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Prediction of pulsed heat loads in manufacturing plants

Florian Fuhrmann*° Alexander Schirrer*
Martin Kozek* Stefan Jakubek*

** Institute of Mechanics and Mechatronics, Technische Universität Wien, Getreidemarkt 9/BA, 1060 Vienna,Austria*
° Corresponding Author: florian.fuhrmann@tuwien.ac.at, Tel.: +43 1 58801 325530

Abstract: Predictive control is beneficial for effective energy demand management. Precise disturbance prediction is a decisive factor for the performance of predictive control. This paper focuses on the accurate prediction of pulsed heat loads caused by heat treatment in manufacturing industry processes. An application-oriented method to predict heat load peaks is developed utilizing basic laws of thermodynamics, validated with process data from an industrial use case, and tested with a model predictive controller. Two core characteristics of the method enable a straightforward application in industry: 1. Historic data from few measurement points are sufficient. 2. Robustness against measurement noise.

Keywords: Manufacturing plant control, Identification and validation, Disturbance prediction, Energy demand management, Industrial application, Model predictive control;

1. INTRODUCTION AND MOTIVATION

Decarbonisation of the power production induces an increasing usage of renewable energy sources like wind, water or solar. The fluctuating availability of these sources are a major challenge for power grid operators. Demand Side Management (DSM) is a portfolio of measures to stabilize the grid at the side of consumption (Palensky and Dietrich, 2011). DSM for industry plants is especially interesting as industry accounted for 41.9% of the worldwide electricity demand in 2017 (International Energy Agency, 2019). Therefore, various methods like energy demand management (EDM) or demand response (DR) were developed to optimize the energy consumption of industry plants. Grid operators introduced varying electricity prices and discounts for uniform power consumption to encourage the industry to use EDM. Though the economic potential for industry plants is shown in several studies, DSM is yet rarely applied in industry (Ding and Hong, 2013; Ayyappan *et al.* 2019). According to (McKane *et al.*, 2008) this is among other reasons caused by the risk of affecting the production safety.

To avoid production losses, sufficient energy has to be available at any time. This is especially challenging for energy-intensive batch-like processes where pulsed energy loads occur. Typical examples are manufacturing processes that include heat treatment steps, in which products undergo certain temperature trajectories in order to reach quality attributes. To change the product temperatures quickly, high heat loads are required, often provided by power-to-heat components. A heating system consisting of a thermal energy storage (TES) and an electrical boiler and/or heat pump (HP) controlled by a model predictive controller (MPC) is a standard use case for heat distribution networks considered in literature (Killian, Mayer and Kozek, 2014; Fischer *et al.*, 2016; Baeten, Rogiers and Helsen, 2017). In these studies, two major benefits of the MPC concepts were shown: reduced energy costs by load shifting and reduced investment costs through efficient utilization of the equipment. A precise load prediction is crucial to realize both benefits and provide production safety. Previous publications based on that use case focused on building heating systems and thereby did not consider batch-like heat loads in their studies. In the field of heat integration, the time-integrated heat load of batch processes is predicted using basic laws of thermodynamics (Sebelebele and Majozi, 2017). However, a research gap is evident for practically applicable prediction methods for time-resolved batch-like heat loads. Therefore, in the present paper, the concept presented in (Sebelebele and Majozi, 2017) is adapted and extended. The main contributions of this paper are as follows:

1. An efficient, accurate, and well-adjustable batch-consumer heat load prediction model is proposed, obtained by
    a. a reformulation of the heat balances to fully exploit measurement data based on heat meter sensors, and
    b. a simple but expedient method to recreate the typical time-domain behaviour of the batch consumer's heat flow.
2. The robustness and accuracy of the proposed prediction method is tested with measurement data from an industrial plant.
3. An MPC-based closed-loop simulation study is conducted to compare the performance of a basic MPC concept when utilizing different load prediction strategies, based on historical industrial plant data.

This paper is organized as follows: In Section 2 the problem statement is made. In Section 3 the load prediction method is presented. In Section 4 the method is tested with measurement data from an industrial use case, and a closed-loop simulation study is conducted. In Section 5 the conclusions are made and an outlook is given.

