Czech Technical University in Prague
Faculty of Electrical Engineering

Modeling and identification of a chemical storage tank

Diploma thesis

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ZADÁNÍ DIPLOMOVÉ PRÁCE

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Studijní program: Elektrotechnika a informatika (magisterský), strukturovaný
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Název tématu: **Modelování a identifikace chemického zásobníku**

Pokyny pro vypracování:

1. Seznamte se s problematikou identifikace termodynamických procesů v chemickém průmyslu.
2. Sestavte vhodný model pro termodynamické procesy probíhající v chemickém zásobníku. Model navrhněte tak, aby jej bylo v budoudnu možno použít pro řízení (model-based control).
3. Na základě naměřených dat (dodá vedoucí práce) identifikujte model z předchozího bodu a validujte jeho výsledky.

Seznam odborné literatury:

LJUNG, L. System Identification: Theory for the User (2nd edition). Prentice Hall, 1999.
JUANG, N.J. Applied System Identification. Prentice Hall, 1994.

Vedoucí: Ing. Zdeněk Váňa

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Declaration

I declare that I have created my Diploma Thesis on my own and I have used only literture cited in the included reference list.

In Prague 13.5.2011

Ondřej Bruna

Signature

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Abstract

The objectives of this diploma thesis are to learn about thermodynamical processes in a chemical industry, based on the knowledge learned, to create and to identify a model of a thermodynamical process in a real chemical tank. To create a model the chemical tank itself is described with regards to its shape, sensor placement and physical properties. Model will be identified using real data. Data for identification will be analysed to avoid problems during identification. Methods used will be both linear and nonlinear according to own choice, validated on a real data samples. Results of all approaches taken to identify the model will be compared to decide which method prvided the best results. Current control approach is described and possible improvements are suggested.

Anotace

Cílem této práce je seznámit se s termodynamickými procesy v chemickém průmyslu a na základě těchto znalostí vytvořit a identifikovat matematický model termodynamického procesu na konkrétním chemickém zásobníku. Aby mohl být vytvořen podel, zásobník je podrobně popsán (včetně umístění sensorů a tvaru) a také jeho vlastnosti jsou zevrubně rozebrány.Model je identifikován na reálných datech, která jsou nejprve posouzena z hlediska vhodnosti pro identifikaci, aby se předešlo potencionálním problémům. K identifikaci jsou použity lineární i nelineární přístupy a výsledky jsou validovány prostřednictvím simulací s reálnými daty. V závěru jsou srovnány výsledky jednotlivých metod které srovnají přesost modelu se skutečným systémem. Je popsáno současné řízení a navrženo možné vylepšení.

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Chapter 1

Introduction

The company ENASPOL a.s. is located in surroundings of Teplice (Velvěty). Its main focus is chemical industry. Company produces material called ABESON, which is an intermediate product mainly for producing goods for drugstores - e.g. shampoos, shower gels, etc. ABESON needs to be stored somewhere before its final expedition. In the chemical factory there are two storage tanks: vertical and horizontal, to store ABESON. Generally in chemical tanks there are many variables to control - pH, temperature, vacuum, pressure. This thesis will address only temperature control of ABESON inside the tank, becuase to keep its qualities it needs to stay in certain range of temperatures. Eventhough there are two tanks, this thesis focuses only on the vertical tank.

Thesis' main objective is to create a mathematical model of thermodynamical processes in the vertical tank storing ABESON. Mathematical model describes the temperature of ABESON inside the tank. Model is a differential equation with variables and constants on right handside and with output on left hand side. Output is ABESON's temperature. Some variables are inputs, some are varying parameters and some are unknown parameters. Constants are fixed numbers determining the geometry and material properties of both tank and ABESON. Identification of the model means estimating unknown parameters of the model.

Determining unknown parameters is secondary objective of this thesis. To estimate parameters several approaches are used. Identification covers both linear and non-linear approach. Results are verified and compared.

Despite it is not an objective of this thesis, model predictive controler was designed. Controler uses identified model of thermodynamical process. Controler was simulated in MATLAB®and implemented in the real process.

Chapter 2 describes the tank itself, its inputs, outputs, shape, sensor placement and everything what is somehow related to the tank. It covers how the temperature inside the tank is affected and what can influence the ABESON's and supply water temperature. Chapter also explains terms heating and control unit and describes their tasks.

Chapter 3 derives thermodynamical differential equaiton describing desired temperature. Firstly, it is derived from physical principles, secondly, it is derived using resistor – capacitor network in circuit that is equivalent to the thermodynamical process. Chapter also introduces discretization and models used in control. It explains how a smapling frequency was chosen.

Chapter 4 explains how the data are used. It describes artefacts, which are the main complication to deal with. Chapter explains how these artefacts arise and how to get rid of them.

Chapter 5, along with Chapter 3, is one of the main chpaters. It desribes approaches used to identify the model. Approaches are explained and described in detail in this section.

Chapter 6 summarises the results achieved by identification approaches from Chapter 5. It shows how the models performed on chosen data set and compares them.

Chapter 7 describes former control approach and introduces new one. Model predictive control is explained.

Chapter 8 presents comparison of former control approach with new control approach. It pointss out the advantages of model predictive control and explains why this control is superior to former control.

Chapter 9 closes the thesis. It summarises achieved results, comments them and proposes improvements of control and future direction of development.

Chapter 2

Description of the tank

Chapter describes the tank's dimensions, shape, insulation, sensor placement, control unit equipment and placement. It describes ABESON's properties and things going on inside the tank.

2.1 Physical properties

To describe physical properties data provided by the company and availible photographs from the factory are used. The chemical product stored in the tank – ABESON (Dodecylbenzene Sulfonic Acid) – is a liquid of gold color with some properties close to the ones of water. For example specific heat and density are similar. Its viscosity changes with temperature. The higher the temperature is, the lower the viscosity gets. Therefore it is necessary to keep ABESON within a certain range of temperatures. And espetially before pumping it out it requires temperature high enough so its viscosity is the same as water's. When the viscosity of ABESON is same as water's, then it is very easy to pump it out from the tank. When the temperatures are low the viscosity is high – similar to honey like liquid. Under these circumstances it becomes much harder to pump ABESON out.

The product is required to have temperature above 30 °C and under 55 °C. If above, it changes its properties (especially affecting its color) making ABESON degenerated. Therefore the company wants the temperature of ABESON to be within this range. To maintain the temperature it is necessary to measure it. The placement of sensors and tank's scheme is shown on Figure 2.1.

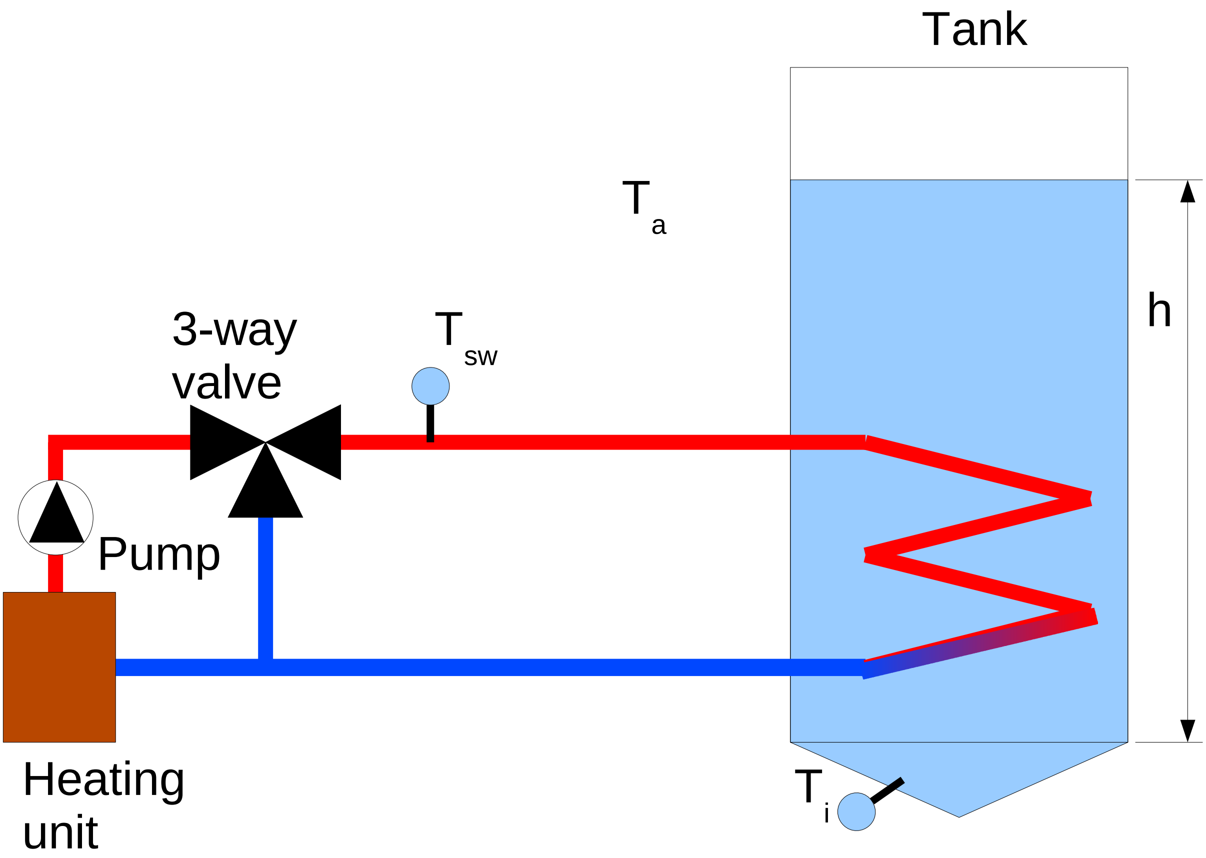
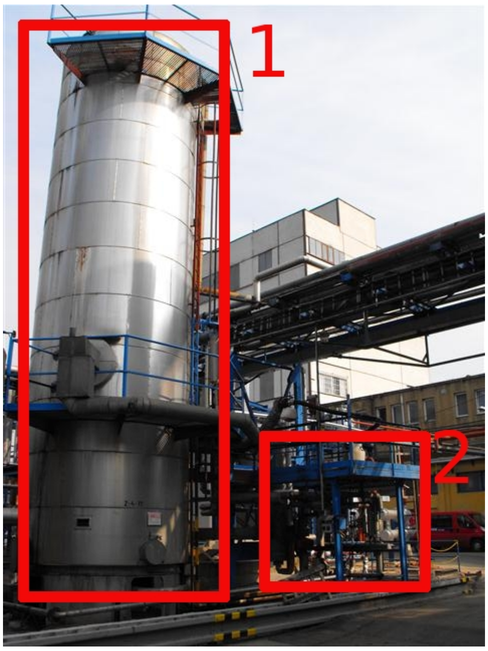


Figure 2.1: Schematic description of the tank

The tank is heated-up using supply water. The supply water and the temperature inside the tank measurements are available. Also level is measured. Ambient temperature is provided from National Oceanic and Atmospheric Administration (NOAA) server using their weather forecast. The weather forecast is with a tolerance of $\pm 3\,^{\circ}\mathrm{C}$. Temperatures are measured by the resistive temperature sensors Pt100, the level is measured by hydrostatic pressure sensor. The sensors inside the tank – inside temperature and level – are placed at the very bottom of the tank. Heating pipes go around the shell of the tank, do not cover the bottom base and reach the hight 1.5 m from the bottom edge of the tank.

In reality the tank is about 10 m tall, insulated and covered in a metal shell. The insulation used is orsil, widely used insulation material in civil engineering and also in technological processes. The material, the tank is made of, is unknown, but operators provided information it is metal-like material. Not plastic.

There are actually two tanks of the same volume. First is worked with in this thesis, second not. Second tank is horizontally placed and it serves as an emergency buffer



(a) Vertical storage tank of ABESON.

(b) Horizontal storage tank of ABESON.

Figure 2.2: ABESON tanks in ENASPOL.

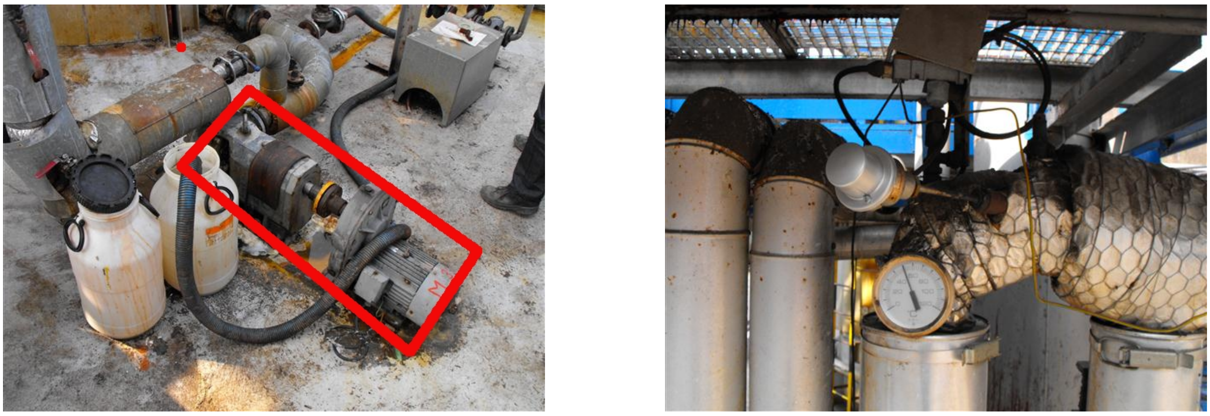
when the main tank is full. Horizontal tank is empty most of the time and can be seen on Figure 2.2b. The tank is marked with red rectangle with red number three.

2.2 Control set-up

Next to both tanks is a control station with heating unit, sensors and pumps. Heating unit is in principle a heat exchanger where steam warms up the supply water. Supply water is then pumped to the pipes. Thanks to the use of steam it warms it up very fast. The temperature sensor is located at the control station on Figure 2.3b. Principle is depicted on Figure 2.1 and actual real-life situation is on Figure 2.2a, where the red number one denotes tank itself and number two is a control station.

Control staion is approximately 5 m away from actual tank. During its way the pipes are not very well insulated, so supply water is affected by ambient environment. The temperature is measured inside the station and is not measured at the point where it enters the tank. The return water was not incorporated into the process.

Part of a control station is also a pump (see Figure 2.3a, where the pump is marked by a red rectangle, (barrels there are not part of the ABESON storage tanks) pump drains ABESON out from the tank. This process of pumping it out takes about few minutes.



(a) Pump. (b) Temperature sensor of supply water.

Figure 2.3: Pump and temperature sensor Pt100.

The very same pump is used to mix the ABESON in tank. Only the pipes are connected in a way that the output pipe does not go to cistern, but it is connected to the input pipe of the tank. This process runs for about 10 minutes. The ABESON from the bottom of the tank gets to the top of the tank and the temperature is then the same in the whole tank. Input pipe transports new ABESON to the storage tank. The influx is constant.

In this station it is possible to turn heating on or off siply by closing proper valve.

Notice that on Figure 2.3b is temperature sensor of supply water Pt100 and temperature on analog thermometer says 50 °C, which was the temperature set for heating on the beginning of February and it can be found in corresponding data set.

2.3 Former control approach

Former control approach used only one programmable logical controler to control proper temperature of supply water. To control the temperature PID controler was employed. This PLC also collets all the data from the tank and provides it to higher layer of control chain. There are physically two tanks - the PLC is controling and collecting data from both of them.

So far only feed forward control of heating temperature was implemented, which is an unaccurate and money-consuming approach. The desired supply water temperature was set manualy by an operator who knows the process. If the set temperature was not able to maintain ABESON within desired range, operator just raised it. This might be avoided by use of more sofisticated contol system, which would take into account weather forecast and properties of ABESON describing its temperature development. Using model based control system company would be able to reduce costs. This approach can then be applied on any other tank or to similar class of control problems.

Advantage is that operators know when the factory will finish producing new ABESON, when will a customer arrive to transport ABESON and when will the factory stop producing it because of maintenance or for other reasons. This is very useful and helps to decide whether to heat at all.

Eventhough there are good points in this way of controling system, it has abundance of bad qualities. For this reason is the tank heated even when it is not neccessary because the weather temperature is enough to maintain safe temperature. This means, that the supply water happens to be 50 °C even when ambient temperature is 32 °C and the Sun shines directly to the tank and the ABESON level is low. This leads to significant energy loss, which can be improved by use of more sofisticated control.

Chapter 3

Creating a model

This chapter introduces how the mathematical model of thermodynamical processes was created. Firstly, the physical principles are explained and using them the mathematical model is introduced. Secondly, to validate aproach taken in first step the equations describing heat exchanger using resistor–capacitor network are derived. At last the model is discretized and discrete transfer function and discrete state space model for parameter estimation and control are introduced . It was decided to employ a simple model rather than very detailed model, so for that reason some details which have mild effect on the model are neglected. Incorporating them into the model would bring more variables to work with. The complexity would grow over acceptable limits and it would be very complicated to estimate model's parameters.

3.1 Physical principles

Supply water pipes pass the heat to tank's shell and heat-up ABESON. Modeling of a tank can be understood as modeling of a heat exchanger. The energy flow is from a heating pipes to ABESON and from ambient environment to the tank or vice versa depending on the temperature. The general heat exchanger looks like the one on a Figure 3.1.

On the Figure 3.1 the thermal exchange takes place in between the pipe and the liquid inside the exchanger. In this case heating pipes are going through the tank. For the storage tank the pipes are mounted on the surface, but it does not mean any complication. It only affects the thermal resistivity between the heating pipes and ABESON. Storage tank will have greater resistivity than pipes going directly through the liquid. Let us

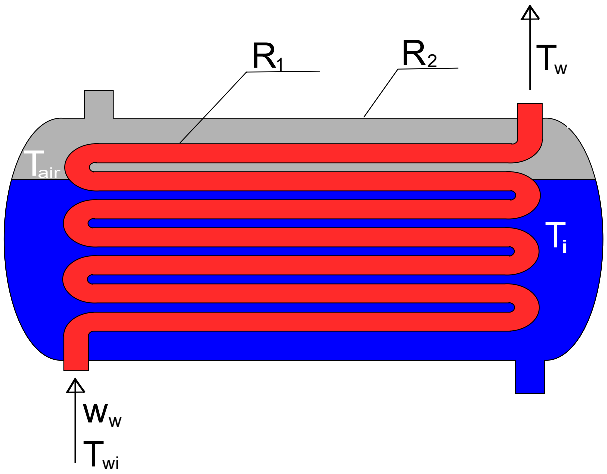


Figure 3.1: General heat exchanger.

consider the heat exchanger on Figure 3.1 first. The energy flow

$$\dot{Q} = \frac{T_{wi} - T_i}{R_1}, \tag{3.1}$$

where $\dot{Q}[\mathrm{W}]$ is an energy flow, $T_{wi}[^\circ\mathrm{C}]$ and $T_i[^\circ\mathrm{C}]$ are water input and water output temperatures, respectively $R[\mathrm{K\ W^{-1}}]$ is a thermal resistivity. Sign of temperatures difference determines the direction of energy flow. In our case this will tell whether the tank is warmed up or cooled down.

From thermodynamics is known [6] that any thermal capacitance of any material is defined as

$$C_i = \frac{dQ}{dT} = \frac{\dot{Q}}{\dot{T}}, \tag{3.2}$$

which can be rewritten and regrouped into

$$\begin{aligned} \dot{Q} &= C_i\,\dot{T}, \\ \dot{T} &= \frac{\dot{Q}}{C_i}. \end{aligned} \tag{3.3}$$

Where Q, T and $C_i[\mathrm{J\ K^{-1}}]$ are energy, temperature and thermal capacitance of any material.

