Application of feedback-corrected Optimal Scheduling for Reducing the Energy Consumption of a Mixing Process in Foundry

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***Abstract*—We present a feedback-corrected optimal scheduling approach to reduce the demand of electrical energy of batch processes, exemplified at the sand preparation in foundry. The main energy driver in the exemplary foundry is the idle time of the batch-wise working sand mixers. In this novel approach, we use linear integer programming to minimize the demand of energy of the sand mixers by scheduling the batches in real-time. For the optimization we use a physical model of the sand preparation, which takes dwell-times of the processes as dead-time systems into account. In this paper, we present the steps to make the optimal scheduling approach applicable for the production process. The application at the real production plant proves the performance of the suggested approach. Compared to the conventional control, the feedback-corrected optimal scheduling approach leads to an reduction in energy consumption of approximately 6.5 % without modifying the process or the aggregates.**

***Index Terms*—optimal scheduling, real-time, application, linear integer programming, dwell-time, soft constraint, batch-wise parallel process, foundry**

I. Introduction

Using energy efficiently is a key competitiveness factor in energy-intensive industry [1], [2]. Capacity utilization and energy costs in Germany are high compared with other countries [3]. Thus, the consumption of electrical energy is important to satisfy the increasing requirements of environmental legislation and to reduce costs. Green sand casting is energy intensive and preparing the moulding sand is a important energy driver. A study on the energy consumption in a foundry's sand preparation demonstrates possible energy savings of 10 %. We expect a comparable potential at the exemplary foundry Heinrich Meier Eisengießerei GmbH & Co. KG in Rahden.

The sand preparation produces sand for the moulding machine. At Heinrich Meier Eisengießerei GmbH & Co. KG two mixers produce sand parallel and batch-wise. Attached to each mixer is one hopper for storing the sand after processing. Furthermore, the machine hoppers for storing the sand before moulding are located in the plant. The sizing of the hoppers leads to a trade off between space requirements in the plant and hopper size. In the exemplary foundry, these hoppers are small and can only store approximately to two batches of sand. Due to the small size of the hoppers, the mixers have to react fast on fluctuations of the sand demand and mixer idle times occur.

The actual rule-based control system fills all hoppers to their limit. Energy cost, especially idle energy are not considered. Further, the dwell-time between dosing the sand for the mixing process and filling the prepared sand in the moulding machine is long. Therefore, optimal scheduling of the operation time of the mixing machines promises great potential for reducing energy consumption.

Related work for scheduling complex industrial processes with large dwell-times and switching process variables aims at offline production planing. A formalism for scheduling the production planning in foundry is explained in [4]. An optimization approach for constraint scheduling in steelmaking processes is shown in [5]. Recent papers [6], [7] present mixed integer programming approaches for scheduling parallel industrial processes. Theoretical work on model predictive control for switching process variables and average dwell-times mostly bases on [8]. Other recent approaches handle switching processes with rounding strategies [9] or use stochastic approaches for energy efficient switching [10].

The disturbance impacts strongly on the optimization. Therefore, updating the process variables and solving the optimal scheduling problem in real-time is preferred. This leads to the novelty of this approach, the real-time application of feedback-corrected optimal scheduling. The process model bases on the integrated modelling approach represented in [11]. The application at the foundry's sand preparation leads to a reduction in energy consumption of approximately 6.5 % without modifying the process or the aggregates.

The paper is structured as follows: In section II, we illustrate the conventional control system with mixing sequence and transport condition. Section III introduces the mathematical representation of the optimal scheduling problem. The preliminary examinations before applying the optimal scheduling approach at the plant are shown in section IV. In section V we present the results of the test at the production plant.

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II. Conventional Control System

The sand preparation processes the sand for the moulding machine. The moulding sand properties are adjusted in the sand mixers. Before mixing, the different components, like water, have to be dosed. Directly after mixing, the sand is stored in the mixer hoppers and can be transported via transport belts to the machine hoppers, in which the sand is buffered for the moulding machine. The conventional control system aims at maximum filling both mixers and machine hoppers, see Fig. 1. Whereby the filling of the machine hoppers is prioritized. In the mixing sequence, both mixers are filled batch-wise via one common scale, see Fig. 1 (top). The sequence is deterministically controlled in seven steps. As a result, the mixers always work alternately. When the mass in a mixer hopper is above the upper bound, the process stops, see step two or five, respectively. The scale buffers the next batch and the related mixer runs in idle mode. Directly when the mixer hopper can store a batch, the mixing process begins. While the transport condition is fulfilled, the belts convey the mixed sand into the machine hoppers, see Fig. 1 (bottom). A scraper splits the sand into the two hoppers. With full hoppers, the sand extraction from the mixer hoppers stops.

