

Energy-efficient operation of a Medium Density Fibreboard flash dryer through Nonlinear MPC

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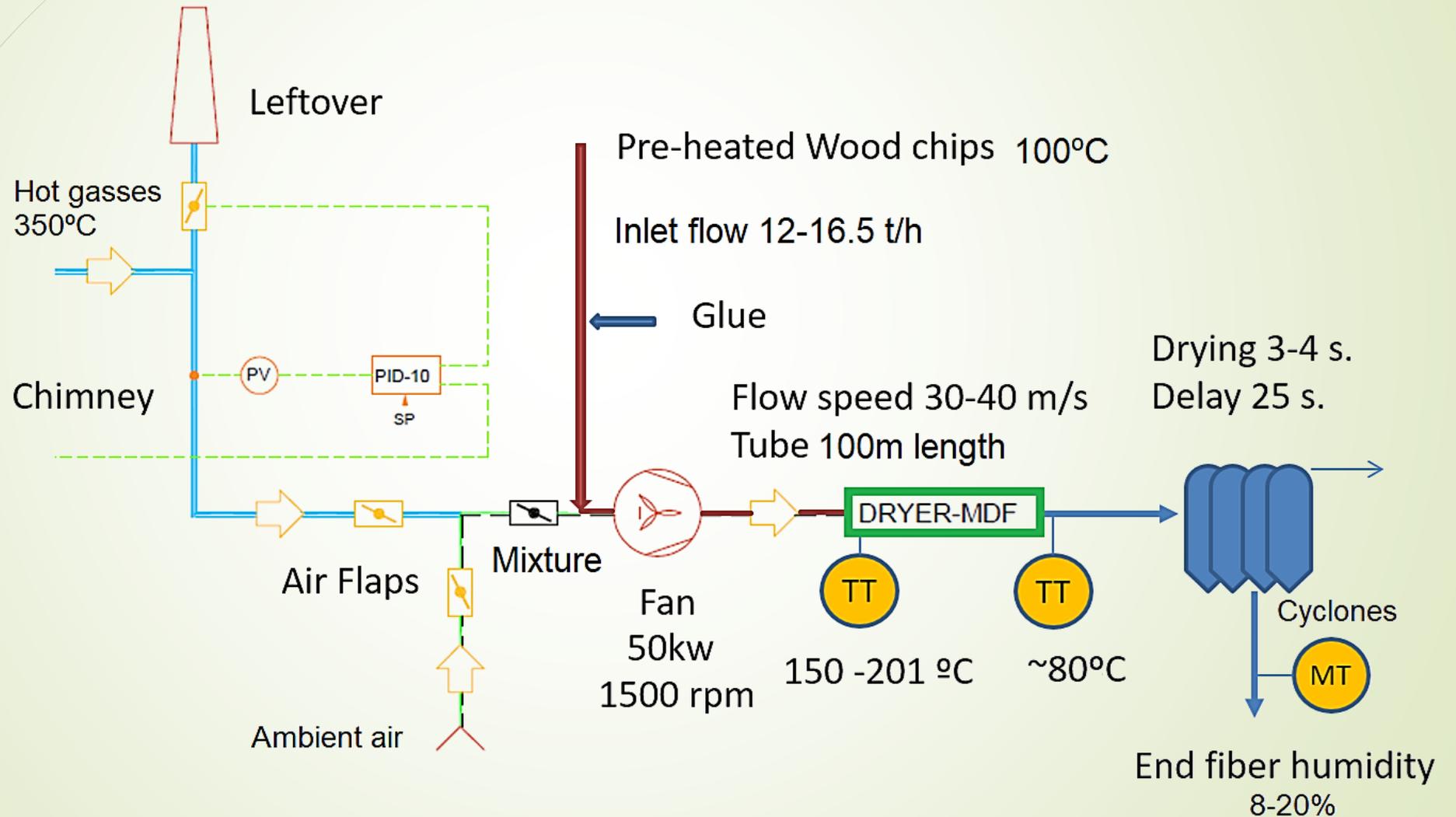


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Sonae Arauco's facilities to produce wood-based panels



