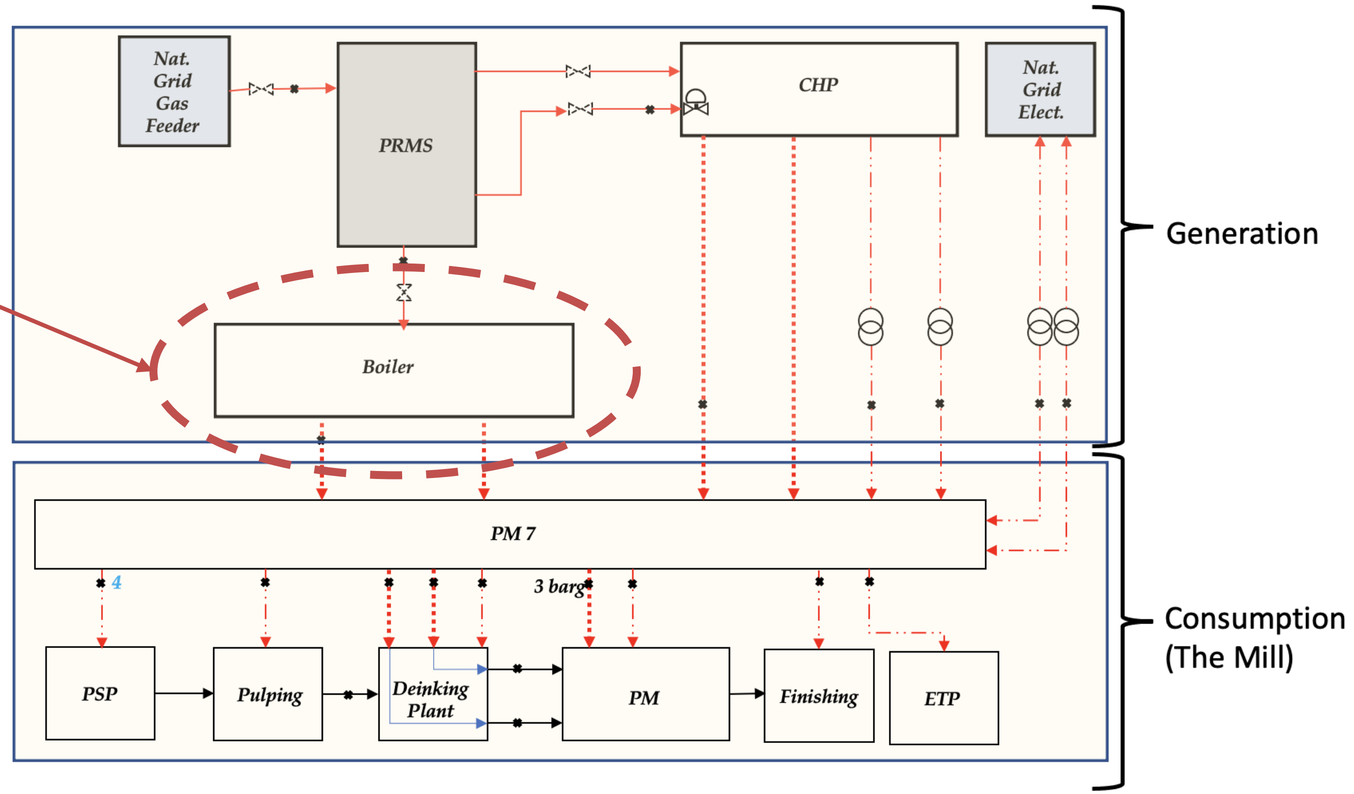
The Paper Machine (PM) consumes between 80% to 90% of total steam and 58%-70% of electricity in the mill

Measurement points indicated by asterisks

Identification of sub-systems

Main components:

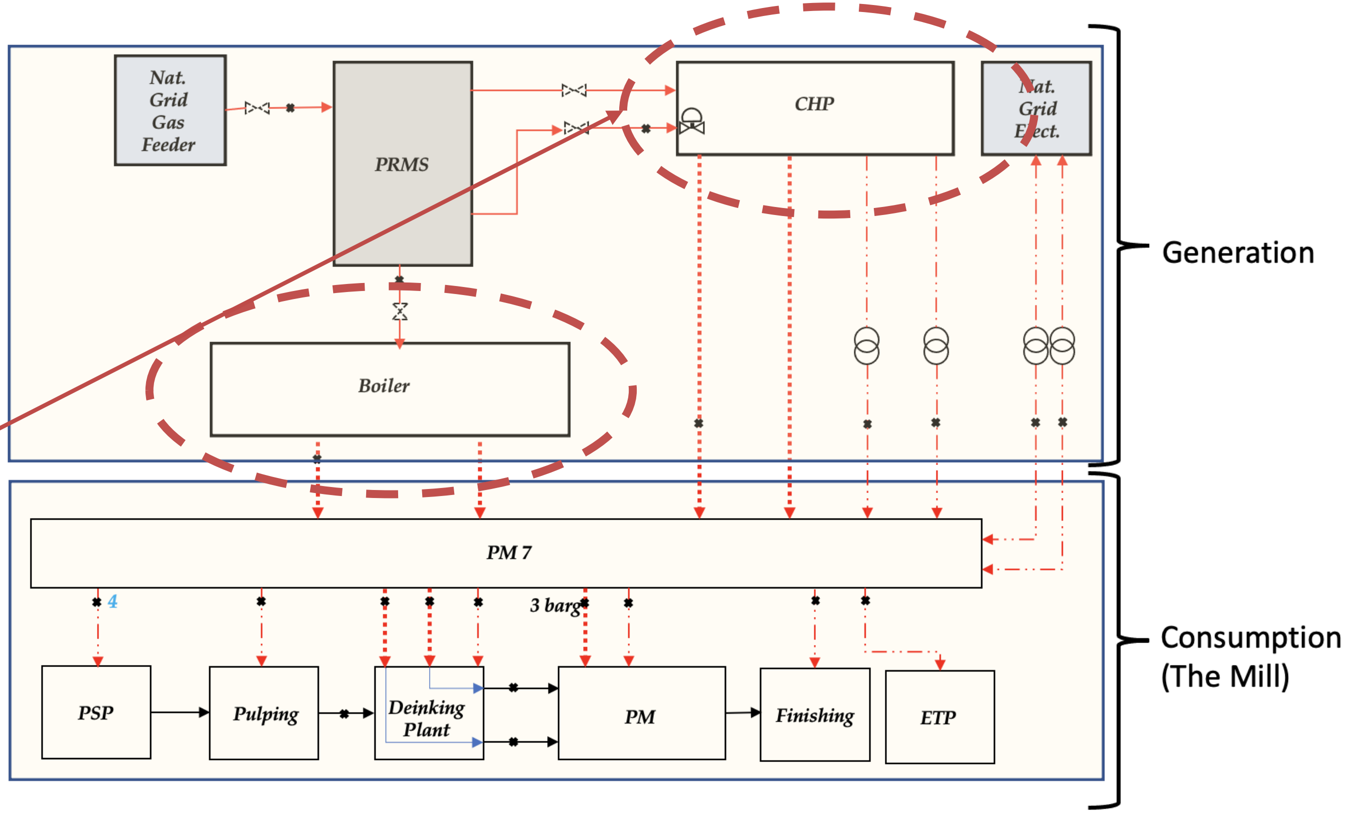
✓ **Boiler**



Identification of sub-systems

Main components:

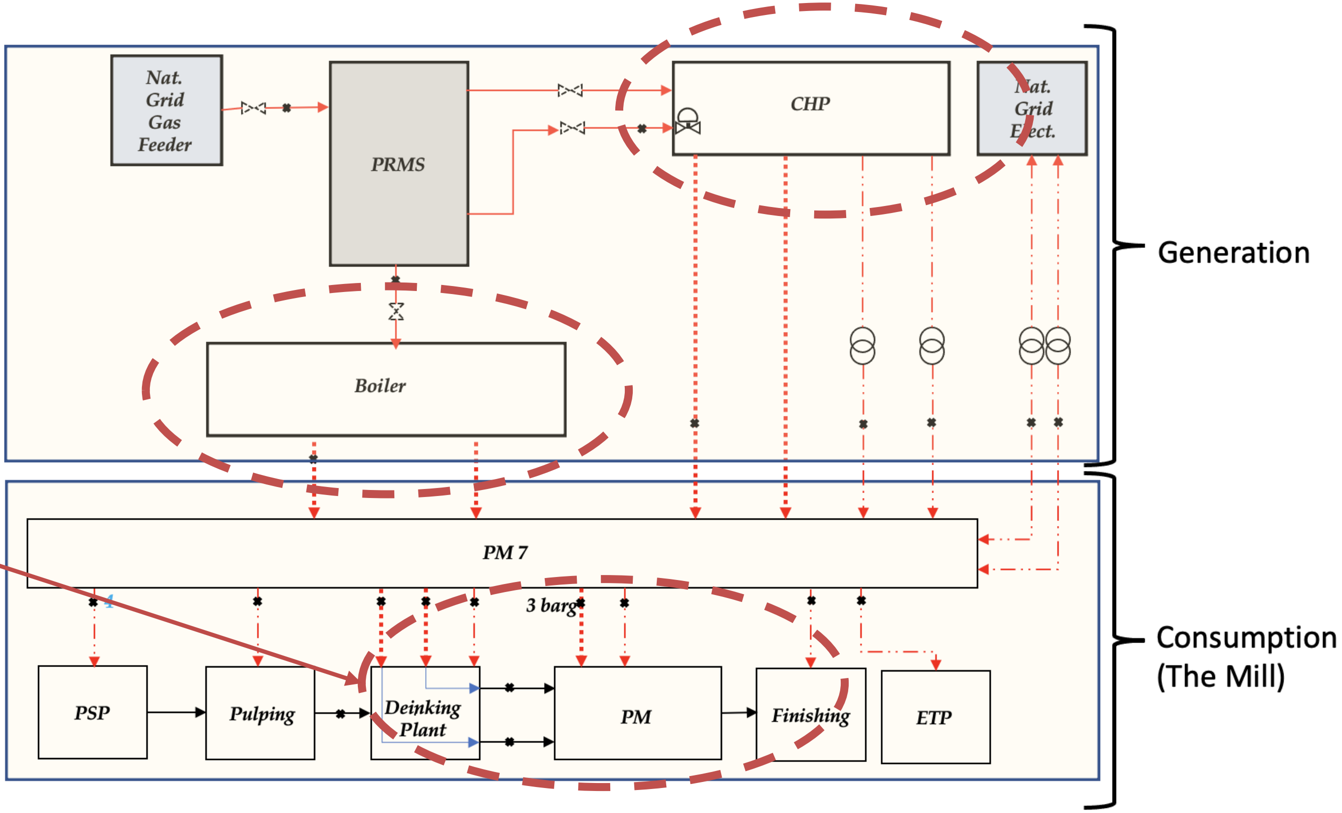
- ✓ **Boiler**
- ✓ **Combined heat and power (CHP) plant**