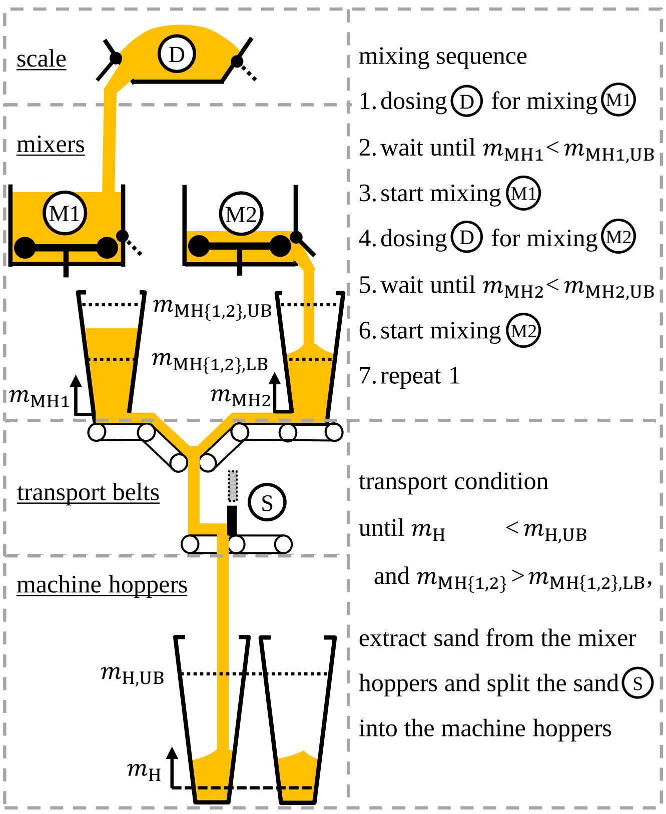

Fig. 1. Schematic moulding sand process (left side) and conventional deterministic control system (right side). Mixing sequence with scale, mixers and hoppers (top). Transport condition with belts and machine hoppers (bottom).

III. Optimal Scheduling Problem

The dosing, mixing and transport processes are modelled as discrete dead-time systems. The detailed process description, modelling approach and problem formulation are given in [11]. For the list of inputs, states, slacks and parameters, see Table I. The specific process in the exemplary foundry requires starting the mixers after dosing the sand in the scale. During the start up time of the mixers, the sand remains in the scale. If the mixers are in state *OFF* before mixing, an additional time delay for dosing of one step is necessary. Switching the mixers states $x_{\mathrm{M}\circ}$ with the input $u_{\mathrm{M}\circ}$ and separating the mixers starts $s_{\mathrm{MS}\circ}$ by constraint pushing leads to:

$$x_{\mathrm{M}\circ}(k+1) = x_{\mathrm{M}\circ}(k) + u_{\mathrm{M}\circ}(k) \tag{1a}$$

$$u_{\mathrm{M}\circ}(k) - s_{\mathrm{MS}\circ}(k) \leq 0. \tag{1b}$$

TABLE I
Variables, Inputs, States, Parameters, Bounds and Weights

Variable	Explanation	Size	Unit
k	time-step		–
K	prediction horizon		–
$\circ$	scale and mixer abbreviations $\{1,2\}$		
Input			
$u_{\mathrm{S}\circ}$	dosing start scale $\{0,1\}$		–
$u_{\mathrm{M}\circ}$	switch mixer state $\{-1,0,1\}$		–
$u_{\mathrm{T}\circ}$	*OFF*, *ON* extraction belt $\{0,1\}$		–
State			
$\tilde{m}_{\mathrm{S}\circ,i}$	counter i for the normalized masses of the dosing process $\{0,1\}$		–
$x_{\mathrm{M}\circ}$	mixer state $\{0,1\}$		–
$\tilde{m}_{\mathrm{M}\circ,j}$	counter j for the normalized masses of the mixing process $\{0,1\}$		–
$m_{\mathrm{MH}\circ}$	mass in mixer hopper		kg
$m_{\mathrm{T},n}$	counter n for the transported mass		kg
m_{H}	mass in machine hopper		kg
Δm_{HD}	mass extracted from the machine hoppers		kgs^{-1}
Slack			
$s_{\mathrm{S}\circ}$	buffering sand in scale $\{0,1\}$		–
$s_{\mathrm{MS}\circ}$	mixer start $\{0,1\}$		–
$s_{\mathrm{MH}\circ,\mathrm{LB}}$	lower bound mixer hopper		–
$s_{\mathrm{MH}\circ,\mathrm{UB}}$	upper bound mixer hopper		–
$s_{\mathrm{H,LB}}$	lower bound machine hopper		–
$s_{\mathrm{H,UB}}$	upper bound machine hopper		–
Parameter		**Size**	
Δt	duration of one time step	10	s
T_{S}	time steps for dosing	6	–
T_{M}	time steps for mixing	14	–
$c_{\mathrm{S}\circ}$	mass per batch	6000	kg
T_{T}	time steps for transporting	2	–
$c_{\mathrm{T}\circ}$	extracted mass from mixer hoppers per time step	$58\Delta t$	kg
Bound			
$m_{\mathrm{MH}\circ,\mathrm{UB}}$	upper bound mixer hopper	12000	kg
$m_{\mathrm{MH}\circ,\mathrm{LB}}$	lower bound mixer hopper	0	kg
$m_{\mathrm{H,UB}}$	upper bound machine hopper	19000	kg
$m_{\mathrm{H,LB}}$	lower bound machine hopper	12000	kg
Weight			
$w_{\mathrm{S}\circ}$	buffering sand in scale	-10^{-2}	–
$w_{\mathrm{MS}\circ}$	start mixer	2025	–
$w_{\mathrm{MI}\circ}$	idle time mixer	$75\Delta t$	–
$\boldsymbol{w}_{\mathrm{MH}\circ}$	slacks mixer hopper	$[10^2 \, 10^2]$	[– –]
$\boldsymbol{w}_{\mathrm{H}}$	slacks machine hopper	$[10^2 \, 10^3]$	[– –]