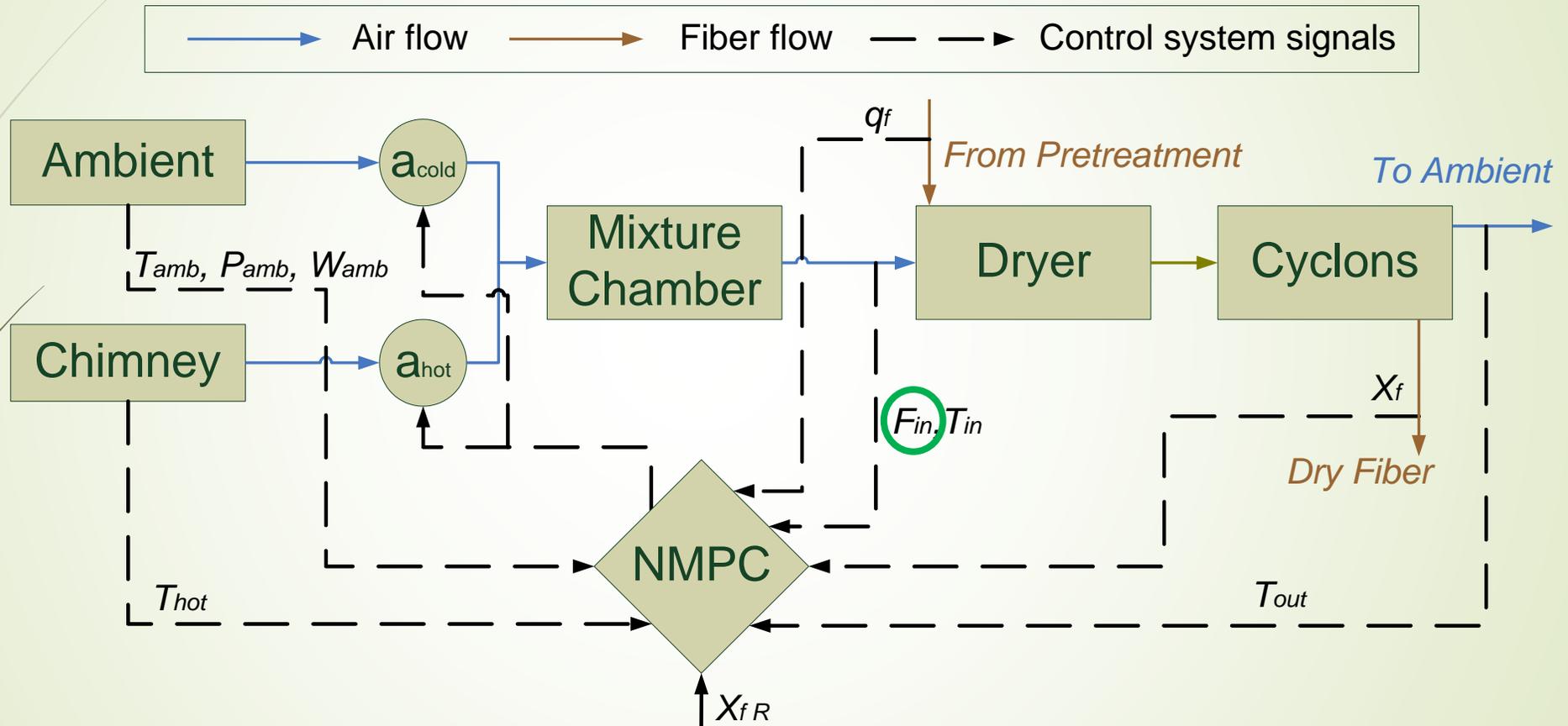
MDF tube flash dryer at Sonae



Challenges to face

- **Important system delay:** ~25 sec. residence time of fibers in the cyclone stage
- **Scarce measured variables for modeling and control:** only air temperatures at the tube extremes and fiber humidity after the cyclones
- **Sampling time larger than the residence time of fibers in the tube dryer:** no information about the (spatial) drying dynamics
- **Different operation regimes due to product changes:** inlet fiber humidity X_0 , fiber diameter/length, fiber flow q_f ...
- **Nonlinear effect of the actuators** (air flaps) in the controlled variables.

Proposed centralized MPC scheme



- No fixed temperature SP is required: degree of freedom for economic optimization
- All reliable measurements are employed to enhance prediction performance

Grey-box lumped-parameter model

➤ First principles:

- Global mass & energy balances
- Heat loss to ambient
- First-order dynamics plus delay at the cyclones

➤ Need of experimental equations:

- Air flows (hot and cold) as function of the control actions (a_{hot} , a_{cold} openings)
- Relationship between outlet air temperature T_{out} and fiber humidity X_f
- Some model parameters p

➤ Assumptions:

- Thermal equilibrium at dryer outlet
- Instantaneous drying: spatial dynamics (PDEs) neglected
- Energy accumulation in the tube dryer
- “Constant” Inlet fiber humidity

$$\begin{aligned} \dot{x} &= f(x, u, z, p, d), \\ h(x, u, z, p, d) &= 0 \end{aligned}$$

$$x := [T_t, X_f]$$

$$u := [a_{\text{hot}}, a_{\text{cold}}]$$

$$d := [q_f, T_{\text{amb}}, W_{\text{amb}}, T_{\text{hot}}, X_0]$$

Grey-box modeling procedure

1. COMPUTE COHERENT ESTIMATIONS FOR ALL PROCESS VARIABLES
 - ▶ With all sensors data and the first-principles equations, solve a dynamic data reconciliation problem
 - ▶ Estimated values over time are consistent with the process physics
 - ▶ Not-trustable sensors are automatically discarded
2. FORMULATION OF ADDITIONAL EXPERIMENTAL EQUATIONS
 - ▶ With previous estimations, get each black-box submodel via constrained regression
 - ▶ Consistency of data-driven equations with process physics is ensured