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2. PROBLEM STATEMENT

The structure and characteristics of the considered heat distribution network are displayed in Figures 1 and 2. The core components are a heat source (HS), a thermal energy storage (TES), and N batch-like heat consumers (BC) with temperatures $T_{BC,n}$, $(n = 1,2,\dots,N)$ which demand pulsed heat loads. The total heat flow $\dot{Q}_{\mathrm{BC,sum}}$ of the BC shall be predicted in order to keep the heat stored in the TES Q_{TES} within admissible bounds, via predictive control of the heat flow of the heat source $\dot{Q}_{HS}$. Typical BC are heat treatment (HT) steps in the manufacturing industry, used to alter the physical or chemical properties of a material (e.g. annealing, tempering, pasteurization). Heat treatments start with a heating phase, were the treated material is brought from the initial temperature $T_{\mathrm{M},0}$ to a desired temperature level $T_{\mathrm{M,end}}$. As these temperatures are crucial for the effect of the HT, they are considered known in advance and can be utilized for the heat load prediction. The heating phases induce short pulse-like heat loads as displayed in Figure 2. Delayed or incomplete heating phases, caused by insufficient heat supply, may affect product quality and thereby cause economic losses. One central heat source provides the heat, thermal liquid and heat exchangers transport it to the BC. The maximum of $\dot{Q}_{\mathrm{BC,sum}}$ is typically many times higher than the maximum heat production rate $\dot{Q}_{HS}$. Therefore, a TES is installed to buffer the transient heating process.

In this setting, precise load-prediction provides multiple economic benefits: 1. bottlenecks in the heat supply can be detected before the production process is affected, 2. the energy consumption can be shaped according to the objectives of EDM (e.g. reduce energy costs), 3. the usage of the HS can be smoothened, which reduces wear, 4. better exploitation of TES and HS enables a smaller design of these components, lowering investment costs.

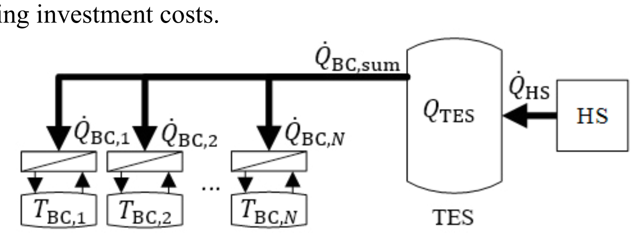

Fig. 1 Industrial use-case consisting of a heat source (HS), a thermal energy storage (TES) and N batch consumers (BC).

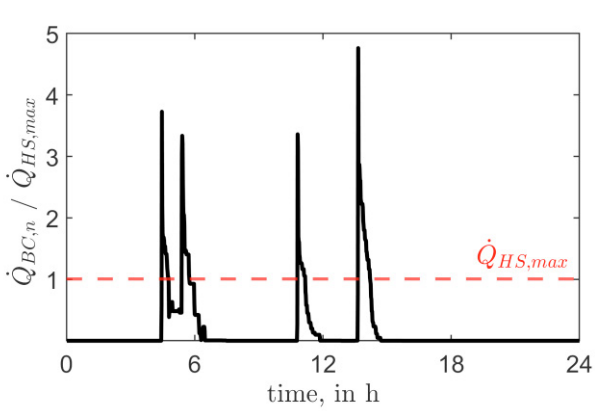

Fig. 2: Typical pulse-like heat loads of BC compared to the maximum heat production.

Modelling a pulse-like heat flow $\dot{Q}$ directly from measurement data is error-prone when the heating phase is short compared to the measuring intervals. Few data points available per HT, high measurement noise, inertia of the measurement, or simply unknown data pre-processing complicate data-based modelling significantly in practice. For these reasons, the following load prediction method was developed in a way that it does not rely on direct measurements of $\dot{Q}$ with high time resolution. Instead, the integrated heat flow Q before and after each heat treatment (HT) is utilized. At those times Q is constant and no time delay or inertia affects the measurement accuracy.