Substituting Equation (3.1) into Equation (3.3) yelds for Figure 3.1

$$\dot{T}_i = \frac{1}{C_i}\,\dot{Q} = \frac{T_{wi} - T_i}{R_1\,C_i}, \tag{3.4}$$

where $C_i = m\,c$ is a thermal capacitance of heated medium, where $m[\mathrm{kg}]$ is a mass of heated medium and $c[\mathrm{J\ kg^{-1}\ K^{-1}}]$ is a specific heat of heated medium.

For the chemical storage tank with ABESON, the thermal capacitance and resistivity under the assumption that the shape of the tank is a cylinder can be determined as

$$C_i = m\,c = \rho\,V\,c = \rho\,\pi\,r^2\,h\,c, \qquad (3.5)$$
$$R = \frac{l}{\lambda\,S}\,,$$

where $S[\,\mathrm{m}^2]$ is an area of the surface the heat will be passing to, $\rho[\,\mathrm{kg\ m}^{-3}]$ is a density of heated medium, $V[\,\mathrm{m}^3]$ is a volume of heated medium – here it is a cylinder, π is a mathematical constant, $r[\,\mathrm{m}]$ is a radius of top or bottom-base, $h[\,\mathrm{m}]$ is a height of cylinder, tank respectively, $l[m]$ is a thickness of material through which the energy flows and $\lambda[\,\mathrm{W\ m}^{-1}\ \mathrm{K}^{-1}]$ is a thermal conductivity. All geometrical and physical constants metioned above will be refered to as $\mathcal{P}$.

To describe the process properly there are two phenomenas taking part in changing tank's temperature. Firstly, it is direct heating to the metal surface of tank. Secondly, there is a weather, which is considered as a known disturbance. Weather temperature is forecasted using NOAA weather forecast. It has been verified that forecasted temperature fits real temperature within range of $\pm 2\,^{\circ}\mathrm{C}$. These are two parts, which have to be included in model of chemical storage tank. For cooling down the area will vary with content's level and will be refered to as $S_2(h, \mathcal{P})$. But the top-base is not considered, because ABESON never touches the top lid. Heating the tank is limited by the reaching point of heating pipes. Pipes reach $h_1 = 1.5\,\mathrm{m}$ from the bottom of the tank and therefore the area is constant and will be refered to as to $S_1(\mathcal{P})$, which is area of tank's shell covered by supply water pipes.

$$S_1(\mathcal{P}) = 2\,\pi\,r\,h_1 \qquad (3.6)$$

Area representing the ABESON in the tank is denoted $S_2(\langle, \mathcal{P})$. It takes into account the bottom base and the shell, but does not count with top-base.

$$S_2(h, \mathcal{P}) = 2\,\pi\,r\,h + \pi\,r^2 = \pi\,r\,(2\,h + r) \qquad (3.7)$$

Now one can introduce the variables which concern our problem in Equation (3.8).

$$\dot{T}_i = f(T_i, T_{sw}, T_a, h, \mathcal{P}), \qquad (3.8)$$

where T_i is ABESON's temperature, T_{sw}, T_a are supply and ambient water temperatures, respectively, h is ABESON's level inside the tank and $\mathcal{P}$ covers all physical and geometric parameters. With use of basic principle of heating from Equation (3.4)

$$C_i(h,\mathcal{P})\dot{T}_i = -\frac{T_i - T_{sw}}{R_1(h,\mathcal{P})} - \frac{T_i - T_a}{R_2(h,\mathcal{P})}\,, \tag{3.9}$$

$$\begin{aligned}
\dot{T}_i &= -\frac{T_i - T_{sw}}{C_i(h,\mathcal{P})\,R_1(h,\mathcal{P})} - \frac{T_i - T_a}{C_i(h,\mathcal{P})\,R_2(h,\mathcal{P})} = \\
&= -\frac{1}{\rho\pi r^2 hc}\,\frac{\lambda_1 2\pi r h_1}{l_1}\,(T_i - T_{sw}) - \frac{1}{\rho\pi r^2 hc}\,\frac{\lambda_2\pi r(2h+r)}{l_2}\,(T_i - T_a) = \\
&= -\frac{2h_1}{\rho rc}\,\frac{\lambda_1}{l_1}\,\frac{1}{h}\,(T_i - T_{sw}) - \frac{2}{\rho rc}\,\frac{\lambda_2}{l_2}\,(T_i - T_a) - \frac{1}{\rho c}\,\frac{\lambda_2}{l_2}\,\frac{1}{h}\,(T_i - T_a),
\end{aligned} \tag{3.10}$$

$$\frac{1}{C_i(h,\mathcal{P})\,R_1(h,\mathcal{P})} = \frac{2\,h_1\,\lambda_1}{r\,\rho\,c\,l_1\,h}\,, \tag{3.11}$$

$$\frac{1}{C_i(h,\mathcal{P})\,R_2(h,\mathcal{P})} = \frac{2\,\lambda_2}{r\,\rho\,c\,l_2} + \frac{\lambda_2}{\rho\,c\,l_2\,h}\,, \tag{3.12}$$

with thermal conductivity of heating pipes λ_1, thermal conductivity of tank's insulation λ_2, thickness of insulation of supply water l_1, thickness of tank's insulation l_2.

Constants r, ρ, h_1 are known parameters and subjects of estimation are parameters λ_1, λ_2, l_1, l_2, c. ABESON level can be viewed upon as yet another input to the system or as 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 Equation (3.9) can be rewritten into

$$\dot{T}_i = \frac{p_1 a_1 a_2}{h}\,(T_i - T_{sw}) + \left(p_2 a_1 a_3 + \frac{p_3 a_1 a_3}{h}\right)(T_i - T_a). \tag{3.13}$$

This equation can be rewritten with use of substitution $a_1\,a_2 = \alpha$ and $a_1\,a_3 = \beta$ to

$$\dot{T}_i = \frac{p_1\,\alpha}{h}\,(T_i - T_{sw}) + \left(p_2\,\beta + \frac{p_3\,\beta}{h}\right)(T_i - T_a), \tag{3.14}$$

which is the final continuous-time model to be identified.

To identify the model defined by Equation (3.14), α and β has to be determined. Any method used later in this thesis always interprets results as parameters α and β. It is not necessary to identify each parameter λ_1, λ_2, l_1, l_2 and c. Two parameters are sufficient to describe the cooling and warming process. Anytime in this thesis, when refered to parameters it regars to α and β.

3.2 Resistor – capacitor network

Thermodynamical processes can be modeled using electrical circuits with resistors and capacitors, here capacitor represents tank's content – ABESON. Resistors represent thermal resistivities. Power sources are sources of heat. Resistor network for chemiacal storage tank with ABESON is on Figure 3.2.

There are two power sources - the first represents supply water and is denoted as u_{sw} and the second power source u_a represents ambient temperature. Capacitor is marked as C_i and represents ABESON. Voltage constitutes temperature and current is a energy flow. As power supplies charge capacitor, its voltage rises. It means that ABESON's temperature rises too. R_2 is thermal resistivity of metal dividing heating pipes and ABESON, R_1 is thermal resistivity of orsil. Weather and supply water are considered to be power supplies because their temperatures are not affected by any other source.

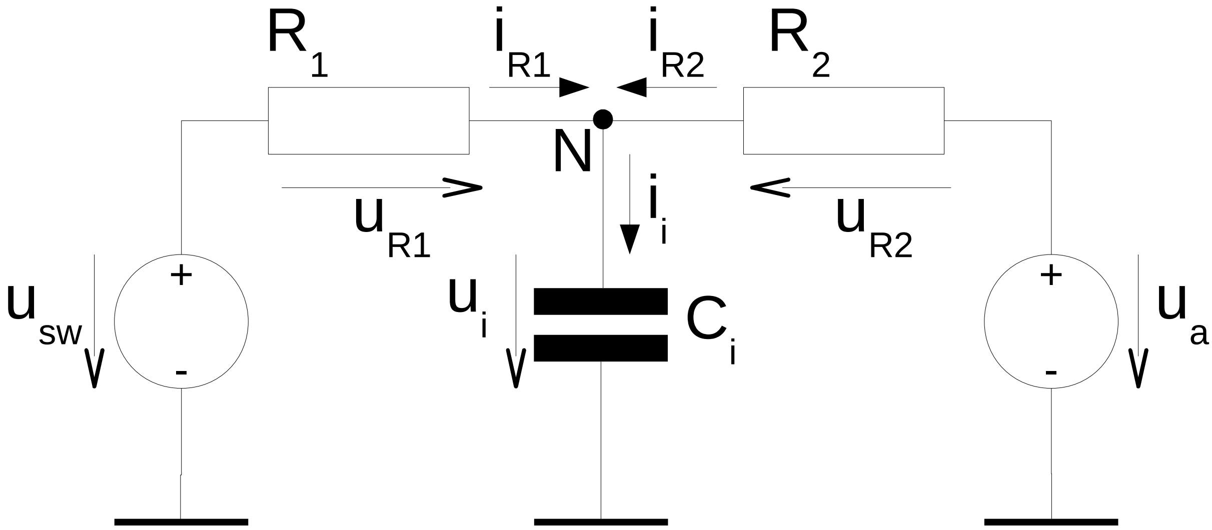


Figure 3.2: Resistor network simulating tanks behaviour.

To describe tank's inner temperature, equation for u_i(capacitor voltage) must be derived. Krichhof's current law will be used. This law says, that sum of all currents entering a nod is equal to zero. Namely for nod N on Figure 3.2:

$$\begin{aligned} \frac{u_{r1}}{R_1} + \frac{u_{r2}}{R_2} &= i_i, \\ \frac{u_i - u_a}{R_1} + \frac{u_i - u_{sw}}{R_2} &= i_i. \end{aligned} \tag{3.15}$$

Current through capacitor is described as:

$$i_i = C_i \frac{du_i}{dt} = C_i \dot{u}_i, \tag{3.16}$$

which will be plugged into Equation (3.15), resulting in:

$$\begin{aligned} \frac{u_i - u_a}{R_1} + \frac{u_i - u_{sw}}{R_2} &= C, \dot{u}_i \\ \frac{u_i - u_a}{C_i R_1} + \frac{u_i - u_{sw}}{C_i R_2} &= \dot{u}_i. \end{aligned} \tag{3.17}$$

Equation (3.17) verfies, that chosen concept is correct and can be applied for modeling aforementioned chemical tank. Equation (3.17) can be rewriten in a way that describes temperature transfers. It is similar to equation as in Equation (3.9). **Note**:the system is nonlinear and this fact is not represented in this model. Nonlienarity might be expressed by making capacity and resistivity dependent on some varialbes. Changing capacity would cause the same effect as does the water level.

3.3 Model for control

For practical reasons of control, model had to be discretized. Discretized model was then used in to run simulations and to compute optimal temperature of supply water.

3.3.1 Sampling time selection

The data are saved into database every minute. So one minute time interval is the shortest time interval to use. To determine the sampling time, frequency spectra of data were used. Frequency spectra on Figure 3.3 shows average spectra of input and output signals. Significant peak at frequency $7.27 \cdot 10^{-5}[\text{rad s}^{-1}]$ represents a day. Plot auggests that there is no important information above frequency $0.8 \cdot 10^{-3}[\text{rad s}^{-1}]$, repectively there is only noise.

Shannon–Kotelnikov theorem says that sampling frequency should be at least twice as greater as the frequency of our interrest. This means, that if frequency of our interrest is $0.8 \cdot 10^{-3}[\text{rad s}^{-1}]$, which corresponds to the period $T = 131[\text{min}]$, then the sampling time should be at least $T_s = 65[\text{min}]$. To be more realistic it is better to choose one hour as the lowest possible sampling time. To meet the Shannon–Kotelnikov theorem the sampling time was chosen approximately six times lesser: $T_s = 10[\,\mathrm{min}]$.

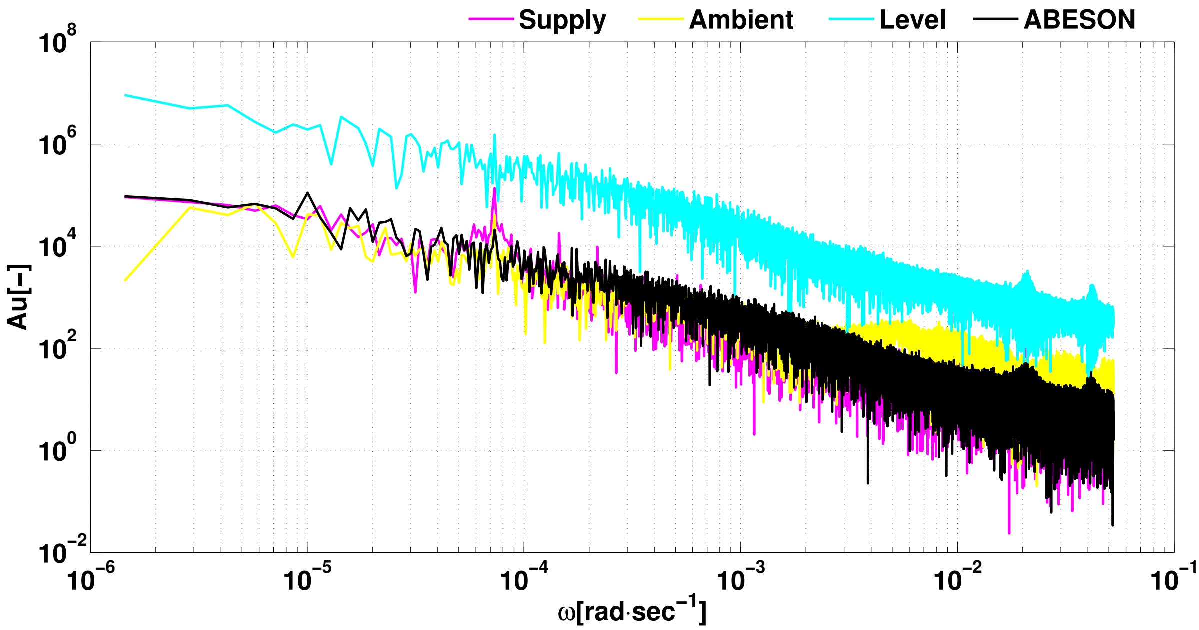


Figure 3.3: Frequency spectrum of data.

3.3.2 Discretization

For discretization Euler's discretization with sampling time T_s is used.

$$T_i(k+1) \approx \dot{T}_i T_s + T_i(k), \tag{3.18}$$

Discrete model can be then obtained simply from plugging $\dot{T}_i$ into Equation (3.18) and as a result is derived:

$$T_i(k+1) = \left[\frac{p_1\alpha}{h}(T_i(k) - T_{sw}(k)) + \left(p_2\beta + \frac{p_3\beta}{h}\right)(T_i(k) - T_a(k))\right] T_s + T_i(k). \tag{3.19}$$

3.3.2.1 Discrete transfer function

For future estimation purposes is derived discrete transfer function representaition of the discrete equaiton.

$$\begin{aligned}\mathcal{Z}\{T_i(k+1)\} &= \mathcal{Z}\{T_i(k)\}\, z,\\ \mathcal{Z}\{T_i(k)\} &= \hat{T}_i,\end{aligned}\tag{3.20}$$

where z^{-1} is a time delay. Equation (3.19) is interpreted as a transfer function description with $1/h$ as a varying parameter.

$$\begin{aligned}
\hat{T}_i\, z &= \left[\frac{p_1 a_1 a_2}{h}\,(\hat{T}_i - \hat{T}_{sw}) + \left(p_2 a_1 a_3 + \frac{p_3 a_1 a_3}{h}\right)(\hat{T}_i - \hat{T}_a)\right] T_s + \hat{T}_i,\\
\hat{T}_i\, z &= T_s\, p_1\, \alpha\, \frac{1}{h}\, \hat{T}_i - T_s\, p_1\, \alpha\, \frac{1}{h}\, \hat{T}_{sw} +\\
&\quad + T_s\, p_2\, \beta\, \hat{T}_i - T_s\, p_2\, \beta\, \hat{T}_a +\\
&\quad + T_s\, p_3\, \beta\, \frac{1}{h}\, \hat{T}_i - T_s\, p_3\, \beta\, \frac{1}{h}\, \hat{T}_a,\\
\hat{T}_i\, z &= \left(T_s\, p_1\, \alpha\, \frac{1}{h} + T_s\, p_2\, \beta + T_s\, p_3\, \beta\, \frac{1}{h} + 1\right) \hat{T}_i\\
&\quad - \left(T_s\, p_1\, \alpha\, \frac{1}{h}\right) \hat{T}_{sw}\\
&\quad - \left(T_s\, p_2\, \beta + T_s\, p_3\, \beta\, \frac{1}{h}\right) \hat{T}_a,\\
\hat{T}_i\, \left(z - \left(T_s\, p_1\, \alpha\, \frac{1}{h} + T_s\, p_2\, \beta + T_s\, p_3\, \beta\, \frac{1}{h} + 1\right)\right) &=\\
&= -\left(T_s\, p_1\, \alpha\, \frac{1}{h}\right) \hat{T}_{sw} - \left(T_s\, p_2\, \beta + T_s\, p_3\, \beta\, \frac{1}{h}\right) \hat{T}_a,\\
\hat{T}_i &= \begin{bmatrix} \frac{-\left(T_s\, p_1\, \alpha\, \frac{1}{h}\right)}{z-\left(T_s\, p_1\, \alpha\, \frac{1}{h} + T_s\, p_2\, \beta + T_s\, p_3\, \beta\, \frac{1}{h} + 1\right)} & \frac{-\left(T_s\, p_2\, \beta + T_s\, p_3\, \beta\, \frac{1}{h}\right)}{z-\left(T_s\, p_1\, \alpha\, \frac{1}{h} + T_s\, p_2\, \beta + T_s\, p_3\, \beta\, \frac{1}{h} + 1\right)} \end{bmatrix} \begin{bmatrix} \hat{T}_{sw}\\ \hat{T}_a \end{bmatrix}.
\end{aligned}\tag{3.21}$$

Let us substitute:

$$\begin{aligned}
K_{sw}(h) &= -\left(T_s\, p_1\, \alpha\, \frac{1}{h}\right)\\
K_a(h) &= -\left(T_s\, p_2\, \beta + T_s\, p_3\, \beta\, \frac{1}{h}\right)\\
D(h) &= \left(z - \left(T_s\, p_1\, \alpha\, \frac{1}{h} + T_s\, p_2\, \beta + T_s\, p_3\, \beta\, \frac{1}{h} + 1\right)\right)
\end{aligned}\tag{3.22}$$

and then it is possible to write following transfer function description of the model:

$$G(z,h) = [G_{sw}(z,h)\ ,\ G_a(z,h)] = \left[\frac{K_{sw}(h)}{z + D(h)}\ ,\ \frac{K_a(h)}{z + D(h)}\right],\tag{3.23}$$

Note, that in Equation (3.23), are only two inputs. This is because this model is parameter varying with parameter h.

