Czech Technical University in Prague

Faculty of Electrical Engineering

BACHELOR THESIS

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Virtual sensor of mixing ratio of air

Department of Control Engineering

Supervisor of the bachelor thesis: Ing. Vladimír Horyna

Study programme: Cybernetics and Robotics

Specialization: Systems and Control

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České vysoké učení technické v Praze
Fakulta elektrotechnická

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ZADÁNÍ BAKALÁŘSKÉ PRÁCE

Student: **Denis Efremov**

Studijní program: Kybernetika a robotika
Obor: Systémy a řízení

Název tématu: **Virtuální senzor směšovacího poměru vzduchu**

Pokyny pro vypracování:

1. Navrhněte virtuální senzor nastaveného směšovacího poměru vzduchu uvnitř vzduchotechnické jednotky, odpovídající poloze směšovací klapky uvnitř vzduchotechnické jednotky.
2. K odhadování polohy klapky využívejte informaci o spotřebě vzduchotechnické jednotky, informaci o spotřebě zařízení sloužícího jako zdroj chladu a tepla (tepelné čerpadlo, elektrický kotel) a běžně měřené teploty (případně i tlaky) měřené uvnitř komerčních vzduchotechnických jednotek.
3. Virtuální senzor realizuje a otestujte v prostředí MATLAB a otestujte na reálné vzduchotechnické jednotce.

Seznam odborné literatury:

[1] UHLÍŘ, Jan a Pavel SOVKA. Číslicové zpracování signálů. Vyd. 2. přeprac. Praha: Vydavatelství ČVUT, 2002, vii, 327 s. ISBN 80-01-02613-2.
[2] MADISETTI, V a Douglas B WILLIAMS. Digital signal processing handbook. Boca Raton, Fla.: Chapman & Hall/CRCnetBase, 1999, CD-ROMs. ISSN 1523-3022. Annual.
[3] AFRAM, Abdul; JANABI-SHARIFI, Farrokh. Review of modeling methods for HVAC systems. Applied Thermal Engineering, 2014, 67.1: 507-519.

Vedoucí: Ing. Vladimír Horyna

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I hereby declare that I have completed this thesis with the topic "Virtual sensor of mixing ratio of air" independently and that I have included a full list of used references. I have no objection to the usage of this work in compliance with the act §60 Zákon č.121/2000 Sb. (copyright law).

In .... date .... signature of the author

Abstrakt:

Tato bakalářská práce je zaměřena na rozbor a otestování možností odhadování směšovacího poměru uvnitř vzduchotechnické jednotky. V práci je zpracován podrobný State of the Art zaměřený obecně na virtuální měření a popisuje krok po kroku návrh virtuálního senzoru na základě modelu pro měření směšovacího poměru vzduchu uvnitř vzduchotechnické jednotky. AutoRegressive eXogenous (ARX) model byl použit jako základ modelu systému, a metoda nejmenších čtverců byla použita pro odhad parametrů modelu. V závěrečné části práce jsou zhodnoceny jednotlivé přístupy, sepsány výhody a nevýhody jednotlivých modelů a návrhy pro budoucí využití popsaných přístupů.

Klíčová slova: HVAC, Kontrola Vlhkosti, Ventilace, Klimatizace, Matematický Model, Virtualní Senzor, Autoregresivní Model, Směšovací Klapka.

Abstract:

This bachelor thesis aims to develop and test possibility of estimation of the mixing ratio inside AHU unit. The work presents the State of the Art in Virtual Sensing and describes step by step the design of modelling methods-based Virtual Sensor of the mixing ratio of the air inside AHU unit. The AutoRegressive eXogenous (ARX) model was used as modelling approach and Least Mean Square algorithm as parameter estimation technique. At the end of this work, different approaches are evaluated, advantages and disadvantages of different models are enumerated, and suggestions of the future applications of the described approaches are presented.

Keywords: HVAC, Heating, Ventilation, Air Conditioning, Mathematical Model, Virtual Sensor, Autoregressive Model, Mixed Valve.

Contents

1. Introduction

One of the aims of the **Intelligent Building** is optimization of energy consumption and comfort inside these buildings [21]. HVAC (eq. Heating, Ventilating, and Air-Conditioning) systems are used for achievement of these aims. But the commonly used HVAC systems are not optimal yet. There is no accurate mathematical model, which can describe the behaviour of this difficult system, because of non-observable states, which are not measurable in commonly installed HVAC systems.

Virtual Sensing, also Soft Sensing techniques, can provide the measurement of one of the non-observable states in HVAC without substantial economic costs. It does not affect the value of commercial systems and can be installed in already used units.

Virtual Sensor of mixing ratio of the air inside Air Humidity Unit (AHU) was chosen as the object of presented work. One of the Black Box modelling approaches was used for design of the mathematical model of the mixing valve.

1.1 Outline

This work is divided into five parts.

In the first part, which is **Introduction**, work description and objectives are given.

The part **State of the Art** describes the Virtual Sensing technology and General steps in developing of Virtual Sensor. Then the review of modelling methods is given, and HVAC system is described.

In the part, which is named **Theoretical basis and design of Virtual Sensor**, the used laboratory AHU unit with proposed sensors is shown, mathematical models are deducted, measured training set is given, and signal pre-processing is presented.

The fourth chapter, which is **Comparison of proposed models**, provides the behaviour all of the models used training and test data sets.

Chapter **Conclusion** summarises this thesis and proposes the future of the designed Virtual Sensors.

1.2 Objectives

This capitol describes the primary objectives of this thesis:

- Determine current State of the Art in Virtual Sensing.
- Present theoretical basis for Virtual Sensor of the position of the mixing valve, which is inside of standard AHU units.
- Design the mathematical model, which will be used for implementation of Virtual Sensor, using Matlab software.
- Test the resulted Virtual Sensor on real AHU unit.

2. State of the Art

2.1 Introduction to Virtual Sensing

Virtual Sensing techniques are used to provide measurements when it cannot be provided by standard physical methods or when this measurement will be economically cheaper than the real physical analogy.

According to Haorong Li, Daihong Yu, and James E.Braun [2], the history of Virtual Sensors has been rapidly developed since the 1980s. Virtual Sensing has been used in different domains such as avionics, autonomous robots, traffic, auto mobiles and buildings. Researchers characterize these sensors like software that includes measurements of characteristics and dynamics that are processed together to calculate new quantities that need not be measured directly [2]. Accordingly, Virtual Sensors represent a mathematical model, which is described by equations, estimates non-measured state(-s) using mathematical transformation techniques.

Nowadays these techniques are used ubiquitously. For instance, about ten different Virtual Sensors are used in modern vehicles [2] such as tire-air-pressure sensor, tire-road forces sensor, vehicle velocity sensor, etc.

Aims of developing Virtual Sensors can be different as well as used techniques, but the main categorization can be provided like in Figure 2.1 [2]. This diagram shows three main interrelated criteria that have effect on development approaches: **measurement characteristics**, **modelling methods**, and **application purposes**.

The **measurement characteristics** category refers to the type of output of the developed sensor: **transient-state** or **steady-state**. The former, for instance, would be necessary for feedback control. The latter would be used in case of slow changes of the measured input quantities or when the modelled process has a quick respond to a small change of inputs. [2]

According to **modelling methods** there are three types, which will be described deeper in one of the following capitols (**Review of modelling methods**).

The **application purposes** category refers to the following two types of Virtual Sensors: **for backup/replacement** and for **observing**. The former is used either to replace or backup existing physical sensor. This sensor can be used, for example, to check the accuracy of an installed sensor or to provide the calibration. Observer sensors can be used for end-use applications such as fault diagnostic and detection (FDD), monitoring and control. [2]

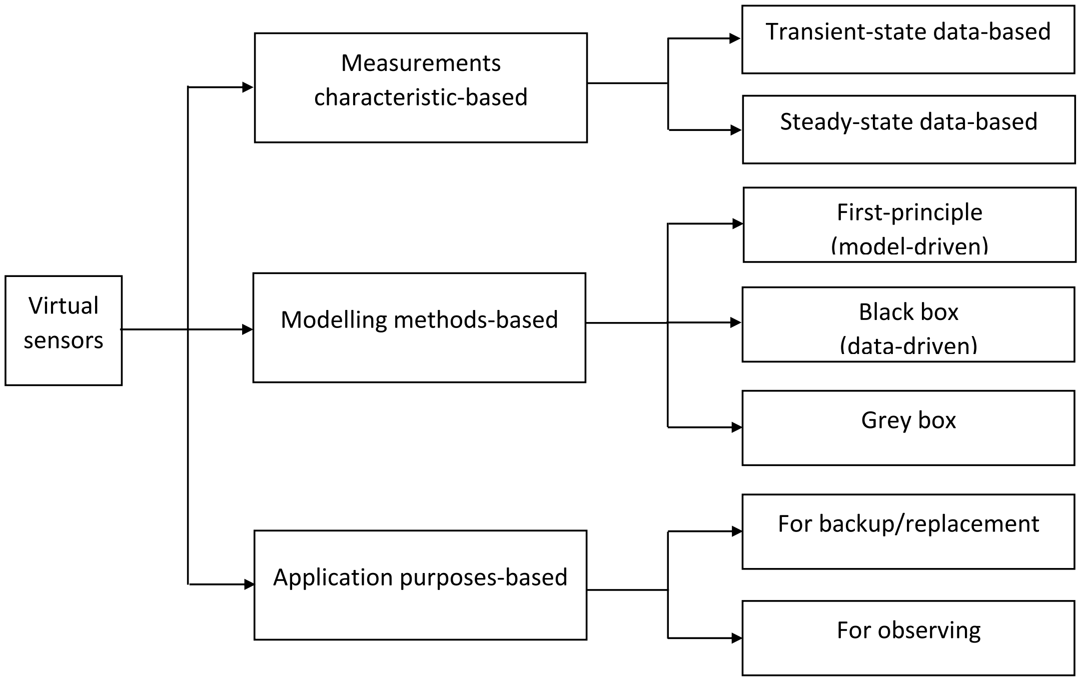

Figure 2.1: Categorization scheme for Virtual Sensors [2]

2.2 General steps in developing Virtual Sensors

How Haorong Li, Daihong Yu and James E.Braun describe in [2], a number of studies has been done for developing Virtual Sensors. Due to this studies, we can generalize this process by dividing into three steps: **data collection and pre-processing**, **model selection and training**, **implementation and validation**. Figure 2.2 shows this division.

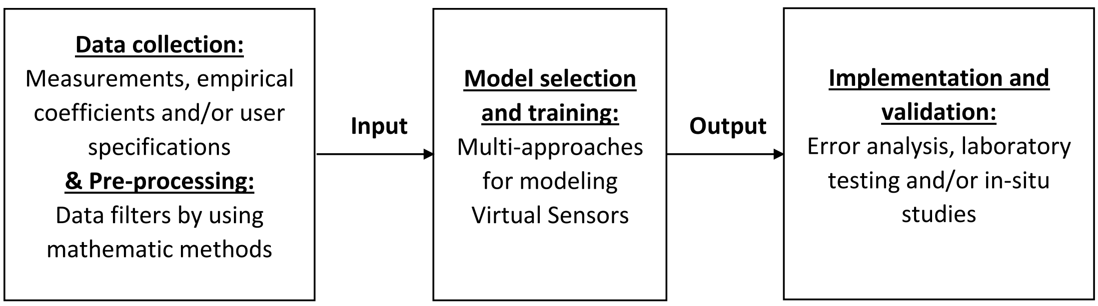

Figure 2.2: General steps in developing Virtual Sensors [2]

Data collection and pre-processing is the fundamental part in the development of Virtual Sensor. The type and range of measured data depend on modelling approaches, the aim of a sensor and required accuracy. The signals pre-processing methodology is deeper described by Paul B. Deignan Jr., Peter H. Meckl, Matthew Franchek and John Abraham in [3] and Przemyslaw Maziewski, Adem Kupryjanow, Katarzyna Kaszuba and Andrzej Czyzewski in [4]. The main idea of signal pre-processing is preparation of measured data for usage in model estimation.

The second part of the development of Virtual Sensor is **model selection and training**. In this part one of the mathematical methods, which will be described in one the following chapter (**Review of modelling methods**), can be used to derive dependencies of the states of a model on measured signals. The parameters estimation are made in this part too.

In the last part, which is **implementation and validation**, calculated model should be implemented in software or hardware. After implementation, the model validation is be provided. It means, that the accuracy of realized Virtual Sensor is checked in real environment.