In summary, the following assumptions are made for the prediction method: The final $T_{\mathrm{M,end}}$ and the initial temperatures $T_{\mathrm{M},0}$ of the treated material and the starting time t_0 of the HT are known in advance and can be used as input for the prediction model. Further, a record of Q_{BC} with low time resolution is available for a sufficient number of HT for all BC.

3. LOAD PREDICTION METHOD

The proposed load prediction method consists of two steps. First, the total heat quantity applied during heat treatment process $Q_{\mathrm{HT,total}}$ is estimated utilizing the first law of thermodynamics. Second the time constant of a first order delay element is estimated to recreate the typical time-domain behaviour of the heat flow $Q_{\mathrm{HT}}(t)$. To apply this method values of the integrated heat flow Q at t_0 and at t_{end} for a sufficient amount of HT is required for each BC.

3.1 Prediction of $Q_{HT,total}$

Predicting the total heat $\mathrm{Q}_{HT,total}$ instead of directly predicting $\dot{Q}_{\mathrm{HT}}$ enables a convenient usage of the conservation of energy with little available process data. The first law of thermodynamics states that the change in internal energy ΔU is a function of the net quantity of heat supplied to the system Q and the work done by the system W:

$$\Delta U = Q - W \tag{1}$$

For most heat treatments, the assumptions are valid, that: 1. no work is done by the system ($W = 0$), 2. the change in internal energy is defined by the heat capacity of the system C_{S}, and the difference between the starting temperature of the system $T_{\mathrm{S},0}$ and the end temperature of the heating phase $T_{\mathrm{S,end}}$. Therefore, the heat quantity of the m-th heat treatment $Q_{\mathrm{HT},m}$ is described by:

$$C_{\mathrm{S},m}\left(T_{\mathrm{S,end},m} - T_{\mathrm{S},0,m}\right) = Q_{\mathrm{HT,total},m} \tag{2}$$

The considered system for heat treatments consists of two parts: the treated material and the surrounding component (e.g. oven, burner, cooker). The temperature of the treated material T_{M} is critical for each kind of heat treatment process. Therefore, $T_{\mathrm{M,end},m}$ and $T_{\mathrm{M},0,m}$ of each single heat treatment process are known in advance and measured accurately. The component temperature distribution at the beginning of the process is usually unknown, as it depends on multiple factors like timing, end temperature of the previous treatment or ambient temperature. In addition, the heat capacity of the components is usually unknown and thus the change in internal energy of the component during a heat treatment $\Delta U_{\mathrm{BC},n}$ is considered as an unknown constant that has to be estimated for all BC. Therefore, (2) is rearranged to:

$$\Delta U_{\mathrm{BC},n} + C_{\mathrm{M},n}(T_{\mathrm{M,end},m} - T_{\mathrm{M,0},m}) = \hat{Q}_{\mathrm{HT,total},m} \tag{3}$$

where $\Delta U_{\mathrm{BC,n}}$ and $C_{\mathrm{M,n}}$ are unknown parameters. These $2N$ constants are estimated utilizing the measurement data. Instead of $\dot{Q}$ measurements with high time resolution the estimation only needs the time-integrated heat flow Q at t_0 and at t_{end} for each HT. There is little effect of measurement noise on these values because Q stays constant between single HT and the big difference between Q_{t_0} and $Q_{t_{end}}$ causes a high signal to noise ratio. The values for $T_{\mathrm{M,end},m}$ and $T_{\mathrm{M,0},m}$ can be extracted from production plans. For the estimation of $\Delta U_{\mathrm{BC},n}$ and C_{M} the least absolute residual (LAR) is used as statistical optimality criterion to decrease the effect of outliers.

