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Practical PLC-based Implementation of Adaptive Dynamic Matrix Controller for Energy-Efficient Control of Heat Sources

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***Abstract*— For the efficient control of industrial heat sources, adaptation to significant changes in operating conditions and in heat demand variations are the critical issues. This paper presents the concept of the adaptive Dynamic Matrix Controller dedicated to control of heat sources operated as a part of heat distribution systems. The adaptation is based on interpolation of the process nonlinearities. The implementation in Programmable Logic Controller in the form of a general purpose function block is presented and practical issues of the minimization of the memory load and computational complexity are addressed. The suggested concept is experimentally validated by both virtual and real commissioning in the industrial conditions. The aspect of energy efficiency of the heat source control systems is also discussed and for assessment of the energy supply performance, the energy error index is proposed. In terms of this index, the results show superiority of the suggested controller over the conventional approaches.**

***Index Terms*—Adaptive control, Dynamic Matrix Controller (DMC), Energy supply performance, PLC-based implementation**

I. Introduction

APART from proper design, the efficient operation of industrial Heat Distribution Systems (HDS) requires effective low-level control of each of their parts [1]-[5]. In the literature, relatively high attention has been paid to the problem of the effective control of heat receivers (HR) such as heat exchange networks, vessel heating jackets, showing the superiority of advanced control strategies over the conventional PID control [6]-[11], including a potential improvement in energy efficiency [12]. However, the majority of those works assume a perfect performance of the heat source (HS) that supplies the energy for heating. Such a performance is unattainable in practice, but one can derive a dedicated control system for the HS to increase its efficiency. Thus, it is surprising that the control of HS received incomparably lower attention in the literature. In fact, their performance in the presence of large variations in operating conditions (e.g., heat demand) significantly influences the overall efficiency of HDS operation. Every misperformance in the HS control, resulting from changes in the HS dynamics, significantly disturbs the operation of the HR control system. Hence, it is obvious that the effective elimination of the disturbances by the HS control system will have a positive effect on the performance of HR control systems. At the same time, the effective HS control also has a very large impact on the energy efficiency of the whole HDS. The examples of studies on the problem of HS control are presented in [13]-[15]. In [16], the multi-input, single output control problem for HDS is presented and effects on the HS control performance, and the energy efficiency aspects are discussed.

In this work, the problem of effective control of the HS operating in the HDS for heating water is addressed. In such systems, high level of resilience is required because the HS must supply a desired heat flux in the presence of significant variations in heat demand. These variations change the operating conditions so the dynamics of the HS varies. Additionally, the heat is usually transported between the HS and the HR through relatively long pipeline that introduces a significant time delay in the system. This time delay also varies, due to changes in the operating conditions. Consequently, the effective control of HS is a challenging nonlinear control task, which cannot be successfully solved by the conventional PID controller. The candidate control algorithm must be able to compensate for both varying time delay and the HS nonlinearity. It should also prevent from excessive or insufficient energy supply because both can result in undesirable increment of production costs. Easy and efficient tuning without complex and strenuous modeling process is also an important issue. Finally, from practical point of view, such a controller should be easily implemented in Programmable Logic Controller (PLC) to ensure its application at the low-level industrial control systems. Thus, possibly low memory load and computational complexity are crucial. These requirements are especially important in industrial practice when many control loops must be implemented in a single PLC to provide reliable plant control. Even if the amount of memory in modern PLCs is gradually increasing, this memory is mainly dedicated to additional

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functionalities, such as web servers, communication facilities, etc. Thus, the available amount of Data Block memory is still a major limitation for professional PLC programmers.

In the presence of a time delay in the HS dynamics, model predictive control (MPC) strategies can be effective. Different approaches can be proposed for the conventional MPC and their review can be found in [17]-[18]. Their common limitation is the assumption that a model of the process is linear. Then, based on the process model, the objective function is minimized, which results in the final form of the control law. Apart from the linear design, all the conventional MPC algorithms suffer from lack of simple tuning methods and a PLC-based implementation in the form of the general-purpose function block. For nonlinear processes, nonlinear MPC approaches could be proposed, but they require nonlinear modeling of the process and advanced mathematical techniques [19]-[21]. They often result in high computational complexity, high memory load for a PLC-based implementation and difficulties with offset-free control [22]. Apart from the bottlenecks recognized for the conventional MPC, such nonlinear approaches also suffer from lack of generality and their implementation is always case dependent.

From a practical viewpoint, for the HS control, a compensation for heat demand variations can be ensured by applying an adaptive MPC that compensates for a time delay in the controlled system and process nonlinearities. Then, the adaptation can be based on linear nonstationary models or the gain-scheduling technique. In some recent papers on adaptive predictive controllers one can find: the robust MPC that applies recursive on-line update of the linear process model in the state-space form [23], the robust adaptive MPC for linear systems with constant but unknown model parameters [24] and, for more case-dependent approaches, the adaptive MPC for the control of a Fresnel collector field, based on the gain-scheduling design [25]. Ref. [23]-[24] show very general considerations, but their practical applicability is very limited. Only the paper [25] shows a more practical solution with its validation for the real plant. However, even in this case, aspects of PLC-based implementation in the general form are not considered.

From among a range of different MPC algorithms, Dynamic Matrix Controller (DMC) [26] offers its low computational complexity (its control law can be derived analytically), its general and intuitive process modelling in the form of series of samples of the process step response and the availability of very simple and deterministic tuning rules [27]. Its design also assumes linearity of the process, but accounting for the process nonlinearities, different adaptive DMC approaches can be included. In [28] it is proposed to tune the linear DMC in several operating points. Then, depending on the current value of the process variable, the process model is modified in the control law. Ref. [29] presents the basic concept of the adaptability of DMC based on the interpolation of tuning parameters and the algorithm is validated in simulations. The initial practical validation of this method is presented in [30], but without any considerations of PLC-based implementation. A similar approach is presented in [38], where the control output is the weighted sum of outputs of several local DMC controllers. However, the authors do not exactly specify how to design the local controllers and how to choose the weighting parameters. The PLC-based implementation issues are not discussed, as well. Other approaches [39]-[40] can also be effective, but due to their complexity, the implementation on industrial PLC units may be difficult.

In this paper, the concept proposed in [29]-[30] is significantly extended and it includes the novelties listed below:

- Based on the linear DMC framework, step by step, it presents the consistent procedure of designing the adaptive DMC. This procedure includes the local tuning of DMC and the general approach to the interpolation of the tuning parameters. A special attention is paid to the problem of reduction of the number of the interpolation nodes in correlation with a potential drop in the control performance. For this reduction, a systematic approach is also proposed and discussed.
- The practical aspects of the PLC-based implementation are addressed. Namely, the implementation in the form of the general-purpose function block is presented. Apart from computing the control law, this block directly supports the adaptation. It results from the built-in functionality of the interpolation of the tuning parameters obtained by the design procedure. Let us note that even industrial implementations of PID function blocks do not support the adaptability directly, not to even mention of such functionalities that are dedicated for any advanced control strategy implemented as a function block, especially at this level of generality.
- The new control performance index (*energy error*) is proposed and its importance over the existing conventional control performance indices is discussed. This index is exclusively dedicated to quantify the performance of the HS control systems in terms of their energy efficiency.
- The results for practical validation of both the concept of the adaptive controller and its implementation are presented. The validation is made for two different structures of the HS control system, in the presence of significant nonlinearities in the HS plant. The results show the superiority of the suggested adaptive DMC over two other considered controllers in terms of the energy efficiency, evaluated by the proposed *energy error*.

