Economic Model Predictive Control for Spray Drying Plants

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engineering for a better world

Outline

- Introduction
- Spray Dryer Modelling
- Control strategies
  - Proportional and integral (PI) Control
  - Linear tracking MPC with RTO
  - Economic Nonlinear Model Predictive Control
- Comparison
- Industrial application of MPC with RTO
- Conclusion

- Introduction

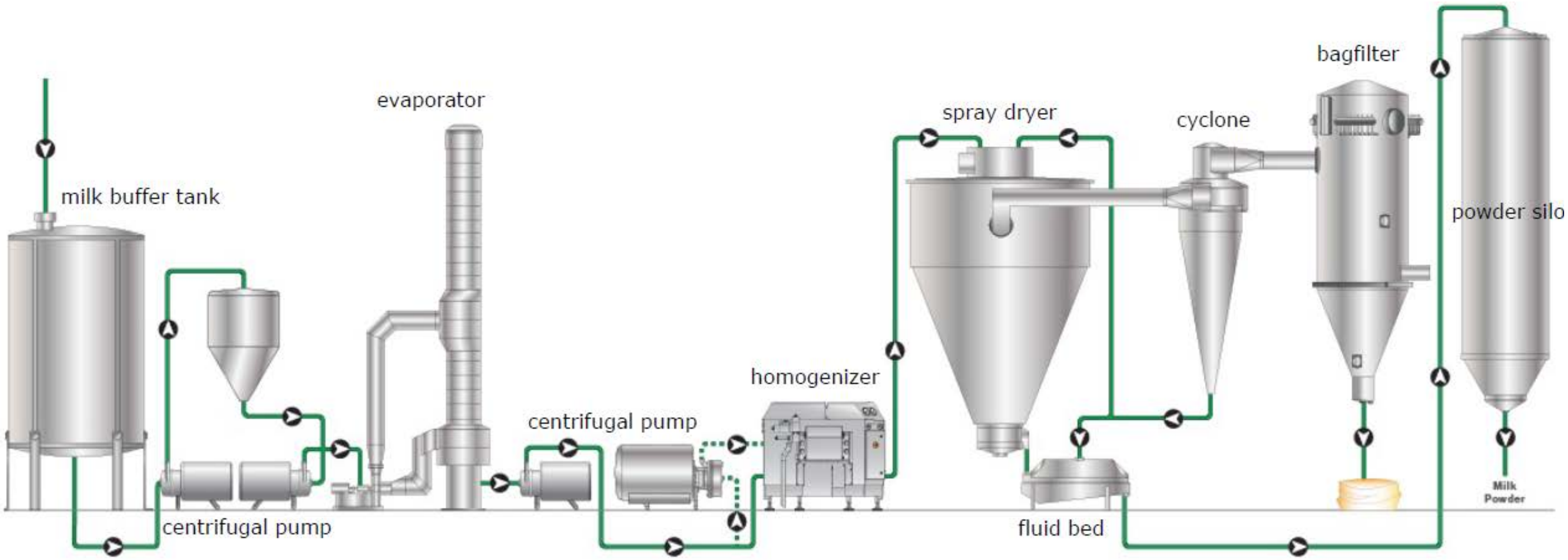
Megatrends in the Food Industry

- Global changes such as population growth, urbanization, climate changes etc. pose new challenges to the food industry.

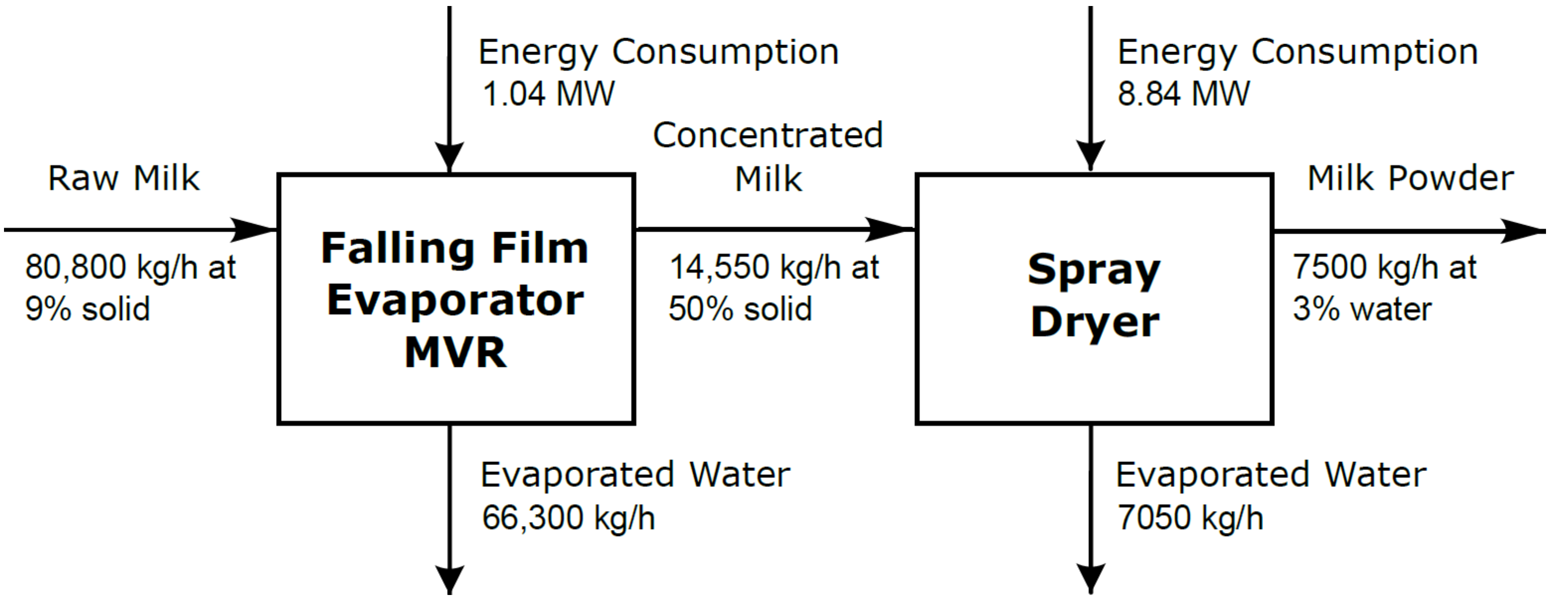
Megatrend	Significance for demand		Demand
 Urbanization/ expansion of middle class	Continuously rising demand for processed food and pharmaceuticals		Processed foods/ready meals Enriched lifestyle drinks and food Pharmaceuticals
 Growing concern about food safety and quality	Willingness to pay for process safety		Rising standards of hygiene aseptic processes
 Rising energy costs/ environmental regulations	Growing interest in efficient production processes that conserve resources		Resource-conserving technologies Energy-saving machines and processes/heat recovery “Intelligent” engineering solutions

Milk Powder Plant

- Enables transportation of surplus milk to areas with a deficit of milk.