3.2 Prediction of $\dot{Q}_{HT}$

To model the transient behaviour of the heat treatment process, first order dynamics are assumed:

$$Q_{\mathrm{HT},m}(\mathrm{t}) = \mathrm{Q}_{\mathrm{HT,total},m}\left(1 - e^{-\frac{t}{\tau}}\right) \tag{4}$$

with unknown time constant τ. Data evidence shows that this linear PT1-structure is suitable when the state of charge (SOC) of the TES is sufficient to fully supply the heating process. In contrast, during a HT where the TES reaches a critically low SOC, $\dot{Q}_{\mathrm{HT}}$ does not show first order dynamics. Thus, such HT should be excluded from the estimation of τ. To detect affected HT, $\mathrm{Q}_{\mathrm{TES,use},m}$ is defined as the enthalpy above the temperature level of a heat treatment stored in the TES at the beginning of the heat treatment:

$$\mathrm{Q}_{\mathrm{TES,use},m} = C_{TES}(T_{TES,t_{0,m}} - T_{\mathrm{end},m}) \tag{5}$$

where C_{TES} is the heat capacity of the TES. To exclude data of HT with critically low SOC only HT fulfilling

$$\mathrm{Q}_{\mathrm{TES,use},m} \geq 2\hat{Q}_{\mathrm{HT,total},m} \tag{6}$$

are considered in the estimation of τ. For the remaining of all N HT $\tau_{n,m}$ is calculated for all M BC from measurement data using:

$$Q_{\mathrm{HT},m}(3\tau_{n,m}) = 0.95\ Q_{\mathrm{HT,total},m} \tag{7}$$

The time constant $\hat{\tau}_n$ used for the heat load prediction is calculated as the mean of all calculated $\tau_{n,m}$. Next, $\hat{Q}_{\mathrm{HT},m}(\mathrm{t})$ is predicted with (4), and finally the discrete $\dot{\hat{Q}}_{\mathrm{BC,sum}}(\mathrm{t_i})$ is calculated for the desired sampling time t_{s} as sum of all M HT:

$$\dot{\hat{Q}}_{\mathrm{BC,sum}}(t_i) = \sum_{m=1}^{M} \frac{\hat{Q}_{\mathrm{HT},m}(t_i + t_{\mathrm{s}}) - \hat{Q}_{\mathrm{HT},m}(t_i)}{t_s} \tag{8}$$

3.3 Model predictive controller

A basic MPC formulated in the Matlab toolbox YALMIP (Lofberg, 2019) was utilized and modified for this paper. The system is represented by a discrete linear state-space model:

$$\begin{aligned} \mathrm{x}(k+1) &= \mathrm{Ax}(k) + \mathrm{Bu}(k) + \mathrm{Ez}(k) \\ \mathrm{y}(k) &= \mathrm{Cx}(k) \end{aligned} \tag{9}$$

where x is the state, u is the control input, z is the disturbance, y is the plant output and A, B, E, C are scalars. The cost function is defined as

$$\begin{gathered} \mathrm{J_i} = \frac{1}{2}\sum_{k=i}^{i+N_P-1} [(y_{k+1} - r_{k+1})^T Q_R (y_{k+1} - r_{k+1}) \\ + u_k^T R u_k + (u_k - u_{k-1})^T P (u_k - u_{k-1})] + sQ_s \\ s.t. \\ x_{crit} - s \leq x_k \leq x_{max} \\ u_{min} \leq u_k \leq u_{max} \\ s \geq 0 \end{gathered} \tag{10}$$

where N_P is the prediction horizon, Q_c, Q_s R and P are weight factors and s is a slack variable. Defining the storage as simple integrator with $x = Q_{TES}$ as state, $u = \dot{Q}_{HS}$ as input and $z = \dot{Q}_{\mathrm{BC,sum}}$ as disturbance, the system is represented by:

$$Q_{TES}(\mathrm{t_i} + 1) = Q_{TES}(\mathrm{t_i}) + t_s\dot{Q}_{HS}(t_i) + \mathrm{t_s}\dot{Q}_{\mathrm{BC,sum}}(t_i) \tag{11}$$

The limits of Q_{TES} and $\dot{Q}_{HS}$ were taken from Table 1. The reference trajectory r_k is defined at $0.5x_{max}$ and x_{crit} as $0.3x_{max}$ for all time-steps. Gurobi is used as solver (Gurobi, 2018). For more details on the optimization problem see Lofberg (2004).

4. RESULTS & DISCUSSION

In this Section, the industrial use case is presented. Industrial measurement data is used to validate the proposed prediction method and the results are discussed. Finally, different control strategies for the use case are tested in a simulation study, including an MPC utilizing the predicted heat load.

