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Modelling And Control Of Aqueous Parts Cleaning Machines For Demand Response

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Abstract

With the aim of enabling better utilization of renewable power and reducing the environmental impact of industrial sites, we propose an approach for implementing electric demand response. Cleaning machines provide significant potential for demand response due to their large water tanks, which can be used for thermal energy storage. Furthermore, many batch cleaning machines allow process interruptions without impacting the cleaning result. We show that utilizing inherent energy storage and process interruptions are practical ways to implement demand response.

Hence, we present a mathematical demand response model of an aqueous parts cleaning machine and integrate it in a cyber-physical production system. The mathematical demand response model is used to determine the energy consumption of the machine resulting from the cleaning process and the tank heater. The model is divided into an event-based part describing the individual steps of the cleaning process and a time-based part representing the energy required by the tank heater to satisfy specified tank temperature limits.

In addition to the mathematical model, we present the data model required for communication with the physical machine. We validate the mathematical model and the complete cyber-physical production system including a real machine in a field test in the ETA research factory for their demand response capabilities.

Keywords

carbon neutral production; energy-flexibility; cyber-physical production system; model predictive control; single machine scheduling; data model; inherent energy storage

1. Introduction

Purchasing electricity is currently more expensive than ever for industrial companies. Average annual electricity spot market prices in Germany rose from 28.20 €/MWh in 2016 to 93.35 €/MWh in 2021 and 235.52 €/MWh in 2022 [1]. The latest price increase is caused by the dependence on conventional energy sources such as oil and gas [2]. The worldwide average price for gas already increased by 549 % between December 2020 and one year later. [3]. One way to reduce dependence on fossil fuels is to expand the use of renewable energy. Between 2011 and 2021, renewable generation worldwide has nearly doubled from 402 TW h to 763 TW h [4]. An adjustment of the electricity system is required for the switch to renewable electricity generation. Due to the stochastic nature of renewable electricity generation consumers should adapt to fluctuating generation through the integration of energy storage and by using demand response (DR) as part of demand side integration [5], thus reducing energy costs.

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In previous research we performed an analysis of the DR potential of an industrial aqueous parts cleaning machine [6]. We also developed an automation data model to be used for the communication between DR services and the machine automation in cyber-physical production systems (CPPS) [7]. In [8] we implemented a CPPS based on the automaton data model including a simulation model of the cleaning machine and a simple rule-based DR service to control the tank heater of the machine. The approach shown in the present paper extends this research with a mathematical model for the machine's production schedule. The model integrates the flexibility potentials identified in [6]. We also extend the automation data model to include the newly required information and update the automation structure of the machine.

In section 2 of this article we provide a literature review of industrial process and production scheduling. Then, we briefly describe the cleaning machine and its DR potential in section 3. We subsequently present the DR service in section 4. The data model for interaction between the machine automation and the DR service is shown in section 5. Finally, we apply the DR service to a cleaning machine in a field test in section 6 and draw a conclusion in section 7.

2. Literature

The literature review identified many research articles focused on energy flexible or energy efficient scheduling of single machines. Some exemplary approaches for minimizing the energy cost of production by applying DR are [9], where the schedule is optimized for an unspecified single machine, and [10], where a machining process is considered and multiple factors are optimized, including the cutting speed. Biel et al. [11] provide a comprehensive overview of research in this area, and a more recent review has been published by Bänsch et al. [12].

Most of the previously mentioned research lacks a standardized method for the implementation of the proposed optimization on actual machines in real production environments. The creation of cyber-physical production systems might offer a path towards further proliferation of the proposed scheduling optimizations. In [13], Meissner et al. describe how the development of cyber-physical production systems influences process planning and scheduling. They point out a variety of factors affecting the implementation of data driven process planning and scheduling approaches, such as the interconnectedness of machines and products, big data, and cyber security. The benefits of integrated process planning and scheduling lie mostly in the increased capacity for real-time adaptation of process plans and schedules.

Leiden et al. present an approach for energy and resource efficient operation of plating process chains using a cyber-physical system implementation [14]. They created an agent based discrete-event simulation of the process chain to support planning and operational processes. The authors assert that the implementation as a cyber-physical system led to high process transparency and attest good applicability of their system by utilizing it for decision support as well as direct control of processes [14].