2.3 Review of modelling methods

According to [1] Abdul Afram and Farrokh Janabi-Sharifi three generally types of modelling approaches for searching the mathematical model of systems exist:

"Black box"
: also **"Data Driven Models"**; finding relationship between input and output variables using the mathematical techniques (for example: **Least Mean Square**, **Linear Regression**, **Artificial Neural Networks**, etc.)

"White box"
: also **"Physics based models"**; is based on physical laws (for example, **Bond Graphs Modelling**, **Euler-Lagrange equation** using, etc.)

"Gray box"
: the model is based on physical laws, like a White Box model, but the model parameters will be determined by using parameter estimation algorithms on the measured data of the system, like a Black Box model

Referring to [1] Abdul Afram and Farrokh Janabi-Sharifi, models can also be classified as shown in the following diagram (Figure 2.3). The definition of the classification of mathematical models is deeper described by N. Gershenfeld in [5].

A **linear model** is a model, where all the operators exhibit linearity. But the definition of linear and non-linear depends on the context. For instance, the static linear model consists of linear parameters, but it may be non-linear in the predictor variables. Linear model is a typical output of Black Box modelling approach. A model can be called **non-linear** when one or more of the objective functions, which describe the model, are represented by the non-linear equation. Non-linear model is standard output of White Box or Grey Box modelling approaches.

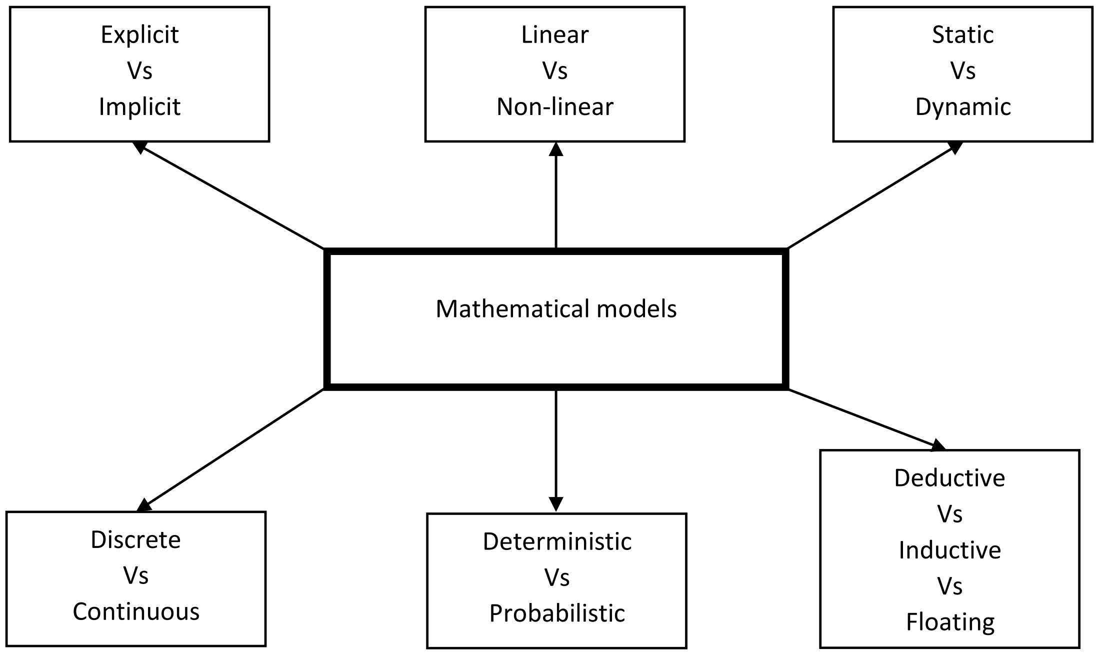

Figure 2.3: Mathematical model classification

A **static model** calculates the system in equilibrium and is time-invariant. A **dynamic model** is typically represented by differential equations and accounts for time-dependent changes in the state of the system.

An **explicit model** is a model, for which all of the input parameters are known, and the output parameters can be calculated by a finite series of computations. Opposite to explicit models are **implicit models**, for which the output parameters are known, but the relations between inputs and outputs must be calculated by iterative methods.

A **discrete model** works in discrete time or space, while a **continuous model** represents objects continuously.

In a **deterministic model** every set of variable states is uniquely determined by previous states of model's variables and by parameters in the model; while in **probabilistic** randomness is present, and state variables are rather described by probability distributions than the unique values.

A **deductive model** is a logical structure based on theory while an **inductive model** is the result of empirical observations and generalization from them. There also exist models, for which neither theory nor observation are not used, but the invocation of the expected structure is used; this model is called **floating model**. The White Box modelling approach has a deductive model as result while an inductive model and a floating model are the results of Black Box or Gray Box modelling approaches.

2.3.1 Black Box

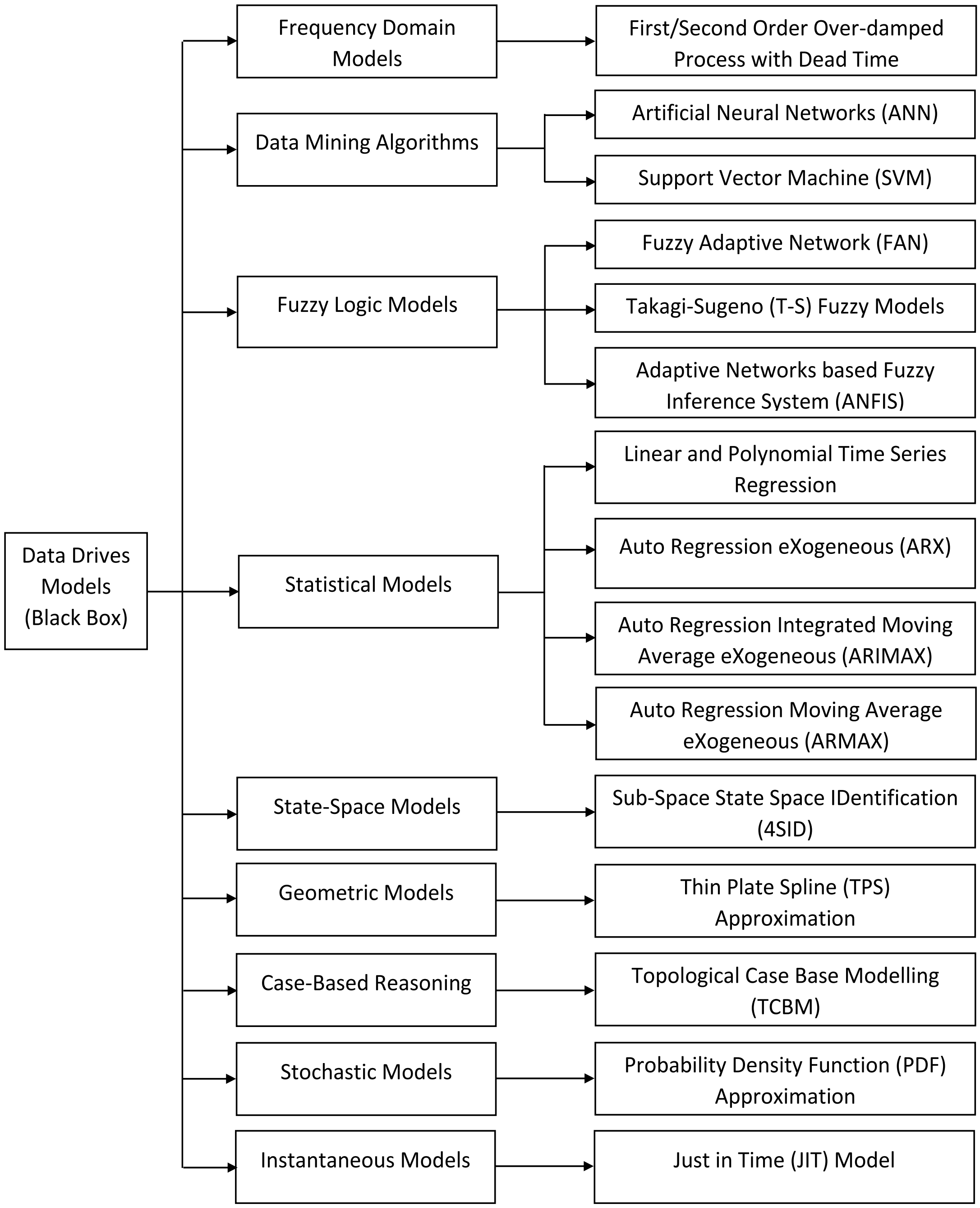

Figure 2.4: Data driven modelling techniques [1]

In this capitol, I want to enumerate the most useful Data Driven technique approaches. The Black Box models are divided into **Frequency Domain Models**, **Data Mining Algorithms**, **Fuzzy Logic Models**, **Statistical Models**, **State-Space Models**, **Geometric Models**, **Case-Based Reasoning**, **Stochastic Models**, and **Instantaneous Models**. This division is shown in the diagram (Figure 2.4). All of this models can be developed by one or more modelling approaches. These techniques are deeper described in [1]. But in the following list short description of all of this methods is present:

"Frequency domain models with dead time"
: this modelling approach is used for slow-moving processes. First and second-order frequency domain models with dead time have a few parameters to estimate from measured data and simple structure for straightforward implementation.

"Data mining algorithms"
: this modelling approach uses machine learning algorithms such as **Artificial Neural Networks** and **Support Vector Machine** for model and parameter estimation.

"Fuzzy logic models"
: are developed by if-then-else statements and can develop the local linear models blended to central non-linear model.

"Statistical models"
: the generalized structure of the statistical model is classical Black Box model with relationships between inputs and outputs, which are represented by mathematical expressions.

"State-space models"
: these models are directly represented in state-space form. As the result, the system is represented by matrices which transform inputs into outputs.

"Geometric models"
: this method provides a representation of model by curves, surfaces and volumes into "map" of the system, then fitting algorithm such as linear regression are used. The example of using geometric modelling approach is in [14].

"Case-based reasoning"
: is suitable for non-linear systems. For instance, **Topological case-based modelling** (**TCBM**), which is one of the case-based reasoning modelling approaches, is based on topology and identifies the input space topology by specifying the output error limit. According to [15], this algorithm accumulates features of input and output data. For every input, it estimates the output value using the topological distance between the input and collected input cases. The usage of this method is perfectly described by Tadahiko Matsuba, Hiroaki Tsutsui and Kazuyuki Kamimura in [15].

"Stochastic models"
: these models deal with random process, which can be approximated to standard and uniform distributions. They use the **probability density functions** (**PDF**).

”Instantaneous models”

they combine the statistical and pattern recognition modelling approaches. For instance, the reference to [1], **Just in Time** (**JIT**) model uses previous data to find the patterns similar to the current data.

2.3.2 White Box

In this capitol, I want to shortly describe the most useful White Box modelling approaches. Every model which rests on this technique is unique and always based on physical laws. There are several most commonly used methods, which are described by F. T. Brown in [6], by Samuel J. Mason in [10] and by Romeo Ortega, Antonio Loria, Per Johan Nicklasson and Hebertt Sira-Ramirez in [11]:

”Bond-graphs method”

a method in which a special graphical representation of the physical dynamic system is used. It is similar to **Signal-flow graph**, but between nodes, there is a flow of the generalized energy, not a signal, which represents only one physical variable. This method is used for a description of systems, which exist in one or more physical domains: mechanical, electrical, magnetic, hydraulic and thermal. The main idea of this method is a generalization of transferred energy as the product of a generalized effort and generalized flow. This method is deeper analysed in [6] and is used in [7].

”Euler-Lagrange equation”

a method that uses the law of conservation of energy. It is used in mechanical and electrical domains. For using the Euler-Lagrange method, it is necessary to express the kinetic and potential energies and co-energies of the modelled system. Then the Euler-Lagrange equation is used to calculate the system of model’s equations. This modelling approach is deeper described in [11].

”Signal-flow graph”

a classical method of system modelling, which has nodes for representation system variables and uses branches, also signal-flow junctions, between nodes for representation of functional connections between two physical variables. This method is invented by Samuel J. Mason [10] and also is called **”Mason graph”**.

2.3.3 Gray Box

As mentioned above, this technique uses physical laws for a derivation of equations and mathematical algorithms for estimation of parameters. Typically, when this method is used, at the beginning of derivation of equations describing the system one of the White Box methods is used. But as the opposite to White Box, in Gray Box for estimation of parameters of the model (also identification), one of the methods enumerated in capitol **Black Box** or one of the iterative optimization algorithms is used, which are perfectly described by Tomas Werner in [8] and by David G. Luenberger in

[9] such as **Gradient method**, **Newton's method** or **Gauss-Newton's methods**.