Identification of sub-systems

Main components:

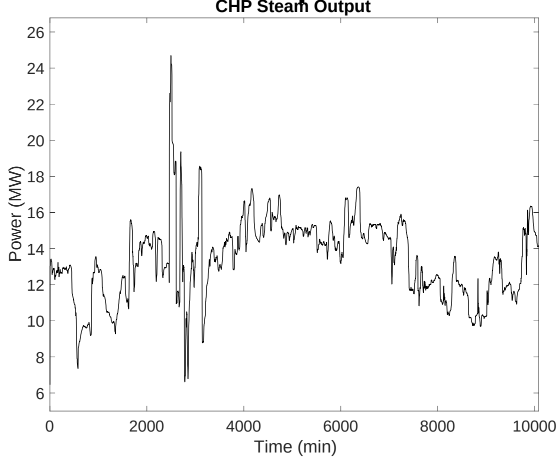
- ✓ Boiler
- ✓ Combined heat and power (CHP) plant
- ✓ Paper machine (PM)

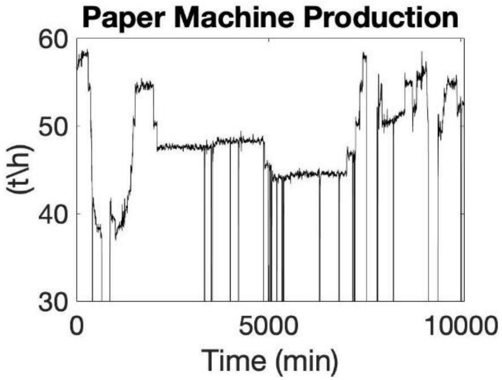


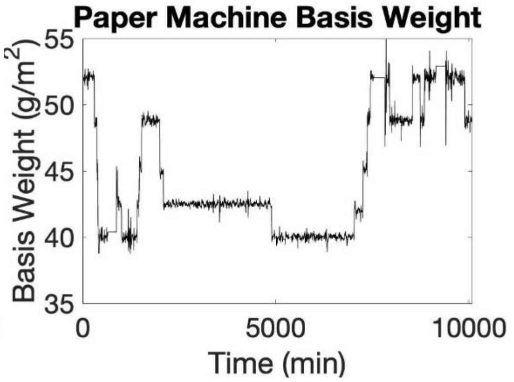
Datasets

- A yearlong data collected and sampled every minute
- Available data in their raw and unprocessed form
- Necessary to pre-process data, e.g., :
    - ✓ Resampling
    - ✓ Noise reduction
    - ✓ Elimination of outliers
    - ✓ Detrending to remove data offsets