II. Statement of the Problem

This work concentrates on control of the HS schematically presented in Fig. 1 and operating as a part of the HDS. In general, it can consist of a heating unit HU (e.g., gas or electric flow heater), which heats the flowing liquid that is transferred to the heat receiver HR (e.g., heat exchanger network, heating jacket, etc.). Flow rate F is adjusted by the control valve Z. After heating, the liquid flows through a pipeline that introduces a transportation delay between the HS and the HR. The control goal is to stabilize the liquid temperature $T_{out} = T_{sp}$ at the inlet of HR and potentially, this goal can be achieved by implementing one of the two control structures shown in Fig. 1. In both cases, it is assumed that for the effective control, the flow rate F and the temperatures T_{in} and T_{out} are measurable. The upper diagram (CS1 in Fig.1) shows the case when the temperature controller (TC) manipulates directly the heating unit (HU) power supply P_h and the flow controller (FC) is used only to stabilize the flow rate F by adjusting the control valve Z. Then, both the inlet temperature T_{in} and the flow rate F are the disturbances, but the latter can only vary, tracking its setpoint F_{sp} adjusted by the user or by a supervisory control system, subject to operation requirements. The lower diagram (CS2 in Fig.1) shows the different configuration, in which the HU has a constant power supply P_h and TC manipulates directly the control valve Z, adjusting the flow rate F. In this structure, only the inlet temperature T_{in} is the disturbance and the variations of the flow rate F are forced by the TC. In both cases, the setpoint temperature T_{sp} is adjusted by user or by supervisory control level, depending on the heat demand.

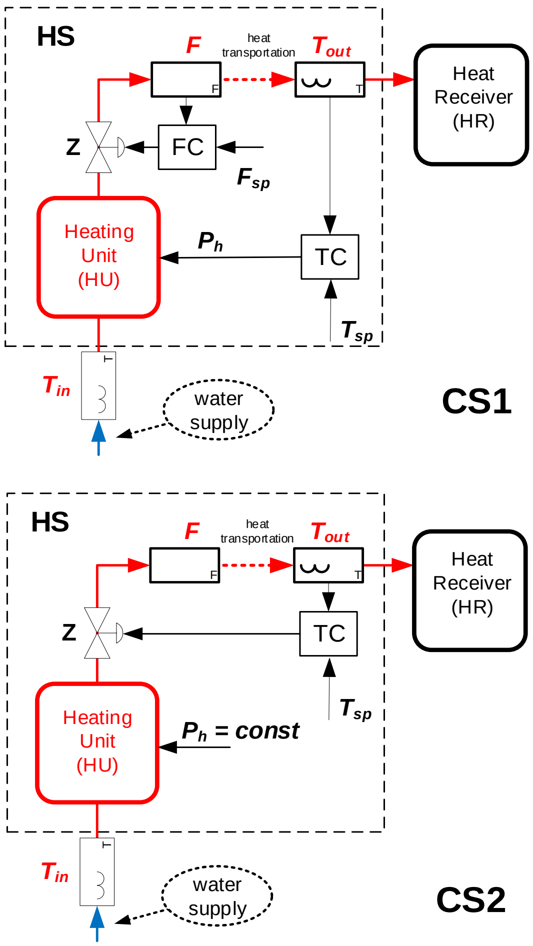

Fig. 1. Schematic diagrams of two control systems for heat source.

For both CS1 and CS2, variations in the flow rate F result in variations in the HS dynamics including a heat transportation delay introduced by the pipeline. Thus, in both cases, the HS must be considered as a nonlinear dynamical process with time-varying parameters, which makes the control problem difficult. Readers should note that for CS1, the flow rate F is the disturbance. At the same time, for CS2 the situation is more complex because the TC itself introduces variations in the process dynamics by changing the manipulated variable - the flow rate F. These changes are forced not only by the variations of the required heat demand but also by any change in P_h or T_{in}. Thus, even if the variations in P_h or T_{in} do not introduce direct changes in the process dynamics, the forced TC reaction does, which makes CS2 even a more challenging case.

The design criteria for the HS controller are defined as easy and reliable tuning, and simple implementation in PLC, with possibly low computational complexity and high generality. High ability of tracking of the desired heat demand regardless of changes in the operating conditions is also an important requirement.

III. Design and Implementation of Adaptive DMC

A. Conventional DMC tuning and implementation issues

For the SISO (Single Input Single Output) processes with the controlled output y and the manipulated variable u, the conventional DMC algorithm is based on the time-discretized finite step response of a process. Its detailed description can be found in many textbooks (e.g., [17]-[18]). Here, only the general idea is described to help the readers to follow the concepts presented in the paper.

At the discrete time instant k, the predicted process output over the prediction horizon H_P can be calculated as follows:

$$\underline{y}_P(k) = \underbrace{\left(y(k)\boldsymbol{I_p} + \boldsymbol{G_P}\underline{\Delta u}_P(k)\right)}_{free\ response} + \underbrace{\boldsymbol{G}\underline{\Delta u}(k)}_{forced\ response}, \qquad (1)$$

where $\underline{\Delta u}_P(k)$ includes H_D (dynamics horizon) past increments of the manipulated variable u, $\underline{\Delta u}(k)$ consists of its H_C (control horizon) future increments, $y(k)$ is the current measured process output, $\boldsymbol{G}$ (H_P x H_C) and $\boldsymbol{G_P}$ (H_P x H_D) are matrices, whose entries are determined from the process step response data (see [18] for details) and $\boldsymbol{I_p}$=[1 1 … 1]^T is the unitary column vector containing H_P elements. The vector of future control increments $\underline{\Delta u}$ can be analytically derived from minimization of the objective function, which is the sum of future control errors over the prediction horizon H_P and of future control increments over the control horizon H_C:

$$MIN_{\underline{\Delta u}(k)} \left\{ \left\| \underline{y}^{sp}(k) - \underline{y}_P(k) \right\|^2 + \lambda \left\| \underline{\Delta u}(k) \right\|^2 \right\}. \qquad (2)$$

$\underline{y}^{sp}$ contains H_P samples of reference trajectory, usually assumed to be constant over the prediction horizon. λ is the move suppression coefficient penalizing too large control increments $\Delta u(k)$. The analytical solution of Eq. (2) leads to the following DMC control law:

$$\underline{\Delta u}(k) = \underbrace{(\boldsymbol{G}^T\boldsymbol{G} + \lambda\boldsymbol{I})^{-1}\boldsymbol{G}^T}_{\boldsymbol{K}} \left[\underline{y}^{sp}(k) - y(k)\boldsymbol{I} - \boldsymbol{G_P}\underline{\Delta u}_P(k)\right], \qquad (3)$$

where $\boldsymbol{I}$ (H_C x H_C) is the identity matrix. From the vector $\underline{\Delta u}$, only the first increment Δu is applied to the process. The next elements are rejected and at the next sampling instant, the same calculations are repeated to determine the future increments of the manipulated variable u.