In the literature review we observed a lack of cyber-physical production system implementations which aim to make single machine scheduling with an energy-related objective more attainable. We therefore attempt to fill this gap by presenting a scheduling model with an energy-cost objective which is integrated in a cyber-physical production system.

3. System description and demand response potential

We develop a demand response scheduling model for the aqueous parts cleaning machine MAFAC KEA in the ETA Factory at the Technical University of Darmstadt [15]. The machine has a total rated power of 20.7 kVA. It is equipped with one closed treatment chamber and a 320 l tank for cleaning fluid, which is heated by an electrical tank heater with 10 kW nominal load. The cleaning process duration is 12 minutes and consists of the three energy-relevant process steps *spray cleaning* (600 s), *impulse blowing* (30 s) and *convection drying* (90 s).

We analysed the potential of the cleaning machine for DR measures in [6]. The DR potential analysis of the machine showed that it has high potential to implement the DR measures *interrupt process* and *store energy inherently* defined in [16]. *Interrupt process* means pausing between cleaning processes or between the process steps. By controlling the tank heater with a DR service and using the thermal inertia of the tank as a thermal storage, the heating system can be used to *store energy inherently* [6].

In this study we aim to replace the simple control strategy previously described in [8] with a mathematical optimization model, executed as a model predictive controller (MPC). While we previously presented a simple rule-based approach for controlling just the tank heater, we now design a more sophisticated model for the temperature of the cleaning fluid in the tank, which takes the cleaning stages into account. We also integrate the ability to make the *interrupt process* decision. These changes of the model also require some adaptations of the automation structure. The entire implementation of the cyber-physical production system is based on the eta-utility software framework [17].

4. Demand response scheduling model

To use the cleaning machine for DR we create a mixed integer linear programming (MILP) scheduling model. The model is used as the DR service by executing it in a MPC loop. The objective function of the scheduling model aims to minimize the energy cost of the cleaning machine which depends on the machine's power consumption and the changing energy price. We separate the model into two parts: We develop an event-based approach to model the cleaning process for the DR measure *interrupt process* and a second discrete-time model for the control of the tank heating system to implement *store energy inherently*.

The total energy costs are the sum of the energy costs for every cleaning process event $n \in \{1, \dots, N\}$, plus the sum of the energy costs for tank heating for every timestep $k \in \{0, \dots, K\}$, where $N \in \mathbb{N}$ is the total number of cleaning process events and $K \in \mathbb{N}$ is the optimization horizon. Every cleaning process event is defined by its start time $s_n \in \mathbb{N}_0$ and duration $d_n \in \mathbb{N}_0$. The energy costs of each cleaning process event are determined by the time-dependent energy price $c_k \in \mathbb{R}$ for every timestep *k* and the power consumption $p_n \in \mathbb{R}_{\geq 0}$ of the cleaning process event *n*. The energy cost of the tank heater is the product of the tank heaters power consumption $p_{\text{heat}} \in \mathbb{R}_{\geq 0}$, the tank heater state $h_k \in \{0,1\}$, and the energy price c_k. We minimize the costs over the durations of cleaning process events $\mathbf{d} = (d_1, \dots, d_N) \in \mathbb{N}_0^N$ and the switching state of the tank heater $\mathbf{h} = (h_0, \dots, h_K) \in \{0, 1\}^{K+1}$, i.e.

$$\min_{\mathbf{d},\mathbf{h}} \sum_{n=1}^{N} \sum_{k=s_n}^{s_n+d_n-1} p_n c_k + p_{\text{heat}} \sum_{k=0}^{K} h_k c_k. \tag{1}$$

4.1 Event-based model of the cleaning process

Each cleaning process event *n* has an associated power consumption value

$$p_n = \begin{cases} p_{\text{int}}, & \forall n = 1, 3, \dots, N \\ p_{\text{clean}}, & \forall n = 2, 6, \dots, N-3 \\ p_{\text{dry}}, & \forall n = 4, 8, \dots, N-1 \end{cases} \tag{2}$$

with $p_{int} \in \mathbb{R}_{\geq 0}$ representing the power consumption in interruption, $p_{\text{clean}} \in \mathbb{R}_{\geq 0}$ during process steps spray cleaning and impulse blowing combined due to the short duration of impulse blowing, and $p_{\text{dry}} \in \mathbb{R}_{\geq 0}$ during drying. n_{start} represents the MPC's process event currently activated on the machine. Since all previous events lie in the past, the starting time s_n of the active event and all prior events is zero, i.e.

