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:
  - 01: Data analysis and processing
  - 02: Identification of benchmark representative production activities
  - 03: Development of a data-driven modelling framework
  - 04: Formulation of the optimisation problem
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%.

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International energy Agency (IEA), *World Energy Outlook 2021*


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
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

• Advanced optimisation framework as decision-support system
• Data-driven modelling
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
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.
Identification of sub-systems

Main components:
✓ Boiler
Identification of sub-systems

Main components:
- Boiler
- Combined heat and power (CHP) plant
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

![CHP Steam Output Graph]

![Paper Machine Production and Basis Weight Graphs]
**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)

\[
\begin{align*}
\text{Model:} & \quad y_B(t) = E_B \ u_B(t) + v_B(t) \\
\text{ON Mode:} & \quad E_B = 75.47\% \ v_B(t) = 1.0698 \\
\text{Standby Mode:} & \quad E_B = 3.01\% \ v_B(t) = 5.03
\end{align*}
\]

*Validation: Fit % = 93.6 %*
CHP model

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

No data available
CHP model

- Model: $y_{CHP} = E_{CHP} \ u_{CHP} + v_{CHP}$

- $E_{CHP} = \begin{bmatrix} -0.2009 & 0.4411 \\ 0.1076 & 0.2158 \\ 0.3894 & -0.0064 \end{bmatrix}$, $v_{CHP} = \begin{bmatrix} 27.4471 \\ -4.1602 \\ -7.1348 \end{bmatrix}$

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

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

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 ($u_{PM}$): steam, electrical power and material flow
- Outputs ($y_{PM}$): paper machine production (t/h)

Validation: Fit % = 94.73%
Paper Machine model

- Model:
  \[ x_{PM}(t + 1) = A x_{PM}(t) + B u_{PM}(t) + w_{PM}(t) \]
  \[ y_{PM}(t) = C x_{PM}(t) + v_{PM}(t) \]

- Model order: 4th order

- \( y_{PM}(t) \) = PM Production

- \( u_{PM}(t) = \begin{bmatrix} u_{PM}^1(t) \\ u_{PM}^2(t) \\ u_{PM}^3(t) \end{bmatrix} = \begin{bmatrix} PM Elect \\ PM Steam \\ Material Flow \end{bmatrix} \)

- \( u_{PM}^1(t) = y_{CHP}^2(t) + y_{CHP}^3(t) + u_{grid}(t) \)
- \( u_{PM}^2(t) = a_{CHP} y_{CHP}^1(t) + a_B y_B(t) \)
- \( a_{CHP} = 0.6346 \)
- \( a_B = 3.1259 \)

- \( A = \begin{bmatrix} 0.694 & -0.263 & -0.250 & -0.061 \\ 0.404 & 0.615 & 0.714 & 0.043 \\ 0.057 & 0.145 & 0.130 & 0.720 \\ 0.030 & -0.207 & -0.291 & 0.300 \end{bmatrix} \)
- \( B = \begin{bmatrix} 0.006 & 0.010 & -0.009 \\ 0.004 & -0.021 & 0.063 \\ 0.042 & 0.029 & -0.064 \\ -0.016 & -0.008 & -0.001 \end{bmatrix} \)
- \( C = [111.5 \  -12.76 \  -39.78 \  -49.63] \)
Part II: MPC problem formulation
MPC formulation

Minimise energy costs

\[
\min_u \sum_{t=0}^{N-1} \left\{ c_{gas}(t)[u_B(t) + u_{CHP}^1(t) + u_{CHP}^2(t)] + c_{elect}(t)u_{grid}(t) + \gamma \| \alpha(t) \|_2^2 \right\}
\]

s. to

\[
\begin{align*}
    y_B(t) &= E_B u_B(t) + v_B(t) \\
    y_{CHP}(t) &= E_{CHP} u_{CHP}(t) + v_{CHP}(t) \\
    x_{PM}(t+1) &= A x_{PM}(t) + B u_{PM}(t) + w_{PM}(t) \\
    y_{PM}(t) &= C x_{PM}(t) + v_{PM}(t) \\
    u_{CHP} \leq u_{CHP}(t) \leq \bar{u}_{CHP}, & \quad y_{CHP} \leq y_{CHP}(t) \leq \bar{y}_{CHP} \\
    u_B \leq u_B(t) \leq \bar{u}_B, & \quad y_B \leq y_B(t) \leq \bar{y}_B \\
    -\bar{u}_{grid} \leq u_{grid}(t) \leq \bar{u}_{grid} \\
    -\alpha(t) + y_{PM}^R(t) \leq y_{PM}(t) \leq \alpha(t) + y_{PM}^R(t) \\
\end{align*}
\]

Boiler model

CHP model

PM model

Bounds/Capacity limits

Tracking \((\alpha = \text{slack variable})\)
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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