3.3.2.2 Discrete state-space model

In control state space model is used. To create it Equation (3.19) can be used and rewritten as follows:

$$T_i(k+1) = \left[\frac{p_1\alpha}{h}(T_i - T_{sw}) + \left(p_2\beta + \frac{p_3\beta}{h}\right)(T_i - T_a)\right] T_s + T_i(k) \tag{3.24}$$

$$\begin{aligned} T_i(k+1) = & \left(\frac{T_s\,p_1\,\alpha}{h} + T_s\,p_2\,\beta + \frac{T_s\,p_3\,\beta}{h} + 1\right) T_i \\ & - \left(\frac{T_s\,p_1\,\alpha}{h}\right) T_{sw} \\ & - \left(T_s\,p_2\,\beta + \frac{T_s\,p_3\,\beta}{h}\right) T_a. \end{aligned} \tag{3.25}$$

Equation (3.24) is basically a state space description, let us consider T_i as state, T_{sw} as input and T_a as disturbance input, then the system can be rewritten into:

$$T_i(k+1) = A(h)\,T_i + B(h)\,T_{sw} + V(h)\,T_a, \tag{3.26}$$

where the system matrices are:

$$\begin{aligned} A(h) &= \left(\frac{T_s\,p_1\,\alpha}{h} + T_s\,p_2\,\beta + \frac{T_s\,p_3\,\beta}{h} + 1\right) \\ B(h) &= -\left(\frac{T_s\,p_1\,\alpha}{h}\right) \\ V(h) &= -\left(T_s\,p_2\,\beta + \frac{T_s\,p_3\,\beta}{h}\right) \end{aligned} \tag{3.27}$$

Chapter 4

Analysis of measured data

Chapter gives an overview of complication with data. It explains what is understood by artefact in data and explains why the data had to be preprocessed. It also covers what caused artefacts and why it made it difficult to estimate parameters. Solution of problems is described.

4.1 Artefacts in data sets

During the identification process some problems were encountered. These problems made it too difficult or even impossible to estimate parameters correctly. Estimated parameters happened to be way out of acceptable bounds. After verifying that estimation approached work well it was concluded that problem is caused by data sets. Therefore the analysis of data was necessary to find the problems and decide how to avoid them and how to estimate parameters correctly.

The data include artefacts, which are areas where the data behave as not expected or in a way that is not covered by model. If the model does not descibe the data, it cannot be used. Two possible solutions arise - either to create a new more complex model covering discovered artefacts or to preprocess the data to avoid problems. Both ways were examined. The first way turned out to be very complex, since the model got very complicated. The second approach was taken because it is faster to solve the problems by preprocessing the data. The example of data with artefacts is on Figure 4.1.

The model is designed only to describe heating and cooling in tank. It does not take into account following artefacts:

- sudden increase of ABESON's temperature,
- outlayers of temperature or level,
- changes in weather forecast,
- non-realistic changes of level,
- loss of data,
- no numeric values stored - NaN (not a number) error.

The most artefacts were caused by mixing ABESON in the tank and by pumping it of the tank. Because of sensor placement and poor insulation measurement of ABESON's temperature is much more affected by ambient environment than the rest of the tank. It cools down faster than the ABESON on the top and when ABESON inside is mixed temperature rises rapidly for even more than 10 °C. This process cannot be described by an input since this happens irregularly and is strictly manually controlled. The same result - temperature step - is caused by pumping ABESON out from a tank. The reason is similar - temperature on the top is higher than on the bottom. When pumping ABESON out, a valve on the bottom of the tank is opened and hotter ABESON from the top of

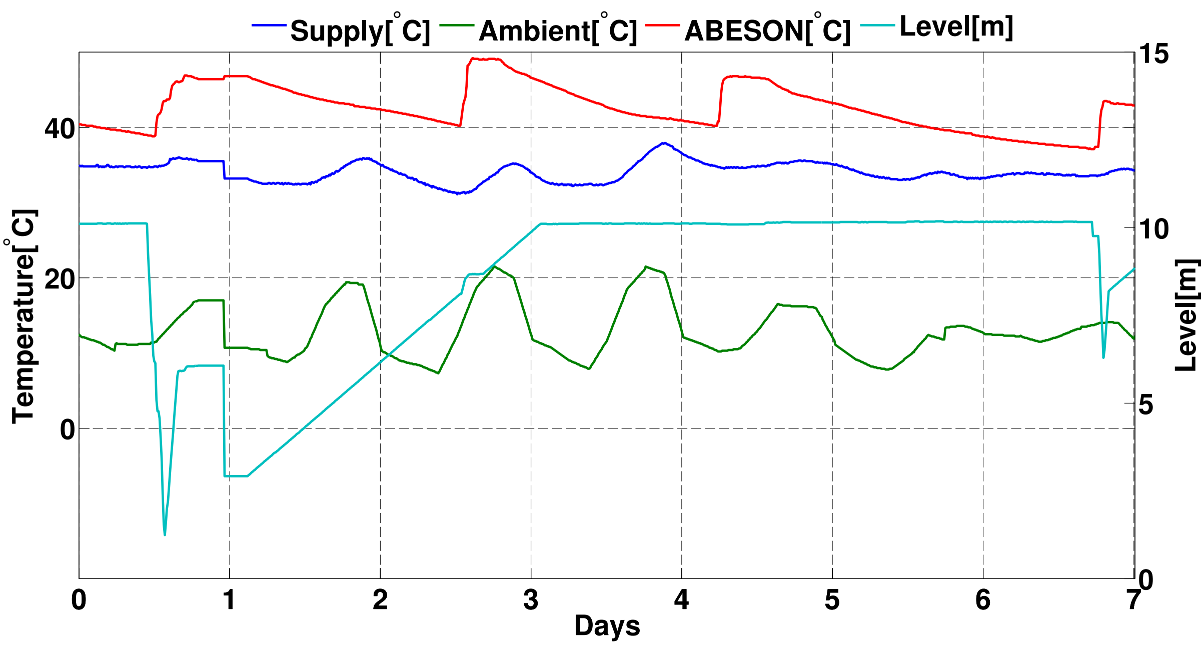


Figure 4.1: Data example.

the tank gets down, where the temperature sensor is placed. This lasts a very short time. This can be detected since there is a significant drop in an ABESON level.

These are the major issues to deal with, but there are also some minor complications. Firstly, the sun is also affecting inner temperature and it slows down cooling process. This can affect estimated parameters. Secondly the temperature sensors measuring the heating water and return water are placed at the control station and not at the tank itself making it possible for ambient environment to affect heating water (because of a poor insulation on heating pipes). Thirdly, there are problems with data measurement and time from time there is a data loss, which has to be taken care of.

Solution to these complications is in data preprocessing. Before running any simulation or estimation, the input data are scanned for NaNs and these are removed. Then the data are cut into many different parts where there are no artefacts. This means that only data with clear cooling or heating pattern are taken into account.

Chapter 5

Indentification of model

Identification methods itself are described in detail in this chapter. The list of approaches taken to identify parameters α and β follows.

1. **First principle modeling.** Thorough analysis of the physics on the background of the process.

2. **Family of prediction error methods (PEMs).** Since not all the system parameters are known, the statistical methods are recommended to employ. Moreover, PEMs serve mainly for identification of linear systems. Which this case under some special circumstances is.

3. **Subspace identification (4SID).** Yet another linear system identification method which, on contrary to PEMs, includes order selection.

4. **Linear parameter varying (LPV) systems identification.** The level in the tank is a varying parameter. Therefore these approaches were employed too.

5. **Identification by ACADO software.** Physical principle model comprises many unknown constant parameters, that need to be identified. ACADO is a software tool allowing identification of unknown parameters of nonlinear continuous or discrete time systems.

6. **Decoupled identification of cooling and heating parts.** This approach used ACADO software for parameter estimation, but heating and cooling part was estimated separately.

5.1 First principle modeling.

5.1.1 General overview

Thanks to ENASPOL a.s. some parameters of the model are already known: $h_1 = 1.5\,\mathrm{m}$, $r = 1.4\,\mathrm{m}$, $\rho = 1080 kg\ \mathrm{m}^{-3}$. The rest of parameters will be estimated.

Material	$c[\mathrm{J\ kg^{-1}\ K^{-1}}]$	$\lambda[\mathrm{W\ m^{-1}\ K^{-1}}]$
water	4180	0.6062
iron	450	80.2
air	1003	0.0262
diamond	N/A	895-2300
orsil	N/A	0.040

Table 5.1: Table of material properties.

Based on the data in table[1] Table 5.1 it is assumed that the properties of insulation should be similar to orsil. Widely used insulaiton material in technological processes and in houses. It is also supposed the specific heat is similar to water. On site measurements in ENASPOL a.s. provided the thickness of insulation material. The thinckness of insulation is not consistent and it might have changed its properties due to long exposure to outside conditions. This would cause the tank to cool down faster, than when the insulation would be in a good shape.

Description of tank's insulation and thickness is depicted on Figure 5.1.1 and shows that λ_2 and l_2 is related to orsil and outside environment and λ_1 and l_1 is related to heating pipes. Heating pipes have a quite long way to get to the tank itself and therefore heating temperature is not the same as when measured.

Thanks on site measurements it was figured that the insulation between the shell and the tank is $l_2 = 0.2\,\mathrm{m}$ and the thickness of heating tubes shell together with thickness of tank's shell is $l_1 = 0.02\,\mathrm{m}$. Based on the data from Table 5.1 it is supposed that the material thermal insulation conductivity $\lambda_2[\mathrm{W\ m^{-1}\ K^{-1}}]$ is in interval $\langle 0.02; 0.06\rangle$ and that tank and pipes thermal conductivity $\lambda_1[\mathrm{W\ m^{-1}\ K^{-1}}]$ is $\langle 50; 100\rangle$. Specific heat of ABESON is similar to the water with $c = 4180 J/(kg^{-1}K^{-1})$. All the assumptions point to the following values of the parameters $\alpha = \langle 1\cdot 10^{-2}; 1\cdot 10^{-1}\rangle$ and $\beta = \langle 1\cdot 10^{-4}; 9\cdot 10^{-3}\rangle$.

[1] `http://www.engineeringtoolbox.com`

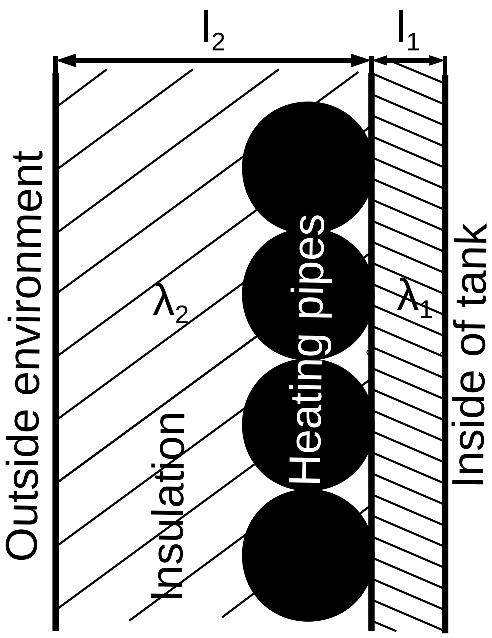


Figure 5.1: Cut through tank.

Note: The estimation process was started with all five parameters as subject of estimation, later reduced into three as shown in Equation (3.13). At last, model using only parameters α and β was used. This provided acceptable results and was very simple to interpret.

The decision to use model with two parameters was made, because there is no need to find the exact value of parameters λ_1, λ_2, l_1, l_2 and c. It is only necessary to create a model which will cover the change of temperature properly in a control point of view.

5.1.2 Margin estimates

In order to make rough estimate of what the parameters α and β should be, there is an estimation based on known data and experience of current ENASPOL a.s. operators manning the tank.

Let us suppose that parameters lie in within the range set by previous chapter. It is very important for future estimation. If the range is wrong, it would not be possilbe to estimate right parameters. All following methods use constraints. It constraints are set wrong, then also resulting data will be most likely wrong. From aforementioned intervals is computed the first aproximate estimate of parameters to demonstrate that the priciple works. If the real value of ABESON's temperature lies within simulated output, than it means that values were set right. If not, the range has to be modified.

$$\begin{aligned} \langle \alpha_{min}; \beta_{min} \rangle &= \langle 1 \cdot 10^{-2}; 1 \cdot 10^{-4} \rangle, \\ \langle \alpha_{min}; \beta_{max} \rangle &= \langle 1 \cdot 10^{-2}; 9 \cdot 10^{-3} \rangle, \\ \langle \alpha_{max}; \beta_{min} \rangle &= \langle 1 \cdot 10^{-1}; 1 \cdot 10^{-4} \rangle, \\ \langle \alpha_{max}; \beta_{max} \rangle &= \langle 1 \cdot 10^{-1}; 9 \cdot 10^{-3} \rangle. \end{aligned} \quad (5.1)$$

To demonstrate that margin stated in Equation (5.1) is correct, simulations were performed.

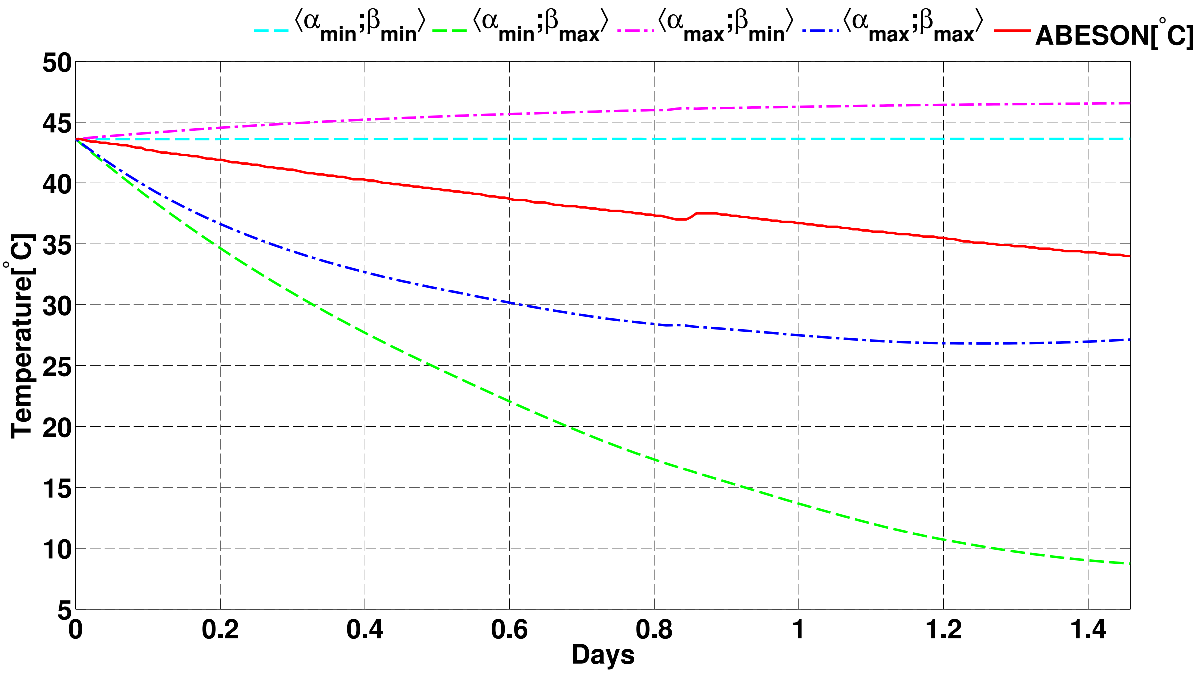


Figure 5.2: Simulation of margin.

Simulations are whown on Figure 5.2 It proves that the margin covers the range in within the real parameters should be, because the real ABESON temperature lies between simulated lines.

On Figure 5.3 there are data with simulation of cooling part compared with original ABESON's temperature. It is possible to see, that cooling component was estimated correctly because it cools very fast, but ABESON's temperature stays about the same.

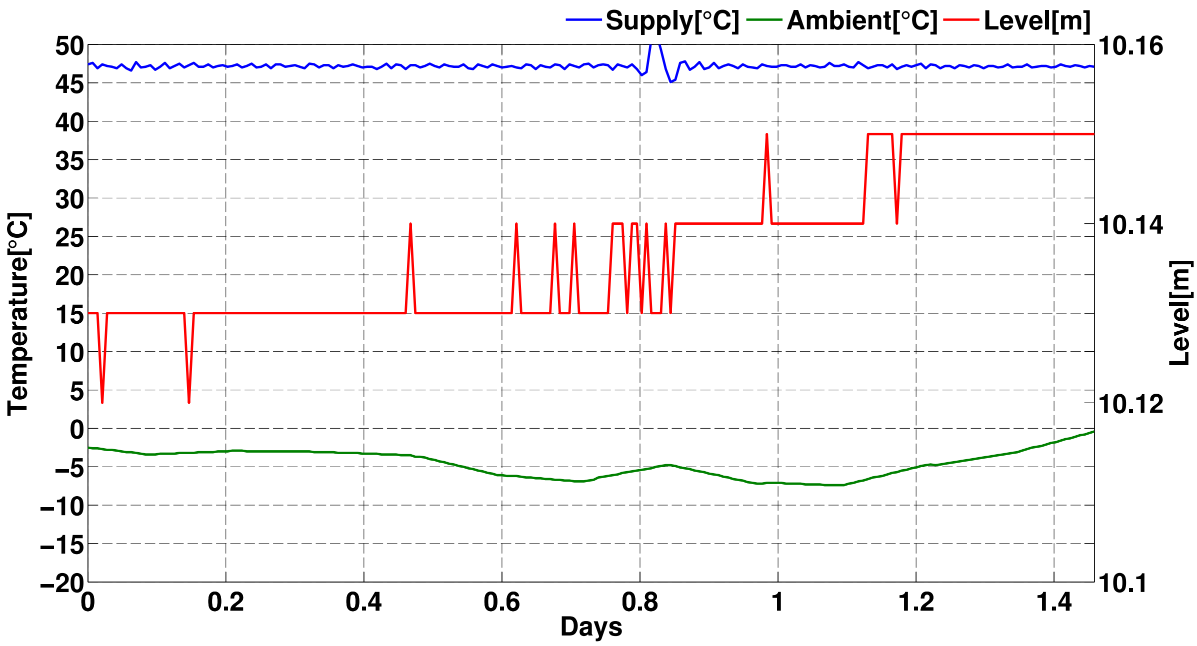


Figure 5.3: Data used to simulate margin.

5.2 Linear time invariant approach

5.2.1 Prediction error methods - PEMs

The most common way of identifying models is to use PEMs. It is also the first choice for purposes of this thesis. This methods are well known and widely used. PEMs are usually employing ARX (autoregresive with external input) models. Their parameters are then identified by LS (least squares) or by recursive algorithms. This approach is suitable for linear time invariant systems.

The nonlinear model of the system is proposed. Nevertheless, in measured data can be found such cases, where the model can be considered as linear and time invariant. It happens when ABESON level is fixed: the input h then happens to be a constant. It changes the way to look at the model. Thus the model is linear.

Prediction error methods minimize the prediction error $\varepsilon(t, \theta) = y(t) - \hat{y}(t, \theta)$, where ε is error of prediction, $y(t)$ is measured output, $\hat{y}(t, \theta)$ is estimated output and θ is a vector of parameters.The criterion function of this approach is

$$\hat{\theta}^* = \arg\min_{\theta} \sum_{t=1}^{N} \varepsilon(t, \theta), \tag{5.2}$$

where $\hat{\theta}^*$ is called optimal estimate of θ. The hat stands for estimate and star denotes optimality in terms of Equation (5.2). N is the length of data. For more details, see for instance [9].

