System identification for control of temperature and humidity in buildings

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Abstract

HVAC systems are widely used to provide a good indoor air quality in buildings. Buildings stand for a substantial part of the total energy consumption in developed countries, and with an increased focus on cost reductions and energy savings, it is necessary to use intelligent and energy-efficient controllers.

Accurate models describing the dynamics of the building system is a good basis for intelligent control. In countries like Sweden there are large seasonal variations in the outdoor climate, and these variations interfere with the indoor condition and thus affects the control. In this thesis the seasonal variations are investigated, and the aim is to determine how these differences affect identified models for control of temperature and relative humidity in buildings. Two MISO (Multiple Input-Single Output) systems and one MIMO (Multiple Input-Multiple Output) system is used to describe the mean room temperature and relative humidity in a selected room in the Q-building at KTH, Stockholm. The models are identified following the black-box approach, and data from four different months during 2014, representing the winter, spring, summer and autumn season respectively, are collected and preprocessed.

The validation of the identified models for the humidity and temperature, shows that it is possible to use identical orders and input delays for all seasons, with good results. Based on the results one would not recommend using models with the same model parameters throughout the year, since the conditions varies too much from season to season.

Acknowledgements

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1
Introduction

The goal of HVAC (Heating, Ventilation and Air Condition) systems is to ensure an acceptable indoor air quality and thermal comfort. With todays high energy demand and strict environmental standards, it is required that the HVAC systems is controlled in an energy-efficient way. In order to implement efficient solutions, good models are needed as basis for the control. In countries like Sweden the outdoor climate is varying throughout the year. The variations in the outdoor conditions affects the indoor conditions. These variations should not be neglected in order to ensure an efficient use of the HVAC system all year round. In this thesis different models for control of relative humidity and temperature are constructed using System Identification. The models are identified using data from four different months in order to get a good representation of the seasonal variations that occurs in countries like Sweden.

Dealing with system identification it is common to follow two different routes: The black-box approach (having no a priori information regarding the system dynamics) or the gray-box approach (based on physical knowledge). Because of the difficulties regarding the thermodynamics in buildings, the black-box approach is the most common route to follow when modeling HVAC systems, but the interest in gray-box modeling is increasing as well.

1.1 Previous work

One can find a great amount of literature dealing with system identification for HVAC systems. A selection of the work, especially applicable for this study are mentioned in this section.

In the master thesis [Scotton, 2012], physics-based models are identified for humidity, temperature and CO_2-level, using data from four days in May 2012. The object of study is room A:225 in the Q-building at KTH (Kungliga Tekniska Högskolan) in Stockholm, which is the same test-bed as used in this thesis. The paper conclude that the ARMAX (AutoRegressive Moving Average with eXternal input) and state-space models identified performs very well compared to similar studies. The models proposed in [Scotton, 2012] are also presented and validated in [Scotton et al., 2013].

[Maasoumy, 2011], focuses on modeling the thermal behavior in buildings in order to design an optimal control algorithm for HVAC systems. The control algorithm is based on an estimated temperature model for three different rooms in the same building, identified following the gray-box approach.

Wu and Sun [Wu and Sun, 2012] proposes a physics-based linear parametric ARMAX model of room temperature in an office building, where thermodynamics equations are used to determine the structure and the order of a linear regression model.

In [Yiu and Wang, 2007] a MIMO (Multiple Input-Multiple Output) ARMAX model is identified using the black-box approach. The model is used to forecast the performance of an air conditioning system of an office building in Hong Kong. The parameters are estimated using the Recursive Extended Least Squares Method (RELS). The MIMO ARMAX model is then compared to a SISO (Single Input-Single Output) ARMAX model.

In [Mustafaraj et al., 2010] ARX (AutoRgressive with eXternal input), ARMAX and BJ (Box-Jenkins) models are identified for humidity and temperature following the black-box approach. The object of study is a building in London, where data from the summer, autumn and winter seasons have been collected and used for identification. The paper conclude that the BJ models generally performs better than the other models. The orders and input delays in both the temperature and the humidity models are varied throughout the year.

Mustafaraj *et al.* continues the work in [Mustafaraj et al., 2011] by identifying NoNlinear AutoRegressive models with eXogenous inputs, i.e., NNARX-models, to represent the room temperature and relative humidity. The NNARX models are compared to linear ARX models, where the paper conclude that the former outperforms the latter.

[Jiménez et al., 2008] presents tools for how to use The System Identification Toolbox (SIT) in MATLAB to identify ARMAX models for HVAC-systems following the gray-box approach. One of the key elements is how to select suitable outputs and inputs and the paper demonstrates how to estimate both MIMO and MISO (Multiple Input-Single Output) systems.

Based on the previous literature, the physics-based models have generally shown better results than the models estimated using black-box-techniques. On the other hand, dealing with complex mechanisms such as thermodynamics in buildings, in combination with especially multiple outputs, the black-box approach is much easier to follow. In this thesis the possible relative difference between the seasons is the main focus, so using black-box techniques to estimate the models gives a sufficient performance in this context, and are chosen for convenience.

1.2 Aim of the thesis

The aim of this thesis is to study how seasonal differences affect identified models for temperature and relative humidity in buildings. The overall goal is to find suitable models to use for control of the variables in question. As an aid to reach the goal, the problem is formulated using the following questions:

- Is it possible to use identical or at least similar models to describe the dynamics all year round?
- How does temperature and relative humidity relate to each other? How will this relationship impact the model identification and control?
- Which control strategies are most eligible based on the findings regarding the previous points.

1.3 Methods and limitations

The models are identified using the System Identification Toolbox in MATLAB. Four different datasets, containing data for 1 month each, are used to represent the winter, spring, summer and autumn season. To look at the possibility of using two-output models the datasets are subjected to a correlation test prior to identification. Throughout the thesis black-box techniques are used.

The work is limited to examining the possibility of using the same or at least similar models for all the seasons for control of temperature and humidity in buildings. The focus is not on finding the best possible models that can be achieved for each season, but are limited to finding models that work well enough.

1.4 Contribution

This thesis proposes MISO and MIMO models for control of temperature and humidity in HVAC systems. Using four months, where each month represents a specific season, it is concluded that it is possible to use models of the same structure, having the same orders and input delays for all seasons. This implies that one can use certain known control strategies to ensure a good indoor climate, also in buildings located at places where the outdoor climate changes throughout the year.

1.5 Thesis outline

In Chapter 2 the test-bed used in this thesis is described. The chapter also contains an introduction to the system identification procedure and a presentation of the thermodynamical principles relevant for buildings.

In Chapter 3 the methods used for identification are presented, as well as information regarding data preprocessing and the correlation between variables. At the end of the chapter the identified models are presented.

In Chapter 4 the models identified in Chapter 3 are validated, using some standard validation metrics.

Chapter 5 presents the conclusions that can be drawn from the results, and improvements and possible further work is discussed.

2

Background

This chapter is dedicated to describe some key features behind this study. It starts with a brief introduction to the system identification procedure and some of the aspects regarding thermodynamics and buildings. The purpose of this is to explain some of the choices made during the identification process and to support the assumptions made regarding which inputs and outputs are used later on. A detailed description of the test-bed, the HVAC system and its components follows thereafter. Finally, some of the previous work based on the test-bed are presented.

2.1 Introduction to system identification

Using the terms and principles presented in [Ljung, 1999], some basic features regarding system identification are introduced in the following subsections.

Definition

The subject of system identification is to construct or select suitable mathematical models of dynamical systems, to serve certain purposes. The models are based on observed data from the system.

Model-building approaches

Mathematical models can be developed using two different approaches: Analytical modeling or system identification. Using analytical methods, basic laws of physics are used to describe the behavior of the system. Following this approach doesn't necessarily involve any experimentation on the actual system; instead, one could say it relies on earlier empirical work. System identification on the other hand, is an experimental approach. It is most common to use parametric methods, meaning that the behavior of the system in question is described by using a model with a finite number of parameters. The parametric models are developed by:

1. Choosing a model structure from a set of standard models (black-box approach) or deriving a model structure based on physical knowledge (gray-box approach)

2. Estimate the model parameters from the input- and output signals of the system.

Using the black-box approach, no a priori information regarding the physical system is needed. The gray-box approach is based on physical knowledge of the system, and the method somewhat combines analytical modeling with black-box identification.

The system identification procedure

The procedure of system identification follows a natural order, consisting of the following steps:

- Collection of data
- Choosing a model set
- Picking the “best” model in this set
- Validating the model

In every step of the identification process, problems may occur, resulting in insufficient models. Common problems are e.g. that the data used for identification isn’t informative enough, or that the chosen model sets can’t capture the system dynamics sufficiently well. The system identification procedure is thus an iterative process, where the outcome of previous attempts and prior information determines what step to take next. The iterative manner of system identification can be considered as working in a loop, where it might be necessary to go back and revise previous steps several times until a “good enough” result is obtained. An illustration of the work flow is shown in Figure 2.1

2.2 Basic thermodynamical principles

When modeling systems, it is important to have a feel of how the system of study behaves. Despite that black-box modeling techniques are used in this thesis, it is beneficial to have some knowledge about the thermodynamical properties of the system. In this study it is, first of all, important to have some ideas of how the system behaves in order to select the inputs of interest. The selection typically involves disregarding the signals that only have a small impact on the system, compared to the signals that impact the system largely. It is also helpful to know how the system behaves when examining the data, analyzing the results etc. If the gray-box approach had been used, the thermodynamical relationships would have been used more directly when building the models. In that case, the model parameters would reflect real physical quantities, such as control variables, properties of the room and so on, in a more obvious way. In the following sections some of the key features of thermodynamical systems are presented.

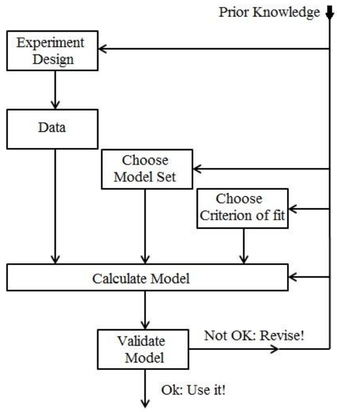

Figure 2.1 The System Identification Loop. [Ljung, 1999]

Heat storage and transfer

The thermal properties of a building are often explained in terms of heat storage and heat transfer [Maasoumy, 2011]. The building components, such as walls, rooms and internal devices have the capability to store heat. The amount of heat that can be stored depends on the mass and material of the component. The specific heat capacity, c_p, is a basic material property that can be used to determine the material in questions ability to store heat. More specific, the c_p determines the amount of heat or thermal energy required to increase the temperature of a unit quantity of a substance by one unit. More heat is needed to increase the temperature of substances with a high specific heat capacity, than substances with a low specific heat capacity.

Heat transfer occurs via three different mechanisms, convection, conduction and radiation. Convection is the term for heat transfer through circulation of air. Conduction means the transfer of heat through solid materials. It is caused by a difference in temperature, meaning that due to the interactions between particles in a medium, energy is transferred from the more energetic (warm) particles of the medium to the

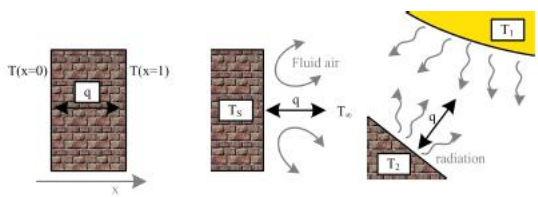

Figure 2.2 Heat transfer mechanisms:

Conduction (left), convection (middle) and radiation (right). [Maasoumy, 2011] less energetic (cold) particles. Radiation is the transfer of heat by electromagnetic waves (or photons). The radiation is emitted by a matter at a finite temperature. The heat transfer mechanisms are illustrated in Figure 2.2.

The effect of the outside conditions

How the heat transfer affects the indoor environment is dependent on the outside conditions. During the summer season, it is usually warm outside and the sun shines for many hours a day. This means that the main challenge in keeping the indoor temperature at a comfortable level relies on effective cooling. Radiation and conduction of heat from the outside make the buildings warm up fast. During the winter season, less amount of solar radiation causes the outside temperature to drop. In this case, heat from the inside is conducted to the outside through the walls, windows and roof of the building. In order to minimize the effect of the heat transfer, it is important to have good insulation and to have an effective heating and cooling system. Figure 2.3 illustrates how the heat transfer mechanisms work in a building.

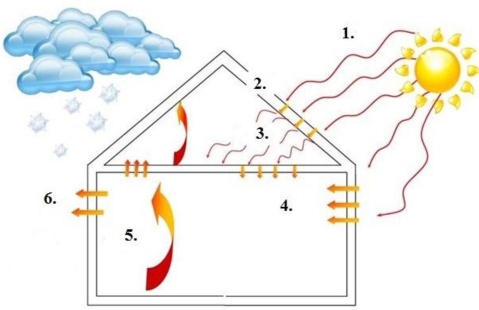

Figure 2.3 Heat transfer through a building:

1. The sun radiates heat to roof and walls. **2.** Heat conducts through roof. **3.** The roof radiates heat to ceiling **4.** Heat is conducted through the material of the walls and ceilings throughout the building **5.** Convection makes warm air rise **6.** Heat seeks cold by conducting through the walls, wasting heat

When examining how the outdoor conditions affects the indoor conditions, the effects from the wind can't be neglected. The wind is the primary force behind convective heat transfer acting on the exterior surfaces of the building. When the wind blows on the external walls, warm alternatively cold air is "pushed" through cracks and holes in the wall facing the wind direction. The excess inside air caused by the wind is then pushed out of the building at different locations. This ongoing replacement of air is affecting the building's indoor temperature and humidity, especially when there is a large difference in temperature between the interior and the exterior of the building. The speed of change in the indoor conditions is tightly connected to the wind speed and the building material/construction [Straube, 2011].

Relationship between temperature and humidity

As explained in [Pisupati, 2014], humidity is the measure of the amount of water vapor in the air. Humidity can be expressed in different ways. In this context it is sufficient to present absolute humidity and relative humidity. Absolute humidity refers to the total amount of water vapor in a given volume of air. It does not take temperature into consideration. Relative humidity is a measure of the water vapor content of the air at a given temperature. The amount of moisture in a volume unit of air is compared with the maximum amount of moisture the same volume of air can contain at the same temperature. It is expressed as a percentage. For a given temperature, T, the relative humidity is calculated according to Equation (2.1):

$$RH[\%] = \frac{Actual\ amount\ of\ water\ vapor\ in\ the\ air[\frac{g}{m^3}]}{Max\ amount\ of\ water\ vapor\ the\ air\ can\ hold\ [\frac{g}{m^3}]} \cdot 100\% \qquad (2.1)$$

In order to ensure a comfortable indoor climate, it is important to take the relative humidity into consideration. Discomfort can occur if the relative humidity is too high or too low. Generally, as temperature increase, relative humidity decrease and vice versa. The reason for this is that as the temperature rises the air will expand. If the amount of water vapor in the air remains the same, the capacity of the air to hold water vapor increases. Similarly, when the temperature drops, the air's capacity to hold water vapor decreases due to a compression of the air, causing the relative humidity to increase, as explained in [Jenkins, 2014].

From now on, no distinction will be made between the terms 'humidity' and 'relative humidity', and both terms will be used to refer to the latter.

2.3 Control of HVAC systems

To make sure that the HVAC systems doesn't overcool or overheat the indoor spaces, it is of great importance to control the system in a proper way. A Control system is required e.g to ensure that optimal thermal comfort standards are met, to maintain an optimum indoor air quality (IAQ) and to reduce energy use, to name a few.

According to [Pattarello, 2013], an important aspect to consider when controlling HVAC systems is that the building dynamics are highly affected by uncertainties. Examples are unpredictable room occupancy levels and unexpected manual actions like opening and closing of windows etc.

Because of the changing conditions that are typically surrounding HVAC systems, a few control-strategies become extra interesting to consider regarding such systems. Using adaptive and/or predictive control strategies could be a good choice.

Based on the nature of the HVAC systems, the controllers should at least adapt to the changing conditions and possibly also predict future behavior of the system.

One simple adaptive control strategy is *Gain Scheduling*. This strategy is commonly used to control systems that are subjected to predictable parameter variations. The method uses that the system parameters change with the operating condition. If the process gain is known at every operating point, the controller parameters, applicable for controlling the system under different conditions, can be calculated in advance and stored in look-up-tables. When the process reach a certain operating point the controller parameters change according to the stored values.

Much effort has also been put into exploring the possibilities of *Model Predictive Control (MPC)*. The idea behind the strategy is to utilize a model of the system dynamics to predict and optimize the future behavior of the system. The strategy is applicable for HVAC-system for many reasons, one being that it is especially meaningful to exploit predictions when dealing with slow systems, like the dynamics in buildings. Other advantages to MPC is that it is possible to deal with constraints on both inputs and outputs, and that it is easy to implement also for multi-variable systems.

2.4 Description of the test-bed

The object of study is room A: 225, also called LAB3, located at the second floor of the Q-building at KTH (Kungliga Tekniska Högskola). The room has one external wall, equipped with four windows, and three internal walls. The area of the room is about 80 m^2 and its volume about 270 m^3 [Scotton, 2012]. The room is mainly used for student laboratories. The information regarding the test-bed and how it functions, presented in the following sections, are mainly taken from KTH's HVAC team's wiki page [KTH-HVAC-Wiki, 2015].

Monitoring and control

The Q-building, as well as the whole KTH campus is equipped with a large amount of HVAC-units. These are monitored and controlled centrally by a SCADA system. The Q-building has several heating and cooling units, including radiators and cooling coils and three separate ventilation units for fresh air supply. Each ventilation unit is controlled by a soft PLC, which is a software package that emulates the functionality of a standard PLC inside a PC, and in addition has Internet access. One soft PLC is located on the 2nd floor and is directly connected to the sensors, cooling/heating processes and the ventilation unit used on the second and third floor of the Q- building, thus including room A:225. The soft PLC can be controlled manually and remotely by the SCADA system, and is programmed to keep a constant room temperature within seasonal-dependent temperature ranges, and to keep the CO_2 level below 850 ppm throughout the year. This is achieved by using cooling and heating actuators and Demand Controlled Ventilation (DCV) methods.

The DCV system supplies the rooms with fresh air as needed between 07:00-16:00 Monday through Friday, and is automatically turned off outside this time period.

In addition to the “central building system” the second floor in the Q-building is equipped with a Wireless Sensor Network (WSN). The sensors are of the type TMote Sky and are equipped with onboard temperature, humidity and light sensors. Some of the devices in the WSN are equipped with CO_2 sensors as well. All the motes are located on the second floor, and are organized in a star topology. The center of the motes is called a coordinator, which receives the data from the surrounding motes, and forwards it to the root mote. The root mote is connected to a PC that forwards the data to a database. Room A:225 is the center of the WSN, and the root mote is located here. The data processing is accomplished using LabVIEW. To keep track of the number of occupiers in the room, a photoelectric sensor based people counter is used.