$$s_n = 0, \qquad \forall\, n \le n_{\text{start}}. \tag{3}$$

The start of the next event s_{n+1} is the sum of the start s_n and duration d_n of the anterior event, i.e.

$$s_{n+1} = s_n + d_n, \qquad \forall\, n = n_{\text{start}}, \dots, N-1. \tag{4}$$

The first, last and all uneven events $n = \{1,3,\dots,N\}$ of a process are defined as interruptions. Only the duration of interruptions can be changed, the duration of cleaning and drying events is fixed. Hence the duration is set to

$$d_n = \begin{cases} 0 & , \forall\, n < n_{\text{start}} \\ d_{\text{start}} & , \forall\, n = 2,4,\dots,N-1 \text{ with } n = n_{\text{start}} \\ d_{\text{clean}} & , \forall\, n = 2,6,\dots,N-3 \text{ with } n > n_{\text{start}} \\ d_{\text{dry}} & , \forall\, n = 4,8,\dots,N-1 \text{ with } n > n_{\text{start}} \end{cases} \tag{5}$$

where the duration of past events is zero, the durations of the cleaning and drying events $d_{\text{clean}} \in \mathbb{N}$ and $d_{\text{dry}} \in \mathbb{N}$ and the remaining time of the current cleaning or drying event is $d_{\text{start}} \in \mathbb{N}$. The total process duration is limited by the fixed end time of all cleaning processes $S \in \mathbb{N}$ and the optimization horizon K i.e.

$$s_N + d_N \le \min(K, S). \tag{6}$$

At the end of each cleaning process, there must be unscheduled time to allow for loading the machine, except when approaching the end time of all scheduled processes S. The duration for loading is specified by:

$$d_n \ge \min(d_{\text{load}}, S), \qquad \forall\, n = 5,9,\dots,N \text{ with } n \ge n_{\text{start}} \tag{7}$$

4.2 Time-based model of the tank temperature

The optimization of the tank heater is time-based, and the operation of the tank heater depends on the temperature inside the machine's cleaning fluid tank $t_k \in \mathbb{R}_{\ge 0}$, which must remain within the hysteresis limits determined by a lower bound $t_{\text{lb}} \in \mathbb{R}_{\ge 0}$ and an upper bound $t_{\text{ub}} \in \mathbb{R}_{\ge 0}$:

$$t_{\text{lb}} \le t_k \le t_{\text{ub}}, \qquad \forall\, k = 0,\dots,K \tag{8}$$

The tank temperature at a specific time step is determined by the starting temperature $t_{\text{start}} \in \mathbb{R}_{\ge 0}$, the temperature loss to the environment and to cleaned parts $f_k \in \mathbb{R}_{\ge 0}$ and the temperature increase due to tank heater operation $e_k \in \mathbb{R}_{\ge 0}$.

$$t_{k+1} = t_k + e_k - f_k, \qquad \forall\, k = 0,\dots,K \tag{9}$$

$$t_0 = t_{\text{start}} \tag{10}$$

To determine experimental factors for the heat losses in section 4.3, we need approximate analytical models to integrate them appropriately with the optimization. Therefore, we assume the fluid inside of the tank of the cleaning machine to be a closed homogenous system. There is no exchange of work between the system and the environment, and the heat exchange is isobaric. The conversion from electric energy to heat in the tank heater has an efficiency near one, hence the heat flow into the system by the tank heater is equal to its electric power rating ($\dot{Q}_{\text{heat}} = p_{\text{heat}}$). The positive heat flow of the tank heater into the system leads to a temperature change dependent on the specific heat capacity $c_{\text{p,fluid}}$, the volume V_{tank}, and density ρ_{fluid} of the cleaning fluid and the time step duration $\delta \in \mathbb{N}$. h_k is the decision variable for tank heater operation:

$$e_k = \frac{p_{\text{heat}}\, \delta}{c_{p,\text{fluid}}\, V_{\text{tank}}\, \rho_{\text{fluid}}} \cdot h_k, \qquad \forall k = 0,\dots,K \tag{11}$$

