Preprints of the 2012 20th Mediterranean Conference on Control & Automation (MED), Barcelona, Spain, July 3-6, 2012

Parameters identification of a chemical tank: A case study

Ondřej Bruna, Zdeněk Váňa

Abstract— **Even though a modeling of a chemical tank is, in our case, in principle the modeling of a heat exchanger and belongs to the classical tasks, there are always some phenomena in practice, which are either difficult or impossible to include into the model. This especially holds in case of the old devices, where these parasitic events can have quite a large effect and can degrade both the model and the control strategy. The chemical tank being dealt within this paper suffers from many unpleasant phenomena, making it hard to come up with a proper identification method and model. In this paper, several modeling and identification approaches applied to the industrial type of shell and tube heat exchangers are presented. The goal is to show that less complex model serves the purpose better than a complex model and is also suitable for model based control. The control of a heat exchanger has been treated in many papers using some of the "classical" control concepts. In contrary, we propose a predictive control scheme, which compared to previous control approach have saved 25 % of energy.**

I. Introduction

Chemical tanks are storage containers for chemicals and from control engineering point of view, there are several crucial aspects of interest, such as a control of the tank temperature, pH of chemicals, inside pressure, vacuum etc. The following text will be confined only to tanks with the temperature control. Such a class of tanks can be interpreted as heat exchangers.

There have already been some attempts to employ advanced control techniques for control of thermodynamical systems, mainly for buildings, which have proven, both by simulation studies and industrial practice, significant energy savings potential. The attribute *advanced* in this case stands for model-based control techniques taking into account predictions of disturbances acting on the system [1]. A well identified model is then necessary, however not sufficient, aspect for perfect control.

Modeling of a heat exchanger as a common industrial process has been broadly studied in a number of papers. From the physical point of view, it is a first order process, thus the general description seems not to be very difficult, however, many limitations and constraints arise in the practice. Therefore it will be referred rather to those papers which employ innovative techniques. A very comprehensive survey of heat exchangers modeling can be found in [2]. The paper by [3] can be highlighted as one of the first attempts to deal with non-linearity in this process, where some specific transformations of the process variables lead to a reduction of the non-linear effects. Further, several modern techniques have been applied such as non-linear statistical approach using a neural networks [4], [5], physically-based pinch method [6], [7] or fuzzy models (see e.g. [8], [9]). The papers cited above cover many of control strategies from classical to predictive.

The paper is devoted to the modeling and control of the real heat exchanger in chemical industry. Particularly, a complex solution for a tank is proposed, where the chemical intermediate product is kept until it is drained out. A number of practical issues arising during modeling of such a heat exchanger is treated.

The process is non-linear from its physical nature. By a closer look, it can be seen, that the nonlinearity is caused by the liquid level in the tank. Thus, it can be modeled as a linear parameter varying system or, for a fixed liquid level as a linear system. This is plausible since draining out and pumping in occurs only rarely, identification of the model can be performed in sections of data with steady level. The approaches to be applied are as follows [10].

1) **First principles modeling.** This is one of the oldest approaches counting on the physical properties of the process. This method is necessary for the understanding and insight into the process.
2) **Family of the prediction error methods (PEMs).** Since not all the system parameters are known, the statistical methods are useful to employ. They provide a functionality to identify both linear and non-linear models minimizing error between measured and predicted data.
3) **Subspace identification (4SID).** Yet another linear system identification method which includes automatic order selection. 4SID methods yields state-space models. 4SID family is a representative of black-box approaches. It is often used when the structure of the process is unknown, which is not the case. However, it is used here for comparison reasons.
4) **Linear parameter varying (LPV) system identification.** The influx to the heat exchanger can be viewed upon as either the system input or a time-varying parameter. In the latter case, the underlying model is modeled as LPV. Since this model allows to incorporate the liquid level it is challenging to compare this model with linear models.
5) **Grey-box identification.** First principle model comprises unknown parameters that need to be identified. ACADO Toolkit is used since it enables the identification of unknown parameters of a continuous time system. The software is still in experimental phase and

Ondřej Bruna is with Department of Measurement and Zdeněk Váňa is with Department of Control Engineering (DCE), both Faculty of Electrical Engineering (FEE) of Czech Technical University (CTU) in Prague, Technická 2, 166 27 Praha 6, Czech Republic

978-1-4673-2529-5/12/$31.00 ©2012 IEEE

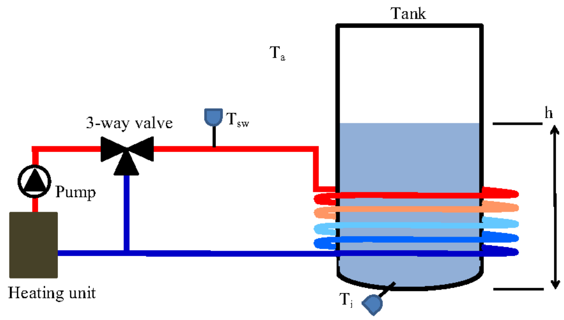


Fig. 1: A scheme of ABESON tank

is very interesting to use, as it was designed to be used for such class of problems as introduced in this paper. Thus, the motivation for using this program is to see its performance in real application out of test data.