For practical implementation, the matrices $\boldsymbol{G}$ and $\boldsymbol{G_P}$ must be computed off-line, based on the process step response data collected at a single operating point. Additionally, the vector $\underline{\Delta u_P}$ must be stored in PLC memory and successively updated to store H_D past increments of the manipulated variable u that were previously applied to the process. Then, due to the repetition rule, DMC control law (3) can be implemented in the simplified form that allows for computing only the first control increment that is applied to the process:

$$\Delta u(k) = K^e[y^{sp}(k) - y(k)] - \underline{K^u}\,\underline{\Delta u_P}(k), \tag{4}$$

where K^e is a scalar representing the controller gain and $\underline{K^u}$ is a vector of H_D elements, which is defined by the first row of $(\boldsymbol{KG_P})$ matrix.

Tuning of the conventional DMC requires adjusting of (H_D+1) parameters: K^e and the elements of the vector $\underline{K^u}$. These parameters are directly defined by a given sampling time τ_s, the controller horizons H_C, H_P, H_D and by λ. However, the DMC tuning determines not only the closed-loop performance but also the computational complexity and the memory load that are essential for practical implementation in PLC. This problem is discussed in details in [27] where the authors propose a simple and effective tuning method that provides good control performance combined with relatively low memory load and computational complexity. That method is based on the first order plus delay time (FOPDT) approximation of the process step response at a chosen operating point. The FOPDT parameters (k_g – the process gain, τ – the overall time constant and τ_0 – the time delay) are easily recalculated into the DMC tuning parameters and readers are referred to [27] for details.

B. Adaptive DMC controller

For nonlinear processes, such as the considered HS, whose dynamical properties vary due to technological conditions, the conventional DMC is not suitable because it is based on the assumption that the process is linear. Thus, the adaptability must be included to provide a satisfactory control performance at different operating points. This adaptability consists in making the DMC tuning parameters dependent on the operating point of the process, as it was suggested in [34] for PID controller (gain-scheduling). However, for DMC, the adaptability is much more complex and it requires high memory load for the PLC implementation, because not only K^e but also all the elements of the vector $\underline{K^u}$ must be updated when the operating point varies. Namely, the adaptation of DMC requires continuous update of (H_D+1) tuning parameters and without any optimization, it stands as the significant load for the computing resources of PLC.

In this paper, the innovative method for deriving the DMC adaptability is proposed, based on the gain-scheduling approach. This method combines high generality with saving the computational resources for practical PLC implementation and its design consists of the following steps.

- <u>STEP 1 – determine the local linear models of the controlled process to capture its nonlinearities</u>

Depending on process nonlinearities, one can select N_r representative operating points uniquely parameterized by a so-called scheduling variable (SV). The SV should be selected as the quantity that is measurable and that has a significant influence on the process dynamics. Then, for each operating point, the parameters of the local FOPDT models should be determined, e.g., from the process step response data.

- <u>STEP 2 – determine local DMC tunings for each operating point</u>

The local DMC tunings should be derived based on the corresponding FOPDT models and the tuning rules described in [27]. In effect, a set of the DMC local parameters K^e_p and $\underline{K^u}_p$ are adjusted for N_r operating points consecutively numbered by subscript p=1,2,...,N_r. Note that the number of elements in each $\underline{K^u}_p$ vector is determined by H_{Dp} so for implementation, a maximal size $H_{Dmax} = \max\{H_{D1}, H_{D2}, ..., H_{DNr}\}$ of the $\underline{K^u}_p$ vectors must be defined and for $H_{Dp}<H_{Dmax}$, the last elements in $\underline{K^u}_p$ are set to zero. At the same time, the overall time constant τ_p can also vary depending on the operating point. Thus, a minimal sampling time $\tau_s=0.1\cdot\min\{\tau_1, \tau_2, ..., \tau_{Nr}\}$ must be defined.

- <u>STEP 3 – interpolate DMC tuning parameters over the whole range of operating conditions</u>

Once the p sets of the DMC tuning parameters K^e_p, $\underline{K^u}_p$ have been adjusted at each operating point, there is a need to ensure that each parameter is described by the continuous functions $K^e(SV)$, $\underline{K^u}(SV)$ because operating conditions (and, consequently, SV) vary smoothly. Different solutions were considered including polynomial interpolation or approximation, but for the irregular shape of $\underline{K^u}(SV)$ relationship, the linear spline interpolation [29] is proposed for this purpose. It ensures computational simplicity and generality on the one hand and relatively high accuracy on the other. Thus, for a single tuning parameter $K^e(SV)$ or each element of the vector $\underline{K^u}(SV)$), generally denoted as $TP(SV)$:

$$TP(SV) = \frac{TP_{p+1} - TP_p}{SV_{p+1} - SV_p} SV + \frac{TP_p SV_{p+1} - TP_{p+1} SV_p}{SV_{p+1} - SV_p}, \tag{5}$$

where subscript p = 1,…, N_r denotes the p-th operating point, TP_p and SV_p respectively denote the values of TP and of SV at the p-th interpolation node (operating point). At each sampling instant, based on a current measurement of SV, the new value of each tuning parameter (e.g., $K^e(SV)$) is interpolated by Eq. (5) and applied to DMC control law (4), which ensures adaptability.

- <u>STEP 4 – minimize the PLC memory load by off-line reduction of the number of interpolation nodes N_r</u>

Theoretically, this approach is effective but when the number of interpolation nodes N_r or the value of dynamics horizon H_{Dmax} are large, the excessively high memory load is required for the PLC implementation. This can be a rigorous limitation in industrial control systems when many control loops with additional logical control and safety features have to be implemented in a single PLC. In the considered case, for each DMC-based control loop, $N_r\cdot(H_{Dmax}+1)$ parameters must be stored in the PLC memory to provide adaptation. However,

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while both τ_s and H_{Dmax} are determined by the process dynamics and cannot be changed without a significant loss in the control performance, N_r can be reduced by the user depending on the process nonlinearities. The problem of reducing the number of interpolation nodes can be solved by the proposed algorithm.

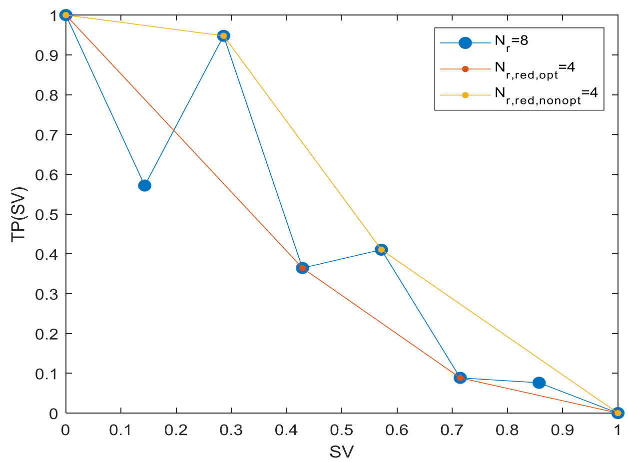

Fig. 2. Linear spline interpolation $TP(SV)$ for N_r = 7 interpolation nodes (blue line) and for two possible reductions when N_{r_red} = 4: optimal selection (red line) and non-optimal selection (yellow line).