Preconditions of using of all these enumerated iterative algorithms are availability of big data for parameter's estimation, using vectorization for data representation and problem formalization for finding the local minimum of the functions that describe the system.

2.4 Description of HVAC

HVAC (Heating, Ventilating, and Air-Conditioning) system is the system, which is used to support the environmental comfort indoor. This system is based on the principles of thermodynamics, heat transfer, and fluid mechanics. The common used HVAC systems include the following units, whose functions are correctly described by Vladimir Horyna in [12] and more detailed in ASHRAE Handbook [13]:

"Air Handling Unit (AHU)"
: this unit responds for intake of the fresh outdoor air and mixing this air with indoor. Then it conditions the taken air with depending on the temperature and humidity of the air. This unit is typically located in large buildings, outside the conditioned area.

"Roof Top Unit (RTU)"
: this unit responds for the same things like AHU but is used in smaller buildings. In larger buildings one central AHU unit and several RTU units can be used.

"Variable Air Volume (VAV) box"
: is a terminal device in a decentralized system. The input of VAV box is the AHU's output air (or the RTU's air). This unit responds for a preparation of incoming air for a particular zone and is fitted with automatic controlled heating coil, cooling coil and supply fan.

"Fan Coil Unit (FCU)"
: this unit responds for air-conditioning in a particular room. It takes the output air of central AHU unit and prepares it for conditions, that are installed for each room. Larger rooms can include a several FCU units.

This thesis will be concentrated on Air Handling Unit (AHU), because of the aim of the project. An example of AHU configuration is shown in Figure 2.5. The main goal of this project is the development of Virtual Sensor, which can estimate the angle of opening of the mixing valve. This valve is placed after Right Filter before Heat recovery ventilator. The position of the valve affects one of the non-observable states, the temperature before Cooling and Heating coils (bold point in Figure 2.5) of whole AHU system, which is commonly used in commercial buildings.

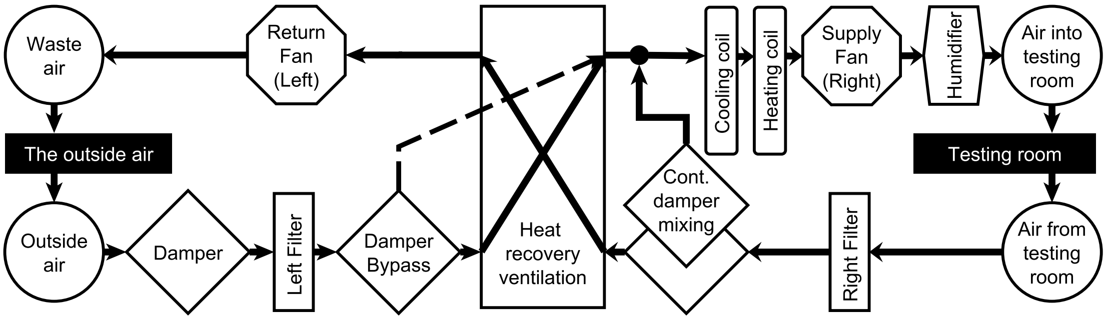

Figure 2.5: Example of AHU configuration [12]

2.5 Summary

In this capitol, I want to describe the procedure which will be used for development of Virtual Sensor of mixing valve.

Firstly, this Sensor will be one of the Modelling Methods-based Virtual Sensor because this model will calculate the angle of opening of mixing valve (further position of valve).

Secondly, the goal is to have a linear model because of easier implementation in hardware and software. This model will be dynamic because of time depending changes of states of the system. The model will be explicit: the input parameters are known, and the output is needed. Due to used sensors, this model will be discrete. Because of determinism of whole HVAC system, the model will be deterministic too. Due to big data, which I can use for parameters estimation, the model will be inductive.

For the reasons above, the mathematical model describing the position of valve used for Virtual Sensor will be implemented using one of the Black Box modelling approaches.

There are available measured big data from sensors placed in HVAC, in the laboratory and outside. One of the requirements is easy hardware and software implementation of Virtual Sensor. For these two reasons I will use the Statistical model as modelling method.

3. Theoretical basis and design of Virtual Sensor

3.1 Used sensors in AHU unit

The AHU unit in our laboratory has the following sensors, which are shown in Figure 3.1.

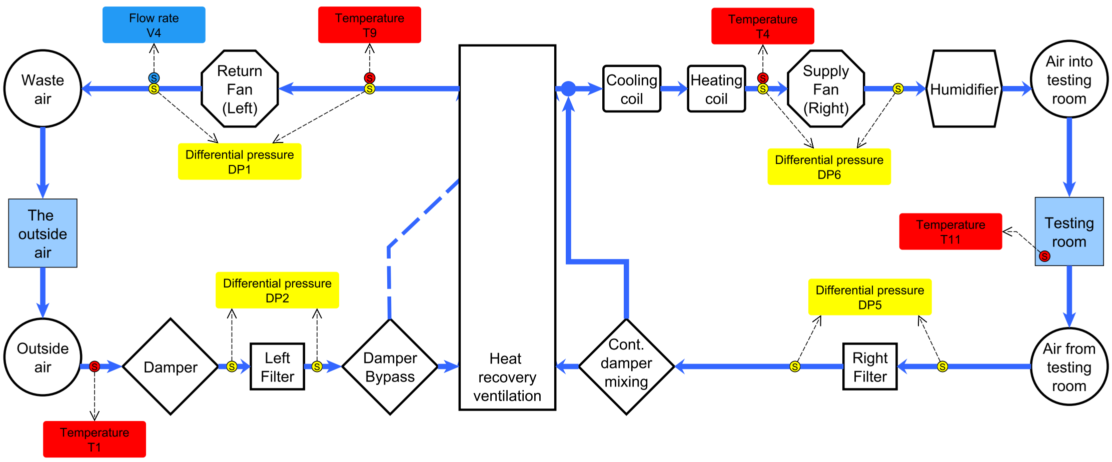

Figure 3.1: Placed sensors in a AHU unit

This model of AHU isn't commonly used in commercial buildings. It contains many of sensors placed by Vladimir Horyna for testing aims. One of the primary goals of this project is using commonly used sensors for model estimation: DP2, DP5, T4, T9, and the measured data of power consumption of the whole AHU unit, which depends on the power consumption of the Supply Fan and the Return Fan. These Fans generate the difference of their input and output pressures. It means that the power consumption of whole AHU unit is directly proportional to differential pressures DP1 and DP6, hence measured data from sensors DP1 and DP6 can be used for further model calculation.

The standard AHU units use Thermometers on the input duct for the air going from the outside (T1 in this model); and Thermometers on the input tubes of the Return Fan and the Supply Fan (T4 and T9 is this model). In small buildings the temperature inside is commonly measured, consequently, data from the temperature sensor T11 can be used for model estimation too.

For one experimental model, which is described in capitol **Model based on V4, DP2, DP5**, data from the sensor V4 also will be used. The sensor V4 is an anemometer that measures the airflow after the Return Fan.

3.2 The physical point of view on the problem

From the physical point of view on this problem, we can imagine all of the pressures like generalized efforts and all of the flows like generalized flows. Nomenclatures of the generalized flow and generalized effort are perfectly described by F. T. Brown in [6]. In modelling theory valves are usually modelled as generalized resistances. Because of the fact that the flow, which can pass through the opened valve, is directly proportional to the angle of opening of the valve, it can be modelled as modulated resistor. For the reason above, the idea of using the differential pressures as the basic of every model arises.

For developing of Virtual Sensor, I need to identify general steps of the process. According to the capitol of the previous chapter, **General steps in developing Virtual Sensors**, I want to interpret the general steps in developing Virtual Sensors as shown in Figure 2.2 for solving problem.

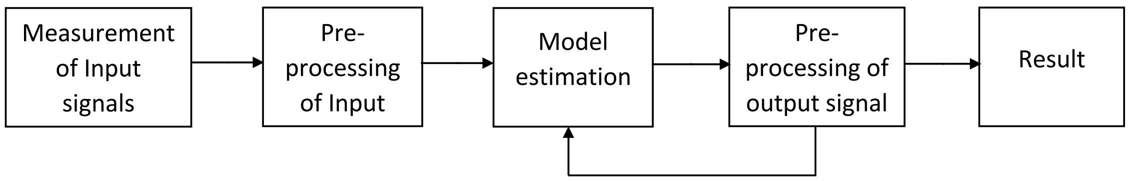

Figure 3.2: Diagram of model processing

The first step is **Data collection & Pre-processing**. It means that for developing of mathematical model of position of the mixing valve measured data from sensors is needed. Then the filtration of measured data is provided. This step is represented by two steps **Measurement of Input signals** and **Pre-processing of Input** in Figure 3.2.

The second phase is **Model selection and training**. In this step, the used signals are chosen, and model parameters are calculated. Then the internal filtration is provided during model developing. This step is represented by **Model estimation** and **Pre-processing of Output signal** in Figure 3.2.

The third step, which is **Implementation and validation** will be provided in one of the following chapters, after model estimation (**Comparison of proposed models**).

3.3 Deducting of the mathematical models

As mentioned above, the chosen modelling approach is one of the Black Box methods - Statistical model. Statistical models are based on one equation or a system of equations, which strictly describe the relationship between inputs and outputs of the system. I intend to use AutoRegressive eXogenous (ARX) model. This modelling approach is used by Jingran Ma, S. Joe Qin, Bo Li and Tim Salsbury in [16].

The model of the position of the valve is multi-input and single-output, which can be described by the following equation (3.1):

$$A(q)Mix(k) = B(q)u(k) + e(k), \tag{3.1}$$

where $Mix(k)$ is the position of the mixing valve at the time k and the $e(k)$ is a white noise sequence.

$u(k)$ is the model input in the form of (3.2).

$$u(k) = \begin{bmatrix} u_1^T(k) & u_2^T(k) & \dots & u_n^T(k) \end{bmatrix}, \tag{3.2}$$

where $n \in \mathbb{N}, n \geqslant 1$ is the count of used inputs, $u_i(k)$, $i \in (1, ..., n)$ is the i-th input at the time k.

In (3.1) q is a shifting factor of model parameters A and B which can be written in following forms (3.3) and (3.4). z is the order of model. Shifting factor q^{-i} for signal $x(k)$ at the time k means that the value of $x(k-i)$ (at the time $k-i$) is used.

$$A = 1 - a_1 \cdot q^{-1} - a_2 \cdot q^{-2} - a_3 \cdot q^{-3} - ... - a_z \cdot q^{-z}, \tag{3.3}$$

$$B = \begin{bmatrix} B_{u_1}(q) \\ B_{u_2}(q) \\ \vdots \\ B_{u_n}(q) \end{bmatrix}, \tag{3.4}$$

where, for instance, vector $B_{u_i}(q)$ can be expanded into (3.5):

$$B_{u_i}(q) = b_1 \cdot q^0 + b_2 \cdot q^{-1} + b_3 \cdot q^{-2} + ... + b_z \cdot q^{-(z+1)}. \tag{3.5}$$

Parameter estimation is provided by **Least Mean Square**. This method is used in [17] and is correctly described by Tomas Werner in [8]. The system of equations, which is solved by this algorithm, is (3.6):

$$
\begin{aligned}
Mix(k) = {} & a_1 \cdot Mix(k-1) + ... + a_z \cdot Mix(k-z) + \\
& + b_{1,1} \cdot u_1(k) + b_{1,2} \cdot u_1(k-1) + ... + b_{1,z+1} \cdot u_1(k-z) + \\
& + b_{n,1} \cdot u_n(k) + ... + b_{n,z+1} \cdot u_n(k-z), \\
& \vdots \\
Mix(z+1) = {} & a_1 \cdot Mix(z) + ... + a_z \cdot Mix(1) + \\
& + b_{1,1} \cdot u_1(z) + b_{1,2} \cdot u_1(z-1) + ... + b_{1,z+1} \cdot u_1(1) + \\
& + b_{n,1} \cdot u_n(z) + ... + b_{n,z+1} \cdot u_n(1),
\end{aligned}
\tag{3.6}
$$

where z is the model order, a_1, ..., a_z are the coefficients of matrix A and $b_{i,1}$, ..., $b_{i,z+1}$ are the coefficients of matrix B for the i-th row, which is vector of parameters for u_i. In this system of equations there are $m-z-1$ equations, where m is the number of samples of the measured data.