In addition to the heat flow generated by the tank heater, there is a heat flow f_k from the cleaning liquid to the environment and to the cleaned parts. We chose to separate the heat flow to the environment during the operational state of the machine and the heat flow to environment and washed parts during the working state because they differ significantly. Equation (12) yields the heat flow to the environment $\dot{Q}_{\mathrm{env}}$ due to conduction and convection. We did not consider the effects of radiation and judging from the experimental results this simplification is acceptable. The heat flow depends on the surface area A_{tank}, the thermal conductivity between tank and environment $\lambda_{\mathrm{tank,\,env}}$, the heat-transfer coefficient α_{env} and the environment temperature t_{env}:

$$\dot{Q}_{\mathrm{env}}(t_k) = \left(\lambda_{\mathrm{tank,\,env}} + \alpha_{\mathrm{env}}\right) A_{\mathrm{tank}}\,(t_k - t_{\mathrm{env}}) \tag{12}$$

Assuming an equilibrium between the temperature of the washed parts and the cleaning fluid at the end of the cleaning process, the total change of inner energy of the parts $\Delta U_{\mathrm{parts}}(t_k)$ with specific heat capacity $c_{\mathrm{p,\,wp}}$, the number of parts n_{wp}, the mass of each part m_{wp} and the temperature when being loaded $t_{\mathrm{wp}} = t_{\mathrm{env}}$ is defined as

$$\Delta U_{\mathrm{parts}}(t_k) = c_{\mathrm{p,\,wp}}\, n_{\mathrm{wp}}\, m_{\mathrm{wp}}\,(t_k - t_{\mathrm{wp}}) \tag{13}$$

The third factor contributing to heat loss to the environment is most likely mainly based on forced convection between the cleaning fluid and the walls of the cleaning chamber because of the spray cleaning process $\dot{Q}_{\mathrm{spray}}(t_k)$ with a separate heat-transfer coefficient α_{spray}:

$$\dot{Q}_{\mathrm{spray}}(t_k) = \alpha_{\mathrm{spray}} A_{\mathrm{tank}}\,(t_k - t_{\mathrm{env}}) \tag{14}$$

Based on the analytical heat transfer equations (12), (13) and (14), we identify three regression factors to simplify the models. β_{env} describes the heat loss to the environment, β_{parts} describes the heat loss to the parts during cleaning and β_{spray} describes the heat loss due to spray cleaning.

$$\beta_{\mathrm{env}} \cong \frac{(\lambda_{\mathrm{tank,\,env}} + \alpha_{\mathrm{env}})\, A_{\mathrm{tank}}}{c_{\mathrm{p,\,fluid}}\, V_{\mathrm{tank}}\, \rho_{\mathrm{fluid}}} \tag{15}$$

$$\beta_{\mathrm{parts}} \cong \frac{c_{\mathrm{p,\,wp}}}{c_{\mathrm{p,\,fluid}}\, V_{\mathrm{tank}}\, \rho_{\mathrm{fluid}}} \tag{16}$$

$$\beta_{\mathrm{spray}} \cong \frac{\alpha_{\mathrm{spray}}\, A_{\mathrm{tank}}}{c_{\mathrm{p,\,fluid}}\, V_{\mathrm{tank}}\, \rho_{\mathrm{fluid}}} \tag{17}$$

Using these factors, we can simplify the above equations and determine f_k, which includes the temperature change of the cleaning fluid during the cleaning process $f_{k,\mathrm{clean}}$:

$$f_{k,\mathrm{clean}} = \left(\beta_{\mathrm{spray}}\delta + \beta_{\mathrm{parts}} n_{\mathrm{wp}} m_{\mathrm{wp}}\right)(t_k - t_{\mathrm{env}})\ \forall k = 0, \dots, K \tag{18}$$

Using this in combination with the heat loss to the environment yields the total temperature difference due to losses to the environment and during the cleaning process f_k:

$$f_k = -\beta_{\mathrm{env}}\delta(t_k - t_{\mathrm{env}}) - \begin{cases} f_{k,\mathrm{clean}}, \text{if } s_n \le k < s_n + d_n, \forall n = 2, 6, \dots, N-3 \\ 0, \text{else} \end{cases} \quad \forall k = 0, \dots, K \tag{19}$$