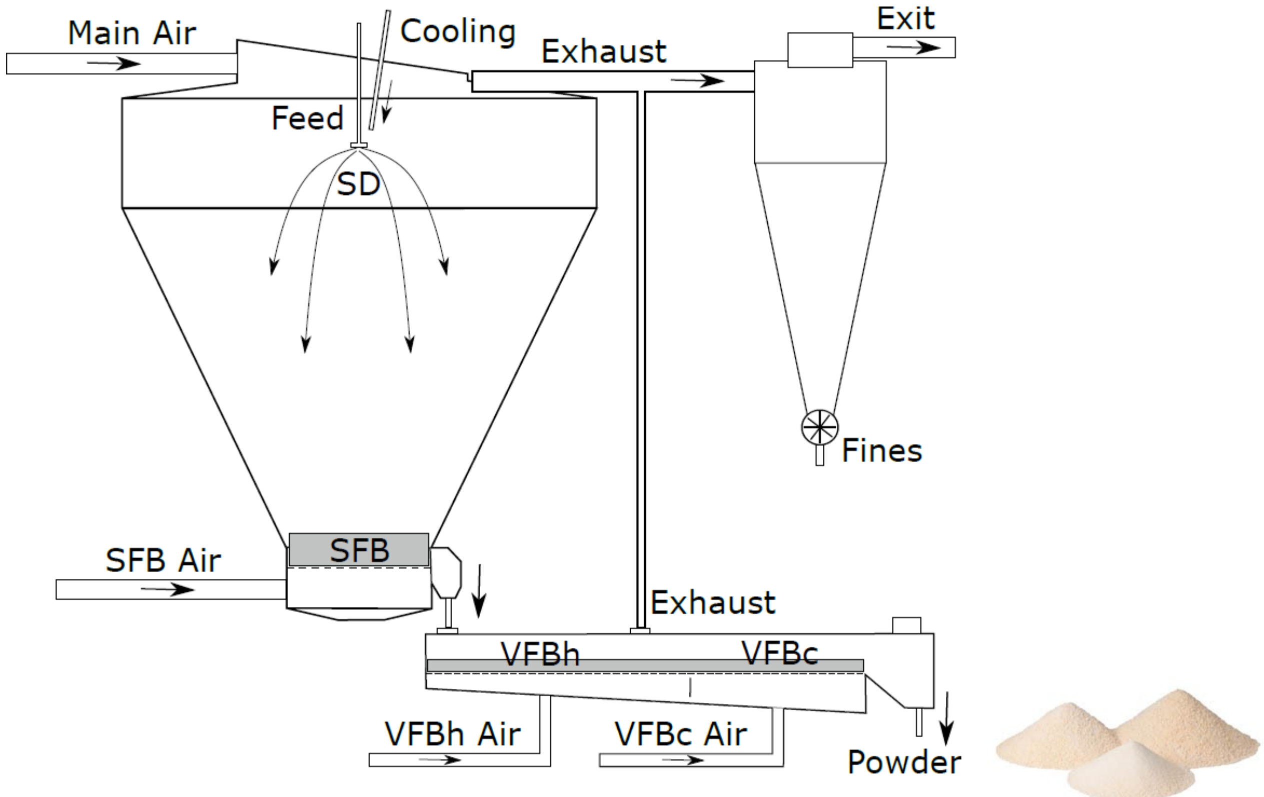


Milk Powder Plant



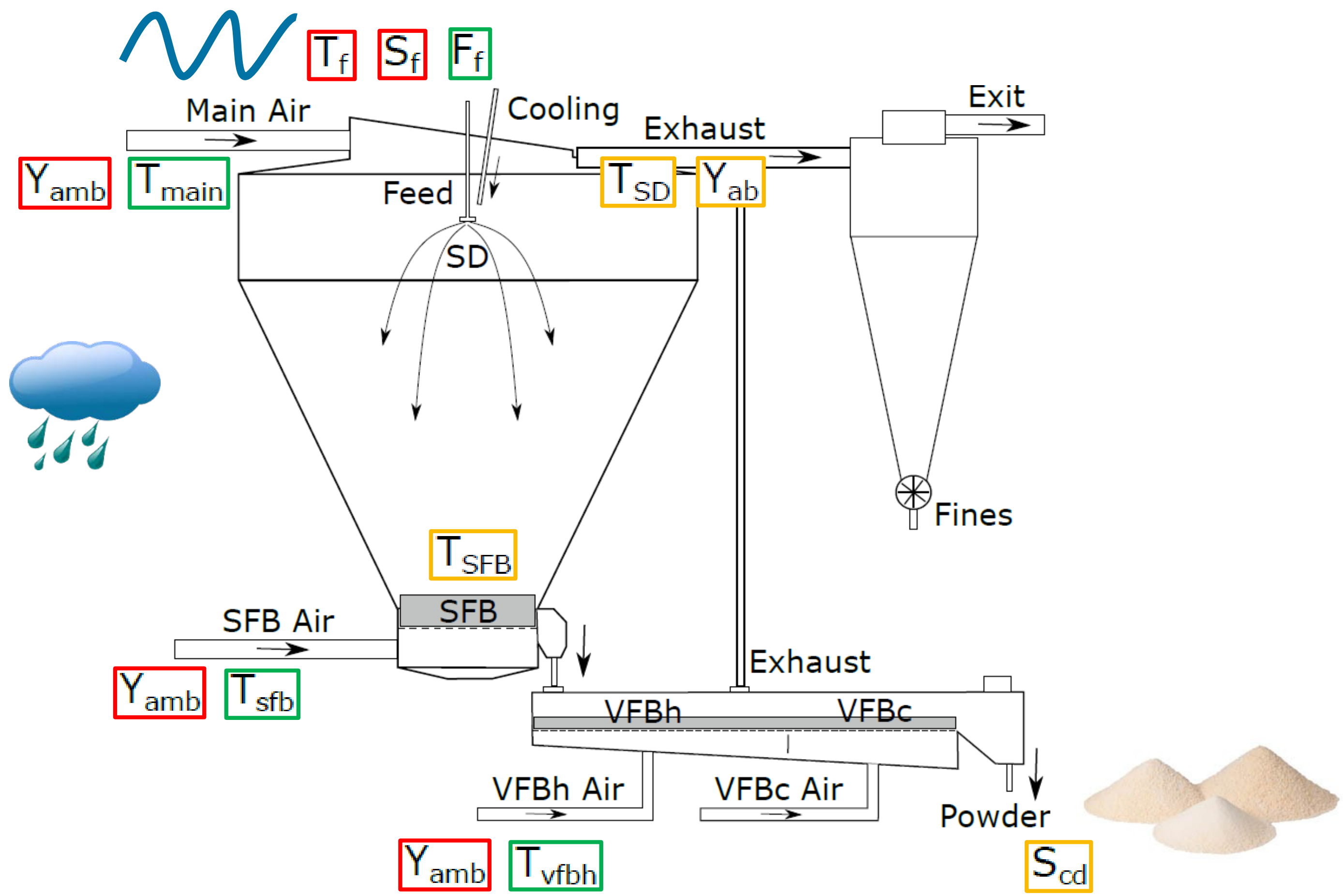
- Increasing the energy efficiency and the residual moisture content (yield) of the spray drying process is the main concern and topic of this thesis.

The Multi-Stage Spray Dryer



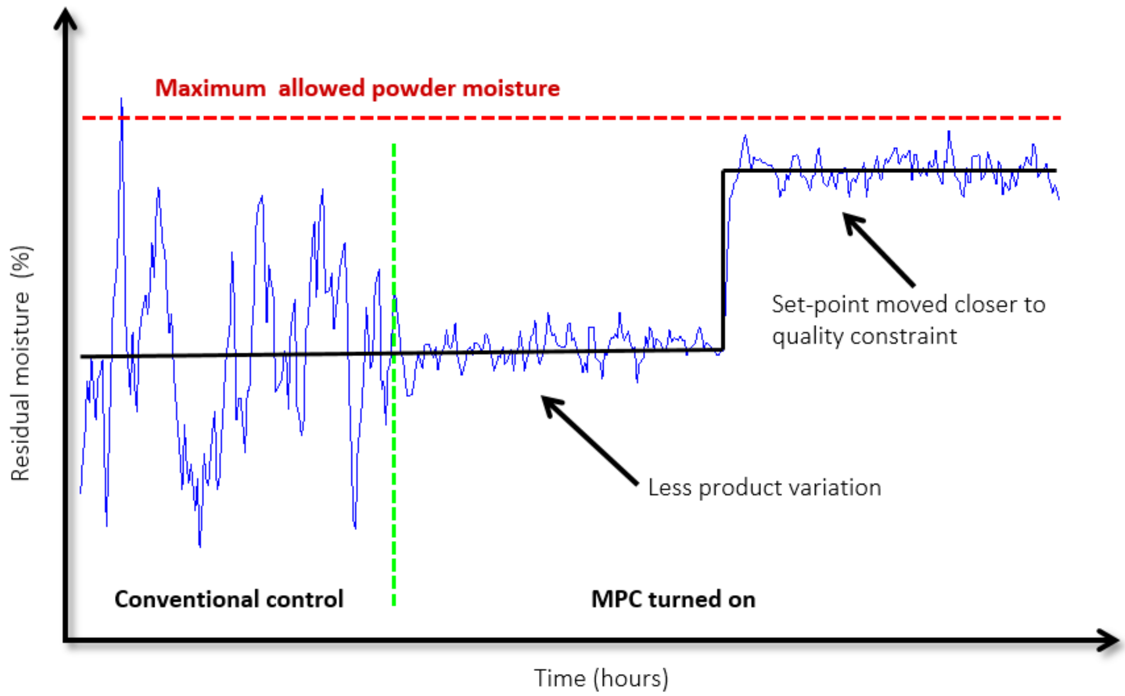
The Multi-Stage Spray Dryer

- Inputs, main disturbances and controlled outputs
- Complex dynamics, fast disturbance changes and constraint satisfaction



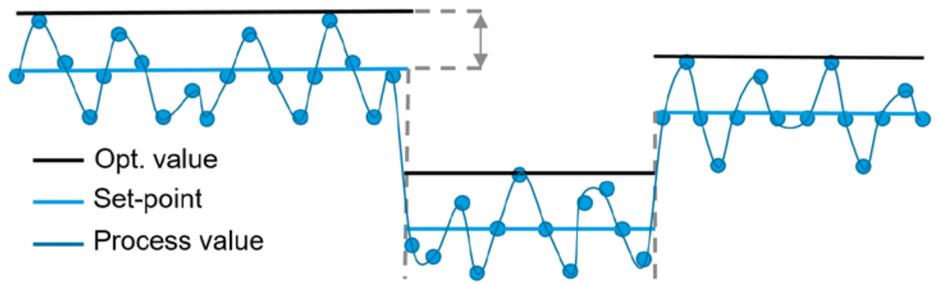
The Value of Good Control

- “Squeeze and shift” of controlled outputs
  - Moves the residual moisture closer to the specification
  - Increases the product flow rate
  - Increased the energy efficiency