The extended model for the dosing process reads

$$\tilde{m}_{\mathrm{S}\circ,1}(k{+}1) \quad = u_{\mathrm{S}\circ}(k) \tag{2a}$$

$$\tilde{m}_{\mathrm{S}\circ,i}(k{+}1) \quad = \tilde{m}_{\mathrm{S}\circ,i-1}(k), \quad i = 2,\cdots, T_{\mathrm{S}} - 1 \tag{2b}$$

$$\tilde{m}_{\mathrm{S}\circ,T_{\mathrm{S}}}(k{+}1) = \tilde{m}_{\mathrm{S}\circ,T_{\mathrm{S}}-1}(k) + s_{\mathrm{S}\circ}(k) + s_{\mathrm{MS}\circ}(k) \tag{2c}$$

and the mixing process denotes

$$\tilde{m}_{\mathrm{M}\circ,1}(k{+}1) = \tilde{m}_{\mathrm{S}\circ,T_{\mathrm{S}}}(k) - s_{\mathrm{S}\circ}(k) - s_{\mathrm{MS}\circ}(k) \tag{3a}$$

$$\tilde{m}_{\mathrm{M}\circ,j}(k{+}1) = \tilde{m}_{\mathrm{M}\circ,j-1}(k), \quad j = 2,\cdots, T_{\mathrm{M}}. \tag{3b}$$

The mixer hoppers are modelled by

$$\begin{aligned} m_{\mathrm{MH}\circ}(k{+}1) = {} & m_{\mathrm{MH}\circ}(k) + c_{\mathrm{S}\circ}\tilde{m}_{\mathrm{M}\circ,T_{\mathrm{M}}}(k) \\ & - c_{\mathrm{T}\circ}u_{\mathrm{T}\circ}(k). \end{aligned} \tag{4}$$

The mass extraction from the mixer hoppers and the mass transport reads

$$m_{\mathrm{T},1}(k{+}1) = \sum\nolimits_{\circ\in\{1,2\}} c_{\mathrm{T}\circ}u_{\mathrm{T}\circ}(k) \tag{5a}$$

$$m_{\mathrm{T},n}(k{+}1) = m_{\mathrm{T},n-1}(k), \quad n = 2,\cdots, T_{\mathrm{T}}. \tag{5b}$$

The machine hopper is modelled by

$$m_{\mathrm{H}}(k{+}1) = m_{\mathrm{H}}(k) + m_{\mathrm{T},T_{\mathrm{T}}}(k) - \Delta m_{\mathrm{HD}}(k). \tag{6}$$

The optimal scheduling problem contains costs for mixing, hopper levels and buffering sand in the scale. For the list of bounds and weights, see Table I. The costs for mixing processes include starting costs

$$h_{\mathrm{MS}} = \sum\nolimits_{\circ\in\{1,2\}} w_{\mathrm{MS}\circ}s_{\mathrm{MS}\circ}(k) \qquad \text{s.t. } s_{\mathrm{MS}\circ}(K) = 1 \tag{7}$$

and costs for idle times

$$\begin{aligned} h_{\mathrm{MI}} \; &= \sum\nolimits_{\circ\in\{1,2\}} w_{\mathrm{MI}\circ}\left[x_{\mathrm{M}\circ}(k) - \sum\nolimits_{j=1}^{T_{\mathrm{M}}} \tilde{m}_{\mathrm{M}\circ,j}(k)\right] \\ \text{s.t.} & \sum\nolimits_{j=1}^{T_{\mathrm{M}}} \tilde{m}_{\mathrm{M}\circ,j}(k) \le x_{\mathrm{M}\circ}(k) \\ & \tilde{m}_{\mathrm{S}\circ,T_{\mathrm{S}}}(k) \le x_{\mathrm{M}\circ}(k). \end{aligned} \tag{8}$$