4.1 Description of the Industrial Use Case

The components of the industrial use case are a heat pump as heat source, a stratified storage tank with five temperature measurements as TES and four batch consumers. The key process parameters taken from datasheets are summarized in Table 1. The dataset encompasses 602 heat treatments recorded with one-minute time intervals ($t_s = 60s$). No temperatures or durations of heat treatments of the industrial use case are reported here due to a confidentiality obligation.

Table 1. Key process parameters of industrial use case.

$\dot{Q}_{\mathrm{HS,max}}$	0.206 MW
$Q_{\mathrm{TES,max}}$	504.000 MJ
$\sum_{n=1}^{4} \dot{Q}_{BC,max}$	1.367 MW

The major challenge in the presented use case is the limited heat source power and heat storage capacity compared to the consumed loads. The maximum heat load $\dot{Q}_{\mathrm{BCsum,max}}$ is the six-fold of the maximum heat production $\dot{Q}_{\mathrm{HS,max}}$, and a fully loaded TES can buffer $\dot{Q}_{\mathrm{BCsum,max}}$ for approximately six minutes. Even though the maximum heat load is rarely applied, bottlenecks in the heat supply occur regularly in operation.

4.2 Testing the prediction method with measurement data

The data points necessary for the prediction method, $Q_{\mathrm{HT},m}$, $T_{\mathrm{M,end},m}$ and $T_{\mathrm{M,0},m}$, were read out of the dataset for all heat treatments. These data points were bisected into training and validation data and a regression using least absolute residuals as statistical optimality criterion was executed with the training data utilizing the Matlab® Curve-Fitting-Toolbox to estimate $\Delta U_{\mathrm{BC},n}$ and C_{M}. The results for all four BC are listed in Table 2. Figure 3 shows a histogram of the resulting prediction error calculated with the validation data. It shows that the prediction method shows good results for most heat treatments, but outliers occur. Still, the prediction method shows good results, as the standard deviation lies at 12.5% and the estimation error is less than 20% for 85% of the heat treatments. The outliers were further examined and two causes detected. First, there were several exceptional tests and special programs run during the period causing different heat loads. Second, the temperature of the treated material at the beginning of the heat treatment $T_{\mathrm{M,0},m}$ was in some cases recorded at wrong time-instants. Excluding the ouliers with more than 30% estimation error, the standard deviation further reduces to 7.8%.

Next, the quality of the estimation of $Q_{HT}(t)$ is discussed. Figure 4 displays the measurements and prediction results for ten representative HT. To put the focus on the estimation of the transient behaviour the measured $Q_{\mathrm{HT,total},m}$ was used to calculate the estimations. Thus, the black line shows

$$\hat{Q}_{\hat{\tau},m}(\mathrm{t}) = Q_{\mathrm{HT,total},m}\left(1 - e^{-\frac{t}{\hat{\tau}}}\right) \tag{12}$$

Table 2: Results of the parameter estimation.

	$\Delta U_{\mathrm{BC},n}$, in MJ	C_{M}, in MJ	R^2	RMSE in MJ
BC 1	35.2	87.3	0.993	5.36
BC 2	55.8	65.52	0.996	4.58
BC 3	32.2	105.4	0.995	3.60
BC 4	30.8	61.74	0.996	2.67

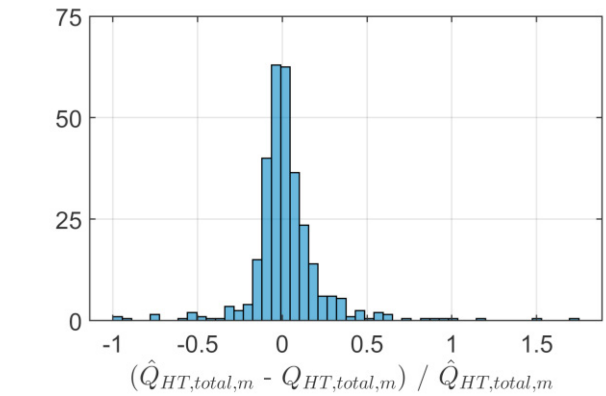

Fig. 3 Histogram of the estimation errors of all heat loads.