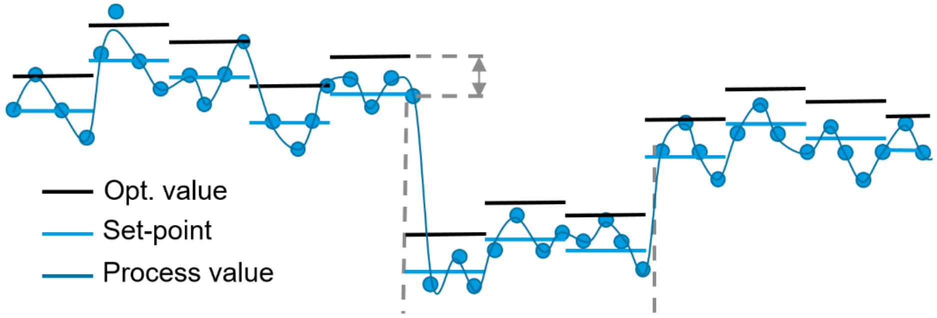


The Value of Good Control

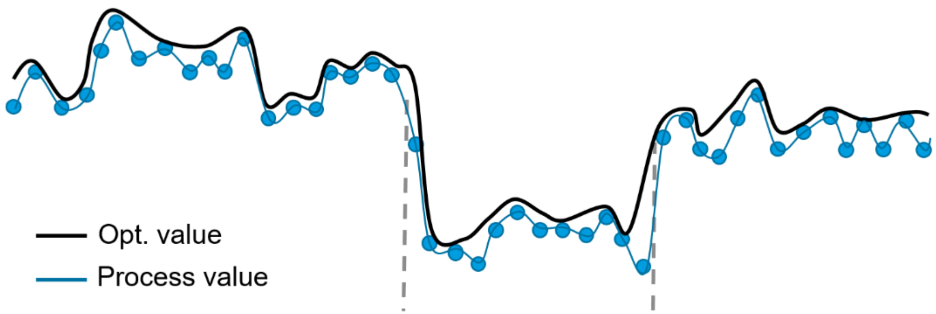
- PI control



- MPC with RTO



- E-MPC



- Spray Dryer Modeling

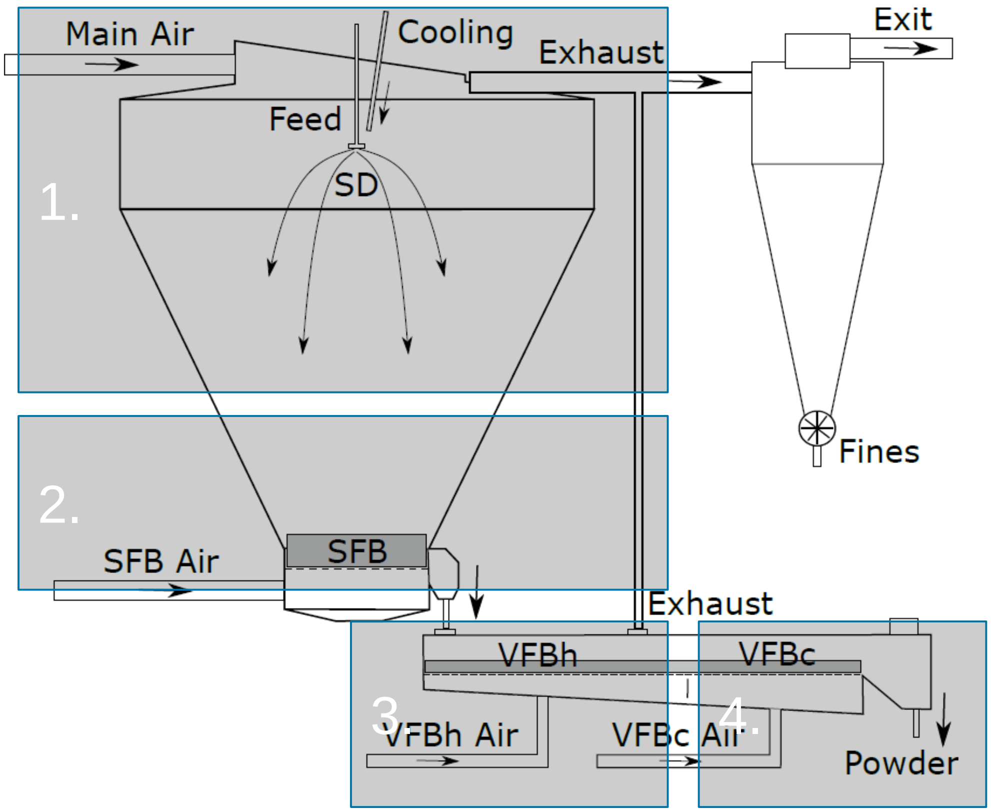
Spray Dryer Modeling

- Simulation model
  - First-principles engineering model
  - Best simulation accuracy
  - Differential algebraic equation (DAE) index-1 model
- Complexity reduced control model
  - Lumped model
  - Fewer states and parameters
  - Ordinary differential equation (ODE) model
- State-space model
  - Obtained by linearization of the ODE model

Simulation Model

- Modeling principle

- Assumptions
  - The air satisfies the ideal gas law
  - Hold-ups of dry air and solid powder are constant.
  - The stages are assumed well stirred.
  - The kinetic and potential energy are negligible.



Simulation Model – Stage Model

- Conservation equations

$$\frac{dm_{\mathrm{w}}}{dt} = \overbrace{X_{\mathrm{in}}F_{\mathrm{s}}}^{\text{water in}} - \overbrace{XF_{\mathrm{s}}}^{\text{water out}} - \overbrace{R_{\mathrm{w}}}^{\text{water evaporation rate}}$$

Moisture content

$$\frac{dm_{\mathrm{v}}}{dt} = \overbrace{Y_{\mathrm{in}}F_{\mathrm{da}}}^{\text{vapor in inlet air}} - \overbrace{YF_{\mathrm{da}}}^{\text{vapor in outlet air}} + \overbrace{R_{\mathrm{w}}}^{\text{water evaporation rate}}$$

Air humidity

$$\frac{dU}{dt} = \overbrace{(h_{a,\mathrm{in}} - h_{a,\mathrm{out}})F_{\mathrm{da}}}^{\text{enthalpy of air flows}} + \overbrace{(h_{p,\mathrm{in}} - h_{p,\mathrm{out}})F_{\mathrm{s}}}^{\text{enthalpy of powder flows}} + \overbrace{\Delta H_{\mathrm{e}}^{\mathrm{in2out}}}^{\text{enthalpy of mass exchange}} - \overbrace{Q_{\mathrm{e}}^{\mathrm{in2out}}}^{\text{heat exchange}} - \overbrace{Q_{\mathrm{l}}}^{\text{heat loss}}$$

Temperature

- State functions

$$m_{\mathrm{w}} = m_{\mathrm{s}}X$$

$$m_{\mathrm{v}} = m_{\mathrm{da}}Y$$

$$U = m_{\mathrm{da}}(h_a - RT) + m_{\mathrm{s}}h_p + m_{\mathrm{m}}h_m$$

Simulation Model – Stage Model

- Constitutive equations
  - Evaporation rate

$$R_{\mathrm{w}} = k_1 D_{\mathrm{w}}(X - X_{\mathrm{eq}}) m_{\mathrm{s}}$$

in which the diffusion term and the equilibrium moisture content is

$$D_{\mathrm{w}}(T, X) = \exp\left(-\frac{c_1}{R}\left(\frac{1}{T} - \frac{1}{T_0}\right)\right)\frac{X}{c_2 + X}$$

$$X_{\mathrm{eq}} = X_{\mathrm{eq}}(T, Y) + X_{\mathrm{add}}$$

  - Heat exchange

$$\Delta H_{\mathrm{e}}^{\mathrm{in2out}} = k_1(T^a - T^b)F_s + k_2 X_f + k_3 T_f - k_4 \quad , \quad Q_{\mathrm{e}}^{\mathrm{in2out}} = k_5(T^a - T^b)$$

  - Heat loss

$$Q_{\mathrm{l}} = k_{\mathrm{UA}}(T - T_{\mathrm{amb}})$$

Simulation Model

- Stochastic DAE model with piecewise constant inputs

$$\begin{aligned} x_{k+1} &= F(x_k, u_k + w_{\mathrm{u},k}, d_k + w_{\mathrm{d},k}, \theta) \\ y_k &= h_{\mathrm{y}}(x_k) + v_k \end{aligned}$$

in which F is the solution of the system of differential equations

$$\begin{aligned} x(t_k) &= x_k \\ \frac{d}{dt} g(x(t)) &= f(x(t), u_k + w_{\mathrm{u},k}, d_k + w_{\mathrm{d},k}, \theta) \quad t_k \leq t \leq t_{k+1} \\ x_{k+1} &= x(t_{k+1}) \end{aligned}$$

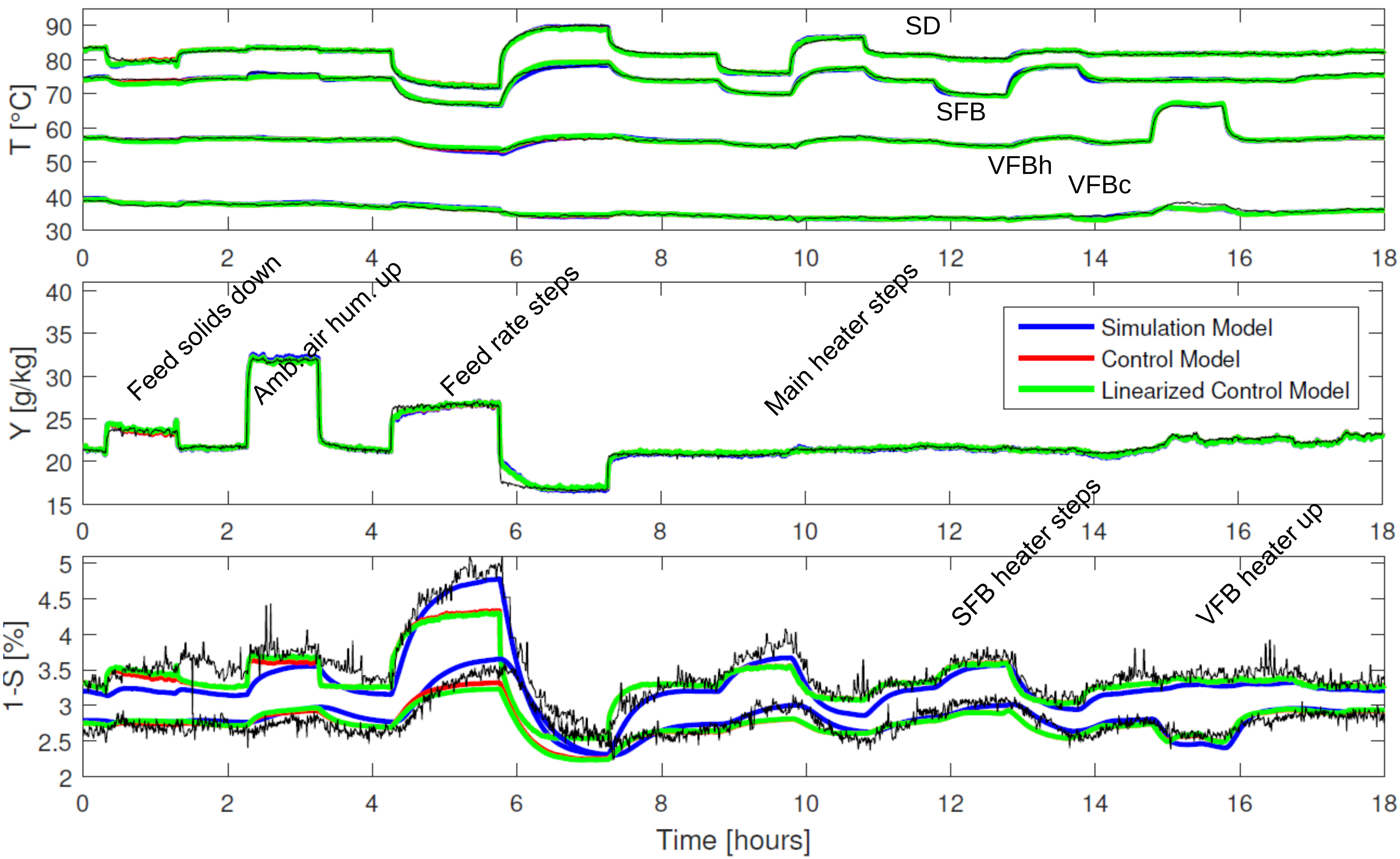
- In addition, the model provides
  - Key performance indicators
  - Stickiness of the powder based on a laboratory experiment.