Exceeding the mixer and machine hopper bounds is punished with a soft constraint formulation by

$$\begin{aligned} h_{\mathrm{MH}} = & \sum\nolimits_{\circ\in\{1,2\}} \boldsymbol{w}_{\mathrm{MH}\circ}\begin{bmatrix} s_{\mathrm{MH}\circ,\mathrm{LB}}(k) \\ s_{\mathrm{MH}\circ,\mathrm{UB}}(k) \end{bmatrix} \\ \text{s.t. } & m_{\mathrm{MH}\circ,\mathrm{LB}} - s_{\mathrm{MH}\circ,\mathrm{LB}}(k) \le m_{\mathrm{MH}\circ}(k) \\ & m_{\mathrm{MH}\circ,\mathrm{UB}} + s_{\mathrm{MH}\circ,\mathrm{UB}}(k) \ge m_{\mathrm{MH}\circ}(k) \\ & s_{\mathrm{MH}\circ,\mathrm{LB}}(k), s_{\mathrm{MH}\circ,\mathrm{UB}}(k) \ge 0, \end{aligned} \tag{9a}$$

$$\begin{aligned} h_{\mathrm{H}} \; = & \; \boldsymbol{w}_{\mathrm{H}}\begin{bmatrix} s_{\mathrm{H},\mathrm{LB}}(k) \\ s_{\mathrm{H},\mathrm{UB}}(k) \end{bmatrix} \\ \text{s.t. } & m_{\mathrm{H},\mathrm{LB}} - s_{\mathrm{H},\mathrm{LB}}(k) \le m_{\mathrm{H}}(k) \\ & m_{\mathrm{H},\mathrm{UB}} + s_{\mathrm{H},\mathrm{UB}}(k) \ge m_{\mathrm{H}}(k) \\ & s_{\mathrm{H},\mathrm{LB}}(k)\, s_{\mathrm{H},\mathrm{UB}}(k) \ge 0 \\ & m_{\mathrm{H}}(0) - m_{\mathrm{H}}(K) \le 0. \end{aligned} \tag{9b}$$

Buffering sand in the scale is penalized by

$$\begin{aligned} h_{\mathrm{S}} \; &= \sum\nolimits_{\circ\in\{1,2\}} w_{\mathrm{S}\circ}s_{\mathrm{S}\circ}(k). \\ \text{s.t.} & \sum\nolimits_{\circ\in\{1,2\}} \left[u_{\mathrm{S}\circ}(k) + \sum\nolimits_{i=1}^{T_{\mathrm{S}}} \tilde{m}_{\mathrm{S}\circ,i}(k)\right] \le 1. \end{aligned} \tag{10}$$

The economic cost function is completely linear:

$$\begin{aligned} \min_{\substack{\text{Inputs,}\\ \text{Slacks}\\ \forall k\le K}} \quad & J = h_{\mathrm{MS}} + h_{\mathrm{MI}} + h_{\mathrm{MH}} + h_{\mathrm{H}} + h_{\mathrm{S}} \\ & \text{s.t. } (7-10). \end{aligned} \tag{11}$$

IV. Preliminary Examination

The aim of the optimization is reducing the energy consumption of the mixing machines. The optimization problem takes the process restrictions as well as the sand extraction from the machine hoppers into account. We focus on reducing the energy consumption by optimizing the trade-off between idle energy and the consumption during mixers starts. Idle times occur when the mixers are in state *ON* without processing a batch. Therefore, the process strategy is scheduling the starts of dosing and the transitions, for example between dosing and mixing, to minimize the costs.

In the real production plant two machine hoppers store the sand for the moulding process. For every moulding process, sand is required from both hoppers. The sand extraction from the hoppers is proportional to each other. Thus, both hoppers are modelled as a common one (6) and a subordinated control regulates the even sand splitting to both hoppers. Upper and lower bounds of the modelled machine hopper are set to 19000 kg and 12000 kg, respectively. Due to process stability, the upper bounds of the mixer hopper masses are set to 12000 kg and the lower bounds are set to 0 kg, see Table I *Bound*. The sand extraction from the common machine hopper considered as a disturbance, has a strong impact on optimization, is measured in the time step $k = 0$ and is fix for all steps of the optimization horizon. Responding to the changing disturbance, the optimization has to be solved in real-time.

For feedback-corrected optimal scheduling the state feedback has to be determined in real-time. The model presented in [12] is used for estimating the sand masses in all hoppers during extraction and filling. We use soft constraint bounds to handle uncertainties of the estimated hopper masses (9a, 9b). The demand of sand of the moulding machine fluctuates for example with the production program and interruptions. For example, a moulding model change is performed approximately 20 times per day. This can lead to a different sand demand, because of changes in mould cavity, casting time and production interruptions resulting from start-up problems with the model. Furthermore, process interruptions are not predicted. Therefore, the actual measured value of the moulding sand demand is assumed to be constant over the prediction horizon.

