Simulation Validation of the Model-based Control of the Plate Heat Exchanger with On-line Compensation for Modelling Inaccuracies

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Abstract: This paper describes the stage of initial validation of the model-based control of the plate heat exchanger (PHE) by simulation. For the distributed parameter model of PHE validated on the basis of the measurement data collected from the real process, the approximation by the orthogonal collocation method is applied and then the linearizing controller with the on-line compensation for the potential modelling inaccuracies is suggested. This approach ensures relatively low computational complexity due to the low dimension of the approximating dynamical model, which allows for its practical implementation in the programmable logic controllers. The suggested controller is tested by simulation under the realistic experiments scenario and it shows its superiority and robustness over the conventional PI controller, for both tracking and disturbances rejection. The results show that the suggested concept can be considered as an interesting model-based alternative for the PID-based control systems that are still widely applied in the industrial practice.

1 INTRODUCTION

For last decades, the plate heat exchangers (PHE) have become more and more popular in the industrial and domestic heat exchange and distribution networks, due to their compact dimensions and very high heat transfer efficiency. At the same time, the control of such units is still the challenge due to their nonlinear dynamics, especially because the modern industrial systems demand growing improvement in product quality at possibly lowest energy consumption and other operation costs, combined with high safety and environmental goals (Bauer and Craig, 2008).

Dynamical modelling of PHEs that would account for their characteristic construction is more complex in comparison to the conventional approach based on tubular double-pipe approximation. In literature, only few approaches to this problem can be found - e.g. (Georgiadis and Macchietto, 2000; Gut and Pinto, 2003). Based on the interaction between the plates, the fundamental energy conservation law is applied to derive a set of approximating dynamical equations, describing the variation of the temperatures in the cold and hot zones.

This paper deals with the synthesis of the model-based controller for PHEs and the intension is to incorporate the nonlinearities and the complex dynamics of such a unit into the resulting control law. Thus, it is crucial to derive the model of possibly lowest complexity that would be able to describe the heat exchange process taking place in PHE with possibly high accuracy and this goal requires the distributed parameter modelling. Then, such a model can be considered as a basis for deriving the model-based controller.

This approach is very promising but in the practice, there is always a problem resulting from potential modelling inaccuracies. Any model-based controller suffers from the limited accuracy of the model and thus, one of the possible methods for the inaccuracy compensation should be applied. One of them is the application of the integral action, which always ensures offset-free control but at the same time, it introduces the inconvenient dynamics to the control system. The examples of this approach for the control of the tubular heat exchangers can be found in (Maidi, Diaf and Corriou, 2009; 2010). The other possibility is to compensate for the modelling inaccuracies by the on-line adjustment of the chosen model parameters, which represents the case of the

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nonstationary modelling with the on-line model update. This possibility was studied for the tubular flow reactors (Czeczot, 2003).

In this paper, it is suggested how the linearizing control methodology (e.g. Isidori, 1989; Henson and Seborg, 1997) can be applied to control PHE and how the linearizing controller can be derived based on its distributed parameter model. The lower complexity of the model is ensured by applying the tubular double-pipe approximation with the model parameters optimally adjusted on the basis of the measurement data collected from the PHE working in the real heating system. This model is further simplified by its space discretization by the orthogonal collocation method (OCM) (Villadsen and Michelsen, 1978), which ensures significantly lower dimension of the approximating state vector. Then, based on this simplified model, the linearizing controller is derived and the compensation for modelling inaccuracies is ensured without any integral action in the resulting control law. The suggested controller is finally tested by simulation under the realistic experiments scenario in the application to control the PHE modelled as the complete distributed parameter system.

2 PROBLEM STATEMENT

In this work, the problem of the model-based control of the counter-current PHE operating in the setup presented schematically in Fig. 1 is considered. It is assumed that the unit is equipped with the sensors for both flow rates F_1, F_2 [L/min] and for inlet and outlet temperatures T_{in1}, T_{in2}, T_{out1}, T_{out2} [^{o}C], respectively.