Today, the HVAC-system is controlled by Proportional Integrative (PI) controllers. One of the controllers are used to control the temperature and the other one is used to control the IAQ, i.e, the CO_2-level. Because no focus is on the CO_2-level in this thesis, only the mechanisms of the PI controller for the temperature is mentioned. This PI regulator is set to keep the room temperature in the test-bed within a specified temperature range, and is not programmed to follow a specific reference temperature. Generally, the controller actuates the cooling system during the summer season to ensure that the temperature lies within a comfort range of $21^{o}C-23^{o}C$. During the winter season the controller mainly uses the heating system to keep the room temperature in the range $20^{o}C-22^{o}C$. According to [Pattarello, 2013] and [Fabietti, 2014], the current control system suffers from out of bounds temperature values and neither actuator wear nor energy-efficiency is taken into consideration.

HVAC components in room A:225

Room A:225 is equipped with four radiators, four fresh air inlets, four AC units and two exhaust air outlets. These actuators, depicted in Figure 2.4, provide the heating, cooling and ventilation services. In the following sections the HVAC-devices and their functionality are described in detail.

Heating system The heating system is mainly based on the four radiators in the room. For convenience they will be called R1, R2, R3 and R4 from now on. The radiators are equipped with a valve, whose opening percentage can be set from the SCADA web interface. Hot water, generated in a central boiler, is circulated through the building via pumps. When the radiator valve of room A:225 is open, hot water runs through R1-R4 and heats up the room. The soft PLC is programmed to keep the temperature in the range $20^{o}C$-$22^{o}C$ during the winter season, i.e., when the heating system is mainly used. Because of this, the heating system is automatically turned on only when the temperature is below $20^{o}C$, and turned off when the temperature reach $22^{o}C$.

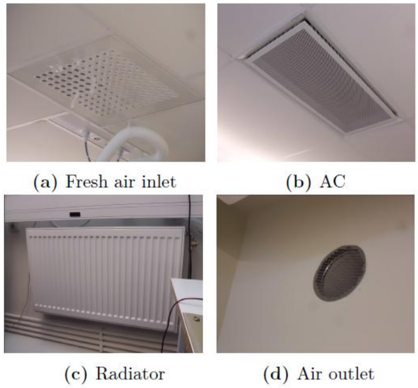

Figure 2.4 HVAC components in the test-bed. [KTH-HVAC-Wiki, 2015]

There are several sensors attached to or near the radiators. For R1 they are placed approximately as shown in Figure 2.5. The other radiators have fewer sensors nearby, but they all have in common that a sensor is attached to the radiator inlet, corresponding to the placement of sensor 1008 in Figure 2.5. For device IDs for all the sensors connected to the radiators, see Figure 2.8.

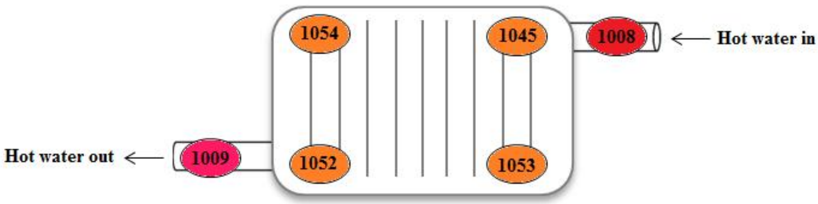

Figure 2.5 The sensors associated with radiator number 1

Cooling system The main task of the AC devices is to provide cooling services. Similar to the heating system the AC units are connected to a valve, which is controlled by the SCADA web interface. One of the ventilation units supplies the device with primary air as marked in Figure 2.6. When the device is on, i.e., when the valve is open, this air is injected into a plenum, which stores the air at a pressure above 1 atm (the standard atmospheric pressure). The plenum is equipped with small pipes or nozzles in various sizes, for which the stored air can be discharged into the room. Due to the high pressure in the plenum the air is discharged into the room at a high velocity. The increased velocity causes the pressure of the air to drop, and thus creates a low-pressure zone. The pressure difference between the area around the device and the rest of the room then causes the room air to be sucked up through a heat exchanger, consisting of a coil containing flowing chilled water. In the heat exchanger, the air is cooled and mixed with the primary air, before it is discharged into the room from the sides of the device, as seen in Figure 2.6.

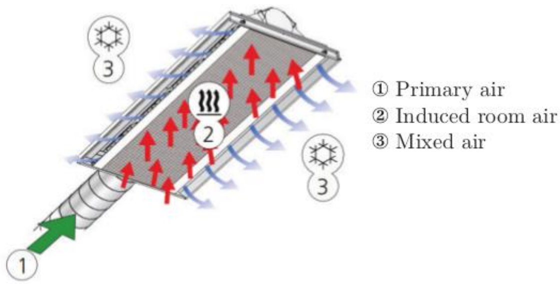

Figure 2.6 The AC device in working mode. [KTH-HVAC-Wiki, 2015]

When used for cooling, chilled water is transported to the heat exchanger. To ensure a fast and effective cooling process, it is necessary that also the fresh air inlets and exhaust air outlets in the room are 100% actuated, during the time the AC units are running (on). The AC devices can alternatively be used for heating. The only difference is that hot water, instead of chilled water, is transported to the heat exchanger.

Ventilation system In room A:225 the ventilation system is implemented by the four air inlets and two air outlets. The air inlets supply the room with fresh air, coming from one of the ventilation units. A damper regulates the airflow coming into the room, and its opening percentage can be controlled by the SCADA web interface. The air outlets consist of two holes in the wall, where a tube leads the air from room A:225 to the hallway. The tube is equipped with a damper, whose opening percentage can be regulated from the SCADA web interface. The air inlet device is depicted in Figure 2.7.

The central ventilation system uses air from the outside, filters it, and runs the air through a heat exchanger. The heat exchanger exploits the heat from the exhaust air outlets. The imported air is heated up to 19.4°C by the heat exchanger and passes through sequentially heating and cooling systems via pumps. This is done to keep the fresh air, discharged into the rooms from the fresh air inlets, at a temperature of approximately 20°C. Since the temperature of the air is fixed, the ventilation system affects heating and cooling as well. When the room temperature is below 20°C, the fresh air helps to increase the indoor temperature. Similarly when the room temperature is above 23°C, the ventilation system helps to decrease the temperature.

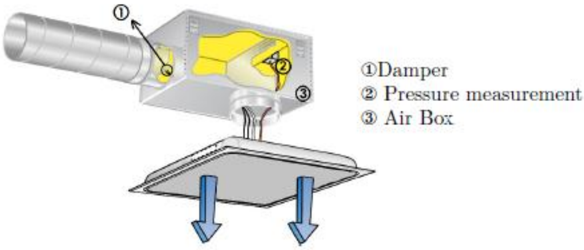

Figure 2.7 The air inlet device in working mode. [KTH-HVAC-Wiki, 2015]

Control variables in the test-bed Since the temperature of the air and water provided to the HVAC-units in the test-bed are distributed from a central source, there are only four variables that can be controlled by the user directly. To affect the condition in the test-bed, the user can set the opening percentages of the valves connected to the radiators, the AC-devices, the fresh air inlets and the exhaust air outlets, respectively. The temperature of the "hot" and "cold" water used for heating and cooling are controlled by external units, and are statically dependent on the outside temperature. By setting the opening percentages, the user can control the temperature indirectly by choosing what amount of the available heating or cooling capacity to use [Fabietti, 2014].

As for today, there are no devices to directly modify the humidity, i.e, there are no humidifiers/dehumidifiers installed. Therefore, the user can't actively control the humidity in the test-bed.

Test-bed map

Figure 2.8 depicts the map of the test-bed and its sensors. The sensors are marked with device IDs, and their color depends on the type of device. The orange circles represent temperature sensors attached to the surfaces of the radiators. The temperature and humidity sensors attached to walls, ceiling and floor are represented by gray/purple circles and the red and fuchsia circles mark the temperature sensors at the radiator inlets and outlets. The cyan colored device (1012) and the green one (1047) are temperature and humidity sensors located near one of the AC inlets and the Fresh Air Inlets respectively. The dark red circle, located in the center of the room (1043), and the blue circle (1042) placed near one of the exhaust air outlets, represents sensors measuring humidity, CO_2, temperature and current natural lighting in the room. The black circle shows where the root mote for the WSN is located.

In addition to the sensors located inside the room or nearby, information is received from the central system. An overview of the device IDs for these signals is listed in Appendix A.1. More information regarding the devices shown in Figure 2.8, can be found in Appendix A.2.

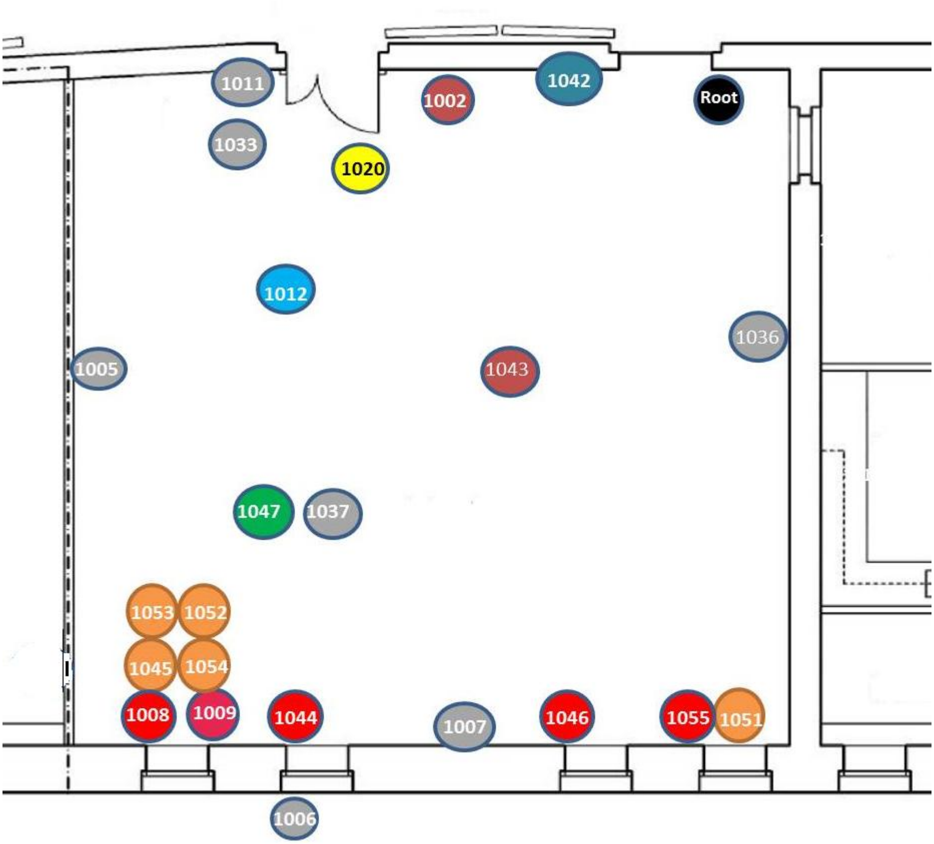

Figure 2.8 Test-bed Map:

The figure shows: Sensors attached to walls, ceiling and floor (gray/purple circles), sensors attached to radiator surfaces (orange circles), radiator outlet sensor (fuchsia circle), radiator inlet sensors (red circles), sensors near the AC inlet (cyan circle) and the fresh air inlet(green circle), sensors located in the center of the room (dark red circle) and near the exhaust air outlet (blue circle), and the root mote for the WSN (black circle). [KTH-HVAC-Wiki, 2015]

2.5 Previous work with connections to the test-bed

In addition to the work presented in Chapter 1, there are some work that are tightly connected to this specific test-bed. The test-bed is constantly under development, and works as a base for the research in fields involving modeling and control of HVAC-systems at KTH. The main focus is improving the efficiency of the HVAC-system to ensure energy-savings and cost reductions. There are several publications connected to the test-bed, where the majority of them explores the potential of using Model Predictive Control (MPC) strategies. Examples are [Parisio et al., 2013] and [Parisio et al., 2014], as well as the mater theses [Fabietti, 2014] and [Pattarello, 2013] .

There is a strong connection between MPC and modeling, and the development of suitable models is an integral part of MPC. There are not many publications concentrated solely on the modeling aspect using this test-bed, but there are some work, including the mentioned [Scotton, 2012], that proposes physics based models developed following the system identification path. The additional publications connected to this test-bed mainly focuses on expanding the knowledge regarding HVAC-system dynamics. This is done by establishing connections between different variables that affects the system. In e.g. [Ebadat et al., 2013] the relationship between the CO_2-level, temperature and actuation of the ventilation system is studied, in order to identify a dynamic model that estimates the number of occupiers in the room.

There are not any recently published work, connected to this specific test-bed, that uses system identification for building models following the black-box approach.

3

Modeling and identification

The aim of this chapter is to present the identified models for temperature and humidity and explain how they are obtained. The methods and tools used in the process are described, including how the data is collected, systematized and preprocessed.

3.1 Data collection and systematization

The study is based on historical data and no on-line experiments at the location is performed. Data from four months during 2014 has been used, and each dataset are preprocessed and divided into an estimation part and a validation part. For each season 2/3 of the usable data are used for estimation and 1/3 for validation. The datasets used are:

- **Winter season:** January
  Measurements taken from 01/01/2014, 00:00:00 to 31/01/2014, 23:59:59
- **Spring season:** April
  Measurements taken from 01/04/2014, 00:00:00 to 30/04/2014, 23:59:59
- **Summer season:** July
  Measurements taken from 01/07/2014, 00:00:00 to 31/07/2014, 23:59:59
- **Autumn season:** October
  Measurements taken from 01/10/2014, 00:00:00 to 31/10/2014, 23:59:59

All the data is extracted from KTH HVACs homepage [KTH-HVAC, 2015], then transported to and made visible in MATLAB. The usable signals for this thesis' purpose are then selected based on the information given in Chapter 2 and the models presented in [Mustafaraj et al., 2010].

Regarding room A:225's surroundings, only the effects from the outside are considered. The effects due to i.e., heat convection through the walls from adjacent rooms and the hallway are neglected. The reason for this is that the effect from the heat convection between rooms is very small compared to the impact from the outside. This choice is also supported by [Scotton, 2012]. Because black–box techniques are used, it is not necessary to establish exactly how the outdoor conditions affects the system. It is enough to determine to what degree the system is affected by the outside. This is a benefit here since we lack adequate information regarding e.g. the temperature near the window surfaces (no sensors are attached to the windows). Some of the other signals are left out as well, simply because they don't provide any valuable information. An example is the sensors attached to the radiators.

After selecting the usable signals, they are divided into groups and systematized according to Figure 3.1, inspired by [Ljung, 1999].

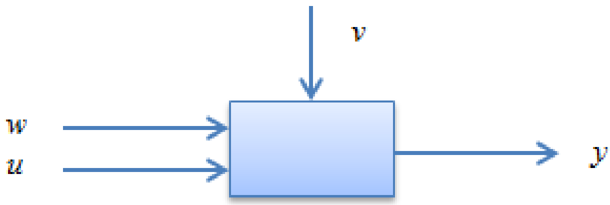

Figure 3.1 The system with inputs, u, outputs, y, measured disturbances, w and unmeasured disturbances, v.

The systematization gives the following collection of signals:

Outputs, y:

- T_R**:** The mean room temperature in ^{o}C.
- H_R**:** The mean room relative humidity in %.

Control inputs, u:

- T_{AC}**:** The temperature, in ^{o}C, of the air coming from the AC device.
- T_{Air}**:** The temperature in ^{o}C of the air coming from the fresh air inlet.
- T_H**:** The temperature in ^{o}C of the hot water, circulating through R1-R4.
- H_{AC}**:** The relative humidity in % of the air coming out of the AC device.
- H_{Air}**:** The relative humidity in % of the air coming from the fresh air inlet.

Measured disturbances, w:

- T_O**:** The outside temperature in ^{o}C.
- H_O**:** The outside relative humidity in %.

- N: The number of occupiers in the room.

In addition several unmeasured disturbances, v, impact the system in varying degree. Examples are: excess heat from electrical devices in the room, solar radiation and wind speed. Also the automatic start and stop of the central system is treated as an unmeasured disturbance. From now on the measured disturbances will be treated as inputs and the unmeasured disturbances will be taken care of by the disturbance term in the models.

The signals in the raw data are given sensor by sensor, so in order to get the signals shown above, some adjustments have to be made. To get representative and informative outputs, the mean room temperature and humidity is calculated by taking the mean value of a selected number of the signals given by sensors located at different positions in the rooms. Some of the inputs are also determined using a similar approach. Table 3.1 gives an overview of the sensors used and how they are grouped.

Table 3.1 The sensors used to determine the inputs and outputs of the system

Signal	*Sensors*
T_R	The room temperature given by the mean of sensors: 1011, 1005,1007, 1036, 1043, 1033 and 1037
H_R	The room humidity given by the mean of sensors: 1002, 1005, 1007, 1043 and 1051
T_{AC}	Given by sensor 1012, located close to the AC discharge
T_{Air}	Given by sensor 1047, located close to the fresh air inlet
T_H	Temperature at the radiator inlets given by the mean of sensors: 1008, 1044, 1046 and 1055
H_{AC}	Given by sensor 1012, located close to the AC discharge
H_{Air}	Given by sensor 1047, located close to the fresh air inlet
T_O	The outside temperature given by the mean of sensors: 1006, 2000 (from central system) and 5000 (from web-based weather forecast source)[1]
H_O	The outside humidity given by the mean of sensors: 1006 and 1254[2]
N	Given by sensor 3000

[1] See Subsection "Non-accurate measurements" in Section 3.4 for more information.
[2] See Subsection "Missing signals" in Section 3.4 for more information.

3.2 Correlation between variables

From Section 2.2 one knows that temperature and relative humidity are connected to each other, and here this relationship is examined more in detail. Having an idea about how the different inputs and outputs relates to each other, is helpful when identifying the models and evaluating the results. Information regarding the relationship between the variables may give valuable clues about possible fault-sources etc.

Before identification the inputs and outputs are thus subjected to a correlation test using the correlation coefficient, R. The correlation coefficient is a simple measure to determine the linear dependency between two variables. According to [Blom et al., 2005] the correlation coefficient for two datasets are given by:

$$R_{x,y} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{3.1}$$

where $\{x_i, \cdots, x_n\}$ and$\{y_i, \cdots, y_n\}$ are the two datasets in question, n is the number of data pairs and $\bar{x}$ and $\bar{y}$ are the sample means for x_i and y_i respectively.

The calculations results in a number in the range from -1 to +1. If $R = 1$, a perfect positive correlation between the variables occurs. Generally, positive values of R indicates a relationship between the x and y variables such that as values for x increases, values for y also increase. If $R = -1$ a perfect negative correlation occurs and negative values of R indicate a relationship between x and y such that as values for x increase, values for y decrease. If $R = 0$ there is no linear dependency between the variables, indicating a random, nonlinear relationship between the two variables.

In this thesis MATLAB is used to calculate the correlation coefficient, by using the function `corrcoef`. The correlation between the two outputs for each respective seasons are calculated by using `corrcoef(y)`, where y is a matrix containing T_R, H_R. The results are shown in Table 3.2. The correlation between each respective output and the inputs are presented in Table 3.3 . For the correlation between the inputs, see appendix A.3

Table 3.2 The correlation between the humidity and temperature outputs

Signals	***Winter***	***Spring***	***Summer***	***Autumn***
T_R, H_R	-0.18	0.06	-0.13	-0.20

Evaluating the R-values in Table 3.2, the data from the winter, summer and autumn seasons confirms the negative correlation between temperature and relative humidity described in Section 2.2. Using the data from these months suggests a negative correlation in the range of 13%-20%. The data for the spring season however suggest a slightly positive correlation, which is the opposite of what is expected. With a correlation of only 6% it seems as if there is almost no dependency between the variables. The distinction between the spring season and the other seasons is an interesting aspect that might be of use later on.