Experimental customization to actual plant

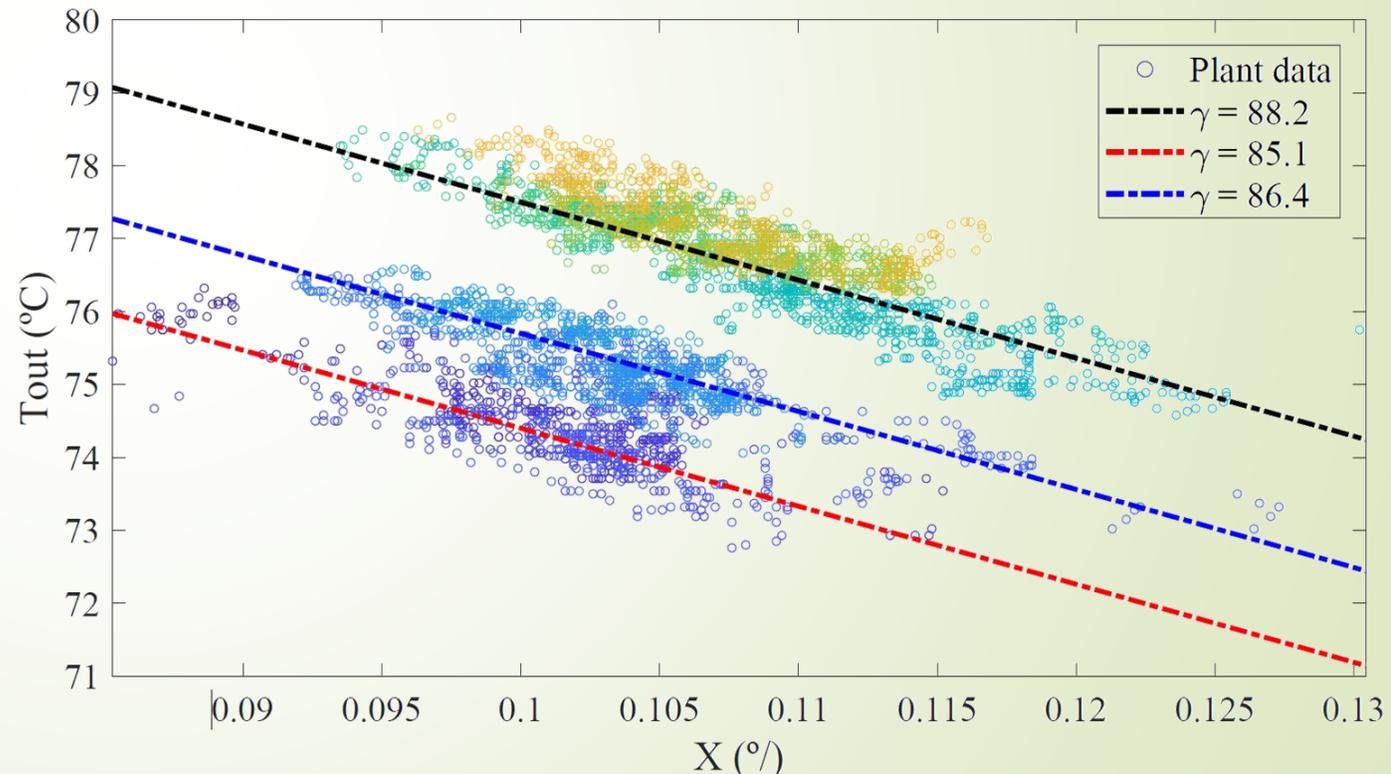
➔ $F_{in} = K_f \cdot (1 - e^{-7,1(a_{hot}+a_{cold})})$ K_f, K_T are "constant" regression parameters

