DYNAMIC MODELING AND FUZZY LOGIC CONTROL OF A LARGE BUILDING HVAC SYSTEM

by

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Abstract

Energy and cost-efficient management of a building's thermal properties requires heating, ventilation and air conditioning (HVAC) systems controllers to be working at optimal settings. However, many HVAC systems employ nonlinear time variances to deal with issues that affect the system's optimal operation. The present work considers an HVAC system at Memorial University's S. J. Carew Building which has been mathematically modeled using a state space multi-input and multi-output system (MIMO) approach for analyses and control system design. An IDA-ICE (Indoor Climate and Energy) simulation program has been applied for modeling the building, note that the four-story Carew Building includes an air-handling unit (AHU) on every floor. Compared with real data for one year's (2016) power consumption, the simulated annual power consumption for the building shows good agreement. Based on that data, two scenarios are applied for building the system models. Scenario 1 considers the HVAC system as a single unit with energy consumption (kWh) as inputs and zonal temperature and CO_2 concentrations as outputs. By employing the MATLAB system identification toolbox, a MIMO-based system forms the basis for a state space model. In the model for Scenario 1, there are eight main AHU inputs (hot water power usage and power usage) and eight main outputs (return airflow temperature and CO_2 levels). The state feedback controller obtains good results for both responses rise time and stability. In Scenario 2, there are four AHUs in total. Each of this scenario's AHUs features three main inputs (hot water, internal-to-internal air flow, and external-to-internal air flow) and three main outputs (static air pressure, CO_2 levels, and temperature). In the first AHU (AHU_1), we apply state-of-the-art fuzzy logic controllers (FLCs) to control fan speeds, CO_2 concentrations, and temperature in the building in accordance with the flow rates for air and hot water. This strategy represents a novel approach for adapting FLCs by modifying fuzzy rule using the Simulink. The modified system shows improved levels of thermal comfort. The final part of the work presents the design for a supervisor fuzzy logic controller (SFLC) that can be applied to the entire S. J. Carew Building HVAC control. This SFLC features 24 inputs and 12 outputs and employs a state-space model that considers each AHU as an individual system. The SFLC detailed design and system simulation results are presented in this thesis.

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List of Symbols and Abbreviations

HVAC	Heating, Ventilation, and Air Conditioning System
IDA-ICE	IDA Indoor Climate and Energy Simulation Program
AHU	Air-Handling Unit
VAV	Variable Air Volume System
IS	System Identification
MIMO	Multi-Input/Multi-Output System
FLC	Fuzzy Logic Controller
SFLC	Supervisor Fuzzy Logic Controller
IAQ	Internal Air Quality
BIM	Building Information Model
IFC	Industry Foundation Classes format
U	System Inputs
Y	System Outputs
Ts	Sample Time
w	System Disturbances
PU	Power Usage
WPU	Water Power Usage
K	Feedback Gain
K_r	Input Gain
INW	Inches of Water
℃	Degree Celsius
PPM	Parts Per Million
MFs	Fuzzy membership function
T_z	Zonal Temperature
P_s	Static Air Pressure
CO_2	Concentration of Carbon Dioxide
ΔT_z	Temperature Differences
ΔP_S	Static Air Pressure Differences
ΔCO_2	Differences in CO2 Levels

T_{setp}	Setpoint of Zone Temperature
$P_{S\text{-}setp}$	Static Pressure Setpoint
$CO_{2\text{-}Setp}$	CO_2 Levels setpoint
$d\Delta T_z$	Ratio for The Difference of Temperature Differences
$d\Delta P_S$	Ratio for The Difference of Static Air Pressure Differences
$d\Delta CO_2$	Ratio for The Differences in CO2 Levels
HWV	Aperture on Hot Water Valve of AHUs
SFS	Supply Fan Speed of AHUs
FAD	Fresh Air Dampers Position of AHUs

Chapter 1

Introduction and Literature review

1.1. Introduction

Energy demand for construction has increased significantly over the last two decades, mainly due to emerging market economic growth. This leads to high energy cost and high pollution [1]. To overcome these two problems, many studies focus on energy saving and renewable energy production. The building's heating, ventilation and air conditioning (HVAC) system provides comfort to residents. Since heating and cooling loads change over time, the HVAC control system should provide comfort in all cases. Proper control of the system also reduces energy consumption. The HVAC system is also responsible for adding fresh air to the building.

The modern approach to optimizing internal air quality, managing indoor environments and lowering operational costs is to install a heating, ventilation and air conditioning (HVAC) system. In large commercial and industrial structures, HVAC systems comprise one-third of the power consumption [1] -[4].

The main purpose of installing and using an HVAC system in a structure is to improve the users' ability to control the air quality for factors such as heat and humidity to achieve a comfortable interior environment. Nowadays, HVAC systems have become so popular that they account for more than half of the world's overall energy consumption [5]-[8]. Part of the reason for the increase in usage of these systems is their ability to optimize the efficiency of the heating and cooling processes. There are other reasons for the increasing use of the HVAC system, such as [64].

1. The HVAC system can continuously improve the air quality by replacing the indoor air with fresh air, which is filtered for optimum quality.

2. The HVAC system is heated and cooled in one unit. This not only saves installation space, installation time, and cost but also reduces the required energy consumption.

3. The system also works with renewable energy, sometimes in the form of solar panels. Energy saving is even better because the coolant is not based on chlorine; it damages the ozone layer.

These systems aim to create an interior environment which highlights energy efficiency, cost efficiency, and user comfort, all while mitigating adverse effects that may be caused by large-scale energy usage [1]. The ideal approach to maintaining optimal system performance under circumstances of changing variables involves applying a control system that is specifically tailored to the structure. One approach applies data to develop a mathematical-based HVAC system which uses input/output variables for both ascertaining and setting the parameters for the system. The advantage of data-driven HVAC systems is that they are easily able to find strategies that will improve and refine the system. Although the research shows the promising potential of using simulation software to estimate a building's structure's dynamic response, there are still some challenges inherent in the approach. The main issue, beyond the time-consuming nature of the software, is that the results tend to lack crucial information on a building's fast dynamic behavior. This lapse in data is caused by the software using a discrete time step which is usually set for one-hour time frames. In this case, if data are required related to the fast-dynamic behavior of a specific control strategy such as ON/OFF, these data will be unobtainable, as they are located within the one-hour time step. Such issues can cause system-wide problems and skew results due to data scarcity.

S. J. Carew building with an interior size of 25,142 m^2 is used as a case study. The building is located on the campus of Memorial University, St. John's, Newfoundland. There are four individual air-handling units (AHUs) in the building. Figure 1.1 shows clearly the apply fan and the heat exchanger of the AHU_1. There is some reasoning for selecting the S.J.Carew building. The energy inefficiency and cost inefficiency comparing with buildings on the campus. The building has four AHUs and Four floors that is means each level has AHU separated, although it will be easy to present the model as Multi-Input/Multi-Output system with 12 inputs and 12 outputs.

Also, there are some issues for heating system such as the valves of some radiators on the third floor, some of the rooms in this floor have just one thermostat.

Figure 1.1 Apply fan and the heat exchanger of the AHU_1

Figure 1.2 shows the building of the central heating plant at the campus, which supplies hot water for most buildings on campus at temperatures as high as 168 °C by the primary side (red pipes), as shown in Figure 3.1. Each building has heat exchangers to reduce the high temperature to 81 °C, approximately as shown by the secondary side in the figure. Also, the figure illustrates two return pipes (pink pipes). The first one retunes from the building, and another one returns directly from the heat exchangers.

Figure 1.2 The main campus heating plant

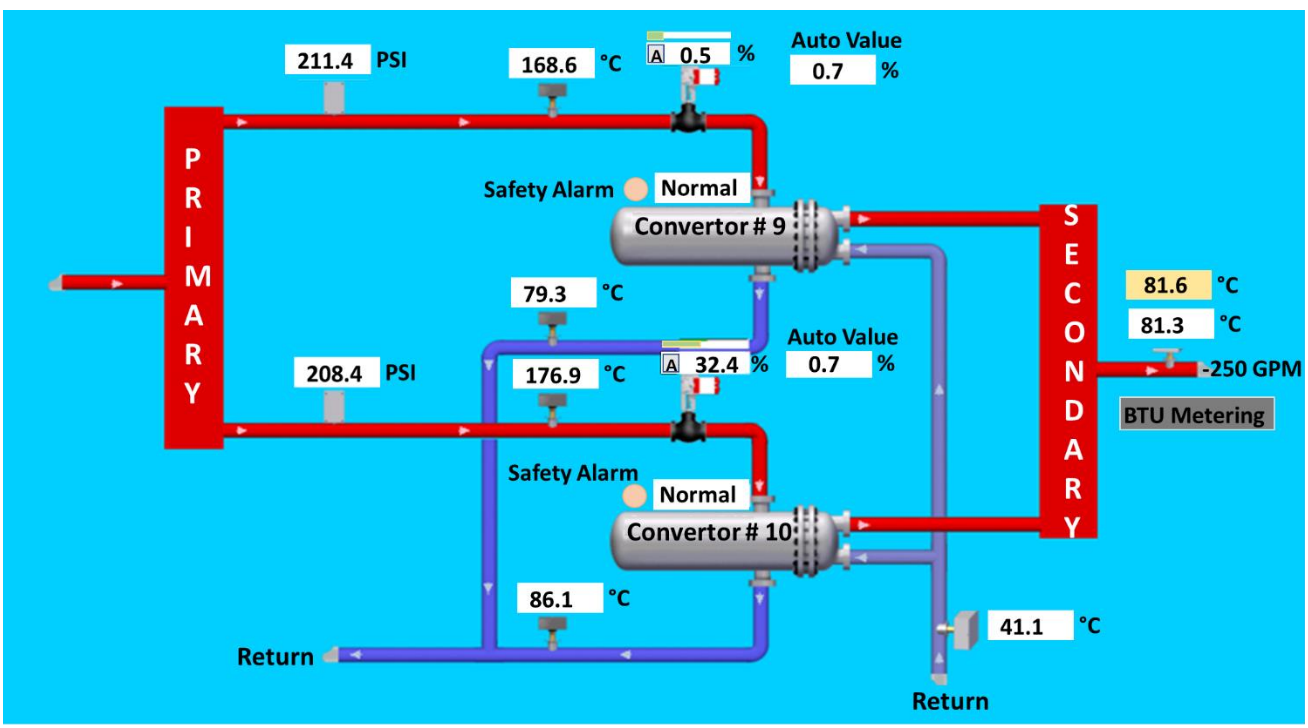

Figure 1.3 Main heat exchangers (Convertor 9 and Convertor 10)

1.2. Literature review

1.2.1. Modeling of the system

In the literature, these models of the HVAC system, which are having the inputs and output data classified as system identification (SI) models. Earlier research classified modeling methods as either a gray box or a black box. In the grey box approach, pre-existing knowledge was required to build the model, whereas none was required for the black box approach. Hence, the black box modeling strategy has become more popular with researchers. In relation to HVAC systems, some examples of black-box models include polynomial forms (e.g., ARMAX, ARX, OE, and BJ). Despite its ease of use, the black box approach often ignores the physical properties of a system and presents design problems implemented in a suitable environment.

There are several examples of black box strategies being employed in recent research. For instance, Chi-Man Yiu et al. [9] applied the black box method to air-conditioning systems by comparing two ARMAX models. One of the models was a single-input/single-output system, and the other was a multi-input/multi-output (MIMO) system. In their MIMO system model, Chi-Man Yiu et al. [9] applied parameters obtained from recursive extended least squares calculations. Another research group that worked recently with the black box method is Mustafaraj et al.[10], who looked at humidity and temperature models (ARMAX, ARX, OE, AND BJ) in commercial office buildings. In [11], these same researchers employed nonlinear auto-regressive models (with NARX inputs) to measure humidity and temperature levels. They then compared their test results with results from linear ARX models. Mustafaraj et al. [11] also investigated how CO_2 concentrations impact model performance, based on the understanding that a building's occupancy levels are related to CO_2 levels. In related work, Rabl [12] modeled heat dynamics to perform dynamic analysis of energy consumption, while Sonderegger [13] and Boyer et al. [14] did essentially the same thing but using differential equations instead. Note that, in dynamic models, system identification and parameter estimation are considered by many researchers to be the self-same process of investigation.

Recent research points to the validity of applying system identification (SI) as the ideal method for energy simulation when the aim is to analyze a building's heating and cooling systems. In [15], Lowry and Lee used a data-driven model for estimating thermal response, while in [16], Madsen and Holst employed a similar SI strategy, using data from discrete time performance to estimate the heating dynamics in a building. In [17], Cunningham used the SI approach to calculate a building's moisture release rates according to psychometric data, and Mechaqrane and Zouak in [18] applied SI to estimate air temperature readings in apartment buildings. Other studies compared test models and theoretical estimations by employing simulation software (e.g., TRNSYS). Utilizing a strategy that employed a one-hour time step, Peippo et al. in [19] applied simulation software to estimate a building's dynamics based on discrete time results calculated in simulation software.

The present work employs the grey box approach to model dynamic systems, as this strategy allows information on a building's thermal characteristics to be harvested [20]-[22]. In general, grey box models use continuous time stochastic differential equations as well as discrete time measurement equations. By utilizing performance analysis tools (e.g., IDA-ICE, TRNSYS, HVACSIM+, energy plus and eQUEST) set to one hour or fewer timeframes, it is possible to estimate the annual energy consumption of a specific HVAC system by applying a set of equations that express the system's thermal performance. These estimations can be further refined by comparing full- or part-load performance results for different design options [23]-[26].