This paper is organized as follows. Sec. II is devoted to modeling of the heat exchanger and identification of its parameters. We thoroughly examine the problem and provide a description of the methods used for the identification. The control problem is formulated in Sec. III. A comparison of a number of modeling approaches and evaluation of the performance of MPC applied to the real system is described in Sec. IV. Finally, the last section concludes the paper.

II. Identification

A. Description of the modeled system

The examined tank is used as a storage of ABESON (Dodecylbenzene Sulfonic Acid) before its final expedition. The temperature of the product before draining out is required to be within the range of 30 °C to 55 °C. If the temperature drops below the lower bound, ABESON becomes very dense and is difficult to pump out of the tank. In case of breaking the upper bound, the properties of the ABESON change and it becomes undesirable. Schematic sketch of the system is depicted in Fig. 1 and shows the integration of the heating system. Tank's content is tempered by a pipe going around the shell of the the tank. The tank is heated-up using supply water coming from three-way valve where the return water is mixed with the hot water from heating unit. Measurements of the supply water and temperature inside the tank are available using resistive temperature sensor Pt100. Ambient temperature is provided from NOAA[1] server using their weather forecast. Finally, level of the ABESON is also measured by hydrostatic pressure sensor. Note, that all the sensors inside the tank are placed at its very bottom.

During the data analysis we encountered several issues. The most of them were caused by mixing the ABESON in order to make temperature homogeneous. Unfortunately, this process cannot be described by an input since this happens only irregularly, there is no sensor indicating it, and it is a strictly manually controlled operation. Consideration of incorporating the mixing procedure into the model as an artificial input had taken place. The resulting model would be hybrid thus contradicting strict request for simplicity.

[1]National Oceanic and Atmospheric Administration (NOAA)

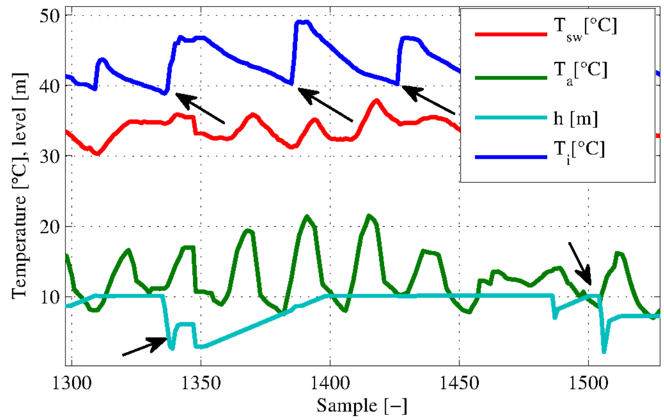


Fig. 2: Corrupted data example

As the temperature of the ABESON is measured at the very bottom of the tank and due to the lower radius of the tank at the bottom, the measured temperature is affected by the ambient environment more than if the sensor would be placed higher inside the tank. From this reason, the measured temperature (at the very bottom of the tank) rises rapidly for more than 10 °C during one mixing of the ABESON. The same result – a temperature step – is caused by pumping the ABESON out from the tank. The reason is similar – the temperature on the top is higher than one on the bottom. Specifically, when pumping the ABESON out, a valve on the bottom of the tank is opened and the hotter ABESON from the top of the tank gets down, where the temperature sensor is located. This causes a sudden rise of the temperature. This can be detected since there is a significant drop in the ABESON level.