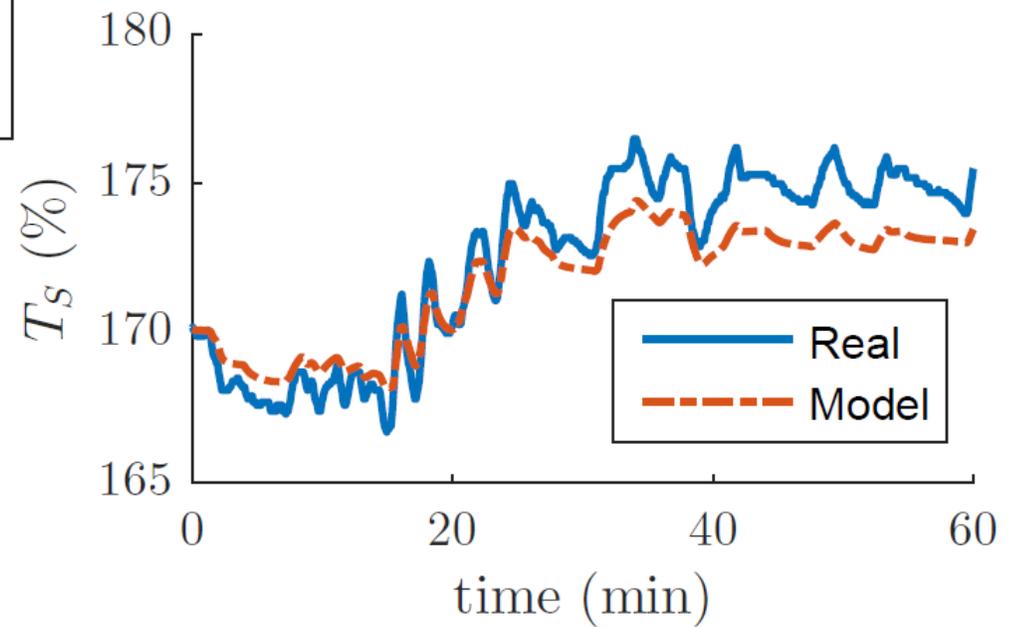
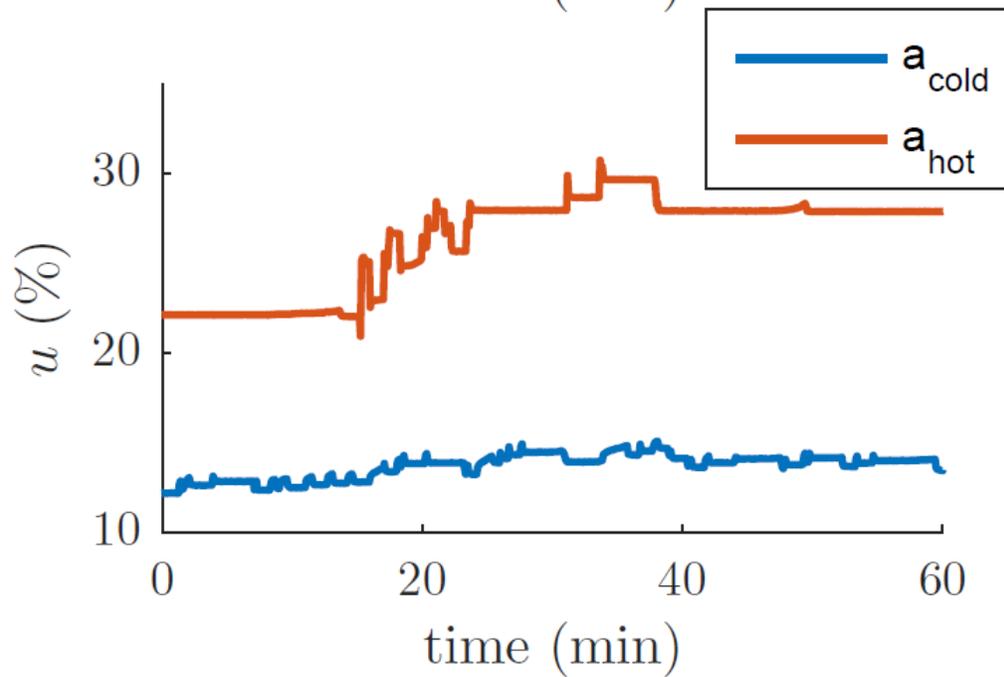
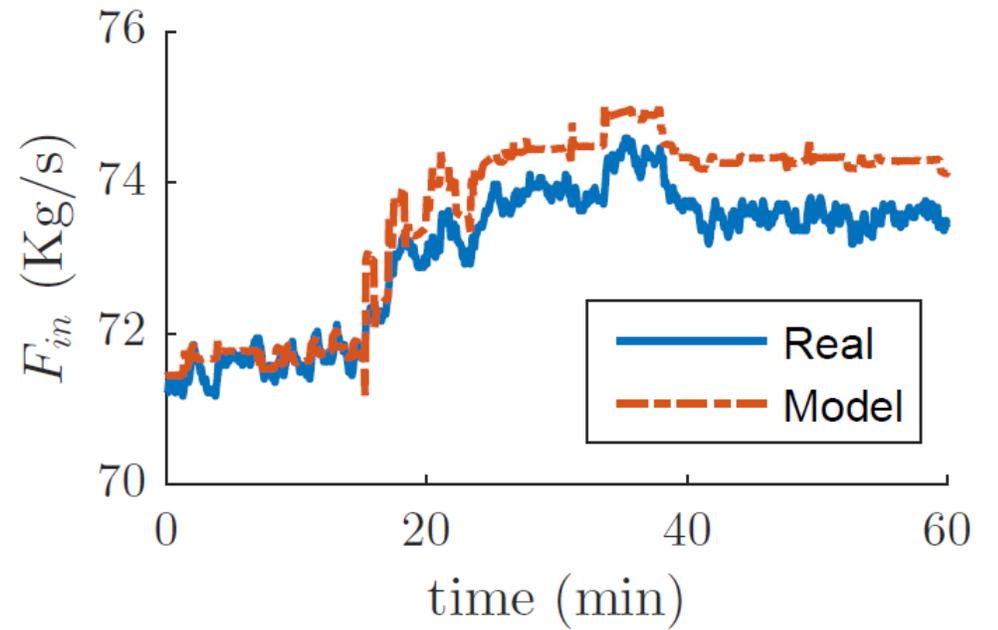
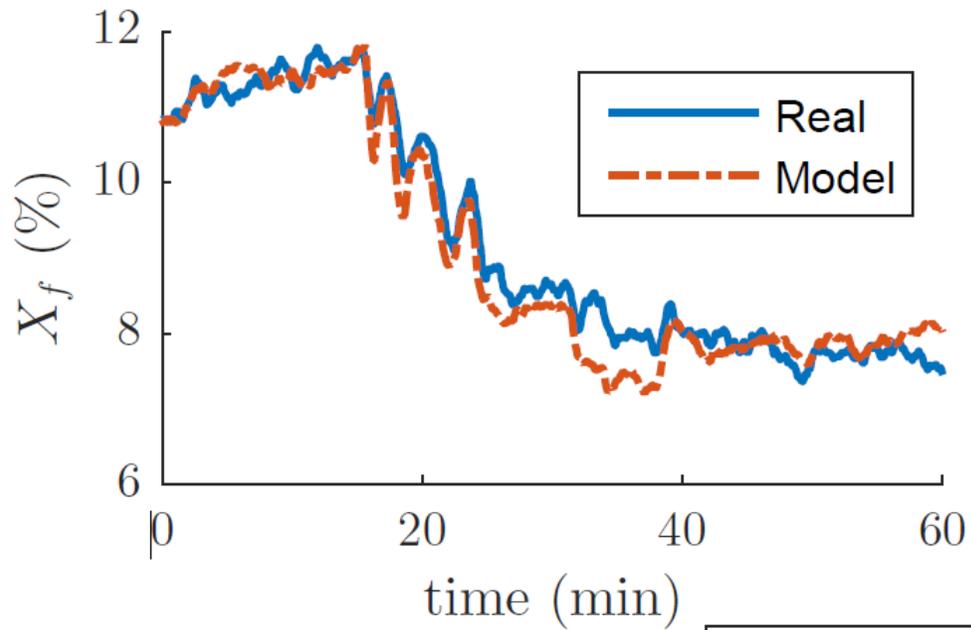
➔ $\frac{F_{hot}}{F_{amb}} = K_T \sqrt{\frac{a_{hot}}{a_{cold}}}$