A cursory review of the literature shows the evolution of HVAC systems. When the systems were first introduced, the modeling focus was on heat and humidity levels [27]-[31]. Then, a nonlinear HVAC model based on a temperature/humidity ratio coupled with an observer that gauged thermal/moisture loads was debuted [27], [28], which led to the development of an adaptive fuzzy output feedback controller [29] based on the HVAC system observer. Next, researchers built a model featuring a decentralized nonlinear adaptive controller [30] as well as a back-stepping controller [31]. Subsequent research focused on getting rid of CO_2 concentrations in the interior environment, as these have negative effects on the general level of user comfort [32], [33]. From these investigations came a hybrid HVAC system which could maintain the temperature at contiguous states while dealing with CO_2 concentrations as discrete states [34], [35]. However, because the continuous and discrete states are interdependent, integrating these two dynamics in a model would be the logical next step. A dynamic system's current state predicts that system's future development, based on interrelated variables. Hence, control systems, by aiming for specific control targets, essentially form a stable state from a non-linear system.

1.2.2. Control strategies

In current AHU unit system design, a strategy known as feedback linearization is used extensively [36]-[38]. Utilizing state feedback to develop subsequent system dynamics creates a multi-input system which is controllable via a linear state model. Feedback control is then developed by way of a step-by-step procedure devised according to closed-loop eigenvalues inserted at specific points. For more details on this process, please see Chapter 3. The outcome of this development has led to intelligent systems, as explained below.

Intelligent systems form the basis for Building Intelligent Energy Management Systems (BIEMS). The primary aim of BIEMS is optimizing energy consumption in a structure while also optimizing the structure's interior comfort levels. In general, BIEMS tend to be used mostly in large commercial or industrial buildings (e.g., office towers, hotels, and university facilities) for controlling and tracking the structure's environmental parameters to develop a range of suitable yet cost-effective microclimates. Following the somewhat successful application of conventional control systems in BIEMS, intelligent systems have shown enhanced improvement when conventional systems are replaced with fuzzy or even neural techniques [39]-[42].

Conventional control approaches require the use of a structure's operations as a mathematical model, whereas intelligent systems do not require mathematical or indeed any modeling. Through the application of intelligent controllers in a system, there is no need to gauge variables like temperature, air speed or humidity [43]. Instead, comfort levels can be chosen by employing optimized fuzzy controllers that utilize adaptive control strategies informed by genetic algorithms. The newest furnace installations in homes are using fuzzy logic control via adaptive heating control to enhance comfort levels while ensuring better energy efficiency and lower costs [44]. Fuzzy controllers have also been installed for modulating air flow, with impressive results [45], [46].

Although there are many different methods for using fuzzy logic as closed-loop control, fuzzy PI controllers are the most popular [47], [48]. This approach employs process-derived measurement signals for the fuzzy logic controller (FLC) inputs/outputs to the actuators. Generally speaking, a fuzzy PI controller is essentially an incremental controller. Equation (4.1) expresses a traditional fuzzy PI controller where fuzzy rules dictate the outputs [49]. For additional details on FLCs, please refer to Chapter 4 on the FLC in AHU_1.

Since the introduction of HVAC systems around four decades ago, numerous control approaches have been developed in the research and industry for use in various applications (e.g., Honeywell [50]; Levenhagen and Spethmann [51]; Wang and Jin [52]; Zaheer-Uddin and Zheng [53]; Hordeski [54]; Haines and Hittle [55]; Nassif et al. [56]; Wang [57]). In the developed methods, primary supervisory control is especially popular and has been categorized as either model-based or model-free, as well as hybrid or performance map-based. In [58], Kanagaraj, Sivashanmugam, and Paramasivam looked at tuning input scaling factors in controllers using parameters based on error and process in closed-loop systems. The purpose of their research [58] was to improve the controller's performance for setpoint change and load disturbances with the online setting method, which significantly reduced operator input. This method uses an intelligent upper-level supervisory fuzzy controller (for introducing suitable changes to achieve the main goals of the system) and a lower-level direct fuzzy controller (for providing resolutions to issues that might arise).

A couple of years later , Soyguder, Servet, Karakose, and Alli [59] applied Simulink as a basis for modeling HVAC systems with variable flow-rates. Their fuzzy adaptive controllers, which featured self-tuning PIDs for allocating PID parameters in Kp (Proportional gain), Ki (Integral gain), and Kd (Derivative gain), performed equally as well as conventional PID or fuzzy-PD type controllers. Shepherd and Batty [60] applied a high-level fuzzy supervisor to make control decisions. The goal of the strategy was to improve air quality, lower costs, and regulate temperature through the use of a modified fuzzy supervisor. Their test results showed the viability of their approach in achieving their stated outcomes.

In [61], Lianzhong and Zaheeruddin developed a non-linear dynamic model to heat water in HWDH systems using an intelligent fuzzy logic-based hybrid control approach. The results of the fuzzy logic-based PI simulation tests showed improvements in water return temperature, especially when the approach included IATP methods in zonal air temperature control. The results also showed that lower power consumption led to improved energy savings of around 17%. Improving energy consumption was the main aim in research conducted in [62], where Hussain, Sajid, and Gabbar employed GAs to tune an FLC. Their test results indicated that their air conditioner provided 15% more energy savings than those which used basic ON-OFF controls. Additionally, the discomfort index fell from 91% to 62%. Finally, researchers in [63] proposed lower- and higher-level controllers, with the lower level being a conventional PID controller and the higher-level being a fuzzy controller that controlled the parameters of the lower-level.

The present research uses a fuzzy control approach for improving energy and cost efficiency as well as thermal/air quality comfort levels in an interior environment. Because fuzzy controllers are able to collaborate with incomplete control process models, these "flexible" fuzzy models enable the modeling of non-linear processes, which can then be applied in HVAC systems (which are nonlinear). Furthermore, the multi-input/multi-output parameter options in a fuzzy controller are easily controlled.

1.3. Research objectives

There are six primary aims in this study.

1. Our first aim develops a simulation for a whole building, using IDA Indoor Climate and Energy 4.7 as a simulation program and compare this data with actual data from the Department of Facilities Management at Memorial University using the structure's hot water and power usage for the whole year 2016.
2. The second aim is to test system identification viability as a means for shortening the calculation times needed to simulate more complicated structures in Air Handling Unit One (AHU1).
3. The third aim is to test the usefulness of system identification in the identification of the dynamic for structural climate control design when applying discrete time data for one-hour samples.
4. The fourth aim is to develop a state feedback controller and then apply it toward the optimal functionality of a control system.
5. Fifth aim to develop fuzzy logic controller FLC structures that feature six inputs and three outputs and use this to develop a controller in an AHU1 state space model.
6. The sixth aim is to develop supervisor fuzzy logic controller SFLC that features 24 input and 12 outputs for all building — modeling building each floor as a separate system results in four spatial

models that offer the advantage that the rules of the supervisor controller are reduced to 180. Also, by adding additional rules between the entry steps, the SFLC can control energy-saving features and results in an improved performance in the heating and cooling of buildings.

To achieve the stated objectives, the following steps need to be taken:

1. Employ a commercially available computer simulation program which has the ability to measure/model a building's temperature, CO_2 levels, and static pressure. This program should also be able to measure/model the building materials' moisture retention and total energy recovery, and ultimately be able to develop a building model which uses these measurements to include four air-handling units as features.

2. Run simulations of HVAC systems on the four air-handling units, measuring individual room comfort levels (e.g., static pressure, temperature, etc.) and gauging the system's energy usage.

3. Use MATLAB to run a series of simulation tests to measure the performance levels in potential and adopted control strategies.

4. Following the adoption of control algorithms and rules, apply theoretical analysis to measure overall control performance as well as the specific 'pros' and 'cons' of individual controls.

5. Using Honeywell software data, analyze control performance and any enhancements to the quality of the indoor environment.

1.4. Challenges of the research

In addition to the steps outlined above, several issues related to the design of the building and controller must be resolved if the stated objectives are to be achieved. The most important of these issues are listed below, in no particular order.

1. MATLAB and Simulink are used for the simulation tests and involve a fuzzy logic controller. Using this particular controller design, we will not be able to measure the system's consumption levels.

2. The construction maps referred to in the project are dated and do not include recent renovations and additions such as the Suncor portion of the building or the cafeteria.
3. Several of the inputs/outputs (e.g., number of occupants, wind direction, etc.) cannot be validated during system identification.
4. There are numerous kinds of pollutants in a typical building, not all of which need to be monitored and/or controlled. This makes indoor air-quality monitoring a very complex situation. Overall, however, the controller should provide good adaptability, fast response, small degrees of overshoot, and an intelligent algorithm that is coded to the building's needs. So, for instance, the present control strategy takes certain concentrations of CO_2 in the indoor environment for a control signal, but it can be impacted by issues related to loosely defined parameters or improper (i.e., faulty) measurements. Therefore, the controller needs an intelligent algorithm which is not only has a fast response time but is also highly adaptable to changing circumstances.
5. Simulation tests performed during the winter months, which means that we were only measuring and recording system variables for the heating process (not the cooling stage). Because the weather is very cold in this region for most of the year, that is means the heating system always on all the year, and we can see that clearly in the table of consumptions of the energy in next chapter.
6. The software uses boilers as a hot water supply, whereas the primary hot water supply for the entire building comes from the main room.
7. Numerous pieces of equipment and moveable infrastructure, such as cookers, fridges, freezers, TVs, computers, etc., were not taken into account in the heating/cooling features, even though they can contribute significantly to these elements.

1.5. Organization of the thesis

This thesis is organized in a manuscript format, including four journal papers as chapters. The journal papers completed during the research and demonstrates the objectives and related tasks. The overview of each chapter is explained as follows:

1. In Chapter 2, we model the S. J. Carew building on the campus of Memorial University, St. John's, Newfoundland by employing the simulation tool IDA Indoor Climate and Energy (IDA-ICE) 4.7. We then look at energy consumption in the Carew Building before developing an IDA-ICE model library as well as 3D and heat models. We use the IDA-ICE for examining various climate zones in the structure's interior environment. Overall, the four main objectives of Chapter 2 are as follows:
   1) Use the tool IDA-ICE to model the S. J. Carew building.
   2) Do a comparison of the structure's logged data with IDA-ICE data in order to determine energy consumption differences (if any).
   3) Measure time-saving values (if any) in using the system identification (SI) method for simulating the structure.
   4) Apply the results from the system model simulation to determine whether there are any dynamics associated with the Carew building's interior climate control.
2. In Chapter 3, we apply real-life data for the whole building and validate the results. We also examine the usefulness of system identification (SI) for time-reduction in simulation calculations for large buildings. As well, we gauge the usefulness of SI in identifying climate control dynamics when employing samples of one-hour discrete time data. Finally, in Chapter 3, we also investigate the validity of a state feedback controller using a state space model.
3. In Chapter 4, we use the IDA-ICE 4.7 tool to build a simulation for the S. J. Carew building. Launched in 1998, the IDA-ICE energy program was developed to study thermal climate zones.

Our simulation tests power usage for both heating and cooling and will comparatively look at results presented in where real-life data were applied to build systems for entire structures.

The three main aims of the present study are as follows:

i. To test the applicability of using SI to reduce the time required for calculations related to simulating complex structures found in AHU_1.

ii. To test SI's viability to identify dynamics in structural climate control design using one-hour discrete time data.

iii. To build fuzzy logic controller structures with six inputs and three outputs and then apply these structures as controllers for the AHU_1 state space model.

4. In Chapter 5, our primary aim is to optimize the developed model to satisfy the system's real-life demands. As the Carew Building features four AHUs, the state space model is best suited for our stated purpose. Furthermore, as our SI data were harvested during the winter months (November to April), the air conditioner was not being used at that time. There are four AHUs in the S. J. Carew Building (one AHU for each floor), which feature three inputs $[U]$ and three outputs $[Y]$ each, or 12 inputs and 12 outputs in total. The three inputs are: 1) fresh air (external source), 2) supply fan speed, and 3) hot water valve (for heating coil/zones radiators), while the three outputs are: 3) CO_2 levels (measured as parts per million [PPM]) to regulate fresh air dampers., 2) static air pressure P_S (measured as inch in water [INW]) of the ducts to regulate supply fan speed, and 3) return air temperature to regulate hot water valve aperture. Please refer to chapter 4 for detailed information on the state space model applied in the AHU_1 controller design. Overall, the present research aims to investigate the following:

1) A fuzzy level control approach which regulates the four AHU outputs to consistently maintain the desired temperatures, static air pressure, and CO_2 concentrations.

2) The optimal strategy or strategies in using fuzzy control to obtain the most suitable outcome (i.e., action) in every parameter, to be determined parameter by parameter.
3) Whether the proposed fuzzy supervisor can successfully determine if an action is beneficial or not to the entire system regarding overall performance levels.
4) Whether the proposed fuzzy supervisor is able to control energy savings towards the building's overall performance levels of heating and cooling, with the individual demands of every floor being considered in the performance evaluation.

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Chapter 2

2. Modeling, Energy Consumption Analysis of a Large Building at Memorial University

Preface

A first manuscript has been submitted in the Journal of Energy at Hindawi. I am the primary author of this journal. Along with the co-authors, Tariq Iqbal and Kevin Pope, I model the S. J. Carew building on the campus of Memorial University, St. John's, Newfoundland by employing the simulation tool IDA Indoor Climate and Energy (IDA-ICE) 4.7. We then look at energy consumption in the Carew Building before developing an IDA-ICE model library as well as 3D and heat models. I conducted the literature review, performed the simulation, and analysis the results. The co-authors helped in providing reviewed and corrected the achieved results and contributed in preparing, reviewing and revising the manuscript. Also, contributed through support in the conceptual development of the study, research methodology design, analysis, and discussion of the results.