The example of data corrupted by the aforementioned events is depicted in Fig. 2, where the cyan line is the level of ABESON. There are three increases of a product temperature – blue color. The occurrence is marked by arrows pointing in the direction of the artifact. The first is caused by draining out of the ABESON and the temperature sensor measures the hot liquid coming from the top. Then the level increases steadily when suddenly a second and third increase of temperature appears – this is caused by a mixing. Later the level is fixed at 10 m and yet another temperature increase appears, again due to the mixing. Due to mentioned issues the data sets had to be selected very carefully, altogether there were over 30 eligible samples. Note, when the level increases, the temperature increases as well. It is caused by the fresh ABESON – it has high temperature which is not measured. Therefore it cannot be incorporated into the model. Another phenomena in data are pointed by bottom arrows – when ABESON level drops down and then grows up again. It is caused by the pressure level sensor, which is sensitive for draining liquid in and out. Apart from the aforementioned issues, there are several other smaller problems, some of them follows. Firstly, the solar radiation also affects the inner temperature and it slows down the cooling process. The global solar radiation is not incorporated into the model as input (unmeasured disturbance), it affects the final estimate. Secondly, the temperature sensor measuring the supply water is placed at the control station and not at the tank itself. Ambient environment affects the supply water (because of a poor insulation of heating pipes) however is not measured.

B. Identification approaches

Multiple approaches were used to show, that not only methods such as LPV can yield acceptable results and to test how will the ACADO toolkit perform with real-life application. Use of several methods also enables that there will be more models to use and to objectively compare so the appropriate model of the system can be selected.

1) First principles models: The first principle model is solely based on known physical processes. The thermal flow from supply water to tank is described by the first fraction. In this case there is no insulation and the heat transfers through the shell of pipes and tank's metal shell only. The supply water flow is constant. The fact that heating pipes reach only 0.5 m from the bottom of the tank is also taken into account. The second fraction describes the heat transfer from ambient environment to the tank. In this case the process is slowed down by insulation.

Considering the measured signals, the general model of the tank can be written as

$$\begin{aligned}\dot{T}_i &= -\frac{T_i - T_{sw}}{C_i(h,\mathcal{P})\,R_1(h,\mathcal{P})} - \frac{T_i - T_a}{C_i(h,\mathcal{P})\,R_2(h,\mathcal{P})} = \\ &= -\frac{\lambda_1\,2\,\pi\,r\,h_1}{\rho\,\pi\,r^2\,h\,c\,l_1}\,(T_i - T_{sw}) - \frac{\lambda_2\,\pi\,r\,(2h + r)}{\rho\,\pi\,r^2\,h\,c\,l_2}\,(T_i - T_a) = \\ &= -\frac{2h_1\lambda_1}{\rho r c l_1 h}\,(T_i - T_{sw}) - \left(\frac{2\,\lambda_2}{r\,\rho\,c\,l_2} + \frac{\lambda_2}{\rho\,c\,l_2\,h}\right)(T_i - T_a),\end{aligned} \tag{1}$$

where T_i is the temperature in the tank, T_a is the ambient temperature, T_{sw} is the supply water temperature and where

$$\frac{1}{C_i(h,\mathcal{P})\,R_1(h,\mathcal{P})} = \frac{2\,h_1\,\lambda_1}{r\,\rho\,c\,l_1\,h}, \tag{2}$$

$$\frac{1}{C_i(h,\mathcal{P})\,R_2(h,\mathcal{P})} = \frac{2\,\lambda_2}{r\,\rho\,c\,l_2} + \frac{\lambda_2}{\rho\,c\,l_2\,h}, \tag{3}$$

with thermal conductivity of heating pipes λ_1, thermal conductivity of tank's insulation λ_2, thickness of the supply water pipe insulation l_1, thickness of tank's insulation l_2. Some parameters ($r = 1.4\,\mathrm{m}$, $\rho = 1080$ kg m^{-3}, $h_1 = 1.5$ m) are known whilse the others (λ_1, λ_2, l_1, l_2, c) are to be estimated. ABESON level can be viewed upon as input to the system or as a time varying parameter. By substitution for known parameters as $p_1 = -\frac{2h_1}{r\rho}$, $p_2 = -\frac{2}{r\rho}$ and $p_3 = -\frac{1}{\rho}$ and unknown parameters as $a_1 = \frac{1}{c}$, $a_2 = \frac{\lambda_1}{l_1}$ ans $a_3 = \frac{\lambda_2}{l_2}$, the (1) can be rewritten into

$$\dot{T}_i = \frac{p_1 a_1 a_2}{h}(T_i - T_{sw}) + \left(p_2 a_1 a_3 + \frac{p_3 a_1 a_3}{h}\right)(T_i - T_a). \tag{4}$$

For the sake of simplicity substitution $a_1\,a_2 = \alpha$ and $a_1\,a_3 = \beta$ is used. Moreover a prior information about the unknown parameters from data sheets is known as well, namely, the width of the insulation layer $l_2 = 0.2$ m and the thickness of heating pipes together with tank $l_1 = 0.02$ m. Then λ_2 can be expressed as $\langle 0.2; 0.6\rangle\,\mathrm{W\,m^{-1}\,K^{-1}}$ and that tank-pipes thermal conductivity λ_1 lies within $\langle 2; 10\rangle$ W m^{-1} K^{-1}. Specific heat of ABESON is similar to the water with $c = 4180$ J kg^{-1} K^{-1}. Finally, all the substitutions lead to the prior of the parameters to be estimated, $\alpha = \langle 0.02; 0.1\rangle$ and $\beta = \langle 2\cdot 10^{-4}; 6\cdot 10^{-4}\rangle$.