ARX model is described by

$$y(k) + \sum_{i=1}^{n_a} a_i\, y(k-i) = \sum_{l=1}^{n_u} \sum_{j=0}^{n_b} b_{j\,l}\, u_l(k-j) + e(k), \tag{5.3}$$

where u_l is l–th input, e is white noise sequence with $\mathcal{N}(0, \sigma_e^2)$, n_b is number of parameters for inputs, n_a is number of parameters for outputs. The Equation (5.3) can be rewritten using

$$\theta = \begin{bmatrix} a_1 & a_2 & \dots & a_{n_a} & b_{01} & b_{11} & \dots & b_{n_b 1} & b_{02} & \dots b_{n_b n_u} \end{bmatrix}^T, \tag{5.4}$$

which is a vector of parameters and

$$\psi = \begin{bmatrix} -y(k-1) & \dots & -y(k-n_a) & u_1(k) & \dots & u_1(k-n_b) & \dots & u_{n_u}(k-n_b) \end{bmatrix}^T, \tag{5.5}$$

which is a vector of data, called regresor. The Equation (5.3) is possible to express as a vector multiplication

$$y = \psi^T \theta + e, \tag{5.6}$$

where ψ and θ were defined above. This is possible when parameters of the system are known and there is no disturbance. For parameter estimation the situation is different. Usually the vector θ is unknown and it is desired to estimate it in a fashion that satisfies Equation (5.2). The inputs and output are measured. This approach is suitable only for MISO (multiple input single output) systems. Measured inputs and output are assembled into regresor. Ouput is known.

The best estimate in terms of Equation (5.2) is $\hat{\theta}^*$. It can be obtained by using least squares, which minimizes:

$$\hat{\theta}^* = \arg\min_{\theta} ||y - \psi\, \theta||_2^2. \tag{5.7}$$

To get the optimal vector of parameters $\hat{\theta}^*$ is Equation (5.7) processed as follows:

$$\begin{aligned}
\frac{\partial}{\partial\theta}\left(y^T\,y - y^T\,\psi^T\,\theta - \psi\,\theta^T\,y + \psi\,\theta^T\,\psi^T\,\theta\right) &= -2\,\psi\,y + 2\,\psi\,\psi^T\,\theta, \qquad (5.8)\\
0 &= -2\,\psi\,y + 2\,\psi\,\psi^T\,\hat{\theta}^*,\\
\psi\,y &= \psi\,\psi^T\,\hat{\theta}^*,\\
(\psi\,\psi^T)^{-1}\,\psi\,y &= \hat{\theta}^*,\\
\hat{\theta}^* &= (\psi\,\psi^T)^{-1}\,\psi\,y.
\end{aligned}$$

The methods used for the identification have been implemented both in the identification toolbox ([8]) and by ourselves, which has advantages of additional physical constraints on the model to be identified. This was converted to transfer function and from transfer function it is easy to compute actual results for parameters.

The wanted parameters α, β are obtained from Equation (3.23). Additionally, there are physical constraints on K_{sw}, K_a to be positive.

$$\begin{aligned}
\alpha &= \frac{-K_{sw}\,h}{T_s \cdot p_1}\\
\beta &= \frac{-K_a\,h}{(p_2+p_3)T_s}\,,
\end{aligned} \qquad (5.9)$$

Firstly, the estimation of parameters α and β was performed on the whole available data, but the result was not satisfactory due to artefacts described in Chapter 4. Artefacts caused the resulting model to create a curve which was almost not responding to any significant input from supply water or weather temperature.

Secondly, the decision was made to cut the whole original data set into sets without any significant loss of data and without any artefacts. The estimation was run on each one of them and provided results listed in Table 5.3. The zeros in the table are due to aforementioned constraints.

5.2.2 Subspace identification

As well as previous methods this is also used for identifying linear time invariant systems, but on contrary it can be used to identify multiple input multiple output (MIMO) systems as well. This approach is also widely used for identification purposes as ARX [4, 3, 11]. In this case, only the identification toolbox in Matlab has been used. The greatest advantage is that it can merge more data sets together, so it can compute results

Data set	α	β	Data set	α	β
1	$3.30 \cdot 10^{-2}$	$1.00 \cdot 10^{-9}$	11	$6.37 \cdot 10^{-2}$	$1.00 \cdot 10^{-9}$
2	$4.50 \cdot 10^{-2}$	$1.00 \cdot 10^{-9}$	12	$2.43 \cdot 10^{-2}$	$1.00 \cdot 10^{-9}$
3	$2.76 \cdot 10^{-2}$	$0.16 \cdot 10^{-2}$	13	$7.03 \cdot 10^{-2}$	$0.53 \cdot 10^{-2}$
4	$0.20 \cdot 10^{-2}$	$1.00 \cdot 10^{-9}$	14	$4.23 \cdot 10^{-2}$	$1.00 \cdot 10^{-9}$
5	$1.00 \cdot 10^{-9}$	$0.19 \cdot 10^{-2}$	15	$1.00 \cdot 10^{-9}$	$1.07 \cdot 10^{-2}$
6	$4.04 \cdot 10^{-2}$	$0.03 \cdot 10^{-2}$	16	$6.52 \cdot 10^{-2}$	$1.00 \cdot 10^{-9}$
7	$9.51 \cdot 10^{-2}$	$1.00 \cdot 10^{-9}$	17	$1.71 \cdot 10^{-2}$	$0.22 \cdot 10^{-2}$
8	$1.00 \cdot 10^{-9}$	$1.00 \cdot 10^{-9}$	18	$0.98 \cdot 10^{-2}$	$0.33 \cdot 10^{-2}$
9	$1.32 \cdot 10^{-1}$	$1.00 \cdot 10^{-9}$	19	$1.00 \cdot 10^{-4}$	$3.54 \cdot 10^{-2}$
10	$0.91 \cdot 10^{-2}$	$1.00 \cdot 10^{-9}$	Mean Value	$3.56 \cdot 10^{-2}$	$0.32 \cdot 10^{-2}$

Table 5.2: Table of ARX estimated parameters.

using cooling or heating sets together. Method is also able to estimate the order of the system. The objective of the subspace algorithm is to find a linear, time invariant, discrete time model in an innovation form

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) + Ke(k) \\ y(k) &= Cx(k) + Du(k) + e(k), \end{aligned} \tag{5.10}$$

where A, B, C, D are system matrices, K is Kalman filter gain and e is a white noise sequence [12]. The objective of the algorithm is firstly to determine the system order, and afterwards, to find the system as well as state and measurement noise covariance matrices given the sequence of input $u(k)$ and output $y(k)$ measurements. The main difference between classical and subspace identification is, as follows:

- **Classical approach.** Find the system matrices, then estimate the system states, which often leads to high order models that have to be reduced thereafter.
- **Subspace approach.** Use orthogonal and oblique projections to find Kalman state sequence, then obtain the system matrices using least squares method.

Data set	α	β	Data set	α	β
1	$3.33 \cdot 10^{-2}$	$-0.04 \cdot 10^{-2}$	11	$4.24 \cdot 10^{-2}$	$-0.05 \cdot 10^{-2}$
2	$5.00 \cdot 10^{-2}$	$0.10 \cdot 10^{-2}$	12	$3.46 \cdot 10^{-2}$	$-0.33 \cdot 10^{-2}$
3	$7.33 \cdot 10^{-2}$	$-0.06 \cdot 10^{-2}$	13	$6.85 \cdot 10^{-2}$	$0.35 \cdot 10^{-2}$
4	$0.75 \cdot 10^{-2}$	$-0.24 \cdot 10^{-2}$	14	$2.95 \cdot 10^{-2}$	$0.09 \cdot 10^{-2}$
5	$-4.87 \cdot 10^{-2}$	$0.07 \cdot 10^{-2}$	15	$-2.25 \cdot 10^{-2}$	$0.16 \cdot 10^{-2}$
6	$4.21 \cdot 10^{-2}$	$0.02 \cdot 10^{-2}$	16	$6.80 \cdot 10^{-2}$	$-0.15 \cdot 10^{-2}$
7	$8.48 \cdot 10^{-2}$	$1.00 \cdot 10^{-9}$	17	$3.56 \cdot 10^{-2}$	$0.08 \cdot 10^{-2}$
8	$0.60 \cdot 10^{-2}$	$-0.93 \cdot 10^{-2}$	18	$0.93 \cdot 10^{-2}$	$0.25 \cdot 10^{-2}$
9	$11.9 \cdot 10^{-2}$	$0.03 \cdot 10^{-2}$	19	$0.51 \cdot 10^{-2}$	$-0.66 \cdot 10^{-2}$
10	$2.19 \cdot 10^{-2}$	$0.08 \cdot 10^{-2}$	Mean Value	$4.30 \cdot 10^{-2}$	$0.12 \cdot 10^{-2}$

Table 5.3: Table of subspace (n4sid) estimated parameters.

5.3 Nonlinear approach

5.3.1 Linear parameter varying models (LPV)

These methods described for example in [10] and [1] are used to identify non–linear or time varying systems. It is assumed, that the varying paramter is measured. LPV separates a paramter causing nonlienarity from the system. It allows to identify the linear part of the system. In 5.11 is introduced a LPV system. Parameter dependent plant is depicted on Figure 5.4.

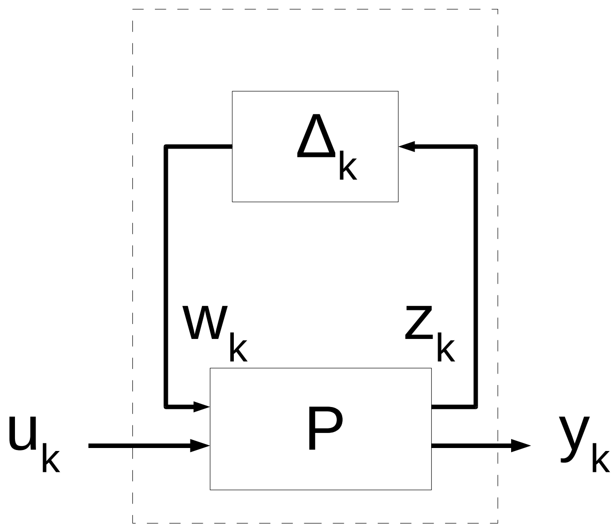


Figure 5.4: Parameter dependent plant.

Since here is only one varying parameter, it will be denoted $\delta(k)$ instead of $\Delta(k)$, where k represents time step. $\delta(k)$ is extracted parameter causing non–linearity, in case of ABESON chemical storage tank it is level h. On Figure 5.4 – u_k is measured input data, y_k is measured output and z_k with w_k are unmeasurable signals internal to the plant. The system can be expressed by following system equations:

$$
\begin{aligned}
X(k+1) &= AX(k) + B_1 u(k) + B_2 w(k), \\
z(k) &= C_1 X(k) + D_{11} u(k) + D_{12} w(k), \\
y(k) &= C_2 X(k), \\
w(k) &= \delta(k) z(k),
\end{aligned}
\tag{5.11}
$$

where $A \in \mathcal{R}^{n\times n}$, $B_1 \in \mathcal{R}^{n\times m}$, $B_2 \in \mathcal{R}^{n\times 1}$, $C_1, C_2 \in \mathcal{R}^{1\times n}$, $D_{11} \in \mathcal{R}^{1\times m}$ and $D_{12 \in \mathcal{R}^{1\times 1}}$. Where n is model order and m is number of inputs. For thesis' system $n = 1$ and $m = 2$. There are two measured inputs and one measured output and one measured parameter – level h. Using this fractional transformation, it is possible to identify system as a linear system with one varying parameter using recursive least square (RLS) algorithm.

For our case of the first order model, the matrices $A = a_{11}$, $B_1 = [b_{11}\, b_{12}]$, $B_2 = 1$, $C_1 = c_1$, $C_2 = 1$, $D_{11} = [d_{11}\, d_{12}]$ and $D_{12} = d_2$. So the Equation (5.11) can be rewritten into

$$
\begin{aligned}
T_i(k+1) &= a_{11}\, T_i(k) + b_{11}\, T_{sw}(k) + b_{12}\, T_a(k) + w(k), \\
z(k) &= c_1\, T_i(k) + d_{11}\, T_{sw}(k) + d_{12}\, T_a(k) + d_2\, w(k), \\
y(k) &= T_i(k), \\
w(k) &= \delta(k)\, z(k).
\end{aligned}
\tag{5.12}
$$

In order to find regresor and vector of parameters, it is necessary to proceed further by regrouping terms as

$$
\begin{aligned}
T_i(k+1) - a_{11}\, T_i(k) - b_{11}\, T_{sw}(k) - b_{12}\, T_a(k) &= w(k), \\
\frac{1}{d_2}\, (c_1\, T_i(k) + d_{11}\, T_{sw}(k) + d_{12}\, T_a(k)) &= \frac{1}{d_2}\, z_k - w(k), \\
w(k) &= \delta(k)\, z(k).
\end{aligned}
\tag{5.13}
$$

From Equation (5.13) is possible to collect z_k and substitute for w_k

$$
\begin{aligned}
T_i(k+1) - a_{11}\, T_i(k) - b_{11}\, T_{sw}(k) - b_{12}\, T_a(k) = \delta_k\, z_k, \\
\frac{1}{d_2}\ \left(c_1\, T_i(k) + d_{11}\, T_{sw}(k) + d_{12}\, T_a(k)\right) = z_k\, \left(\frac{1}{d_2} - \delta_k\right),
\end{aligned}
\tag{5.14}
$$

and it allows to divide both equaitons and cancel z_k, getting

$$
\begin{aligned}
\left(\frac{1}{d_2} - \delta_k\right)\ (T_i(k+1) - a_{11}\, T_i(k) - b_{11}\, T_{sw}(k) - b_{12}\, T_a(k)) = \\
= \delta_k\, \frac{1}{d_2}\ \left(c_1\, T_i(k) + d_{11}\, T_{sw}(k) + d_{12}\, T_a(k)\right).
\end{aligned}
\tag{5.15}
$$

Equation (5.15) is almost in a form for use of least squares method. To simplify it, let us substitute $\alpha_1 = \frac{1}{d_2}$, $\alpha_2 = -\frac{a_{11}}{d_2}$, $\alpha_3 = -\frac{b_{11}}{d_2}$, $\alpha_4 = -\frac{b_{12}}{d_2}$, $\alpha_5 = a_{11} - \frac{c_1}{d_2}$, $\alpha_6 = b_{11} - \frac{d_{11}}{d_2}$, $\alpha_7 = b_{12} - \frac{d_{12}}{d_2}$, .

While the vector of parameters Θ and regressor Ψ are defined as

$$
\begin{aligned}
\Theta &= [\alpha_1,\ \alpha_2,\ \alpha_3,\ \alpha_4,\ \alpha_5,\ \alpha_6,\ \alpha_7]^T \\
\Psi_{k+1} &= \begin{bmatrix} T_i(k+1) & T_i(k) & T_{sw}(k) & T_a(k) & \delta(k)\, T_i(k) & \delta(k)\, T_{sw}(k) & \delta(k)\, T_a(k) \end{bmatrix},
\end{aligned}
\tag{5.16}
$$

Parameters in vector Θ are obtained from solving Equation (5.17) using RLS.

$$
\delta(k) T_i(k+1) = \Psi_{k+1} \Theta. \tag{5.17}
$$

Tank's discretized equation according to [10] is as follows:

$$
\begin{aligned}
T_i(k+1) &= \begin{bmatrix} p_2 \beta T_s + 1 & 0 & -p_2 \beta T_s \end{bmatrix} \begin{bmatrix} T_i(k) \\ T_{sw}(k) \\ T_a(k) \end{bmatrix} + w(k), \\
w(k) &= \delta(k) z(k), \\
z(k) &= \begin{bmatrix} p_1 \alpha T_s + p_3 \beta T_s \\ -p_1 \alpha T_s \\ -p_3 \beta T_s \end{bmatrix}^T \begin{bmatrix} T_i(k) \\ T_{sw}(k) \\ T_a(k) \end{bmatrix}.
\end{aligned}
\tag{5.18}
$$

Using this method, estimated paramters converged to $\alpha =$ 0.029 and $\beta =$ 0.0019. The trajectory of parameters suggests there are two possible models - first summer and second winter. Once the heating started working the parameters dropped to different values. Changes of trajectory were caused by artefacts described in section Chapter 4.

The algorithm for providing results was recursive least sqares and least squares. LPV was - unlike ARX, Subspace and ACADO - run on the whole data set taken from the end of september till the end of January.

$$\hat{\Theta}(k) = \hat{\Theta}(k-1) + L(k)\left[y(k) - \psi^T(k)\hat{\Theta}(k-1)\right], \tag{5.19}$$

$$L(k) = \frac{P(k-1)\psi(k)}{\lambda + \psi^T(k)P(k-1)\psi(k)}, \tag{5.20}$$

$$P(k) = \frac{1}{\lambda} \cdot \left[P(k-1) - \frac{P(k-1)\psi(k)\psi^T(k)P(k-1)}{\lambda + \psi^T(k)P(k-1)\psi(k)}\right], \tag{5.21}$$

where P is covariance matrix, λ is forgetting parameter, $\hat{\Theta}$ is an estimate of vector of parameters and L is Kalman's gain.

5.3.2 Identification by ACADO software

ACADO[2] stands for the Automatic Control and Dynamic Optimization ([7, 5]). It enables the computation of an optimal input, identification of optimal parameters of non-linear systems and solving non-linear equations in continuous or discrete time domain. ACADO can be used as a standalone program using C/C++ source code or it can work as an interface for Matlab. The results using ACADO software are displayed in Table 5.4 and in Table 5.5.

Algorith uses the Levenberg–Marquardt Algorithm, which is the most often used optimization algorithm. It is a combination of vanilla gradient descent and Gauss–Newton iteration. In many ways it overcomes simple gradient algorithms.

Even though it might seem as the most straightforward method of determining searched parameters, it turned out that there are too many data and computer was not able to process more than certain size of input files, which made its use very limited. However, it produced perfect results which matched the input data plausibly, although it did not work on the whole data set.

This identification also underwent some development. At the beginning the idea was to determine also all parameters of the model – l_1, l_2, λ_1, λ_2 and c. However it proved to be too complicated and it was decided not to proceed with these estimates. The results

[2] `http://www.acadotoolkit.org/`

were out of physical bounds or sometimes also illogicaly negative. The accuracy was very good, but provided values did not make any sense in a real world. ACADO turned out to be the very useful tool and produced plausible results.

Set	α	β	Set	α	β
1	$2.77 \cdot 10^{-2}$	$1.82 \cdot 10^{-3}$	11	$2.80 \cdot 10^{-2}$	$1.00 \cdot 10^{-4}$
2	$4.46 \cdot 10^{-2}$	$1.00 \cdot 10^{-3}$	12	$3.11 \cdot 10^{-2}$	$1.00 \cdot 10^{-4}$
3	$6.68 \cdot 10^{-2}$	$9.73 \cdot 10^{-3}$	13	$7.63 \cdot 10^{-3}$	$2.00 \cdot 10^{-2}$
4	$1.39 \cdot 10^{-2}$	$8.79 \cdot 10^{-3}$	14	$3.74 \cdot 10^{-2}$	$1.00 \cdot 10^{-4}$
5	$1.00 \cdot 10^{-6}$	$1.32 \cdot 10^{-3}$	15	$3.70 \cdot 10^{-2}$	$1.00 \cdot 10^{-4}$
6	$1.26 \cdot 10^{-2}$	$1.00 \cdot 10^{-4}$	16	$3.66 \cdot 10^{-2}$	$1.00 \cdot 10^{-4}$
7	$2.51 \cdot 10^{-2}$	$1.30 \cdot 10^{-2}$	17	$3.00 \cdot 10^{-2}$	$1.00 \cdot 10^{-4}$
8	$1.00 \cdot 10^{-6}$	$9.93 \cdot 10^{-3}$	18	$1.04 \cdot 10^{-2}$	$1.74 \cdot 10^{-2}$
9	$3.54 \cdot 10^{-2}$	$1.00 \cdot 10^{-4}$	19	$2.38 \cdot 10^{-2}$	$6.32 \cdot 10^{-3}$
10	$2.29 \cdot 10^{-2}$	$1.87 \cdot 10^{-2}$	Mean Value	$2.58 \cdot 10^{-2}$	$5.72 \cdot 10^{-4}$

Table 5.4: Estimated parameters by ACADO from reference set.