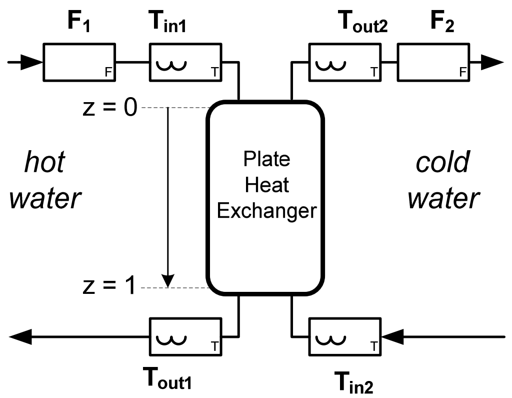

Figure 1: Schematic diagram of the considered PHE setup.

The control goal is defined to stabilize the outlet temperature of the cold water $Y = T_{out2}$ by manipulating the inlet temperature of the hot water $u = T_{in1}$. The flow rate of the hot water F_1 is assumed to be adjustable and constant while the unit is disturbed by the measurable variations of the inlet temperature T_{in2} and by the flow rate F_2 of the cold water, which represent the variations of the heat demand.

In this paper, the real PHE is described by the simplified tubular double-pipe model based on the energy balance and assuming perfect insulation of the unit. This model consists of two partial differential equations describing respectively the temperatures of the hot water T_1 [^{o}C] and of the cold water T_2 [^{o}C]:

$$\frac{\partial T_1(z,t)}{\partial t} = -\frac{F_1(t)}{p_1}\frac{\partial T_1(z,t)}{\partial z} - h_1\big(T_1(z,t) - T_2(z,t)\big) \quad (1a)$$

$$\frac{\partial T_2(z,t)}{\partial t} = \frac{F_2(t)}{p_2}\frac{\partial T_2(z,t)}{\partial z} + h_2\big(T_1(z,t) - T_2(z,t)\big) \quad (1b)$$

with the boundary conditions:

$$T_1(0,t) = T_{in1}(t), \quad T_2(1,t) = T_{in2}(t), \quad (1c)$$

and the initial profiles $T_1(z,0), T_2(z,0)$. At the same time, the outlet temperatures are defined as $T_{out1}(t) = T_1(1,t), T_{out2}(t) = T_2(0,t)$, for the hot and cold water, respectively.

In Eqs. (1), $z \in [0,1]$ denotes the normalized space variable, which makes the model independent from the geometrical dimensions of the certain PHE under consideration. For tubular heat exchangers, the space variable is normalized as $z = x/L$, where $x \in [0, L]$ and L denotes the length of the tube. However, readers should note that in the case of any PHE, its geometrical length is not equivalent to the substitute length of the channels between the plates that usually is unknown. Thus, it was decided to avoid this length in the model (1) and its influence is lumped in the substitute geometrical parameters p_1 and p_2. Two other model parameters h_1 and h_2 denote the substitute heat exchange coefficients.

During the simulation experiments, the model (1) was solved numerically by the space discretization finite difference method (FDM) (Carver and Hinds, 1978) with the constant space discretization instant $\Delta z = 0.02$.

The suggested model (1) is the simplification because its form does not match the construction of the real PHE unit. However, this simplification is fully justified if the parameters p_1, p_2, h_1 and h_2 were assumed to be time-varying with the values depending on the variations of the operating point of the heat exchange process. In this work, their values were indentified based on the measurement data collected from the real PHE working as a part of the laboratory heat exchange and distribution plant. The experiments were carried out for different operating points defined by different inlet temperatures and flow rates in both circuits. Both flow rates F_1, F_2 were successively adjusted within the range between 1.5 and 3.5 with the increment of 0.5, always keeping the flow F_2 equal or smaller than the flow rate F_1. For each operating point, the variations of the inlet temperature of the hot water T_{in1} were applied to the unit by the successive step changes of the power supplied to the electric flow heater warming the hot water flowing into PHE.

Based on the modelling error $\underline{e} = (\underline{T}_{out,P} - \underline{T}_{out,M})$, where $\underline{T}_{out,P}$ represents the vector of the measured values of T_{out1}, T_{out2} while $\underline{T}_{out,M}$ represents the vector of the corresponding temperatures computed from the model (1) excited with the same measured input signals, the following quality factor was defined:

$$J(p_1, p_2, h_1, h_2,) = \sum \underline{e}^T \mathbf{Q} \underline{e}\,,\ \mathbf{Q} = \mathrm{diag}(q > 0) \quad (2)$$

and the optimal values of the parameters p_1, p_2, h_1 and h_2 were identified for each operating point by the minimization of $J(.)$ applying the Nelder and Mead Simplex numerical algorithm (Nelder and Mead, 1965; Lagarias, Reeds, Wright, and Wright, 1998). It was found that the optimal values of these parameters vary from one operating point to another in a relatively narrow range so the averaged values $p_1 = 1.078$, $p_2 = 1.598$, $h_1 = 0.112$, $h_2 = 0.071$ were finally accepted for further simulations. This choice ensures that the model (1) represents the dynamical behaviour of the real PHE with acceptably small modelling inaccuracies for wide variations of the of the operating point.