For the construction of the discrete-time model, the Euler's discretization has been utilized:

$$T_i(k+1) = \dot{T}_i T_s + T_i(k), \tag{5}$$

with $T_s = 600\,\mathrm{s}$ being an identification sampling time. This sampling time has been chosen mainly due to fast dynamics of disturbances entering the system. However, the process itself is rather slow, therefore for control purposes $T_{s,cont} = 3600\,\mathrm{s}$ is used. State-space description of a discrete-time system is then

$$T_i(k+1) = AT_i(k) + BT_{sw}(k) + VT_a(k), \tag{6}$$

where $A \in \langle 1.03 - 7.34\cdot 10^{-1}/h; 1.01 - 1.43\cdot 10^{-1}/h\rangle$, $B \in \langle 1.43\cdot 10^{-1}/h; 7.14\cdot 10^{-1}/h\rangle$ and $V \in \langle -0.01 - 1.33\cdot 10^{-2}/h; -0.03 - 4.00\cdot 10^{-2}/h\rangle$.

2) Prediction error methods: In case that the level of the ABESON is fixed, the process can be modeled as a linear and time-invariant. For these cases, the well-known multivariate ARX model can be used [10].Then, the description of the system can be expressed in form of the transfer function as follows

$$G(z) = [G_{sw}(z)\ ,\ G_a(z)] = \left[\frac{K_{sw}}{z + D}\ ,\ \frac{K_a}{z + D}\right], \tag{7}$$

where $K_{sw} = \frac{p_1\alpha T_s}{h}$, $K_a = p_2\beta T_s + \frac{p_3\beta T_s}{h}$, $D = -\frac{p_1\alpha T_s + p_3\beta T_s}{h} - p_2\beta T_s + 1$.

From these equalities, the unknown parameters α, β can be obtained. Additionally, the parameters K_{sw}, K_a have to be positive. The results of estimated parameters using ARX is listed in Tab. I.

3) Subspace identification: The family of subspace identification methods (4SID) is widely used for identification of linear multiple-input multiple-output (MIMO) systems [11], [12]. The objective of the subspace algorithm is to find a linear, time invariant, discrete time model in an innovation form

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) + Ke(k), \\ y(k) &= Cx(k) + Du(k) + e(k), \end{aligned} \tag{8}$$

where A, B, C, D are system matrices, K is Kalman filter gain and e is a white noise sequence [13]. The algorithm firstly determine the order of the model, and afterwards find the model as well as state and measurement noise covariance matrices. The results of estimated parameters using subspace algorithm are listed in Tab. I.

4) Linear parameter-varying system idenfitication: Linear parameter-varying (LPV) models assume, that the parameters of the model vary in time and are measured [14], [15].

Let the varying parameter $\delta(k)$ is measured. Identification method using LPV model separates a parameter causing non-linearity from the system $y = f(u, \delta)$, where u, y is the measured experimental data, and it allows to identify the linear part of the system of the following structure:

$$\begin{aligned} X(k+1) &= AX(k) + B_1 u(k) + B_2 w(k), \\ z(k) &= C_1 X(k) + D_{11} u(k) + D_{12} w(k), \\ y(k) &= C_2 X(k), \\ w(k) &= \delta(k) z(k), \end{aligned} \tag{9}$$

where $A \in \mathcal{R}^{n\times n}$, $B_1, B_2 \in \mathcal{R}^{n\times 1}$, $C_1, C_2 \in \mathcal{R}^{1\times n}$, D_{11}, D_{12} are scalars and n is model order. Using the fractional transformation, it is possible to identify system using a linear model with one varying parameter by means of recursive least square (RLS).