α	β	Heating temp	α	β	Heating temp
$1.00 \cdot 10^{-6}$	$0.12 \cdot 10^{-2}$	35.0	$9.03 \cdot 10^{-3}$	$0.60 \cdot 10^{-3}$	40.0
$4.42 \cdot 10^{-2}$	$0.08 \cdot 10^{-2}$	35.0	$1.24 \cdot 10^{-2}$	$1.00 \cdot 10^{-3}$	40.0
$7.50 \cdot 10^{-2}$	$0.26 \cdot 10^{-2}$	45.0	$3.14 \cdot 10^{-3}$	$2.60 \cdot 10^{-3}$	40.0
$2.35 \cdot 10^{-2}$	$0.11 \cdot 10^{-2}$	45.0	$7.92 \cdot 10^{-3}$	$3.20 \cdot 10^{-3}$	40.0
$4.85 \cdot 10^{-2}$	$0.19 \cdot 10^{-2}$	45.0	$1.59 \cdot 10^{-2}$	$3.50 \cdot 10^{-3}$	40.0
$3.23 \cdot 10^{-2}$	$0.07 \cdot 10^{-2}$	40.0	$1.74 \cdot 10^{-3}$	$1.10 \cdot 10^{-3}$	40.0
$2.40 \cdot 10^{-2}$	$0.14 \cdot 10^{-2}$	40.0	$1.05 \cdot 10^{-4}$	$0.70 \cdot 10^{-3}$	55.0
$1.00 \cdot 10^{-9}$	$0.19 \cdot 10^{-2}$	40.0	$5.90 \cdot 10^{-5}$	$0.17 \cdot 10^{-3}$	55.0

Table 5.5: Estimated parameters by ACADO from nonlinear sets.

In the second table there are identified parameters for winter time. It is possible to tell because there is a column with supply water temperature.s

5.4 Decoupled identification approach

As another approach to verify the results and to get more accurate parameters it was decided to use ACADO to identify separetly heating and cooling parts. This approach required data preprocessing. Instead of parts with obvious cooling pattern, data, where ABESON's temperature was in steady state or where it was very close to the heating temperature, were choosen for identification. The assumption was that when the temperature is about the same as supply water temperature then it can be neglected.

Second point is to choose the same data as in previous cases with cooling pattern to identify cooling constant only - this means setting the $\alpha = 0$. Then on parts with clear heating α was identified separately.

Data set	Cooling - β	Data set	Cooling - β
1	$1.35 \cdot 10^{-3}$	6	$1.04 \cdot 10^{-3}$
2	$1.01 \cdot 10^{-3}$	7	$0.53 \cdot 10^{-3}$
3	$1.19 \cdot 10^{-3}$	8	$0.21 \cdot 10^{-3}$
4	$1.45 \cdot 10^{-3}$	9	$1.44 \cdot 10^{-3}$
5	$1.16 \cdot 10^{-3}$	10	$0.88 \cdot 10^{-3}$
Mean Value	$0.9794 \cdot 10^{-3}$		

Table 5.6: Table of decoupled estimated parameters for cooling.

Using the mean value from table 5.6 as fixed parameter for β the other parameter – α – was estimated from heating parts. The parameter was determined as $\alpha = 0.028$.

Data sets with appropriate heating sets were less than with cooling sets, therefore there are only few items in Table 5.7. Despite its limited resources, this approach turned out very important in terms of realising the energy flow. If one of the estimated components represented by parameters α and β is steeper than the other, it results in increasing the ABESON's temperature or decreasing it depending on which component has stronger influence. Decoupled approach also tells, how long it will take for ABESON to cool down when not heated. If days, it might be used to turn the heating off entirely. Thanks to decoupled identification it is possible to tell, when will the ABESON's temperature decrease under desired value and when the heating will be needed again.

The parameters in Table 5.7 have very small deviation. It is a very good result. It might be because there were only few data sets. The problem was, that supply water was not able to maintain the ABESON's temperature when full tank. For that reason the sets where the temperature was actually rising thanks to the supply water were rare. When more data are measured, more estimations can be done to support this approach.

Data set	Heating – α
1	$2.05 \cdot 10^{-2}$
2	$2.80 \cdot 10^{-2}$
3	$2.76 \cdot 10^{-2}$
4	$3.70 \cdot 10^{-2}$
5	$2.72 \cdot 10^{-2}$
6	$2.38 \cdot 10^{-2}$
Mean Value	$2.75 \cdot 10^{-2}$

Table 5.7: Table of decoupled estimated parameters for heating.

Chapter 6

Verification of identified models

Chapter describes the files written to simulate results and extimate parameters. It includes figures of simulated models and compares them. The chapter states criateria for a model to be acceptable and to be used in control and then evaluates identified models.

6.1 Files description

To perform simulations numerous files were written. This section will describe each one of them.

- `LPV_enaspol.m`- loads desired data and then identifies parameters of linear parameter varying model using recursive least squares.
- `LPV_identification.m`- uses modified linear parameter varying model and identifies parameters using recursive least squares method,
- `ACADO_parameter_estimation.c`- source code for using ACADO to identify parameters. Source file has to be compiled first and then run with input files with input data.
  - `ENA_h_short.txt`- level input data.
  - `ENA_Theat_short.txt`- supply water temperature.
  - `ENA_Ttank_short.txt`- ABESON's temperature.
  - `ENA_Tw_short.txt`- ambient temperature.

- `get_fit_factor.m`- includes code to compapre two signals.
- `ENASPOL_simulation.m`- simulates the ABESON's temperature and plots graphs.
- `ARX_estimate.m`- estimation of parameters of ARX model.
- `parse_data.m`- data parser to prepare export of data from MATLAB®to ACADO input files.
- `write_data.m`- writes data for ACADO to txt files.
- `read_data.m`- reads data from txt files for simulation purposes.
- `ACADO_matlab.m`- ACADO interface incorporating ACADO to MATLAB.

6.2 Validation of models

For simulation script `ENASPOL_simulation.m` was used. This script used input data to simulate ABESON's temperature and as a result plots the original ABESON's temperature along with simulated to see the difference. To evaluate the result properly, other script computed fit factor. Fit factor is a percentage value suggesting how similar the two signals are. The closer to 100%, the better, but it is still acceptable fit of 50%. The script computes the difference between single points from simulation and original data and then normalises it.

A storage tank was modelled, the model describing heat exchanger was used as described in Chapter 3. To identify parameters of the system, five approaches were applied:

- Linear - ARX and Subspace.
- Non-linear - ACADO software and Linear parameter varying model's parameter estimation.
- Decoupled cooling and heating parts identification.

Estimated parameters of identified models are in Table 6.1.

The parameters are in expected range, but PEM and Subspace parameters are significantly greater than others. It is caused by the extimation process where mean was computed from set of input data. The estimation process of PEM was constrained, but

Subspace did not have any constraints. For that reason the results of both linear methods are different.

On the other hand, the non–linear methods have parameter α about the same, but parameter β is different. Also decoupled approach provided results similar to non–linear approches.

On the Figure 6.1 are simulated results and ABESON's temperature with original data. The data were obtained in winter time as suggests the negative ambient temperature. Supply water has high temperature, because ABESON was required to stay warm. This data set was chosen also because the level is changing and therefore it is possible to verify whether the model is working also unde this condition.

The method using ARX model seems to have trouble with matching the original data. It means that parameters are not estimated correctly. On contrary, Subspace identification covers the original data well. It is almost like ACADO. Subspace method did not have any contraints, so some estimated parameters from which the mean was calculated were even negative. It shifted the resulting parameters in Table 6.1. ARX model without constraints was also tested, but it did not provide acceptable results.

ACADO simulation is very close to Subspace simulation. It is because the ration between parameters α and β is about the same, so the development of temperature will be very similar. LPV model's simulation of the temperature is also plausible. From all the methods it covers the original data the best.

Estimation of parameter for previous methods was based on estimating parameters from different data sets and them computing mean value, which was considered as resulting parameter. LPV approach could work with the whole data set as the only approach used. ACADO has also the capability to process the non–linear input, but it required a great computation power which was not avalible to author when writing this thesis. Using LPV was very convenient.

Convergence of parameters is shown on Figure 6.2 along with data used to estimate parameters. The values of the estimated parameters α, β varying in time are depicted

Parameter	ARX	SubSpace	LPV	ACADO	Decoupled
α	$3.56 \cdot 10^{-2}$	$4.30 \cdot 10^{-2}$	$2.58 \cdot 10^{-2}$	$2.41 \cdot 10^{-2}$	$2.80 \cdot 10^{-2}$
β	$3.20 \cdot 10^{-3}$	$1.20 \cdot 10^{-3}$	$1.56 \cdot 10^{-3}$	$7.89 \cdot 10^{-4}$	$1.02 \cdot 10^{-3}$

Table 6.1: Table of resulting parameters.

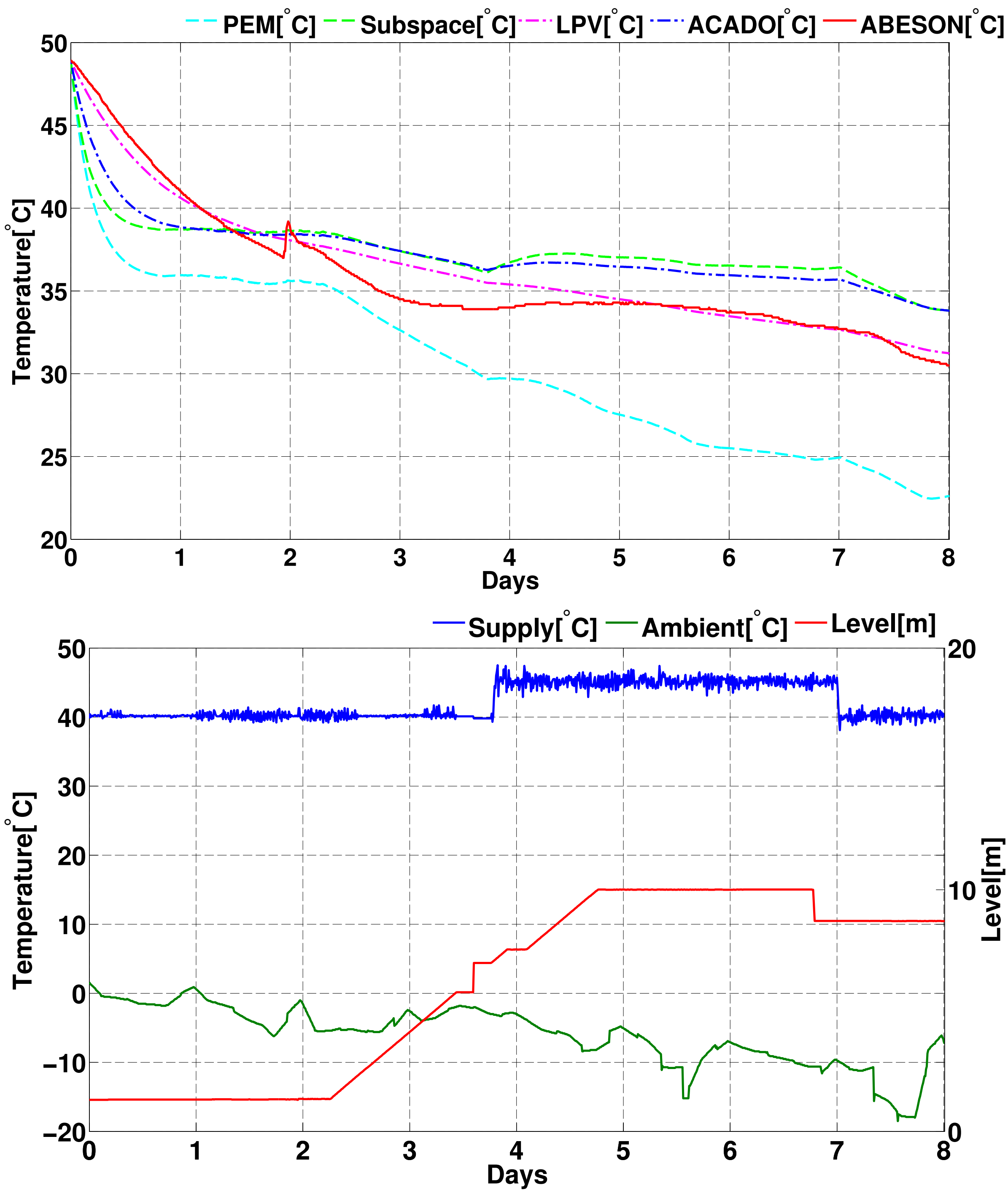


Figure 6.1: Result of identification and input data used for simulation.

in Figure 6.2. The trajectory of the parameters was affected neither by changes of supply water temperature, nor by drops in level. It was a great advantage that there was no need for data preprocessing. In data there are obvious artefacts, but despite them, the parameters converged succesfully and as Figure 6.1 shows the result was acceptable.

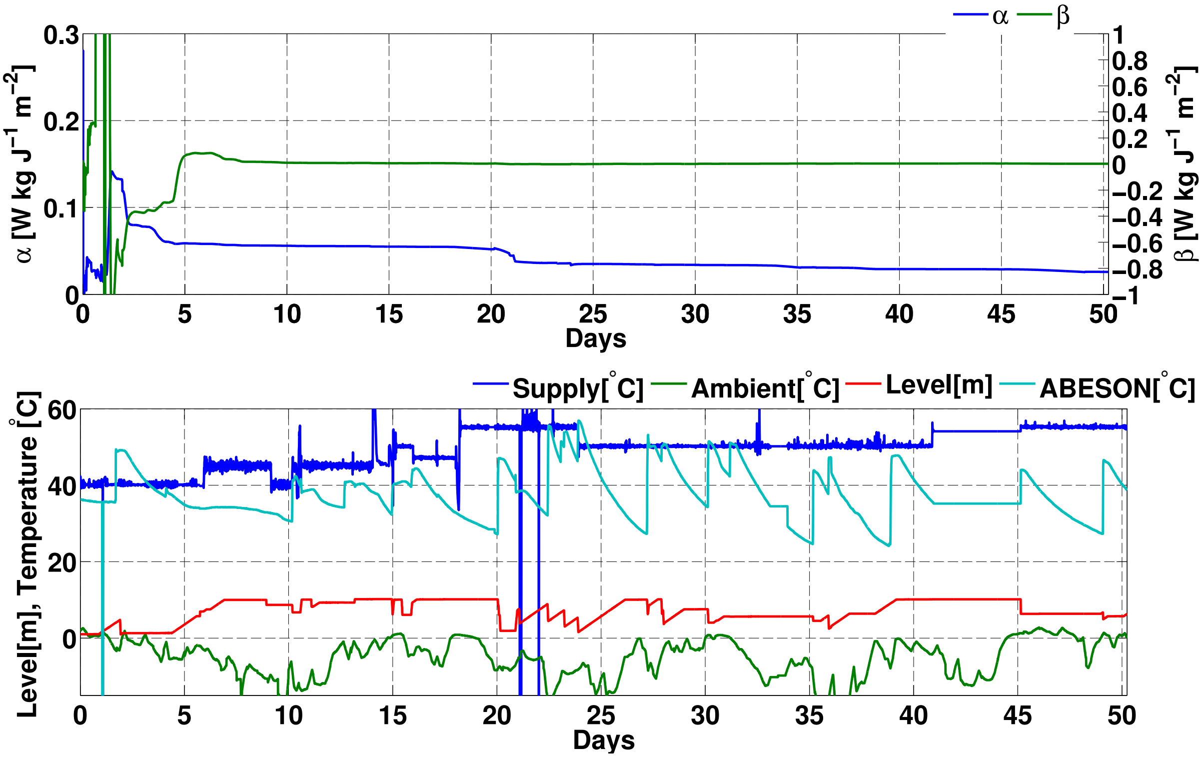


Figure 6.2: Convergence of parameters and used data for parameter estimation.

Typical output of ACADO software is on Figure 6.3. This outpus shows the status of convergence and every line is one step of optimization. In the end it displays optimal parameters for desired input set and plots graphs using gnuplot. Grahical output example is on Figure 6.4.

Identification using ACADO has certain requirements for the input data. It needed time stamp for every measurement and eventhough there were examples able to deal with a data loss, in reallity it seemed to cause trouble. It caused the system to report `Segmentationfault`. Therefore input data sets were cleaned from NaN (not a number) values. This was done by script `parse_data.m` as noted above.

On Figure 6.4 gnuplot plots the output computed by ACADO. The upper left graph shows the comparisement of original data entered - red line - with simulated result - black line. The black line in this case is almost not visible, since there is very high fit factor. ACADO produced on this sets always very precise outputs with high fit factor.

Approach suitable for the problem was applied- decoupled identification of heating and cooling parts, which proved to provided good parameters as well. This approach was based on data preprcessing and to identify parameters ACADO was used as well. To perform this, data sets with clear heating part were needed. Unfortunately there were

```
INIT!!

ACADO Toolkit::SCPmethod -- A Sequential Quadratic Programming Algorithm.
Copyright (C) 2008-2009 by Boris Houska and Hans Joachim Ferreau, K.U.Leuven.
Developed within the Optimization in Engineering Center (OPTEC) under
supervision of Moritz Diehl. All rights reserved.

ACADO Toolkit is distributed under the terms of the GNU Lesser
General Public License 3 in the hope that it will be useful,
but WITHOUT ANY WARRANTY; without even the implied warranty of
MERCHANTABILITY or FITNESS FOR A PARTICULAR PURPOSE. See the
GNU Lesser General Public License for more details.

  1:  KKT tolerance = 1.501e+02    line search parameter = 1.000e+00    objective value =
2.6442e+01    merit function value = 2.0141e+02
  2:  KKT tolerance = 6.579e+00    line search parameter = 1.000e+00    objective value =
4.2468e+01    merit function value = 4.5668e+01
  3:  KKT tolerance = 2.026e+00    line search parameter = 1.000e+00    objective value =
4.4569e+01    merit function value = 4.4569e+01
  4:  KKT tolerance = 1.169e-04    line search parameter = 1.000e+00    objective value =
4.4569e+01    merit function value = 4.4569e+01
  5:  KKT tolerance = 1.276e-09    line search parameter = 1.000e+00    objective value =
4.4569e+01    merit function value = 4.4569e+01

convergence achieved.



Results for the parameters:
-----------------------------------------------
    3.003e-02 &    1.000e-02
-----------------------------------------------
```

Figure 6.3: Text output from ACADO.