Abstract

In this paper, energy consumption analysis and a process to identify appropriate models based on heat dynamics for large structures is presented. The analysis uses data from heating, ventilation, and air-conditioning (HVAC) system sensors, as well as data from the indoor climate and energy software (IDA Indoor Climate and Energy (IDA-ICE) 4.7 simulation program). Energy consumption data (e.g., power and hot water usage) agrees well with the new models. The model is applicable in a variety of applications, such as forecasting energy consumption and controlling indoor climate. In the study, both data-derived models and a grey-box model are tested, producing a complex building model with high accuracy. Also, a case study of the S. J. Carew building at Memorial University, St. John's, Newfoundland, is presented.

Keywords: State space model, building modeling and simulation, IDA-ICC program, HVAC, energy consumption, system identification.

2.1. Introduction

Heating, ventilation and air conditioning (HVAC) systems are crucial for indoor climate management and air quality. These systems are also a key factor in overall operational costs. For industrial buildings, nearly one-third of the energy usage depends on HVAC system operation [1]-[3]. The recent rapid industrialization of the world's developing nations has led to an increase in energy demand, followed by a rapid rise in pollution levels. As a result, researchers are investigating ways to mitigate or prevent further environmental damage through a combination of conservation methods and wide-scale adoption of renewable energy systems [4].

Ideally, HVAC (heating, ventilation, and air-conditioning) systems are developed to form an interior environment that provides user-comfort with operational cost-efficiency. To maintain consistent user-comfort and affordability amidst changing variables, a suitable control system is needed. Several options have been modelled. One popular method uses data to create a mathematical-based HVAC system that considers input and output variables to find and set system parameters. Data-driven HVAC can readily identify strategies for system refinement and enhancement. These types of model determination are termed system identification (SI) in the literature (ASHRAE, 2005) [5].

In previous studies, researchers categorized modeling approaches into two main types, namely black box and grey box. For the black box method, no prior information is required, but for the grey box strategy, there must be a reservoir of pre-existing knowledge. Due to these constraints, the black box modeling approach is generally better represented in the literature. Examples of black box models applied to HVAC systems are polynomial forms such as ARX, ARMAX, BJ, and OE. Despite its popularity, the black box model strategy overlooks the physical features of a system, leading to issues around the practical application in real-world designs.

For example, Chi-Man Yiu et al. [6] looked at black box strategies for air-conditioning systems. The researchers contrasted two ARMAX models – the first, a single-input / single-output system, and the second, a multi-input / multi-output (MIMO) system. For the MIMO system, Chi-Man Yiu et al. [6] employed parameters derived from the recursive extended least squares method. Mustafaraj et al. [7] investigated temperature and humidity models (ARX, ARMAX, BJ, and OE) for office environments, using a black box approach. The same researchers [8] continued their work by applying nonlinear auto-regressive models with NARX inputs to gauge temperature and humidity levels while comparing and contrasting the outcomes for these models with those of linear ARX models. Additionally, Mustafaraj et al. [8] examined CO_2 concentrations' effect on model performance, considering that occupancy levels in a building are directly correlated to CO_2. Rabl [9] provided a summary of approaches applied for dynamic analysis of power usage by modeling heat dynamics. These models were applied in studies by Sonderegger [10] and Boyer et al. [11], using differential equations. For dynamic models, parameter estimation and system identification are essentially the same processes.

This research uses the Gray Box method to model dynamic systems. This precise and global approach makes it possible together, information about the thermal properties of structures [12]-[14]. Gray box models use discrete timing equations and continuous time stochastic differential equations. An HVAC system's yearly power usage can be predicted using energy performance analysis tools, such as SIMBAD, EnergyPlus, eQUEST, HVACSIM+, IDA ICE, and TRNSYS at set time frames (hourly or less) in accordance with a set of equations is describing a building's thermal performance. Calculations comparing various design options are usually made for part-load and full-load performance [15]-[18].

This paper simulates a whole building (the S. J. Carew building in St. John's, Newfoundland) using the IDA Indoor Climate and Energy (IDA-ICE) 4.7 simulation program. In addition to examining the modeled structure's power use, the study investigates a 3D model, a heat model (with variable parameters), and an IDA-ICE model library. The IDA-ICE was developed to investigate different thermal climate zones occurring in indoor environments [19].

Exact details of the construction of the building and logged data from Honeywell software use as the detail to build the model of the building in IDA-ICE software. We propose 12 inputs and 12 outputs dynamic model for the system. The dynamic model is required to design and test system controllers before actual implementation. To determine a state space system model, we use the Matlab system identification toolbox. For the model determination, we used data from IDA-ICE software. Contributions of this paper are building data, a proposed system dynamic model, a method to determine the system model, and developed system dynamic model parameters. The primary objectives of this paper are:

1. Apply the IDA-ICE software to model the S. J. Carew building (Memorial University, St. John's, Newfoundland), all real dimensions and building materials information are available. This is the reason for selecting the building, which the Department of Facilities Management and the Honeywell office are responsible for running and monitoring the system.
2. By using the IDA-ICE software we can divide the single valve of hot water coming from the main room to four distinct units, enabling each air-handling unit (AHU) to have an individual valve for control the mechanical hot water flow for each zone as another input of the system are supply fan speed and fresh air dampers position.
3. Compare the data from the IDA-ICE software with the building logged data for validating the power use outcomes

4. Determine the potential of applying the system identification approach to reduce the time needed to simulate the building and use the system model simulation results in identifying the dynamics related to a building's climate control.

2.2. The building for this case study

A case study on the S. J. Carew building, with an interior size of 25,142 m^2 is conducted. The building is located on the campus of Memorial University, St. John's, Newfoundland, and includes several teaching rooms and research labs for the Memorial's Faculty of Engineering and Applied Science. The building also features a large cafeteria. There are four individual air-handling units (AHUs) in 300 zones within the building. Figure 2.1 illustrates a 3D model for the structure, applying the IDA-ICE software mentioned in the previous section, while Table 2.1 provides an energy report.

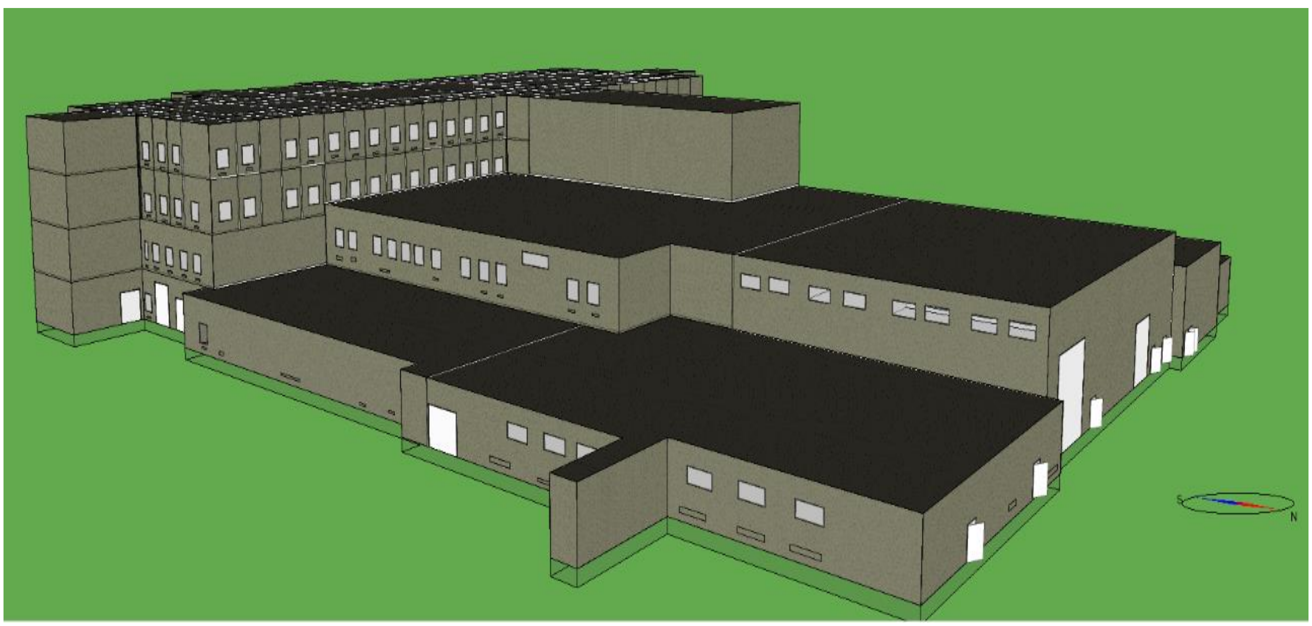

Figure 2.1 3D model for the structure

Table 2.1 Energy report for the building.

EQUA SIMULATION TECHNOLOGY GROUP		Input data Report		Building envelope					Windows					
Project		Building		Building	Area [m^2]	U [W/(m^2 K)]	U*A [W/K]	% of total	Side	Area [m^2]	U Glass [W/(m^2 K)]	U Frame [W/(m^2 K)]	U Total [W/(m^2 K)]	U*A [W/K]
Customer		Model floor area	25141.7 m^2	Walls above ground	7450.19	0.54	4002.24	44.85	N	174.36	2.86	2	2.77	483.51
Created by	Almahdi Abdo-Allah	Model volume	128952.9 m^3	Roof	10529.8	0.17	1811.13	20.3	E	131.08	2.86	2	2.77	363.49
Location	Newfoundland (St. John's Airport)_718010	Model ground area	10544.5 m^2	Windows	713.73	2.77	1979.24	22.18	S	213.24	2.86	2	2.77	591.35
Climate file	CAN_NF_St.Johns.718010_CWEC	Model envelope area	29440.0 m^2	Doors	201.72	0.59	118.38	1.33	W	195.05	2.86	2	2.77	540.89
Case	building2017_AHU8	Average U-value	0.3031 W/(m^2 K)	Walls below ground	0	0	0	0	Total	713.73	2.86	2	2.77	1979.24
Simulated	1/19/2017 22:04	Envelope area per Volume	0.2283 m^2/m^3	Floor towards ground	10544.5	0.09	991.82	11.11						
				Total	18567.2	0.41	7689.82	100						

2.3. Simulation Tool

The S. J. Carew building is modelled by employing IDA-ICE as a dynamic thermal simulation tool. This program is selected because it is widely accepted as a viable thermal building performance simulator towards the study of power usage and indoor thermal climate of whole buildings [19]. The IDA-ICE software uses symbolic equations framed in a modeling language and a variable time-step differential-algebraic (DAE solver). The models, which can be expressed through Neutral Model Format (NMF)/Modelica and act as both computer code and readable document, which are applicable to various simulation environments [20], [21].

The simulation tool IDA-ICE 4.7 is employed to predict the power usage and interior climate of the S. J. Carew building. The IDA-ICE 4.7 tool is ideal for modeling of multiple-zone HVAC systems as in the S. J. Carew building. IDA-ICE 4.7 is able to determine the general thermal comfort level of the building by measuring the internal air quality (IAQ) and performing dynamic simulations. The heat exchanger uses controllers to maintain zonal temperatures, which can be set as fixed points by modulating control valves. Meanwhile, in the real system (as shown in Figure 2.2), a hot water valve collects relevant data for water heated by a heating coil. Although the building's system features a single valve for its hot water production, the IDA-ICE software divides the single valve into four distinct units, enabling each air-handling unit (AHU) to have an individual valve [22], [23].

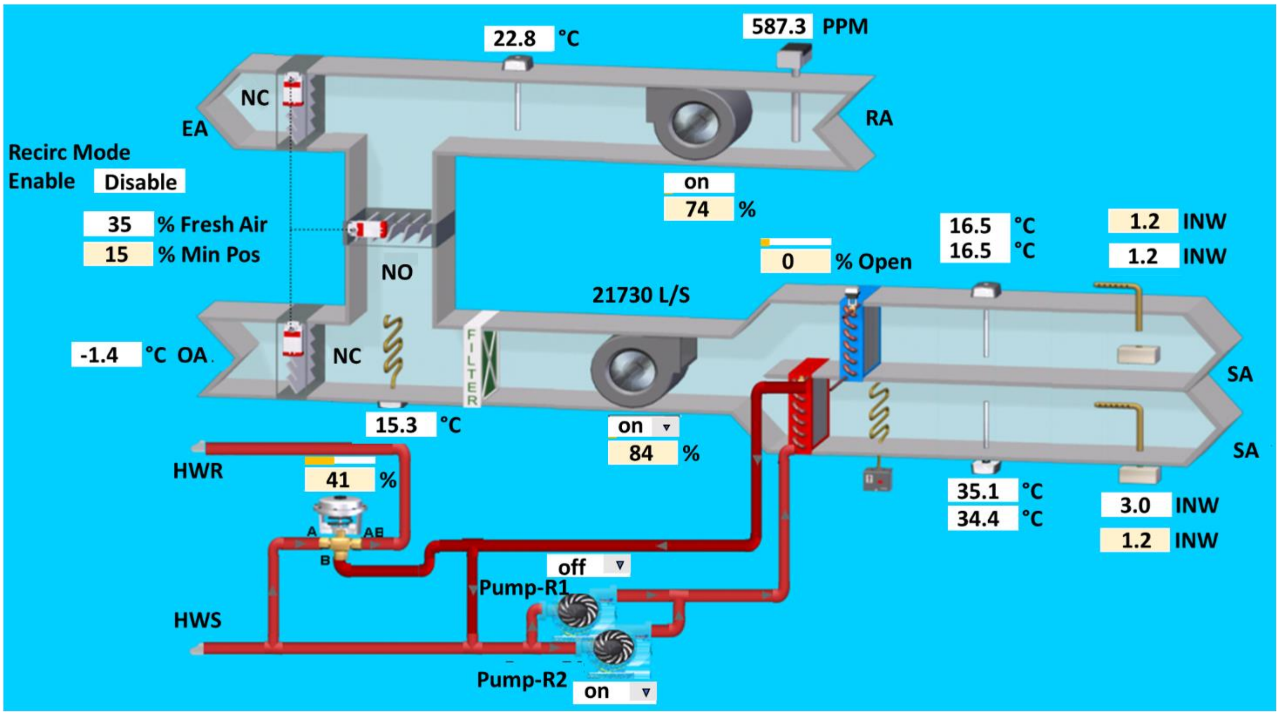

Figure 2.2 AHU_2 for S.J. Carew building

2.4. Building Model

IFC files were used to develop a simulation model from the building information model (BIM). As shown in Figure 2.3, the East side of the third floor features an AHU, and all floors in the building have their own individual AHU.