Simulation Model – Equipment and Experiments

- Equipment
  - GEA MSD-20 spray dryer
  - Residual moisture measurements (NIR)
  - Exhaust air humidity measurement

- Experiment
  - Drying of sugar (maltodextrin)
  - 28 hours for estimation and 17 hours for validations
  - Steps in inputs and disturbances

Simulation Model – Validation Data



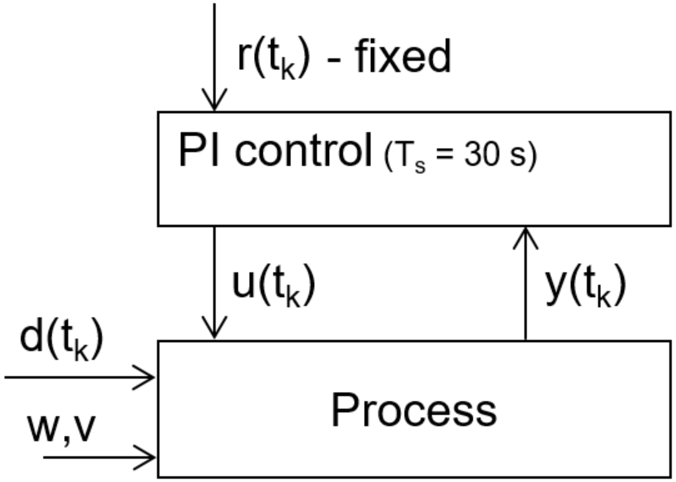
- Control strategies
  - Proportional and integral (PI) Control
  - Conventional Tracking MPC with an RTO layer
  - Economic Nonlinear Model Predictive Control

PI Control

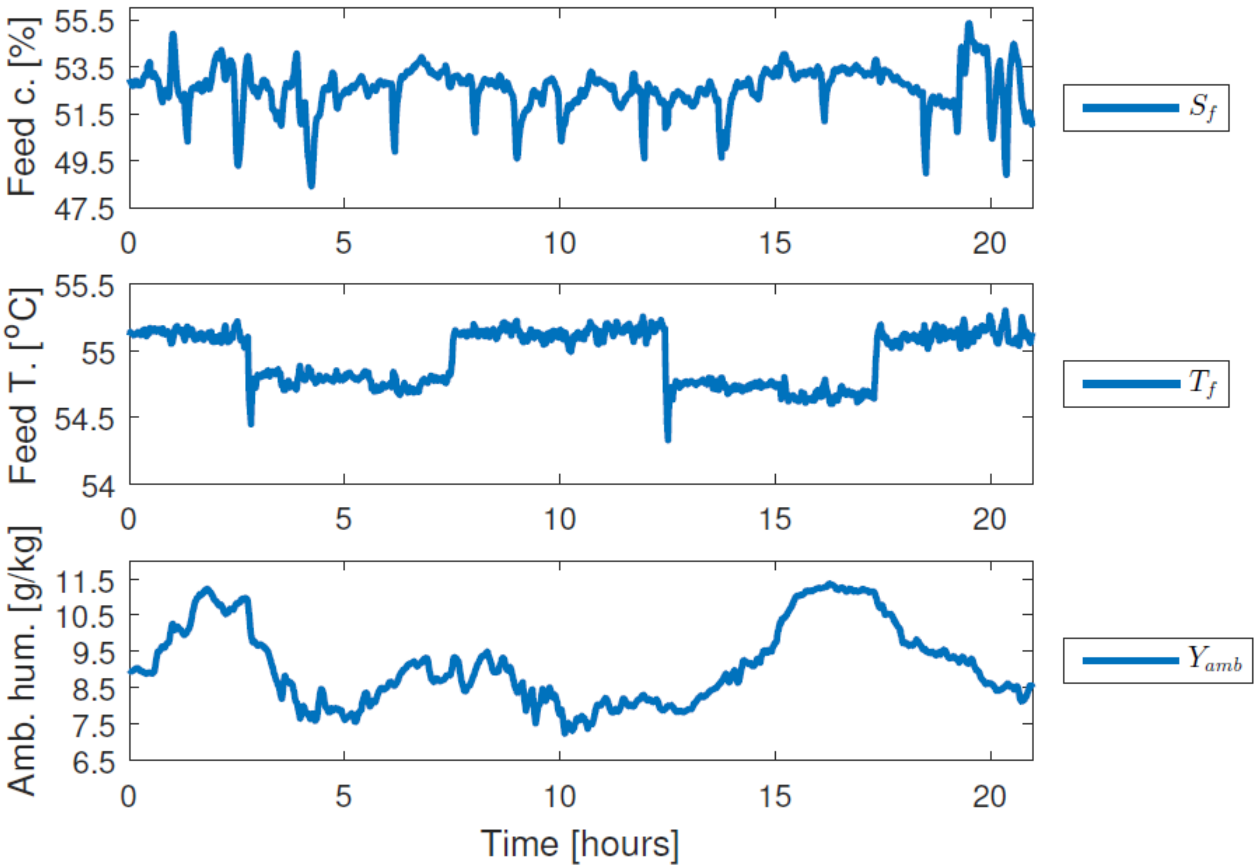
- Measures and controls the exhaust air temperature, to a target, by manipulating the feed flow.
- Inlet air temperatures are not manipulated.

- Disadvantages
  - Stickiness of powder and residual moisture content are not controlled
  - Optimal back-off and inlet air temperatures unknown
  - Cross-coupled dynamics make adjustment difficult for the operator

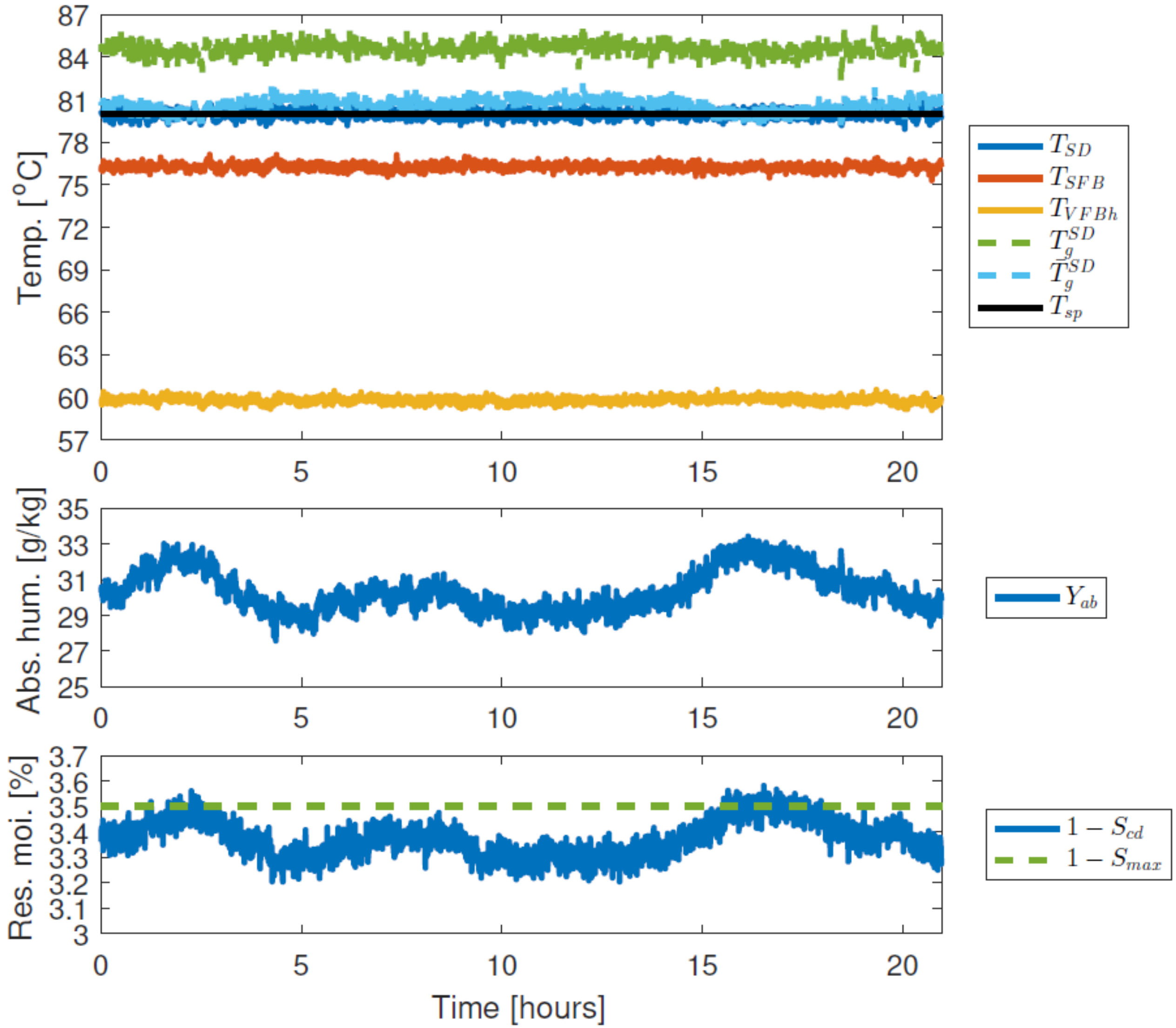
- Consequently, energy consumptions is high and residual moisture is low.