Data of one week of operation

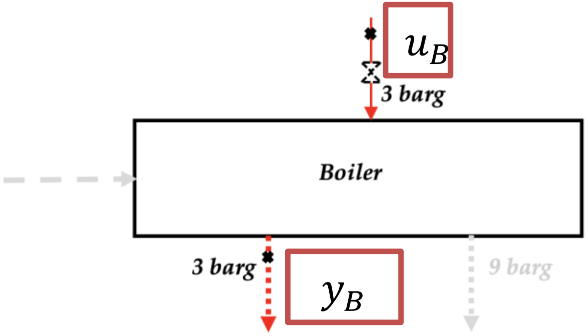


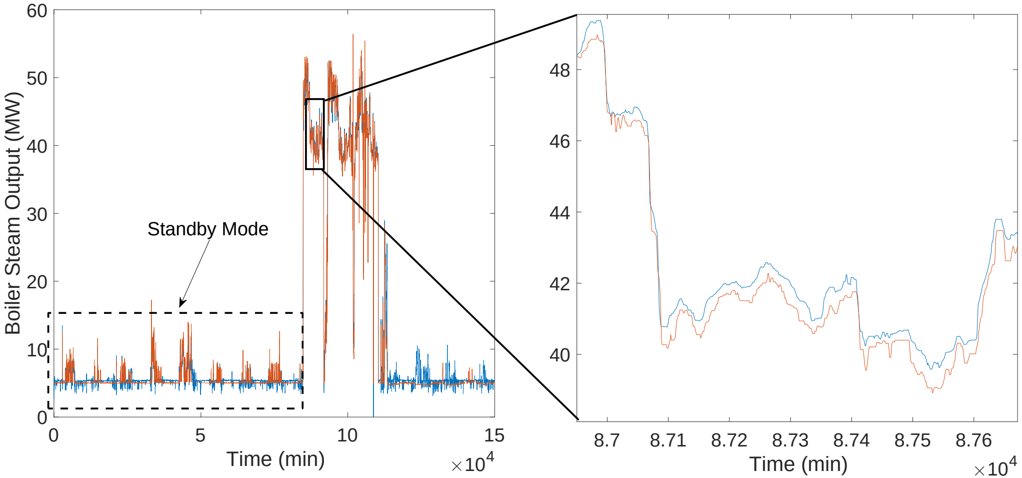




Boiler model

- Type of model: *static (least square estimation)*
- Input (u_B) = gas supply from the boiler pressure reduction and metering station (BPRMS)
- Output (y_B) = steam flow at 3 barg (9 barg pressure output negligible and unavailable)



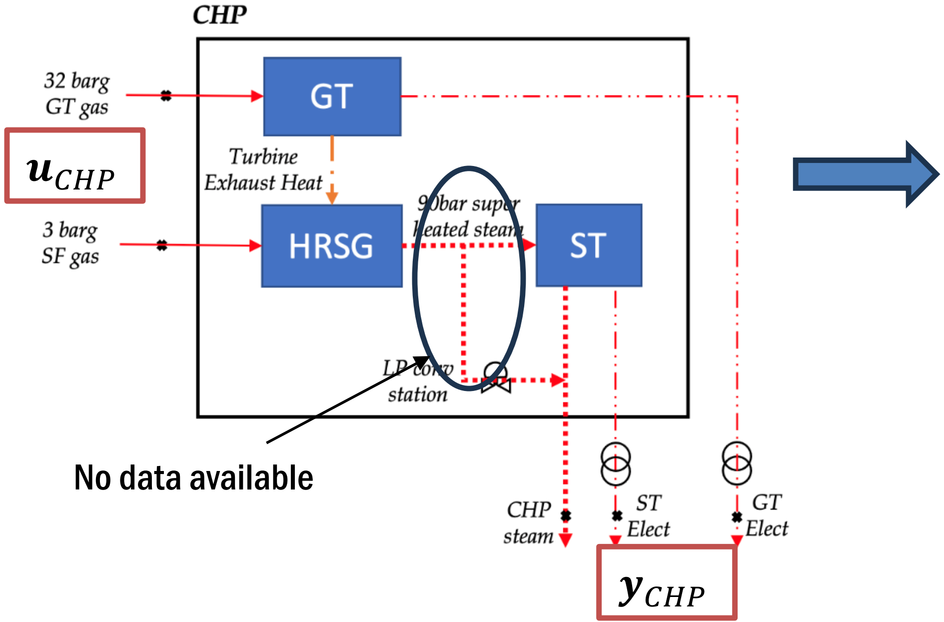


Validation: Fit % = 93.6 %

- **Model:** $y_B(t) = E_B\ u_B(t)\ + v_B(t)$
- **ON Mode:** $E_B = 75.47\%\ v_B(t) = 1.0698$
- **Standby Mode:** $E_B = 3.01\%\ v_B(t) = 5.03$