The concept is presented in Fig. 2. For clarity and without loss of generality, only a single tuning parameter $TP(SV)$ ($K^e(SV)$ or a single element of $\underline{K}^u(SV)$) is shown and SV and $TP(SV)$ are normalized. Note that the irregular shape of this relationship is characteristic for DMC tunings and it makes any polynomial approximation highly inaccurate. For example, Fig. 2 shows two possibilities how to reduce the original number of interpolation nodes N_r=7 to N_{r_red} = 4 by neglecting three internal nodes (two boundary nodes must always be preserved).

In general, for each tuning parameter, there are many possible combinations for the location of $N_{r\_red} \in [2..N_r]$ interpolation nodes. Reduction of N_r results in a lower memory load but it also leads to the loss of information on the process nonlinearities. Thus, to evaluate this loss, the error:

$$e_{red} = \int_{SV_{min}}^{SV_{max}} (TP(SV) - T_{red}(SV))^2 \, dSV, \quad (6)$$

is computed for each combination of N_{r_red} nodes, where $TP(SV)$ and $TP_{red}(SV)$ are the interpolated values of TP, for N_r and for N_{r_red} interpolation nodes, respectively. This error must be computed for each of (H_{Dmax}+1) DMC tuning parameters TP (namely, for $K^e(SV)$ and for each element of $\underline{K}^u(SV)$), and for each of them, the results can be different. Thus, to ensure the same location of the reduced interpolation nodes for each tuning parameter, the total error is defined:

$$E_{red} = \sum_{j=1}^{H_{Dmax}+1} e_{red,j}, \quad (7)$$

and calculated for (H_{Dmax} +1) DMC tuning parameters where $e_{red,j}$ is the error computed by Eq. (6) for the j-th parameter. Then, by finding MIN(E_{red}), the optimal location for the considered N_{r_red} interpolation nodes can be chosen.

It should be noted that the reducing procedure allows for a significant reduction in the memory load required for PLC-based implementation but it also degrades the closed-loop control performance due to the loss of information on the process nonlinearities. Thus, a compromise between the closed-loop performance and the memory load must be made and this problem is discussed in Section IV.

C. PLC-based implementation

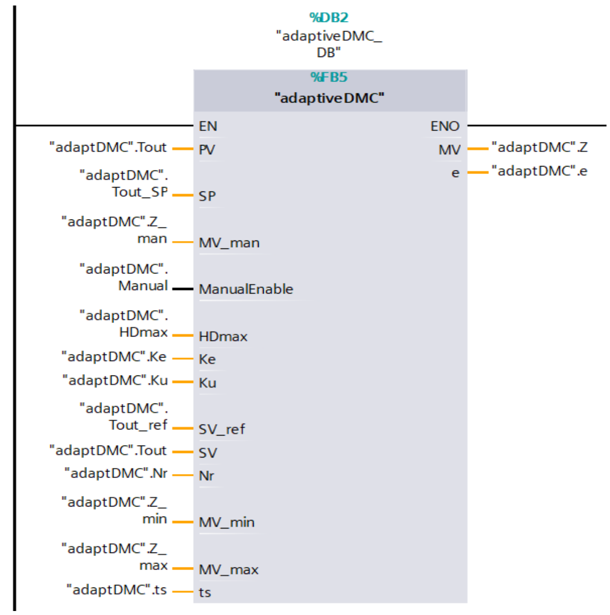

Fig. 3. Adaptive DMC Function Block implemented in SIEMENS® TIA Portal v13.

Once the steps of designing the adaptive DMC are completed, the user has the optimal number N_{r_red} of the local DMC tuning parameters. They can be used for the PLC-based implementation in the form of the ready-to-use general-purpose function block.

In this paper, the adaptive DMC is implemented in SIEMENS TIA Portal v13 and the function block is presented in Fig. 3. It provides the connectors for the process output (PV) and for the set point (SP). It also encapsulates all the calculations required for computing the general form of the control law (4) and of the proposed adaptation procedure. Additionally, this block provides all functionalities required for practical implementation, such as bumpless transfer between AUTO/MAN modes (ManualEnable) with manual value (MV_man) as an input, constraints on manipulated variable (MV_min, MV_max) and anti-windup action. The DMC tuning parameters calculated off-line by the procedure described in the previous section are stored in PLC Data Block memory and used as the input signals to the function block: K^e parameters as the vector (Ke), $\underline{K}^U$ vectors as the matrix (Ku), a number of applied interpolation nodes N_r after reduction (Nr) and H_{Dmax} (HDmax). The measured value of SV (SV) and SV values defining the interpolation nodes (after reduction) lumped in the vector (SV_ref) can be connected as inputs to allow for online adaptation, according to Eq. (5). The outputs are the control error (e) and the manipulated variable (MV).

This block should be executed every sampling time τ_s in PLC by calling it as a subroutine in the control loop, in the same way as the library PID function block is implemented in the industrial control applications. At the beginning of each call, for the measured value of *SV*, the new set of tuning parameters is computed using the data stored in the vector (SV_ref). Then, they are used to compute the control increment by Eq. (4). All the control increments are summed in the block to provide a substitute of integral action and after putting the constraints, the resulting manipulated variable (MV) is applied to the process.

IV. Experimental Results

The validation of the adaptive DMC was performed using the laboratory setup that directly represents the HDS shown in Fig. 1, with water as the heating liquid. It consists of the electric flow heater (HU) and of the control valve for adjusting the flow rate *F*. The plate heat exchanger LM25-6 (made by TAU Energy®) is the HR. The temperatures (T_{in}, T_{out}) are measured by platinum-wire resistance sensors (RTD) directly-coupled to 0 – 10 [V] transmitters. Flow rate *F* is measured by magnetic flow meter SIEMENS® Sitrans fm mag 1100. The heating power P_h of the electric flow heater can be adjusted within the range 0 – 4.5 [kW] by the thyristor-based unit controlled by PWM (Pulse Width Modulation) algorithm. All the process signals are connected to SIEMENS® ET-200 module connected to PLC (SIEMENS® S7-1512C-1PN). The control algorithm is implemented in the PLC that provides 250 kB for program memory and the maximum size of Data Block (where controller parameters can be stored) is limited to 64 kB, which is a very common limitation in industrial practice.

A. Practical validation

The first stage of validation is performed by virtual commissioning procedure that involves a virtual (simulated) plant connected to the real PLC where the control system is implemented. In comparison to the conventional simulation validation, the virtual commissioning validates not only the concept of the control strategy but also its practical PLC-based implementation with all the functionalities. The virtual commissioning requires a dedicated software environment both for the process simulation and the emulation of the PLC connection to the real sensors and actuators, along with scaling functions and range limitations. This approach is widely used for manufacturing systems [35]-[37] and it is proposed for the industrial automation [38]-[39]. In [40], it is reported that by virtual commissioning, the significant time reduction of about 75% is possible, in comparison to the real commissioning. The virtual commissioning is very useful for initial validation of newly designed (advanced) control systems, because it allows for safe validation, easy redesign and estimation of the potential benefits resulting from the practical implementation of every new control strategy.