3 CONTROLLER SYNTHESIS

In this Section, the model-based controller for the considered PHE is derived on the basis of the simplification of the distributed parameter model (1). It is also suggested how to compensate for the potential modelling inaccuracies to ensure the offset-free control in the practical cases.

3.1 Linearizing Control Law

For the model-based linearizing controller synthesis, there is a need to derive the dynamic equation of the proper degree describing directly the controlled variable $Y(t) = T_{out2}(t) = T_2(z=0,t)$ and including the manipulated variable $u(t) = T_{in1}(t) = T_1(z=0,t)$ in the input-affine form. It can be obtained by rewriting Eq. (1b) for $z = 0$, which corresponds to the outlet of the warmed water:

$$\frac{dY(t)}{dt} = \frac{F_2(t)}{p_2}\frac{\partial Y(t)}{\partial z}\Big|_{z=0} + h_2\big(u(t) - Y(t)\big). \quad (3)$$

Eq. (3) clearly shows that the considered dynamical system has the unitary relative degree. Thus, the linearizing controller can be derived by assuming constant set point Y_{sp} and the first order reference model (Bastin and Dochain, 1990):

$$\frac{dY(t)}{dt} = \lambda\big(Y_{sp} - Y(t)\big), \quad (4)$$

where $\lambda > 0$ denotes the tuning parameter. Then, after combining Eqs. (3) and (4), the following form of the linearizing controller can be derived:

$$u(t) = \frac{1}{h_2}\left[\lambda\big(Y_{sp} - Y(t)\big) - \frac{F_2(t)}{p_2}\frac{\partial Y(t)}{\partial z}\Big|_{z=0} + h_2 Y(t)\right] \quad (5)$$

The control law (5) ensures very good control performance, due to the fact that it compensates for the process dynamics and that it provides the feedforward action from the measurable disturbing flow rate F_2. However, there are some very hard difficulties that must be managed when it is to be applied in the practice:

- the controller (5) requires on-line information about the space derivative $\frac{\partial Y(t)}{\partial z}\Big|_{z=0}$; its accessibility is limited if there is a lack of any measurement data from the temperature T_2 inside the unit;
- this is the model-based controller and in this form, its performance strictly depends on the modelling accuracy; any modelling inaccuracies will result in the regulation offset.

In the next Sections, it is shown how to manage these difficulties in the practical applications.

3.2 Space Derivative Approximation

Apart from measurement data for the controlled output Y, the on-line approximation of the space derivative $\frac{\partial Y(t)}{\partial z}\Big|_{z=0}$ requires additional measurements for the temperature T_2 inside the unit. For the simplest approximation by the first order discrete forward difference, this space derivative could be computed as:

$$\frac{\partial Y(t)}{\partial z}\Big|_{z=0} \approx \frac{Y(t) - T_2(z = 0 + \delta z, t)}{\delta z} \tag{6}$$

and the information from a single additional sensor would be required. If the higher-order forward difference was considered for the approximation, the corresponding higher number of sensors would be required to measure the temperature T_2 at the certain locations along the unit. For Eq. (6), the accuracy of the approximation depends strictly on the choice of the distance δz between the outlet of the cold water where Y is measured and the neighbouring location of the second sensor at $z = 0+\delta z$.

In the practice, even if the heat exchanger was constructed as a tubular double-pipe unit, locating the temperature sensor inside the tube would be very difficult, especially that it is required to keep the distance δz as small as possible. In the case of PHE, from practical viewpoint, this approach is unacceptable due to the construction of the unit based on the single plates. Thus, for the practical applications, another more realistic solution must be suggested.