4.3 Experimental parameter identification

We performed three experiments to determine the β-factors specified in equations (15), (16) and (17). During the experiments we measured the temperature of the environment t_{env} as 22.5 °C. To determine the heat loss to the environment, we heated-up the cleaning machine to a specified temperature, then allowed the machine to cool down for 127 minutes. We then set β_{env} to be equal to the average temperature gradient of the cleaning fluid $\Delta \mathrm{t}_{\mathrm{env}}$ during the measured time interval, divided by the average temperature difference between the cleaning fluid and the environment $t - t_{\mathrm{env}}$ as given by equation (20). β_{spray} describes the temperature gradient $\Delta \mathrm{t}_{\mathrm{spray}}$ during *spray cleaning* without any parts in the machine (only an empty cleaning basket) calculated by equation (21). Finally, we measured the temperature gradient Δt_{parts} while cleaning 42 metal parts each weighing 0.262 kg to determine β_{parts} using equation (22). Prior to cleaning the parts, their temperature was 22.5 °C.

$$\beta_{\text{env}} = -\frac{\text{avg}(\Delta t_{\text{env}})}{\text{avg}(t - t_{\text{env}})} \cong 1.67 \cdot 10^{-5} \tag{20}$$

$$\beta_{\text{spray}} = -\frac{\text{avg}(\Delta t_{\text{spray}} - \Delta t_{\text{env}})}{\text{avg}(t - t_{\text{env}})} \cong 1.72 \cdot 10^{-5} \tag{21}$$

$$\beta_{\text{parts}} = -\frac{\text{avg}(\Delta t_{\text{parts}} - \Delta t_{\text{spray}} - \Delta t_{\text{env}})}{\text{avg}(t - t_{\text{wp}})\, n_{\text{wp}}\, m_{\text{wp}}} \cong 1.03 \cdot 10^{-5} \tag{22}$$

4.4 Additional equations for the implementation of the optimization problem

For the implementation of the model in the Python-based modelling language Pyomo we had to adapt the event-based model of the cleaning process, since it was not natively possible to implement an objective function with variable sum limits. Therefore, we introduce $a_{n,k} \in \{0,1\}$ which is 1 during the execution of process event *n* at time step *k*. The objective function (1) then becomes

$$\min_{\mathbf{d},\mathbf{h}} \sum_{n=1}^{N} \sum_{k=0}^{K} a_{n,k} p_n c_k + p_{heat} \sum_{k=0}^{K} h_k c_k. \tag{23}$$

To construct $a_{n,k}$ we introduce $\tilde{a}_{n,k} \in \{0,1\}$ which is 1 during and before the execution of process event *n* at time step *k* and thereby ensure the correct order of the process events, such that

$$\sum_{k=0}^{K} \tilde{a}_{n,k} = \sum_{i=0}^{n} d_i \,, \forall n = 1, \ldots, N \tag{24}$$

With the binary help variable $b_n \in \{0,1\}$ and

$$\tilde{a}_{n,0} = \begin{cases} b_n \,, \forall n = n_{start}, \ldots, N \\ 0 \;\;\,, \forall n < n_{start} \end{cases} \tag{25}$$

$$d_n \leq b_n d^{up}, \forall n = 1, \ldots, N \tag{26}$$

$$\tilde{a}_{n,k} \leq \tilde{a}_{n,k-1}, \forall n = 1, \ldots, N, \forall k = 1, \ldots, K \tag{27}$$

where $d^{up} \gg max(d_{start}, d_{clean}, d_{dry}, d_{load})$, we guarantee that $\tilde{a}_{n,k} = 0$ for $n < n_{start}$ and $\tilde{a}_{n,0} = 0$ or $\tilde{a}_{n,0} = 1$ else. This allows interruptions with a duration $d_n = 0$. Now, we construct $a_{n,k}$ by subtraction

$$a_{n,k} = \begin{cases} \tilde{a}_{n,k}, & \forall n = 1 \\ \tilde{a}_{n,k} - \tilde{a}_{n-1,k}, & \forall n = 2, \ldots, N \end{cases}, \forall k = 0, \ldots, K \tag{28}$$

and introduce the interruption variable $i_k \in \{0,1\}$ which is like the tank heater state h_k and defined by

$$i_k = \sum_{n=1}^{N} a_{n,k} \,, \forall n = 1,3, \ldots, N, \forall k = 0, \ldots, K. \tag{29}$$