While a mixer is waiting for a batch, idle energy occurs. Thus, buffering sand in the scale is preferred and weighted negatively in the objective function (11), see Table I *Weight*.

The costs for the mixers starts represent the start up energy and wear (7). Safe plant behaviour under failure is ensured by existing plant safety systems. These intercept all errors which could lead to damage of the plant, e.g. overfilling the hoppers.

The calculation cost is reciprocal to sample time and, thus to the number of states resulting from the dead-time systems for dosing T_{S}, mixing T_{M} and transport T_{T}, see Table I *Parameter*. This leads to a trade-off between calculation cost and reaction on changes of the disturbance. In comparison to the initial plant test results, shown in [11], this trade-off is resolved with a less sample time of 10 s. The number of states of the dead time systems is adjusted accordingly.

Based on [11], we formulate the optimal scheduling problem in *matlab R2020b* and use *YALMIP* [13] for the interaction with the solver *IBM CPLEX ILOG v12.10*. For the optimal scheduling approach, the following preliminary examinations are the offline feedback-corrected optimal scheduling (subsection *A*) and counting the switch-off suggestions in an open-loop simulation parallel to the conventional control (subsection *B*). Both serve as preparation for the application of feedback-corrected optimal scheduling in real-time test at the production plant.

A. *Offline feedback-corrected Optimal Scheduling*

Solving the optimal scheduling problem cyclically every time step and updating the states and the disturbance leads to feedback-corrected optimal scheduling. The prediction horizon of every optimization is 200 steps (approximately 33 minutes). The sample time for real-time capacity is 10 s, see Table I *Parameters*. The feedback states are error-free and originate from the simulated plant model.

Similar to the real production plant, the moulding sand demand out of the machine hopper (disturbance) fluctuates between the demand for producing moulds (marker A) and zero, during production stops (sectors B), see Fig. 2 (top). The demand is mostly in range of 70 kgs^{-1} (marker A) and thus corresponds to production at medium speed, e.g. when casting spheroidal graphite iron. Previous tests show a high calculation effort at this demand. Data pre- and post-processing need below 2.5 s. Therefore, the calculation time for solving the optimal scheduling problem is capped at 7.5 s (limit), see Fig. 2 (second). Mostly the problem converges before the limit is reached, in all other cases convergence is almost achieved. In approximately 40 % of the time steps, convergence is achieved below 6 s, see Fig. 2 (second, sectors C). Therefore, solving the optimal scheduling problem at the plant is also expected to converge in real-time.

The masses in the hoppers are standardised to the upper bound (1.0) and lower bound (0.0), see Fig. 2 (middle). Both masses in the mixer hoppers $m_{\mathrm{MH}\{1,2\}}$ fluctuate in the entire range between their bounds (0.0 to 1.0). The mass in the machine hoppers m_{H} varies in an interval of approximately 72 % of the entire range (0.25 to 0.97), see Fig. 2 (middle, sector D). The range below 0.25 is not used, due to the disturbance going to zero (top, sectors B).