The simplest choice is to benefit directly from the model (1) that was tuned based on the real measurement data and thus it ensures relatively high accuracy. After discretization by FDM, it is possible to use any discrete-space value of T_2 computed from Eq. (1b) assuming $\delta z = k*\Delta z$ with k chosen freely as any natural number. At the same time, for higher-order forward approximating difference, any required number of the discrete-space values of T_2 can be computed. This approach is effective but the FDM discretization of the model (1) usually requires high order of the approximating set of the ordinary dynamical differential equations and this set has to be integrated numerically on-line jointly with the controller (5). It can be a significant difficulty when the controller is to be implemented in the PLC (Programmable Logic Controller) already existing in the industrial control loops. In such cases, the computational complexity of this approach still can be too high.

Another possibility is to simplify the model (1) by applying the space discretization method, which ensures relatively low order of the approximating set of the dynamical equations without significant drop of the modelling accuracy. In this paper, the orthogonal collocation method (OCM) is suggested for this purpose (Villadsen and Michelsen, 1978).

For OCM, N+1 discretization points are chosen. Two of them are always fixed as the boundary points $z_0 = 0$ and $z_N = 1$ while the other $M = N$-1 internal points are determined as roots of the general orthogonal Jacobi polynomial, whose coefficients are calculated by the formula depending on the values of two parameters: α and β. Consequently, the location of M internal discretization points can be adjusted by choosing the values of $\alpha > -1$ and $\beta > -1$. Then, after applying OCM to the model (1), the approximating set of the ordinary dynamical equations is obtained:

- for $z_0 = 0$ (outlet of the cold water):

$$\begin{cases} T_1(z_0, t) = T_{in1}(t) \\ \dfrac{dT_{out2}(t)}{dt} = \dfrac{F_2(t)}{p_2} A_{2,i}(t) + h_2 d_0 \left(T_{in1}(t) - T_{out2}(t)\right) \end{cases} \tag{7a}$$

- for z_i (i = 1..N-1):

$$\begin{cases} \dfrac{dT_1(z_i, t)}{dt} = -\dfrac{F_1(t)}{p_1} A_{1,i}(t) - h_1 d_i \left(T_1(z_i, t) - T_2(z_i, t)\right) \\ \dfrac{dT_2(z_i, t)}{dt} = \dfrac{F_2(t)}{p_2} A_{2,i}(t) + h_2 d_{i-1} \left(T_1(z_i, t) - T_2(z_i, t)\right) \end{cases} \tag{7b}$$

- for $z_N = 1$ (inlet of the cold water):

$$\begin{cases} \dfrac{dT_{out1}(t)}{dt} = -\dfrac{F_1(t)}{p_1} A_{1,i}(t) - h_1 d_{N-1} \left(T_{out1}(t) - T_{in2}(t)\right) \\ T_2(z_N, t) = T_{in2}(t) \end{cases} \tag{7c}$$

where $A_{1,i}(t)$ and $A_{2,i}(t)$ respectively denote the OCM-based approximation of the corresponding space derivatives, calculated for i = 0 .. N as:

$$\begin{cases} A_{1,i}(t) = \displaystyle\sum_{j=0}^{N} \left(\frac{d\hat{L}_j(z)}{dz}\Big|_{z_i} T_1(z_j, t) \right), \\ A_{2,i}(t) = \displaystyle\sum_{j=0}^{N} \left(\frac{d\hat{L}_j(z)}{dz}\Big|_{z_i} T_2(z_j, t) \right) \end{cases} \tag{7d}$$

and $\hat{L}_j(z)$ is the j-th component of the Lagrange interpolating polynomial. At the same time, d_j (j = 0 .. N-1) denote the distances between the corresponding neighboring discretization points as $d_j = z_{j+1} - z_j$.

Based on the OCM approximation (7) of the PHE model, the approximation of the space derivative required for computing the control law (5) can be suggested by (7d) as $\frac{\partial Y(t)}{\partial z}\big|_{z=0} \approx A_{2,0}(t)$. It requires that the whole approximating OCM model (7) must be excited by the measurement data accessible from the real process and computed on-line jointly with the controller (5).