CHP model

- Type of model: *static (least square estimation)*
- Inputs ($\boldsymbol{u}_{CHP}$): gas supply to gas turbine and supplementary firing gas supply
- Outputs ($\boldsymbol{y}_{CHP}$): CHP steam, CHP Gas Turbine electrical power and CHP Steam Turbine electrical power



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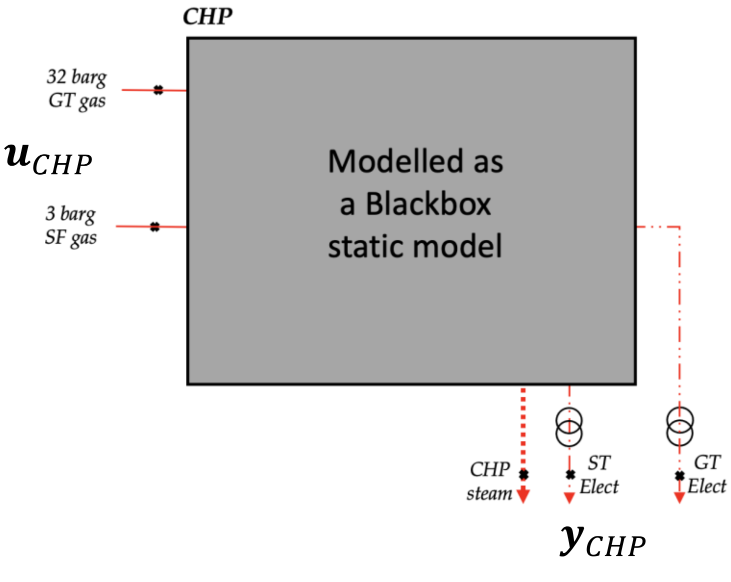


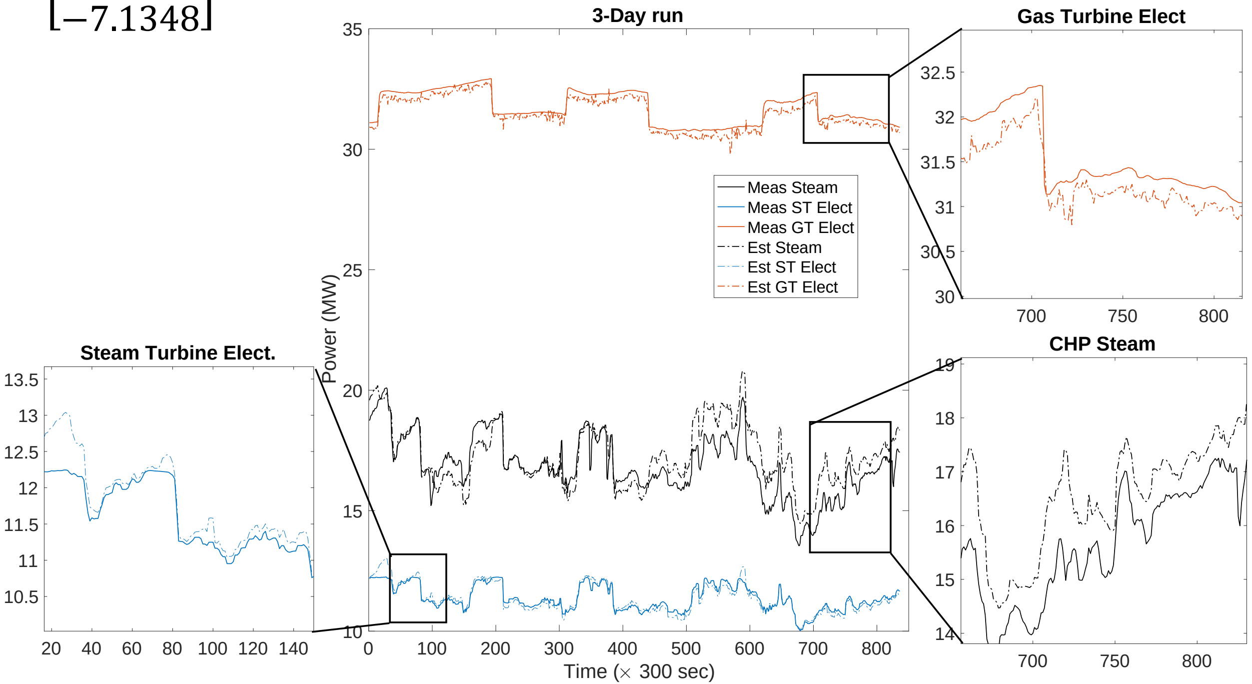
CHP model

- Model: $\boldsymbol{y}_{CHP} = \boldsymbol{E}_{CHP}\ \boldsymbol{u}_{CHP} + \boldsymbol{v}_{CHP}$