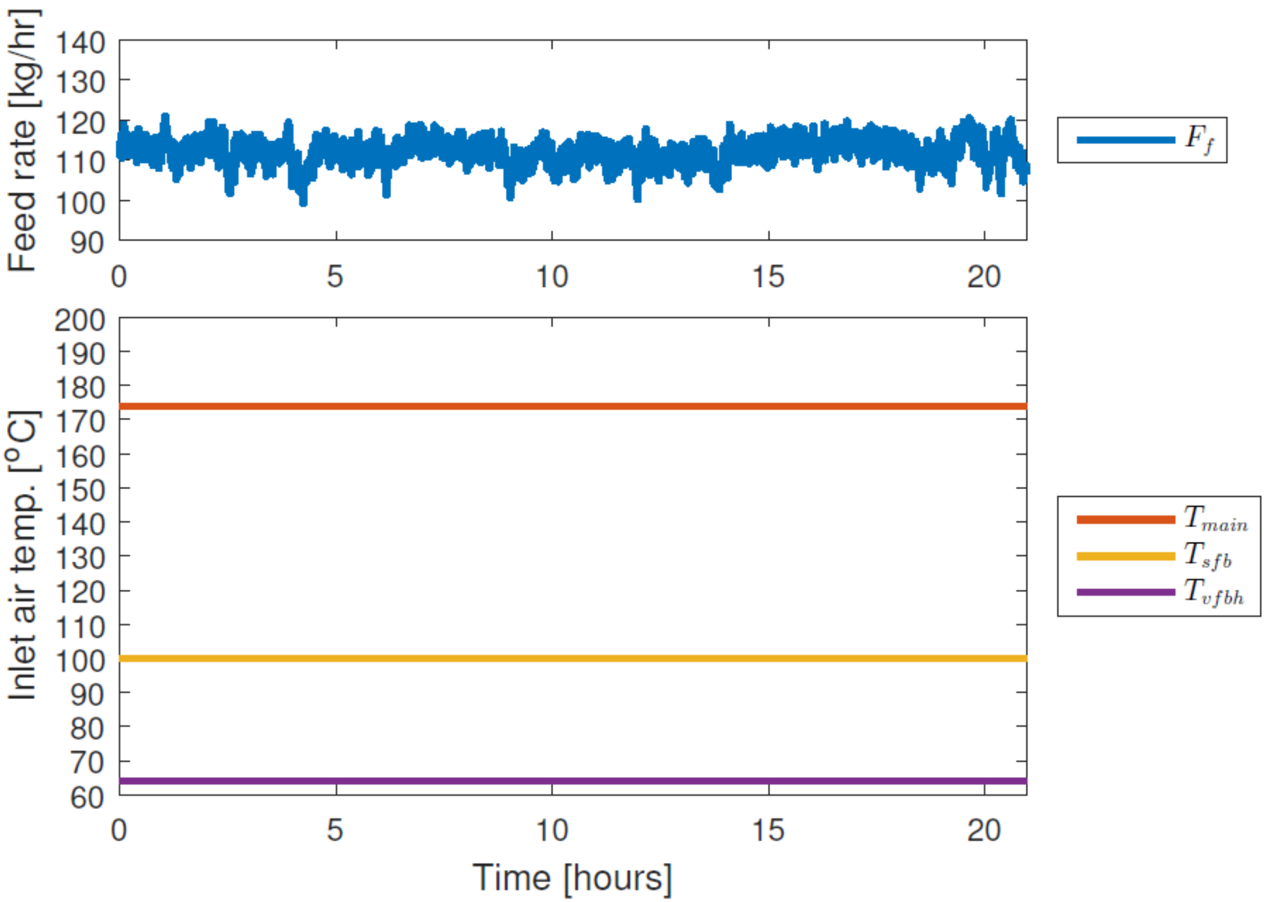
Industrially recorded disturbances



PI Control – Measured Outputs



PI Control – Manipulated Variables



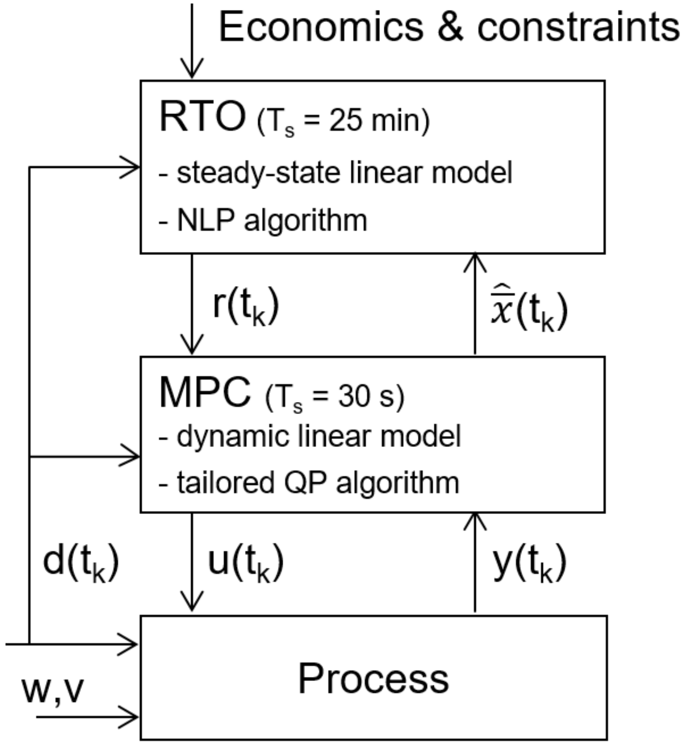
- Control strategies
  - Proportional and integral (PI) Control
  - Conventional Tracking MPC with an RTO layer
  - Economic Nonlinear Model Predictive Control

MPC with RTO

- MPC with RTO is a two layer optimization based controller
  - MPC brings the controlled outputs, z, to the target, r, by manipulating, u.
  - RTO provides steady-state cost optimal targets
  - Uses a state-space model, nonlinear constraints and profit function

- Advantage
  - Stickiness of powder is controlled
  - Product quality is controlled
  - Setpoints are updated according to the measured disturbances
  - Cross-coupled dynamics are handled

- Consequently, profit of operation is increased



MPC

- State estimator
  - Linear time varying (LTV) Kalman filter used for state estimation, and handles different sample frequencies of the measurements
  - Maximum Likelihood (ML) tuning
  - Offset-free control and output estimation by model augmentation

- The optimal control problem
  - Convex objective and linear constraints

$$
\begin{aligned}
\min_{\{u_{k+j}\}_{j=0}^{N-1}} \quad & \phi = \frac{1}{2}\sum_{j=1}^{N} \|z_{k+j} - r_k\|_{2,Q_z}^2 + \frac{1}{2}\sum_{j=0}^{N-1} \|\Delta u_{k+j}\|_{2,S_u}^2 \\
\text{s.t.} \quad & \bar{x}_k = \hat{\bar{x}}_{k|k}, \\
& \bar{x}_{k+j+1} = \bar{A}\bar{x}_{k+j} + \bar{B}u_{k+j} + \bar{E}d_k + \bar{\sigma}_{\mathrm{x}}, \qquad j \in \mathcal{N}_u \\
& z_{k+j} = \bar{C}_{\mathrm{z}}\bar{x}_{k+j} + \sigma_{\mathrm{z}}, \qquad j \in \mathcal{N}_z \\
& u_{\min} \le u_{k+j} \le u_{\max}, \qquad j \in \mathcal{N}_u
\end{aligned}
$$

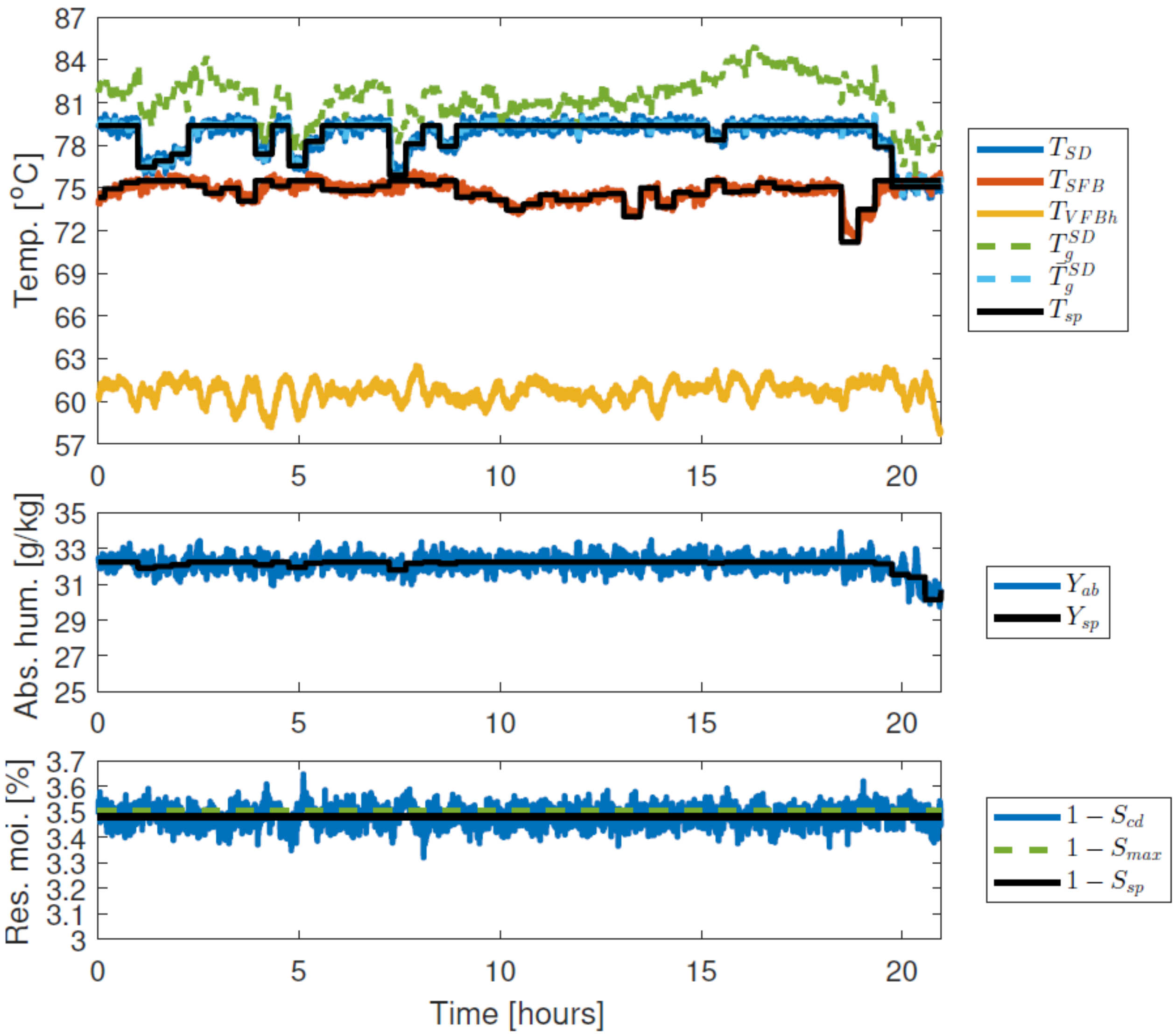
RTO

- The Real-Time Optimization
  - Linear model, nonlinear objective and constraints