Fig. 2 shows the modelling accuracy of the OCM model for the chosen operating point defined by the flow rates F_1 and F_2. This accuracy depends on the

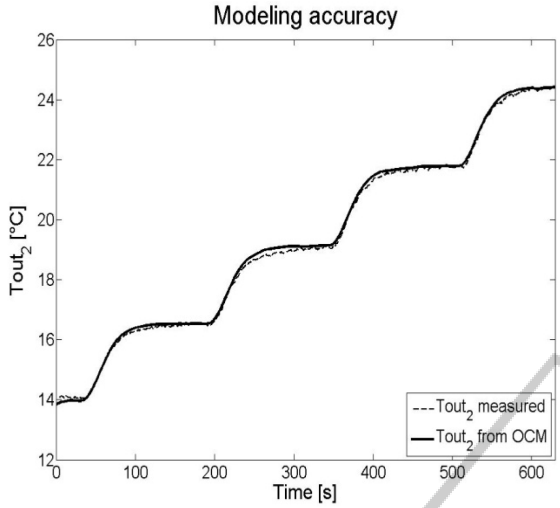

Figure 2: Accuracy of the OCM model for the chosen operating point.

choice of the number of the discretization points N+1 and on the values of the parameters α, β. For the considered case, the values of N = 6, α = -0.06 and β = -0.53 were adjusted experimentally to ensure the modelling accuracy comparable to the accuracy of the FDM approximation. It can be noticed that the order of the OCM approximation of the model (1) is several times lower than the one for the FDM approximation. Thus, in the case when the OCM approximating model (7) is to be implemented jointly with the controller (5), the computational complexity of this approach is acceptable from the practical viewpoint.

3.3 On-line Compensation for Modelling Inaccuracies

Even if the parameters p_1, p_2, h_1 and h_2 are adjusted based on the real measurement data collected from the laboratory PHE to ensure relatively high modelling accuracy of the OCM approximation (7), in the practical cases it must be assumed that this accuracy is limited and its compensation should be included in the final form of the linearizing controller. For this purpose, the idea suggested in (Czeczot, 2003) for the adaptive control of the distributed parameter biochemical reactors is applied. Eq. (3) is completed with the single additional time-varying parameter R_Y that represents the additive modelling inaccuracies:

$$\frac{dY(t)}{dt} = \frac{F_2(t)}{p_2} A_{2,0}(t) + h_2\big(u(t) - Y(t)\big) - R_Y(t) \,. \tag{8}$$

Its value must be estimated on-line based on the measurement data from the real process. After discretization of Eq. (8) with the sampling time T_S and defining the auxiliary variable w:

$$\underbrace{\frac{Y(t) - Y(t - T_S)}{T_S} - \frac{F_2(t)}{p_2} A_{2,0}(t) - h_2\big(u(t) - Y(t)\big)}_{w(t)} = \\ = -R_Y(t) \tag{9}$$

the scalar form of the Weighted Recursive Least-Squares (WRLS) method can be applied to calculate the estimate $\hat{R}_Y$:

$$P(t) = \frac{P(t - \mathrm{T_S})}{\alpha_f}\left(1 - \frac{P(t - \mathrm{T_S})}{\alpha_f + P(t - \mathrm{T_S})}\right), \tag{10a}$$

$$\hat{R}_Y(t) = \hat{R}_Y(t - \mathrm{T_S}) - P(t)\big(w(t) + \hat{R}_Y(t - \mathrm{T_S})\big), \tag{10b}$$

where $\alpha_f \in (0,1)$ is the forgetting factor.

After substituting the unknown parameter R_Y by its on-line estimate $\hat{R}_Y$ and combining Eqs. (4) and (8), the final discrete form of the linearizing controller with the on-line compensation for the modelling inaccuracies can be derived:

$$u(t + \mathrm{T_S}) = \\ = \frac{1}{h_2}\left[\lambda\big(Y_{sp} - Y(t)\big) - \frac{F_2(t)}{p_2} A_{2,0}(t) + h_2 Y(t) + \hat{R}(t)\right] \tag{11}$$

It should be implemented jointly with the on-line numerical integration of the OCM approximation of PHE (7) and computing of the estimation procedure (9)-(10).

This approach is very similar to the Balance-Based Adaptive Controller (B-BAC) suggested by Czeczot (2001) for control of the nonlinear lumped parameter systems and from this viewpoint, it can be considered as the extension of the B-BAC methodology for the control of the distributed parameter heat exchangers. The major difference is the direct application of the distributed parameter model for the synthesis of the final form of the control law.

4 SIMULATION RESULTS

This section shows the results of the simulation experiments carried out to validate the control performance of the suggested B-BAController (11). The model (1) numerically integrated by FDM was considered as the real system.