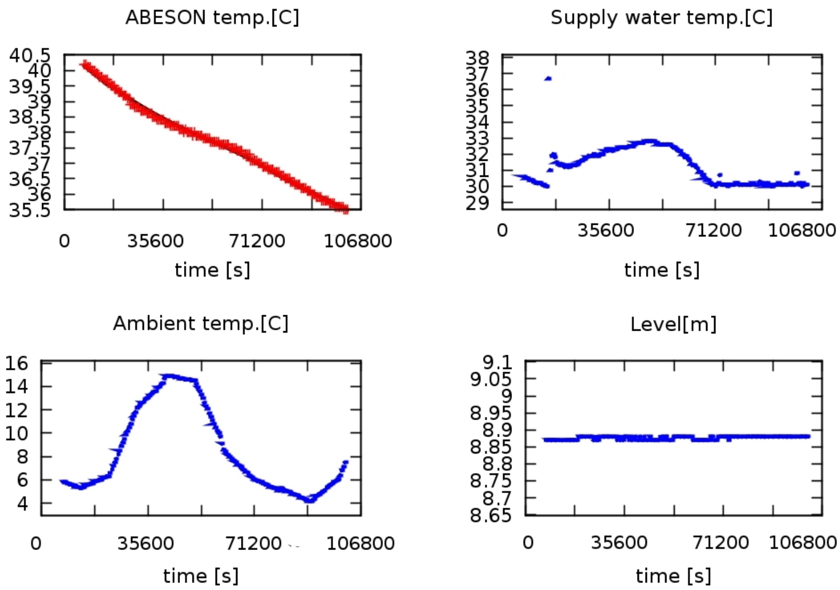


Figure 6.4: Graphical output plotted by gnuplot.

not sets enough to improve the estimates, but despite limited options it yielded some usable results.

The data set was chosen with high temperature of supply water. That is the main idea of using decoupled approach. The part of cooling was already identified using ACADO on data sets where the supply water was off. Since parameter β determining the cooling part is estimated, the next step is to determine parameter α.

Figure 6.6 shows, how the date looked like. The line called cooling is a simulation, how the temperature would develop, if only cooling was employed. The real ABESON's temperature is above this line. That means, that the heating is supplying energy to the system. Contribution of heating part can be expressed by subtracting the simulated cooling part from original ABESON's temperature and the result identify using ACADO. The result of subtraction is on Figure 6.5. The parameter obtained will be parameter of α.

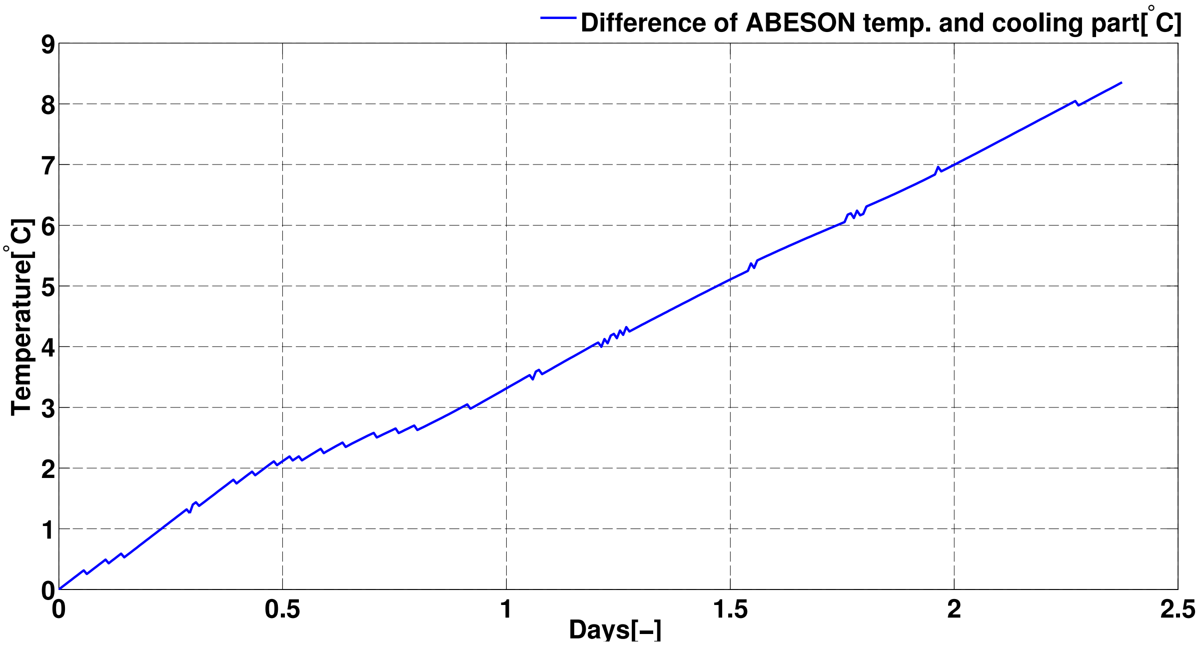


Figure 6.5: Difference between ACADO temperature and estimated cooling part is heating part – subject to estimate.

The Figure 6.5 is almost linear line. This is confirms that supply water is providing constant energy to the system.

6.3 Summary

Is is necessary to determine which approach would be the most suitable for implementing control. The model should have the greatest fit factor in average. For that reason all

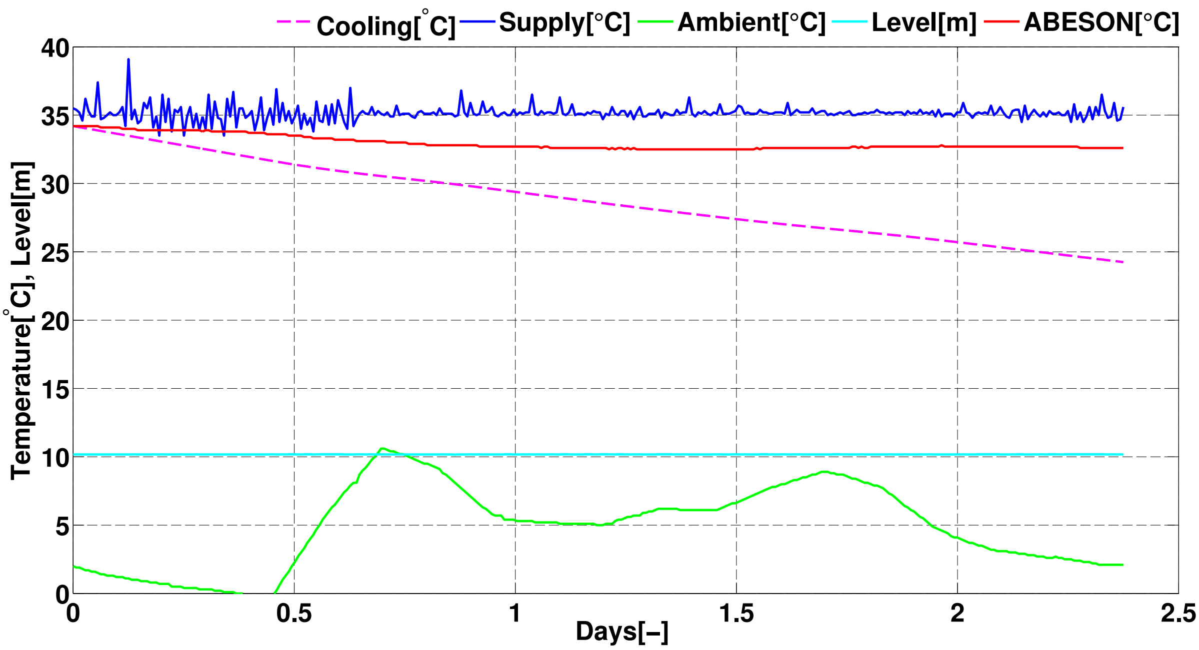


Figure 6.6: Decoupled input data exmaple.

data sets used for estimation were taken and estimated parameters from Table 6.1 used to compute fit factor for every single data set. The couple of parameters with highest fit tactor in average will be then used for control.

Acording to results table Table 6.2, it was decided to use parameters from LPV model. Eventhough there are some negative numbers, it has the highest fit factors in table. Generally it is not necessary to achieve very high fit factor. Fit factors above 50% are still acceptable.

PEM[%]	Subspace[%]	LPV[%]	ACADO[%]
-2	51	72	46
-251	-50	-54	-75
-292	4	-35	-25
-28	12	46	32
-435	-85	-45	20
-66	-19	76	-5
-138	-25	82	29
48	-4	36	13
-52	24	63	54
-52	24	63	54
60	41	43	45
-82	4	80	34
32	-98	12	-58
-75	13	65	44
-25	38	60	65
-9	43	74	57
-73	9	79	37
78	39	38	42
-352	16	62	25

Table 6.2: Table of fit factors.

Chapter 7

Control and Implementation

7.1 Control strategy

The main objective of the control of this process is to reduce the energy consumption. Since the process includes disturbance and physical and chemical constraints, and since the control demands are the reference tracking and the optimality (from the point of energy consumption), the only possible control strategy is the model predictive control (MPC). Due to its great properties, the MPC is widely used in many real application, and, moreover, is recently thought of as the best way to save the energy.

As was mentioned above, there is no measurement of return water, thus the problem of derivation of the amount of consumed energy arises. To cope with this problem, one can assume the following. Since the supply water can be only heated up using the steam, and since during the winter (as main heating season) the steam is the only source of heat, it holds that the lower supply water temperature, the lower energy cost. Therefore, instead of the energy consumption, the MPC criterion contains the supply water temperature.

7.2 Formulation of the control problem

Let us denote the model for control as

$$T_i(k+1) = A(h,T_s)T_i(k) + B(h,T_s)T_{sw}(k) + V(h,T_s)T_a(k), \tag{7.1}$$

where $A(h,T_s), B(h,T_s), V(h,T_s)$ are appropriate parameter dependent model matrices and the signals were defined in Chapter 2. 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:

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

such that the Equation (7.1) and

$$\begin{aligned} T_{sw,min} \leq\ & T_{sw} \leq T_{sw,max}, & (7.3)\\ Z_{sw,min} \leq\ & Z_{sw} \leq Z_{sw,max}, & (7.4)\\ Z_{i,min} \leq\ & Z_i \leq Z_{i,max}, \\ \Delta_{min}T_{sw} \leq\ & \Delta T_{sw} \leq \Delta_{max}T_{sw}, \end{aligned}$$

hold as well as the other standard assumptions on the optimal problem to be solvable [2]. Z_i and Z_{sw} are called slack variables and define ranges where the T_i and T_{sw} are not penalized. The subscripts min, max denote minimum and maximum possible values of appropriate variables and Δ denotes rate of change of corresponding variable. Q, R are weighting matrices.

Since ABESON has to be kept in certain range, slack variables were set to $Z_{i,min} =$ 30 °C $Z_{i,max} =$ 55 °C,$Z_{sw,min} =$ 30 °C, $Z_{sw,max} =$ 30 °C and $T_{sw,min}$30 °C, $T_{sw,max} =$ 50 °C. It tells that controler keeps the ABESON's temperature within 30 °C and 55 °C and that the supply water temperature will not go over 50 °C or under 30 °C, also when higher or lower than 30 °C it will be penalized. The horizon of prediction is three days. The data from NOAA are provided 7 days in advance, but it can change significantly. ABESON changes its temperature very slowly, so three days are enough to maintain its temperature within desired range with regard to weather. More than three days are not necessary.

7.3 Implementation of control system

The solution of the system is based on programable logical controlers (PLC's) DOMAT and JUMO. These two controlers are part of the lowest layer. Higher layer is then operated by remote RcWare server from ENERGOCENTRUM Plus s.r.o. This approach allows to monitor system from anywhere and make any corrections, if desired. On the same level is WebPanel which is a web–based application for direct access to process control.

JUMO is responsible for controling of temperature of the supply water and for reading measurements - level, temperature of supply water, inner product temperature. Weather temperature is not meausured directly and is not provided from sensor on site. Ambient temperature is provided by NOAA from their weather forecast.

DOMAT takes care of communicating with superior layer. It recieves instruction of what the desired temperature is and ensures that only valid data will be handed over to JUMO. It also checks, whether the communcation with control server is online and in case of any interruption it is able to set safe temperature.

RcWare is server, where SoftPLC application is running and executing root operations. In 30 min cycles it starts MATLAB, runs computation of MPC problem (solving the optimization) using designed model and returns a vector of temperatures to use for next 30 min. Since the process is very slow, there is no need to care about the whole vector and only first value is taken and sent to DOMAT.

Time interval 30 min was chosen, because for control are used data with sampling time 60 min and for safety reasons is the computation run twice rather than once.

From WebPanel can be viewed the current desired temperature from controler and

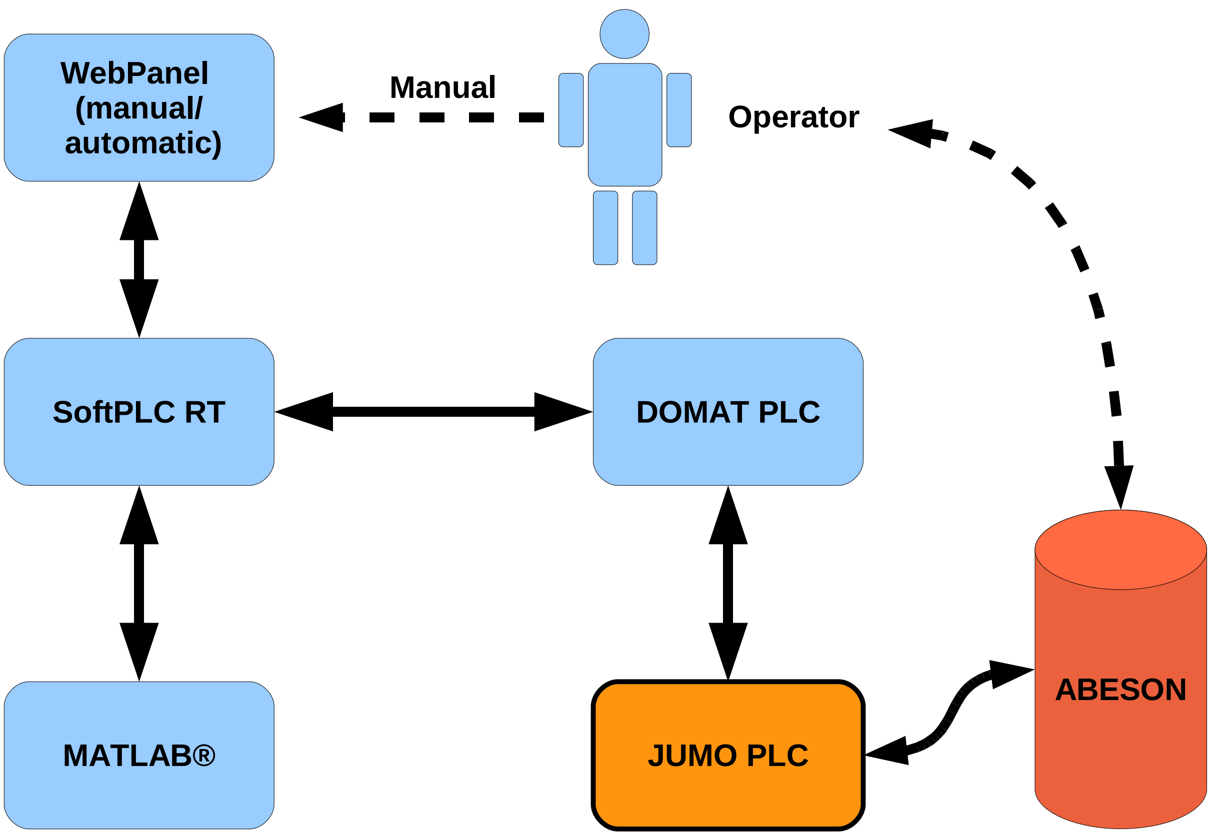


Figure 7.1: Control set-up.

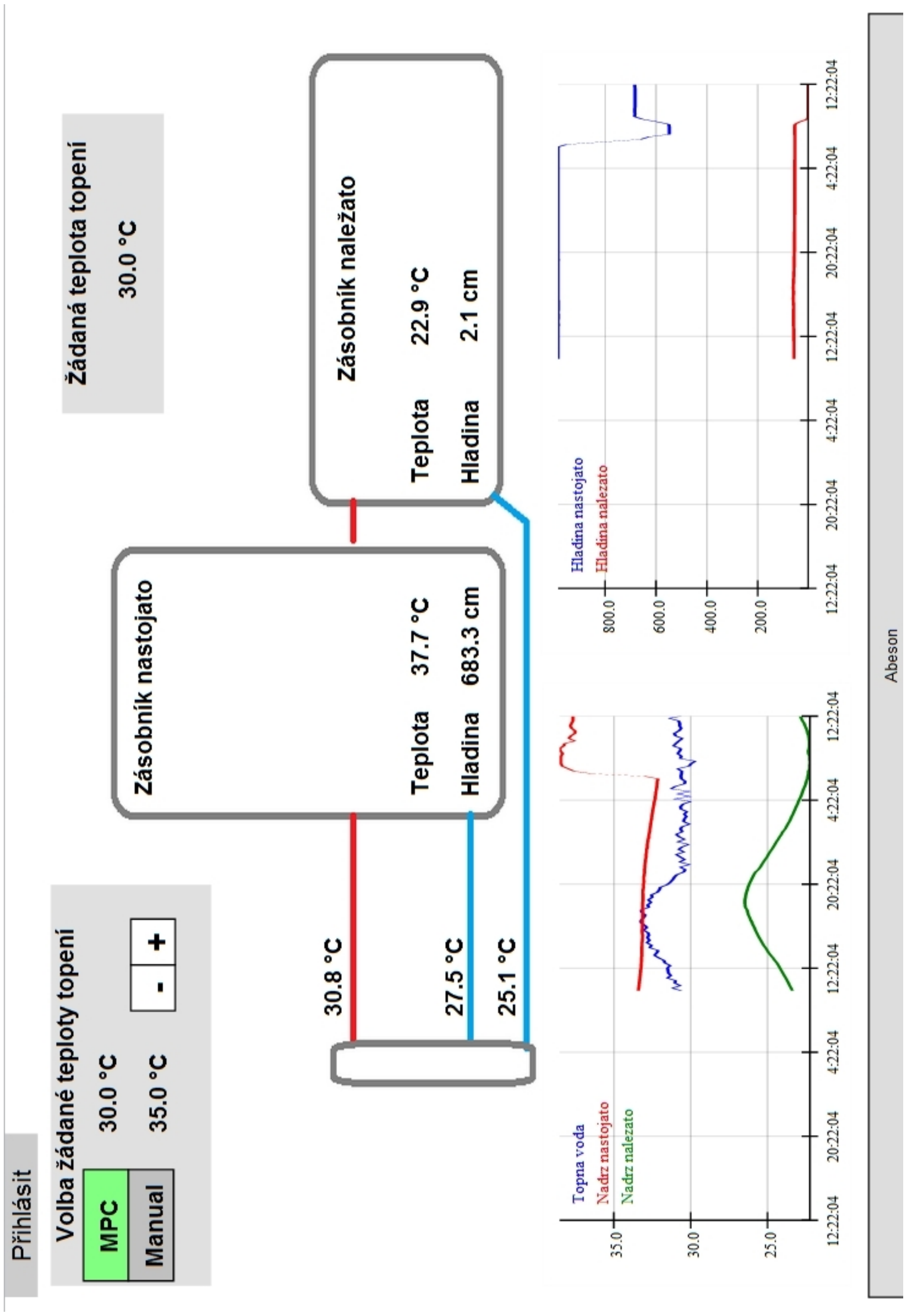


Figure 7.2: WebPanel window.

it is possible to switch to manual control and set the temperature manually. Because it is web–based application it is possible to access it from everywhere to make corrections. The access is protected by password. It also shows current level, ABESON's temperature and current supply water temperature of both tanks.

Chapter 8

Results of control

The parameters used in control are parameters from LPV identification, as was justified in Chapter 5. How the tank performes after using model predictive control can be compared on Figure 8.1. At the very moment when MPC started its operation, it set the lowest heating temperature in accordance to its constraints.