The model order z in all of the proposed models equals to 0, because of small average errors of the mathematical models in the result. It means that all of the proposed models use for estimation of $Mix(t)$, the value of the output at the time t, only input values at the time t. The errors are calculated and shown in chapter **Comparison of proposed models**.

3.3.1 Model based on DP1, DP2, DP5, DP6

This model is based on differential pressures only. DP_1 is the differential pressure on the Return Fan, DP_2 on the Left Filter, DP_5 on the Right Filter, DP_6 on the Supply Fan. The input matrix $u(k)$ has the following form (3.7):

$$
u(k) = \begin{bmatrix} DP_1^T(k) & DP_2^T(k) & DP_5^T(k) & DP_6^T(k) \end{bmatrix}, \tag{3.7}
$$

where $DP_i(k)$ is the measured differential pressure by DPi sensor at the time k.

The matrix of coefficients before inputs B will be the following (3.8):

$$
B = \begin{bmatrix} B_{DP_1}^T(q) & B_{DP_2}^T(q) & B_{DP_5}^T(q) & B_{DP_6}^T(q) \end{bmatrix}^T. \tag{3.8}
$$

3.3.2 Model based on DP1, DP2, DP5, DP6, T11, T4, T1, T9

This model uses combined data from T11, T4, T1 and T9 sensors as the attached inputs to the previous model. The sensor T11 measures the temperature inside; the sensor T1 determines the temperature of the air, which goes from outside into AHU unit; the sensor T4 - before the Supply Fan and T9 - before the Return Fan. The input matrix $u(k)$ has the following form (3.9):

$$u(k) = \begin{bmatrix} DP_1^T(k) & DP_2^T(k) & DP_5^T(k) & DP_6^T(k) & T_{11}^T(k) & T_4^T(k) & T_1^T(k) & T_9^T(k) \end{bmatrix}, \tag{3.9}$$

where $DP_i(k)$ is the measured differential pressure by DPi sensor at the time k; $T_j(k)$ is the measured temperature by Tj sensor at the k time.

The matrix of coefficients before inputs B will be the following (3.10):

$$B = \begin{bmatrix} B_{DP_1}^T(q) & B_{DP_2}^T(q) & B_{DP_5}^T(q) & B_{DP_6}^T(q) & B_{T_{11}}^T(q) & B_{T_4}^T(q) & B_{T_1}^T(q) & B_{T_9}^T(q) \end{bmatrix}^T. \tag{3.10}$$

3.3.3 Model based on V4, DP2, DP5

This is an experimental model with additional signal pre-processing: all of the used signals are normalized (measured values are divided by the expected maximal readings of this sensor), the signals V4 and DP2 are inverted (multiplied by -1 with addition of 1), from the values of the sensor DP5 conversely 1 is subtracted. Described operations are presented in the following formulas (3.11 - 3.13):

$$V_4^*(k) = -\frac{V_4(k)}{1050} + 1, \tag{3.11}$$

$$DP_2^*(k) = -\frac{DP_2(k)}{11.31} + 1, \tag{3.12}$$

$$DP_5^*(k) = \frac{DP_5(k)}{21.63} - 1, \tag{3.13}$$

where $V_4(k)$ is the flow rate of the air after the Return Fan at the time k; $DP_2(k)$ is the differential pressure on the Left Filter at the time k and $DP_5(k)$ - differential pressure on the Right Filter at the time k.

The input matrix $u(k)$ has the following form (3.14):

$$u(k) = \begin{bmatrix} V_4^{*T}(k) & DP_2^{*T}(k) & DP_5^{*T}(k) \end{bmatrix}. \tag{3.14}$$

The matrix of coefficients before inputs B will be the following (3.15):

$$B = \begin{bmatrix} B_{V_4^*}^T(q) & B_{DP_2^*}^T(q) & B_{DP_5^*}^T(q) \end{bmatrix}^T. \tag{3.15}$$

3.4 The measured training set

In this capitol, the measured training set is presented. The measurement lasted for 146 hours: it started on 16.9.2015 at 13:57 and stopped on 22.9.2015 at 16:00. The measurement was conducted under the following conditions: Return Fan and Supply Fan were set to 4-th out of 7 velocity states; cooling mode was started with the set point at 11 °C and the hysteresis 3 °C.

In the following Figures (3.4 - 3.7) differential pressures, temperatures, and airflow are shown. All of this data need be filtered. Because, for instance, data from the sensor DP1 contains white noise with magnitude 15 Pa with the domain for this measurements from 167 Pa to 468 Pa. Used filters are presented in one of the following capitols, **Filtration of inputs**. In this capitol only filtered data are shown.

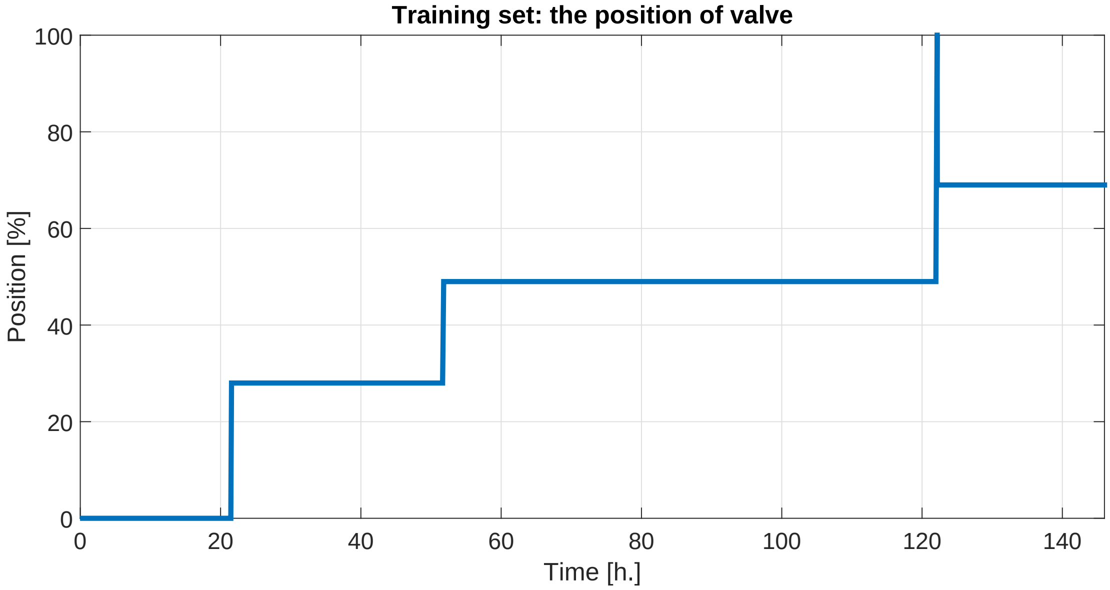

Figure 3.3: The position of the valve during the measurement of training set

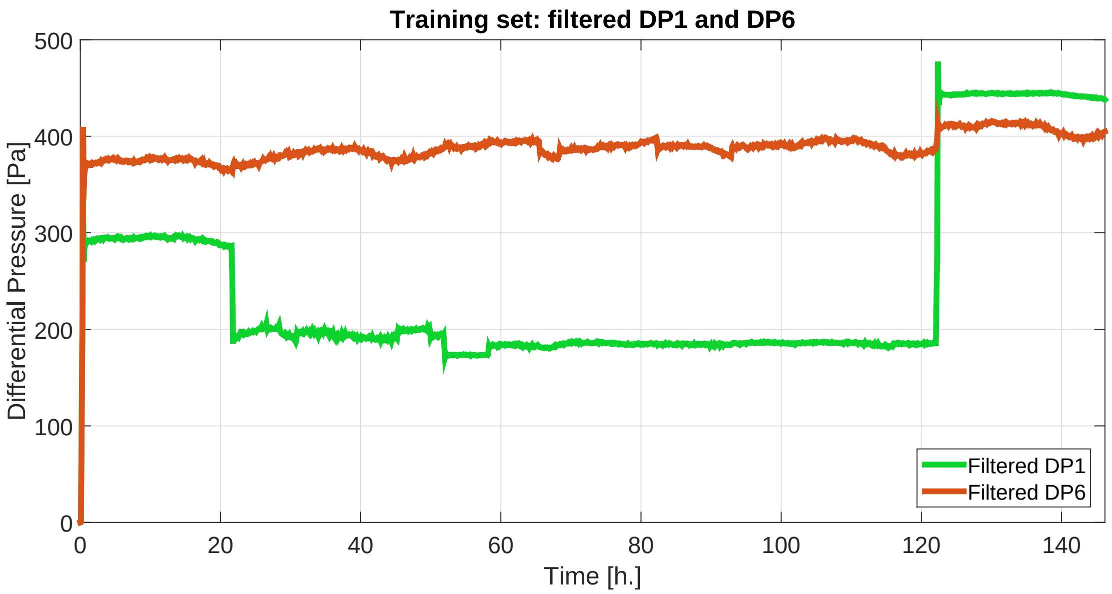

Figure 3.4: Measured DP1 and DP6

Figure 3.3 shows the position of the mixing valve during the measurement of the training set. 0 % on the y axes means completely opened valve while 100 % means completely closed valve. The measurement is provided for 4 cases of opening, which are represented in Table 3.2. The peak between 7328 and 7330 means that the AHU unit calibrates the position of the valve by the following method: it completely closes the valve and then opens it to the required position.

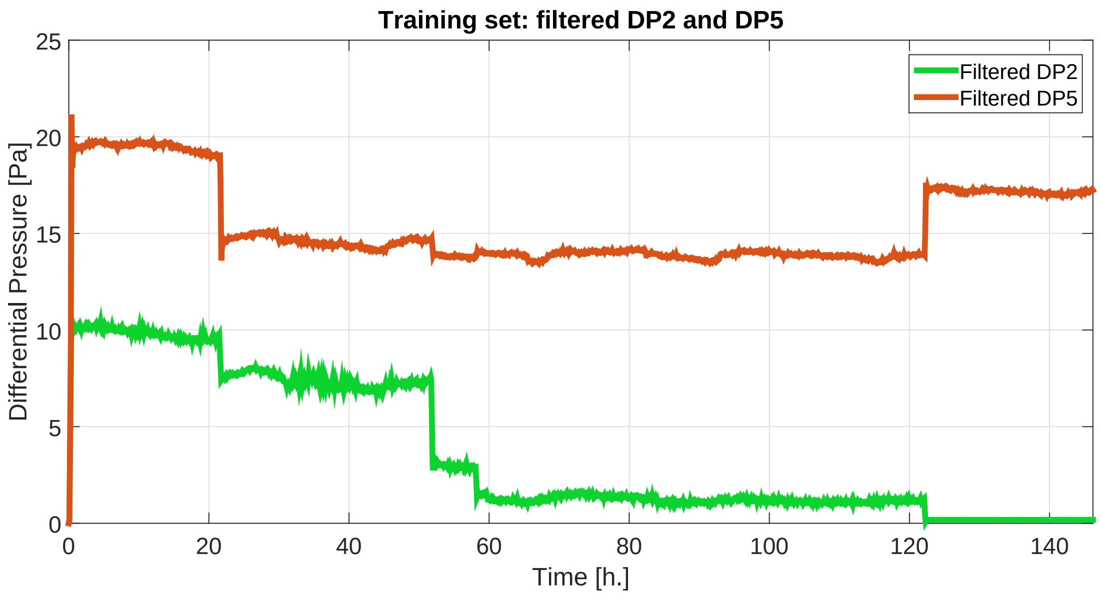

Figure 3.5: Measured DP2 and DP5

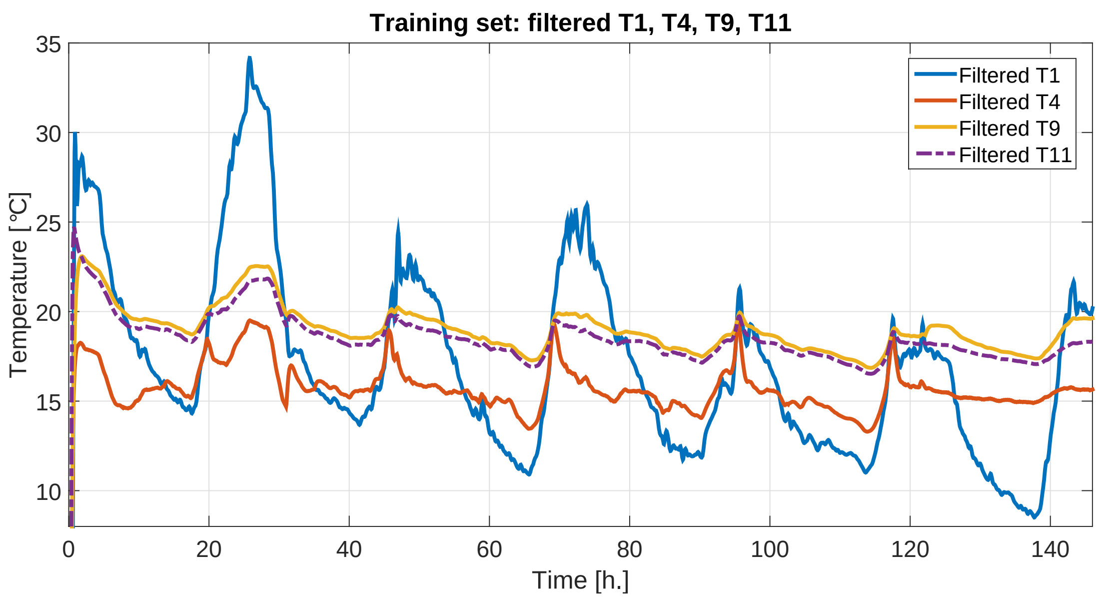

Figure 3.6: Measured T1, T4, T9, T11

Position [%]	0	28	49	69
Setting time	16.9.2015 13:57	17.9.2015 11:22	18.9.2015 17:36	21.9.2015 15:56