In the practice, the variations of the manipulated variable $u(t) = T_{in1}(t) = T_1(z=0,t)$ must be applied as the set point for the heating system with the inner control loop that ensures possibly high tracking properties. Thus, this actuating system has its own dynamics that can deteriorate the performance of the suggested PHE control system. During simulation experiments, this dynamics was simulated by the additional first-order lag system with unitary gain and time constant adjusted as T_H = 6 [s]. Readers should note that this dynamics is not included in the model applied for the synthesis of the B-BAController (11) and it can be considered as the unknown substitute dynamics of the actuating system.

It was also decided to make the simulation results more realistic by adding the additive random noise to the measurement data from the controlled temperature T_{out2} and for the measured disturbances F_1, F_2 and T_{in2}. This noisy data was used for computing the estimation procedure (9) - (10) and the manipulated variable by the control law (11). The same data was also applied to excite the OCM model used for approximation of the space derivative $\frac{\partial Y(t)}{\partial z}\big|_{z=0} \approx A_{2,0}(t)$ for both the estimation and the B-BAController.

The control performance of the suggested B-BAController (11) is compared with the performance of the conventional PI controller that is still in use in the vast majority of the industrial control loops. The PI controller was tuned based on the process step response. Then, its tunings were recalculated into the tunings of the B-BAController (11) (namely, into its gain λ and the forgetting factor for the estimation procedure α_f) by the tuning method suggested by Stebel *et al.* (2014). Finally, both controllers were retuned manually to ensure possibly the same aperiodic tracking properties. Thus, it can be assumed that both controllers were tuned equivalently with the tunings k_r = 1.7, T_I = 19.8 [s] for the conventional PI controller and λ = 0.12, α_f = 0.9949 for the B-BAController (11). This equivalence can be seen in Fig. 3 that shows the tracking properties of both controllers in the presence of the indicated step changes of the set point Y_{sp}.

For this equivalent tuning, the disturbances rejection for both controllers was investigated. The system with the B-BAController (11) provides the feedforward action from the measurable disturbances F_2 and T_{in2}, which results from the direct application of the distributed parameter model of PHE for the synthesis of the control law. Thus, the significantly better disturbances rejection can be obtained for the B-BAController (11), in the comparison with the equivalently tuned conventional PI controller.

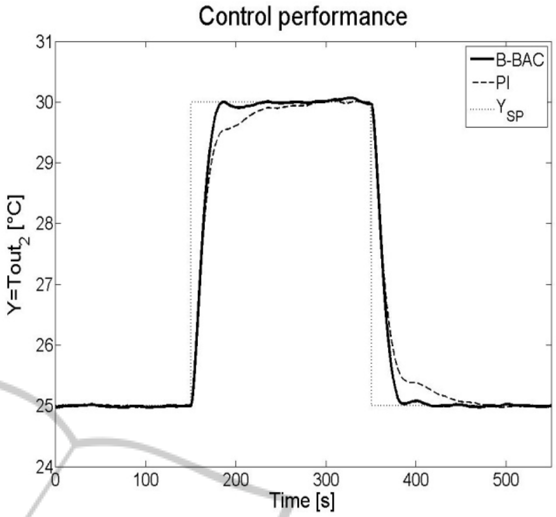

Figure 3: Tracking properties of the considered controllers. Noisy case.

The control performance of both controllers can be seen in Figs. 4 - 6, at the presence of the step changes of the respective disturbing signals F_2, T_{in2} and F_1 applied to the system. Upper diagrams of each figure show the variations of the controlled variable $Y = T_{out2}$, while the lower diagrams show the accuracy of the approximation of the space derivative $A_{2,0}$ at the outlet of the cold water and required for computing the estimation procedure (9)-(10) and the control law (11). The FDM model is used to compute the real value of $A_{2,0}$ while its approximation is computed from the OCM model. Readers should note relatively high accuracy of the space derivative approximation and the fact that such comparison is possible only in simulation - in the practice, the real value of $A_{2,0}$ is always unknown.

Note that at each case, the B-BAController (11) ensures significantly shorter settling time with smaller overregulation, even in the presence of the changes of the disturbing flow rate F_1, whose measurement data is not included in the B-BAController (11). At the same time, the presence of the measurement noise does not corrupt the control performance of the B-BAController (11) more significantly as it does in the case of the conventional PI controller, which makes the suggested approach an promising alternative in the industrial practical systems for the control of PHE.