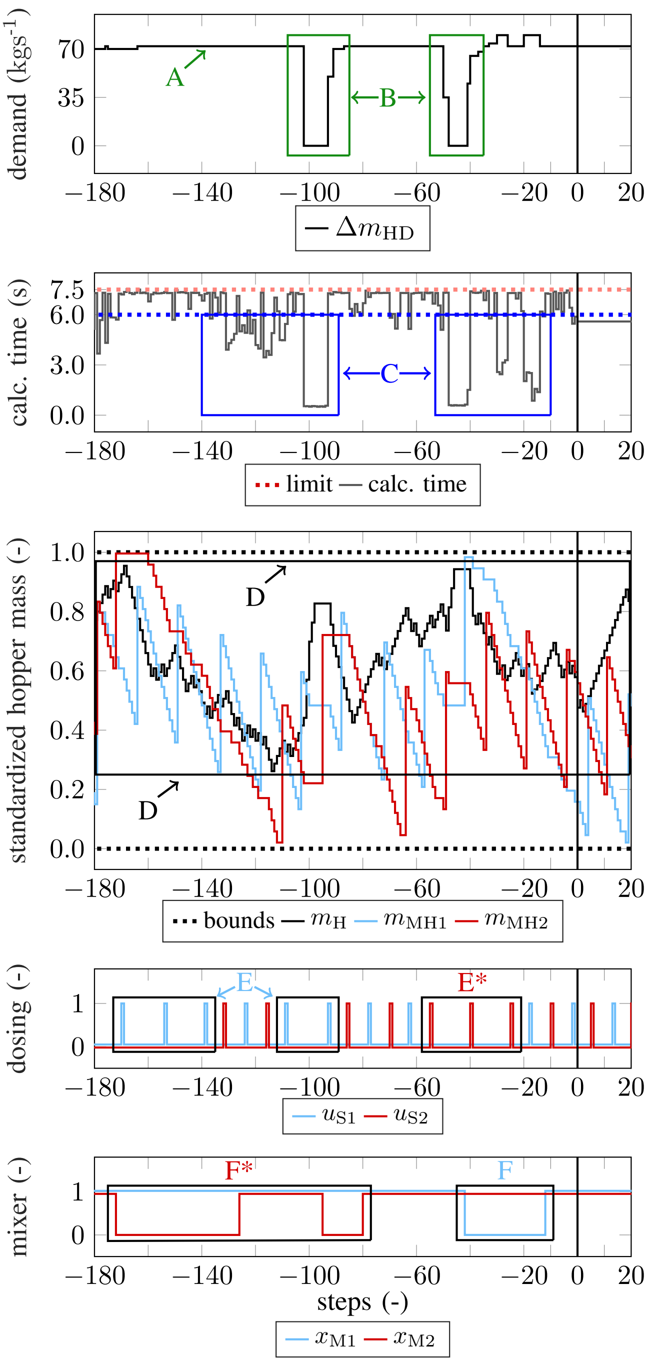

Fig. 2. Cyclically solved offline feedback-correceted optimal scheduling for 180 steps with a prediction horizon of 200 steps. From top to bottom: Moulding sand demand (disturbance), calculation time, standardized masses in the hoppers, starts of dosing and mixers states.

The starts of dosing and the mixers states are *OFF* (0) and *ON* (1), see Fig. 2 (forth and bottom). Sand dosing is performed blocks-wise by consecutive dosing for each mixer, see Fig. 2 (forth, sectors E and E*). Thus, the mixer switch off block-wise, see Fig. 2 (bottom, sectors F and F*). Therefore, the offline simulation shows a great potential for energy savings.

B. Switch-off Suggestions

Running feedback-corrected optimal scheduling, parallel to the conventional control, and counting the switch-off suggestions allows an evaluation before applying the scheduling approach at the production plant. Inputs are the measured disturbance as well as the measured and estimated states from the real production plant. The configuration for optimal scheduling is the same as in the previous simulation.

The optimal scheduling runs for 10 hours in $10s$ time steps during production times with high and low moulding sand demand. During high demand, the disturbance is in range of approximately 73 kgs^{-1} and also less production interruptions occur. Analysing the switch-off suggestions results in 69 suggestions in the approximately 2900 steps. This corresponds to 2.38 % of steps with a recommendation for switch-offs. During low demand the disturbance is approximately 68 kgs^{-1} and more interruptions appear. Counting the switch-off suggestions results in 51 suggestions in approximately 550 steps (9.27 %). This indicates high energy saving potential, especially for low sand demand. Counting the switch-off suggestions proves the potential for energy savings from the offline optimal scheduling.

V. Application Results

The feedback-corrected optimal scheduling problem is solved cyclically every time step in real-time and applied at the production plant in a 4-hour test at a typical production day. The prediction horizon is 200 steps and the disturbance is measured in step $k = 0$ and fixed for the prediction horizon.

During the entire test period the reduction in energy consumption is approximately 6.5 % and real-time capacity is reached. The mixers consume approximately 140 MWh/a. At this level of consumption, approximately 9.1 MWh/a can be saved. From the 4-hour test, two excerpts each 210 steps long are shown. The first excerpt discusses the advantage in energy consumption and the second excerpt aims at the computation time.

A. Energy consumption

The moulding sand demand fluctuates due to production, see Fig. 3, (top, sector A). The maximum sand demand is below 72 kgs^{-1} (line B) and long production interruptions occur (sector C). Overall, this is a medium sand demand, e.g. when casting spheroidal iron.

All masses in the hoppers are standardised to the upper bound (1.0) and lower bound (0.0), see Fig. 3, (second). The sand mass in the machine hoppers is combined into one mass m_{H}. This mass varies in the entire range between the bounds (0.0 to 1.0). In comparison to the mass in the machine hoppers, the mass in the mixer hoppers $m_{\mathrm{MH}\{1,2\}}$ fluctuate in range of approximately 70 % of their bounds (0.0 to 0.7), see Fig. 3, (second, sector D). This leads to a potential of 0.3 (0.7 to 1.0). The difference to the simulation could result from the varying moulding sand demand and the production interruptions, see Fig. 3, (top, sectors A and C).