Measurement data is displayed as dotted blue lines. Two of them show a qualitatively different much slower behaviour, caused by limited heat supply. As described in Section 3.2 these data-points were excluded from estimating $\hat{\tau}$. The red dashed line shows $\hat{Q}_{\hat{\tau}_{\mathrm{outliers}},m}(\mathrm{t})$ were outliers where included in the estimation of $\hat{\tau}_{outliers}$. Figure 4 shows that the first-order-delay element is a good choice to recreate the trajectorie of the heat flow. In Figure 5 the estimation error of $\hat{\tau}$ is plotted against the ratio of $Q_{\mathrm{TES,use},m}$ to $Q_{\mathrm{HT,total},m}$. It visualizes that $Q_{\mathrm{TES,use},m}$ is a good measure to detect bottlenecks in the heat supply. The estimation error of $\hat{\tau}$ is in close bounds for most HT where $Q_{\mathrm{TES,use},m} \geq 2\hat{Q}_{\mathrm{HT,total},m}$ (dashed line). At smaller ratios, time delays due to insufficient heat supply occurred regularly.

In summary, the testing of the prediction method with measurement data showed that little measurement data is needed to achieve a precise prediction. To apply this prediction method in industry, only measurement data from a heat meter and production plans for a sufficient time ahead are necessary. In case no heat meters are available in the plant, portable heat meters can be installed flexible and cost efficient in most heat distribution networks. Further process knowledge can be used to detect outliers and $Q_{\mathrm{TES,use},m}$ is an adequate measure to detect bottlenecks in the heat supply.

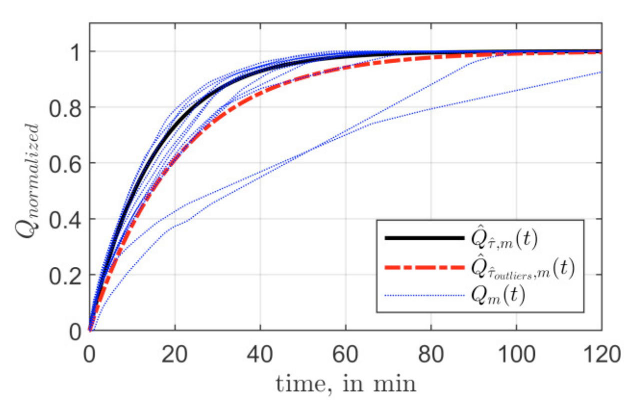

Fig. 4 Comparison of measured trajectories of Q_{HT}, estimated trajectories and estimated trajectories excluding outliers for ten heat treatments from a selected timespan.

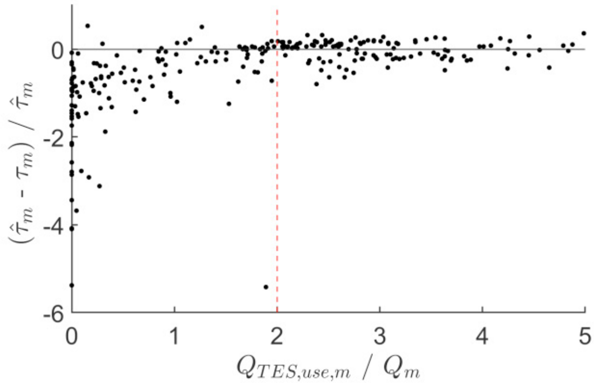

Fig. 5 Estimation error of τ versus the normalized useable enthalpy in the TES.