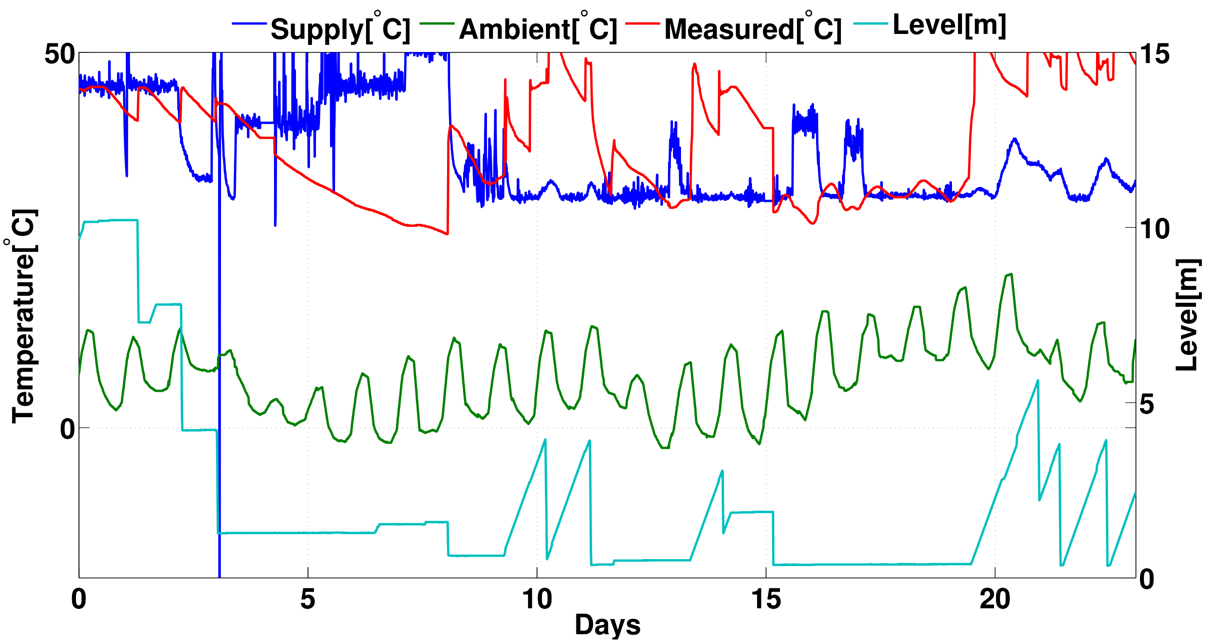


Figure 8.1: MPC implemented.

The change is very significant, it happens in eigth day. The supply water temperature then changes value according to weather temperature and ABESON temperature. Which is a great improvement comapared to previous approach, where the operators did not take care about setting the temperature lower or higher at the moment when it was needed.

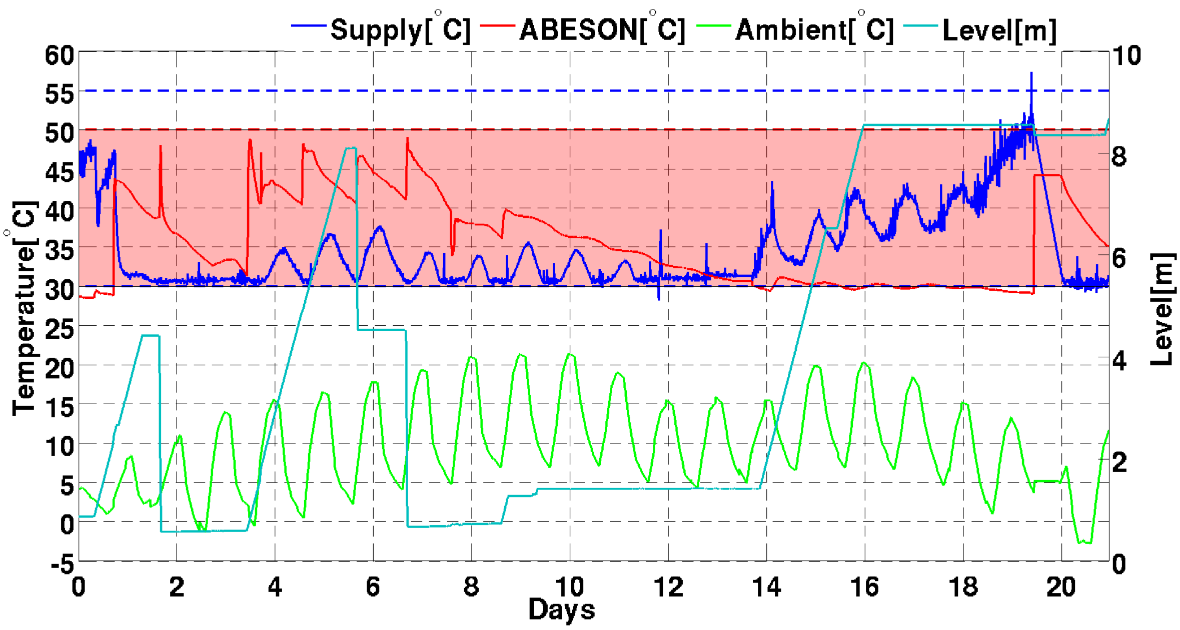


Figure 8.2: Heating ranges and actions taken from MPC.

The ABESON's temperature was set to be maintained within desired 30 °C and 55 °C. On Figure 8.2 is possible to see, that when the temperature gets bellow this range, contoler starts heating–up till the ABESON temperature is in the range. Eventhough it might set higher temperature it leaves it less than maximum. These ranges are marked by red area, which shows where the supply water temperature is allowed to get and blue dashed lines show the acceptable range for ABESON.

When looking at Figure 8.2, one important question arises. There is a segment between second and fourteenth day, where the supply water temperature is higher than 30 °C, eventhough the ABESON's temperature is in desired range. This is due to a warm weather during that time. Notice, that peaks in supply water temperature correspond to top peaks in ambient environment temperature.

It is also interresting to see, that implemented controler is able to maintain the temperature when level is rising. The controler dealt with the situation well not letting the temperature decrease bellow desired range. At the last day, the temperature of ABESON rises because of mixing. Before that it seems that ABESON's temperature was getting below allowed range even when supply water temperature was on its maximum.

To compare the former control approach with new control approach some data from September 2010 were taken, where the conditions were similar to ones in March 2011. Find the same data where every input variables except supply water would be the same

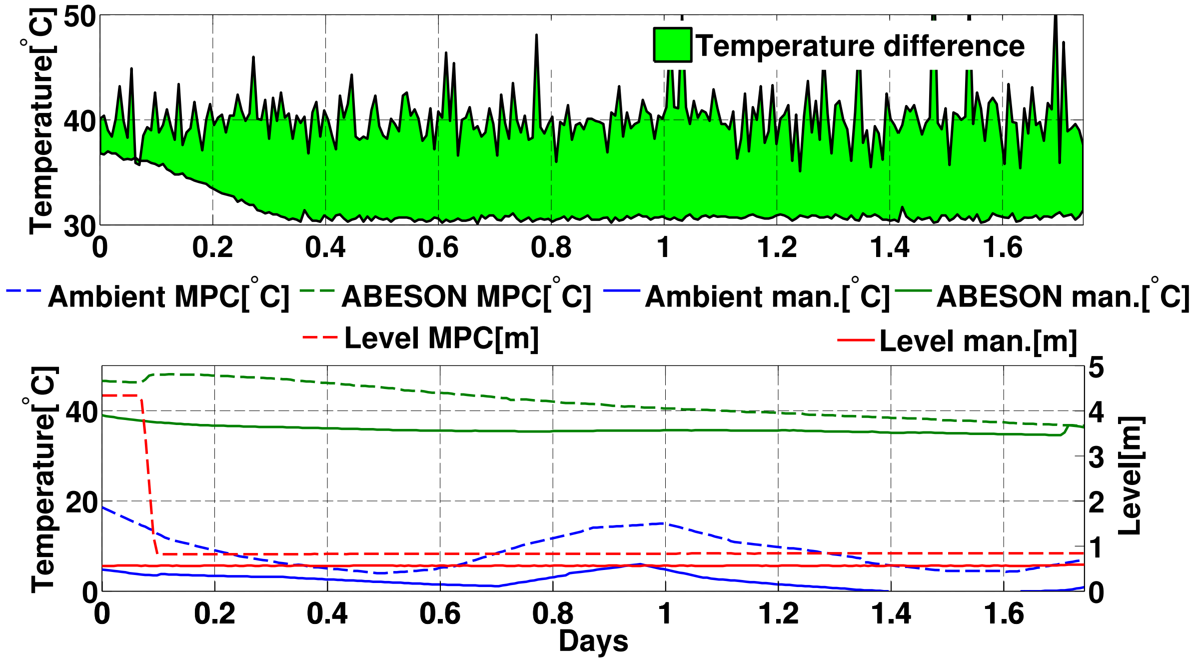


Figure 8.3: Temperature difference.

is impossible, since the controler is in operation only a short time. Figure 8.3 shows part, where the inputs are similar.It is not possible to provide better comparison among all available data at the moment.

Chapter 9

Conclusion

The main focus was to create a suitable model for model based predictive control. In total 5 couples of models parameters are designed for control and their performance was tested. The plausible model was created using LPV. This model performed well in terms of fit factor. Another well working model was identified using ACADO. This software allowed use of wide range of testing data which improved final solution and eased search of parameters.

Prediction error method provided so far worst results due to its linear character and limited options for choosing the data sets. On contrary subspace identification method despite its linear character provided surprisingly good results and the model might be applied as well. It was because the estimation was not performed with constraints.

The error of model within range of $\pm 5\,^{\circ}\mathrm{C}$ was acceptable and worked well for the company. There might be more estimations with more data and final model might be improved even more. But it would take additional time and company was satisfied with provided model.

The identification process suffered from many issues. For example the identification was not performed with return water, sensor is not placed very well, heating pipes were exposed to ambient environment which had an unknown effect on the heating temperature, unpredictible artefacts in data such as mixing and drops of ABESON level, very low ABESON level with no need to heat at all, ABESON nonhomogenity.

Despite the aforementioned complications, proposed models worked very well and ENERGOCENTRUM Plus, s.r.o. established a permanent cooperation with ENASPOL a.s. The model obtained is used as pilot model in model predictive controler. When the controler was brought to the control process it turned the heating from former $40\,^{\circ}\mathrm{C}$ to $30\,^{\circ}\mathrm{C}$, maintaining the heating temperature at its minimum value. MPC records satisfactory results since whenever the ABESON temperature decrease below the desired range due to unmeasured disturbances, it 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.

It might be convinient to allow higher maximum supply water temperature, because from measured data is obvious, that in case of full tank, the supply water is not able to provide enough energy to heat ABESON up and it is barely enough to maintain its temperature and prevent it from cooling.

There is a large gap for possible improvements. It would be very convenient to incorporate return water measurement. Using it it would be possible to verify savings. Also ABESON temperature sensor placed more suitably would be more pleasant. Database, where the operators would enter the dates of expedition and intensive production would provide very useful additional information, i.e.: when expedition date is approaching the temperature is required higher. On the other hand, when production is going on, there is a lots of hot ABESON getting into the tank warming up colder ABESON inside. From this point of view it would be enough to mix ABESON after every production cycle. Automation of the pump would be of great help, espetially in identification process, but also for maintaining the temperature. In case the ABESON's temperature would decrease under specified limit and the tank would be full, controler would execute mixing. Direct ambient temperature measurement would also help.

In this thesis, several basic identification techniques have been tested for ability to suitably approximate the non–linear model. All approaches were tested mainly (and LPV only) under laboratory conditions. We shown their performance/usability in a real life project.

The project was a success and ENERGOCENTRUM Plus s.r.o. is working with ENASPOL a.s. on other chemical tank, where experiences from this thesis can be applied.

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Attachement A

Overview of attached documents

Part of the diploma thesis is also a CD including all the source codes and some additional materials such as pictures and data used to perform identification. The list of data on CD follows.

- Data used for estimation.
- Scripts performing all operations metioned in text.
- ACADO toolkit source codes.
- Digital version of this thesis.
- Pictures from ENASPOL a.s. factory when visited in February 2011.
- ABESON datasheet.
- Paper for conference.

On following pages are additional documents regarding the thesis. The first is a document describing properties of ABESON provided by ENASPOL. a.s. and the second is a paper for conference based on data from this thesis.

ABESON

SKP 24 51 20 PN ENS 058 - 02

PAL – polotovar tenzidu

CHARAKTERISTIKA VÝROBKU

ABESON je lineární alkylbenzénsulfonová kyselina, vyráběná kontinuální filmovou sulfonací n-monoalkylbenzénu s délkou postranního řetězce C_{11-13} (označení CTFA/INCI: Dodecylbenzene Sulfonic Acid).

parametr	zkouší se podle	**ABESON**
typické hodnoty		
charakter		anionický
vzhled při 20°C		hnědá viskozní kapalina
hustota při 20°C, g/cm^3	ČSN 65 0342	1,08
viskozita při 20°C, mPa.s	ČSN 67 3014.B	1400
aktivní látky, % hmot.	PN ENS 058-02	$\geq$95,5
voda, % hmot.	PN ENS 058-02	$\leq$0,5
barva, zneutralizovaný roztok	PN ENS 058-02	$\leq$5°
specifikace		
aktivní látky, % hmot. (M_r=324), min.	PN ENS 058-02	95,0
volná H_2SO_4, % hmot., max.	PN ENS 058-02	1,5
vzhled, zneutralizovaný roztok	PN ENS 058-02	čirá kapalina
barva, 25% zneutralizovaný roztok, stupnice Fe-Co, max.	PN ENS 058-02	6
nesulfonovaný podíl, % hmot., max.	PND 32-5006-94.6	2,5

POUŽITÍ

ABESON je polotovarem pro výrobu tenzidů. Soli ABESONu (obvykle sodná, amonná nebo trietanolaminová), získané po neutralizaci příslušnými bázemi, se zpracovávají nejčastěji na práškové či kapalné prací detergenty, mohou ale být využity i pro přípravu čistících, pomocných průmyslových nebo jiných speciálních povrchově aktivních přípravků. Pro optimalizaci vlastností dodávky ABESONu právě pro Vaše použití doporučujeme předchozí konzultaci s našimi techniky.

PŘÍKLAD ZPRACOVÁNÍ

♦ **Příprava sodné soli (ABESON Na) – násada na 100 kg cca. 40%:**

- NaOH (100%) 5,0 kg
- ABESON (96%) 39,0 kg
- voda 56,0 kg

Násady NaOH a ABESONu je vhodné překontrolovat, případně upravit podle předběžné laboratorní zkoušky. Hydroxid sodný rozpustit v předložené vodě. Pak začít přidávat ABESON tenkým proudem za intenzivního míchání, popř. chlazení. Při nedodržení tohoto postupu mohou v reakční zóně vznikat obtížně rozmíchatelné gely, komplikující další průběh neutralizace. Teplota v reaktoru by neměla přestoupit 60°C. Konec neutralizace se sleduje podle pH reakční směsi. Produkt se následně bez stáčení zpracuje na finální výrobek.

PŘÍKLADY POUŽITÍ

♦ **Práškový prací přípravek:**

• ABESON NA (40%)	30 %
• Syntapon NKS	4 %
• tripolyfosfát (práškový)	17 %
• perboritan sodný	8 %
• vodní sklo (práškové)	5 %
• soda, síran sodný, zeolit, sekvestranty, mýdlo, aktivátory, enzymy, ozp, aj.	do 100 %

♦ **Kapalný čistící či prací přípravek:**

• ABESON NA (40%)	30 %
• SPOLAPON AES	8÷10 %
• ALFONAL KF	0÷3 %
• ethanol	1 %
• voda	do 100 %

♦ **Autošampóny:**
Přídavek 6÷8 % hořečnaté soli (ABESON MG) příznivě ovlivňuje lesk a životnost autolaků.

♦ **Emulgace herbicidů:**
Vápenatá sůl ABESONu, připravená v tolueno-xylenovém roztoku, je výtečným emulgátorem, používaným mj. pro herbicidní přípravky, aj.

HYGIENA A OCHRANA ZDRAVÍ PŘI MANIPULACI S VÝROBKEM

Výrobek je žíravá kapalina silně kyselé reakce, styk s pokožkou, sliznicemi nebo očima může způsobit poleptání. Při manipulaci použít pracovní oděv, gumové rukavice, brýle. Při práci nejíst, nepít, nekouřit. Dodržovat základní pravidla osobní hygieny, ruce po práci umýt vodou, ošetřit reparačním krémem.

První pomoc:

♦ Při vniknutí do oka či potřísnění - důkladně vymýt proudem čisté vody, při zasažení oka vždy vyhledat lékařskou pomoc.

♦ Při požití - ústa vypláchnout čistou vodou, přivolat lékaře, který rozhodne o eventuálním výplachu žaludku, při spontánním zvracení zajistit, aby nedošlo k zadušení zvratky

♦ Při nadýchání - přenést postiženého na čerstvý vzduch, vyhledat lékařskou pomoc.

BALENÍ A SKLADOVÁNÍ

ABESON se dodává v nerezových autocisternách nebo železničních cisternách, nebo v jiných vhodných, předem dohodnutých obalech. ABESON by měl být skladován v suchu v kyselinovzdorných obalech či zásobnících při teplotách 0÷30°C. Za těchto podmínek poskytuje výrobce 6měsíční záruku.

VYRÁBÍ A DODÁVÁ

ENASPOL, a. s., Velvěty 79, 415 01 Teplice 1

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Poznámka:

Identification and Control of a Chemical Tank: A Case Study

Ondřej Bruna, Zdeněk Váňa, Jiří Cigler, Samuel Prívara and Lukáš Ferkl

Abstract— **Even though a modeling of the 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. Two important questions arise: how to detect these events and how to cope with them during the modeling. In this paper, we show several modeling and identification approaches which apply to industrial type of the shell and tube heat exchangers. The control of the heat exchanger has been treated in many papers using some of the "classical" control concepts. In contrary, we propose a predictive control scheme which recorded a superior (in sense of energy consumption) results comparing to the classical control.**

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. In the following text, we will confine ourselves only to tanks with the temperature control. Such a class of tanks can be interpreted as a 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 [18]. 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 we will refer rather to those papers which employ innovative techniques. A very comprehensive survey of heat exchangers modeling can be found in [17]. The paper by [2] 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 [5], [8], physically-based pinch method [12], [1] or fuzzy models (see e.g. [19], [10], [3]). The papers cited above cover many of control strategies from classical to predictive.

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Our contribution is devoted to the modeling and control of the real heat exchanger in chemical industry. Particularly, we propose a complex solution for a tank, where the chemical intermediate product is kept until it is drained out. We introduce a number of practical issues arising during modeling of such a heat exchanger. Moreover, we provide a verification of the applicability of these methods to the real processes. The approaches to be applied are as follows [14]:

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 seem useful to be employed. 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, on contrary to PEMs, includes order selection. 4SID methods yields state-space models.
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.
5) **Grey-box identification.** First principle model comprises many unknown constant parameters that need to be identified. ACADO Toolkit was used for identification since it enables the identification of unknown parameters of a continuous time system.

The contribution also lies in an innovative approach to model predictive control (MPC) of the tank. Proposed MPC scheme takes into account weather forecast and hence it can react to sharp changes in local weather in advance.

This paper is organized as follows. Sec. II is devoted to modeling of the heat exchanger and identification its parameters. We will thoroughly introduce the examined problem and provide a description of the methods used for the identification. The control problem is formulated in Sec. III whilst Sec. IV provides a comparison of a number of modeling approaches and evaluates the performance of MPC controller deployed on real system. Finally, the last section concludes the paper.