Table 3.1: Measured cases

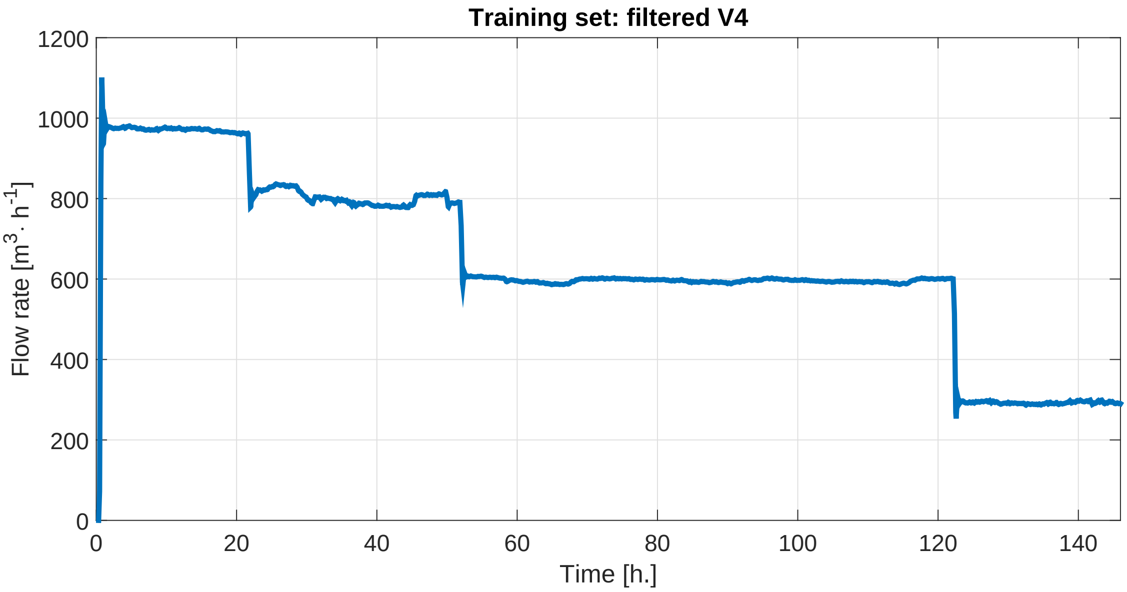

Figure 3.7: Measured V4

3.5 Filtration of inputs

As mentioned above, the measured data has white noise with magnitude about 1-15 % of original signal; it means that it is necessary to provide the filtration of inputs. First of all to design the filter the **Fourier Transform**, which is described by Peter D.Welch in [18], is needed. This transform translates a signal from the time domain into the frequency domain, where we can select the frequency components, which have the biggest magnitude. For obtaining the result of this transform the Matlab implementation of the algorithm **Fast Fourier Transform** (is described in [19]) is used. The example of filter design will be shown on the signal from sensor DP1, whose spectrum is shown in Figure 3.8.

For the filtration of input signals low-pass [20] filter is needed. From the plots of spectrum I estimated the cut-off frequency as 1 % of normalized frequency for differential pressure DP1. I chose the **low-pass digital Butterworth filter** [20] for all of the inputs. Matlab provides the designs of all the used filters. The example of transfer characteristic for signals from the sensors, which measure differential pressures, is shown in Figure 3.9. It can been seen that time delay of used filters is about 8 minutes for pressures (Figure 3.9). In the previous capitol (**The measured training set**) the resulted signals are shown.

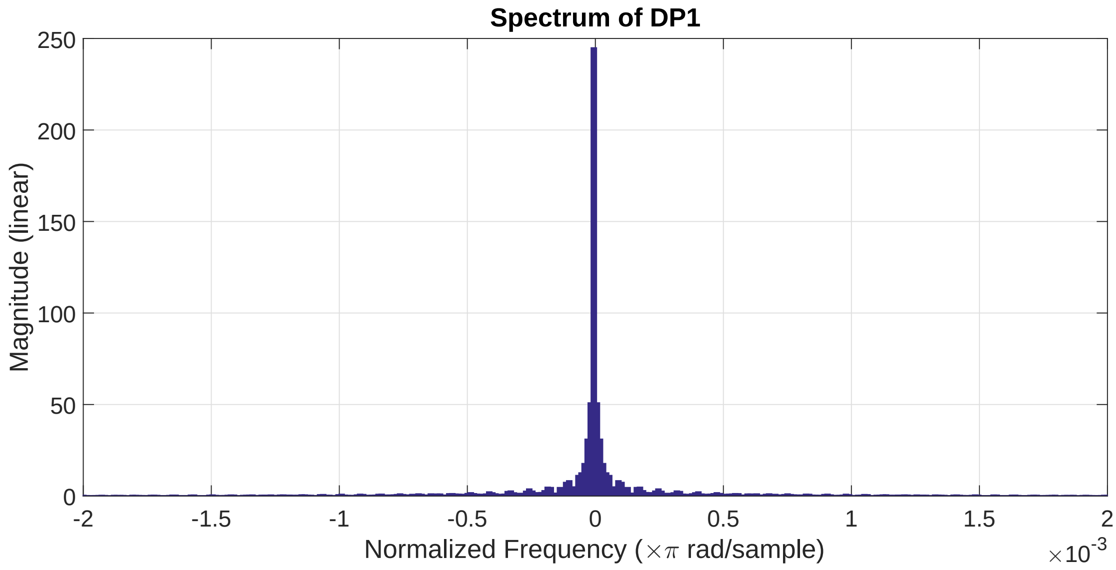

Figure 3.8: Spectrum of DP1

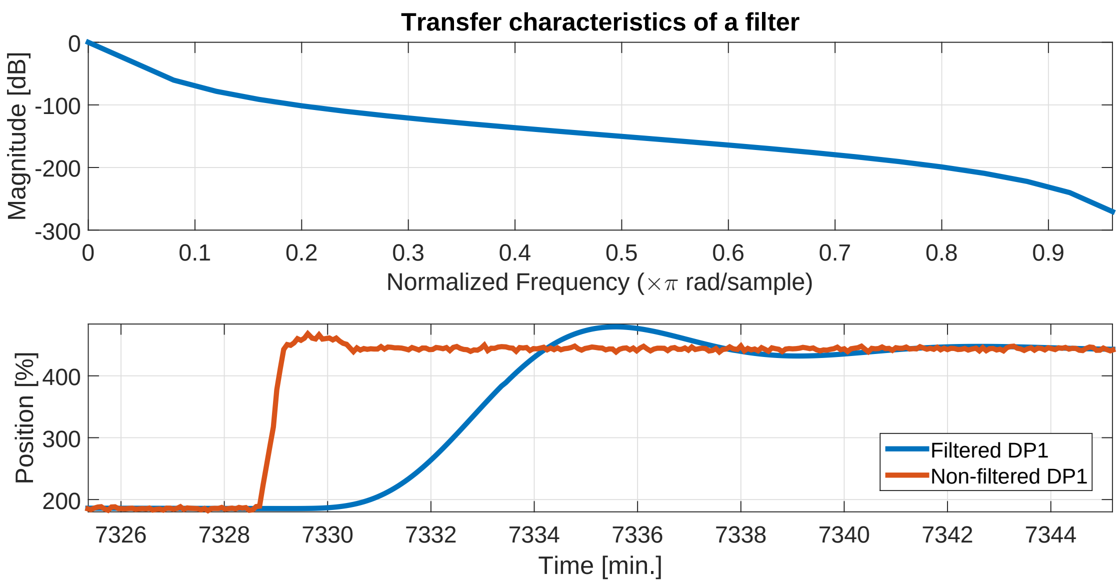

Figure 3.9: The transfer characteristics of the filter for the signal DP1

3.6 Filtration of outputs

All of the proposed models use the internal filters for pre-processing of an output signal. The design and the type of internal filters are the same like in the previous capitol, **Filtration of inputs**. In Figure 3.10 an example of the spectrum of one of the models is shown.

The cut-off frequency for models is chosen at 0.01 % of the Normalized Frequency. This filter has a respectively small (10 min.) time delay, which can be estimated from

Figure 3.11, in which, also, the transfer characteristics of the filter for the model, which is based on DP1, DP2, DP5, DP6, T11, T4, T1, T9, is shown.

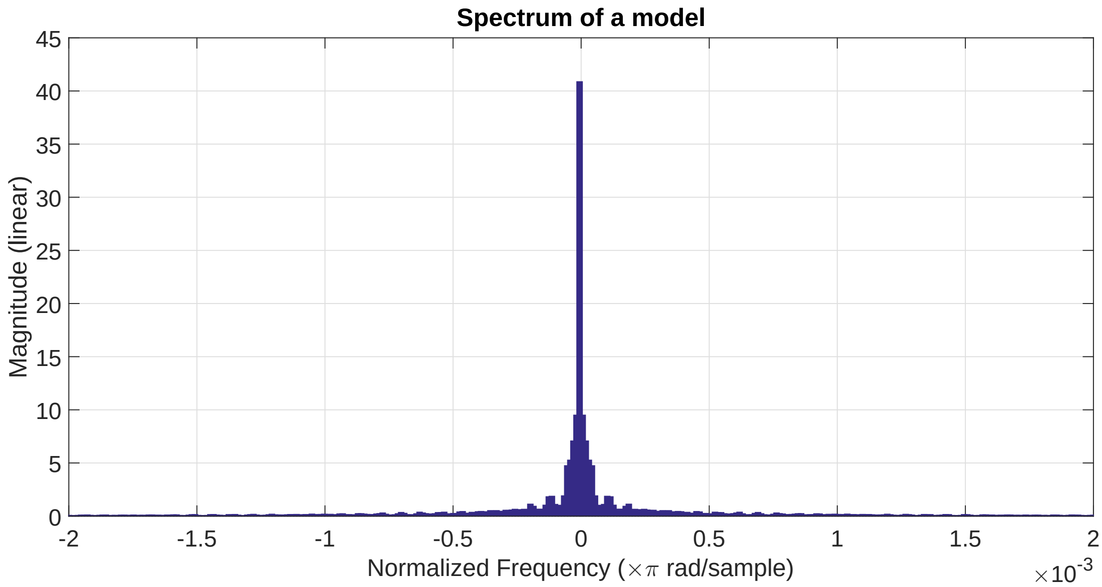

Figure 3.10: Spectrum of the model based on DP1, DP2, DP5, DP6, T11, T4, T1, T9

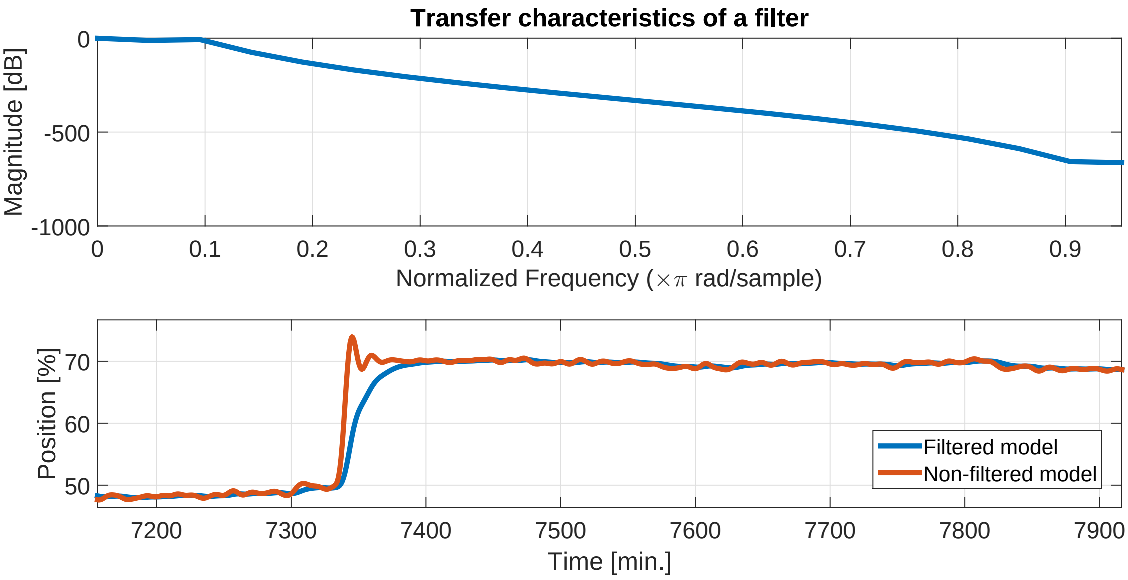

Figure 3.11: The transfer characteristics of the filter for model based on DP1, DP2, DP5, DP6, T11, T4, T1, T9