For the first order case, the matrices $A = a_{11}$, $B_1 = b_{11}$, $B_2 = 1$, $C_1 = c_1$, $D_{11} = d_1$ and $D_{12} = d_2$. While the vector of parameters Θ and regressor Ψ are defined as

$$\begin{aligned} \Theta &= [\alpha_j,\ \alpha_{n+1},\ \alpha_{n+2},\ \alpha_{n+2+j},\ \alpha_{2n+3}]^T \\ \Psi_k &= \left[X(k)^T,\ u(k),\ x^1_{k+1},\ \delta(k)X(k)^T,\ \delta(k)u_k\right] \end{aligned} \tag{10}$$

System parameters are computed as $\alpha_1 = \frac{a_{11}}{d_2}$, $\alpha_2 = \frac{b_{11}}{d_2}$, $\alpha_3 = \frac{1}{d_2}$, $\alpha_4 = a_{11} - \frac{c_{11}}{d_2}$, $\alpha_5 = b_{11} - \frac{d_1}{d_2}$. The parameters in vector Θ are obtained from solving system $\delta(k)x_{k+1} = \Psi_{k+1}\Theta$ using RLS. The discretized equation of the tank can be formulated as follows [14]

$$\begin{aligned} T_i(k+1) &= \begin{bmatrix} -p_2\beta T_s + 1 & 0 & -p_2\beta T_s \end{bmatrix} \begin{bmatrix} T_i(k) \\ T_{sw}(k) \\ T_a(k) \end{bmatrix} + w(k), \\ w(k) &= \delta(k) z(k), \\ z(k) &= \begin{bmatrix} -p_1\alpha T_s - p_3\beta T_s \\ +p_1\alpha T_s \\ +p_3\beta T_s \end{bmatrix}^T \begin{bmatrix} T_i(k) \\ T_{sw}(k) \\ T_a(k) \end{bmatrix}. \end{aligned} \tag{11}$$

Using this method, estimated parameters converged to $\alpha = 2.58 \cdot 10^{-2}$ and $\beta = 1.56 \cdot 10^{-3}$.

5) Identification by ACADO Toolkit: ACADO is a toolbox being developed for purposes of identification of non-linear systems. ACADO[2] is a software environment and algorithm collection for automatic control and dynamic optimization [16]. So far it has been mainly used in laboratory conditions and this was one of the first tests in real world application. It was an opportunity to test its capabilities of identification linear and non-linear systems.

The parameter estimates using ACADO Toolkit are displayed in Tab. I. The resulting parameters were determined as $\alpha = 2.41 \cdot 10^{-2}$ and $\beta = 7.89 \cdot 10^{-4}$ and were used to perform all the simulations.

[2]Automatic Control And Dynamic Optimization Toolkit (ACADO) http://www.acadotoolkit.org/

TABLE I: Table of parameters estimated by ARX, subspace (4SID) and ACADO Toolkit.

Data set	**ARX**		**4SID**		**ACADO**	
	α	β	α	β	α	β
1	0.0330	0.0033	0.0333	0.0009	0.0277	0.0002
2	0.0450	0.0019	0.0500	0.0010	0.0354	0.0001
3	0.0276	0.0016	0.0356	0.0008	0.0311	0.0010
4	0.0171	0.0022	0.0421	0.0002	0.0280	0.0008
5	0.0423	0.0107	0.0424	0.0008	0.0230	0.0018
6	0.0404	0.0003	0.0685	0.0035	0.0238	0.0001
7	0.0241	0.0053	0.0680	0.0016	0.0251	0.0012
Mean value	0.0328	0.0036	0.0486	0.0013	0.0277	0.0007
Standard deviation	0.0104	0.0035	0.0145	0.0011	0.0044	0.0006

TABLE II: Table of parameter β estimates (mean $\overline{\beta} = 1.026 \cdot 10^{-3}$, standard deviation $s = 0.401$)

Data set	β	data set	β
1	$1.353 \cdot 10^{-3}$	6	$1.036 \cdot 10^{-3}$
2	$1.014 \cdot 10^{-3}$	7	$0.528 \cdot 10^{-3}$
3	$1.193 \cdot 10^{-3}$	8	$0.205 \cdot 10^{-3}$
4	$1.449 \cdot 10^{-3}$	9	$1.439 \cdot 10^{-3}$
5	$1.157 \cdot 10^{-3}$	10	$0.881 \cdot 10^{-3}$

6) Decoupled identification of cooling and heating parts: This approach was used since the temperature in the tank was increasing only in very few and special cases (low ABESON level, high temperature of supply water and ambient temperature above zero, etc.) Therefore it was decided to try to identify the two parts separately in such a period of year when they take effect the most.

Using the mean value from Tab. II as fixed parameter for β we estimated the parameter α from heating parts. The parameter was determined as $\alpha = 2.80 \cdot 10^{-2}$.

III. Control

A. Control strategy

The main objective of the project was to propose energy saving solution which was easily understandable for practitioners from operation without higher education in control engineering. In different fields of expertise it was shown (see e.g. [1], [17]), that this can be achieved by predictive control utilizing incorporation of weather predictions into the optimization problem. Predictive control enables treating requirements such as disturbance rejection, satisfying physical and chemical constraints, reasonable reference tracking, counting on the weather forecast and the optimality (in sense of energy consumption). Due to its properties, the Model Predictive Control (MPC) seemed to be a perfect choice for the given process.