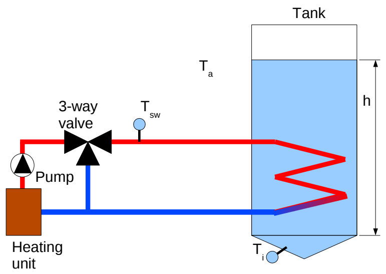


Fig. 1: Principle of ABESON tank

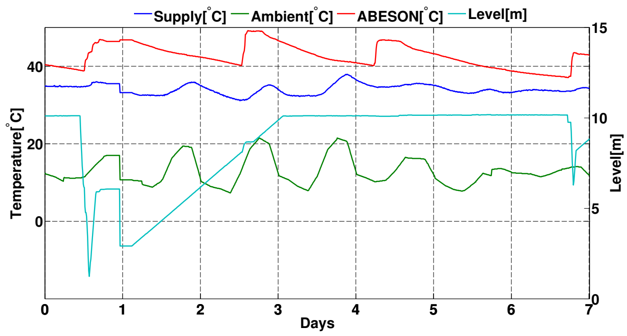


Fig. 2: Corrupted data example

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 is below the lower bound, ABESON becomes very dense and is very difficult to pump it out of the tank. In case of breaking the upper bound, the properties of the ABESON changes and it becomes worthless.

Schematic sketch of the system is depicted in Fig. 1 and shows the integration of the heating system. 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 it more homogenous. Unfortunately, this process cannot be described by an input since this happens only irregularly and is a strictly manually controlled operation. Moreover, due to this fact, it is not possible to get rid of the effect of mixing.

[1]National Oceanic and Atmospheric Administration (NOAA), www.noaa.gov/

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 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. Namely, 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. All happens during a very short time and therefore it suddenly rises to much higher temperature. This can be detected since there is a significant drop in the ABESON level.

The example of the corrupted data is depicted in Fig. 2, where the cyan line is a level of ABESON. There are three increases of a product temperature – red color . The first is caused by draining out of the ABESON and the temperature sensor measures the hot liquid from the top. Then the level increases steadily when suddenly a second 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. Note, when the level is increasing the fresh ABESON has the temperature around 50 °C.

Apart from the aforementioned issues, there are several other smaller problems, some of them follows. Firstly, the sun also affects the inner temperature and it slows down the cooling process. Since the global solar radiation is not incorporated into the model (this type of information is not known), it can affect 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), but this phenomena is not measured.

Usually a return water measurement is used as well. The process did not have incorporated return water measurement. For that reason, the return water temperature is not used in the current model and we focused rather on creating a simple model, which sufficiently describes the process.

B. Identification approaches

1) First principles models: Considering the measured signals, the general model of the tank is

$$\dot{T}_i = f(T_i, T_{sw}, T_a, h, \mathcal{P}), \tag{1}$$

where $T_i[\,°\mathrm{C}]$ is the ABESON temperature, $T_{sw}[\,°\mathrm{C}], T_a[\,°\mathrm{C}]$ are supply and ambient water temperature, respectively, $h[\,\mathrm{m}]$ is the ABESON level inside the tank and $\mathcal{P}$ covers all physical and geometric parameters. From the physical properties described in previous section, we can induce

$$C_i(h,\mathcal{P})\dot{T}_i = -\frac{T_i - T_{sw}}{R_1(h,\mathcal{P})} - \frac{T_i - T_a}{R_2(h,\mathcal{P})}, \tag{2}$$

where $R_1[\,\mathrm{K\ W^{-1}}]$ denotes a thermal resistance between the heating pipes and ABESON, $R_2[\,\mathrm{K\ W^{-1}}]$ denotes a thermal resistance between the heating pipes and outside environment and $C_i[\,\mathrm{K\ W^{-1}}]$ is a heat capacity of the ABESON, in detail

$$\frac{1}{C_i(h,\mathcal{P})R_1(h,\mathcal{P})} = \frac{2\,h_1\,\lambda_1}{r\,\rho\,c\,l_1\,h}, \tag{3}$$

$$\frac{1}{C_i(h,\mathcal{P})R_2(h,\mathcal{P})} = \frac{2\,\lambda_2}{r\,\rho\,c\,l_2} + \frac{\lambda_2}{\rho\,c\,l_2\,h}, \tag{4}$$

with density of the ABESON $\rho[\,\mathrm{kg\ m^{-3}}]$, thermal conductivity of the heating pipes $\lambda_1[\,\mathrm{W\ m^{-1}\ K^{-1}}]$, thermal conductivity of the tank insulation $\lambda_2[\,\mathrm{W\ m^{-1}\ K^{-1}}]$, thickness of the insulation of supply water $l_1[\,\mathrm{m}]$, thickness of the tank insulation $l_2[\,\mathrm{m}]$, specific heat of the ABESON $c[\,\mathrm{J\ kg^{-1}\ K^{-1}}]$, the level reached by heating pipes $h_1[\,\mathrm{m}]$ and the radius of the tank shell $r[\,\mathrm{m}]$.

Parameters r, ρ, h_1 are known, while λ_1, λ_2, l_1, l_2, c are to be estimated. The influence of the time varying ABESON level on the system can be considered as a non-linearity. By substituting the 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 $\alpha = \frac{\lambda_1}{c\,l_1}$ and $\beta = \frac{\lambda_2}{c\,l_2}$, the Eq. (2) can be rewritten into

$$\dot{T}_i = \frac{p_1\alpha}{h}(T_{sw} - T_i) + \left(p_2\beta + \frac{p_3\beta}{h}\right)(T_a - T_i). \tag{5}$$

For sake of simplicity, we consider only estimation of two parameters α and β.

The values of known parameters are: $h_1 = 1.5$ m, $r = 1.4$ m, $\rho = 1080$ kg m^{-3}. Before running the actual identification we roughly estimate the values of unknown parameters to match the physical constraints. From the material data sheets, the insulation layer is of width $l_2 = 0.2$ m and the thickness of heating pipes together with tank is $l_1 = 0.02$ m. We estimate that the insulation material thermal conductivity λ_2 is in interval $\langle 0.2; 0.6\rangle\,\mathrm{W\,m^{-1}\,K^{-1}}$ and that tank-pipes thermal conductivity λ_1 is $\langle 2; 10\rangle$ W m^{-1} K^{-1}. Specific heat of ABESON is similar to the water with $c = 4180\,\mathrm{J\ kg^{-1}\ K^{-1}}$. All the suggestions point to the following values of the parameters $\alpha = \langle 0.02; 0.1\rangle$ and $\beta = \langle 2\cdot 10^{-4}; 6\cdot 10^{-4}\rangle$.

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

$$T_i(k+1) = \dot{T}_i T_s + T_i(k), \tag{6}$$

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

Data set	ARX α	ARX β	4SID α	4SID β	ACADO α	ACADO 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

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

$$T_i(k+1) = AT_i(k) + BT_{sw}(k) + VT_a(k), \tag{7}$$

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) Linear time-invariant models: In case that the level of the ABESON is fixed, which occurs very seldom, the process can be modeled as a linear and time-invariant. For these cases, the well-known ARX model can be used [14]. The multivariable ARX model is described by Eq. (8), where $a_0 = 1$, n_u is number of inputs, n_a and n_b order of the ARX model polynomials and a_i and $b_{j,l}$ are their coefficients

$$\sum_{i=0}^{n_a} a_i\,y(k-i) = \sum_{l=1}^{n_u}\sum_{j=0}^{n_b} b_{j,l}\,u_l(k-j) + e(k). \tag{8}$$

Using Eq. (8) the description of the system can be expressed in form of the transfer function as follows

$$G(z) = [G_{sw}(z)\ ,\ G_a(z)] = \left[\frac{K_{sw}}{z+D}\ ,\ \frac{K_a}{z+D}\right], \tag{9}$$

where

$$\begin{aligned} K_{sw} &= \frac{p_1\alpha T_s}{h}, \\ K_a &= p_2\beta T_s + \frac{p_3\beta T_s}{h}, \\ D &= -\frac{p_1\alpha T_s + p_3\beta T_s}{h} - p_2\beta T_s + 1. \end{aligned} \tag{10}$$

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 [9], [7], [16]. The objective of the subspace algorithm is to find a linear, time invariant, discrete time model in an innovation form

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) + Ke(k), \\ y(k) &= Cx(k) + Du(k) + e(k), \end{aligned} \tag{11}$$

where A, B, C, D are system matrices, K is Kalman filter gain and e is a white noise sequence [20]. The algorithm firstly determine the order of the model, and afterwards find the model as well as state and measurement noise covariance matrices.

For the identification, the System Identification toolbox in MATLAB [13] has been used. The results of estimated parameters using subspace algorithm are listed in Tab. I.

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

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:

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

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 our 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

$$\begin{aligned} \Theta &= [\alpha_j,\ \alpha_{n+1},\ \alpha_{n+2},\ \alpha_{n+2+j},\ \alpha_{2n+3}]^T \\ \Psi_k &= \left[X(k)^T,\ u(k),\ x^1_{k+1},\ \delta(k)X(k)^T,\ \delta(k)u_k\right], \end{aligned} \tag{13}$$

the system parameters can be computed from the $\alpha_1 = \frac{a_{11}}{d_2}$, $\alpha_2 = \frac{b_{11}}{d_2}$, $\alpha_3 = \frac{1}{d_2}$, $\alpha_4 = a_{11} - \frac{c_{11}}{d_2}$, $\alpha_5 = b_{11} - \frac{d_1}{d_2}$. The parameters in vector Θ are obtained from solving Eq. (14) using RLS.

$$\delta(k)x_{k+1} = \Psi_{k+1}\Theta. \tag{14}$$

The discretized equation of the tank can be formulated as follows [15]

$$\begin{aligned} T_i(k+1) &= \begin{bmatrix} -p_2\beta T_s + 1 & 0 & -p_2\beta T_s \end{bmatrix} \begin{bmatrix} T_i(k) \\ T_{sw}(k) \\ T_a(k) \end{bmatrix} + w(k), \\ w(k) &= \delta(k)z(k), \\ z(k) &= \begin{bmatrix} -p_1\alpha T_s - p_3\beta T_s \\ +p_1\alpha T_s \\ +p_3\beta T_s \end{bmatrix}^T \begin{bmatrix} T_i(k) \\ T_{sw}(k) \\ T_a(k) \end{bmatrix}. \end{aligned} \tag{15}$$

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	$0.881 \cdot 10^{-3}$

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 Toolkit[2] is a software environment and algorithm collection for automatic control and dynamic optimization [11]. It provides a general framework for using a great variety of algorithms for direct optimal control, including model predictive control, state and parameter estimation and robust optimization. ACADO Toolkit is implemented as self-contained C++ code and comes along with user-friendly Matlab interfaces.

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.

6) Decoupled identification of cooling and heating parts: Yet another approach is to separate identification of cooling and heating parts. This approach assumes, that during the summer time the influence of the heating pipes is too small to affect the whole process and that the main factor which affects the tank is weather. For that reason we assume that the term associated with coefficient α, which represents the heating part of the model, is 0.

Then we are able to identify the weather constant β using ARX model. After determining the ambient temperature constant, we fix it and that leaves the only α parameter to estimate. To identify it properly, we used the data from the winter time, where the heating was working for 100 %.

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 reason of the applying of the predictive control to the process is to reduce the energy consumption. 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) seems to be a perfect choice for the given process.

As mentioned above, 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

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

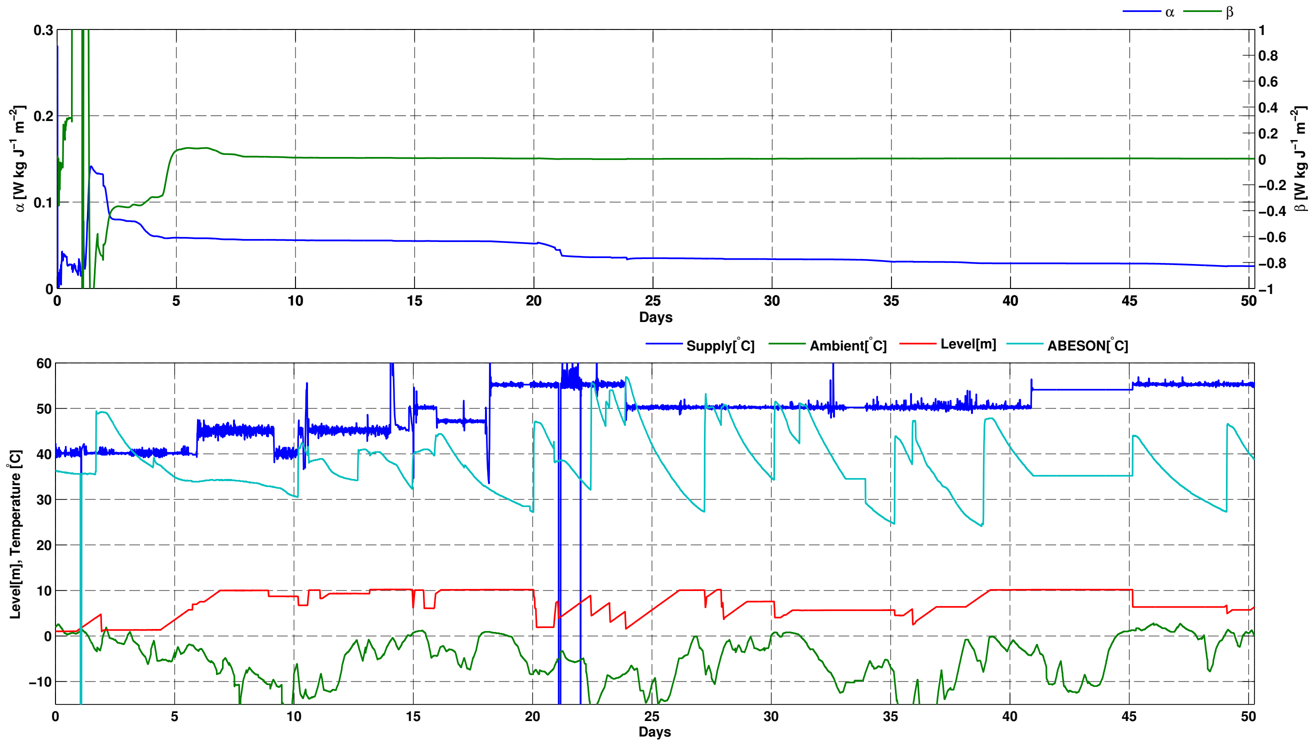


Fig. 3: Convergence of parameters and used data.

can assume following. The supply water can only be heated up by the steam. Moreover, during the winter season (the main heating season) the steam is the only source of heat. Therefore it holds that the lower supply water temperature, the lower energy cost. 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

$$T_i(k+1) = A(\delta, T_s)T_i(k) + B(\delta, T_s)T_{sw}(k) + V(\delta, T_s)T_a(k), \tag{16}$$

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

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

such that Eq. (16) and

$$\begin{aligned} Z_{sw,min}(k) \;&\leq\; Z_{sw}(k) \;\leq\; Z_{sw,max}(k), \\ Z_{i,min}(k) \;&\leq\; Z_i(k) \;\leq\; Z_{i,max}(k), \\ \Delta T_{sw,min}(k) \;&\leq\; \Delta T_{sw}(k) \;\leq\; \Delta T_{sw,max}(k). \end{aligned} \tag{17}$$

hold as well as the other standard assumptions on the optimal problem to be solvable [6]. Z_i and Z_{sw}, which define ranges

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	$2.80\,10^{-2}$	$9.79\,10^{-4}$

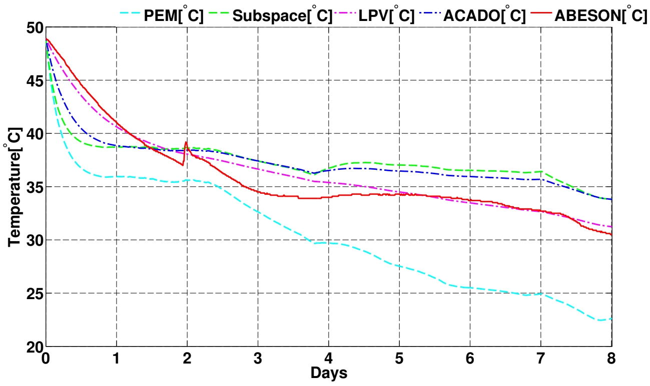
where the T_i and T_{sw} are not penalized. The subscripts min, max denote minimum and maximum possible values of appropriate variables and Δ denotes rate of change of corresponding variable. Q, R are weighting matrices.

IV. Results

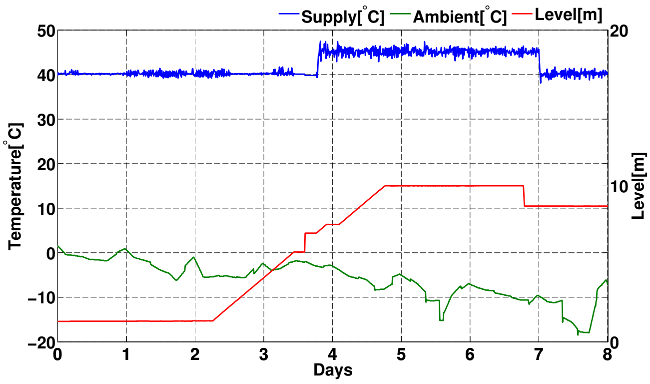
We have modeled a storage tank as described in Sec. II. The obtained models and the individual results are discussed further on.

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



(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.

approaches were not plausible at all 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 (part of the data is displayed in Fig. 3). 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. Hence this way of identifying did not need any data preprocessing and could be used on the whole data set.

The methods discussed up to here have been verified on the same data set (see Fig. 4).

The last approach was used to support our results obtained from all previous identifications. Decoupling of heating and cooling parts of the model, i.e. an identification of separate parts was performed. To estimate parameters ACADO Toolkit was used again. For the estimation, one of the parameters was always fixed and the other one estimated. This yielded results similar to already obtained, so we confirmed that our identification was successful.

Data from the real operation of MPC are depicted in Fig. 5. The blue lines correspond to supply water temperature (solid) and its minimum and maximum constraints (dashed) while

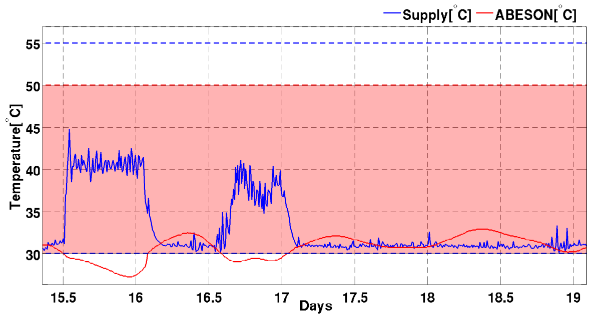


Fig. 5: MPC implemented.

the red 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, it 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 basic identification techniques have been tested for ability to suitably approximate the non-linear model. All approaches were tested mainly (and LPV only) under laboratory conditions. We shown their performance/usability in a real life project. The LPV model parameter estimation approach turned out to be the most applicable from all of the tested methods. Model obtained from this estimation was used for MPC. This approach did not need any data preprocessing.

On the other hand, widely used PEM was not plausible for model estimation. ACADO Toolkit produced acceptable results in regions with increasing level and was able to process non-linear input. In all of these approaches data preprocessing was essential, but while all measured data has been used at once, it did not provide any satisfactory results at all.

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.

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