4.3 Applying prediction method for MPC

The prediction method presented in this paper is motivated by the demand of an accurate load prediction for predictive control methods. In this subsection, the effect of disturbance prediction on the performance of an MPC is demonstrated. Thus, the same MPC formulation was utilized three times: First, with a perfect disturbance prediction as benchmark. Second, with the disturbance prediction estimated with the method proposed in this paper. Third, with no disturbance prediction. Further, a hysteresis control concept, as it is currently applied in the industrial use case, is simulated. The MPC was not tuned. The chosen values for weight factors and N_P are listed in Table 3. The MPC uses $\dot{Q}_{\mathrm{HS}}$ as controlled variable while Q_{TES} is the plant output. One week with 26 HP was taken from the industrial measurement data as simulation-data. The results of the simulations for eight hours are displayed in Figure 6a-c. Figure 6a shows that the disturbance prediction made with the proposed method (dashed line) matches the measured disturbance (solid line) well. In Figure 6b big differences in the utilization of the heat source become visible. It is detectable that the MPC is able to even out the utilization of the HS when a disturbance prediction is used. Naturally, the hysteresis control cannot decouple the heat production from the heat demand and thus cannot support EDM. Figure 6c displays the SOC of the TES. The most interesting behaviour occurs at a process time of five hours. The hysteresis control and the MPC without disturbance prediction cannot keep the SOC above the critical level. This would have caused a bottleneck in the heat supply and a loss of production. In the whole simulation, the SOC falls below the critical value three times with hysteresis control and six times for the MPC without disturbance prediction. The MPC utilizing the disturbance prediction provided a sufficient SOC during the whole simulation. The performance of the MPC (e.g. peak reduction) could be further optimized by tuning the MPC.

Table 3. MPC weighting factors and horizon.

N_P	400
Q_c	10^{-6}
Q_s	10^{8}
R	10^{-1}
P	10^{3}

5. CONCLUSIONS AND FUTURE WORK

The paper proposes a prediction method for pulse-like heat loads. It is validated with measurement data from an industrial use case. For application, only measurements of the batch consumers, heat flows and the production plans are required. Portable heat meters can be retrofitted without big effort. Further, the method is robust against measurement errors and poor data quality. Thus, a straightforward application in industry plants is possible. Utilizing the load prediction as disturbance prediction in an MPC enables an efficient energy demand management. Variable energy prices can be taken into account and load peaks reduced. Thus, reduced energy costs are reached. The investment and operational costs for HS and TES can be decreased through efficient utilization and wear reduction.

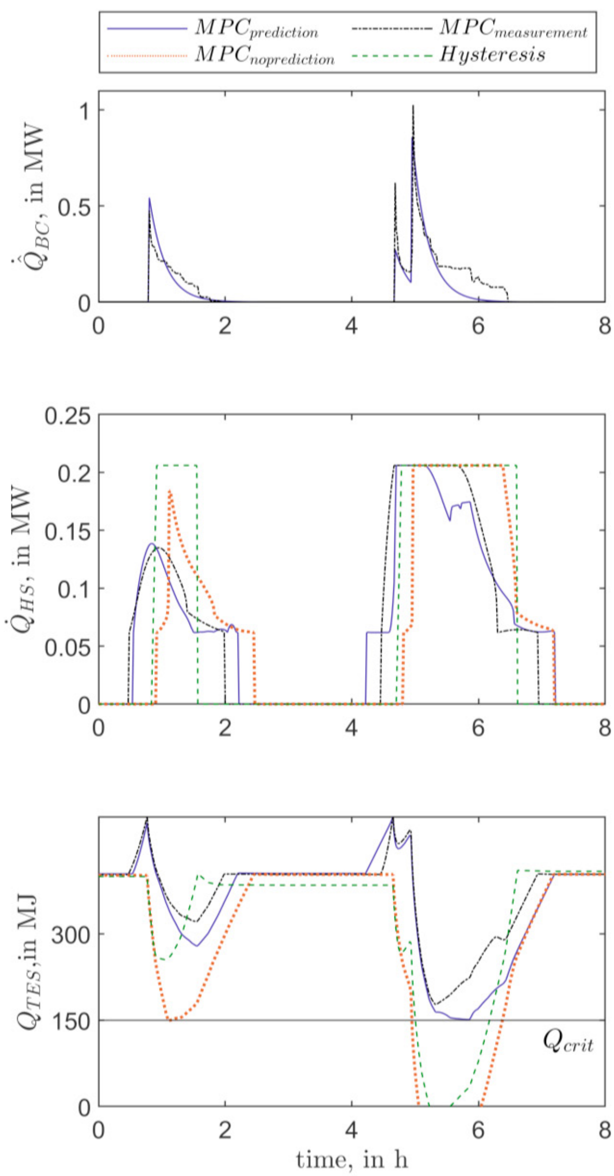

Fig. 6a Disturbance predictions. Fig 6b Utilizations of the HS. Fig 6c Courses of the SOC of the TES