4. Comparison of proposed models

In this chapter comparison of the real position of the valve and output of mathematical models are shown. This chapter has two sections: **Training set** and **Test set**. In the former, behaviour of every model that uses data from training set is shown and the maximum absolute errors and mean absolute errors are calculated. The latter describes the measurement of test set and behaviour of every model.

4.1 Training set

4.1.1 Model based on DP1, DP2, DP5, DP6

This is the basic model of all of the proposed models, which is based on four differential pressures: on the Return Fan, Supply Fan, Left Filter and Right Filter. This model has a relatively significant mean absolute error (calculations of errors is in the capitol **Calculated errors**). Figure 4.1 shows the behaviour of the model used the training data set.

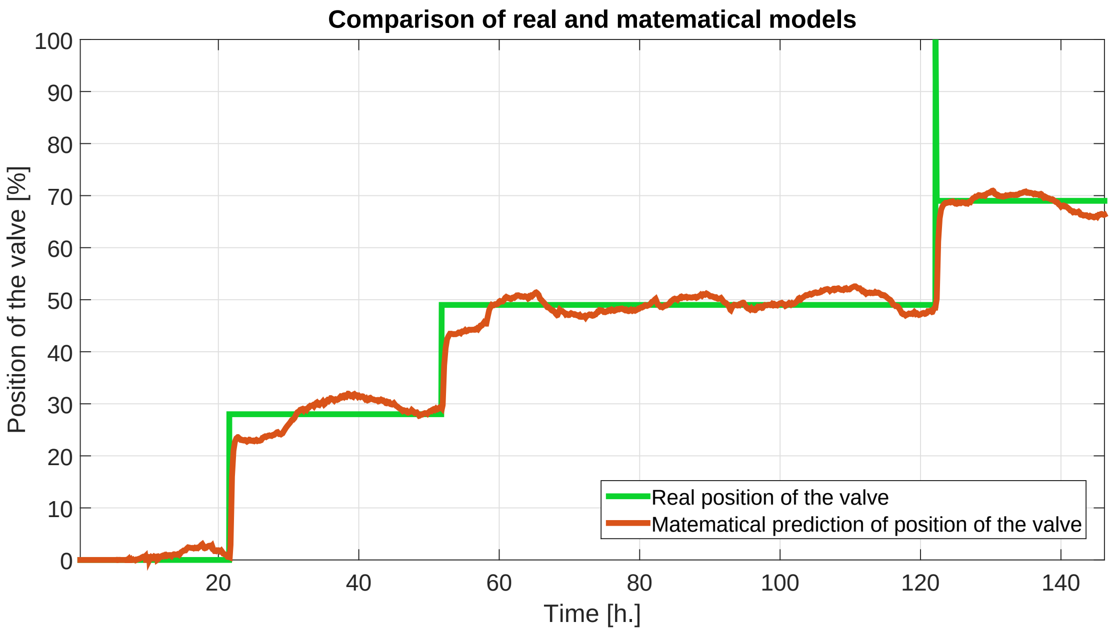

Figure 4.1: Comparison of the real position of the valve and output of the mathematical model, which is based on values of pressures from sensors DP1, DP2, DP5 and DP6

4.1.2 Model based on DP1, DP2, DP5, DP6, T11, T4, T1, T9

This model uses data from all of the used thermometers for estimation of the position of the valve. Due to well fitted output of the mathematical model, we can use it for development of the real Virtual Sensor.

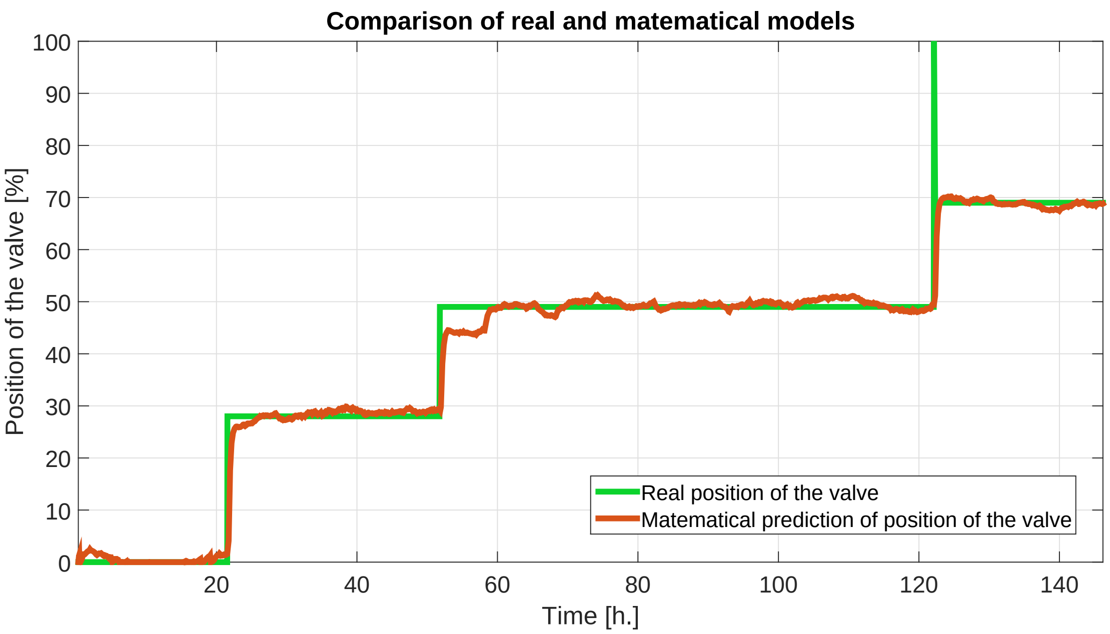

Figure 4.2: Comparison of the real position of the valve and output of the mathematical model, which is based on values of pressures from sensors DP1, DP2, DP5, DP6 and values of temperature from sensors T11, T1, T9 and T4

4.1.3 Model based on V4, DP2, DP5

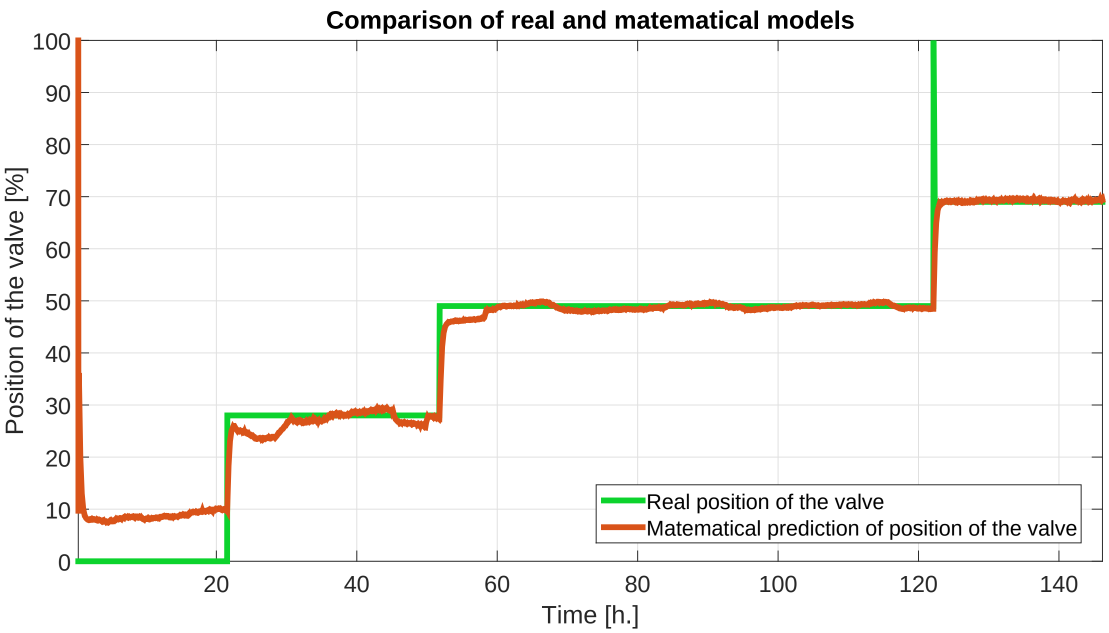

Figure 4.3: Comparison of the real position of the valve and output of the mathematical model, which is based on values of pressures from sensors DP2, DP5 and values of airflow from the sensor V4

This model represents the behaviour of the system very accurately except one extreme angle - 0% (completely closed).

4.1.4 Calculated errors

For comparison of proposed mathematical models, the maximum absolute error (4.1) and the mean absolute error (4.2) are used. The equations for calculation of these errors are taken from [1].

$$\mathrm{MAX_{AE}} = \max |Mix(k) - Mix^*(k)|, \quad k \in [1, n]\,, \tag{4.1}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{k=1}^{n} \max |Mix(k) - Mix^*(k)|, \tag{4.2}$$

where $Mix(k)$ is the real value of the position of the valve at the time k; $Mix^*(k)$ is the output of mathematical model at the time k; n is the count of samples.

Because of time delay of used filters for input signals, which is described in the chapter **Theoretical basis and design of Virtual Sensor** in the capitol **Filtration of inputs**, the peaks were excluded from the calculation of the $\mathrm{MAX_{AE}}$. These peaks arise in the moment of a large variation of input signals, due to described time delay. The example of this processing is shown in Figure 4.4, in which the graph of the absolute error of the mathematical model based on signals from sensors DP1, DP2, DP5, DP6 and T4 is shown. The line 5.89 represents the estimated maximum absolute error for this case.

The calculated errors are presented in the Table 4.1.