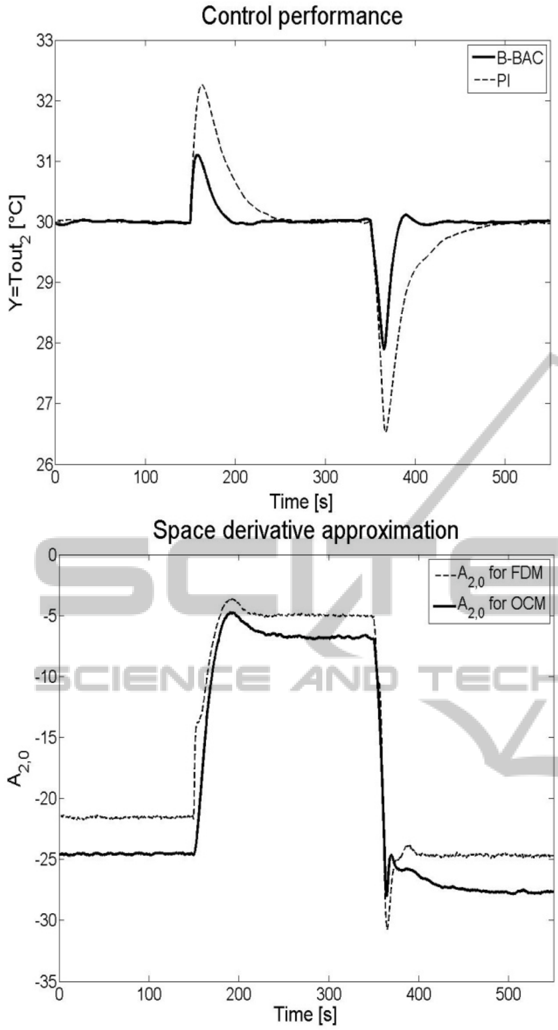

Figure 4: Rejection of the disturbing changes of the flow rate F_2: at t = 100 the step change of F_2: 2.5 → 3.5; at t = 300 the step change of F_2: 3.5 → 1.5. Noisy case. Upper diagram - controlled variable, lower diagram - approximation of the space derivative $A_{2,0}$.

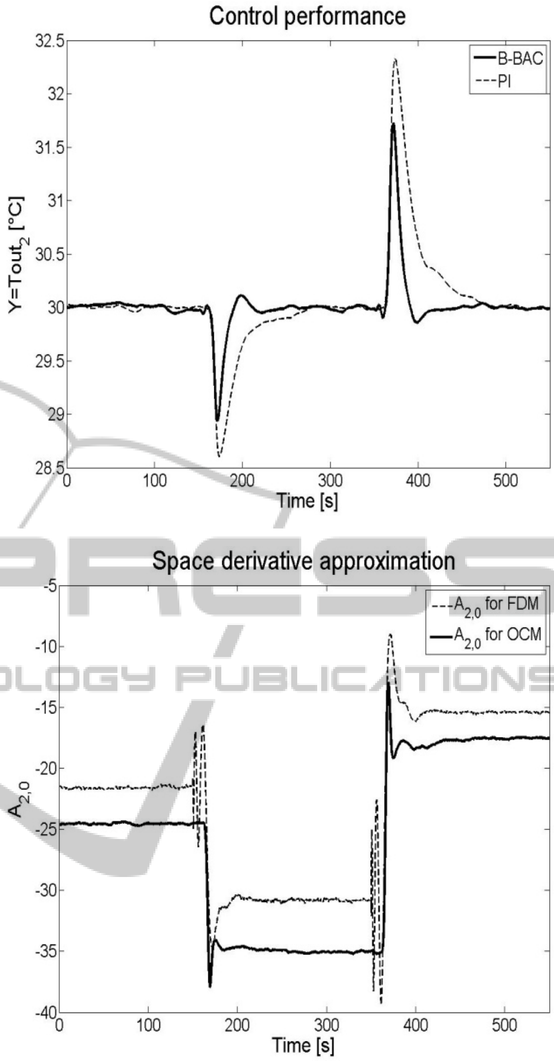

Figure 5: Rejection of the disturbing changes of the inlet temperature of the cold water T_{in2}: at t = 100 the step change of T_{in2}: 15 → 20; at t = 300 the step change of T_{in2}: 20 → 10. Noisy case. Upper diagram - controlled variable, lower diagram - approximation of the space derivative $A_{2,0}$.