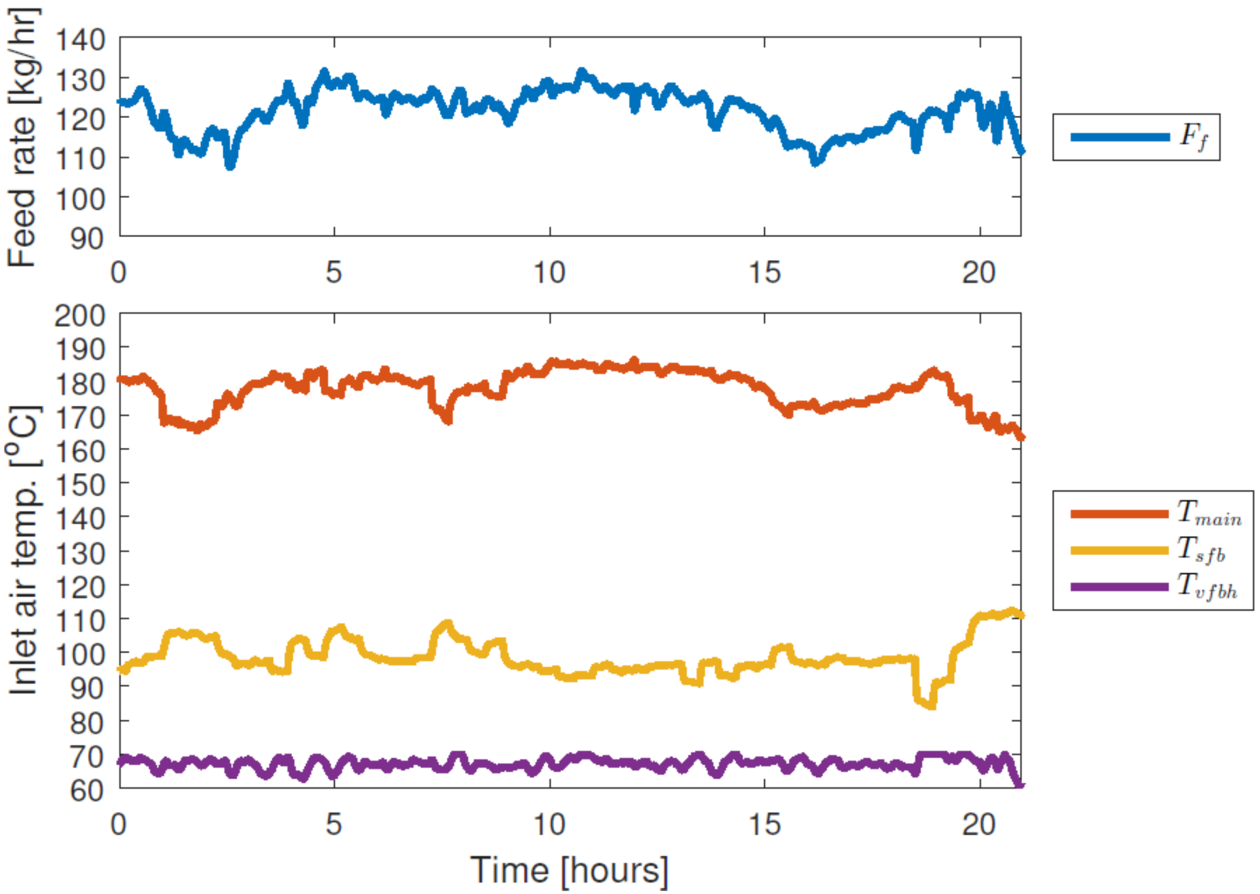
$$
\begin{aligned}
\min_{u_{\mathrm{ss}}, z_{\mathrm{ss}}, s} \quad & \phi_{\mathrm{ss}} = -p(z_{\mathrm{ss}}, u_{\mathrm{ss}}, d_k) + \phi_s(s) \\
\text{s.t.} \quad & [0 \; I]\bar{x}_{\mathrm{ss}} = [0 \; I]\hat{\bar{x}}_{k|k} \\
& \bar{x}_{\mathrm{ss}} = \bar{A}\bar{x}_{\mathrm{ss}} + \bar{B}u_{\mathrm{ss}} + \bar{E}d_k + \bar{\sigma}_{\mathrm{x}} \\
& z_{\mathrm{ss}} = \bar{C}_{\mathrm{z}}\bar{x}_{\mathrm{ss}} + \sigma_{\mathrm{z}} \\
& u_{\mathrm{min}} + \delta_2 \leq u_{\mathrm{ss}} \leq u_{\mathrm{max}} - \delta_2 \\
& c(z_{\mathrm{ss}}) - \delta_1 + s \geq 0 \\
& s \geq 0
\end{aligned}
$$

  - Model mismatch and unknown disturbances are handled by state estimator
  - Back-off to maintain controllability in the MPC and comparable constraint violations.

MPC with RTO – Measured Outputs



MPC with RTO – Manipulated Variables



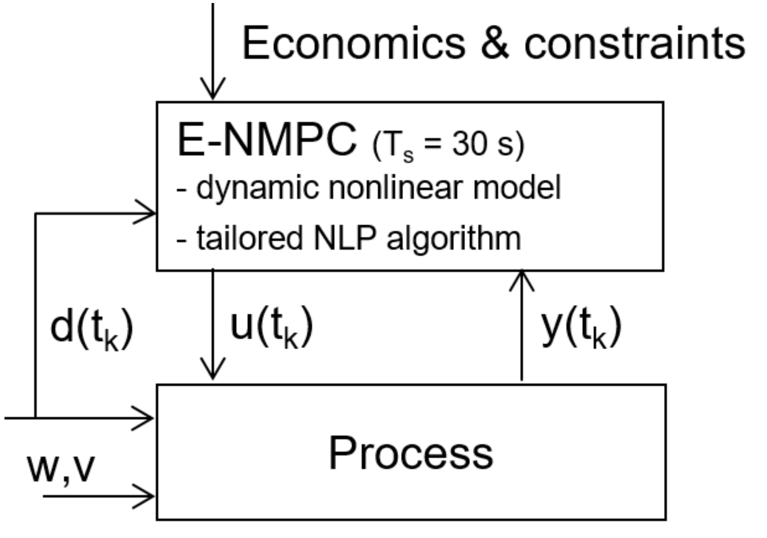
- Control strategies
  - Proportional and integral (PI) Control
  - Conventional Tracking MPC with an RTO layer
  - Economic Nonlinear Model Predictive Control

E-MPC

- E-(N)MPC is a one layer optimization based controller
  - Computes the inputs, u, at each sample time to maximize the predicted profit of operation directly
  - Uses complexity reduced model, constraints and profit function

- Advantage
  - Profit and constraints directly in the control layer
  - Back-off in MVs are not necessary
  - Cross-coupled dynamics are handled

- Consequently, profit of operation may be increased further



E-MPC

- State estimator
  - Nonlinear time varying (LTV) extended Kalman filter used for state estimation
  - Offset-free output estimation provided by model augmentation

- The optimal control problem

$$
\begin{aligned}
\min_{x,u,s} \quad & \phi = \phi_{\mathrm{e}} + \phi_{\mathrm{s}} + \phi_{\Delta \mathrm{u}}, \\
\text{s.t.} \quad & [x_k;\ x_{\mathrm{d},k}] = \hat{\hat{x}}_{k|k}, \quad x(t_k) = x_k, \\
& \frac{d}{dt} x(t) = f(x(t), u_{k+j}, d_k, \theta) + B_{\mathrm{d}} x_{\mathrm{d},k}, && t \in \mathcal{T}_k, \\
& z(t) = h_{\mathrm{z}}(x(t)) + C_{\mathrm{d,z}} x_{\mathrm{d},k}, && t \in \mathcal{T}_k, \\
& u_{\min} \leq u_{k+j} \leq u_{\max}, && j \in \mathcal{N}_{\mathrm{u}}, \\
& c(z(t_{k+j})) + s_{k+j} \geq 0, && j \in \mathcal{N}_{\mathrm{z}}, \\
& s_{k+j} \geq 0, && j \in \mathcal{N}_{\mathrm{z}},
\end{aligned}
$$

E-MPC

- The objective function consists of an economic objective function,

$$\phi_{\mathrm{e}} = -\int_{t_k}^{t_k+T} p(z(t), u_{k+j}, d_k)dt$$

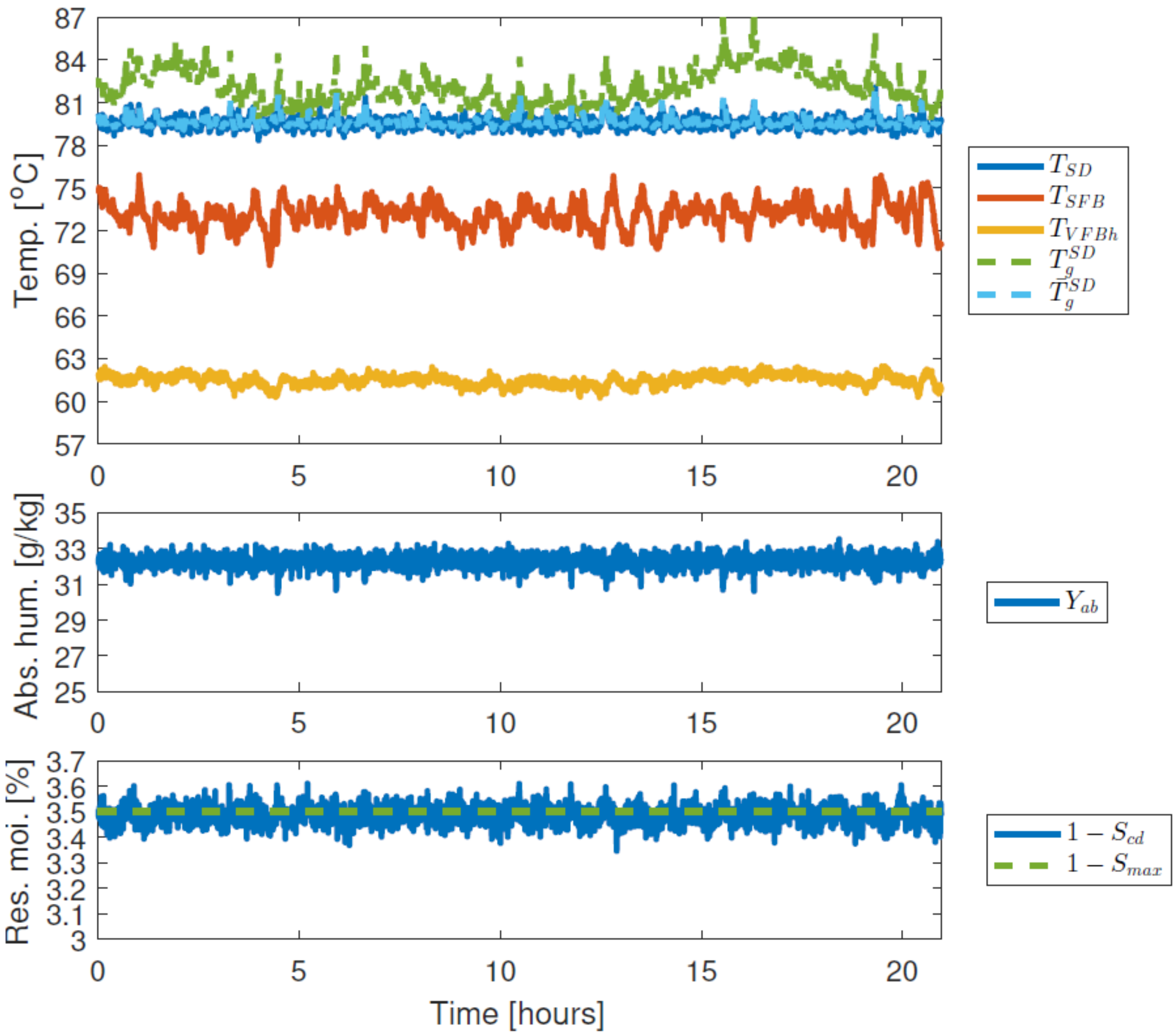
an l2-l1 penalty term,

$$\phi_{\mathrm{s}} = \sum_{j=1}^{N} \frac{1}{2} \|s_{k+j}\|_{2,S_W}^2 + \|s_{k+j}\|_{1,s_w}$$