In this study, for the virtual commissioning, the realistic simulator of the laboratory heat source was prepared in SIEMENS® Simit v9.0 industrial software. It is based on the first principle model with additional terms representing the dynamics of sensors, of electric heater and of the control valve with pneumatic positioner. This model is described in details in [39] and it is used only for the virtual commissioning as a real process. It is not used for the design of the adaptive DMC.

Both control structures CS1 and CS2 shown in Fig. 1 are validated by virtual commissioning and the potential benefits resulting from implementation of the proposed adaptive DMC are investigated. In both cases, the nonlinearities result from variations in the flow rate *F*. For CS1, this flow rate disturbs the process so the validation concentrates on its rejection. For CS2, the flow rate *F* is the manipulated variable so the validation concentrates on tracking properties. In both cases, other disturbances in the system do not change the process dynamics directly so their influence is not shown because the DMC without any adaptation can reject them.

For CS1, the adaptive DMC was implemented as TC (Fig. 1). The flow rate *F* is stabilized by the conventional PI controller implemented as FC. In the laboratory setup, the flow rate *F* can be adjusted within 1.0-4.0 [L/min] and its variations result in significant variations of FOPDT model parameters. Namely, the process gain varies from 0.15 to 0.65, the time constant from 15 to 35 and the time delay from 10 to 25. Based on this knowledge, $SV = F$, $H_{Dmax} = 89$ and $N_r = 7$ interpolation nodes are initially chosen for adaptation.

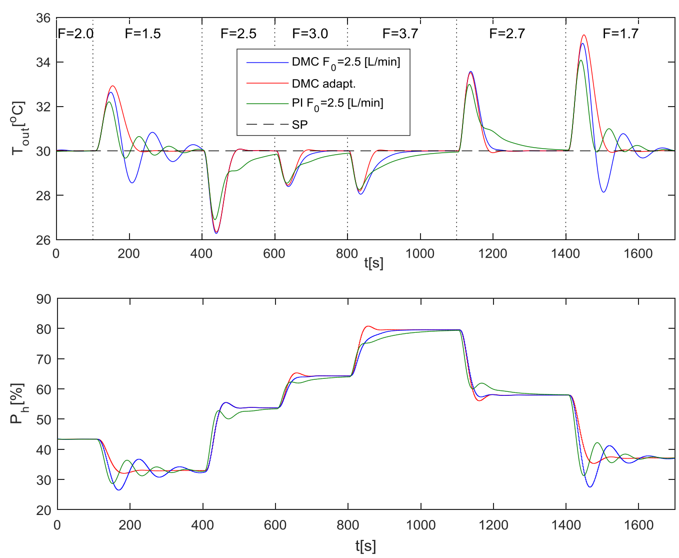

Fig. 4. Comparison of closed-loop performance obtained by virtual commissioning for CS1. Upper figure shows the controlled variable T_{out} and the lower – the manipulated variable P_h.

Fig. 4 shows the results from the closed loop virtual commissioning experiments for the proposed adaptive DMC controller in CS1 structure, assuming constant $T_{in0} = 15.5$ [^{o}C]. For comparison, Fig. 4 also shows the results for conventional DMC and PI controllers without any adaptation, both tuned only for F = 2.5 [L/min]. The PI controller is also implemented in SIEMENS® S7-1512C-1PN by using the standard PID Compact library function block and it is tuned based on the built-in autotuning functionality, which is a common industrial practice. The proposed adaptive DMC ensures the best robustness, but results in the highest overshoots. It provides a very similar control performance for each operating point without any oscillations and with significantly shorter settling time.

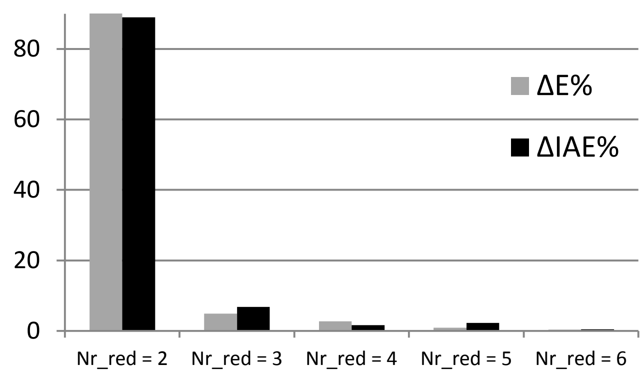

Fig. 5. Correlation between the relative interpolation error *ΔE%* and the relative *ΔIAE%* for different values of N_{r_red}, obtained by virtual commissioning for CS1 control structure, and for the experiment shown in Fig. 4.

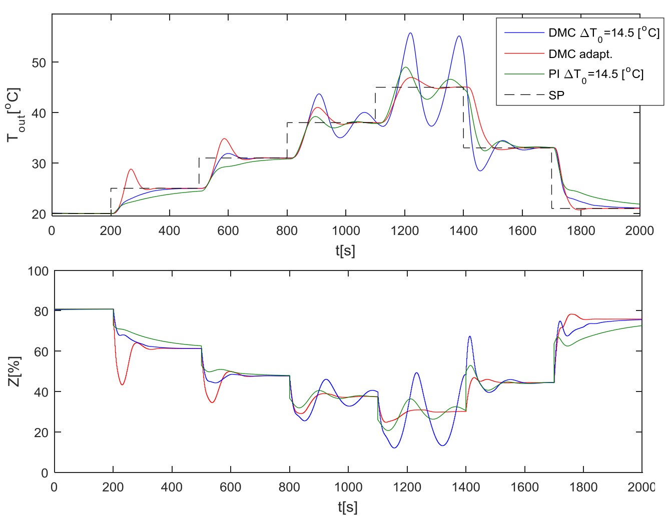

Fig. 6. Comparison of closed-loop performance obtained by virtual commissioning for CS2. Upper figure shows the controlled variable T_{out} and the lower – the manipulated variable *Z* (valve opening).

In practice, the problem of a proper selection of N_{r_red} exists because the proposed reduction procedure is based only on minimization of the interpolation error (7) while the influence of this reduction on the control performance is also significant. To evaluate this influence, it would be necessary to perform time-consuming, closed-loop experiments with the real process, which is difficult or impossible in majority of practical cases. Thus, it is proposed to make the reduction based only on interpolation error (7) that can be determined off-line without any additional closed-loop experiments. This approach is investigated based on the virtual commissioning and the example results are presented for the studies performed for N_{r_red} decreasing from 6 to 2 nodes. For each value of N_{r_red}, the optimal combination of interpolation nodes is determined by Eq. (7). Then, *IAE* (Integral Absolute Error) indices are calculated based on the same experiment shown in Fig. 4. For convenience, the relative percentage values *ΔIAE%* are calculated and the results are presented in Fig. 5. It can be noticed that the deterioration in *ΔIAE%* follows the increase in *ΔE%* and for both values, the most significant drop in the control performance can be observed between N_{r_red} = 3 and N_{r_red} = 2. Thus, based only on the value of *ΔE%*, it can be determined that N_{r_red} = 3 provides a good compromise between the closed-loop performance and the memory load for the adaptive DMC. This conclusion was also confirmed by numerous simulation results. Note that assuming 4 bytes for a single tuning parameter, the reduction in N_r allows for the reduction in memory load from 2520 bytes (for $N_r = 7$) to 1080 bytes (for $N_{r\_red} = 3$).