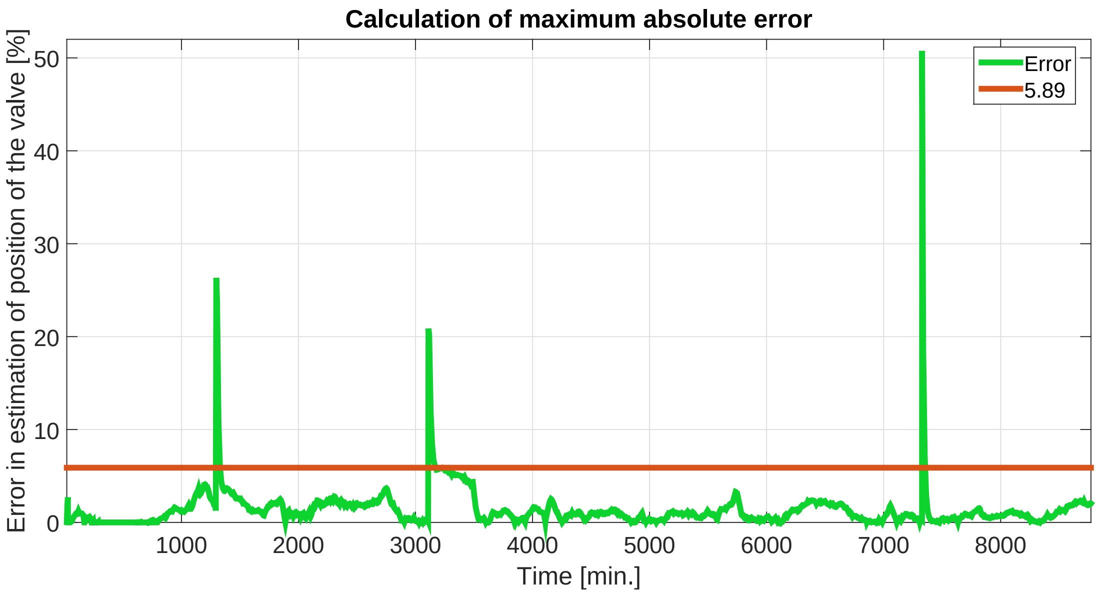

Figure 4.4: Calculation of maximum absolute error of mathematical model, which is based on DP1, DP2, DP5, DP6 and T4

Model is based on	Calculated MAX_{AE} [%]	Calculated MAE [%]
DP1,DP2,DP5,DP6	5.6	1.81
DP1,DP2,DP5,DP6,T11,T4,T1,T9	5.35	1.04
V4,DP2,DP5	10.32	2.03

Table 4.1: Calculated errors

As we can see, the first two models have the difference about 5 % of the estimated position of the valve between 3170 and 3500 minutes. This difference arises because of the same difference in measured data from sensors DP1 and DP2, which can be seen in Figures 3.4 and 3.5. It is unclear why this error in differential pressures measured on Left Filter and Return Fan arises. For example, it can occur because of opened door of AHU unit. Nevertheless, in the third model, this was eliminated due to used V4 and unused DP1.

4.2 Test set

4.2.1 Measured test set

In this capitol, the measured test set is described. The measurement was conducted on 6.5.2016 under the following conditions: Return Fan and Supply Fan were set to 4-th out of 7 velocity states; heating mode was started with the set point at 50 °C.

Position of the mixing valve during the measurement is presented in Figure 4.9 and described in the Table 4.2.

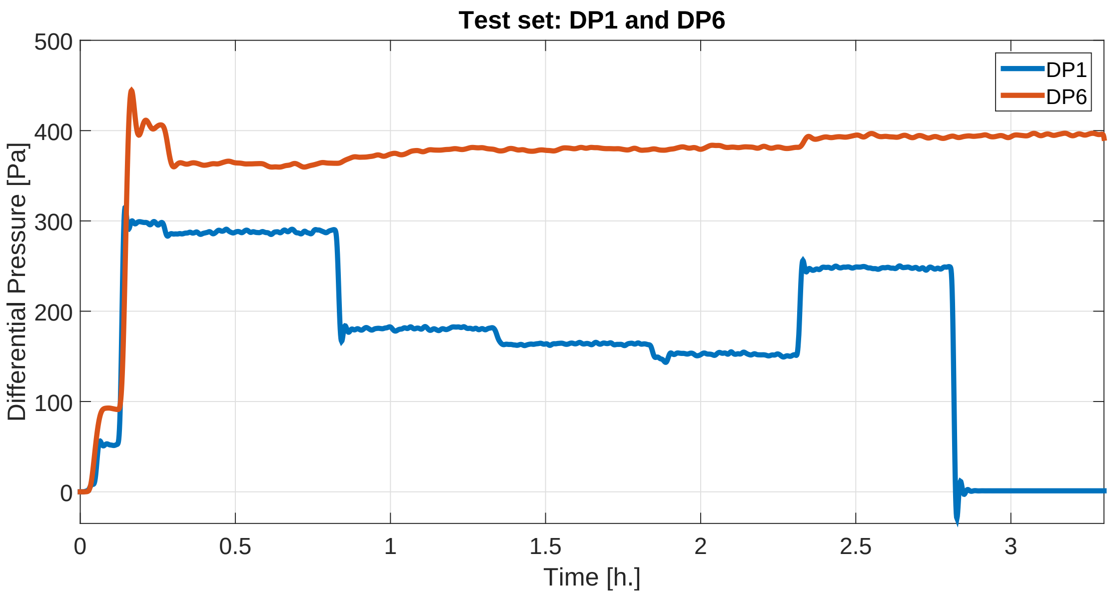

Figure 4.5: Measured differential pressures DP1 and DP6

Position [%]	0	24	37	54	73	100
Setting time	14:17	15:00	15:30	16:00	16:29	17:00

Table 4.2: Measured cases

Differential pressures, temperatures, and airflow are presented in the following Figures (4.5 - 4.8).

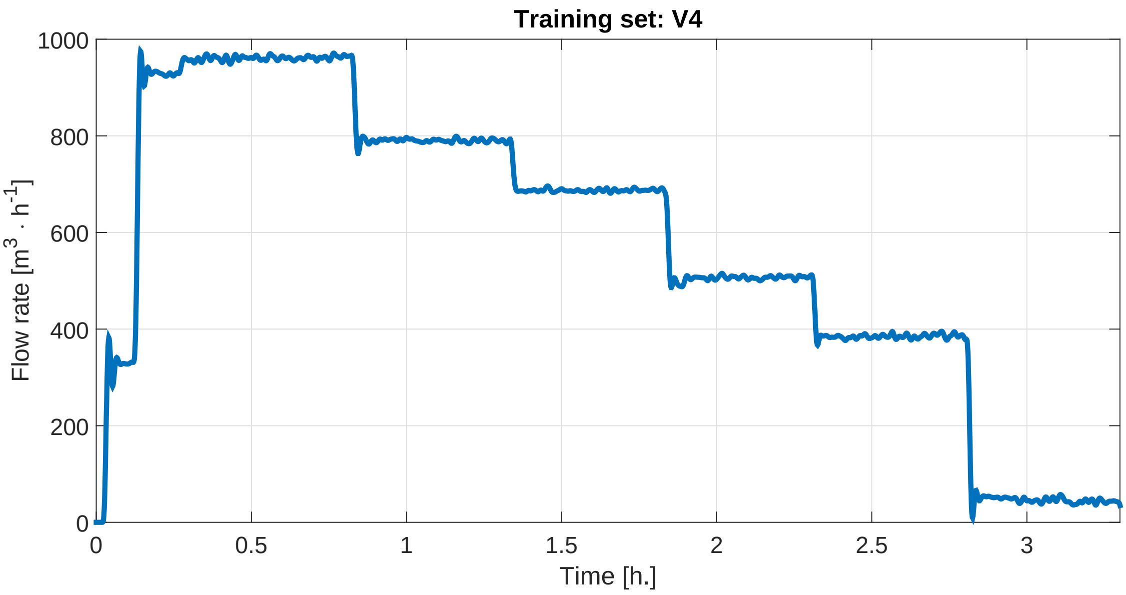

Figure 4.6: Measured airflow V4

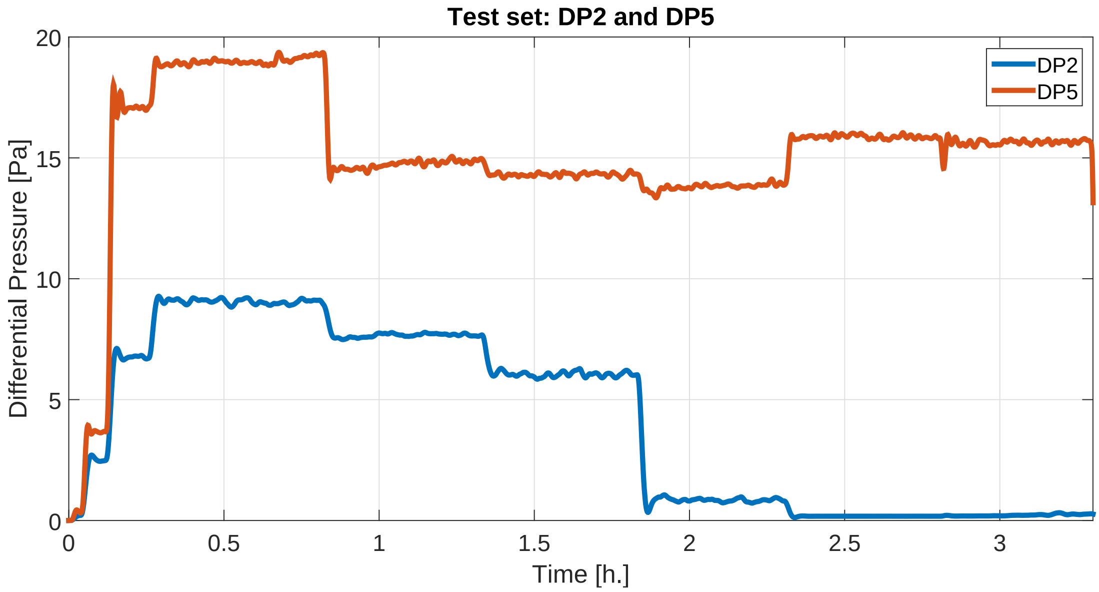

Figure 4.7: Measured differential pressures DP2 and DP5

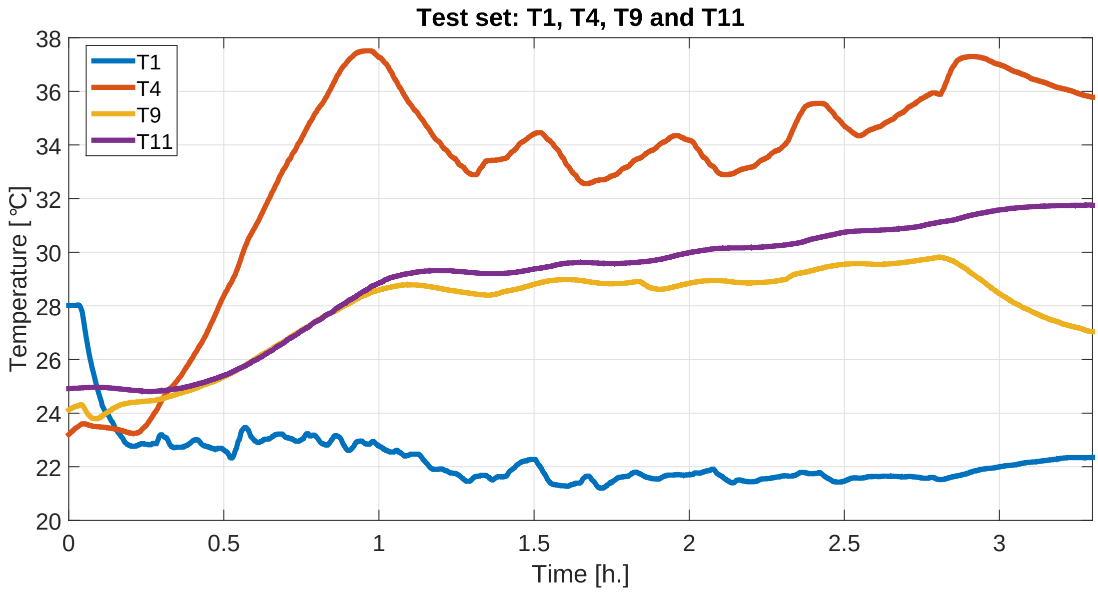

Figure 4.8: Measured temperatures T1, T4, T9 and T11

4.2.2 Model based on DP1, DP2, DP5, DP6

In Figure 4.9 the behaviour of the model based on DP1, DP2, DP5, DP6 is presented. It can be seen that the model has large mean absolute error especially in the last phase when the real model has 100 % state.