Further, bottlenecks in the heat supply can be detected and avoided, increasing the production safety. Future work will deal with tuning an MPC for stochastic load predictions especially considering the influence of human operators on the control performance. Further, a generic control strategy for heat supply systems in manufacturing industry will be developed with focus on energy demand management.

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REFERENCES

Ayyappan, P., Kumar, J. and Venkiteswaran, V. K. (2019) 'Maximum Demand Management: An overlooked energy saving opportunity in industries', *IOP Conference Series: Earth and Environmental Science*, 268(1). doi: 10.1088/1755-1315/268/1/012156.

Baeten, B., Rogiers, F. and Helsen, L. (2017) 'Reduction of heat pump induced peak electricity use and required generation capacity through thermal energy storage and demand response', *Applied Energy*. Elsevier Ltd, 195, pp. 184–195. doi: 10.1016/j.apenergy.2017.03.055.

Ding, Y. and Hong, S. H. (2013) 'A model of demand response energy management system in industrial facilities', *2013 IEEE International Conference on Smart Grid Communications, SmartGridComm 2013*. IEEE, pp. 241–246. doi: 10.1109/SmartGridComm.2013.6687964.

Fischer, D. *et al.* (2016) 'Impact of PV and variable prices on optimal system sizing for heat pumps and thermal storage', *Energy and Buildings*. Elsevier B.V., 128, pp. 723–733. doi: 10.1016/j.enbuild.2016.07.008.

Gurobi, O. (2018) 'Gurobi Optimizer Reference Manual, Version 5.0', *www.Gurobi.Com*.

International Energy Agency (2019) *Electricity Statistics*. Available at: https://www.iea.org/statistics/electricity/ (Accessed: 25 October 2019).

Killian, M., Mayer, B. and Kozek, M. (2014) *Hierachical fuzzy MPC concept for building heating control*, *IFAC Proceedings Volumes (IFAC-PapersOnline)*. IFAC. doi: 10.3182/20140824-6-za-1003.00772.

Lofberg, J. (2004) 'YALMIP : a toolbox for modeling and optimization in MATLAB', *2004 IEEE International Symposium on Computer Aided Control Systems Design*, pp. 284–289. doi: 10.1109/CACSD.2004.1393890.

Lofberg, J. (2019) *YALMIP standard MPC*. Available at: https://yalmip.github.io/example/standardmpc/ (Accessed: 6 November 2019).

McKane, A. T. *et al.* (2008) 'Opportunities, Barriers and Actions for Industrial Demand Response in California Environmental Energy Technologies Division'. Available at: https://industrialapplications.lbl.gov/sites/default/files/lbnl-1335e.pdf.

Palensky, P. and Dietrich, D. (2011) 'Demand side management: Demand response, intelligent energy systems, and smart loads', *IEEE Transactions on Industrial Informatics*. IEEE, 7(3), pp. 381–388. doi: 10.1109/TII.2011.2158841.

Sebelebele, N. and Majozi, T. (2017) 'Heat integration of multipurpose batch plants through multiple heat storage vessels', *Computers and Chemical Engineering*. Elsevier Ltd, 106, pp. 269–285. doi: 10.1016/j.compchemeng.2017.06.007.

Appendix A. NOTATION

Notation	**Description**
Abbreviations	
BC	batch consumer
DSM	demand side management
EDM	energy demand management
HP	heat pump
HS	heat source
HT	heat treatment
LAR	least absolute residuals
MPC	model predictive control
SOC	state of charge
TES	thermal energy storage
Selected Symbols	
N	quantity of batch consumers
M	quantity of heat treatments
Q	heat quantity
T	temperature
τ	time const. of first-order-delay element
Selected Indices	
M	Material
S	System