Similar research has been done for the structure CS2 shown in Fig. 1. In this case, the adaptive DMC was implemented as TC that directly manipulates the opening of the control valve *Z*. Thus, by changing the flow rate *F* (manipulated variable), the DMC introduces variations in the operating point and consequently, in the process dynamics. Based on process nonlinearities, the best results for adaptation are obtained for $SV = \Delta T = (T_{out}\text{-}T_{in})$, $H_{Dmax} = 106$ and $N_r = 8$ interpolation nodes. Fig. 6 shows the results of the closed loop virtual commissioning experiments assuming a constant temperature T_{in0} = 15.5 [°C]. The adaptive DMC controller is compared with the conventional DMC controller tuned for the operating point identified by ΔT_0 = 14.5 [°C]. The results are also compared to the performance of the conventional PI controller tuned by Chien-Hrones-Reswick method (regulatory mode), based on a single step response for the same operating point ΔT_0 = 14.5 [°C]. Once again, the proposed adaptive DMC provides the best robustness with a comparable control performance for each operating point without oscillations.

After the reduction of the interpolation nodes, it was found that a very similar correlation between *ΔIAE%* and *ΔE%* also exists for CS2 and, based on it, the best compromise between the closed-loop control performance and memory load was found for N_{r_red} = 4, which was additionally confirmed by simulation tests. In this case, the reduction of memory load is from 2688 bytes (for $N_r = 8$) to 1344 bytes (for $N_{r\_red} = 4$).

Final validation of the adaptive DMC was made by real experiments based on the laboratory setup. Both control structures (CS1 and CS2) were validated under the same experimental scenarios that were used for the virtual commissioning and shown in Figs. 4 and 6. The results obtained for the considered controllers are very similar to the results shown in Figs. 4 and 6. For clarity, Fig. 7 shows only the results for the adaptive DMC and for different N_{r_red}. Additionally, the correlation between *ΔIAE%* and *ΔE%* was also noticed. Hence, it is confirmed in practice that the optimal number of the interpolation nodes can be adjusted based only on *ΔE%* computed off-line.

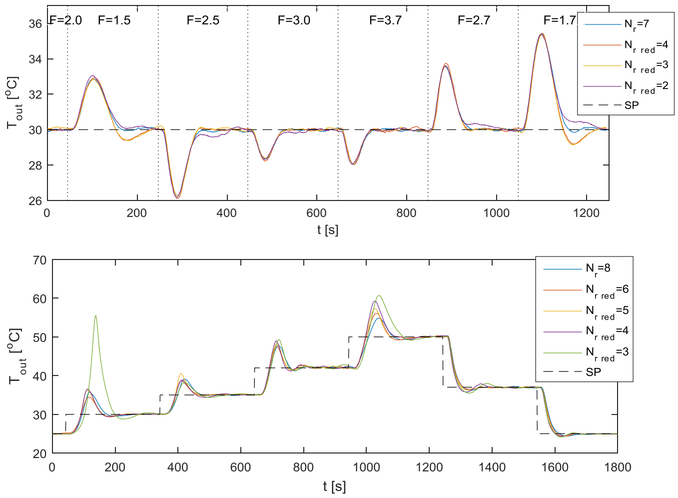

Fig. 7. Control performance for the adaptive DMC with reduced number of interpolation nodes, obtained by real commissioning for CS1 (the upper plot) and CS2 (the lower plot) control structures.

B. Energy performance measure for HS control systems

The performance of every HS control system should be quantified by two criteria: the tracking quality with disturbance rejection (usually measured by the control error $e = T_{sp} - T_{out}$) and the amount of energy used for the control in transients. In general, it is expected to provide accurate control (with possibly the smallest control error in transients) at the price of possibly the smallest energy consumption. However, readers should note that for the HS control, these criteria are contradictory and the design of the control system requires a compromise. Improvement in the control accuracy always requires a more aggressive controller that can result in higher energy consumption during transients. It is relatively easy to quantify both criteria separately, but it is difficult to lump them into a single general criterion that provides representative performance measure, independent from the HS configuration and the operating conditions. Especially, the latter is important because energy consumption for the HS control depends on experiment scenario. For instance, for tracking a step increment in T_{sp}, one can imagine two cases with very similar *IAE* (Integral Absolute Error) values: fast tracking with small overshoots (aggressive tuning) and slow exponential tracking without overshoots (conservative tuning). Comparison of the amount of energy used for heating the liquid in both cases will show that the second case (conservative tuning) is more effective. If we consider the same cases, but for a step decrement in T_{sp}, the situation is opposite – now, the first case (aggressive tuning) is more effective in terms of the energy consumption. This simple example shows that one must be very careful when comparing two HS control systems only in terms of the energy consumption. This comparison depends not only on the design of the control system but also on the scenario of the experiment.

The HS control system should be designed to supply the desired energy to the HR in the presence of the varying heat demand and disturbances. Thus, the novel performance measure for assessing the HS control effectiveness is proposed as the *energy error*. It is defined as a difference between the current energy demand and the energy supplied by HS:

$$P_{e,total} = \int_0^{t_{max}} \left| P_{sp}(t) - P_{sup}(t) \right| dt, \tag{8}$$

where t_{max} denotes the time over which the system is assessed, $P_{sp}(t) = F(t)\rho c_s T_{sp}(t)$ is the heating power demanded by the HR (setpoint for the power) and $P_{sup}(t) = F(t)\rho c_s T_{out}(t)$ is the heating power currently supplied by the HS control system (ρ and c_s denote the density and the specific heat of the liquid, respectively). The absolute value ensures that the system is penalized not only for overshoots (resulting in supplying excessive energy to HR) but also for supplying insufficient amount of energy. In practice, both cases lead to a drop in production efficiency because the excessive energy increases the production costs and can lead to overheating that sometimes can destroy the final product. On the other hand, insufficient energy results in false cost savings, because it extends the heating time, which leads to a drop in productivity due to increase of the batch time.

In the considered cases, the hot liquid is transferred from the HS to the HR and (8) can be rewritten as follows:

$$P_{e,total} = \int_0^{t_{max}} F(t)\rho c_s |e(t)| dt. \tag{9}$$

This measure depends on the absolute value of the control error e and on the flow rate F. Consequently, it depends on the heat demand determined by values of F and T_{sp}.

Table I shows the results of the energy performance assessment of CS1 for three considered controllers. Apart from $P_{e,total}$ computed by Eq. (9), it also shows the total electric energy supplied to the heater and computed over the whole experiment due to the variations in the manipulated variable P_h. Over the whole experiment, the changes in the flow rate are partially symmetrical around the operating point defined as F_0 = 2.5 [L/min]. Thus, the differences in total electrical energy consumption between the controllers are small. The highest energy consumption is required for the suggested adaptive DMC, which is the price for the high control accuracy shown by the lowest value of $P_{e,total}$. The same situation takes place for CS2 (see results in Table II). Note that evaluating this control structure by the consumption of the total electrical energy is misleading, because each controller operates with the same constant P_h = 40%. Thus, for each controller, the same amount of electrical energy is consumed over the whole experiment. However, the suggested evaluation by $P_{e,total}$ still works. Again, the adaptive DMC ensures the lowest value of $P_{e,total}$ and this time, the differences between the controllers are much more significant. At the same time, the experiments have shown that all the controllers ensure comparable water consumption (Table II).