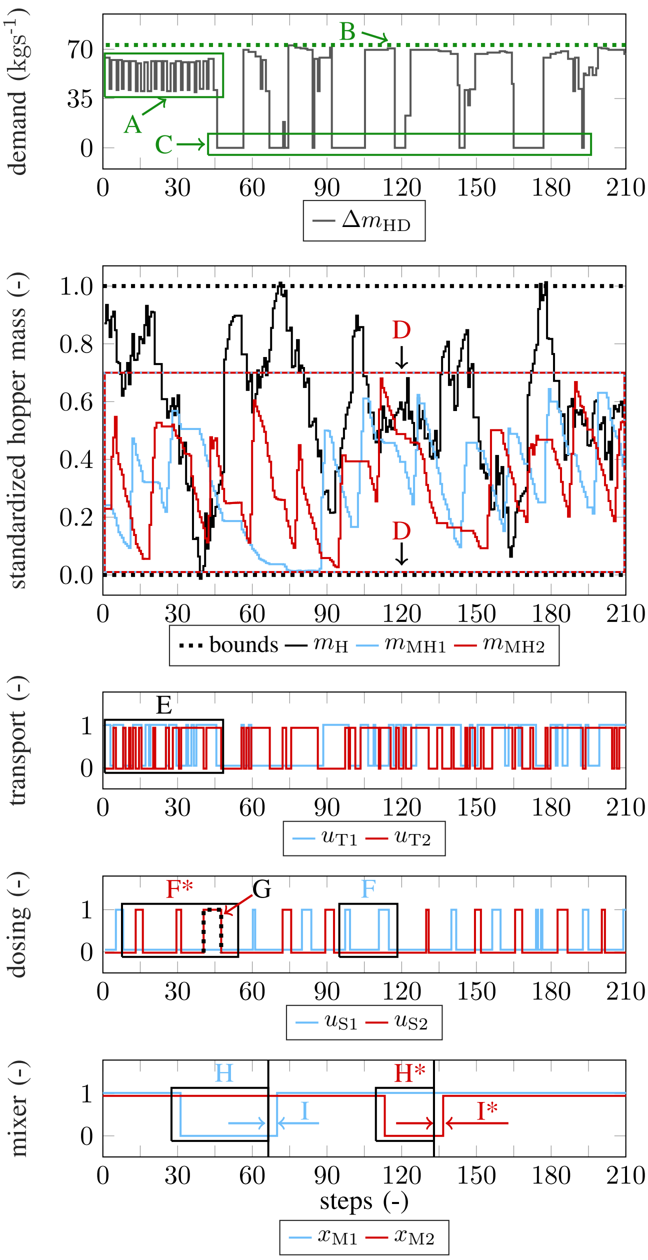

Fig. 3. Excerpt *energy consumption* (210 steps) from the plant test with a prediction horizon of 200 steps. From top to bottom: Moulding sand demand (disturbance), standardised masses in the hoppers, sand transport, starts of dosing and mixers states.

The sand transport, starts of dosing and the mixers states are *OFF* (0) and *ON* (1), see Fig. 3 (middle, forth and bottom). In response to the changing moulding sand demand, the states of the transport belts switch with high frequency, see Fig. 3, (middle). This can be seen particularly well when comparing sector E (middle) and sector A (top). Dosing of sand in scale is executed consecutively, see Fig. 3, (forth, sectors F and F*). Fluctuations in sand demand lead to locking the dosing starts of the next batch until the hopper can store this batch. The locking is caused by rudimentary safety functions of the plant, which protect the hoppers from overfilling. The triggering of the safety functions is very inaccurate and cannot be adjusted. Therefore, in some cases, the signal to start dosing is held for several time steps, see Fig. 3, (forth, marker G). This could explain the potential in mixer hopper mass (second, sector D). The mixers switch off block-wise, see Fig. 3 (bottom, sectors H and H*). While a mixer is switched-off, the scale doses sand only for the second mixer, compare sectors F with H and F* with H*, respectively. The start-up time for switching on the mixers is two time steps, see Fig. 3 (bottom, sectors I and I*). We assume, the conventional control would produce the same amount of sand as the optimal scheduling in the test. The reduction in energy consumption of the optimal scheduling approache is the sum of saved energy in sectors H and H* (mixers are switched off) minus the start-up energy demand in sectors I and I* compared to the energy consumption of the conventional control (idling instead of switching off). The reduction in energy consumption in this excerpt is approximately 12.8 %.

B. Computation time

Previous examinations show high calculation time when the disturbance is very high. Therefore, the computation time is examined for another interval of the same test with a length of 210 steps. The moulding sand demand is high, mostly above 70 kgs^{-1} and only short production interruptions occur, see Fig. 4, (top, line A and sector B). Thus, the mixers run without possible switch-off or idle.

Like the test results from the excerpt *energy consumption*, the mass in the machine hoppers m_{H} varies in the entire range (up to 1.0), see Fig. 4 (middle). Uncritical undercutting of the lower bound (sectors C) show the necessity of formulating soft constraints for the hopper bounds. The masses in the mixer hoppers $m_{\mathrm{MH}\{1,2\}}$ vary in an interval of approximately 85 % of the entire range (0.00 to 0.85), see Fig. 4, (middle, sector D). In comparison to Fig. 3 (second, sector D), the increase of the interval of 0.15 (from 0.70 to 0.85) could be an effect of the less varying disturbance. Maximum filling of the mixer hoppers is probably not reached due to the rudimentary safety functions of the plant (see excerpt *energy consumption*) and due to very high sand demand (top).