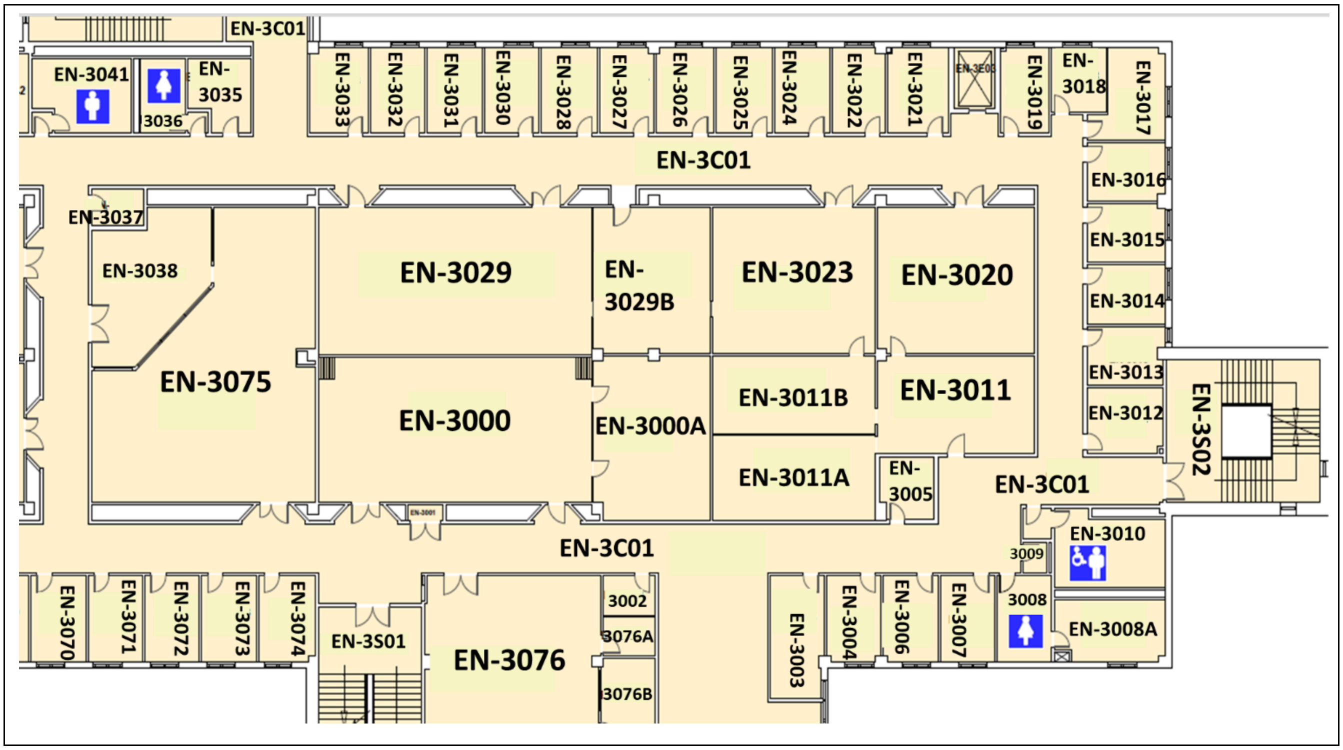

Figure 2.3 Third floor of the building

Data from the Facilities Management department at Memorial University were used to source construction information regarding building dimensions and elements such as windows, doors, and walls. The data then inputted to the IDA-ICE software.

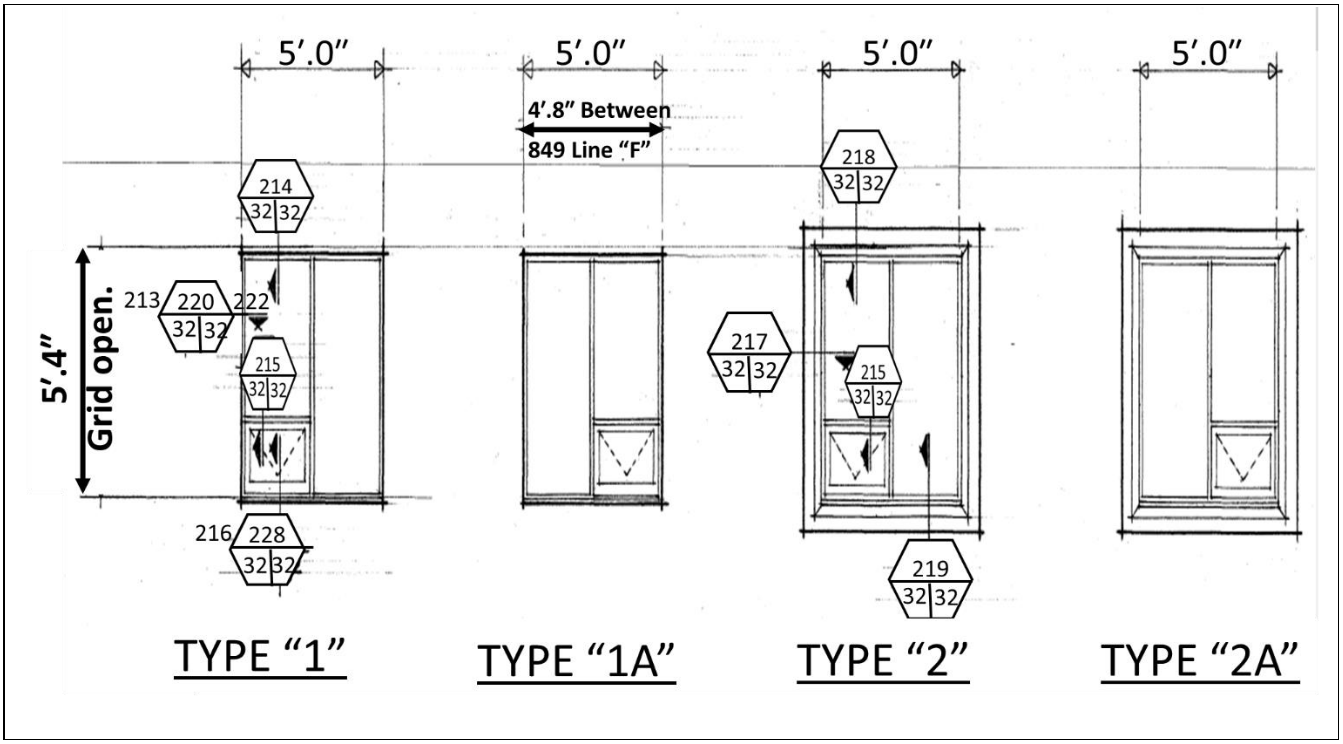

Figure 2.4 Details of windows used in the Carew building

Figure 2.4 depicts two of the eight different kinds of windows used in the Carew building, while Figure 2.5 illustrates the building's south elevation. Heating system information (e.g., radiator type and position) is presented in Figure 2.6, and Figure 2.7 depicts the main room's ventilation system for AHU_1, AHU_2, and AHU_3. Each of the areas has individual internals loads (i.e., occupancy and light based on floor type and usage) that have been determined by applying national building code monthly values. The ventilation design determines the supply and exhaust air flows, with standard commercial building pressure coefficients applied. There are doors dividing nearly all of the areas in the structure, enabling bi-directional air flow (even through closed doors). Air tightness is measured as an n50-parameter, while infiltration and exfiltration are simulated using the IDA-ICE air-flow network feature.