Table 3.3 The correlation between the output and inputs

Inputs	*Winter*		*Spring*		*Summer*		*Autumn*	
	T_R	H_R	T_R	H_R	T_R	H_R	T_R	H_R
T_{AC}	0.29	-0.21	0.58	-0.08	0.65	-0.05	0.71	-0.20
H_{AC}	-0.14	0.95	-0.11	0.91	-0.23	0.75	-0.07	0.95
T_{Air}	0.88	-0.23	0.61	0.16	0.93	-0.11	0.92	-0.22
H_{Air}	-0.16	0.94	-0.02	0.95	-0.30	0.92	-0.16	0.99
T_H	0.53	-0.25	0.60	-0.16	0.99	-0.13	0.71	-0.29
T_O	-0.40	0.90	0.14	0.05	0.58	0.29	0.09	0.83
H_O	0.30	-0.00	0.10	0.56	-0.57	-0.04	-0.01	0.06
N	0.22	-0.04	-0.04	0.35	-0.18	-0.32	-0.31	0.47

Studying the R-values given in Table 3.3 and Appendix A.3, one notices some general tendencies:

- As expected there is a strong positive correlation between the temperature output, T_R, and the inputs T_H, T_{Air} and T_{AC} and a weaker negative correlation between T_R and H_{AC} or H_{Air}. Likewise, there is a strong positive correlation between H_R and the inputs H_{AC} and H_{Air}, and a weaker negative correlation between the relative humidity output and the temperature inputs.

- The correlation between the respective outputs and the humidity and temperature outside does not follow a clear pattern, which also is reflected in the correlation between the inputs. In every case when inputs T_O and H_O are involved, it is hard find a pattern that fits all seasons. The same is the case with the number of occupants.

In addition to the general tendencies above, there are some R-values that especially stand out. One of them is the high correlation between the temperature output and the temperature from the radiators during the summer season, shown in Table 3.3. The high correlation of 99% seems odd, since the radiators aren't used much during the summer. The correlation is probably so high in this case since the temperature by the radiator inlets lies very close to the room temperature when no hot or cold water have been circulating through the radiators for a while. Because of this, one could ideally disregard the radiators as inputs during the summer season. However, since the radiators are occasionally on, also during the summer season, they are considered for this season as well.

3.3 The modeling procedure

Now that the relationship between the inputs and outputs has been evaluated, one can begin to look at different model structures. Since we know there are a correlation between temperature and humidity, it is interesting to explore MIMO (Multiple Input-Multiple Output) models as well as MISO (Multiple Input-Single Output) models. In order to maintain a structured work flow, the modeling procedure is done stepwise. The first step consists of organizing four different input-output relationships, which deals with:

1. Temperature, not considering the humidity inputs
2. Humidity, not considering the temperature inputs
3. Temperature and humidity, considering all inputs and resulting in two MISO systems.
4. Combined temperature and humidity, resulting in one MIMO system.

Thereafter, in the second step, the temperature and humidity relations are presented using suitable basic model structures.

Point 1 and 2 in the first step is only done as preparation and in order to simplify the analysis of the relationships between humidity and temperature later on. Only the models considering all inputs, will be used and presented here and further on. This narrowing is reasonable because of the large amount of models that arises when looking at four different seasons and several model structures. This exclusion is consistent with the aim of the thesis.

Model requirements

Since the models' intended use is control, there are some properties of the models, and demands on them, that are especially important to consider:

- The models should be able to describe the system well, having as low complexity as possible.
- The prediction abilities of the models are more important than the simulation abilities.
- The models should account for disturbances acting on the system in some way.

The first point involves finding the right trade-off between model simplicity and accuracy. This is important because in order to control the system properly, and in an energy-efficient way, accurate models are required. Having as precise models as possible, might on the other hand require a large amount of model parameters. Dealing with many parameters increases the model complexity, and thus might lead to prohibitive computational procedures caused by too large execution times in the controllers.

In Section 2.3 one suggests that adaptive and predictive control strategies are suitable for controlling HVAC-systems. If predictive techniques are to be used, it is first of all important that the models work well for prediction. Therefore the simulation abilities of the models are not as important as their prediction abilities in this context.

Since buildings are complex systems and affected by disturbances of various nature, it is required that the disturbances are presented in the models. This is important to make sure the controllers can take care of the disturbances in the best way possible.

Model structures

Intuitively there are mainly two classes of models structures that are interesting in this study. Both are classes of models for LTI-systems (Linear Time-Invariant systems). A first choice is looking at the family of transfer function models, also called black-box models. This is a natural choice since the main focus is on black-box techniques. An alternative is to use state-space models, which is often used when the focus is on the physical mechanisms of the system, since it is easier to incorporate physical insights into state-space models than in the transfer-function models [Ljung, 1999]. Due to the limited focus on the physics, only the black-box models will be examined for the separate temperature and relative humidity models. The state-space structures are although mentioned here, because state-space models are the easiest structure to work with when it comes to systems with more than one output.

The transfer function models have the following general structure as presented in [Ljung, 1999]:

$$A(q)y(t) = \frac{B(q)}{F(q)}u(t) + \frac{C(q)}{D(q)}e(t) \tag{3.2}$$

where $u(t)$ is the input, $y(t)$ is the output, $e(t)$ is the error, and $A(q)$, $B(q)$, $C(q)$, $D(q)$ and $F(q)$ are polynomials in the shift-operator, q, which works in the following way: $q^{-n}x(t) = x(t-n)$. The polynomials are of orders n_a, n_b , n_c, n_d and n_f respectively.

ARX model structure The ARX structure is the simplest of the model structures presented here. The models is built up by an Autoregressive (AR) part, $A(q)y(t)$, and an extra part (X), $B(q)u(t)$. The model structure is based on the input-output relationship:

$$y(t) + a_1 y(t-1) + \ldots + a_{n_a} y(t-n_a) = b_1 u(t-1) + \ldots + b_{n_b} u(t-n_b) + e(t) \tag{3.3}$$

and in terms of Equation (3.2) the ARX model has the following structure:

$$A(q)y(t) = B(q)u(t) + e(t) \tag{3.4}$$

The disturbance term $e(t)$ is white-noise entering as a direct error in the difference equation.

ARMAX model structure A disadvantage to the ARX structure is the lack of freedom in the disturbance term. To improve the simple ARX structure, the disturbance can instead be described as a moving average of white noise. The input-output relationship becomes:

$$\begin{aligned} y(t) + a_1 y(t-1) + \ldots + a_{n_a} y(t-n_a) &= b_1 u(t-1) \\ &+ \ldots + b_{n_b} u(t-n_b) + e(t) + c_1 e(t-1) + \ldots + c_{n_c} e(t-n_c) \end{aligned} \tag{3.5}$$

Adding this feature to the equation error gives us an ARMAX model, which has the same features as the ARX model, but with an additional moving average (MA) part, $C(q)e(t)$. The ARMAX-model in terms of Equation (3.2) is given by:

$$A(q)y(t) = B(q)u(t) + C(q)e(t) \tag{3.6}$$

OE model structure In many cases it is not natural that the inputs and the noise are subjected to the same dynamics. An alternative way is to parametrize the transfer functions corresponding to the inputs and the disturbances independently. This is done by modeling the relation between the inputs and the undisturbed output, w, as a linear difference equation where the disturbances consist of white noise added to the undisturbed output:

$$\begin{aligned} w(t) + f_1 w(t-1) + \ldots + f_{n_f} w(t-n_f) &= b_1 u(t-1) + \ldots + b_{n_b} u(t-n_b) \\ y(t) &= w(t) + e(t) \end{aligned} \tag{3.7}$$

Writing the relations in terms of Equation (3.2) gives the OE (Output Error)-model structure:

$$y(t) = \frac{B(q)}{F(q)} u(t) + e(t) \tag{3.8}$$

BJ model structure The OE models assumes that the additive output error is white noise with zero mean. This assumption is in many cases not adequate. An improvement is to use the BJ (Box-Jenkins) model structure. Here transfer functions corresponding to the output error are introduced (C/D) and parametrized separately from the system dynamics, described by (B/F). In terms of Equation (3.2) the BJ-model structure is given by:

$$y(t) = \frac{B(q)}{F(q)} u(t) + \frac{C(q)}{D(q)} e(t) \tag{3.9}$$

State-space model structures The state-space models have the following general structures:

- Continuous-time:

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) + Ke(t) \\ y(t) &= Cx(t) + Du(t) + e(t) \end{aligned} \tag{3.10}$$

- Discrete-time:

$$\begin{aligned} x(t+T_s) &= Ax(t) + Bu(t) + Ke(t) \\ y(t) &= Cx(t) + Du(t) + e(t) \end{aligned} \tag{3.11}$$

where the $x(t)$ represents the states of the system and $y(t)$, $u(t)$ and $e(t)$ represents the output, input and error. The A, B, C, D and K matrices contains the model parameters, and T_s is the sampling time of the system.

Temperature and humidity models

In this study there are two MISO systems and one MIMO system to be modeled.

MISO-systems The two different MISO systems, represents either the mean room temperature or the mean room humidity. Each of these input-output relationships have 1 output and 8 inputs. The number of inputs are represented by i, where $i = 1, \cdots, 8$. The A-, B-, C-, D- and F-polynomials of the transfer function models presented in the previous subsection are then given by:

A-polynomials: $A(q) = 1 + a_1 q^{-1} + a_2 q^{-2} + \ldots + a_{na} q^{-na}$
B-polynomials: $B(q) = b_{i,1} + b_{i,2} q^{-1} + \ldots + b_{i,nb_i} q^{-(nb_i - 1)}$, $i = 1, \ldots, 8$
C-polynomials: $C(q) = 1 + c_1 q^{-1} + c_2 q^{-2} + \ldots + a_{nc} q^{-nc}$
D-polynomials: $D(q) = 1 + d_1 q^{-1} + d_2 q^{-2} + \ldots + d_{nd} q^{-nd}$
F-polynomials: $F(q) = 1 + f_{i,1} q^{-1} + f_{i,2} q^{-2} + \ldots + f_{i,nf_i} q^{-nf_i}$, $i = 1, \ldots, 8$

Using these polynomials, models describing the output $y(t)$ can be formed, where $y(t)$ represents either the mean room temperature, $T_R(t)$, or the mean room humidity, $H_R(t)$, as mentioned. The transfer functions B_i/A, B_i/F_i and the polynomials C and D connected to the disturbance, all have known structures and unknown model parameters to be determined during the identification procedure. Since black-box methods are used, nothing is known a priori regarding the orders of the polynomials associated with the inputs, and these have to be determined as well. As before, the orders are expressed as: na, nb_i, nc, nd and nf_i.

Using this information, the inputs from Section 3.1 and the model structures from the previous subsection, the following models are obtained:

ARX model:

$$y(t) = \frac{1}{A(q)} \sum_{i=1}^{8} B_i(q) u_i(t - nk_i) + \frac{1}{A(q)} e(t) \tag{3.12}$$

The adjustable parameters to be determined are:
$\theta_{ARX} = [a_1, \ldots, a_{na}, b_{1,1}, \ldots, b_{8,nb_8}]^T$

ARMAX model:

$$y(t) = \frac{1}{A(q)} \sum_{i=1}^{8} B_i(q) u_i(t - nk_i) + \frac{C(q)}{A(q)} e(t) \tag{3.13}$$

The adjustable parameters to be determined are:
$\theta_{ARMAX} = [a_1, \ldots, a_{na}, b_{1,1}, \ldots, b_{8,nb_8}, c_1, \ldots, c_{nc}]^T$

OE model:

$$y(t) = \sum_{i=1}^{8} \frac{B_i(q)}{F_i(q)} u_i(t - nk_i) + e(t) \tag{3.14}$$

The adjustable parameters to be determined are:
$\theta_{OE} = [b_{1,1}, \ldots, b_{8,nb_8}, f_{1,1}, \ldots, f_{8,nf_8}]^T$

BJ model:

$$y(t) = \sum_{i=1}^{8} \frac{B_i(q)}{F_i(q)} u_i(t - nk_i) + \frac{C(q)}{D(q)} e(t) \tag{3.15}$$

The adjustable parameters to be determined are:
$\theta_{BJ} = [b_{1,1}, \ldots, b_{8,nb_8}, c_1, \ldots, c_{nc}, d_1, \ldots, d_{nd}, f_{1,1}, \ldots, f_{8,nf_8}]^T$

Notice that in the models given by equations (3.12)-(3.15), the inputs from Section 3.1 are renamed according to Table 3.4. In each model structure the variable t denotes the time instant and $nk_1, nk_2, nk_3, nk_4, nk_5, nk_6, nk_7$ and nk_8 are the time delay from the inputs to the output, i.e., the number of samples before the output is affected by a change in the input.

Table 3.4 The inputs used in the models

u_1	u_2	u_3	u_4	u_5	u_6	u_7	u_8
T_{AC}	H_{AC}	T_{Air}	H_{Air}	T_H	T_O	H_O	N

As explained earlier, the main difference between the models is the way the disturbance is presented. Which polynomials that are used in each case of the transfer function models, can because of this, easily be summarized as in Table 3.5.

Table 3.5 Polynomials used in the transfer function models: The 1's means that the polynomial is fixed to 1 and ✓means that the polynomials are to be chosen freely

Model	***A***	B_i	***C***	***D***	F_i
ARX	✓	✓	1	1	1
ARMAX	✓	✓	✓	1	1
OE	1	✓	1	1	✓
BJ	1	✓	✓	✓	✓

MIMO-system The single-output transfer function models presented above can, with smaller modifications, be transferred into black-box models containing two outputs, as explained in [Ljung, 2002]. The overall structure is still the same, and generally one can say that two models are combined into one. Although, there is an important addition present in the MIMO transfer function models, and that is terms considering the coupling between the outputs. Considering the ARX model for the system with eight inputs and two outputs, this coupling is taken into consideration by introducing the polynomials $A_{1,2}(q)$ and $A_{2,1}(q)$. The two-output ARX model is then described by:

$$\begin{pmatrix} A_{1,1}(q) & A_{1,2}(q) \\ A_{2,1}(q) & A_{2,2}(q) \end{pmatrix} \begin{pmatrix} y_1(t) \\ y_2(t) \end{pmatrix} = \begin{pmatrix} B_{1,1}(q) & \cdots & B_{1,8}(q) \\ B_{2,1}(q) & \cdots & B_{2,8}(q) \end{pmatrix} \begin{pmatrix} u_1(t) \\ \vdots \\ u_8(t) \end{pmatrix} + \begin{pmatrix} e_1(t) \\ e_2(t) \end{pmatrix} \tag{3.16}$$

If $na_{1,1}$ and $na_{1,2}$ are the orders of the A-polynomials for output $y_1(t)$ and $na_{2,1}$ and $na_{2,2}$ are the orders of the A-polynomials for output $y_2(t)$, then the entries in the A-matrix are given by:

$$A_{1,1}(q) = 1 + a_{1,1}^{(1)} q^{-1} + a_{1,1}^{(2)} q^{-2} + \cdots + a_{1,1}^{(na_{1,1})} q^{-na_{1,1}}$$
$$A_{1,2}(q) = a_{1,2}^{(1)} q^{-1} + \cdots + a_{1,2}^{(na_{1,2})} q^{-na_{1,2}}$$
$$A_{2,1}(q) = a_{2,1}^{(1)} q^{-1} + a_{2,1}^{(2)} q^{-2} + \cdots + a_{2,1}^{(na_{2,1})} q^{-na_{2,1}}$$
$$A_{2,2}(q) = 1 + a_{2,2}^{(1)} q^{-1} + a_{2,2}^{(2)} q^{-2} + \cdots + a_{2,1}^{(na_{2,2})} q^{-na_{2,2}}$$

As before, the inputs are represented by the number i, and with two outputs one get two sets of B-polynomials which are given by:

$$B_{1,i}(q) = b_{1,i}^{(1)} + b_{1,i}^{(2)} q^{-1} + \cdots + b_{1,i}^{(nb_{1,i})} q^{-(nb_{1,i}-1)}\ , i = 1, \cdots, 8$$
$$B_{2,i}(q) = b_{2,i}^{(1)} + b_{2,i}^{(2)} q^{-1} + \cdots + b_{2,i}^{(nb_{2,i})} q^{-(nb_{2,i}-1)}, i = 1, \cdots, 8$$

State-space models are the most common choice when it comes to modeling MIMO-systems, and using the state-space approach is rather straightforward. For our system with two outputs and eight inputs, a discrete-time state-space model of order n sampled using $T_s = 1$ s is given by:

$$\begin{pmatrix} x_1(t+1) \\ \vdots \\ x_n(t+1) \end{pmatrix} = \mathbf{A} \begin{pmatrix} x_1(t) \\ \vdots \\ x_n(t) \end{pmatrix} + \mathbf{B} \begin{pmatrix} u_1(t) \\ \vdots \\ u_8(t) \end{pmatrix} + \mathbf{K} \begin{pmatrix} e_1(t) \\ e_2(t) \end{pmatrix}$$

$$\begin{pmatrix} y_1(t) \\ y_2(t) \end{pmatrix} = \mathbf{C} \begin{pmatrix} x_1(t) \\ \vdots \\ x_n(t) \end{pmatrix} + \mathbf{D} \begin{pmatrix} u_1(t) \\ \vdots \\ u_8(t) \end{pmatrix} + e(t) \tag{3.17}$$

where the A, B, C, D and K matrices are given by:

$$\mathbf{A} = \begin{pmatrix} a_{1,1} & \cdots & a_{1,4} \\ \vdots & \ddots & \vdots \\ a_{n,1} & \cdots & a_{n,n} \end{pmatrix}, \mathbf{B} = \begin{pmatrix} b_{1,1} & \cdots & b_{1,8} \\ \vdots & \cdots & \vdots \\ b_{n,1} & \cdots & b_{n,8} \end{pmatrix}, \mathbf{K} = \begin{pmatrix} k_{1,1} & k_{1,2} \\ \vdots & \vdots \\ k_{n,1} & k_{n,2} \end{pmatrix}$$

$$\mathbf{C} = \begin{pmatrix} c_{1,1} & \cdots & c_{1,n} \\ c_{2,1} & \cdots & c_{2,n} \end{pmatrix} \quad \text{and} \quad \mathbf{D} = \begin{pmatrix} d_{1,1} & \cdots & d_{1,8} \\ d_{2,1} & \cdots & d_{2,8} \end{pmatrix}$$

Notice that in the models given by (3.16) and (3.17), the output $y_1(t)$ corresponds to the mean room temperature, $T_R(t)$, and $y_2(t)$ corresponds to the mean room relative humidity, $H_R(t)$. From this point on, the two outputs will be referred to as $y_1(t)$ and $y_2(t)$.

Now that the model structures are determined, the next step in the process is the actual identification of the models, which involves finding suitable orders and delays, and estimating the model parameters. How this is done is explained later in this chapter, more precisely in Section 3.5. First, however, one has to ensure that the quality of the data is sufficiently good.