Also, we must modify (18) and include $a_{n,k}$ such that

$$f_{k,\text{clean}} = \sum_{i=0}^{n} (\beta_{\text{spray}} \delta + \beta_{\text{parts}} n_{\text{wp}} m_{\text{wp}})(z_{n,k} - a_{n,k} t_{\text{env}})\, \forall n = 2,6, \ldots, N-3, \forall k = 0, \ldots, K \tag{30}$$

where $z_{n,k} = t_k a_{n,k}$, $z_{n,k} = 0, \forall n \neq 2,6, \ldots, N-3$ and

$$0 \leq z_{n,k} \leq t_{\text{ub}} a_{n,k} \tag{31}$$

$$t_k - t_{\text{ub}}(1 - a_{n,k}) \leq z_{n,k} \leq t_k \tag{32}$$

such that $z_{n,k} = t_k$ if $a_{n,k} = 1$ and $z_{n,k} = 0$, else.

5. Automation structure and data model

We adapt the cleaning machine's automation program to be able to close the control loop and to use the machine for DR measures. For the *interrupt process* DR measure, we add the additional operating state *interrupted* to the machine automation. For communication between the machine's automation system and the DR service, we implement the automation structure and data model described below to standardize the data exchange based on [7,6,8].

The automation program's main system *KEA* extends *System2Point* (see [7] for an in depth explanation of the different classes) and can be set to the two setpoint states *off* or *on* by an external signal which sets the cleaning machine to the machine states *standby* or *operational*. The system *KEA* represents the whole cleaning machine and contains the three subsystems *CleaningChamber*, *Tank* and *InletAirHeating*. The latter two are extensions of *SystemContinuous*, a system with a continuous setpoint, e.g. a tank temperature [7]. The system *Tank* includes the *Actor2Point TankHeater*, the system *InletAirHeating* includes the *Actor2Point InletAirHeater*. The *Actor2Point* class represents an actor with binary setpoint and enables the execution of the DR measure *store energy inherently* by implementing external control by a DR service via OPC UA [7].

We extend the flow control of the cleaning machine such that it can execute the DR measure *interrupt process* [6]. The machine has the states *stand-by, ramp-up, operational* and *working* following [19,18]. We separate the *working* state into the cleaning process stages *spray cleaning, impulse blowing,* and *convection drying* [6]. In the mathematical model, we combine *spray cleaning* and *impulse blowing* into one as described in section 4.1. The DR potential analysis showed that only the stages *spray cleaning* and *convection drying* have a high potential for the DR measure *interrupt process* so we only implemented this option before each of these two stages [6].

The automation data model is used for the communication between the DR service and the machine's automation system. It consists of the automation data specification, an OPC UA data model implemented in the machine automation system, and the automation data dictionary, a JavaScript Object Notation (JSON) file, that includes all information necessary for mapping the OPC UA data to the DR service [8]. To execute the DR measure *store energy inherently*, the extended automation data model includes information about

- nominal load of the tank heater p_{heat},
- current temperature of tank t_{start} and environment t_{env},
- tank temperature limits t_{lb} and t_{ub},
- cleaning fluid density ρ_{fluid} and specific heat capacity $c_{p,\text{fluid}}$,
- tank volume V_{tank},
- workpiece mass m_{wp},
- number of workpieces n_{wp},
- Boolean setpoint variable to control the tank heater h_k.

For the DR measure *interrupt process,* we include the following data points:

- power consumption operational p_{int}, cleaning p_{clean} and drying p_{dry},
- operating state n_{start},
- remaining step duration d_{start},
- duration of cleaning d_{clean} and drying d_{dry},
- Boolean setpoint variable for interruption.

The information is integrated as a OPC UA data structure as part of the automation data specification in the automation program. The DR service reads the OPC UA data structures denoted in the automation data dictionary and writes the contained information into the DR scheduling model variables. This process is part of the eta-utility framework [17].