The computation time consists of calculation time for solving the optimal scheduling problem (up to 7.5 s) and time for pre- and post-processing (approximately 2.5 s). For real-time capacity, the computation time must be below the sample time of 10 s, see Fig. 4 (bottom). In approximately 60 % of the steps the calculation takes less than 4 s, see Fig. 4, (bottom, line G). The calculation time remains always below 7.5 s, see Fig. 4, (bottom, line F). With a calculation time close to 7.5 s, a nearly optimal solution is achieved. We calculate the solution externally and send the results to the plant control system via internet. Exceeding the limit is negligibly small and results from the post-processing time, e.g. in case of delayed data transmission via the internet, see Fig. 4, (sector E). Therefore, real-time capability is proved with this excerpt.

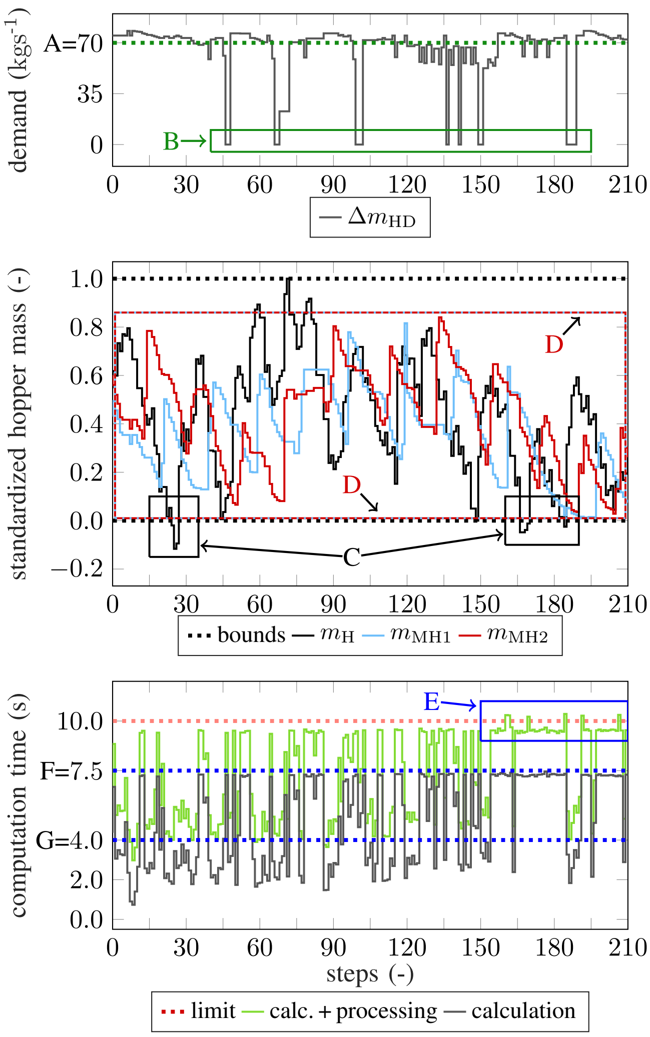

Fig. 4. Excerpt *computation time* (210 steps) from the plant test with a prediction horizon of 200 steps. From top to bottom: Moulding sand demand (disturbance), standardised masses in the hoppers and computation time.

Overall, performing the optimal scheduling at the production plant leads to great savings in energy consumption and proves real-time capacity of the approach.

VI. Conclusion

This paper presents a feedback-corrected optimal scheduling approach for optimizing the energy consumption of independent parallel processes. We use a linear process model based on dead-time systems and a linear economic cost function. The completely linear approach has great advantages in computational effort. With the economic cost function a direct optimization of the energy consumption is possible.

Performing feedback-corrected optimal scheduling in offline simulation promises great potential for energy savings. Simulating feedback-corrected optimal scheduling parallel to the conventional control confirms the potential for energy savings and suggests possible switch-offs, especially in case of low moulding sand demand.

The production plant test results show the improvements by the demonstrated approach compared to the conventional control. The reduction in energy consumption in the 4 hour test is approximately 6.5 %. Optimization and necessary processing of the data is performed in real-time. Furthermore, the application of the demonstrated approach contributes to qualify optimal scheduling for industrial processes.

The demand of sand is essential for the optimization. Thus, the energy savings could be further increased by predicting the demand. We assume that neural networks could be suitable.

Moreover, we want to improve the pre- and post-processing. Further improvements could be reached by adjusting the optimal scheduling problem or the solver settings. The environmental conditions at the plant are changing over a long period, for example due to seasons. Therefore, long-term testing would evaluate this approach under additional conditions.

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