3.4 Data preprocessing

In addition to the changes done to the raw data so far, further preprocessing is necessary before the data is used for identification. Some problems with the raw data occurs, such as missing signals, outliers in the data, missing samples and non-accurate measurements. These problems has to be solved before further use of the data.

Missing signals

In order to get reliable results when comparing the models for the different seasons, it is an advantage if the same input signals are available for all seasons. For the winter season, only one measurement for the outside humidity is available. The available signal is given by sensor 1006, placed on the outside wall of room A:225. Using the information given in [Scotton, 2012] together with examination of the data used in this thesis, it becomes clear that sensor 1006 is too sensitive and therefore does not represent the outside conditions accurately. In the datasets for summer, spring and autumn an additional signal is available for the outside humidity. Taking the mean of the two signals give a more accurate representation of the actual humidity outside the test-bed. Since this is not possible for the winter season, because of the missing signal, the oversensitivity is instead compensated for by multiplying the measurements from sensor 1006 by a scaling factor. This is a reasonable solution, since when examining the differences of sensors 1006 and 1254 for July, October and April, the signals has the same shape and differs only in magnitude. By studying these differences in magnitude in detail, it was found that a good value for the scaling factor is 0.8.

Resampling

The sensors in the test-bed sends a measurement for humidity, temperature and CO_2-level to the coordinator approximately every 30 seconds, giving the system a sampling time of $T_s = 30$ s. The additional signals are sampled and in some cases, e.g. with the weather forecast, resampled, to give all the data the same sampling interval. This is done before the user extract the raw data from the homepage. Before identification the data is resampled to $T_s = 180$ s which means one sample every 3 minutes. The chosen sampling period is based on the sampling interval used in [Scotton, 2012], and through testing different sampling times, it turns out to be a good choice also in this thesis' context. With the chosen sampling interval the slow dynamics of the system is captured and the datasets become suitable in length.

Outliers and missing data

From time to time, one encounters outliers or missing data in the datasets. Since the missing data segments are short, or it is relatively easy to predict what the real values are supposed to be, this problem can be solved by using interpolation. Based on the nature of the data, regarding the number of bad samples and the data surrounding the bad segments, linear- or cubic spline interpolation is employed. This is achieved by calling a MATLAB function `ReconstructData.m` which contains an interpolation function called `interparc.m` [D'Errico, 2012]. The interparc function creates new, equidistantly spaced points where the bad data segments originally occur. The method supports both linear and cubic spline interpolation.

Had the problem with the missing/bad data been more severe, the best solution would probably be to cut the bad data out, and merge the remaining "good" data segments. This is not necessary in this case. For the summer season the dataset is shortened, and the data from approximately 21st to the 31st is completely cut out. This is done because the data following the 20th of July does not carry any valuable information. In the mentioned time period everything is shut off and no occupiers reside in the room.

Means and trends in the data

It is common to remove the means and trends in the data, before it is used for identification. By doing this, it becomes easier to compare the models for the different seasons, since changes in the output(s) caused by the inputs appears more directly. When detrending the data no changes is done to the relative differences between inputs and outputs. For each season the trends and means are removed from the whole dataset before identification, and added to the datasets again before validation and presentation.

Non-accurate measurements

As previously mentioned, especially the sensor located on the outside of the wall, i.e., device 1006, is giving non-accurate measurements. This is because it is too sensitive, regarding direct sunlight etc. Since the outside conditions are such an important part of the study it is crucial to overcome this issue. As explained earlier, the problem with the outside humidity is solved by taking the mean of two signals. The respective sensors are placed at different locations, and thus give a good overview of the actual conditions together. The reason that sensor 1006 isn't totally disregarded is that its location is essential. The problem with the temperature measurements from sensor 1006 is solved in a similar way, but in this case the measurements are taken from three different locations: sensor 1006, the local weather station at KTH, and a web based source KTH uses for weather forecast. It is debatable if this is the optimal way to find the exact temperature outside the test-bed, but at least it gives a better representation of the actual conditions than only using the measurements from device 1006.

3.5 Identification methods

The models are identified using the system identification toolbox (SIT) GUI in MATLAB. Before the data is subjected to identification it is preprocessed according to the previous section. The preprocessing occurs at different stages. First the whole datasets are resampled using a data conversion function obtained by [KTH-HVAC-Wiki, 2015]. The signals to be used, presented in Section 3.1 are then selected and extracted using a MATLAB script, which in addition to the extraction deals with possible outliers or bad data segments by calling the routine `ReconstructData.m` when necessary. The selected signals are then grouped into inputs and outputs and the mentioned problems with missing signals and non-accurate measurements, are compensated for. Finally the processed inputs and outputs are collected and transformed into an `iddata` object and transported to the System Identification Toolbox

GUI. At this stage the means and the trends in the data are removed using the "remove means" and "remove trends" functions in the GUI, and the data is divided into an estimation part and a validation part.

Using the system identification toolbox

The system identification toolbox provides a wide range of features, and it's not trivial how to use the tool in the best possible way. Inspired by the step-by-step procedure suggested in [Ljung, 2002], all the models are obtained by following the same structured work-flow. The steps include :

1. Using the quickstart-function to gain insight regarding possible difficulties.
2. Examine the possible difficulties
3. Determining the orders and input delays
4. Fine tuning of orders and disturbance structures

After possible problems are detected and solved, the remaining work consist of determining polynomial orders and delays and doing some fine tuning. How this is done, depends on which model class the models to be identified belongs to.

To find suitable orders and delays for the transfer function models, the first step involve estimating many ARX-models and compare the models with the focus on finding good values for na and nb_i. This is done using the order selection function. The variables are each varied over a range from 1-10, with $nk_i = 0$, and one ARX model is estimated for each combination of variables. When suitable values for na and nb_i are obtained and selected, different values of nk_i are tested. The next step is to estimate ARMAX, OE and BJ models in order to further improve the accuracies. The orders obtained for the A- and B-polynomials and the input delays, are now used as initial guesses for further modeling. The values of nc, nd and nf_i are determined in a similar manner as before, i.e., by testing different values and comparing the performance of the respective model with the models obtained so far.

When identifying state-space models the procedure is much less time-consuming. The task is to find a suitable system order, i.e., to determine the value of the variable n, and then improve the accuracy if possible. First, using the order selection function, many orders are tested by estimating different sate-space models of the type n4sid (numerical algorithm for subspace Identification). These models are identified using SVD (Singular Value Decomposition) to estimate a subspace that contains information regarding the system. The models of different orders are then compared to each other, and a suitable order is selected. To improve the accuracy, a prediction error model (pem) is estimated using the order that gave the best n4sid model.

When estimating models in the SIT GUI, one has the possibility to choose between different frequency weightings, that either concentrates on the models prediction or simulation performance [Ljung, 2002]. The user decides what weighting should be applied in the model using the "focus" option. The user can choose between the options: 'simulation', 'prediction', 'stability' or 'filtering'. In this thesis only the three first of the above options are tested. The default choice is prediction, which focuses on minimizing the prediction errors. When 'simulation' is selected, the main focus is on estimating a model that produces good simulations. The algorithm uses the input spectrum in a particular frequency range to weigh the relative importance of the fit in that frequency range. If this option is selected the resulting model is guaranteed to be stable. One can also ensure a stable model by selecting 'stability' in the focus options. The weighting corresponds to 'prediction' but in this case a stable model is guaranteed.

Parameter estimation methods

Throughout the work the Prediction Error Method (PEM) is used to estimate the parameters. The technique considers the accuracy of the predictions computed for the observed data. The subject is to minimize, with respect to the parameter vector, θ , the *cost function*, i.e., a weighted norm of the prediction error, $\varepsilon_F(t,\theta)$.

The general form of the cost function, as described in [Ljung, 1999] is given by:

$$V_N(\theta, Z^N) = \frac{1}{N}\sum_{t=1}^{N} \ell(\varepsilon_F(t,\theta)) \tag{3.18}$$

where ℓ is a scalar-valued function to be chosen, Z^N is a vector containing the collected input-output data and the prediction error is the difference between the observed and predicted outputs, i.e., $\varepsilon_F(t,\theta) = y(t,\theta) - \hat{y}(t,\theta)$.

A normal choice for ℓ, is the quadratic norm: $\ell(\varepsilon) = \frac{1}{2}\varepsilon^2$. The quadratic norm is the default choice for ℓ in MATLAB, and is therefore used in this study as well. The cost function to be minimized is now given by:

$$V_N(\theta, Z^N) = \frac{1}{2N}\sum_{t=1}^{N} \varepsilon_F^2(t,\theta) \tag{3.19}$$

and finally, the parameter estimate is given by minimizing (3.19):

$$\hat{\theta}_N = \arg\min_{\theta}(V_N(\theta, Z^N)) \tag{3.20}$$

where arg min means "the minimizing argument of the function".

3.6 Identified models

In order to minimize the complexity of the models, the lowest possible values of orders and delays are chosen consistently, provided that it doesn't affect the performance substantially. Keeping the scope of the thesis and the intended use of the models in mind, it is desirable to use the same orders and delays for all temperature models and the same orders and delays for all humidity models. This is only suitable as long as satisfactory model performances can be achieved for all seasons. The models presented for the respective seasons, aren't necessarily the "best" models that can be achieved in terms of the validation criteria. However, the models are more than "good enough", and overall, possibly a better choice regarding simplicity and similarity to the models used for the other seasons. To simplify the identification process, the values of nb_1-nb_8, nf_1-nf_8 and nk_1- nk_8 are kept equal in each individual model.

Humidity models

Comparisons of the identified ARX models, estimated using the order selector as mentioned, show that combinations of na = 1-5 and nb_i = 2-4 generally give good results. The performance of the models made up by the different combinations of these orders doesn't vary much, and testing shows that $na = 3$ and $nb_i = 2$ are working well for all seasons. Using higher orders (6-10) improves the performance with about 5-10% in all cases, but the increase in the model complexity that occurs due to the large amount of parameters from the B-polynomials, makes this increase in fit insignificant. Further testing with the ARX models gives that $nk_i = 0$ are suitable values for the input delays, and testing different ARMAX and BJ structures gives that $nc = 3$ and $nd = 1$ are good choices for all seasons. Identifying OE and BJ models gives that orders of $nf_i = 1$ works well for all datasets. The orders and input delays chosen for the humidity models are summarized in Table 3.6.

Table 3.6 Polynomial orders and input delays used in the humidity models

Season	na	nb_i	nc	nd	nf_i	nk_i
all	3	2	3	1	1	0

Based on the findings presented in the next chapter the ARMAX and BJ models are chosen to describe the mean room humidity for each season. Since the orders and delays are equal for each season all models have the same structure, but a unique set of parameters. The ARMAX-models to be validated in the next chapter are given by (3.21) together with the estimated parameters listed in Appendix A.4 and the BJ-models are given by (3.22) together with the parameters listed in Appendix A.5.

ARMAX-models:

$$y(t) = \sum_{i=1}^{8} \frac{b_{i,1} + b_{i,2}q^{-1}}{1 + a_1q^{-1} + a_2q^{-2} + a_3q^{-3}} u_i(t) + \frac{1 + c_1q^{-1} + c_2q^{-2} + c_3q^{-3}}{1 + a_1q^{-1} + a_2q^{-2} + a_3q^{-3}} e(t) \tag{3.21}$$

BJ-models:

$$y(t) = \sum_{i=1}^{8} \frac{b_{i,1} + b_{i,2}q^{-1}}{1 + f_{i,1}q^{-1}} u_i(t) + \frac{1 + c_1 q^{-1} + c_2 q^{-2} + c_3 q^{-3}}{1 + d_1 q^{-1}} e(t) \tag{3.22}$$

Temperature models

When examining and comparing the ARX-structures for the temperature models, it is hard to find adequate values of na and nb_i straight away, since none of the ARX-models gives sufficiently good results. The "best of the worst" models are although achieved for na= 1, $nb_i = 2$ and $nk_i = 0$, and little is gained in terms of performance if the orders and delays are increased. Further testing gives that sufficiently good BJ models can be achieved when $nc = 1$, $nd = nf_i = 1$. Marginally improvements can be achieved if the orders/delays are increased for the winter and autumn season, but these improvements are so small, so the orders and delays are kept equal for all seasons. The orders and input delays used for the temperature models, are summarized in Table 3.7.

Table 3.7 Polynomial orders and input delays used in the temperature models

Season	na	nb_i	nc	nd	nf_i	nk_i
all	1	2	1	1	1	0

For the temperature, the ARX-and BJ-models are chosen to present the mean room temperature. Like for the humidity models, each model type has the same structure, but the model parameters vary depending on the season. The ARX-models are given by (3.23) with the estimated parameters listed in Appendix A.6, and the BJ-models are given by (3.24) together with the parameters in Appendix A.7.

ARX-models:

$$y(t) = \sum_{i=1}^{8} \frac{b_{i,1} + b_{i,2}q^{-1}}{1 + a_1 q^{-1}} u_i(t) + \frac{1}{1 + a_1 q^{-1}} e(t) \tag{3.23}$$

BJ-models:

$$y(t) = \sum_{i=1}^{8} \frac{b_{i,1} + b_{i,2}q^{-1}}{1 + f_{i,1}q^{-1}} u_i(t) + \frac{1 + c_1 q^{-1}}{1 + d_1 q^{-1}} e(t) \tag{3.24}$$

Humidity and temperature models

For the combined models different state-space model orders are tested using the order selection function. For all seasons an order of 4 is chosen. Increasing the order further does not increase the performance substantially. When testing different transfer function models following the same procedure as for the MISO-systems, it shows out that ARX-models with orders based on the findings for the separate temperature and humidity models generally have more predictable performances, than any of the other transfer function models tested. Using the orders from the separate models, implies setting $na_{1,1} = na_{1,2} = 1$, $na_{2,1} = na_{2,2} = 3$ and for all $i = 1,\cdots,8$; $nb_{1,i} = nb_{2,i} = 2$ in the two-output ARX model given by Equation (3.16) in Section 3.3.

The discrete-time state-space models used in this thesis are then given by (3.25) together with the parameters in Appendix A.8 and the ARX-models are given by (3.26) together with the parameters in Appendix A.9

State-Space models:

$$\begin{pmatrix} x_1(t+1) \\ \vdots \\ x_4(t+1) \end{pmatrix} = \mathbf{A} \begin{pmatrix} x_1(t) \\ \vdots \\ x_4(t) \end{pmatrix} + \mathbf{B} \begin{pmatrix} u_1(t) \\ \vdots \\ u_8(t) \end{pmatrix} + \mathbf{K} \begin{pmatrix} e_1(t) \\ e_2(t) \end{pmatrix}$$

$$\begin{pmatrix} y_1(t) \\ y_2(t) \end{pmatrix} = \mathbf{C} \begin{pmatrix} x_1(t) \\ \vdots \\ x_4(t) \end{pmatrix} + \mathbf{D} \begin{pmatrix} u_1(t) \\ \vdots \\ u_8(t) \end{pmatrix} + e(t) \tag{3.25}$$

where:

$$\mathbf{A} = \begin{pmatrix} a_{1,1} & \cdots & a_{1,4} \\ \vdots & \ddots & \vdots \\ a_{4,1} & \cdots & a_{4,4} \end{pmatrix}, \mathbf{B} = \begin{pmatrix} b_{1,1} & \cdots & b_{1,8} \\ b_{2,1} & \cdots & b_{2,8} \\ b_{3,1} & \cdots & b_{3,8} \\ b_{4,1} & \cdots & b_{4,8} \end{pmatrix}, \mathbf{K} = \begin{pmatrix} k_{1,1} & k_{1,2} \\ \vdots & \vdots \\ k_{4,1} & k_{4,2} \end{pmatrix}$$

$$\mathbf{C} = \begin{pmatrix} c_{1,1} & \cdots & c_{1,4} \\ c_{2,1} & \cdots & c_{2,4} \end{pmatrix} \quad \text{and} \quad \mathbf{D} = \begin{pmatrix} d_{1,1} & \cdots & d_{1,8} \\ d_{2,1} & \cdots & d_{2,8} \end{pmatrix}$$

ARX-models:

$$\begin{pmatrix} A_{1,1}(q) & A_{1,2}(q) \\ A_{2,1}(q) & A_{2,2}(q) \end{pmatrix} \begin{pmatrix} y_1(t) \\ y_2(t) \end{pmatrix} = \begin{pmatrix} B_{1,1}(q) & \cdots & B_{1,8}(q) \\ B_{2,1}(q) & \cdots & B_{2,8}(q) \end{pmatrix} \begin{pmatrix} u_1(t) \\ \vdots \\ u_8(t) \end{pmatrix} + \begin{pmatrix} e_1(t) \\ e_2(t) \end{pmatrix} \tag{3.26}$$

The entries in the A-matrix are polynomials given by:

$$A_{1,1}(q) = 1 + a_{1,1}^{(1)} q^{-1}$$
$$A_{1,2}(q) = a_{1,2}^{(1)} q^{-1}$$
$$A_{2,1}(q) = a_{2,1}^{(1)} q^{-1} + a_{2,1}^{(2)} q^{-2} + a_{2,1}^{(3)} q^{-3}$$
$$A_{2,2}(q) = 1 + a_{2,2}^{(1)} q^{-1} + a_{2,2}^{(2)} q^{-2} + a_{2,2}^{(3)} q^{-3}$$

and the entries in the B-matrix are polynomials given by:

$$B_{1,i}(q) = b_{1,i}^{(1)} + b_{1,i}^{(2)} q^{-1},\ i = 1, \cdots, 8.$$
$$B_{2,i}(q) = b_{2,i}^{(1)} + b_{2,i}^{(2)} q^{-1},\ i = 1, \cdots, 8.$$

4

Results

In this part of the study the identified models from Chapter 3 are validated, using some basic validation criteria. In the first part each MISO- and MIMO model is validated separately using the validation data from the same month as used for the model estimation. Thereafter the models are validated using data from the other months. The chapter ends with looking into some features regarding the correlation between humidity and temperature and how this affects the use of the models. Some suitable control strategies are also suggested based on the validated the models.

4.1 Validation

The goodness of the models is based on three different validation metrics:

- Goodness of fit in %
- MSE- Mean Squared Error
- MAE- Mean Absolute Error

Consider the measured output y and the predicted or simulated output $\hat{y}$. For N number of input-output pairs the goodness of fit is calculated according to:

$$\text{fit} = \left(1 - \frac{\sqrt{\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}}{\sqrt{\sum_{i=1}^{N}(y_i - \frac{1}{N}\sum_{i=1}^{N} y_i)^2}}\right) \cdot 100,$$

$$\text{for } i = 1, \cdots, N \tag{4.1}$$

Here the pairs y and $\hat{y}$, both $N \times 1$ vectors, correspond to either relative humidity or room temperature. The mean squared error is given by:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{4.2}$$

and the mean absolute error is given by:

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}_i| \tag{4.3}$$

For both the humidity and temperature models the predicted and simulated outputs are considered. The predicted output is obtained by using the current and previous values of the inputs and outputs. More precisely, as explained in [Ljung, 2002]; given a prediction horizon of k, a k-step ahead predicted output, $\hat{y}(t)$ is computed from all available inputs $u(s)$, $s \leq t$, and all available outputs up to time $t-k$, $y(s)$, $s \leq t-k$. In this thesis a 20-step ahead predictor is used, and with a sampling period of 3 minutes this corresponds to a prediction horizon of 1 hour. Calculating the simulated output does not take into consideration the past and current outputs as prediction does, only the inputs are used to compute the output, $\hat{y}(t)$. In other words simulation corresponds to setting $k = \infty$.