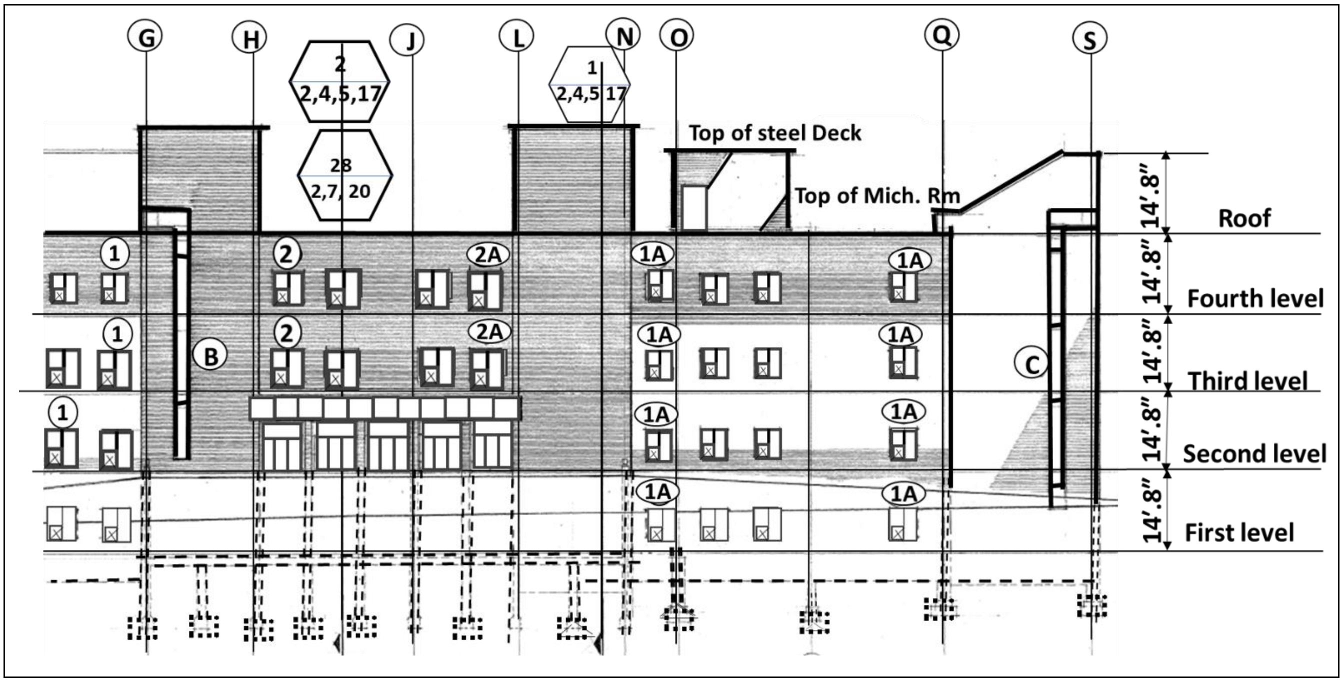

Figure 2.5 South elevation of the building

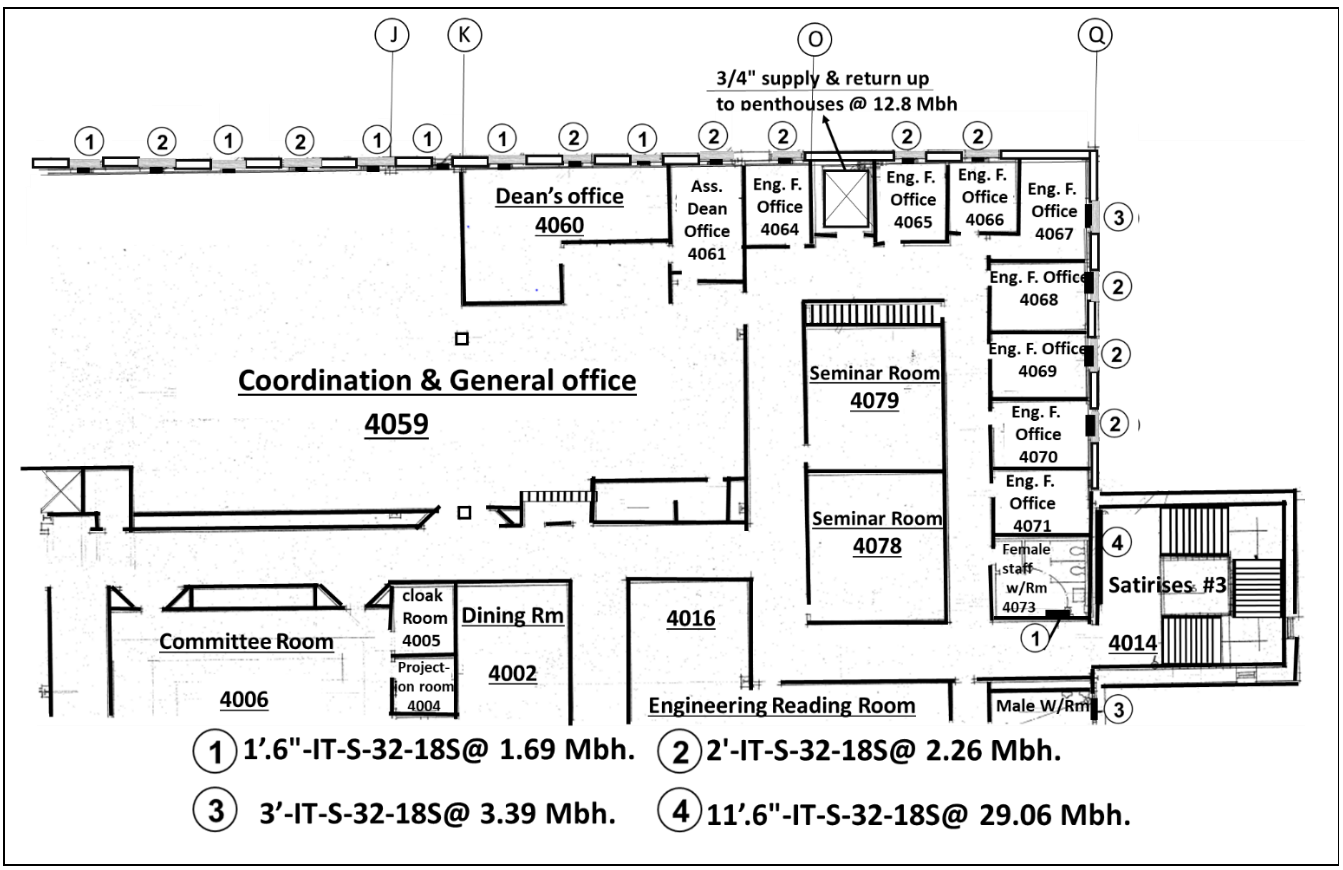

Figure 2.6 Fourth floor layout

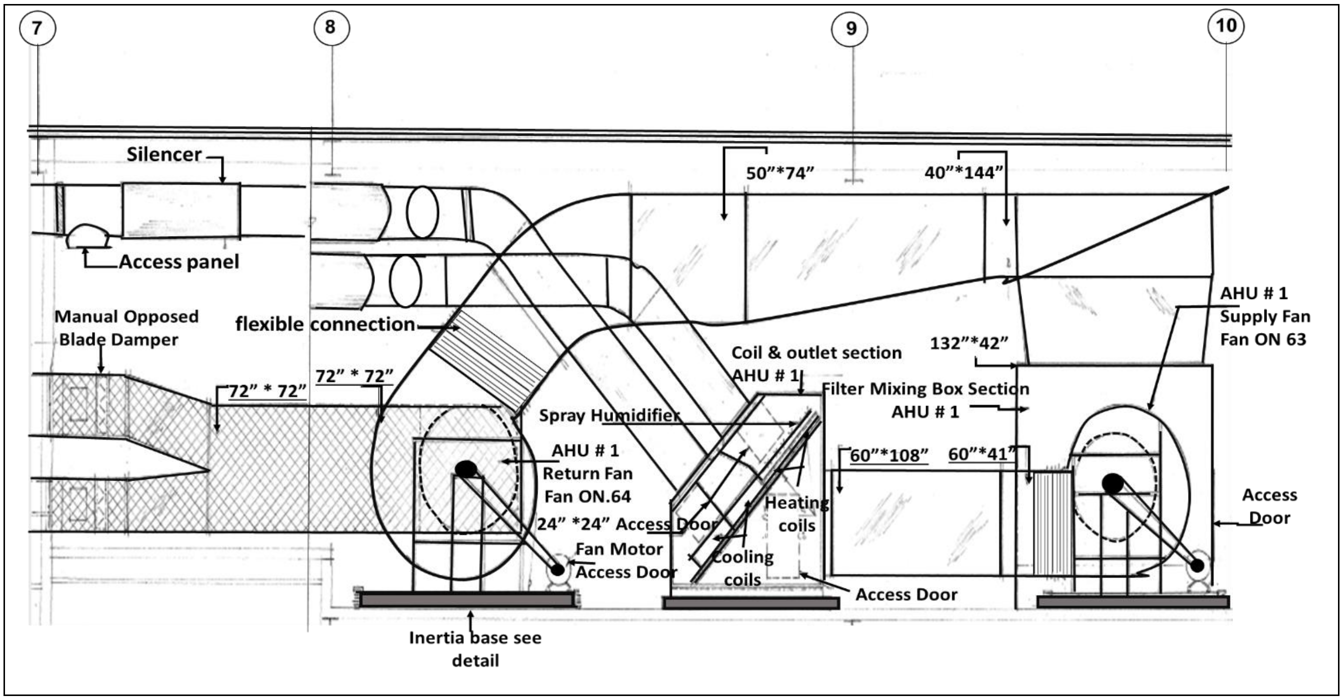

Figure 2.7 Main room's ventilation system

2.5. Simulation Results

The IDA-ICE 4.7 program was used to analyze energy use in the S. J. Carew building at Memorial University, St. John's, Newfoundland. The analysis involved a number of factors, such as weather data, infiltration, external/internal heat gain, and overall heat capacity. The simulation was done for the course of one full year (January 1, 2016, to December 31, 2016). The space heating and total energy consumption analysis results for the building are provided below.

2.5.1. AHU results

- AHUs temperature

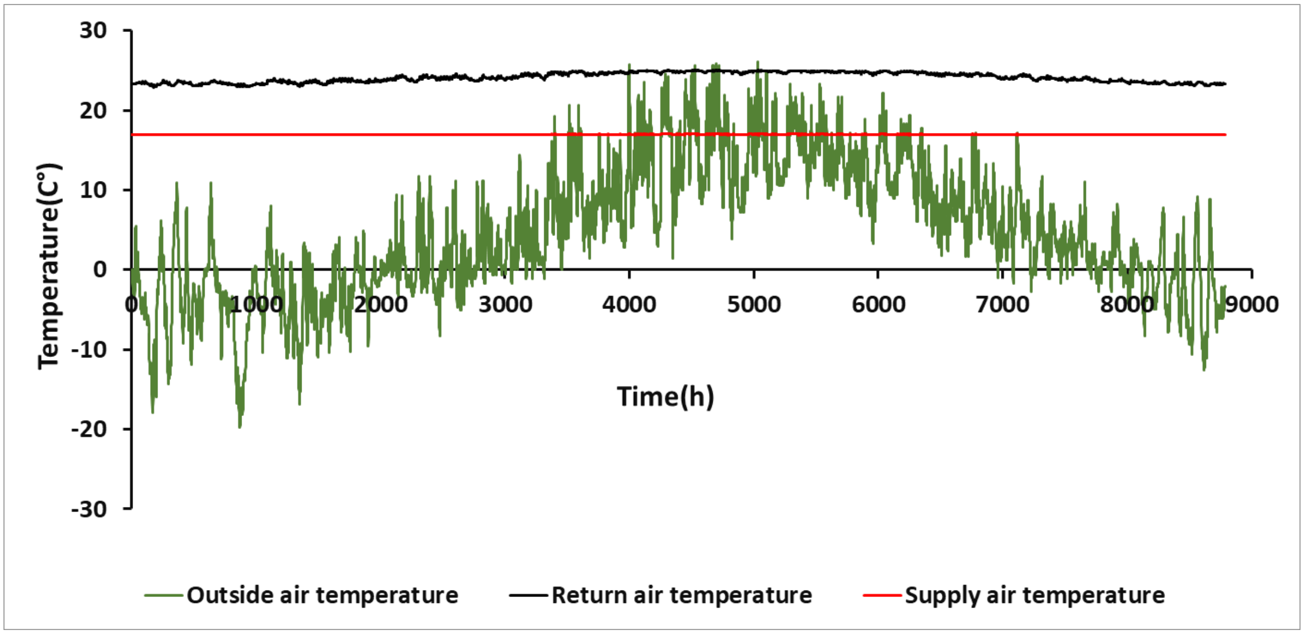

Figure 2.8 AHU_1 supply air, return air and outdoor air temperature

Figure 2.8 shows AHU_1 supply air and return air, as well as the outdoor air temperature. As can be seen, the air temperature represents a mixture of temperatures from individual zones, while the air supply temperature represents the temperature of the air terminal zone following any alterations made to the duct or fan systems. The supply air temperature set-point refers to the air temperature prior to these alterations.

- AHU airflow

The flows represent the total flow from every zone impacted by AHU_1 (Figure 2.9) and have been multiplied according to weight (i.e., how many zones are the same type). This value is included in every zone. The flow is volumetric and assessed for actual temperatures. Therefore, it can differ from the set-point flow for each zone. Set-point flows are determined from mass flows based on variations in density.

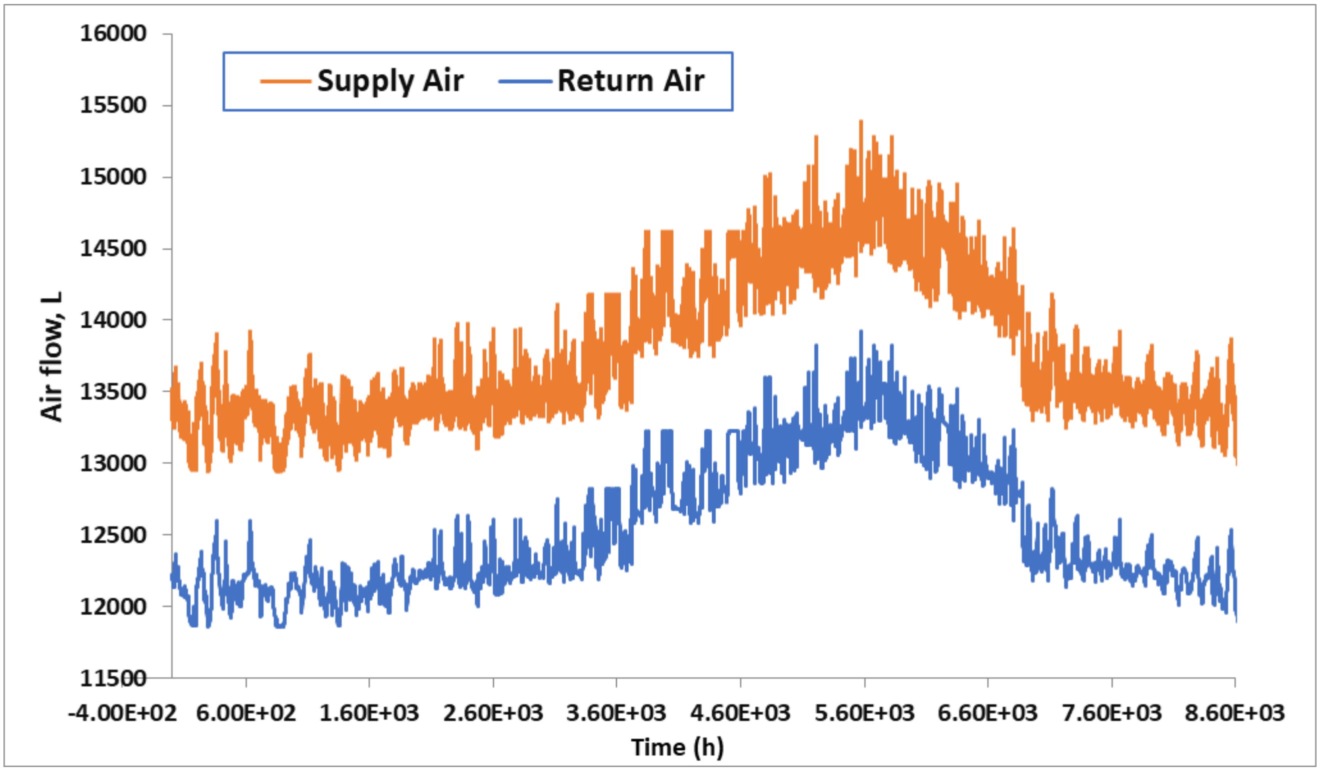

Figure 2.9 AHU_1 supply and return air flow.

- Heating and cooling AHUs coils

Figure 2.10 depicts the central cooling and energy for AHU_1. In circuits that are water-based, the energy consumption can be measured in the circuit according to temperature changes and mass flow (i.e., supply/return). Therefore, heat can be calculated after generation losses are included, but prior to the calculation of emission and distribution losses. Cooling energy is included as a positive quantity in the calculations.