6. Field test

We integrate the demand response scheduling model and the automation data model as a cyber-physical production system using eta-utility and apply it to the aqueous parts cleaning machine model MAFAC KEA in the ETA Factory to show its applicability. For the electricity prices we use data from EPEX Spot [8] and take the prices of December 1st 2021 6:00 am to 9:00 am. Since we are only executing a single cleaning process in the field test, we scaled the interval of price changes from 15 to 5 minutes. This would not be necessary for a typical industrial use case, where multiple cleaning processes may be optimized in sequence. The CPPS uses the IBM ILOG CPLEX solver to solve the mathematical model and was executed on a PC with Intel Core i-5 6200U CPU and 8 GB of RAM in 10 s intervals. We analyse a single cleaning process which should be completed within 30 minutes and set the prediction scope for the model to 30 minutes. The workpiece is a control plate for a hydraulic pump. The model parameters are the following:

$N = 5$	$\delta = 10\ \mathrm{s}$	$n_{wp} = 42$	$p_{\mathrm{heat}} = 10\ \mathrm{kW}$
$K = 1800\ \mathrm{s}$	$V_{\mathrm{tank}} = 320\ \mathrm{l}$	$m_{\mathrm{wp}} = 0.262\ \mathrm{kg}$	$p_{int} = 0.2\ \mathrm{kW}$
$S = 1800\ \mathrm{s}$	$c_{p,\,\mathrm{fluid}} = 4.19\,\frac{\mathrm{kJ}}{\mathrm{kg\ K}}$	$t_{\mathrm{lb}} = 55\ °\mathrm{C}$	$p_{\mathrm{clean}} = 3.43\ \mathrm{kW}$
$d_{\mathrm{load}} = 120\ \mathrm{s}$	$\rho_{\mathrm{fluid}} = 1\,\frac{\mathrm{kg}}{\mathrm{l}}$	$t_{\mathrm{ub}} = 65\ °\mathrm{C}$	$p_{\mathrm{dry}} = 9.35\ \mathrm{kW}$

We reduce *S* by 10 s for every cycle of the MPC to ensure process termination within 30 minutes.