In addition to the quantitative validation metrics presented above, the models are evaluated in a more qualitative manner, based on the model requirements in Section 3.3. Another aspect that is taken under consideration, is the likeness between models, as mentioned in Section 3.5.

Humidity models

From all the humidity models identified in Chapter 3, the ones with the best overall performance is selected for each season. For the humidity, the ARMAX and BJ models outperforms the ARX and OE models, and will thus be presented in the following. In the figures in this section, the ARMAX and BJ models are presented on the following forms: ARMAX [na nb_i nc nk_i], $i = 1, \cdots, 8$, and BJ [nb_i nc nd nf_i nk_i], $i = 1, \cdots, 8$. As described in Chapter 3, na, nb_i, nc, nd and nf_i are the orders of the polynomials and nk_i are the input delays. The orders and input delays for the humidity models, are as we recall, presented in Table 3.6.

Generally the goodness of the models are dependent on the applied weighting to the fit between the data and the model, and the estimation focus chosen for the selected ARMAX and BJ models are summarized in Table 4.1. By default the estimation focus was set to 'prediction'. This option was selected as a first choice, since the prediction abilities of the models are more interesting than the simulation abilities, when the intended use of the models is control. If the prediction choice didn't provide a good model, the 'stability' focus was tested. Finally, if none of the above worked, 'simulation' was selected.

Table 4.1 Selected estimation focuses for the humidity models

Season	***Model***	***Focus***
Winter	ARMAX	'Prediction'
	BJ	'Stability '
Spring	ARMAX	'Prediction'
	BJ	'Prediction'
Summer	ARMAX	'Prediction'
	BJ	'Simulation'
Autumn	ARMAX	'Prediction'
	BJ	'Simulation'

Winter season The calculated values of MAE, MSE and Goodness of fit for the winter season are presented in Table 4.2. It is apparent that both the ARMAX and BJ models gives substantially better results for the predicted output compared to the simulated output, with a difference of about 50% in terms of fit. The goodness of fit between the actual measurements and the simulated or predicted model output are visualized in Figure 4.1.

Table 4.2 Validation of the ARMAX and BJ humidity models, expressed in MSE, MAE and Goodness of fit, winter season

Type of output	*Model*	*MAE (%RH)*	*MSE (%RH)*	*fit (%)*
Simulated	ARMAX	0.9933	1.5537	27.38
	BJ	0.9782	1.5219	28.12
Predicted	ARMAX	0.2078	0.1048	81.14
	BJ	0.2585	0.1576	76.87

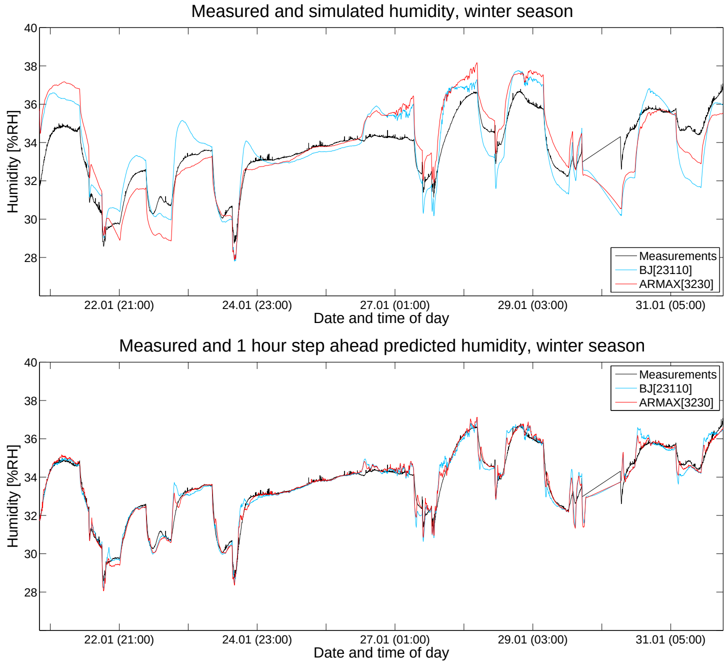

Figure 4.1 Performance of humidity models winter season: **Upper:** Real measurements and *simulated* output from the BJ model (**fit: 28.12%**) and the ARMAX model (**fit: 27.38%**) **Lower:** real measurements and *predicted* output from the BJ model (**fit: 76.87%**) and the ARMAX model (**fit: 81.14%**).

Spring season Examining Table 4.3 one can see it isn't a substantial difference in terms of performance between the ARMAX and BJ models for the 1 hour step ahead predicted output. When the output is simulated, the difference in performance between the ARMAX and BJ models is about 8%. The goodness of fit between measured and simulated output, and the fit between the measured and predicted output are shown in Figure 4.2

Table 4.3 Validation of the ARMAX and BJ humidity models, expressed in MSE, MAE and Goodness of fit, spring season

Type of output	*Model*	*MAE (%RH)*	*MSE (%RH)*	*fit (%)*
Simulated	ARMAX	0.7180	0.7976	77.66
	BJ	1.0050	1.5133	69.23
Predicted	ARMAX	0.2627	0.1426	90.56
	BJ	0.2407	0.1320	90.92

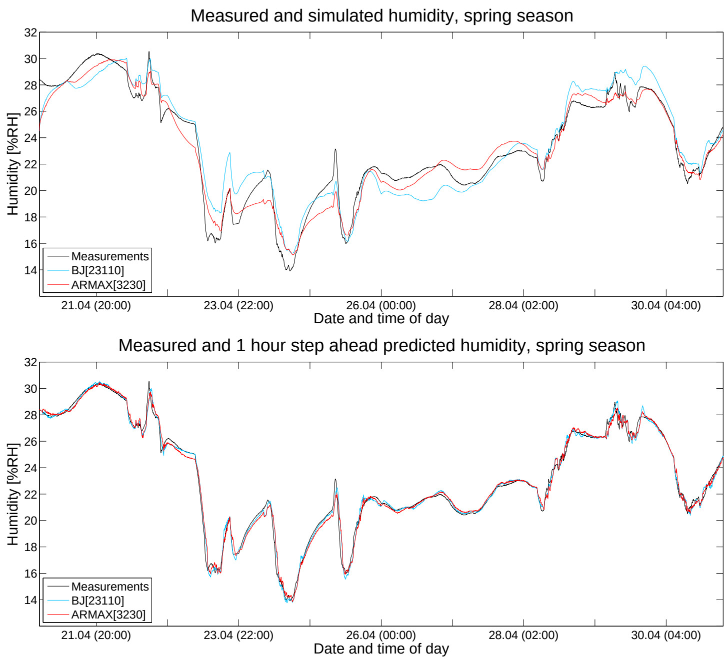

Figure 4.2 Performance of humidity models spring season: **Upper:** real measurements and *simulated* output from the BJ model (**fit: 69.23%**) and the ARMAX model (**fit: 77.66%**). **Lower:** Real measurements and *predicted* output from the BJ model (**fit: 90.92%**) and the ARMAX model (**fit: 90.56%**).

Summer season For the summer season the ARMAX model has the best overall performance, as shown in Table 4.4 and Figure 4.3. The difference in fit between the ARMAX and BJ models is over 50% when comparing measurements with the simulated output. When the output is predicted on the other hand, the models show similar results with a difference in fit of only about 4%.

Table 4.4 Validation of the ARMAX and BJ humidity models, expressed in MSE, MAE and Goodness of fit, summer season

Type of output	*Model*	*MAE (%RH)*	*MSE (%RH)*	*fit (%)*
Simulated	ARMAX	0.4630	0.2898	71.17
	BJ	1.4586	2.3666	17.61
Predicted	ARMAX	0.2561	0.0999	83.07
	BJ	0.1407	0.0578	87.12

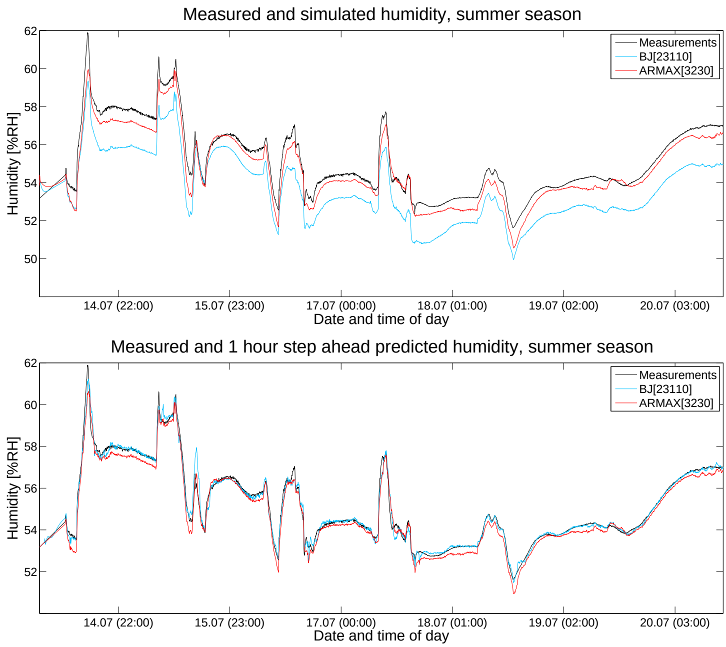

Figure 4.3 Performance of humidity models summer season: **Upper:** Real measurements and *simulated* output from the BJ model (**fit: 17.61%**) and the ARMAX model (**fit: 71.17%**). **Lower:** Real measurements and *predicted* output from the BJ model (**fit: 87.12%**) and the ARMAX model (**fit: 83.07%**).

Autumn season Like for the winter season, the ARMAX model identified from the October data is better in terms of performance than the BJ model. Examining Table 4.5 it can be seen that the ARMAX model performs very well when the output is both simulated and predicted, whereas the BJ model is only suitable for prediction. Notice the large peaks that are present in the output simulated by the BJ model in the upper plot in Figure 4.4. These large deviations from the actual measurements are reflected in the MAE and MSE, which in this case is 10 times larger than for the ARMAX model or the values calculated for any of the other models presented so far. The predicted outputs, on the other hand are in good agreement with the actual measurements. This can be seen in the lower plot of Figure 4.4 as well as in Table 4.5 .

Table 4.5 Validation of the ARMAX and BJ humidity models, expressed in MSE, MAE and Goodness of fit, autumn season

Type of output	*Model*	*MAE (%RH)*	*MSE (%RH)*	*fit (%)*
Simulated	ARMAX	1.0560	1.8150	85.40
	BJ	3.2618	19.897	51.66
Predicted	ARMAX	0.2487	0.1451	95.87
	BJ	0.5304	0.6584	91.21

Summary/comments: Evaluating the results for all the seasons, one can notice some general tendencies:

- Except the models estimated for the winter season, the humidity models are suitable for both prediction and simulation purposes.
- Focusing on the prediction abilities of the models, both the ARMAX and the BJ models performs well for each season. The ARMAX models are the best choices for the winter and autumn seasons, while the BJ models are the best choices for the spring and summer seasons. However, it is possible to use one type of model to describe the mean room humidity for all of the seasons, since both model types gives sufficiently good results.
- Using the BJ models, the fit between measured and predicted output for the respective seasons becomes: 76.87% (winter), 90.92% (spring), 87.12% (summer) and 91.21% (autumn).
- Using the ARMAX models, the fit between measured and predicted output for the respective seasons becomes: 81.14% (winter), 90.56% (spring), 83.04% (summer) and 95.87% (autumn).

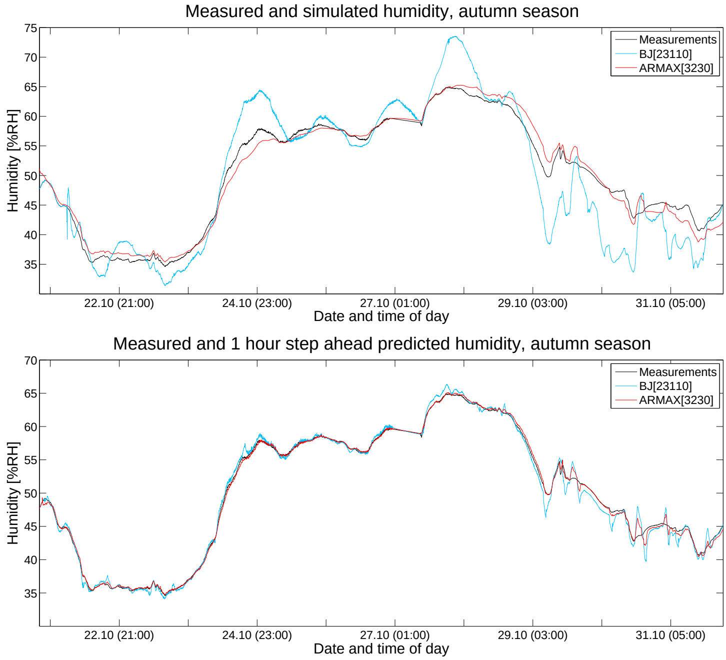

Figure 4.4 Performance of humidity models autumn season: **Upper:** Real measurements and *simulated* output from the BJ model (**fit: 51.66%**) and the ARMAX model (**fit: 85.40%**). **Lower:** Real measurements and *predicted* output from the BJ model (**fit: 91.21%**) and the ARMAX model (**fit: 95.87%**).

Temperature models

Regarding the temperature models identified for all four seasons, the BJ and ARX models generally shows a slightly better performance than the ARMAX models. Using the given datasets and the inputs presented earlier it is hard to find OE models that works for any season. In Figure 4.5 − 4.8, the ARX and BJ model are presented on the forms: ARX [$na\ nb_i\ nk_i$], $i = 1, \cdots, 8$, and BJ [$nb_i\ nc\ nd\ nf_i\ nk_i$], $i = 1, \cdots, 8$, using the orders and input delays presented in Table 3.7.

In Table 4.6 the estimation focus used for the ARX and BJ models are presented. As for the humidity models, the focuses were tested in the order: 'prediction', 'stability' and 'simulation', having the intended use of the models in mind.

Table 4.6 Selected estimation focuses for the temperature models

Season	***Model***	***Focus***
Winter	ARX	'Simulation'
	BJ	'Prediction'
Spring	ARX	'Prediction'
	BJ	'Stability'
Summer	ARX	'Stability'
	BJ	'Stability'
Autumn	ARX	'Prediction'
	BJ	'Simulation'

In the following sections the ARX and BJ models are presented in a similar manner as the humidity models were, with the 1 hour step ahead predicted output presented for each season. One distinct difference between the temperature and humidity models is that the former are not suitable for simulation purposes. For all seasons, except the winter season, it is not possible to get any good results when the outputs are simulated. The reason for this could be that the estimation algorithms fails to converge. Due to this a $k = 200$ step ahead predicted output is presented instead of the simulated output. In this case it would be desirable to set k as high as possible in order to get as close as simulation as possible. Using a $k > 200$, on the other hand, is not an optimal choice since a high value of k increases the computational time significantly. Therefore a prediction horizon of 200 samples (corresponding to 10 hours) is chosen for all seasons.

Winter season Table 4.7 presents the MAE, MSE and goodness of fit for the ARX and BJ models. When k is increased, the fit between the BJ model output and the measurements decreases. The ARX model, on the other hand, performs well in both cases. The fit between the measurements and the model outputs are visualized in Figure 4.5.

Table 4.7 Validation of the ARX and BJ temperature models, expressed in MSE, MAE and Goodness of fit, winter season

Type of output	*Model*	*MAE (^oC)*	*MSE (^oC)*	*fit (%)*
Predicted	ARX	0.0486	0.0041	68.56
k=200 (10 h)	BJ	0.0693	0.0187	33.26
Predicted	ARX	0.0179	0.0011	83.91
k=20 (1 h)	BJ	0.0171	0.0013	82.50

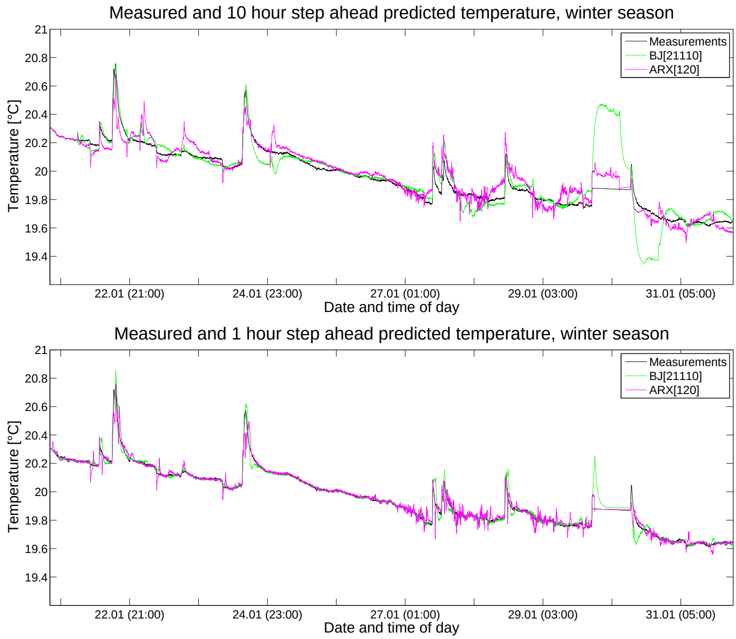

Figure 4.5 Performance of temperature models winter season: **Upper:** Real measurements and *predicted (k=200)* output from the BJ model (**fit: 33.26%**) and the ARX model (**fit: 68.56%**) **Lower:** Real measurements and *predicted (k=20)* output from the BJ model (**fit: 82.50%**) and the ARX model (**fit: 83.91%**).

Spring season For the spring season, the difference in performance between the BJ and ARX models is relatively small. When changing k from 200 to 20 there is a substantial improvement in the performance, implying that the models are not stable and/or nonlinearities may be present for large values of k. The models might still be useful though, provided that this is kept in mind when using them. The MAE, MSE and fit between the measurements and the 1- and 10 hour step ahead predicted outputs are depicted in Table 4.8 and visualized in Figure 4.6.