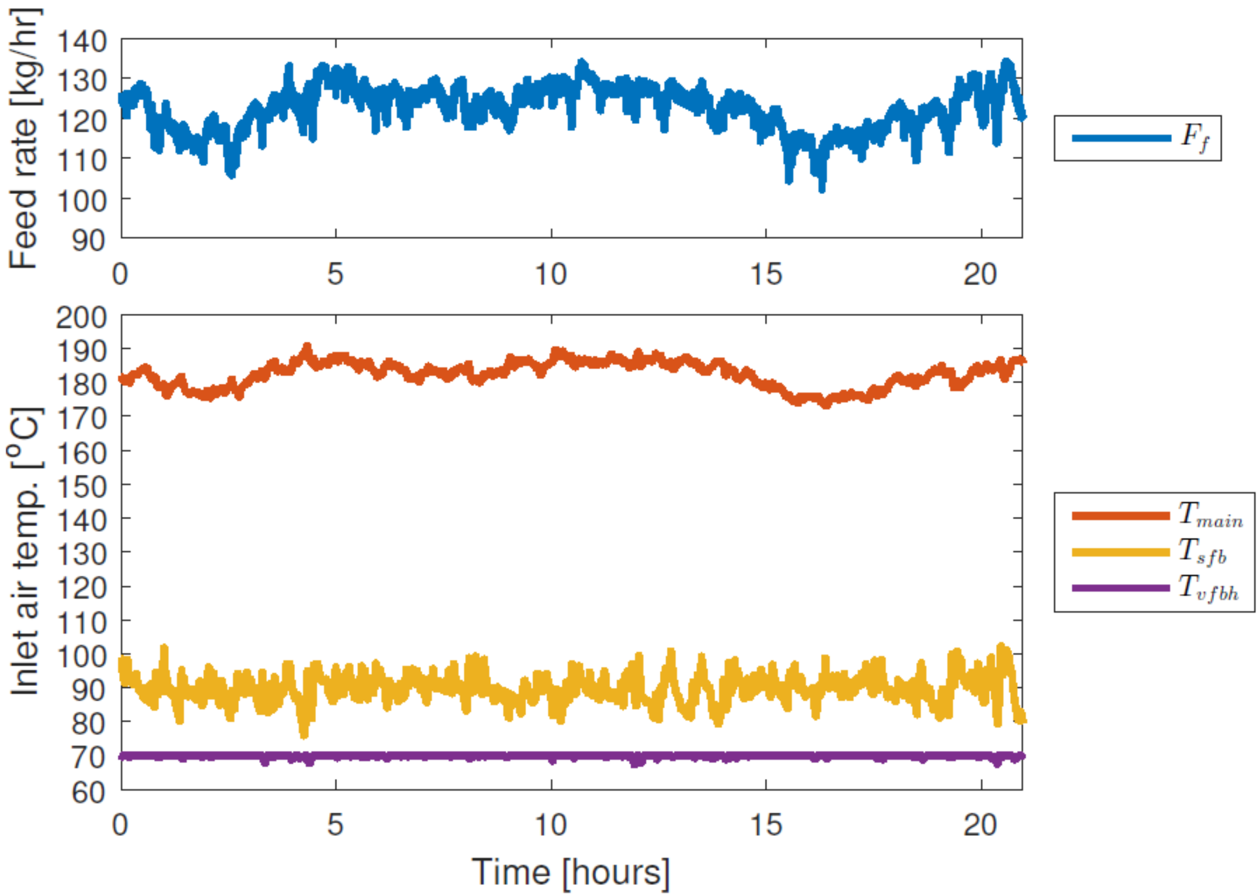
and an input rate of movement regularization term

$$\phi_{\Delta \mathrm{u}} = \frac{1}{2} \sum_{j=0}^{N-1} \|\Delta u_{k+j}\|_{\mathrm{Q}_{\Delta \mathrm{u}}}^2 = \frac{1}{2} \sum_{j=0}^{N-1} \|u_{k+j} - u_{k+j-1}\|_{\mathrm{Q}_{\Delta \mathrm{u}}}^2$$

E-MPC – Measured Outputs



E-MPC – Manipulated Variables



- Comparison

Comparison - KPI

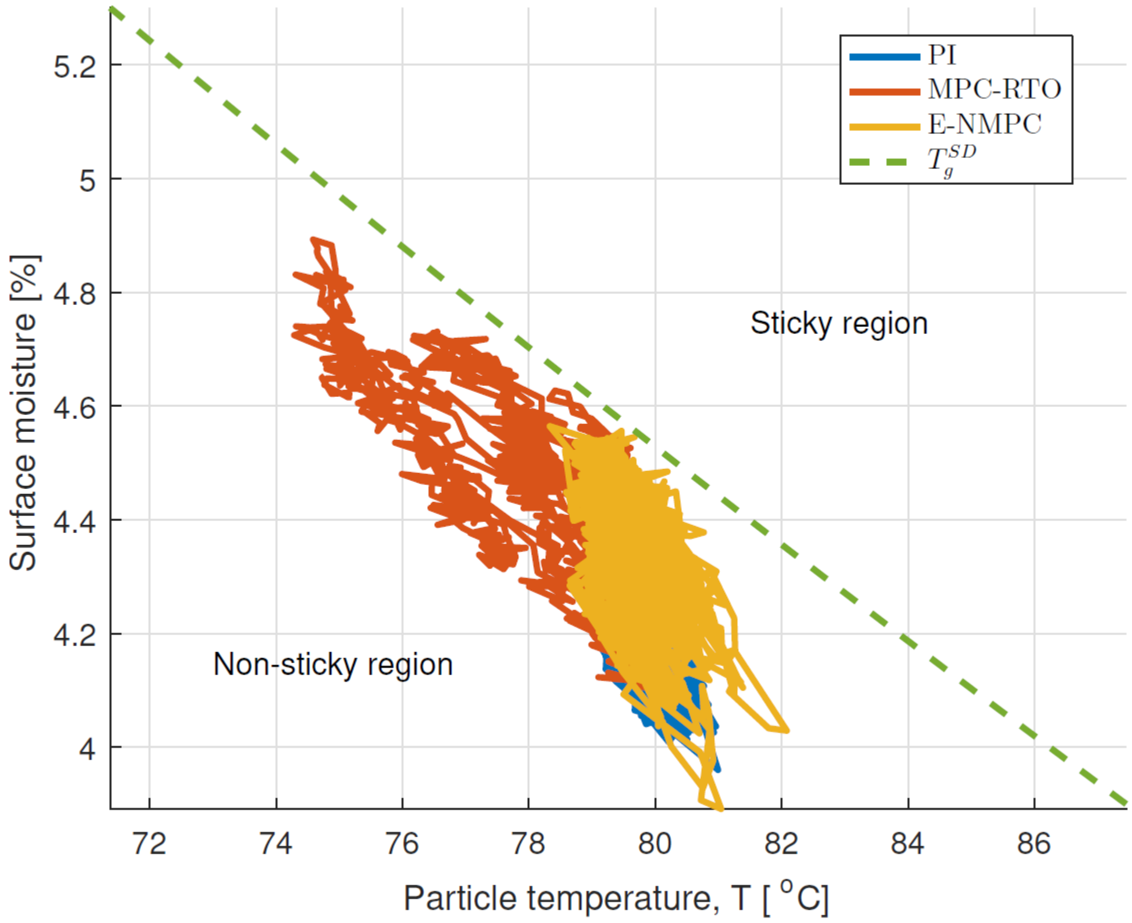
- Key performance indicators

Table 1: Average KPI values.

KPI		PI	MPC-RTO	E-NMPC	% increase to PI MPC-RTO	% increase to PI E-NMPC
Product flow rate	F_p [kg/hr]	60.95	66.21	66.81	8.63%	9.61%
Energy consumption rate	Q_{tot} [kW]	87.2	89.1	90.4	2.21%	3.63%
Specific energy consumption	$\frac{Q_{tot}}{F_p}$ [MJ/kg]	5.16	4.81	4.88	-6.72%	-5.44%
Residual moisture	$1 - S_{cd}$ [%]	3.37	3.48	3.49	3.21%	3.37%
Energy efficiency	η [%]	40.2	42.7	42.5	6.06%	5.52%
Profit of operation	p [€/hr]	123.25	133.98	135.19	8.71%	9.69%