There is no measurement of the return water, thus the problem of derivation of the amount of consumed energy arises. To cope with this problem, we can assume the following. The supply water can be heated up only by the steam. Moreover, during the winter season (the main heating season) the steam is the only source of heat. Therefore the lower supply water temperature, the lower energy cost.

TABLE III: Table of the most reliable parameters estimates.

method	α	β
PEM	$3.56\,10^{-2}$	$3.10\,10^{-3}$
4SID	$4.30\,10^{-2}$	$1.20\,10^{-3}$
LPV	$2.58\,10^{-2}$	$1.56\,10^{-3}$
ACADO	$2.41\,10^{-2}$	$7.88\,10^{-4}$
Decoupled	$2.80\,10^{-2}$	$9.79\,10^{-4}$

From the reasons mentioned above, the (consumed energy is proportional to the water temperature), the supply water temperature replaces the energy in the MPC optimization criterion.

B. Formulation of the control problem

Let us denote the model for control as

$$T_i(k+1) = A(\delta, T_s)T_i(k)+B(\delta, T_s)T_{sw}(k)+V(\delta, T_s)T_a(k), \quad (12)$$

where $A(\delta, T_s), B(\delta, T_s), V(\delta, T_s)$ are appropriate parameter dependent model matrices and the other symbols have been defined in Sec. II-B.1. Aforementioned control strategy implies the following formulation of the MPC problem. The optimal control input sequence $T^*_{sw}(k)$, $k = 0, \ldots, N-1$ minimizes the cost function

$$J = \sum_{k=0}^{N-1} \|(T_i(k) - Z_i(k))Q\|_2^2 + \|(T_{sw}(k) - T_{sw,min})R\|_2^2,$$

such that (12) and

$$\begin{aligned} T_{sw,min} &\leq T_{sw}(k) \leq T_{sw,max}, \\ Z_{i,min}(k) &\leq Z_i(k) \leq Z_{i,max}(k), \\ \Delta T_{sw,min}(k) &\leq \Delta T_{sw}(k) \leq \Delta T_{sw,max}(k). \end{aligned}$$

hold as well as the other standard assumptions on the optimal problem to be solvable [18]. Z_i, which define range where the T_i is not penalized. The subscripts min, max denote minimum and maximum possible values of appropriate variables and Δ denotes a rate of change of corresponding variable and Q, R are weighting matrices.

IV. Results

A model of the storage tank was obtained as described in Sec. II. To identify the parameters of the system, several approaches have been applied. *i)* Linear - estimation of ARX model and use of 4SID methods *ii)* Non-linear - Graybox (using ACADO Toolkit) and LPV model parameter estimation method *iii)* Identification of decoupled cooling and heating parts The best parameter estimates are summarized in Tab. III. The choice of the best or the most reliable estimates is based on the cross validation of model responses on all data sets.

The parameters estimated by linear methods were plausible mainly during summer period; especially 4SID provided good results. But in winter, the parameters obtained by these approaches were not plausible as the data contained non-linearities which could not be tackled.

Using ACADO Toolkit the problem was reformulated in a non-linear fashion. The results were very close to the results provided by the LPV identification, which recorded the best results. We used the data set collected from December 2010 to February 2011. The values of the estimated parameters α, β varying in time are depicted in Fig. 3. The trajectory of the parameters was affected neither by changes of supply water temperature, nor by drops in level.

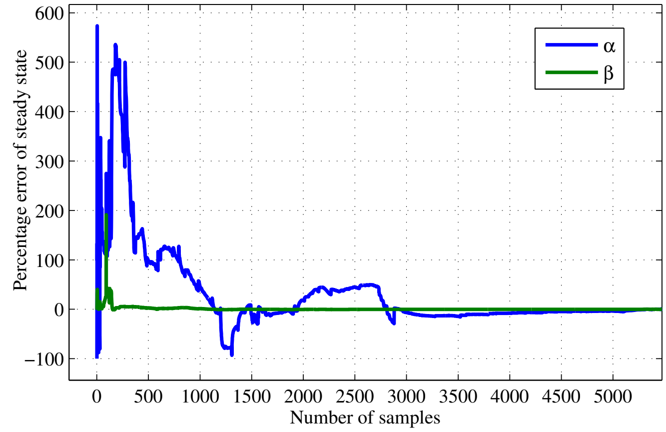


Fig. 3: Convergence of parameters and used data.