➔ $T_{out} = -107 \cdot X + \gamma$

γ is a bias parameter
that fits the operation point

Linearity supported by the
the Gay-Lussac's law





Unknown inputs and state estimation

- A Moving Horizon Estimator (MHE) is used to provide the values of the time-varying parameters, unmeasured states and disturbances
- MHE estimations will be coherent with MPC predictions: model equations are the same for both optimization problems.
- Correct bias-state estimation achieved in steady state.

Output error: Plant-model mismatch
Regularization: penalty to high changes w.r.t. the previous estimation

$$\min_{\alpha, x_0} \int_{t=-H_E}^0 \underbrace{\|w_f \cdot (y(t) - \hat{y}(t))\|_2^2}_{\text{Output error: Plant-model mismatch}} + \underbrace{\|w_\alpha \cdot \Delta_\alpha\|_2^2 + \|w_{x_0} \cdot \Delta_{x_0}\|_2^2}_{\text{Regularization: penalty to high changes w.r.t. the previous estimation}}$$

s. t.: $\dot{x} = f(x, u, z, p, d), x(0) = x_0; h(x, u, z, p, d) = 0; m(x, u, z, d) = 0$

$$\alpha = [T_{t0}, X_{f0}, K_f, K_T, \gamma, X_0]$$

Mixed tracking-economic NMPC design

- **Virtual setpoints** $y_S = [X_{fS}, T_{inS}]$ added to guarantee stability:
Additional decision variables that are always reached at the end of H_P
- **Tracking target:** X_{fR} . The L_1 -norm guarantees X_{fS} eventually reaches X_{fR}
- **Economic target:** T_{inR} . Indirectly minimizes the use of hot gases.