Table 4.8 Validation of the ARX and BJ temperature models, expressed in MSE, MAE and Goodness of fit, spring season

Type of output	*Model*	*MAE (^oC)*	*MSE (^oC)*	*fit (%)*
Predicted	ARX	0.1470	0.0352	-29.73
k=200 (10 h)	BJ	0.1137	0.0228	-4.345
Predicted	ARX	0.0488	0.0073	40.92
k= 20 (1 h)	BJ	0.0428	0.0054	49.40

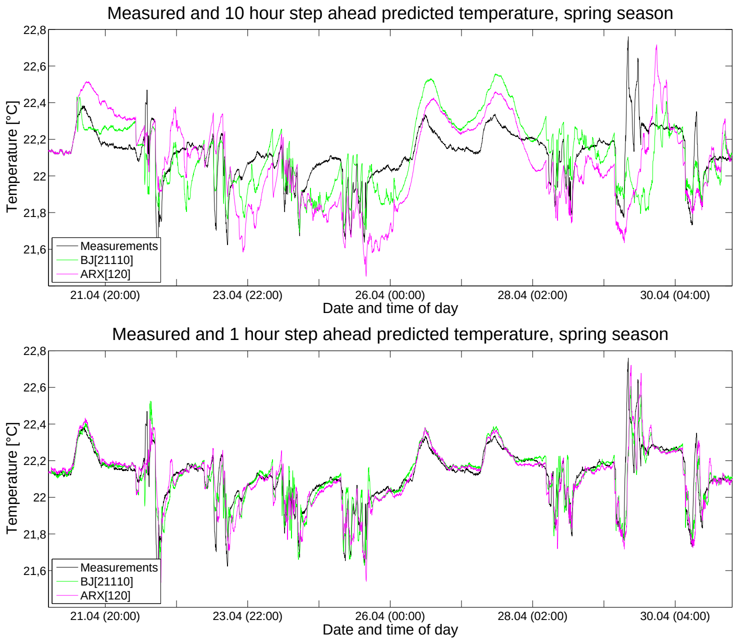

Figure 4.6 Performance of temperature models spring season: **Upper:** Real measurements and *predicted (k= 200)* output from the BJ model (**fit: -4.35%**) and the ARX model(**fit: -29.73%**) **Lower:** Real measurements and *predicted (k=20)* output from the BJ model (**fit: 49.40%**) and the ARX models (**fit: 40.92%**).

Summer season The MAE, MSE and goodness of fit of models identified for the summer season are shown in Table 4.9. In this case, the BJ model shows a better performance than the ARX model. The fit between the 10 hour step ahead predicted output and the real measurements, and the fit between the measurements and the 1 hour step ahead predicted output can be seen in Figure 4.7.

Table 4.9 Validation of the ARX and BJ temperature models, expressed in MSE, MAE and Goodness of fit, summer season

Type of output	*Model*	*MAE (^oC)*	*MSE (^oC)*	*fit (%)*
Predicted	ARX	0.0943	0.0120	53.48
k=200 (10 h)	BJ	0.0342	0.0030	76.94
Predicted	ARX	0.0571	0.0049	70.42
k=20 (1 h)	BJ	0.0269	0.0021	80.36

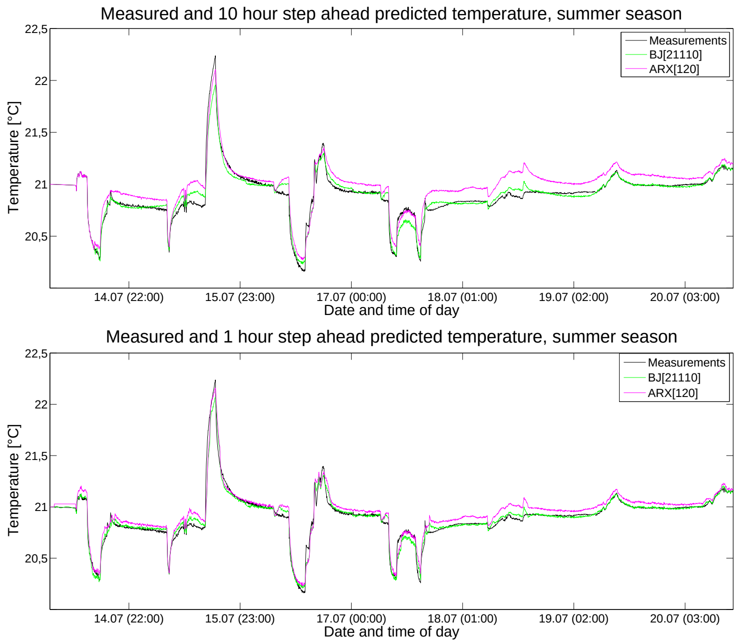

Figure 4.7 Performance of temperature models summer season:**Upper:** Real measurements and *predicted (k=200)* output from the BJ model (**fit: 76.94%**) and the ARX model (**fit: 53.48%**). **Lower:** real measurements and *predicted (k=20)* output from the BJ model (**fit: 80.36%**) and the ARX model (**fit: 70.42%**).

Autumn season The results obtained for the temperature models for the autumn season are depicted in Table 4.10 and Figure 4.8. Independent of the value of k, the BJ and ARX model show similar performance, with the latter model performing slightly better than the former.

Table 4.10 Validation of the ARX and BJ temperature models, expressed in MSE, MAE and Goodness of fit, autumn season

Type of output	*Model*	*MAE (^oC)*	*MSE (^oC)*	*fit (%)*
Predicted	ARX	0.1518	0.0353	55.15
k=200 (10 h)	BJ	0.1492	0.0413	51.50
Predicted	ARX	0.0324	0.0020	89.35
k= 20 (1 h)	BJ	0.0346	0.0026	87.84

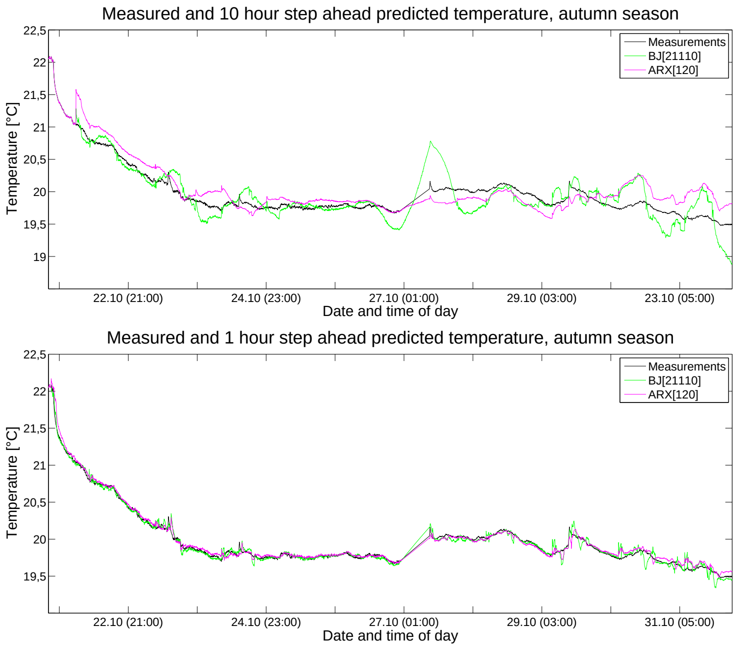

Figure 4.8 Performance of temperature models autumn season: **Upper:** Real measurements and *predicted (k= 200)* output from the BJ model (**fit: 51.50%**) and the ARX model (**fit: 55.15%**). **Lower:** Real measurements and *predicted (k=20)* output from the BJ model (**fit: 87.84%**) and the ARX model (**fit: 89.35%**).

Summary/comments: Evaluating the results for all the seasons, one can notice some general tendencies:

- It is generally harder to find good models for the temperature, than it is for the humidity.
- The temperature models are only suitable for prediction or control purposes. To ensure a good fit for all the seasons, the prediction horizon should not be larger than $k = 20$, i.e, 1 h.
- Comparing the performance of the ARX and BJ models, the ARX models are the best choices for the winter and autumn seasons, while the BJ models are the best choices for the spring and summer seasons.
- It is much harder to achieve a good performance for the spring season compared to the other seasons. The best fit that is achieved for the spring season is 49.40%, while the best fit for the other seasons are: 83.91% (winter), 80.36% (summer) and 89.35% (autumn) respectively. The reason for the problems during the spring season might be connected to sensor 1006, or that the data overall is not representative enough.
- Using the model that gives the best fit for the spring season (the BJ model) as starting point, one can use the same type of model to describe the indoor temperature for all seasons. Using the BJ models results in the fits: 49.40% (spring), 80.36% (summer), 87.84% (autumn) and 82.50% (winter).

Two-output models, temperature and humidity

When using two outputs at the same time, the state-space models and ARX models are the only ones of the tried model structures that performs well for all seasons. The orders of the separate ARX models work well also for the two-output ARX models, and an order of 4 gives the best overall performance of the state-space models. Because of the problems when simulating the temperature, as experienced with the separate temperature models, the 20 step ahead predicted output is presented for all seasons in this section. All the models are estimated with the focus option set to 'prediction'.

Winter season For the winter season the state-space and ARX models are both performing well, but the state-space model is about 10% better than the ARX model. This can also be seen in Table 4.11 and Figure 4.9.

Table 4.11 Validation of the ARX and BJ temperature and humidity models, expressed in MSE, MAE and Goodness of fit, winter season

Type of output	*Model*	*MAE*	*MSE*	*fit (%)*
Predicted (k=20)	ARX	0.0463	0.0047	66.49
temperature (y_1)	State-Space	0.0312	0.0022	76.92
Predicted (k=20)	ARX	0.4415	0.3436	65.85
humidity (y_2)	State-Space	0.2249	0.1370	78.43

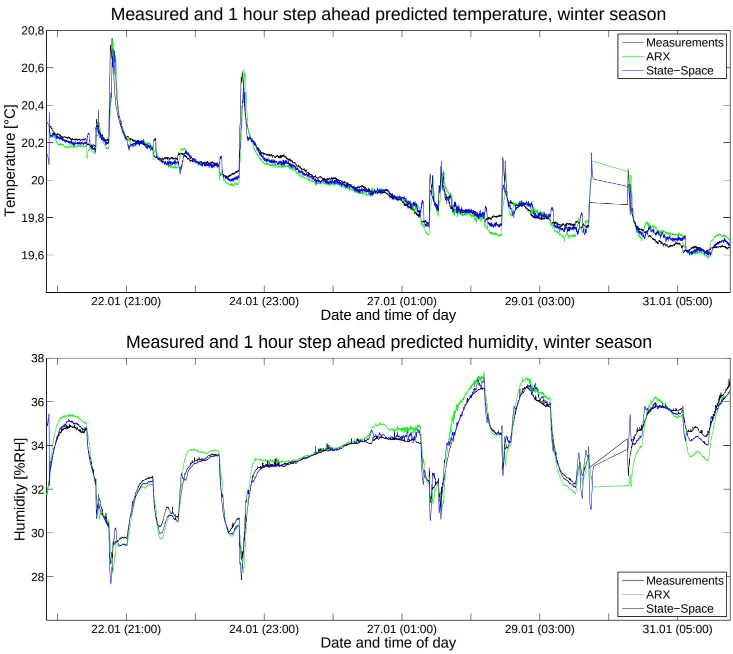

Figure 4.9 Performance of combined models winter season: **Upper:** Real measurements and *predicted (k= 20)* temperature from the ARX model (**fit: 66.49%**) and the state-space model (**fit: 76.92%**). **Lower:** Real measurements and *predicted (k=20)* humidity from the ARX model (**fit: 65.85%**) and the state-space model (**fit: 78.43%**).

Spring season As for the separate temperature model for the spring season, it is hard to find models that give rise to good values for MAE, MSE and goodness of fit in this case as well. For the humidity output on the other hand both the ARX and state-space models performs adequately. The goodness of fit, MSE and MAE are shown in Table 4.12. The goodness of fit for both outputs are visualized in Figure 4.10 as well.

Table 4.12 Validation of the ARX and BJ temperature and humidity models, expressed in MSE, MAE and Goodness of fit, spring season

Type of output	*Model*	*MAE*	*MSE*	*fit (%)*
Predicted (k=20)	ARX	0.0532	0.0074	40.36
temperature (y_1)	State-Space	0.0541	0.0092	33.64
Predicted (k=20)	ARX	0.2794	0.1730	89.60
humidity (y_2)	State-Space	0.2732	0.2860	86.62

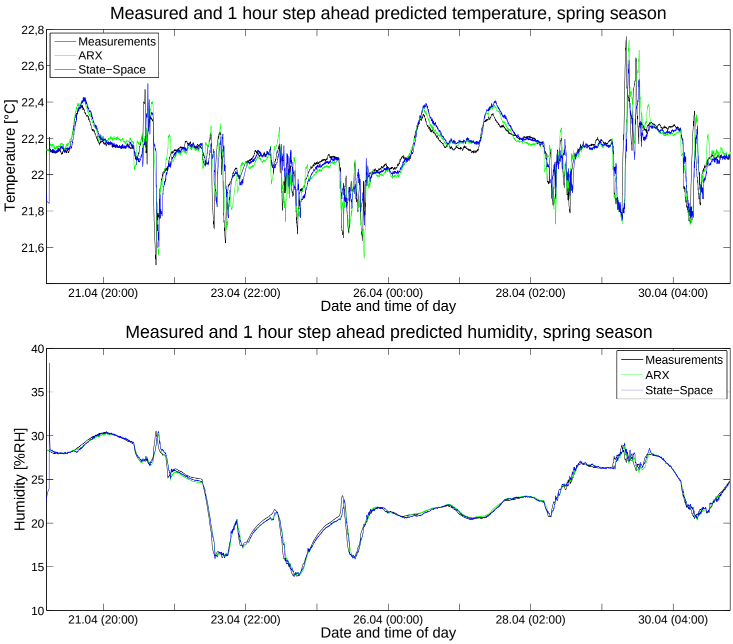

Figure 4.10 Performance of combined models spring season: **Upper:** Real measurements and *predicted (k= 20)* temperature from the ARX model (**fit: 40.36%**) and the state-space model (**fit: 33.64%**). **Lower:** Real measurements and *predicted (k=20)* humidity from the ARX model (**fit: 89.60%**) and the state-space model (**fit: 86.62%**).

Summer season For the summer season, the ARX model is substantially better than the state-space model for the temperature output. In the humidity case the difference between the ARX model and the state-space model is first of all due to the transient present in the output predicted by the state-space model. The results can be seen in Table 4.13 and Figure 4.11.

Table 4.13 Validation of the ARX and BJ temperature and humidity models, expressed in MSE, MAE and Goodness of fit, summer season

Type of output	*Model*	*MAE*	*MSE*	*fit (%)*
Predicted (k=20)	ARX	0.0579	0.0050	70.06
temperature (y_1)	State-Space	0.0882	0.0149	48.32
Predicted (k=20)	ARX	0.2503	0.1042	82.71
humidity (y_2)	State-Space	0.3305	0.3045	70.45

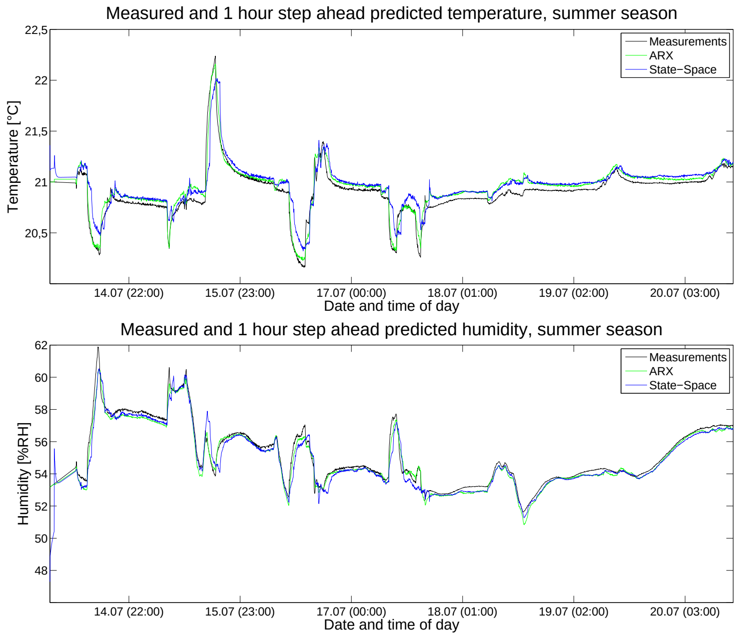

Figure 4.11 Performance of combined models summer season: **Upper:** Real measurements and *predicted (k= 20)* temperature from the ARX model (**fit: 70.06%**) and the state-space model (**fit: 48.32%**). **Lower:** Real measurements and *predicted (k=20)* humidity from the ARX model (**fit: 82.71%**) and the state-space model (**fit: 70.45%**).

Autumn season As seen in Table 4.14 and Figure 4.12, and similar to the summer season, the ARX model is the best to describe both the temperature and the humidity for the autumn season. The difference in performance expressed in fit, MSE and MAE, between the state-space and ARX-models is mainly caused by the transient present in the outputs predicted by the state-space model.

Table 4.14 Validation of the ARX and BJ temperature and humidity models, expressed in MSE, MAE and Goodness of fit, autumn season

Type of output	*Model*	*MAE*	*MSE*	*fit (%)*
Predicted (k=20)	ARX	0.0355	0.0025	88.08
temperature (y_1)	State-Space	0.0576	0.0444	49.73
Predicted (k=20)	ARX	0.3075	0.1719	95.51
humidity (y_2)	State-Space	0.2690	0.2416	94.67

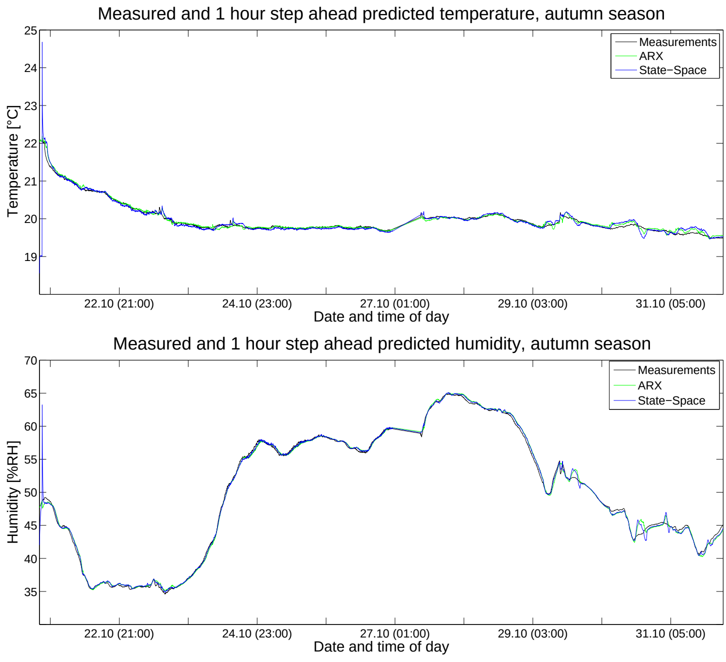

Figure 4.12 Performance of combined models autumn season: **Upper:** Real measurements and *predicted (k= 20)* temperature from the ARX model (**fit: 88.08%**) and the state-space model (**fit: 49.73%**). **Lower:** Real measurements and *predicted (k=20)* humidity from the ARX model (**fit: 95.51%**) and the state-space model (**fit: 94.67%**).

Summary/comments: Examining the identified models for all seasons, one can notice that:

- Generally, it is easier for both the ARX and state-space models to predict the humidity compared to the temperature.
- For all the seasons, except for the winter season, the ARX models performs better than the state-space models.
- Generally the ARX models is the best choice if one should use one type of model for the whole year.
- Using the ARX models the respective fits become: $y_1(t)/y_2(t)$: 66.49%/ 65.85% (winter), 40.36%/89.60% (spring), 70.06%/82.71% (summer) and 88.08%/95.51% (autumn).

4.2 Validation using different seasons

In this section the separate and combined temperature and humidity models from the previous section are tested with the datasets from the other months. Each model is validated using the validation data from the other months. This is done in order to test if some of the models work well for more than one season, which may imply that models with identical orders, delays and model parameters can work well for the whole year. From previous sections one knows that the models are most suitable for prediction purposes, and does not work as well for simulation, so the models will be validated using the 1 hour step ahead predicted output. The validation metrics presented in Section 4.1 are also used in this case.