A. Model performance

For LTI models, the identification data sets were selected such that there are no changes in liquid level and no mixing. On the other hand, the verification data include parts with both steady and changing liquid levels (which makes it even more difficult to evaluate). The performance of the model can be seen in Fig. 4.

To evaluate its efficiency we computed a ratio between energy spent oh heating before applying MPC and after applying it. To compute the ratio we used (13).

$$R = \frac{\int_0^\tau T_{sw}(t)\mathrm{d}\tau}{\int_0^\tau T_{sw\,MPC}(t)\mathrm{d}\tau} \quad (13)$$

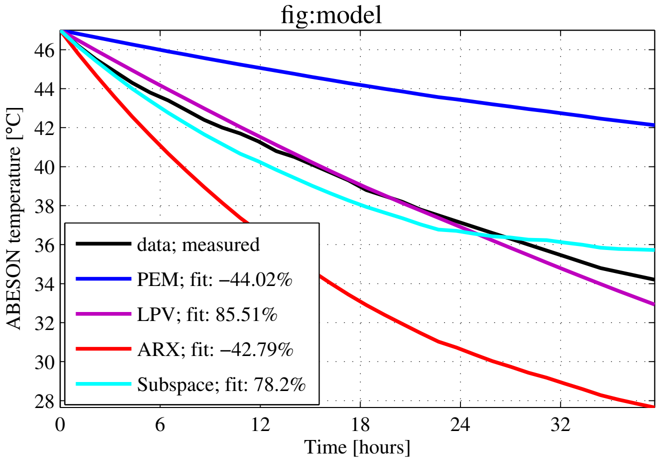
where $T_{sw}(t)$ is temperature of supply water before applying MPC and $T_{sw\,MPC}(t)$ is after MPC was applied.

B. Control performance

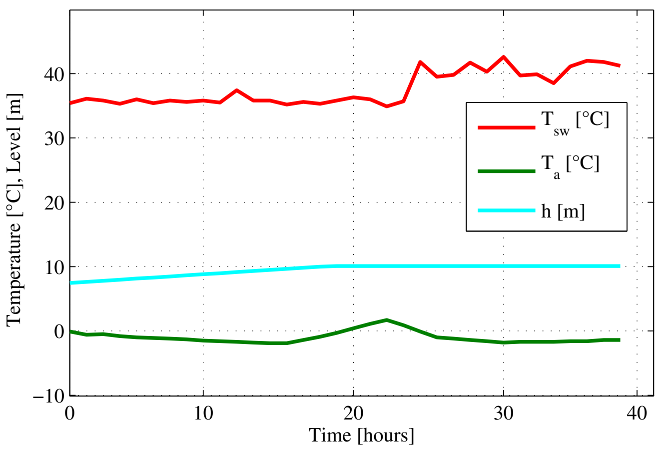
Data from the real operation of MPC are depicted in Fig. 5. The red line correspond to supply water temperature (solid) and its minimum and maximum constraints (dashed) while the blue refer to the ABESON temperature. The highlighted area stands for the range in which the ABESON temperature should stay. Parameters used for control are taken from LPV approach. MPC records satisfactory results since whenever the ABESON temperature decrease below the desired range due to unmeasured disturbances, MPC immediately starts to heat up the tank. In normal operation, when disturbances do not affect the ABESON temperature, MPC keeps the temperature at desired level.

V. Conclusions

In this paper, several identification techniques have been tested for ability of suitable approximation of the general non-linear model. The LPV model parameter estimation approach turned out to be the most applicable from all of



(a) Measured tank temperature and model open-loop responses



(b) Input signals

Fig. 4: Comparison of model responses both for linear and non-linear identification methods.

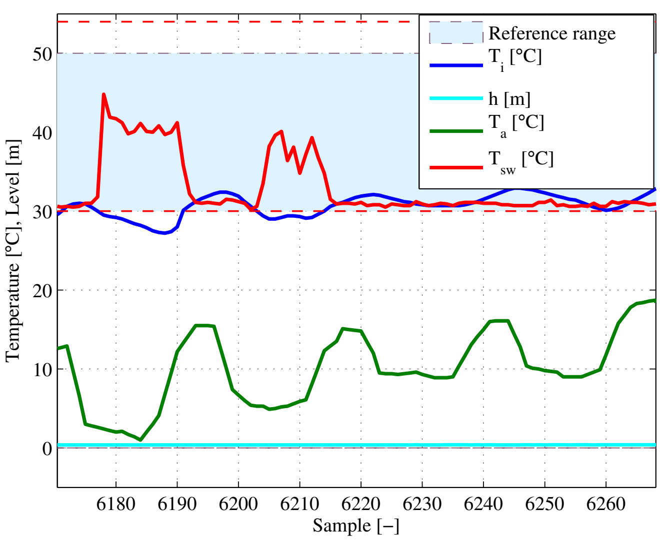


Fig. 5: MPC implemented.