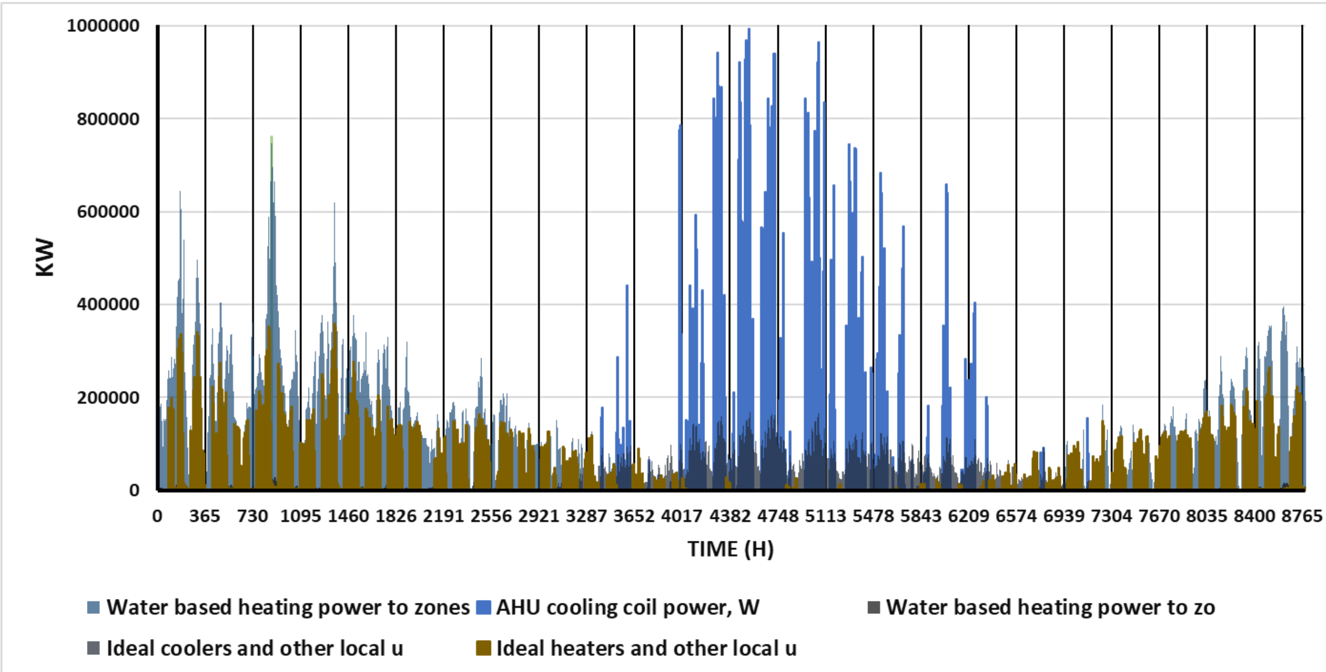

Figure 2.10 Central heating and cooling power of AHU1

2.5.2. Heat balance

Figure 2.11 depicts the zones' sensible (dry) and full latent (moist) heat balance. To find the sensible heat balance only, the details for the zone's power report need to be logged. In this set-up, the control volume indicates air-wetted surface area located at the room unit zone-side, backed by an air gap. Heat balance contributions can be allocated as follows:

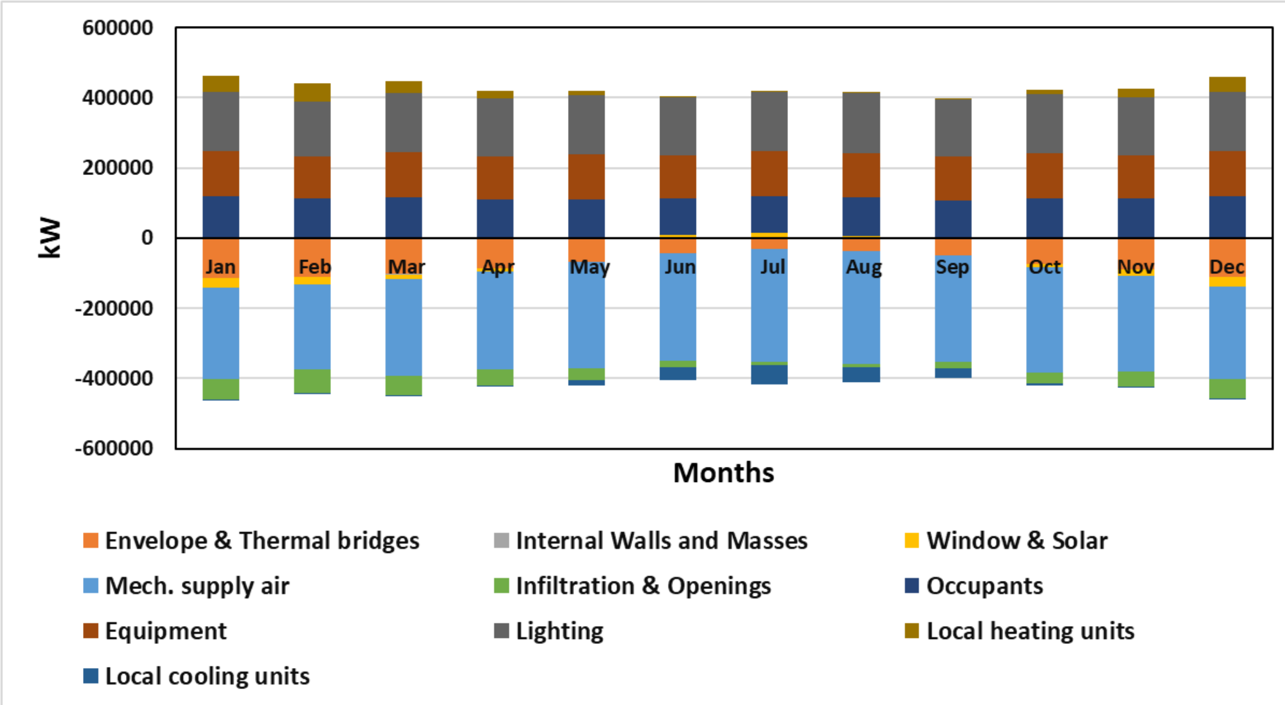

Figure 2.11. Results for building heat balance

➢ Equipment heat

This type of heat emanates out of equipment like printers and computers as a form of radiant or convective heat.

➢ Floor and wall heat

As the control volume is positioned directly below the surface of floors and walls, any measurement of heat indicates the presence of conductive heat passing through the structural element. This type of thermal energy can include net transmission and heat storage, in addition to internal heat functions (e.g., in-floor radiant heat). The thermal energy that has been stored as a function of room masses, such as in furniture, also is in this category.

➢ Daylight heat

This type of heat describes sunlight streaming into open doors or through windows, taking into consideration any shortwave radiation which exists. Solar radiation that has been absorbed and retransmitted is excluded from this category.

- Heating/cooling room heat

This type of heat is represented by controlled room units (e.g., radiators or chilled beams). In hydronic systems, there is an automatic calculation to account for the radiation and convection aspects, as described in the manual. Floor heating is excluded from this category.

- Window heat

This type of heat describes heat emitted from window surfaces, such as through retransmitted absorbed solar radiation or through conduction. Long-wave radiation entering via openings such as opened doors falls under this category of heat. Solar radiation can have two major impacts on a room's heat:

i. It can be absorbed by the window covering or pane and then emanate through the room as a radiative or convective process.

ii. It can be directly transmitted as short-wave radiation and be reflected by room surfaces until finally absorbed by internal room masses (furniture, equipment, people, etc.).

- Airflow heat

This describes all air flows, including infiltration, flowing from other zones and mechanical ventilation.

2.5.3. Energy delivered

The report on the energy delivered provides a general overview of total energy purchased or generated in the S. J. Carew building, as shown in Figure 2.12. The reported items are matched to the energy meters. The report also shows the primary form of energy employed, as well as the cost and estimates for CO_2 emitted. These are presented according to the structure's floor area and with regard to absolute values. Conversion factors from the meter energy to other measures are given as energy meters.

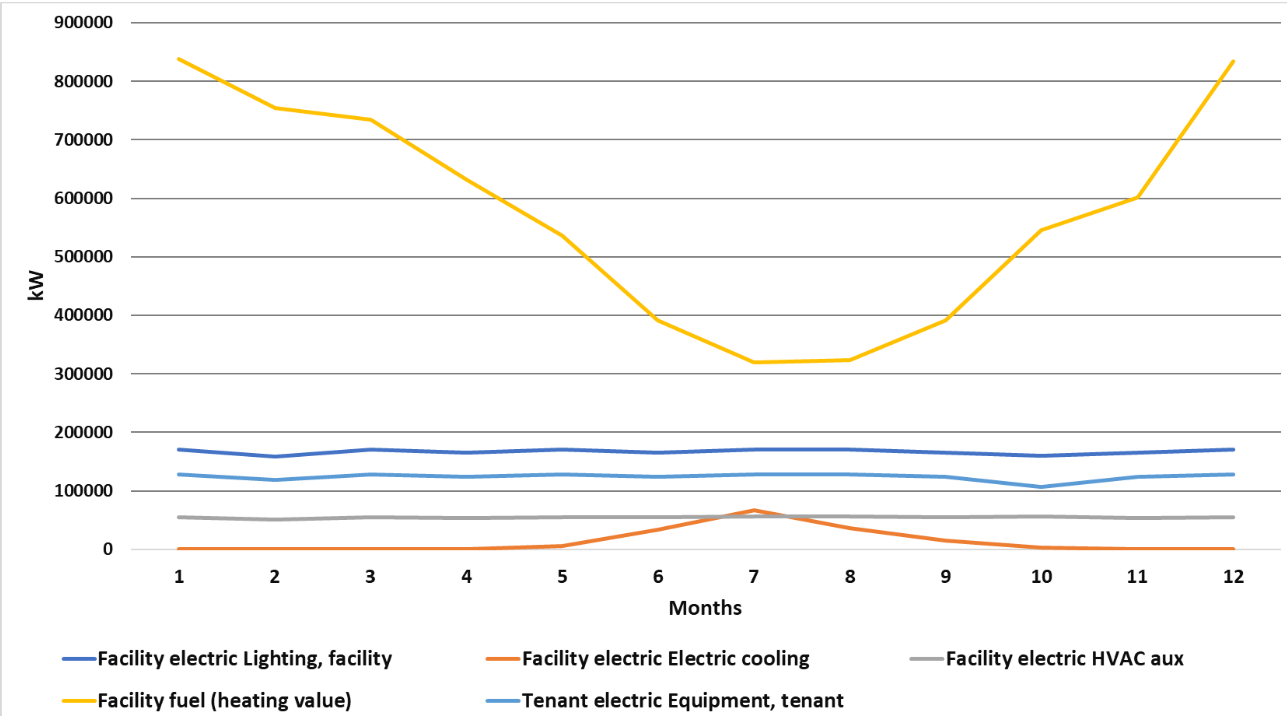

Figure 2.12 Energy delivered

2.5.4. Results – Energy from systems

The results also provide a general review for HVAC system energy flow. As shown in Table 2.2, the review is in three categories: use energy, AHUs heat and cold recovery, and auxiliary energy. The results provide a means to validate real data and then apply this data for system identification to obtain the Carew building's HVAC system's state space model.

Table 2.2 Energy use distribution

	Used energy						Auxiliary energy	
Months	Zone heating (kWh)	Zone cooling (kWh)	AHU heating (kWh)	AHU cooling (kWh)	AHU heat recovery (kWh)	AHU cold recovery (kWh)	Fans (kWh)	Pumps (kWh)
1	244041	108.9	104998	0	639269	0	54672	119.2
2	250651	100.8	108788	0	643065	0	51008	137
3	133363	844.5	99535	0	620252	0	54752	91.4
4	122152	1679	69885	0	527862	0	53215	53.9
5	110590	13874	7648	12537	404205	0	55451	31.4
6	9588.9	37040	5861.1	112465	215982	-91.8	54228	180.1
7	791.4	59348	56780	189447	101874	-196.3	56426	402.5
8	482.2	44485	45673	205557	94640	-0.2	56442	187.9
9	6229.5	27183	75142.4	66266	198208	-0.1	54267	47.6
10	90232	7316	113167	845.2	369420	0	55551	14.4
11	113625	689.4	122842	0	502646	0	53290	42.4
12	240978	40	129368	0	617644	0	54769	100.8

2.5.5. Results – Energy from zones

The results provide information on the sensible heat balance in the Carew building's zones. Information on total (i.e., dry and wet) heat balance, are presented in the heat balance Figure 2.11. The data are provided for monthly and one-year (simulation period) basis. Figure 2.13 provides details on envelope transmission losses, with control volume being positioned at the surface of the floor as well as on the ceiling and inside walls. For slab (embedded) cooling and heating processes, the control volume also involves activated layers and thus includes large thermal masses.

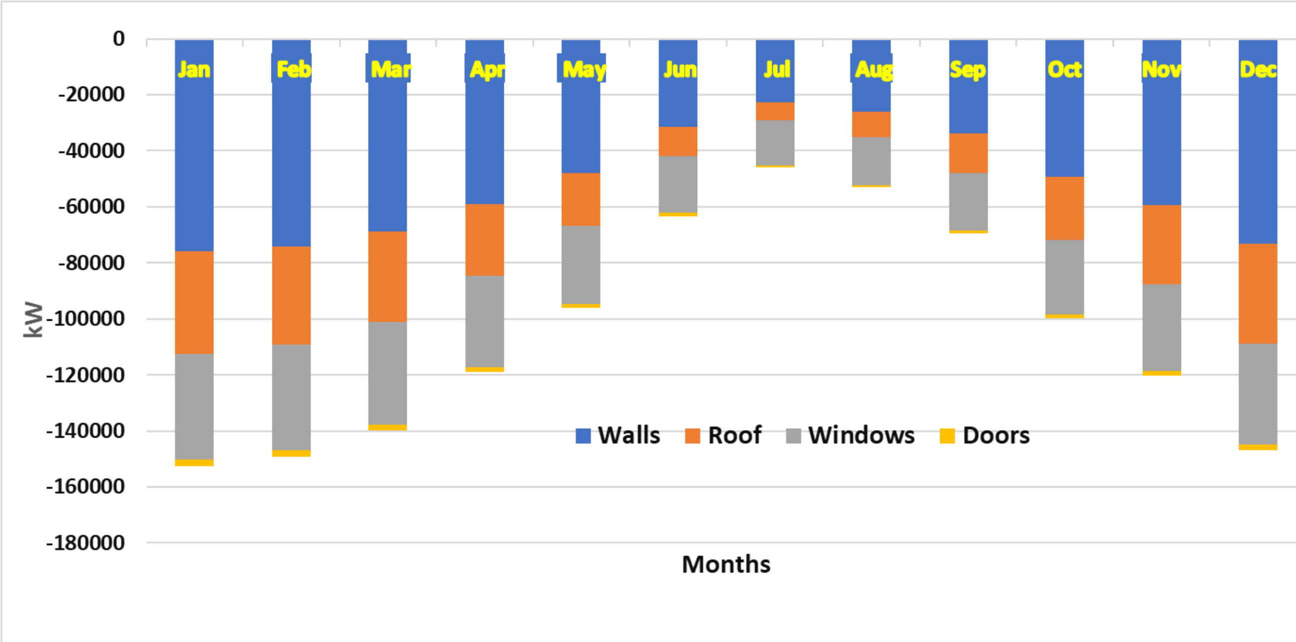

Figure 2.13 Details on envelope transmission losses

2.6. Simulation validation for IDA-ICE

A viable model must provide accurate results and also meet the required specifications. In the present work, the building data used was provided by Memorial University's Department of Facilities Management and the Honeywell Office. The data provided in Tables 2.3 and 2.4 (energy and hot water consumption) for the S. J. Carew building were collected between April 2012 and May 2017, inclusive. These were used to compare, and contrast power consumption derived from real data with power consumption derived from the IDA-ICE software data.