Humidity models

Here each 1 hour step ahead predicted output from the different ARMAX and BJ models is compared to the real measurements from each respective season. Table 4.15 shows the goodness of fit between the real measurements for the given month and the output predicted by the model in question.

Both the ARMAX and BJ models estimated using the data from the spring and winter seasons are able to predict the actual relative humidity for all the seasons. To ensure a good fit for all seasons, the winter BJ model is the best choice, since the lowest value of the fit between measurements and predicted output is 71.35%. As the table shows however, the spring BJ model and the winter ARMAX model also performs well, meaning that more than one model can be used to describe the relative humidity for all seasons.

For both the ARMAX and BJ models estimated for the spring, summer and autumn seasons, it is most difficult to predict the relative humidity during the winter season, and in some cases no good fit is even obtained. The reason for this is probably that the conditions during the winter season are too different from the other

Table 4.15 Validation of the humidity models: goodness of fit in % between the predicted outputs from the four ARMAX and BJ models and the real measurements from each season. The mark(−) means no good fit is obtained.

Model	*Winter*	*Spring*	*Summer*	*Autumn*
$ARMAX_{Winter}$	81.14	86.79	66.08	94.58
$ARMAX_{Spring}$	57.49	90.56	74.39	94.73
$ARMAX_{Summer}$	−	69.55	83.07	81.91
$ARMAX_{Autumn}$	43.14	81.84	71.54	95.87
BJ_{Winter}	76.87	89.38	71.35	95.54
BJ_{Spring}	68.94	90.92	72.44	96.00
BJ_{Summer}	−	77.12	87.12	82.83
BJ_{Autumn}	−	69.30	17.90	91.21

seasons. This assumption is strengthen by the observation that the neither of the models estimated for the summer season are able to predict the humidity during the winter, combined with the observation that the summer data gives the worst fit of all seasons, when using the winter models. This seems reasonable, since we know that the outside conditions differs much between the summer and the winter season. At the same time, the models estimated for the autumn and the spring, are all able to predict the humidity well during both the spring and autumn seasons. This indicates that the conditions are quite similar during those two seasons, which seems reasonable.

Temperature models

Using the same procedure as for the humidity models, each 1 hour step ahead predicted output from the four different the ARX models and the BJ models are compared to the real measurements from each respective season. The results are depicted in Table 4.16.

Table 4.16 Validation of the temperature models: goodness of fit in % between the predicted outputs from the four ARX- and BJ models and the real measurements from each season. The mark(−) means no good fit is obtained

Model	*Winter*	*Spring*	*Summer*	*Autumn*
ARX_{Winter}	83.91	18.38	53.18	87.30
ARX_{Spring}	43.56	40.92	56.42	89.85
ARX_{Summer}	−	−	70.42	−
ARX_{Autumn}	77.56	4.87	46.35	89.35
BJ_{Winter}	82.50	39.10	32.99	89.84
BJ_{Spring}	53.77	49.40	58.49	92.61
BJ_{Summer}	−	−	80.36	−
BJ_{Autumn}	33.94	20.79	44.28	87.84

Unlike for the humidity models, it is difficult to choose one model to represent the whole year. The summer models perform worst, only giving good results for the summer data, and not working at all for the other seasons. The winter models does not result in good fits when validated against the summer data either. It is therefore likely to assume that the bad fits are due to too different conditions during the two seasons, as for the humidity. Due to the problems with the spring season, it is difficult to establish any connections between the spring and autumn seasons. This is in contrast to the results for the humidity. Had the problems with the spring season been resolved one the other hand, one would probably see a similar connection between the temperature during the autumn and spring seasons, as we saw in the humidity case.

If one had to choose one model to represent the temperature for a whole year, only the models estimated using the spring data gives adequate fits for all seasons. This is, however, due to the difficulties in finding good models for the spring season, and these problems narrows the option of using some of the models estimated for the other seasons.

Two-output models

The fit between the validation data from each season and the 1 hour step ahead predicted outputs from the state-space and ARX models are depicted in Table 4.17, showing the temperature output, $y_1(t)$, and Table 4.18, showing the humidity output, $y_2(t)$.

As seen with the separate temperature and humidity models, it is harder for the two-output models to achieve a good fit for the temperature than for the humidity. The fit between the measurements and the predicted humidity outputs shows that several models work well for all seasons. Especially the state-space models identified for the winter and spring season stand out, but the spring ARX model could be used as well. Regarding the temperature output, only the MIMO ARX model estimated for the spring season gives adequate results, and the spring ARX model should be used if only one model is available for use throughout the year. However, for the same reason as for the separate temperature models, the problems with the spring season might limit the use of some of the other models. It is although apparent that in the case of the two-output models, the best choice is definitely to use models with different parameters for the respective seasons, especially since it was difficult to find good enough models for the temperature output for the spring season.

Table 4.17 Validation of the temperature output: goodness of fit in % between the predicted outputs from the four ARX and state-space (SS) models and the real measurements from each season. The mark(−) means no good fit is obtained.

Model	*Winter*	*Spring*	*Summer*	*Autumn*
ARX_{Winter}	66.49	−	−	55.22
ARX_{Spring}	65.49	40.36	54.88	85.59
ARX_{Summer}	−	−	70.06	−
ARX_{Autumn}	61.22	6.35	46.36	88.08
SS_{Winter}	76.92	5.95	17.59	61.98
SS_{Spring}	28.34	33.64	46.19	70.68
SS_{Summer}	−	27.30	48.32	66.57
SS_{Autumn}	−	−	8.314	49.73

Table 4.18 Validation of the humidity output: goodness of fit in % between the predicted outputs from the four ARX and state-space models and the real measurements from each season. The mark(−) means no good fit is obtained.

Model	*Winter*	*Spring*	*Summer*	*Autumn*
ARX_{Winter}	65.85	68.19	10.37	83.86
ARX_{Spring}	56.67	89.60	68.86	93.96
ARX_{Summer}	−	65.50	82.71	80.59
ARX_{Autumn}	18.92	82.18	73.55	95.51
SS_{Winter}	78.43	77.86	60.82	93.20
SS_{Spring}	71.32	86.62	70.79	95.43
SS_{Summer}	−	80.01	70.45	93.35
SS_{Autumn}	37.87	77.99	61.02	94.67

Comments

Examining Table 4.15 - 4.18, one notices that it is possible to use one model to describe the humidity for all seasons. Especially two models stand out; the BJ-models estimated for the winter and spring season respectively.

It is harder to find one (or more) model(s) that describe the temperature for all seasons. Depending on the demand on accuracy, one can use some of the models to describe the temperature for all seasons, e.g. the ARX and BJ models identified using the spring data, but the best choice is definitely to at least use the summer models during the summer season. Three out of the eight models give good fits for both the autumn and winter season, so a possibility is to at least use one distinct model (ARX_{Winter}, ARX_{Autumn} or BJ_{Winter}) for the autumn and winter seasons.

For the models considering both outputs, the temperature limits the use of one (or more) model(s) during the year. Only the models estimated for the spring season are able to describe the conditions during all the seasons in a useful way. However, like for the separate temperature models, the best choice is to use models with different parameters for each season. On the other hand, as mentioned earlier, it is not problematic to use the same model type throughout the year.

4.3 Models and correlation

The validation of both the MIMO and MISO systems, suggests that adequate results can be achieved in both cases. Had the correlation between the relative humidity and temperature been stronger, one would probably benefit more from using the MIMO models. But also in this thesis' context, it is beneficial to use the MIMO models. It is not possible to control the humidity directly, so for solely control purposes it is unnecessary to model the humidity separately. One could e.g benefit from the correlation by indirectly controlling the humidity via the temperature. Choosing the MIMO models before the MISO models will in addition decrease the number of models needed to describe the system.

4.4 Models and control

The validation show that the models, identified based on model requirements presented in Section 3.3, are performing well enough for control purposes. From Section one knows that especially adaptive and predictive control strategies are interesting to explore when it comes to controlling HVAC-systems.

Exploring the validation of the models presented in this thesis, one can confirm that the outside conditions varies throughout the year to such a degree that it has to be considered in order to achieve a good control. Because of this, using predictive control strategies such as MPC, is a good idea. By implementing controllers with predictive abilities one can account for varying outside condition to a much higher degree than is the case of the simple PI-controllers used today. The models identified in this thesis can be used as basic dynamic models for such controllers.

The validation show that it is possible to use models of the same structure and with the same orders and input delays for all seasons. One should although change the model parameters throughout the year. Using an adaptive controller, i.e., a controller that have the ability to adapt to changes in the system, such as varying system parameters, could therefore also be suitable when controlling humidity and temperature on a yearly basis. Implementing e.g a gain scheduler, one could account for the different operating conditions the system are working under. Since the system studied in this thesis is changing relatively slow, one could actually also consider manually changing the control parameters. However, using gain scheduling would make it possible to take into account all the changes that happens to the system on a faster time-scale as well.

5

Concluding remarks

In this chapter, the results from the previous chapters are summarized and evaluated further. The aim is to get an overall view of how the models can be used. Some comments regarding the correlation between the humidity and temperature, and how this relationship affects the models and control follows thereafter. Finally the results and conclusions are discussed, possible improvements are proposed and some ideas regarding further work are suggested.

5.1 Conclusion

Based on the results from Chapter 4 and using what we know from previous chapters, one can draw the general conclusions:

- It is fully possible to use the same type of model, with the same orders and input delays to represent the temperature and relative humidity for all seasons.
- Since the conditions are varies too much through the year, one should not use models with the same parameters for the whole year.
- The results show that one can use both MIMO or MISO models to describe the temperature and relative humidity adequately, but because of the correlation between the two variables, MIMO systems is the preferred choice.
- There are no devices installed in the test-bed to modify the humidity directly. On the other hand, due to the correlation between temperature and humidity one can possibly indirectly control the humidity via the temperature.
- Based on the nature of the system, which is highly dependent on the outside conditions, predictive control strategies, e.g MPC, is suitable, since these techniques gives us the possibility to predict variables such as the outside temperature and expected occupancy levels. Adaptive control strategies such as gain scheduling are also suitable, since the test-bed are subjected to predictable variations and the system is working under varying operating conditions.

One should keep in mind that the results obtained might only be applicable for this specific test-bed. To draw a general conclusion one should use data for a whole year or use data from previous years as well. In addition, one should also use data from buildings at other locations, subjected to similar weather conditions as the test-bed used in this thesis.

5.2 Discussion and further work

Seasonal differences

The results show that the temperature of the spring season is the most challenging to model. However the problems with the spring season does not weaken the assumption that the same orders and delays can be used for all seasons, since other orders/delays doesn't improve the performance significantly. The models identified for the autumn and winter seasons are most robust, and give predictable results for both temperature and humidity. This indicates that the data for October and January are more representative than the data from July and April.

Overall the results show that the autumn and winter seasons are subjected to similar conditions, since it is possible to use identical models for both seasons. The same can not be said when comparing the summer and spring season with each other or with any of the other seasons. However, this does not necessarily exclude any connection between the datasets, but can depend on the representativeness of the spring data caused by the unknown problems, making it hard to find good models for the spring season. The differences between the summer and the winter seasons occurs as expected, since the test-bed during these two time periods are subjected to the most different conditions.

The effect of correlation between humidity and temperature

Based on the correlation tests in Chapter 3 one confirms the negative correlation between relative humidity and temperature, making it interesting to explore MIMO models. In the case of the spring season, neither the state-space or ARX model is able to obtain a good fit for both outputs. This is in contrast to the models for the other seasons, where at least one of the models are able to achieve a good fit for both outputs. The weak positive correlation between the two outputs occurring for the spring season may be part of the explanation. For the other seasons the correlation is negative and stronger than for the spring season, and it is likely that this distinction affects the results.

Reliability of the results

The results show that there are some problems occurring during the process that haven't been properly taken care of. However, solving these problems would probably improve the performance and accuracy of the models, and therefore only strengthen the assumptions that it is possible to use models of the same type and with the same orders and input delays for the whole year.

The sensor (1006), located on the exterior wall of room A:225 is one fault source. It is possible that the sensitivity of this sensor is the main reason for the problems in finding good models describing the temperature for the spring season. With better models for the mentioned season the results and thus the conclusions would be more credible.

Comparing the results achieved in this thesis with the results from the references [Scotton, 2012] and [Mustafaraj et al., 2010], one notice they both conclude that it is generally easier to find good models for the temperature than for the humidity, i.e., opposite of what is the case here. However, it is not a good idea to compare the results straight off, since the conditions are quite different in this work compared to [Mustafaraj et al., 2010] and [Scotton, 2012]. The latter uses e.g a much shorter dataset, only considers one season, and does not consider the outside conditions. It is highly possible that the difference between the results here and those presented in [Scotton, 2012] is due to the effect from sensor 1006, which is left out in the reference because of its sensitivity. The models obtained in [Mustafaraj et al., 2010], are on the other hand identified using data from a building in London, which means that the conditions surrounding the two test-beds are too different to draw any conclusions based on a comparison of the models.

If informative data would have been available regarding the solar radiation, solar position and wind velocity, more accurate representations regarding the outside conditions might have been obtained. In other words one could treat these outside effects as measured disturbances (inputs in this case), instead of unmeasured disturbances as is the case in this thesis.

The correlation between the outputs for the spring season is not following the same pattern as the other seasons, which can have an impact on the performance of the spring models, and thus affect the reliability of the results.

If these problems had been solved, one could probably draw a more definite conclusion regarding the use of identical models for the whole year for both temperature and humidity respectively. Luckily the models are good enough to establish that it is indeed possible to use the same model structures, orders and delays in the type of test-bed studied here.

Improvements and further work

The models perform well overall, but it is always room for improvement. To increase the models' usability and strengthen the assumptions regarding their performance one should e.g.:

- Solve the problems with sensor 1006
- Establish why it is harder to find good models to describe the mean room temperature during the spring season.

- Add information regarding solar radiation/position, wind velocity and other effects from the outside.
- Further examine the disturbances
- Try to determine the values of orders and input delays individually for every input, i.e., not keep the values identical for the eight inputs as done in this thesis.

The models should also be validated using data from previous years, to see if the models still performs adequately.

In a future perspective it would be interesting to use data for a whole year, in order to get the full picture in how the conditions change throughout the year. From the previous work one knows that physics-based models generally performs better than black-box models, so it would be interesting to explore that route as well, and see if the same results are obtained. Last, but not least, it would be interesting to test the control strategies suggested, to see if the models are applicable for practical use.

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A

Appendix

A.1 List of device types and ID groups

Group	*Type of device*
1xxx	Sky TMotes
2000	Fidelix PLC Central system
3000	Photoelectric sensors based people counter
5xxx	Web-based sources
9xxx	Local weather stations

A.2 List of device IDs

Device ID	*Description*
1002	Temperature/Humidity sensors
1005	Temperature/Humidity sensors, attached to wall
1006	Temperature/Humidity sensors, attached to wall (outside)
1007	Temperature/Humidity sensors, attached to wall
1008	Temperature sensor, attached to radiator inlet
1011	Temperature sensor, attached to wall
1012	Temperature/Humidity sensors, near AC inlet
1033	Temperature sensor, attached to floor
1036	Temperature sensor, attached to wall
1037	Temperature sensor, attached to ceiling
1043	Temperature/Humidity/CO_2/Light sensors
1044	Temperature sensor, attached to radiator inlet
1046	Temperature sensor, attached to radiator inlet
1047	Temperature/Humidity/CO_2/Light sensors, near fresh air inlet
1051	Temperature sensor, attached radiator surface
1052	Temperature sensor, attached radiator surface
1053	Temperature sensor, attached radiator surface
1053	Temperature sensor, attached radiator surface
1054	Temperature sensor, attached radiator surface
1055	Temperature sensor, attached to radiator inlet
1254	Humidity sensor
2000	Fidelix PLC Central system
3000	Photoelectric sensors based people counter
5000	http//www.wunderground.com
9001	Local weather station located at KTH, Q-building

A.3 Correlation between inputs

	u1	u2	u3	u4	u5	u6	u7	u8
u1	1.0000	-0.2703	0.2008	-0.1798	0.0564	-0.2260	0.1611	-0.2176
u2	-0.2703	1.0000	-0.1175	0.9906	-0.1903	0.8279	-0.0050	-0.0212
u3	0.2008	-0.1175	1.0000	-0.1355	0.5749	-0.4582	0.2218	0.1187
u4	-0.1798	0.9906	-0.1355	1.0000	-0.2177	0.8167	-0.0037	-0.0751
u5	0.0564	-0.1903	0.5749	-0.2177	1.0000	-0.2807	0.1247	0.0324
u6	-0.2260	0.8279	-0.4582	0.8167	-0.2807	1.0000	-0.0327	-0.0296
u7	0.1611	-0.0050	0.2218	-0.0037	0.1247	-0.0327	1.0000	-0.0022
u8	-0.2176	-0.0212	0.1187	-0.0751	0.0324	-0.0296	-0.0022	1.0000

	u1	u2	u3	u4	u5	u6	u7	u8
u1	1.0000	-0.4370	0.7629	-0.1309	0.2820	0.0727	-0.1428	-0.3732
u2	-0.4370	1.0000	-0.0978	0.9229	-0.2052	-0.0057	0.5744	0.4662
u3	0.7629	-0.0978	1.0000	0.0995	0.1805	0.0951	0.0102	-0.2259
u4	-0.1309	0.9229	0.0995	1.0000	-0.1999	0.0246	0.5448	0.2998
u5	0.2820	-0.2052	0.1805	-0.1999	1.0000	-0.3613	0.2312	0.0372
u6	0.0727	-0.0057	0.0951	0.0246	-0.3613	1.0000	-0.5770	-0.1041
u7	-0.1428	0.5744	0.0102	0.5448	0.2312	-0.5770	1.0000	0.3253
u8	-0.3732	0.4662	-0.2259	0.2998	0.0372	-0.1041	0.3253	1.0000

	u1	u2	u3	u4	u5	u6	u7	u8
u1	1.0000	-0.6032	0.8010	-0.2833	0.6540	0.2733	-0.3626	-0.2247
u2	-0.6032	1.0000	-0.3630	0.8227	-0.2333	0.2204	0.0341	-0.1354
u3	0.8010	-0.3630	1.0000	-0.3747	0.9160	0.5249	-0.6016	-0.2152
u4	-0.2833	0.8227	-0.3747	1.0000	-0.3048	0.1423	0.1504	-0.2133
u5	0.6540	-0.2333	0.9160	-0.3048	1.0000	0.5589	-0.5585	-0.1906
u6	0.2733	0.2204	0.5249	0.1423	0.5589	1.0000	-0.7554	-0.1678
u7	-0.3626	0.0341	-0.6016	0.1504	-0.5585	-0.7554	1.0000	0.1386
u8	-0.2247	-0.1354	-0.2152	-0.2133	-0.1906	-0.1678	0.1386	1.0000

	u1	u2	u3	u4	u5	u6	u7	u8
u1	1.0000	-0.3061	0.8288	-0.2153	0.5348	-0.0338	0.0087	-0.2615
u2	-0.3061	1.0000	-0.1686	0.9643	-0.1684	0.8418	0.0546	0.3998
u3	0.8288	-0.1686	1.0000	-0.2212	0.6396	0.0358	0.0147	-0.3474
u4	-0.2153	0.9643	-0.2212	1.0000	-0.2359	0.8323	0.0522	0.4373
u5	0.5348	-0.1684	0.6396	-0.2359	1.0000	-0.0300	-0.0091	-0.3348
u6	-0.0338	0.8418	0.0358	0.8323	-0.0300	1.0000	0.0251	0.3645
u7	0.0087	0.0546	0.0147	0.0522	-0.0091	0.0251	1.0000	-0.1418
u8	-0.2615	0.3998	-0.3474	0.4373	-0.3348	0.3645	-0.1418	1.0000