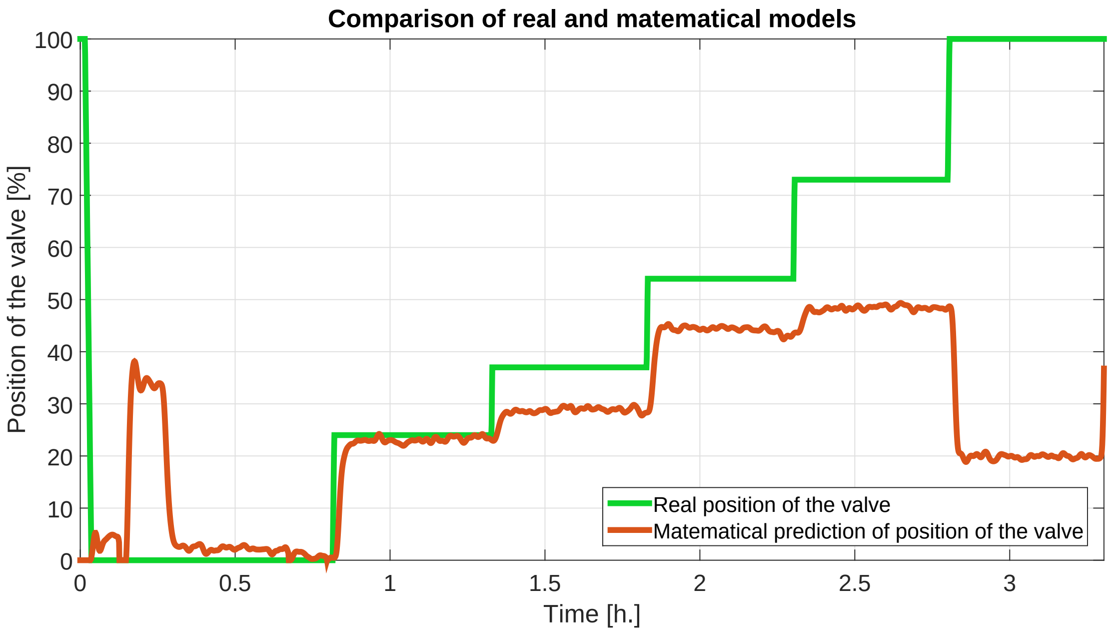

Figure 4.9: Comparison of the real position of the valve and output of the mathematical model, which is based on values of differential pressures from sensors DP1, DP2, DP5, DP6

4.2.3 Model based on DP1, DP2, DP5, DP6, T11, T4, T1, T9

This model, as well as the previous one, does not represent the system behaviour correctly. Both models use the signal DP1 for estimation. The signal DP1 depends on the set mode of air conditioning: heating or cooling. The inaccuracy of the model is caused by the DP1 signal. This problem is deeper described in the capitol **Summary**.

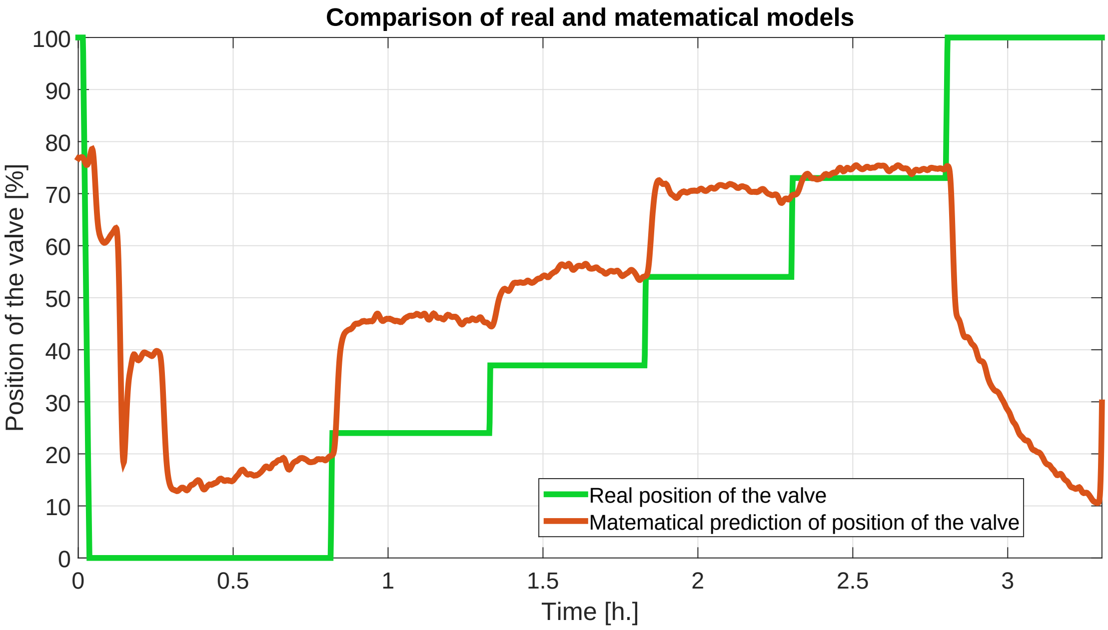

Figure 4.10: Comparison of the real position of the valve and output of the mathematical model, which is based on values of differential pressures from the sensors DP1, DP2, DP5, DP6 and temperatures from the sensors T1, T11, T4, T9

4.2.4 Model based on V4, DP2, DP5

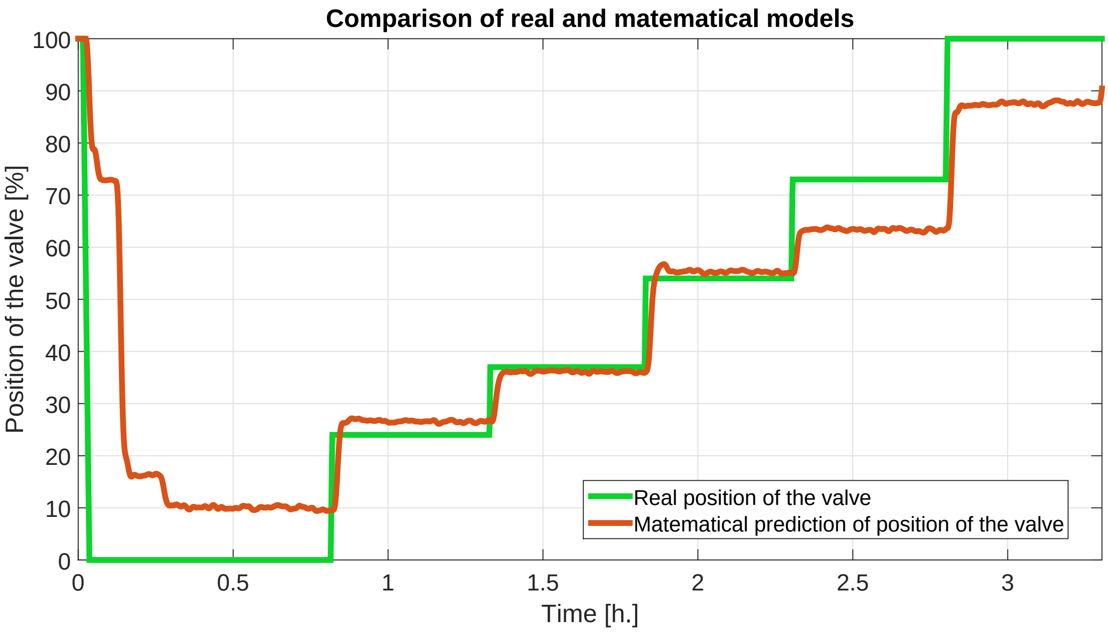

Figure 4.11: Comparison of the real position of the valve and output of the mathematical model, which is based on values of differential pressures from the sensors DP1, DP2, DP5, DP6 and airflow from the sensor V4

This model is more accurate than the previous. The future implemented Virtual Sensor will be based on this model, but as we can see, it is necessary to measure new extensive training set to implement a more precise model.

The calculated mean and maximum absolute errors are 10.24% and 18% respectively. For the two previous models there is no reason for showing this errors because, as we can see in Figures 4.9 and 4.10, they are too large.

4.2.5 Summary

The following problems arise during the estimation of the position of the valve on the test set:

- Training data set does not have all cases of the real model behaviour during the regular AHU unit operation.
- On the motor, which regulates the velocity of rotation of the Return Fan during the test set the saturation of the power consumption was set. Due to this fact the values from the sensor DP1 that is placed on the Return Fan was not the same as during the training set. This difference is shown in Figure 4.12, where the maximum values of this signal are emphasised.
  It means that we cannot use this signal for model estimation because it directly depends on the setting, which is made by user. If user sets the saturation, it will lead to large estimation error in this Virtual Sensor.

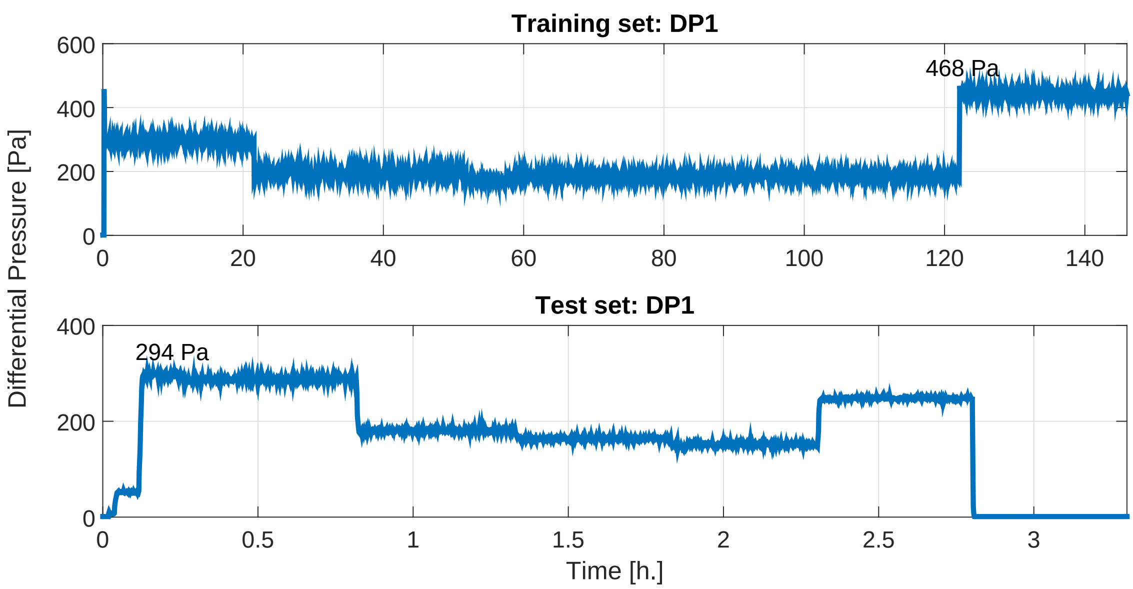

Figure 4.12: Comparison of the measured data from the sensor DP1 in the training set and the test set

- In the extreme cases, all of the proposed mathematical models do not represent the system behaviour correctly. When the valve is fully opened (0 %, in the first period) in the system, the models predict non-zero value. In the last period when the valve is completely closed (100 %), the opposite error arises.

In the future presented inaccuracies will be resolved by the following strategy:

- The new extensive measurement of the training set should be provided, in which all of the possible cases of using the AHU unit will be covered. For instance, in the new training set the behaviour of the model during winter and summer should be measured.
- The model either shouldn't use the data of the differential pressure from the sensor, which is placed on the Return Fan, or this model should have one more parameter for representation of the set saturation of power consumption of this Fan. It can be realised by means of **Finite-State Machine** [22].
- The order of the model should be increased for increasing accuracy. On the other hand, it means that one of the fitting algorithms, such as **Linear Regression**[23], must be used for parameter estimation.
- Nowadays the laboratory model has new sensors of flow rate installed after Fans. It means that this data can be used for model estimation as well.

5. Conclusion

This work completely describes the general steps in design of Virtual Sensor from the choosing of modelling approaches and theoretical basis to model estimation and validation.

Design of the Virtual Sensor of mixing ratio of the air in the AHU unit was the main aim of this project. As mentioned above, mixing ratio is directly proportional to the angle of the mixing valve inside the unit. During this work several models, which estimate the position of the mixing valve, were developed.

The most accurate model, which is based on signals from the sensors V4, DP2, DP5, was chosen for the future work for enhancement of precision of the Virtual Sensor. The ways of this improvement are shown at the end of the chapter **Comparison of proposed models**. In this chapter, in which the results were described, the main problem was emphasised: the new extensive measurement of the training data set should be provided. This training set will cover all of the possible cases of using AHU unit. Also, as mentioned in the previous chapter, the system of equations of the proposed model should be complemented by increasing the order of ARX model and addition of parameters of this system using **Finite-State Machine**. All of these methods should increase the precision of the proposed model as well as the Virtual Sensor, which will be based on this model. The mean absolute error, which is used for evaluation of this accuracy, for the most accurate model was 2.03% in the training set, and 10.24% in the test set. The maximum absolute error, respectively: 10.32% and 18%.

With regards to the objectives of this work, the current State of the art in Virtual Sensing was determined; theoretical basis, which is described in the chapter **Theoretical basis and design of Virtual Sensor**, is presented and can be used in further works; the mathematical models, which represent the behaviour of the Virtual Sensor, are designed. These models passed the test set and the most accurate model was chosen for the further work. It will be finalised by improvement of the accuracy of the designed Virtual Sensor and hardware implementation.

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