- $\boldsymbol{E}_{CHP} = \begin{bmatrix} -0.2009 & 0.4411 \\ 0.1076 & 0.2158 \\ 0.3894 & -0.0064 \end{bmatrix}, \boldsymbol{v}_{CHP} = \begin{bmatrix} 27.4471 \\ -4.1602 \\ -7.1348 \end{bmatrix}$

- $\boldsymbol{u}_{CHP} = \begin{bmatrix} u^1_{CHP} \\ u^2_{CHP} \end{bmatrix} = \begin{bmatrix} GT\ gas\ supply \\ SF\ gas\ supply \end{bmatrix}$

- $\boldsymbol{y}_{CHP} = \begin{bmatrix} y^1_{CHP} \\ y^2_{CHP} \\ y^3_{CHP} \end{bmatrix} = \begin{bmatrix} CHP\ Steam \\ CHP\ ST\ Elect \\ CHP\ GT\ Elect \end{bmatrix}$



Validation:

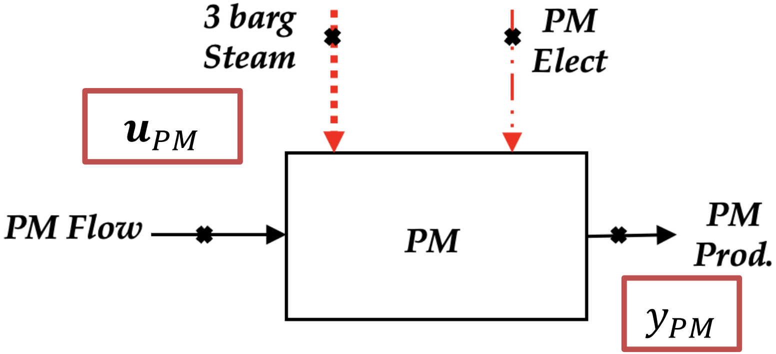
Steam Fit % = 56.87 %

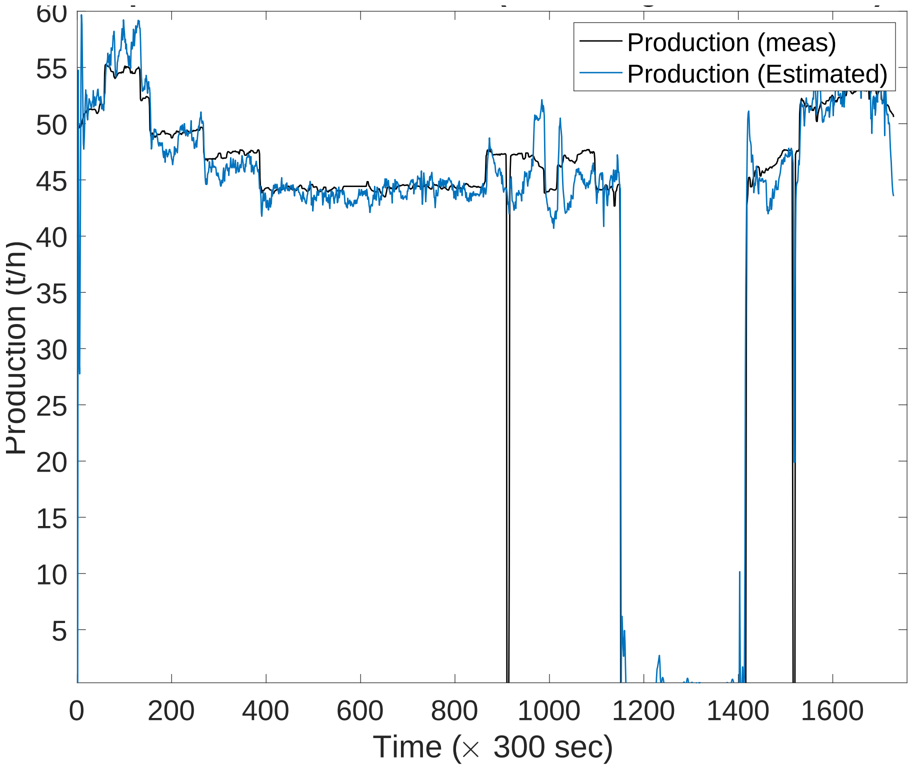
ST Elect Fit % = 87.86 %

GT Elect Fit % = 83.42 %

Paper Machine model

- Type of model: *dynamic state space (subspace identification)*
- Inputs ($\boldsymbol{u}_{PM}$): steam, electrical power and material flow
- Outputs (y_{PM}): paper machine production (t/h)