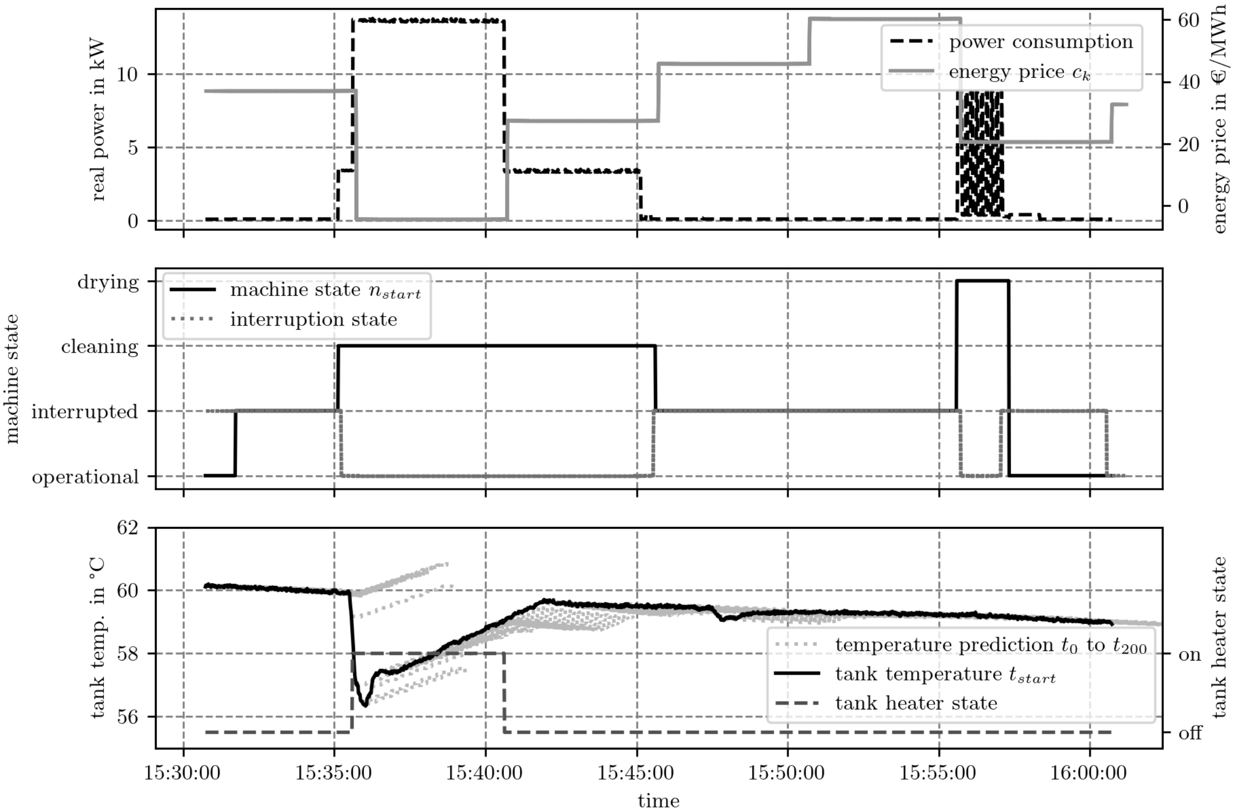

Figure 1: Results of the field test with a duration of 30 minutes. The upper diagram shows the machine's measured total power consumption and the energy price c_k. The middle diagram displays the cleaning process operating state n_{start} and the boolean interruption variable i_k. The lower diagram shows the measured tank heater state, tank temperature t_{start} and tank temperature forecast t_k for 200 seconds.

The results of the field tests are shown in Figure 1. The energy price, displayed in the upper diagram, becomes negative after five minutes which leads the solver to optimize for an increase in the total power consumption during the negative-price-period. The DR service postpones the start of *spray cleaning* by activating the interruption, shown in the middle diagram to utilize the negative price. The tank heater is activated slightly after the start of the cleaning process, visible in the lower diagram. When the energy price increases, the tank heater is deactivated, and *spray cleaning* continues. The DR service interrupts the process again when *spray cleaning* is finished to postpone *convection drying* to a time interval with a lower price at the end of the given period. The cleaning terminates after 30 minutes. In the lower diagram the temperature prediction based on the β-factors is shown in grey. The heat loss to the environment during the first five minutes and at the end of the process is so accurate that the predicted grey temperature values completely align with the actual tank temperature drawn in black. The temperature increase during operation of the tank heater is also predicted accurately (between 15:36 and 15:41), however there are significant dead times after the heater turns on and before the heat transfer stops, which cannot be reproduced by the model. Especially at the beginning of the cleaning process, the temperature drop during *spray cleaning* does not correspond to the real temperature. This is due to a transient response when activating the spray pump. It takes about two minutes for the tank temperature to stabilize after the pump starts. After the transient processes (dead times of the tank heater and response of the cleaning fluid) have settled, the prediction represents the reality accurately. When looking at the cleaning process overall, The model is accurate enough for our the case.

7. Conclusion

In this paper we present a detailed mathematical mixed integer linear programming model which is used as a MPC within the DR service of a cyber-physical production system that uses a cleaning machine for DR. The mathematical model consists of two parts: an event-based model that represents the cleaning process and is used for the DR measure *interrupt process* and a discrete-time model for the tank heating system used to *store energy inherently*. We apply the model to an aqueous parts cleaning machine in a field test and show that the DR service successfully controls the machine depending on a fluctuating electricity price. In the future the model should be used in other field tests to compare an energy-flexible operation implementing DR measures with a conventional operation. The ramp-up process of the tank heating system and the execution of several cleaning processes in a row should also be investigated.

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Appendix

The software code for the presented work is available as an open-source project on GitHub:
https://github.com/PTW-TUDa/cpsl2023-dr-for-cleaning-machines

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Biography

Daniel Fuhrländer-Völker (*1990) received his master's degree in mechatronics in 2016 from Technical University of Darmstadt. He is a research associate at the Institute for Production Management, Technology and Machine Tools at Technical University of Darmstadt. His research focuses on cyber-physical production systems and automation data models for demand response on production machines and industrial supply systems.

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Matthias Weigold (*1977) has been head of the Institute of Production Management, Technology and Machine Tools (PTW) at Technical University of Darmstadt since 2019. Prof. Dr.-Ing. Matthias Weigold directs the research fields of Manufacturing Technologies as well as Energy Technologies and Applications in Production with a focus on digitalization and climate neutrality in production.