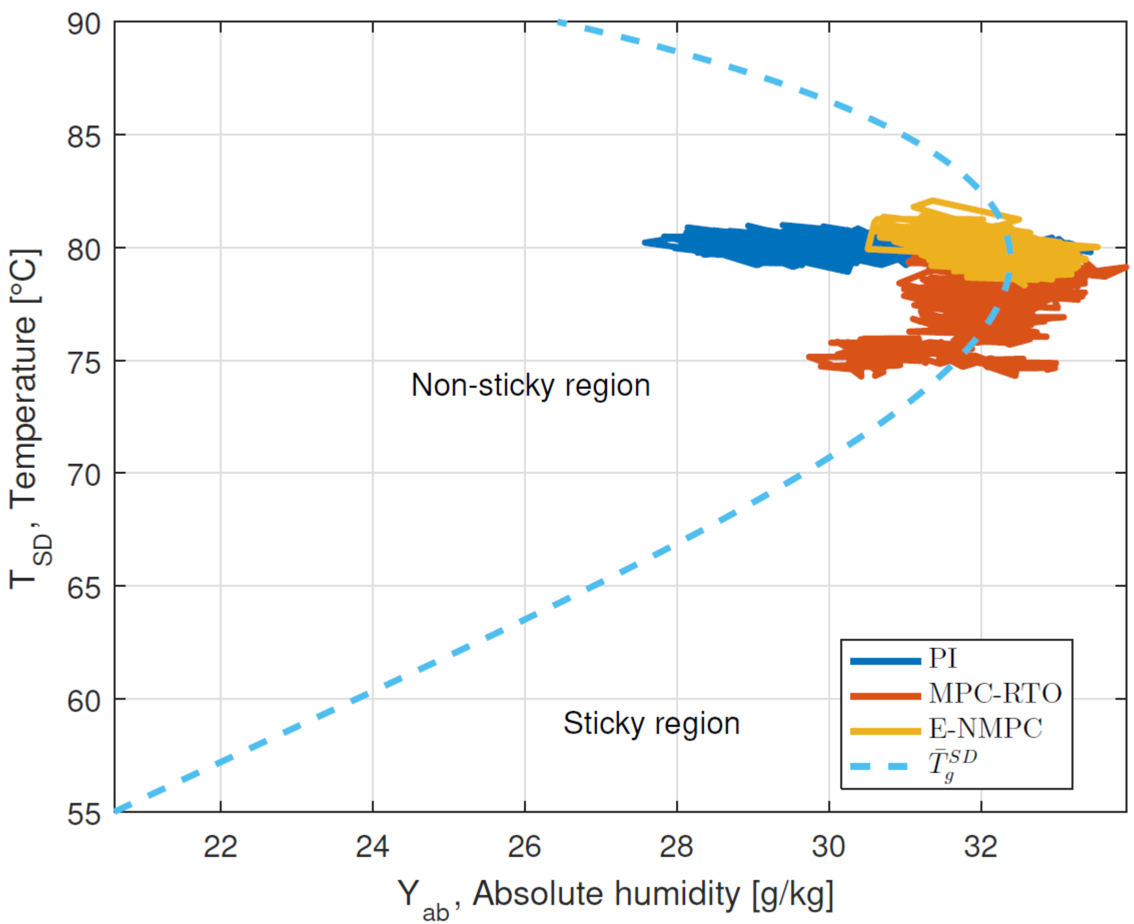
Comparison - Stickiness Estimate

- Simulation model



Comparison - Stickiness Constraint

- Complexity reduced control model



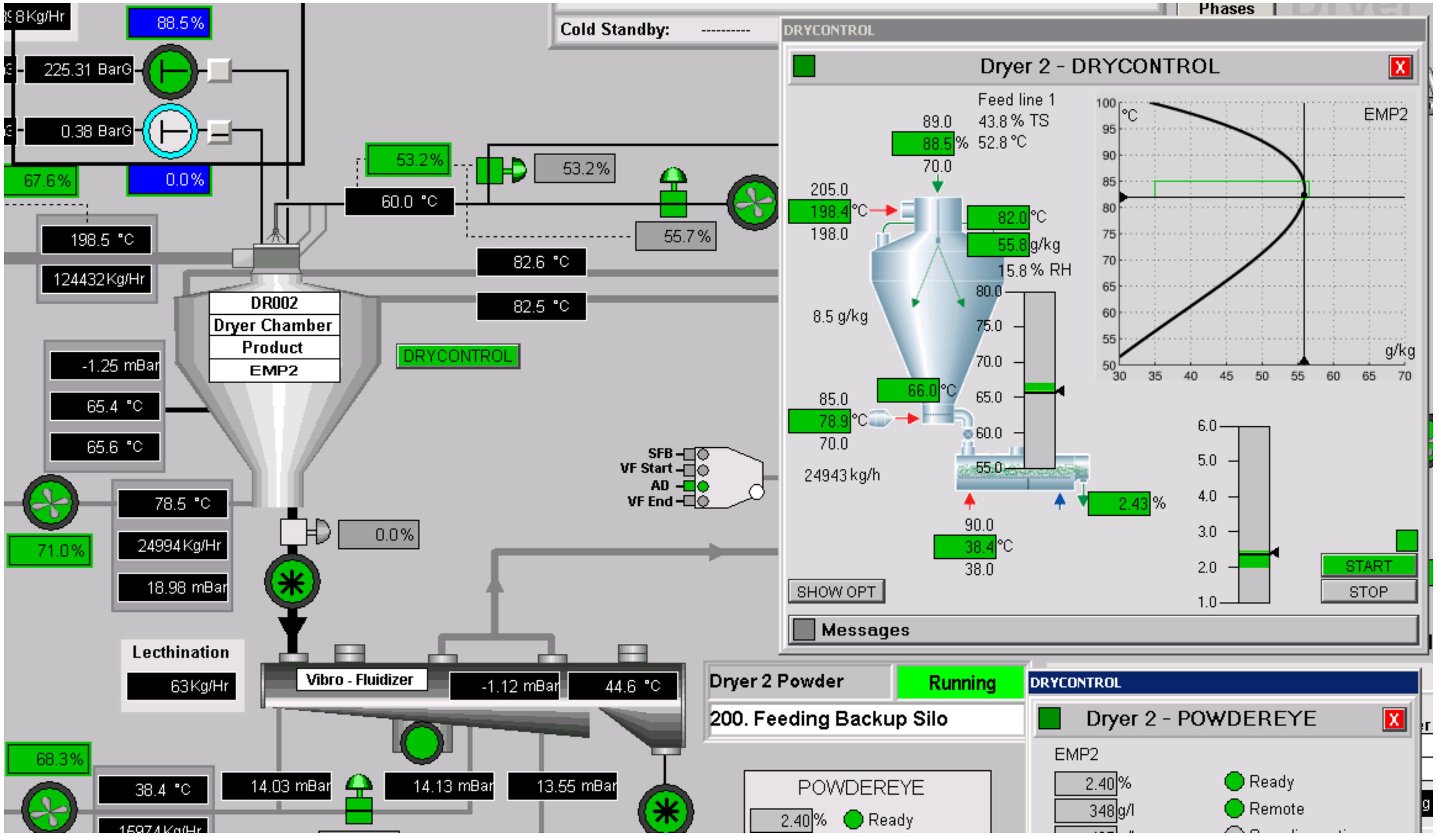
- Industrial application of MPC with RTO

Industrial Implementation

- MPC with RTO is implemented
  - Performance improvement is comparable to E-MPC
  - Attractive model mismatch and disturbance rejection behavior
- First-order plus time delay transfer-function model.
  - Perturbation of plant based on repeated steps on the inputs.
- The MPC sample time is 20 sec and the RTO sample time is 30 sec.
- Running on an industrial PC connected to the plant PLC.

Industrial Implementation

- SCADA faceplate



Industrial Implementation

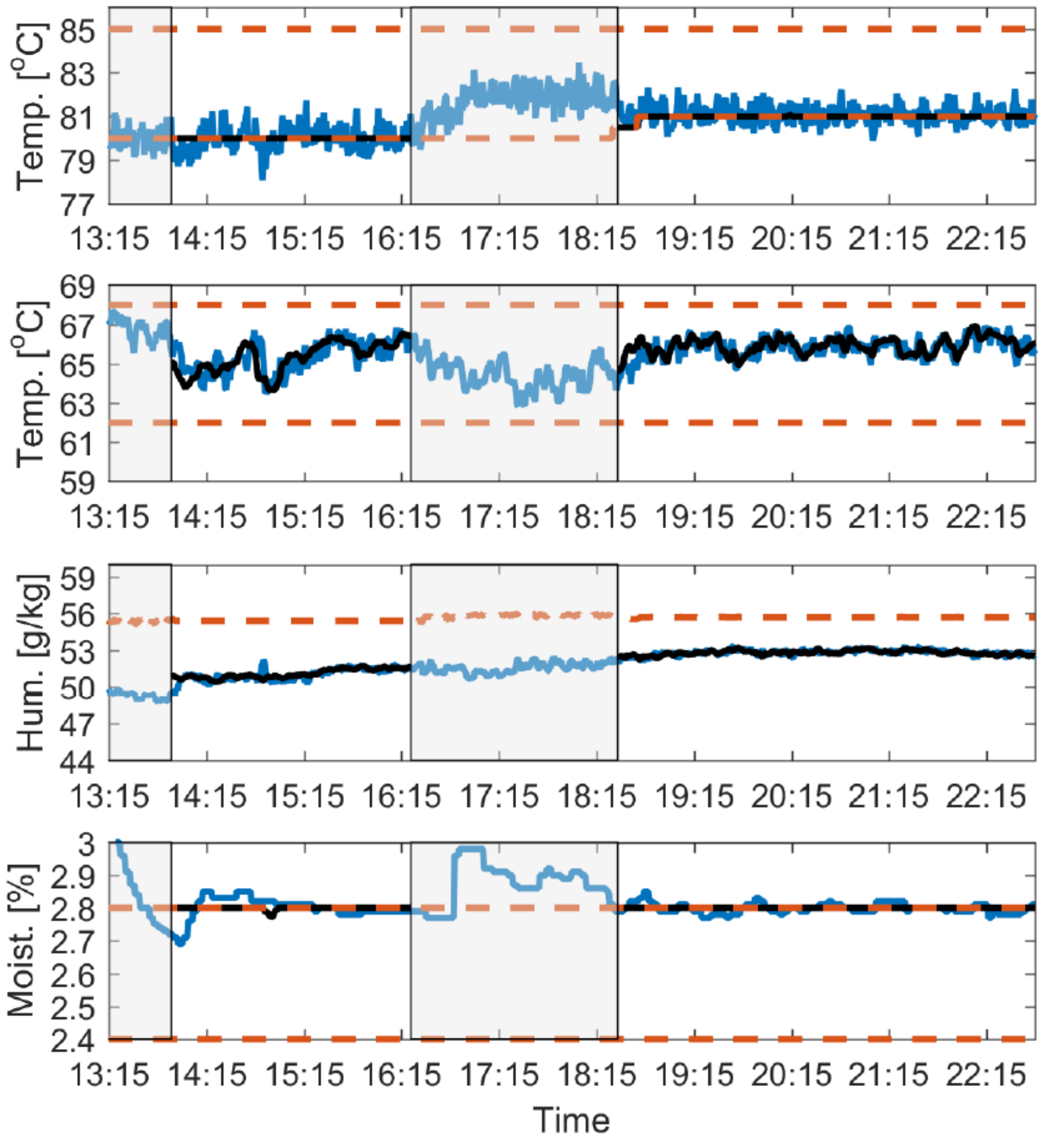
- MPC 2

Exhaust air temperature
at constraint(min limit)

SFB powder temperature
In constraint(min limit)

Exhaust air humidity [g/kg]

Residual Moisture in
powder [%]



Industrial Implementation

- Key performance indicators

Table 2: Average KPI values.

KPI		PI	MPC 1	MPC 2	% increase to PI MPC 1	% increase to PI MPC 2
Product flow rate	F_p [kg/hr]	7,177	7,416	7,499	3.35 [%]	4.44 [%]
Energy consumption	Q_{tot} [MW]	7.40	7.41	7.49	0.1 [%]	1.2 [%]
Specific energy consumption	$\frac{Q_{tot}}{F_p}$ [MJ/kg]	3.714	3.596	3.599	-3.16 [%]	-3.10 [%]
Residual moisture	$1 - S$ [%]	2.633	2.746	2.799	4.28 [%]	6.31 [%]
Energy efficiency	η [%]	63.4	64.4	62.6	1.44 [%]	-1.28 [%]

- The annual profit increase is estimated to be, 186,000 euro/year from the 0.14 p.p. improved residual moisture and 6,900 euro/year from 1 p.p. the energy efficiency increase.

- Conclusion

Conclusion

- Modeling of a four-stage spray dryer
  - Simulation model for validation of controllers
  - Complexity reduced model(s) for design of controllers
  - Validated against experimental data

- Development and simulation of MPC strategies
  - Both methods increases *energy efficiency, production rate and profit of operation*
  - Maintain the process within and closer to process constraints

- Application of MPC to an industrial spray dryer
  - MPC with RTO has been successfully applied and improves the KPIs of the process.

Thanks for Your Attention

- Questions and comments