Validation: Fit % = 94.73%

Paper Machine model

- **Model:** $\boldsymbol{x}_{PM}(t+1)$= **A** $\boldsymbol{x}_{PM}(t)$ + **B** $\boldsymbol{u}_{PM}(t) + \boldsymbol{w}_{PM}(t)$

  $y_{PM}(t)$ = **C** $\boldsymbol{x}_{PM}(t)$ + $v_{PM}(t)$
- **Model order:** 4th order
- $y_{PM}(t)$ = PM Production
- $\boldsymbol{u}_{PM}(t) = \begin{bmatrix} u_{PM}^1(t) \\ u_{PM}^2(t) \\ u_{PM}^3(t) \end{bmatrix} = \begin{bmatrix} PM\ Elect \\ PM\ Steam \\ Material\ Flow \end{bmatrix}$
- $u_{PM}^1(t) = y_{CHP}^2(t) + y_{CHP}^3(t) + u_{grid}(t)$
- $u_{PM}^2(t) = a_{CHP}\, y_{CHP}^1(t) + a_B\, y_B(t)$
- $a_{CHP} = 0.6346$
- $a_B = 3.1259$

- **A** = $\begin{bmatrix} 0.694 & -0.263 & -0.250 & -0.061 \\ 0.404 & 0.615 & 0.714 & 0.043 \\ 0.057 & 0.145 & 0.130 & 0.720 \\ 0.030 & -0.207 & -0.291 & 0.300 \end{bmatrix}$
- **B** = $\begin{bmatrix} 0.006 & 0.010 & -0.009 \\ 0.004 & -0.021 & 0.063 \\ 0.042 & 0.029 & -0.064 \\ -0.016 & -0.008 & -0.001 \end{bmatrix}$
- **C** = $\begin{bmatrix} 111.5 & -12.76 & -39.78 & -49.63 \end{bmatrix}$

Part II: MPC problem formulation

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MPC formulation

Cost functions

$$\min_{u} \sum_{t=0}^{N-1} \{ \overbrace{c_{gas}(t)[u_B(t) + u_{CHP}^1(t) + u_{CHP}^2(t)] + c_{elect}(t) u_{grid}(t)}^{\text{Minimise energy costs}} + \overbrace{\gamma \|\alpha(t)\|_2^2}^{\text{Tracking production objective } [y_{PM}^R(t)]} \}$$

Constraints

$s.\ to$

$y_B(t) = E_B\ u_B(t) \ + v_B(t)$ **Boiler model**

$\boldsymbol{y}_{CHP}(t) = \boldsymbol{E}_{CHP}\ \boldsymbol{u}_{CHP}(t) \ + \boldsymbol{v}_{CHP}(t)$ **CHP model**

$\boldsymbol{x}_{PM}(t+1) = \mathbf{A}\, \boldsymbol{x}_{PM}(t) + \mathbf{B}\, u_{PM}(t) + \boldsymbol{w}_{PM}(t)$ **PM model**

$y_{PM}(t) = \mathbf{C}\, \boldsymbol{x}_{PM}(t) + v_{PM}(t)$

Bounds/Capacity limits

$\underline{\boldsymbol{u}}_{CHP} \leq \boldsymbol{u}_{CHP}(t) \leq \bar{\boldsymbol{u}}_{CHP},\ \underline{\boldsymbol{y}}_{CHP} \leq \boldsymbol{y}_{CHP}(t) \leq \bar{\boldsymbol{y}}_{CHP}$

$\underline{u}_B \leq u_B(t) \leq \bar{u}_B, \underline{y}_B \leq y_B(t) \leq \bar{y}_B$

$-\bar{u}_{grid} \leq u_{grid}(t) \leq \bar{u}_{grid}$

$-\alpha(t) + y_{PM}^R(t) \leq y_{PM}(t) \leq \alpha(t) + y_{PM}^R(t)$ **Tracking (α = slack variable)**