5 CONCLUSIONS

This paper shows the potential possibility of the application of the distributed parameter PHE model for the synthesis of the model-based linearizing controller. This approach is based on the low-degree OMC approximation of the partial differential equations describing the process dynamics. Based on this approximation, the space derivative of the controlled outlet temperature of the cold water is computed and this derivative is directly included in the control law to provide the feedforward action and to compensate for process dynamics. The potential modelling inaccuracies that would result in the regulation offset are compensated by the application of the on-line estimation of a single additive parameter. The estimation procedure requires the same measurement data and the same OMC approximating model that are incorporated in the suggested distributed parameter B-BAController.

The simulation experiments carried out under the realistic scenarios considering the not modelled dynamics of the actuating heating system show the superiority of the suggested controller over the conventional PI controller. The practical applicability of these results is additionally

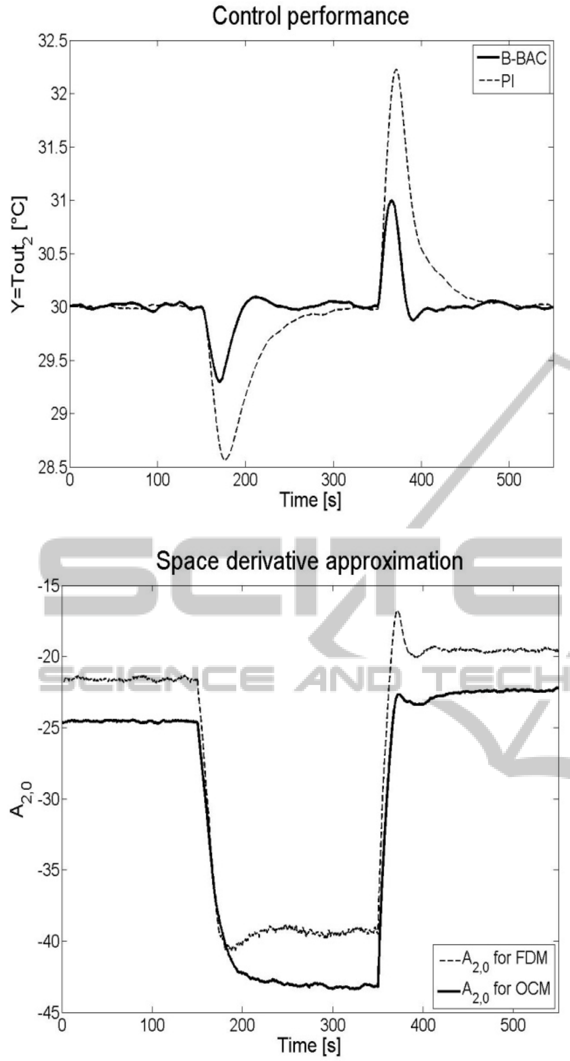

Figure 6: Rejection of the disturbing changes of the flow rate F_1: at t = 100 the step change of F_1: 2.5 → 3.5; at t = 300 the step change of F_1: 3.5 → 1.5. Noisy case. Upper diagram - controlled variable, lower diagram - approximation of the space derivative $A_{2,0}$.

supported by the fact that both the FDM model and its OCM approximation were tuned and verified based on the real measurement data collected from the PHE operating in the laboratory heat exchange and distribution setup.

From the practical point of view, the most important advantage of the suggested distributed parameter B-BAController is its relatively low computational complexity and easy tuning, which are combined with very good disturbances rejection and resistance to the measurement noise. Due to its low dimension, the approximating OCM model can be easily integrated numerically even in the programmable logic controllers that already work in the existing industrial control loops. Readers should note that even if the computational power of the modern PLCs is relatively high and still growing, the practical implementations are still based on the previous well established versions of the PLCs and in the cases when a huge number of control loops are to be operated simultaneously, their computational power still can be a significant limitation.

At the same time, the OCM model accuracy ensures that there is no need to apply any state observer technique for on-line approximation of the space derivative of the controlled variable, which significantly simplifies the tuning of the control system. Surely, it is possible to use the suggested OCM model for the synthesis of any well established observer (Luenberger one or Kallman filter) because this model is always observable but in the considered case, this approach is not relevant. It would require additional tuning of the observer, which can be far from being trivial, especially if the observer is to be nonlinear.

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