Table 2.3 Energy from hot water consumption

MONTH	Y2012 MMBTU	Y2013 MMBTU	Y2014 MMBTU	Y2015 MMBTU	Y2016 MMBTU	Y2017 MMBTU
APR	1,646	1,838	1,932	2,333	2,109	1,640
MAY	1,318	1,446	1,806	1,956	1,745	1,985
JUN	1,164	1,251	1,273	1,615	1,391	0
JUL	774	1,067	856	1,464	1,150	0
AUG	525	932	974	1,019	1,071	0
SEP	391	958	1,017	1,289	1,368	0
OCT	1,438	1,519	1,510	1,793	1,906	0
NOV	1,659	1,740	1,803	2,117	1,946	0
DEC	1,915	2,313	2,143	2,073	2,732	0
JAN	2,389	2,228	2,638	2,546	2,898	0
FEB	2,051	2,175	2,512	2,276	2,473	0
MAR	1,939	2,405	2,615	2,502	2,605	0
TOT	17,210	19,871	21,079	22,983	23,394	3,625
LITRES	565,029	633,115	666,618	719,885	762,559	116,177

Table 2.4 Electrical power consumption

MONTH	Y2012 kWh	Y2013 kWh	Y2014 kWh	Y2015 kWh	Y2016 kWh	Y2017 kWh
APR	366,300	375,458	462,454	526,557	485,348	444,139
MAY	393,773	425,824	471,612	503,663	398,352	434,982
JUN	434,982	357,143	407,509	503,663	489,927	0
JUL	407,509	508,242	563,187	425,824	467,033	0
AUG	366,300	366,300	471,612	462,454	494,505	0
SEP	402,930	393,773	425,824	430,403	370,879	0
OCT	439,560	407,509	425,824	526,557	434,982	0
NOV	412,088	476,190	512,821	439,560	489,927	0
DEC	393,773	444,139	526,557	434,982	508,242	0
JAN	439,560	462,454	476,190	448,718	476,190	0
FEB	398,352	439,560	494,505	444,139	430,403	0
MAR	402,930	416,667	467,033	508,242	476,190	0
TOT	4,858,059	5,073,260	5,705,128	5,654,762	5,521,978	879,121

The first step for comparison was to verify design details for the Carew building. These details included aspects such as building materials, location, dimensions, total area, etc. The second step was to make a comparison using the file for outdoor air temperature/weather as represented in the IDA-ICE software (based on readings from St. John's Airport, [ASHRAE, 2013]) and the building's actual outdoor air temperature obtained from the Honeywell software data. Figure 2.3 depicts the sensor (-1.4° OA); the average of the temperature readings from 2016 in one-hour time samples for both data was the same.

A viable model needs to have both accurate results and the ability to satisfy any required specifications. Figure 2.14 shows the IDA-ICE model of hot water usage from January to December 2016. The energy consumption for hot water was more than 800,000 kWh in Jan and Dec. Also, it was almost 300,000 in the summer time (Jul and Aug). Furthermore, although the actual data for hot water usage measured slightly low in some months and slightly high in others, it compared well to the IDA simulated data. Regarding overall energy consumption, the modeled data are only somewhat different than the actual data. Figure 2.15 shows the actual (measured) data as moderately higher than the simulation data, but these slight differences could be due to discrepancies in the lab readings due to miscalibrated equipment.

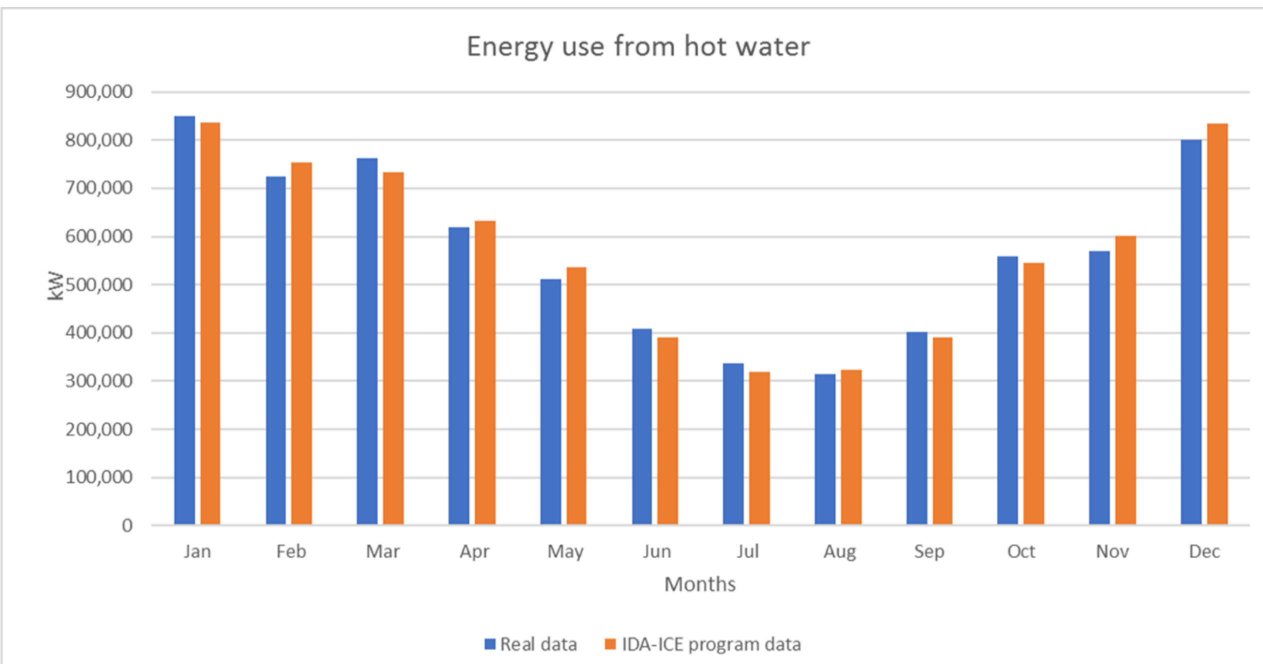

Figure 2.14 Energy use from hot water

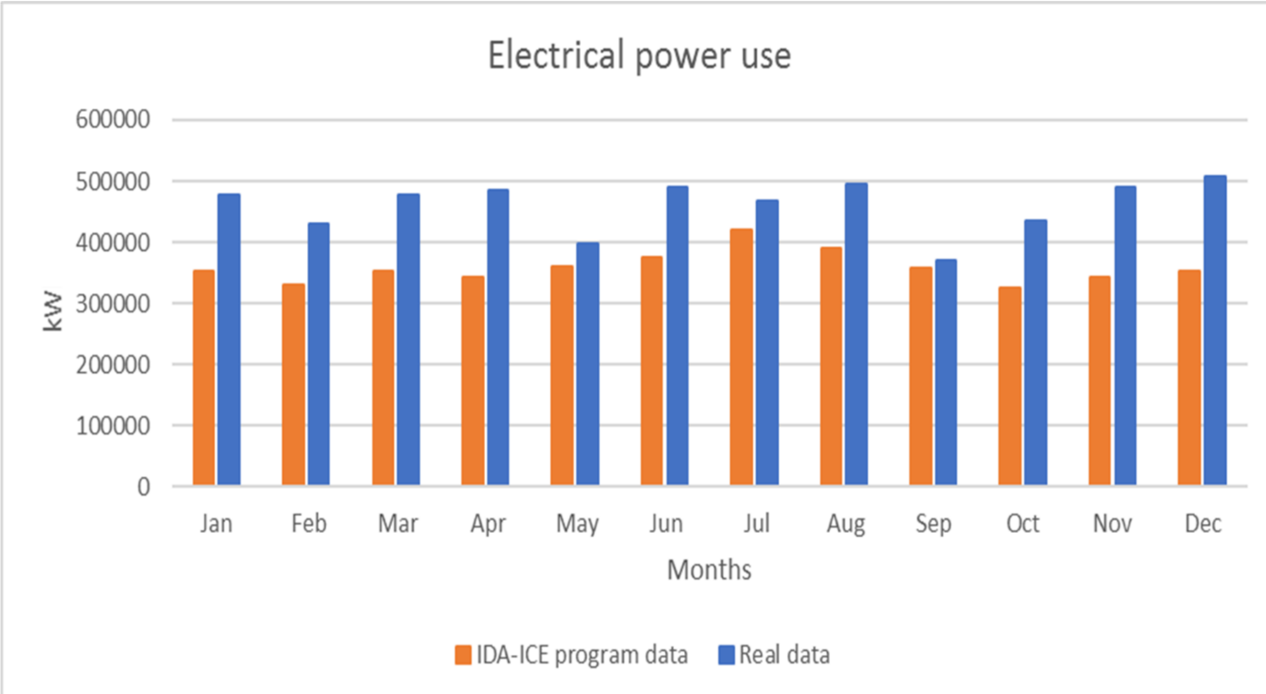

Figure 2.15 Electrical power use

2.7. System Identification

Our study used the IDA-ICE 4.7 simulation software for measuring the interior environment as well as the overall energy performance. This software is able to simulate and model multiple-zoned HVAC systems and is also gauge interior air quality (IAQ), energy requirements, and thermal comfort levels. To model the S. J. Carew building, the zonal inputs and outputs must be included in the identification data. There are three main steps in system identification [24]-[27]:

i. Collecting the data toward model identification.

ii. Choosing an appropriate model structure.

iii. Building a model that provides the best functionality (i.e., satisfies specifications and gives accurate results).

During these steps, the focus is on optimizing the chosen model to suit a real-life system. In this study, a structure is used that features four AHUs as a means for identifying the state space model of the system. The data used for system identification were collected during the winter months, which means that the cold-water valve was not operating. Additionally, because the S. J. Carew building has four floors, the system features twelve inputs and twelve outputs overall, calculated from three inputs (U) and three outputs (Y) per floor. Figure 2.16 illustrates the details.

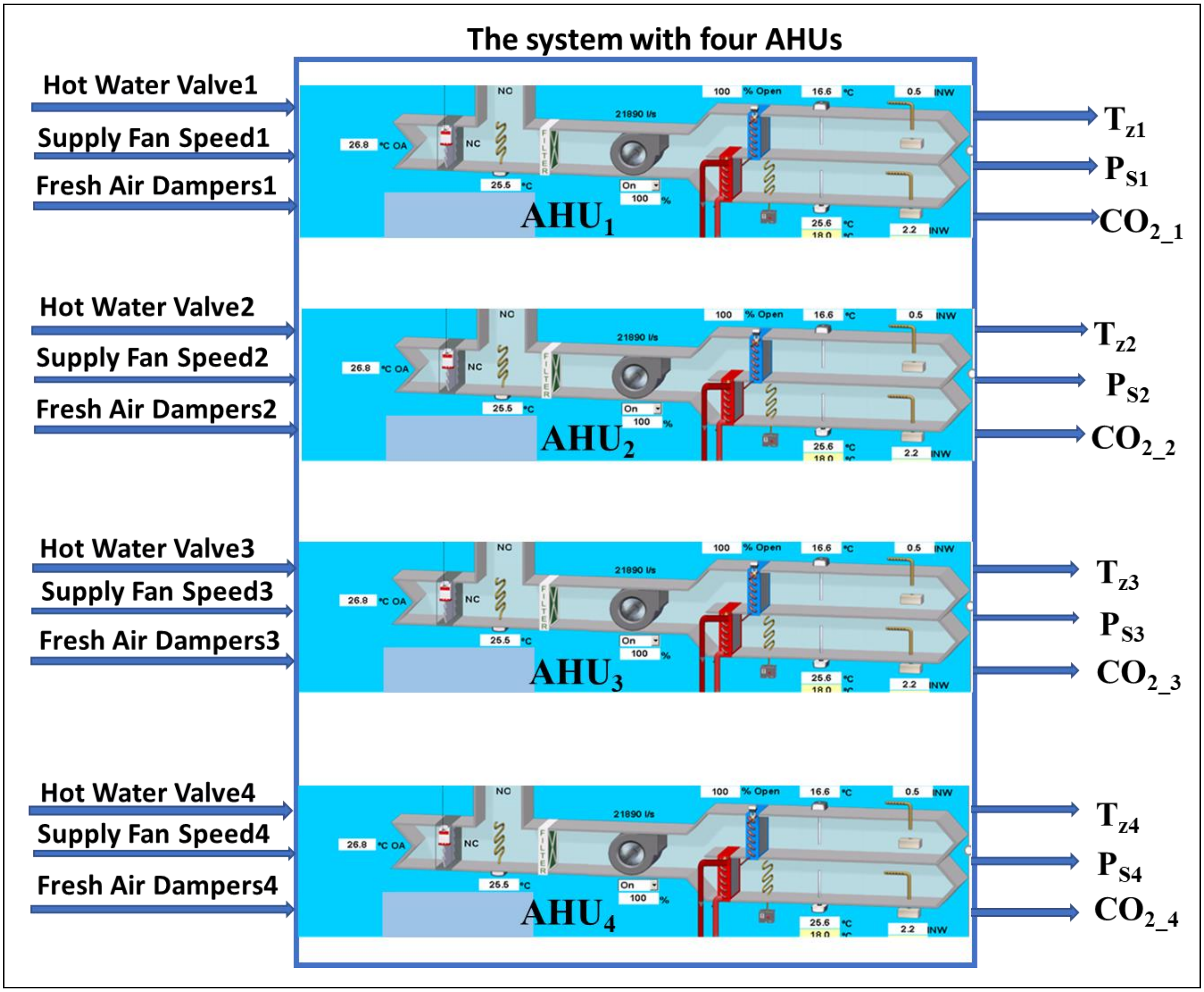

Figure 2.16 Inputs and outputs of the system

1) Zonal Temperature (T_z) (y_1, y_4, y_7, y_{10}): These data are derived from the IDA-ICE software. Although the actual system features sensors in every room, the temperature on each floor still needs

to be measured. The data from the IDA ICE software are used to control the hot water valve. Figure 2.17 illustrates the outputs.