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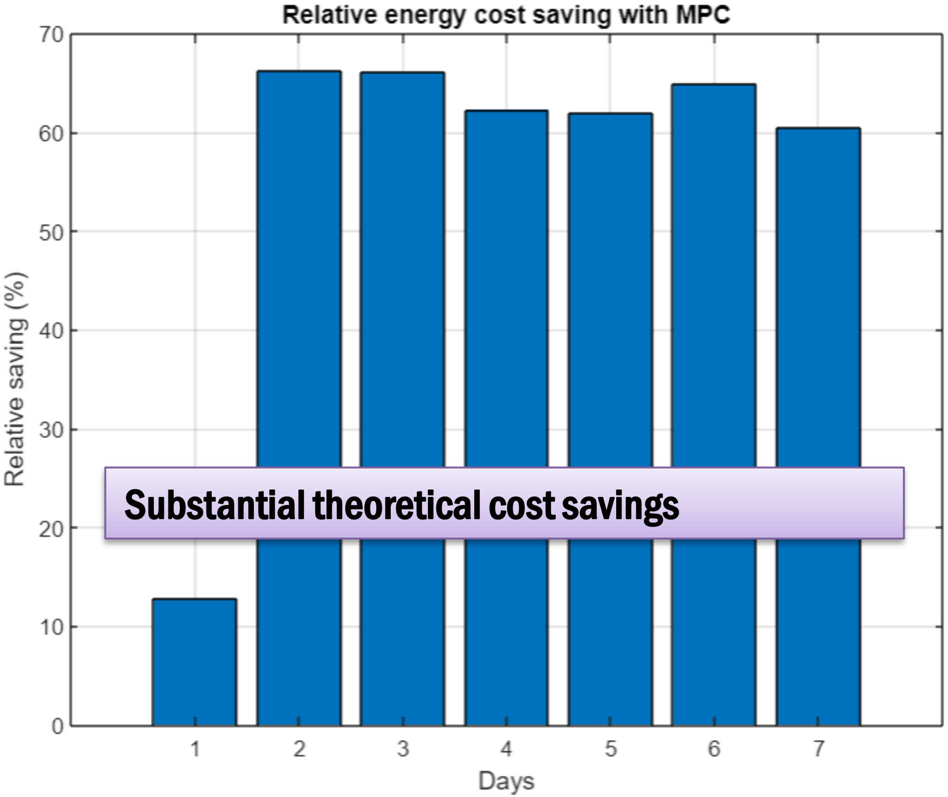
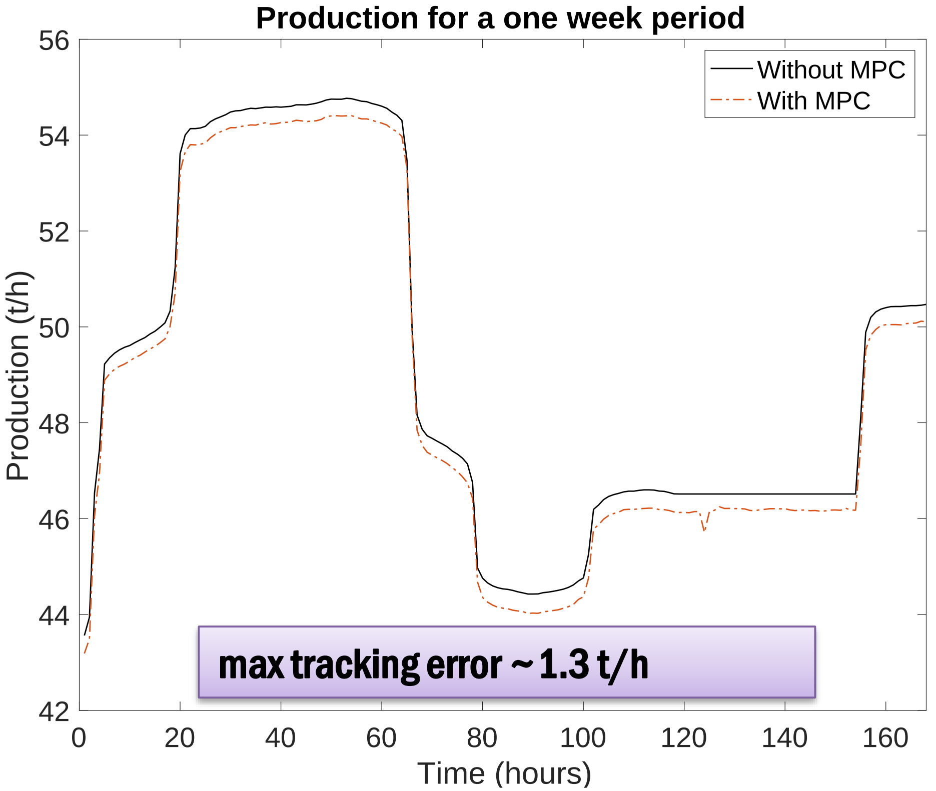
Energy costs and tracking

3 hours prediction horizon - 5 minutes sampling interval



Substantial theoretical cost savings



max tracking error ~1.3 t/h

Conclusions

- Optimisation-based control approaches have the high potential to improve the energy efficiency and minimise costs and emissions

- MPC is likely to become a standard for energy & power applications

- MPC is a promising methodology for energy management and decision-making in industries
  - ✓ cost-effective, environmentally friendly and energy efficient production plans
  - ✓ robustness against several sources of uncertainty, including the communication delays
  - ✓ non-standard objectives, such as grid service provision, can be included

Thank You!

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