$$\begin{aligned}
 & \min_{u, y_S} \underbrace{\sum_{t=1}^{H_P} w_y \cdot \|y(t) - y_S\|_2^2}_{\text{Error w.r.t. virtual SPs}} + \underbrace{\sum_{t=1}^{H_C} w_u \cdot \|\Delta u\|_2^2}_{\text{Penalty to aggressive } \Delta u} + \underbrace{w_{sp} \cdot \|X_{fS} - X_{fR}\|_1}_{\text{Actual tracking objective}} + \underbrace{w_e \cdot T_{inR}}_{\text{Economic target}} \\
 \text{s. t. : } & \dot{x} = f(x, u, z, p, d), x(0) = x_0; h(x, u, z, p, d) = 0; m(x, u, z, d) = 0; \\
 & \underline{\mathbf{T}} \leq T_{in} \leq \bar{\mathbf{T}}; \quad \underline{\mathbf{u}} \leq u \leq \bar{\mathbf{u}}; \quad |\Delta u| \leq \delta \\
 & \left. \begin{aligned} & \dot{x}_S = f(x_S, u_S, p, \delta) = 0; \quad u(t) \equiv u_S \quad \forall t \geq H_C \end{aligned} \right\} \text{Ensure the virtual SPs are stable steady states}
 \end{aligned}$$

Technical implementation

- ▶ Model dynamics discretized in time via Orthogonal Collocation
 - ▶ Finite elements of 5-seconds length, 2-degree interpolation
- ▶ Nonlinear optimization problems coded in CasADi
 - ▶ Automatic-differentiation features
 - ▶ Easy integration with the control system at SONAE through MATLAB
- ▶ Numerical resolution by the NLP solver IPOPT
 - ▶ Horizons set to: $H_E = H_C = 8$; $H_P = 20$ (system delay is 5 samples)
 - ▶ Total execution time (MHE+MPC) is around 1,5 sec. ($<T_s = 5$ sec.)
- ▶ Connection with the plant data-collection system through OPC-DA

Comparison with PID control in simulation

- ▶ Model for simulation taken from specialized literature:

Pang (2000), Mathematical modelling of MDF fibre drying: Drying optimisation. Drying Technology, 18(7), 1433-1448.

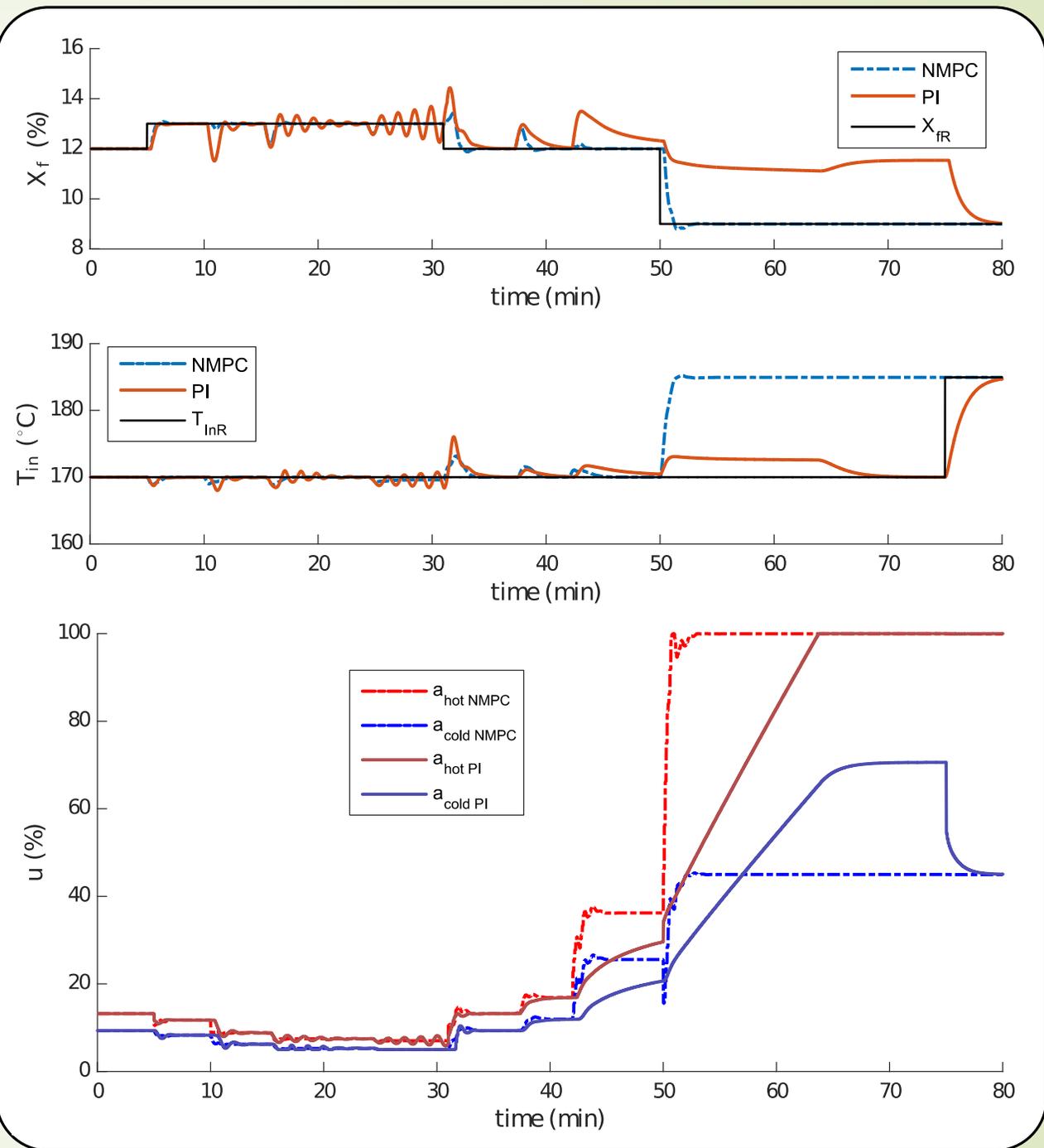
- ▶ Spatial drying PDE dynamics for flash tube dryers:

$$\frac{\partial X}{\partial l} = v \cdot \left(\frac{2}{L_f} + \frac{4}{d_f} \right) \cdot U \cdot \frac{T_{db} - T_{wb}}{\Delta H_w \cdot q_f}$$

- ▶ SISO PID loops were tuned for the simulation model following the SIMC rules

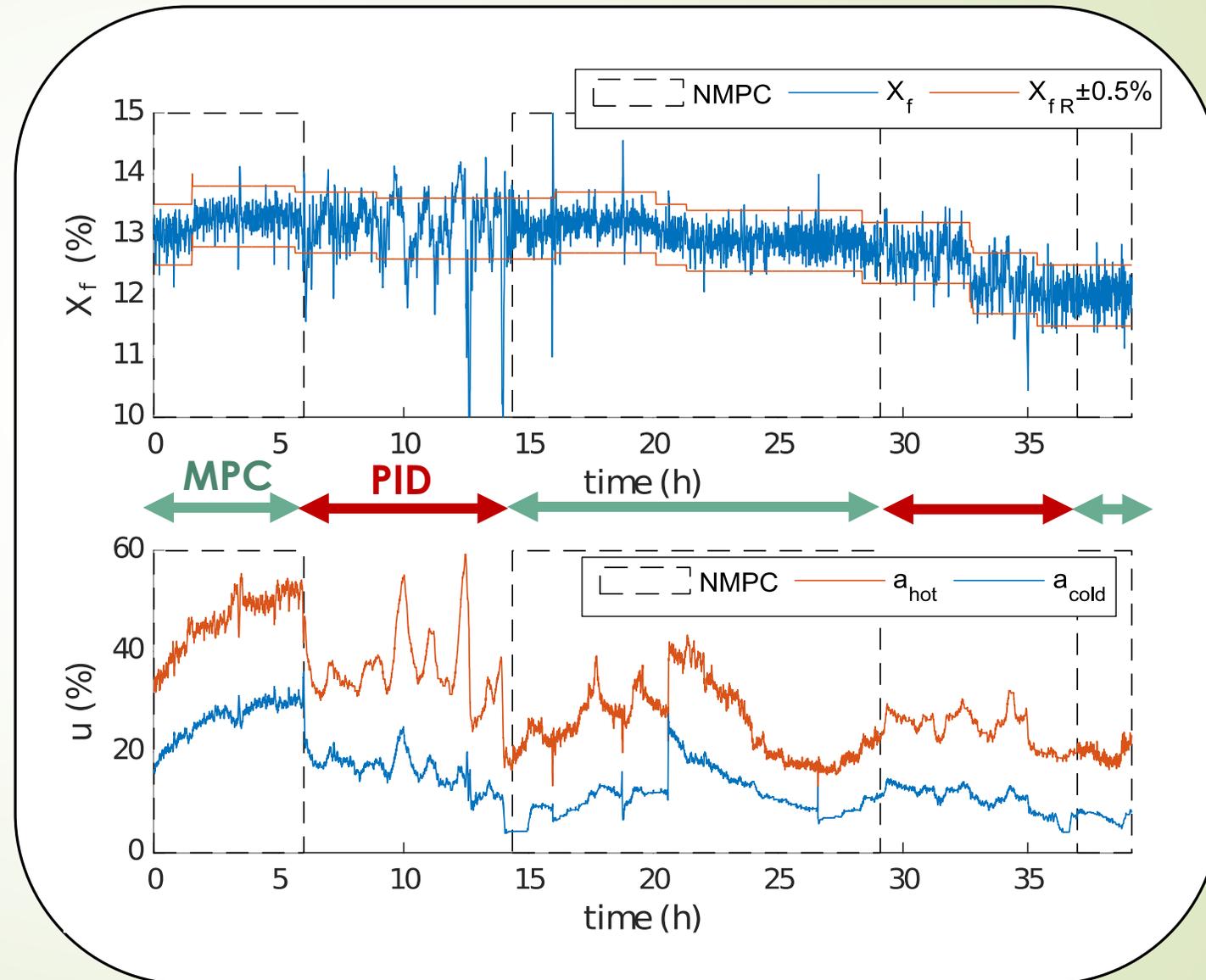
Results

- ▶ Control performance improved when facing disturbances in X_0, q_f
 - ▶ PID control oscillates when operating with flaps a_c, a_h quite closed.
 - ▶ Measured disturbances are instantaneously compensated with NMPC
- ▶ No need for operator intervention when the operation point changes
- ▶ Target humidity always achieved with NMPC, if feasible of course