Figure A.1 Correlation between inputs: winter season (top), spring season (top middle), summer season (bottom middle) and autumn season (bottom)

A.4 Parameters for humidity ARMAX models

Parameters	***Winter***	***Spring***	***Summer***	***Autumn***
a_1	-2.4070	-1.8840	-1.5100	-1.9110
a_2	1.9400	1.0480	0.8310	1.0040
a_3	-0.5327	-0.1615	-0.2950	-0.0920
$b_{1,1}$	0.0342	0.0117	0.0411	0.1190
$b_{1,2}$	-0.0372	-0.0107	-0.0611	-0.1228
$b_{2,1}$	0.0272	0.0335	0.0330	0.0579
$b_{2,2}$	-0.0285	-0.0328	-0.0364	-0.0593
$b_{3,1}$	-0.0024	0.0460	-0.2993	0.0724
$b_{3,2}$	0.0043	-0.0441	0.3874	-0.0685
$b_{4,1}$	0.0029	0.0053	0.0182	0.0487
$b_{4,2}$	-0.0014	-0.0040	0.0078	-0.0468
$b_{5,1}$	-0.0155	-0.0036	-3.4990	-0.0422
$b_{5,2}$	0.0154	0.0013	3.4280	0.0413
$b_{6,1}$	-0.0123	0.0027	-0.0404	-0.0245
$b_{6,2}$	0.0133	-0.0021	0.0409	0.0252
$b_{7,1}$	0.0005	0.0065	-0.0016	0.0015
$b_{7,2}$	-0.0004	-0.0063	0.0017	-0.0014
$b_{8,1}$	0.0090	0.0062	0.0053	-0.0011
$b_{8,2}$	-0.0089	-0.0051	-0.0067	0.0009
c_1	-1.9300	-0.7677	-0.5978	-0.9010
c_2	1.2980	0.2882	0.3561	0.1271
c_3	-0.2977	0.0063	0.0433	-0.0021

A.5 Parameters for humidity BJ models

Parameters	***Winter***	***Spring***	***Summer***	***Autumn***
$b_{1,1}$	0.1167	0.0256	0.0411	-0.0269
$b_{1,2}$	0.0094	-0.0257	-0.0017	0.0165
$b_{2,1}$	0.0851	0.0346	0.0251	0.0186
$b_{2,2}$	-0.0189	-0.0097	0.0106	-0.0082
$b_{3,1}$	0.1076	-0.0580	-0.4508	-0.2165
$b_{3,2}$	-0.1305	0.1277	0.5991	0.2161
$b_{4,1}$	-0.0347	0.0054	0.0194	0.1246
$b_{4,2}$	0.0426	0.0080	0.0189	-0.0084
$b_{5,1}$	0.0106	$6.8e^{-5}$	-3.9270	-0.0048
$b_{5,2}$	-0.0439	-0.0047	3.9200	-0.0086
$b_{6,1}$	-0.0564	0.0118	-0.0034	0.0785
$b_{6,2}$	0.0578	-0.0111	-0.0140	-0.0701
$b_{7,1}$	0.0064	0.0017	-0.0021	0.0420
$b_{7,2}$	-0.0063	-0.0012	0.0025	-0.0426
$b_{8,1}$	0.0089	0.0007	0.0032	-0.0159
$b_{8,2}$	0.0149	0.0063	0.0161	0.0022
c_1	-0.5362	0.1088	-0.9426	0.3742
c_2	0.0186	0.1851	0.1254	0.3797
c_3	0.0391	0.1245	0.0042	0.2611
d_1	-0.9968	-1.0000	-0.8104	-1.0000
$f_{1,1}$	-0.5558	-1.0000	0.4689	-0.9941
$f_{2,1}$	-0.7335	-0.7544	-0.3398	-0.9869
$f_{3,1}$	-0.9748	-0.8510	-0.9249	-1.0000
$f_{4,1}$	-0.9705	-0.9768	-0.9447	-0.8763
$f_{5,1}$	-0.7492	-0.9961	-0.9772	-0.9931
$f_{6,1}$	-0.9977	-1.0000	0.2861	-0.9964
$f_{7,1}$	-0.9959	-0.9960	-0.8707	-0.9750
$f_{8,1}$	-0.5715	-0.9734	-0.6308	-0.9859

A.6 Parameters for temperature ARX models

Parameters	***Winter***	***Spring***	***Summer***	***Autumn***
a_1	-0.9993	-0.9965	-0.9648	-0.9963
$b_{1,1}$	0.0817	0.0072	0.0150	0.0191
$b_{1,2}$	-0.0811	0.0042	-0.0120	-0.0075
$b_{2,1}$	0.0310	-0.0039	-0.0002	-0.0003
$b_{2,2}$	-0.0307	0.0044	0.0008	0.0036
$b_{3,1}$	0.2968	0.1380	0.1321	0.1214
$b_{3,2}$	-0.2957	-0.1393	-0.1355	-0.1292
$b_{4,1}$	-0.0258	-0.0075	-0.002	0.0016
$b_{4,2}$	0.0255	0.0070	-0.0005	-0.0046
$b_{5,1}$	0.0119	0.0112	1.2410	0.0191
$b_{5,2}$	-0.0118	-0.0098	-1.2130	-0.0190
$b_{6,1}$	0.0168	0.0187	0.0027	0.0374
$b_{6,2}$	-0.0167	-0.0185	-0.0025	-0.0379
$b_{7,1}$	-0.0004	0.0017	0.0003	-1.2^{-5}
$b_{7,2}$	0.0003	-0.0016	-0.0002	$1.0e^{-7}$
$b_{8,1}$	0.0255	0.0021	-0.0021	0.0098
$b_{8,2}$	-0.0254	-0.0016	0.0026	-0.0096

A.7 Parameters for temperature BJ models

Parameters	***Winter***	***Spring***	***Summer***	***Autumn***
$b_{1,1}$	0.0173	0.0149	0.0145	0.0256
$b_{1,2}$	0.0186	0.0177	-0.0144	-0.0234
$b_{2,1}$	0.0036	-0.0006	-0.0003	-0.0086
$b_{2,2}$	0.0037	0.0007	0.0004	0.0085
$b_{3,1}$	0.0463	0.1019	0.1386	0.1638
$b_{3,2}$	-0.0538	-0.1009	-0.1383	-0.1603
$b_{4,1}$	0.0011	-0.0048	-0.0003	-0.0223
$b_{4,2}$	-0.0012	0.0047	$-1.6e^{-5}$	0.0224
$b_{5,1}$	0.0020	0.0059	1.3810	0.0195
$b_{5,2}$	0.0002	-0.0039	-1.3510	-0.0177
$b_{6,1}$	-0.0076	0.0088	-0.0002	0.0490
$b_{6,2}$	-0.0102	-0.0033	0.0009	-0.0494
$b_{7,1}$	0.0003	-0.0008	0.0003	$-5.2e^{-4}$
$b_{7,2}$	-0.0010	0.0012	-0.0002	$5.3e^{-4}$
$b_{8,1}$	0.0021	0.0018	-0.0021	0.0100
$b_{8,2}$	0.0010	$-7.2e^{-6}$	0.0103	-0.0095
c_1	0.1670	0.1186	-0.0619	-0.0171
d_1	-0.9985	-0.9968	-0.9655	-1.0000
$f_{1,1}$	-0.4871	-0.3369	-1.0000	-0.9971
$f_{2,1}$	0.9838	-1.0000	-0.9985	-0.9986
$f_{3,1}$	-0.9029	-0.9955	-0.9042	-0.9961
$f_{4,1}$	-0.9975	-1.0000	-0.9497	-0.9978
$f_{5,1}$	-0.9455	-0.9922	-0.9556	-0.9972
$f_{6,1}$	-0.0759	-0.7826	-0.9031	-0.9944
$f_{7,1}$	0.5935	-0.9413	-0.9951	-1.0000
$f_{8,1}$	-0.9003	-0.8485	-0.7391	-0.9973

A.8 State-space models

A =

	x1	x2	x3	x4
x1	1.003	0.01428	0.006332	0.1865
x2	0.01423	0.9846	-0.08059	-0.09344
x3	0.05598	0.01077	0.857	0.345
x4	-0.005516	-0.03263	-0.05302	0.5068

K =

	y1	y2
x1	0.1227	0.001076
x2	0.00801	-0.00589
x3	-0.1413	0.001256
x4	0.1617	0.002332

B =

	u1	u2	u3	u4	u5	u6	u7	u8
x1	0.002577	1.625e-05	-0.00133	-6.676e-05	0.0001827	-0.0009162	-0.0001121	0.0006313
x2	-0.0001279	-0.0003275	-0.000452	-0.0001787	0.0003999	8.778e-05	-1.648e-05	-0.0001128
x3	0.006761	-0.0009481	-0.003464	-0.0002561	0.001178	-0.002255	-0.0003576	0.001398
x4	-0.006935	-0.000307	0.001865	0.0002623	-0.0001549	0.002226	0.0002658	-0.001436

C =

	x1	x2	x3	x4
y1	9.426	1.05	-0.1294	0.1174
y2	13.28	-82.2	-3.222	-3.06

D =

	u1	u2	u3	u4	u5	u6	u7	u8
y1	0	0	0	0	0	0	0	0
y2	0	0	0	0	0	0	0	0

Figure A.2 Parameters for the State-Space model, winter season

A =

	x1	x2	x3	x4
x1	0.9844	0.004767	-0.05547	0.00757
x2	0.002226	0.9926	0.02595	0.06925
x3	-0.01997	0.01653	0.8066	-0.2306
x4	0.01233	0.03303	-0.1624	0.2204

K =

	y1	y2
x1	-0.01479	-0.01045
x2	-0.0377	0.002063
x3	0.05034	0.0445
x4	-0.08229	-0.004898

B =

	u1	u2	u3	u4	u5	u6	u7	u8
x1	-3.858e-05	-0.000119	-0.0004719	-0.000156	0.0001578	5.658e-05	-4.227e-05	-0.0001222
x2	-0.0005782	4.762e-05	-0.001049	0.0001961	-4.252e-05	-0.000124	-3.954e-06	1.348e-05
x3	0.001982	-0.0003913	0.00276	-0.0008047	0.0001397	0.0005604	-5.835e-05	-0.000253
x4	0.007051	-5.88e-05	0.01168	-0.001863	-0.0005286	0.001084	9.197e-05	-2.448e-05

C =

	x1	x2	x3	x4
y1	-5.247	-29.57	0.07006	-0.2185
y2	-94.29	37.55	1.022	0.02585

D =

	u1	u2	u3	u4	u5	u6	u7	u8
y1	0	0	0	0	0	0	0	0
y2	0	0	0	0	0	0	0	0

Figure A.3 Parameters for the State-Space model, spring season

A =

	x1	x2	x3	x4
x1	0.9664	0.02022	0.08273	-0.02142
x2	0.05752	0.8237	-0.1816	0.3592
x3	0.07297	-0.1923	0.6645	0.3483
x4	-0.08398	0.2899	0.3574	0.3922

K =

	y1	y2
x1	-0.04463	-0.01337
x2	-0.2793	-0.01068
x3	-0.01424	-0.01424
x4	-0.1971	-0.01859

B =

	u1	u2	u3	u4	u5	u6	u7	u8
x1	-4.791e-05	-0.0001917	-0.0003297	-0.0006054	0.005615	9.322e-05	4.691e-06	-0.0002752
x2	-0.002453	0.0001989	-0.01334	0.0002438	-0.04424	-0.0002189	-9.188e-05	-0.0001896
x3	-0.001378	0.0007179	-0.01318	0.0007918	-0.05	-0.0004074	-8.902e-05	0.0005599
x4	0.003899	-0.0004621	0.024	-0.0003728	0.07545	0.0003994	0.0001497	-4.246e-05

C =

	x1	x2	x3	x4
y1	0.1907	-4.841	0.0319	0.101
y2	-69.78	16.19	-0.1207	-0.8551

D =

	u1	u2	u3	u4	u5	u6	u7	u8
y1	0	0	0	0	0	0	0	0
y2	0	0	0	0	0	0	0	0

Figure A.4 Parameters for the State-Space model, summer season

A =

	x1	x2	x3	x4
x1	0.9948	0.003216	-0.0007873	-0.02851
x2	-0.002157	0.9891	0.1016	-0.04213
x3	-0.005817	-0.002623	0.7653	-0.2111
x4	-0.01167	-0.02281	-0.1991	0.3477

K =

	y1	y2
x1	0.03222	0.0004004
x2	0.04329	0.01796
x3	0.05729	0.01715
x4	-0.07926	0.002869

B =

	u1	u2	u3	u4	u5	u6	u7	u8
x1	0.0009357	0.0001999	-0.0001209	-0.000134	0.0003517	0.0005697	-1.419e-05	0.0003094
x2	0.0004137	0.0003883	0.002346	0.001088	-0.0007187	-4.188e-05	1.282e-05	0.0003344
x3	0.008499	0.000858	-0.005067	-0.002531	0.004761	0.006379	-0.0001699	0.002448
x4	0.0238	0.003974	-0.00647	-0.003017	0.008902	0.0148	-0.0003726	0.007108

C =

	x1	x2	x3	x4
y1	37.97	-1.131	0.1334	-0.1346
y2	-74.44	59.25	0.3577	0.1445

D =

	u1	u2	u3	u4	u5	u6	u7	u8
y1	0	0	0	0	0	0	0	0
y2	0	0	0	0	0	0	0	0

Figure A.5 Parameters for the State-Space model, autumn season

A.9 Two-output ARX-models

Table A.1 Parameters for temperature output, $y_1(t)$

Parameters	*Winter*	*Spring*	*Summer*	*Autumn*
$a_{1,1}^{(1)}$	-0.9930	-0.9948	-0.9656	-0.9988
$a_{1,2}^{(1)}$	0.0003	0.0005	-0.0002	-0.0012
$b_{1,1}^{(1)}$	0.0175	0.0077	0.0150	0.0190
$b_{1,1}^{(2)}$	-0.0139	-0.0033	-0.0123	-0.0086
$b_{1,2}^{(1)}$	0.0053	-0.0037	-0.0002	-0.0004
$b_{1,2}^{(2)}$	-0.0040	0.0048	0.0007	0.0032
$b_{1,3}^{(1)}$	0.0874	0.1367	0.1321	0.1217
$b_{1,3}^{(2)}$	-0.0955	-0.1389	-0.1357	-0.1303
$b_{1,4}^{(1)}$	-0.0010	-0.0077	-0.0002	0.0014
$b_{1,4}^{(2)}$	0.0003	0.0070	-0.0005	-0.0051
$b_{1,5}^{(1)}$	0.0022	0.0110	1.2410	0.0190
$b_{1,5}^{(2)}$	-0.0014	-0.0102	-1.2120	-0.0180
$b_{1,6}^{(1)}$	-0.0072	0.0198	0.0027	0.0353
$b_{1,6}^{(2)}$	0.0063	-0.0194	-0.0025	-0.0359
$b_{1,7}^{(1)}$	-0.0003	0.0032	0.0003	0.0004
$b_{1,7}^{(2)}$	0.0004	-0.0031	-0.0002	-0.0005
$b_{1,8}^{(1)}$	0.0019	0.0021	-0.0021	0.0096
$b_{1,8}^{(2)}$	-0.0011	-0.0015	0.0026	-0.0095

Table A.2 Parameters for humidity output, $y_2(t)$

Parameters	***Winter***	***Spring***	***Summer***	***Autumn***
$a_{2,1}^{(1)}$	-0.6146	-1.2310	-0.9459	-1.1370
$a_{2,1}^{(2)}$	-0.2776	-0.0668	-0.1039	-0.0364
$a_{2,1}^{(3)}$	-0.0856	0.3035	0.0814	0.1927
$a_{2,2}^{(1)}$	0.1060	0.0723	0.4352	0.2144
$a_{2,2}^{(2)}$	-0.2051	-0.5581	-0.7594	-0.6971
$a_{2,2}^{(3)}$	-0.0608	0.4832	0.2451	0.5193
$b_{2,1}^{(1)}$	0.1093	0.0342	0.0432	0.2053
$b_{2,1}^{(2)}$	-0.1442	-0.0364	-0.0743	-0.2185
$b_{2,2}^{(1)}$	0.0815	0.0384	0.0274	0.0816
$b_{2,2}^{(2)}$	-0.0796	-0.0373	-0.0339	-0.0844
$b_{2,3}^{(1)}$	0.0215	-0.0318	-0.4675	-0.1534
$b_{2,3}^{(2)}$	-0.0297	0.0391	0.5753	0.1993
$b_{2,4}^{(1)}$	-0.0174	0.0034	0.0197	0.0299
$b_{2,4}^{(2)}$	0.0285	-0.0006	0.0141	-0.0103
$b_{2,5}^{(1)}$	0.0039	-0.0140	-4.4400	-0.0052
$b_{2,5}^{(2)}$	-0.0126	0.0096	4.2880	-0.0023
$b_{2,6}^{(1)}$	-0.1017	0.0029	-0.0497	0.0282
$b_{2,6}^{(2)}$	0.1197	-0.0022	0.0498	-0.0250
$b_{2,7}^{(1)}$	0.0203	0.0034	-0.0017	0.0069
$b_{2,7}^{(2)}$	-0.0206	-0.0033	0.0018	-0.0067
$b_{2,8}^{(1)}$	0.0427	-0.0002	0.0099	-0.0099
$b_{2,8}^{(2)}$	-0.0485	0.0016	-0.0122	0.0093

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System identification for control of temperature and humidity in buildings

Abstract

HVAC systems are widely used to provide a good indoor air quality in buildings. Buildings stand for a substantial part of the total energy consumption in developed countries, and with an increased focus on cost reductions and energy savings, it is necessary to use intelligent and energy-efficient controllers.

Accurate models describing the dynamics of the building system is a good basis for intelligent control. In countries like Sweden there are large seasonal variations in the outdoor climate, and these variations interfere with the indoor condition and thus affects the control. In this thesis the seasonal variations are investigated, and the aim is to determine how these differences affect identified models for control of temperature and relative humidity in buildings. Two MISO (Multiple Input-Single Output) systems and one MIMO (Multiple Input-Multiple Output) system is used to describe the mean room temperature and relative humidity in a selected room in the Q-building at KTH, Stockholm. The models are identified following the black-box approach, and data from four different months during 2014, representing the winter, spring, summer and autumn season respectively, are collected and preprocessed.

The validation of the identified models for the humidity and temperature, shows that it is possible to use identical orders and input delays for all seasons, with good results. Based on the results one would not recommend using models with the same model parameters throughout the year, since the conditions varies too much from season to season.

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