the tested methods. Model obtained from this estimation was used for MPC, which, comparing to the previous control method, saved 25 %. ACADO produced acceptable results in regions with increasing level and was able to process a non-linear input. As it can be seen from Fig. 5, designed controller sets the lowest possible temperature to minimize the consumed energy while meeting the control requirements and input constraints. A great improvements in identification and control parts could be achieved if a better placement of the sensors was available and the stochastic manual mixing of the ABESON would be replaced by the automated mixing.

Acknowledgement

This work is supported by the grant of the Grant Agency of the Czech Republic Nr. P103/12/1187.

References

[1] J. Široký, F. Oldewurtel, J. Cigler, and S. Prívara, “Experimental analysis of model predictive control for an energy efficient building heating system,” *Applied Energy*, 2011.

[2] R. Shah, D. Sekulić, and K. (Firm), *Fundamentals of heat exchanger design*. Wiley Online Library, 2003.

[3] A. Alsop and T. Edgar, “Nonlinear heat exchanger control through the use of partially linearized control variables,” in *American Control Conference, 1986*. IEEE, 1989, pp. 1006–1013.

[4] S. Bittanti and L. Piroddi, “Nonlinear identification and control of a heat exchanger: A neural network approach,” *Journal of the Franklin Institute*, vol. 334, no. 1, pp. 135 – 153, 1997.

[5] G. Diaz, M. Sen, K. Yang, and R. McClain, “Dynamic prediction and control of heat exchangers using artificial neural networks,” *International journal of heat and mass transfer*, vol. 44, no. 9, pp. 1671–1679, 2001.

[6] B. Linnhoff and E. Hindmarsh, “The pinch design method for heat exchanger networks,” *Chemical Engineering Science*, vol. 38, no. 5, pp. 745 – 763, 1983.

[7] “Simultaneous optimization models for heat integration–i. area and energy targeting and modeling of multi-stream exchangers,” *Computers & Chemical Engineering*, vol. 14, no. 10, pp. 1151 – 1164, 1990.

[8] I. Skrjanc and D. Matko, “Predictive functional control based on fuzzy model for heat-exchanger pilot plant,” *Fuzzy Systems, IEEE Transactions on*, vol. 8, no. 6, pp. 705 –712, Dec. 2000.

[9] M. Fischer, O. Nelles, and R. Isermann, “Adaptive predictive control of a heat exchanger based on a fuzzy model,” *Control Engineering Practice*, vol. 6, no. 2, pp. 259–269, 1998.

[10] L. Ljung, *System Identification: Theory for user*. Prentice-Hall, Inc., Upper Saddle River, New Jersey, USA, 1999.

[11] S. Prívara, J. Cigler, Z. Váňa, L. Ferkl, and M. Šebek, “Subspace identification of poorly excited industrial systems,” in *Proceedings of the 49th IEEE Conference on Decision and Control*, 2010, pp. 4405–4410.

[12] L. Ferkl and J. Široký, “Ceiling radiant cooling: Comparison of armax and subspace identification modelling methods,” *Building and Environment*, vol. 45, no. 1, pp. 205–212, 2010, international Symposium on the Interaction between Human and Building Environment Special Issue Section.

[13] P. Van Overschee and B. De Moor, *Subspace Identification for Linear Systems*. Kluwer Academic Publishers, 101 Philip Drive, Assinippi Pard, Nowell, Massachusetts: Kluwer Academic Publishers, 1999.

[14] M. Nemani, R. Ravikanth, and B. Bamieh, “Identification of linear parametrically varying systems,” in *Decision and Control, 1995., Proceedings of the 34th IEEE Conference on*, vol. 3. IEEE, 1995, pp. 2990–2995.

[15] B. Bamieh and L. Giarré, “Identification of linear parameter varying models,” *International Journal of Robust and Nonlinear Control*, vol. 12, no. 9, pp. 841–853, 2002.

[16] B. Houska, H. Ferreau, and M. Diehl, “ACADO toolkit: An open-source framework for automatic control and dynamic optimization,” *Optimal Control Applications and Methods*, 2010.

[17] S. Prívara, J. Široký, L. Ferkl, and J. Cigler, “Model predictive control of a building heating system: The first experience,” *Energy and Buildings*, vol. 43, no. 23, pp. 564 – 572, 2011.

[18] E. Camacho and C. Bordons, *Model predictive control*. Springer Verlag, 2004.