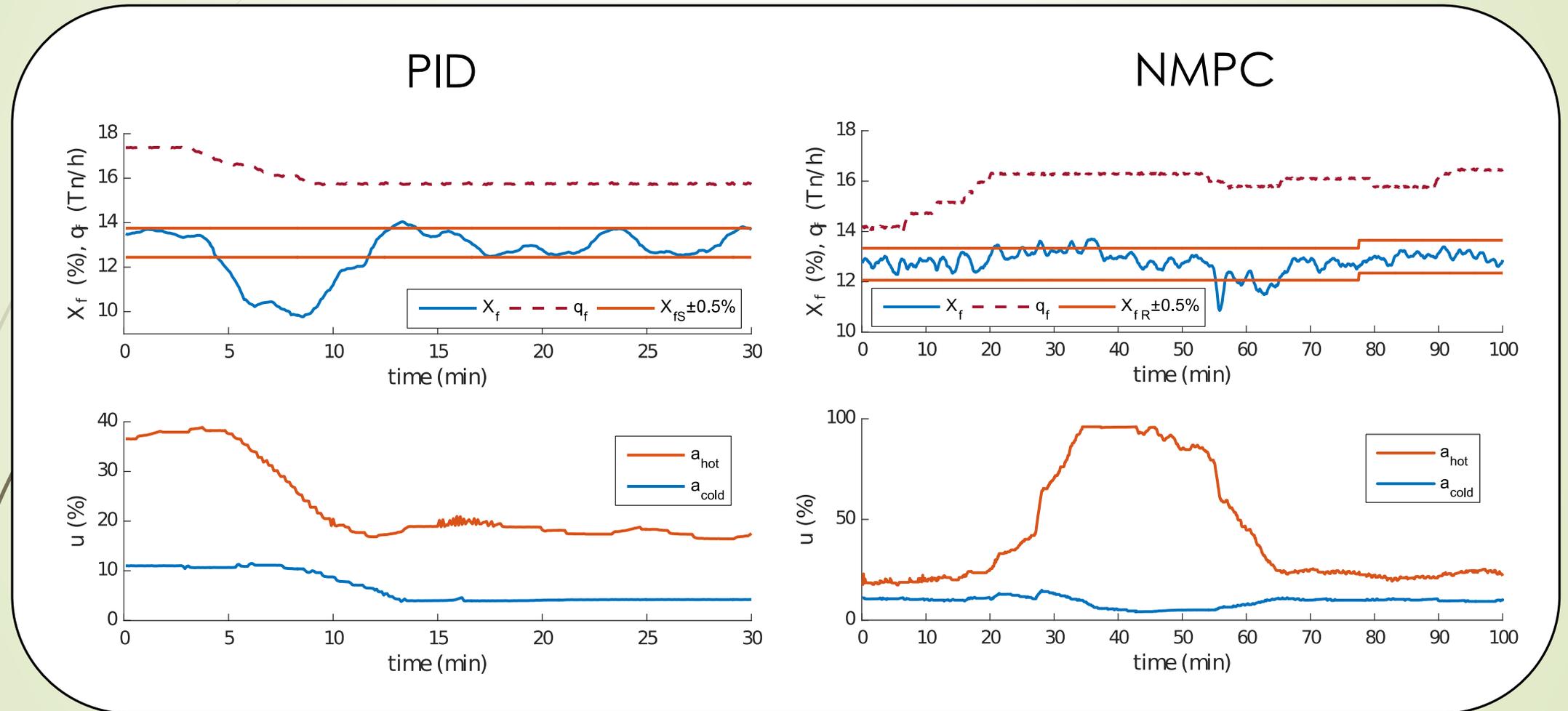


Experimental evaluation onsite

- COMPARISON WITH ACTUAL PID CONTROL:
- ISE reduced by 63%
- Time the humidity is outside a $\pm 0,5\%$ confidence band decreased by 76%



Disturbance rejection



* Actual data recorded from the plant

Summary & final remarks

- ▶ COMBINATION OF FIRST-PRINCIPLES AND DATA-DRIVEN EQUATIONS IN A (LIMITED COMPLEXITY) GREY MODEL IS KEY:
 - ▶ Keeps consistency with the process physics → reliable predictions
 - ▶ Proven suitable for real-time
- ▶ MODEL ADAPTATION IS REQUIRED TO ENSURE LONG LIFE OF DESIGNS:
 - ▶ Unmodelled (microscale) drying dynamics and unmeasured nature of some input disturbances affecting the process (i.e., X_0)
- ▶ STABILITY, FEASIBILITY & OPTIMALITY IS GUARANTEED IN THE NMPC:
 - ▶ Operators' work load is reduced



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