TABLE I
TOTAL ENERGY ERROR AND TOTAL ENERGY CONSUMPTION FOR CS1

controller/quantification factor	$P_{e,total}$ [kJ] computed by Eq. (9)	Total electric energy [kJ] supplied to HS
DMC (F_0 = 2.5 [L/min])	165.50	4042.16
DMC adapt	**138.75**	4078.12
PI (F_0 = 2.5 [L/min])	168.88	4037.75

Results for the experiment scenario shown in Fig. 4.

TABLE II
TOTAL ENERGY ERROR AND TOTAL WATER CONSUMPTION FOR CS2

controller/quantification factor	$P_{e,total}$ [kJ] computed by Eq. (9)	Total amount of water [L]
DMC (ΔT_0 = 14.5 [°C])	450.57	62.52
DMC adapt	**268.34**	61.89
PI (ΔT_0 = 14.5 [°C])	432.22	61.25

Results for the experiment scenario shown in Fig. 6.

The improvement in the control efficiency evaluated by the suggested *energy error* (9) results directly from the improvement in the overall control performance ensured by the adaptive DMC. The measure (9) is not considered during the controller design in any way. However, Eq. (9) depends on the absolute value of the control error e and the norm of e is also taken into account in (2) for computing the optimal control increment (4) in the design of DMC. Of course, the solution (4) is also dependent on the move suppression coefficient λ. If the minimization of the *energy error* (9) is to be addressed directly in the design of DMC, the term $\left\|\underline{y}^{sp}(k) - \underline{y}_P(k)\right\|^2$ in Eq. (2) is substituted by Eq. (9) and then the optimization problem has to be solved. However, this approach has two significant limitations. The first one is its computational complexity, because the rearranged objective function becomes nonlinear and requires numerical minimization in PLC at each sampling instant. The second limitation results from the fact that even if one can handle the computational complexity, there is still a need for separate design of the adaptation because the DMC formulation is based on the linear approximation of the nonlinear process dynamics.

V. CONCLUSIONS

In this paper, the adaptive DMC with interpolated parameters is suggested as the practical robust solution for the effective control of the heating sources operated as a part of industrial heat distribution systems. One of the major goals of the paper was the PLC-based implementation of the controller in the form of the general purpose library function block. Due to practical reasons, a special emphasis is put on the minimization of the PLC memory load that can be achieved by the reduction of the interpolation nodes. The dedicated reduction procedure is proposed and the correlation between the number of reduced nodes and the control performance is shown. Based on this correlation, it is suggested how to perform the off-line reduction to provide a good balance between the PLC memory load and the required control performance.

The superiority of the adaptive DMC in the control performance is confirmed based on the laboratory setup, for two possible control structures and by both the virtual and real commissioning. The comparison is made with the conventional DMC without adaptation and with the conventional PI controller tuned by the built-in auto-tuning functionality for CS1 and by the Chien-Hrones-Reswick for CS2. Additionally, the energy performance index is suggested for assessment of the energy efficiency of the heat source control systems and it is shown that the adaptive DMC ensures its minimal value.

The suggested adaptive DMC provides a significant improvement in the control performance of the HS in comparison to the conventional DMC. However, apart from its superiority, the adaptive DMC requires more information about the process nonlinearities and larger effort for designing the adaptability. Namely, FOPDT approximations of the process dynamics must be locally determined at specified operating points, which requires more extensive experiments with the real process. This difficulty can be overcome, if the accurate nonlinear model of the process is known. Then, it can be linearized and used for deriving the required FOPDT approximations. No matter how these local FOPDT approximations are obtained, the suggested procedure for reducing the interpolation nodes must then be applied, but any additional experiments with the real process are not required. Once this procedure is completed, the PLC-based implementation is greatly simplified by using the ready-to-use, general purpose function block for the adaptive DMC.

The suggested approach is very general because it can be used not only for the HS control but also for the control of any nonlinear SISO process. For the latter, one should follow the procedure described in Section III.B. Then, the same function block shown in Fig. 3 should be used for the PLC-based implementation. However, readers should also note a significant limitation of the proposed adaptive DMC, since it can be easily applied only for SISO processes with a single scheduling variable *SV* that has a significant effect on the process dynamics. If there are more quantities that have such property, then the suggested concept must be modified and its complexity significantly increases. For instance, for two potential *SV1*, *SV2*, the number of interpolation nodes must be increased to cover the whole two-dimensional space (*SV1*, *SV2*). Then, for each interpolation node, the same FOPDT approximation should be applied, but a more complex interpolation formula must be used. Finally, the PLC-based function block must be redesigned to provide the interpolation between the nodes. However, the general concept and the steps of the design procedure are the same, resulting in the minimization of the PLC memory load by the suggested reduction of the number of the interpolation nodes.

REFERENCES

[1] Z. Yuan, B. Chen, G. Sin, and R. Gani, "State-of-the-art of progress in the optimization-based simultaneous design and control for chemical processes," *AIChE Journal*, vol. 58, no. 6, pp. 1640–1659, 2012.

[2] M. Bakošová, and J. Oravec, "Robust model predictive control for heat exchange network," *Applied Thermal Engineering*, vol.73, pp. 922-928, 2014.

[3] Y.Z. Liu, P.S. Varbanov, J.J. Klemeš, and J.Z. Yong, "Recent developments in applied thermal engineering: process integration, heat exchangers, enhanced heat transfer, solar thermal energy, combustion and high temperature processes and thermal process modelling," *Applied Thermal Engineering*, pp. 755-762, 2016.

[4] T. Muszynski, "Design and experimental investigations of a cylindrical microjet heat exchanger for waste heat recovery systems," *Applied Thermal Engineering*, vol. 115, pp. 782-792, 2017.

[5] P. Laszczyk, "Simplified modeling of liquid-liquid heat exchangers for use in control systems," *Applied Thermal Engineering*, vol. 119, pp. 140-155, 2017.

[6] P. Laszczyk, J. Czeczot, R. Czubasiewicz, and K. Stebel, "Practical Verification of the Control Strategies for the Counter-Current Heat Exchanger," in *Proc. 17th International Conference on Methods and Models in Automation and Robotics (MMAR)*, Miedzyzdroje, Poland, 2012, pp. 96-101.

[7] M. Fratczak, J. Czeczot, P. Nowak, and M. Metzger, "Practical validation of the effective control of liquid-liquid heat exchangers by distributed parameter balance-based adaptive controller," *Applied Thermal Engineering*, vol. 129, pp. 549-556, 2018.

[8] M.A. Arbaoui, L. Verniérez-Hassimi, D. Seguin, and M.A. Abdelghani-Idrissi, "Counter-current tubular heat exchanger: modeling and adaptive predictive functional control," *Applied Thermal Engineering*, vol. 27, pp. 2332-2338, 2007.

[9] P. Laszczyk, T. Klopot, D. Pyka, "Comparison of DMC and PFC Control for Heating Process," in *Proc. 18th International Conference on Methods and Models in Automation and Robotics (MMAR)*, Miedzyzdroje, Poland, 2013, pp. 317-322.

[10] M. Bakošová, and J. Oravec, "Robust model predictive control of heat exchangers," *Chemical Engineering Transactions*, vol. 35, pp. 1465-1470, 2013.

[11] J. Oravec, M. Bakošová, M. Trafczynski, A. Vasičkaninová, A. Mészáros, and M. Markowski, "Robust model predictive control and PID control of shell-and-tube heat exchangers," *Energy*, vol 159, pp. 1-10, 2018.

[12] J. Oravec, M. Bakošová, L. Galčiková, M. Slávik, M. Horváthová, and A. Mészáros, "Soft-constrained robust model predictive control of a plate heat exchanger: Experimental analysis," *Energy*, vol. 180, pp. 303-314, 2019.

[13] J. Czeczot, "Modelling for the effective control of the electric flow heaters - Simulation validation," *Simulation Modelling Practice and Theory*, vol. 16, no. 4, pp. 429-444, 2008.

[14] J. Czeczot, P. Laszczyk, and M. Metzger, "Local balance-based adaptive control in the heat distribution system - Practical validation," *Applied Thermal Engineering*, vol. 30, no. 8-9, pp. 879-891, 2010.

[15] P. Nowak, and J. Czeczot, "Observer-Based Cascade Control of the Heat Distribution System," in *Proc. 18th International Conference on Methods and Models in Automation and Robotics (MMAR)*, Miedzyzdroje, Poland, 2013, pp. 633-638.

[16] M. Fratczak, P. Nowak, and P. Laszczyk, "Dynamical aspects of multi-input single-output control for heat distribution processes: case study," in *Proc. 22nd International Conference on Methods and Models in Automation and Robotics (MMAR)*, Miedzyzdroje, Poland, 2017, pp. 301-306.

[17] J. Maciejowski, *Predictive Control with Constraints*. Prentice-Hall, Harlow, 2002.

[18] P. Tatjewski, *Advanced Control of Industrial Processes. Structures and Algorithms*. Springer-Verlag, London, 2007.

[19] B.A. Foss and T.S. Schei. "Putting nonlinear model predictive control into use," in *Assessment and Future Directions Nonlinear Model Predictive Control*, LNCIS 358, Springer Verlag, 2007, pp 407 – 417.

[20] M. Morari and U. Maeder. "Nonlinear offset-free model predictive control," *Automatica*, vol. 48, pp. 2059-2067, 2012.

[21] M. Ławryńczuk. "Nonlinear state-space predictive control with on-line linearisation and state estimation," *Int. J. of Applied Mathematics and Computer Science*, vol. 25, no. 4, pp. 833-847, 2015.

[22] P. Tatjewski, "Offset-free nonlinearModel Predictive Control with state-space process models," *Archives of Control Sciences*, vol. 27, pp. 595-615, 2017.

[23] M. Lorenzen, M. Cannon, and F. Allgöwer, "Robust MPC with recursive model update." *Automatica*, vol. 103, pp. 461–471, 2019.

[24] X. Lu and M. Cannon, " Robust Adaptive Tube Model Predictive Control.", in *Proc. 2019 American Control Conference (ACC)*, Philadelphia, PA, USA, 2019, pp. 3695-3701.

[25] A.J. Gallego, G.M. Merello, M. Berenguel and E.F. Camacho, "Gain-scheduling model predictive control of a Fresnel collector field.", *Control Engineering Practice*, vol. 82, pp. 1-13, 2019.

[26] C.R. Cutler, and D.L. Ramaker, "Dynamic Matrix Control—A Computer Control Algorithm," in *Proc. JACC*, San Francisco, CA: 1980, Vol. 1, WP5-B; 1–6.

[27] T. Klopot, P. Skupin, M. Metzger, and P. Grelewicz, "Tuning strategy for dynamic matrix control with reduced horizons," *ISA Transactions*, vol 76, pp. 145-154, 2018.

[28] W. Klopot, T. Klopot, and M. Metzger, "Adaptive and Non-Adaptive Dynamic Matrix Control for Conical Tank," in *Proc. 14st International Conference on Methods and Models in Automation and Robotics (MMAR)*, Miedzyzdroje, Poland, pp. 543-548, 2009.

[29] T. Klopot, and P. Skupin, "Adaptive Dynamic Matrix Control with Interpolated Parameters," in *Proc. 20th International Conference on Methods and Models in Automation and Robotics (MMAR)*, Miedzyzdroje, Poland, 2015, pp. 683-688.

[30] T. Klopot, and P. Skupin, "Practical verification of adaptive dynamic matrix control with interpolated parameters," in *Proc. 21st International Conference on Methods and Models in Automation and Robotics (MMAR)*, Miedzyzdroje, Poland, 2016, pp. 1182-1187.

[31] D. Dougherty and D. Cooper. "A practical multiple model adaptive strategy for single-loop MPC," *Control Engineering Practice*, vol. 11, pp. 141-159, 2003.

[32] P.M. Marusak. "Advantages of an easy to design fuzzy predictive algorithm in control systems of nonlinear chemical reactors," *Applied Soft Computing*, vol. 9, pp. 1111-1125, 2009.

[33] U.C. Moon and K.Y. Lee "An adaptive dynamic matrix control with fuzzy-interpolated step-response model for a drum-type boiler-turbine system," *IEEE Transactions on Energy Conversion*, vol. 26, pp. 393-401, 2011.

[34] K.J. Äström, and B. Wittenmark, *Adaptive Control. Reading*. Addison-Wesley Publishing Company, 1989.

[35] C.G. Lee, and S.C. Park, "Survey on the virtual commissioning of manufacturing systems," *Journal of Computational Design and Engineering*, vol. 1, no. 3, pp. 213-222, 2014.

[36] S. Alszer, J. Krystek, and S. Bysko, "Simulation and virtual commissioning for intelligent buffer control system - case study," in *Proc. 2nd International Conference on Robotics and Automation Engineering (ICRAE)*, 2017, pp. 207-211.

[37] T. Lechler, E. Fisher, M. Metzner, A. Mayr, and J. Franke, "Virtual commissioning – Scientific review and exploratory use cases in advanced production systems," *Procedia CIRP*, vol. 81, pp. 1125-1130, 2019.

[38] M. Fratczak, P. Nowak, T. Klopot, J. Czeczot, S. Bysko, and B. Opilski, "Virtual commissioning for the control of the continuous industrial processes – case study," in *Proc. 20th International Conference on Methods and Models in Automation and Robotics (MMAR)*, Miedzyzdroje, Poland, 2015, pp. 1032-1037.

[39] P. Grelewicz, P. Nowak, M. Fratczak, T. Klopot, "Practical Verification of the Advanced Control Algorithms Based on the Virtual Commissioning Methodology – a case study," in *Proc. 23rd International Conference on Methods and Models in Automation and Robotics (MMAR)*, Miedzyzdroje, Poland, 2018, pp. 217-222.

[40] L.J. Koo, C.M. Park, C.H. Lee, S.C. Park, and G.N. Wang, "Simulation framework for the verification of PLC programs in automobile industries," *International Journal of Production Research*, vol. 49, no. 16, pp. 4925-4943, 2011.

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