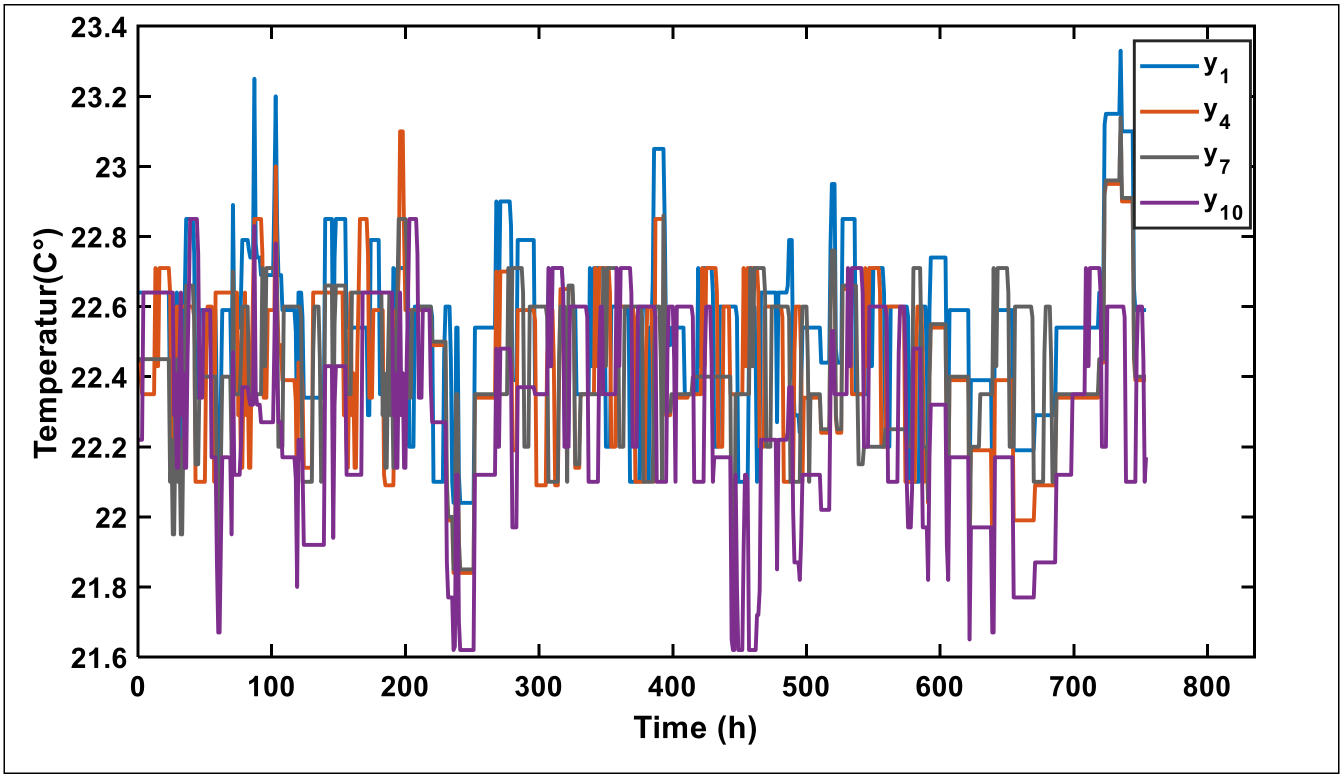

Figure 2.17 Zones temperature

2) Hot Water Valve for Heating Coil/Zones (u_1, u_4, u_7, u_{10}): These data are also derived from the IDA-ICE software. In the actual system (as shown in Figure 2.16), a hot water valve collects data on hot water use. Note that this system only has one valve for hot water production, whereas in the IDA-ICE software there are four valves, which enables every floor to have a separate valve. Figure 2.18 shows these inputs as percentage of opening and closing operation of the hot water valves.

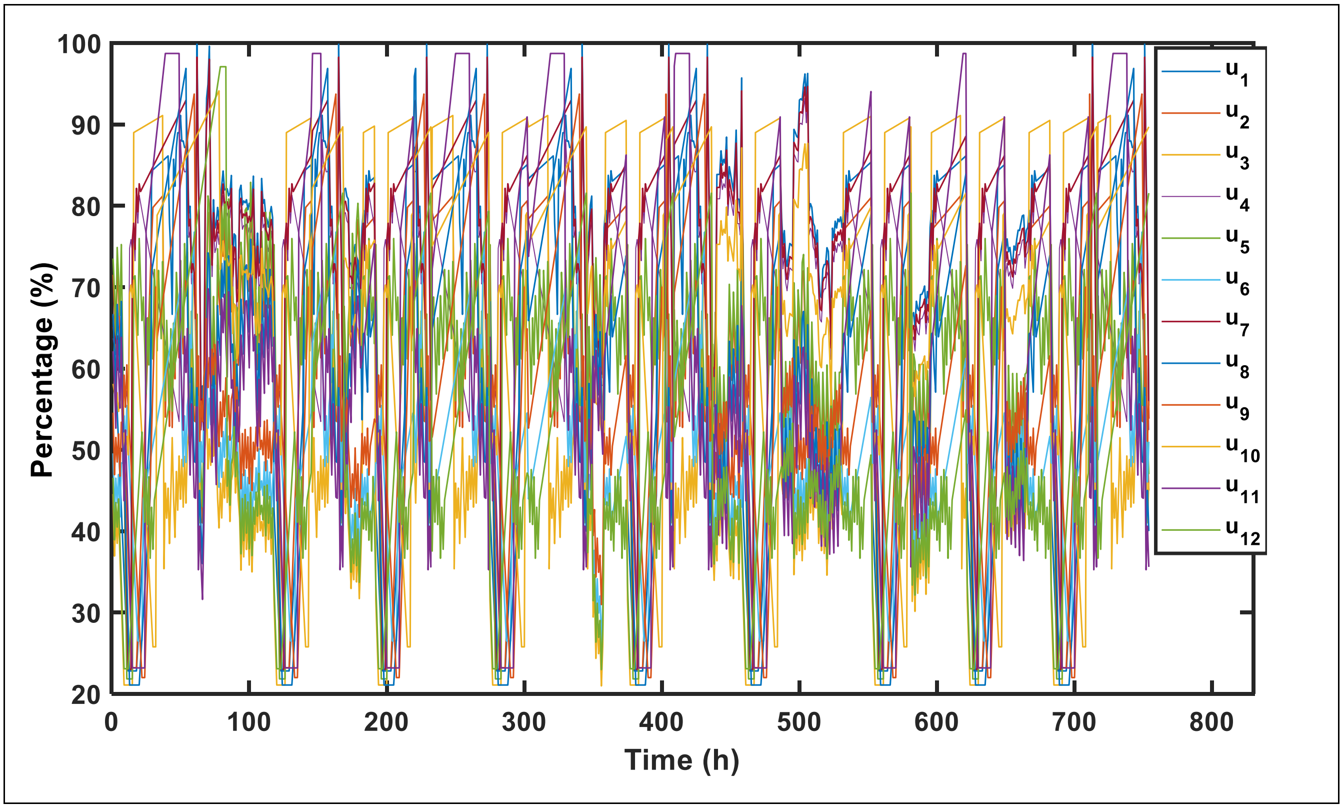

Figure 2.18 All inputs of the system

3) Fresh Air Dampers (u_3, u_6, u_9, u_{12}): As shown in Figure 2.18, the fresh air sensors positioned in AHUs are able to gauge, in percentage, the amount of fresh air is entering the building. The sample time (T_s) used in these calculations is used in all data.

4) CO_2 Levels (CO_2) (y_3, y_6, y_9, y_{12}): This data is obtained from the sensors for return air flow ducts for individual AHUs. Figure 2.19 depicts CO_2 levels occurring in AHUs. These outputs can be applied in moderating fresh air dampers.

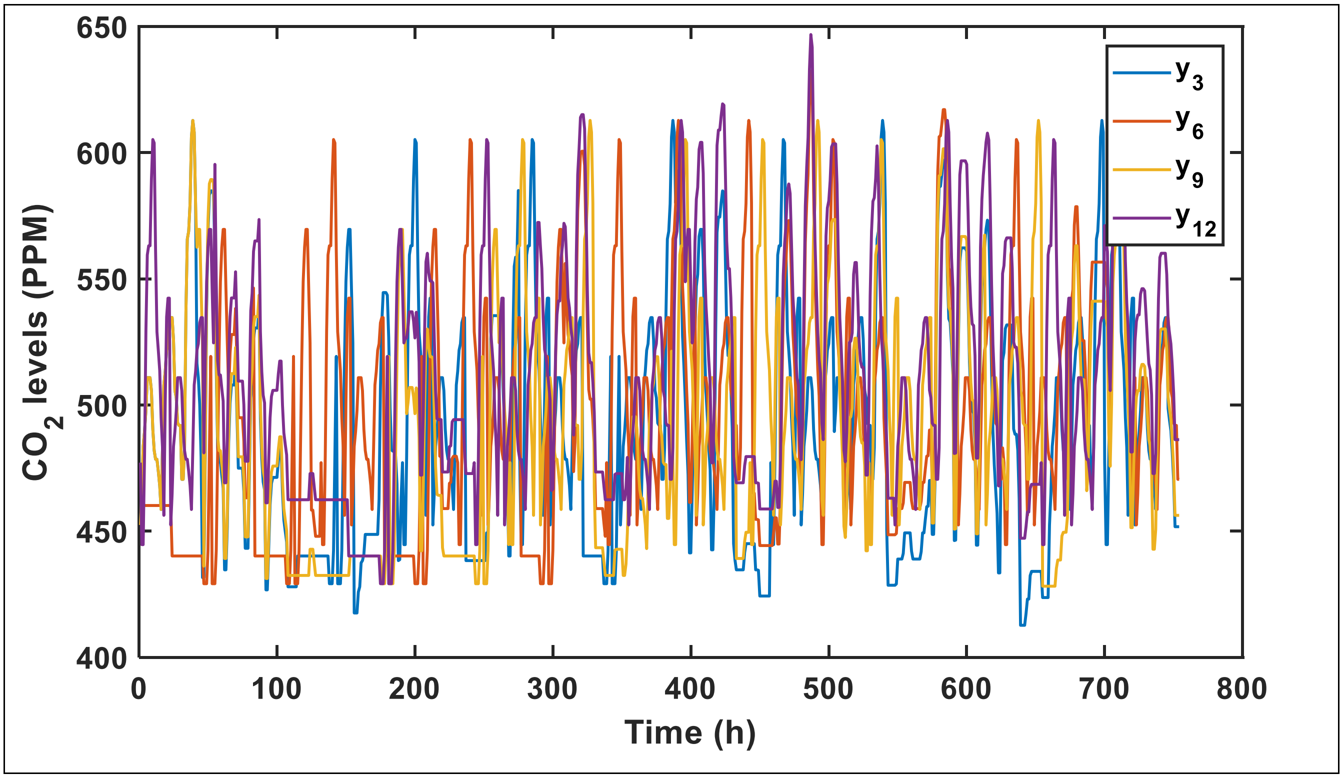

Figure 2.19 CO_2 level of AHUs

5) Static Air Pressure (P_s) (y_2, y_5, y_8, y_{11}): This data comes from two sensors – one for hot ducts and one for cold ducts. As illustrated in Figure 2.20, these outputs can be applied to the control of supply fan speed.

6) Supply Fan Speed (u_2, u_5, u_8, u_{11}): This data is derived from the AHUs sensor. Figure 2.18 depicts the sensors measuring the fan speed of AHUs. The sample time (T_s) for gathering the data is one hour, and the input signals are obtained in percentages.

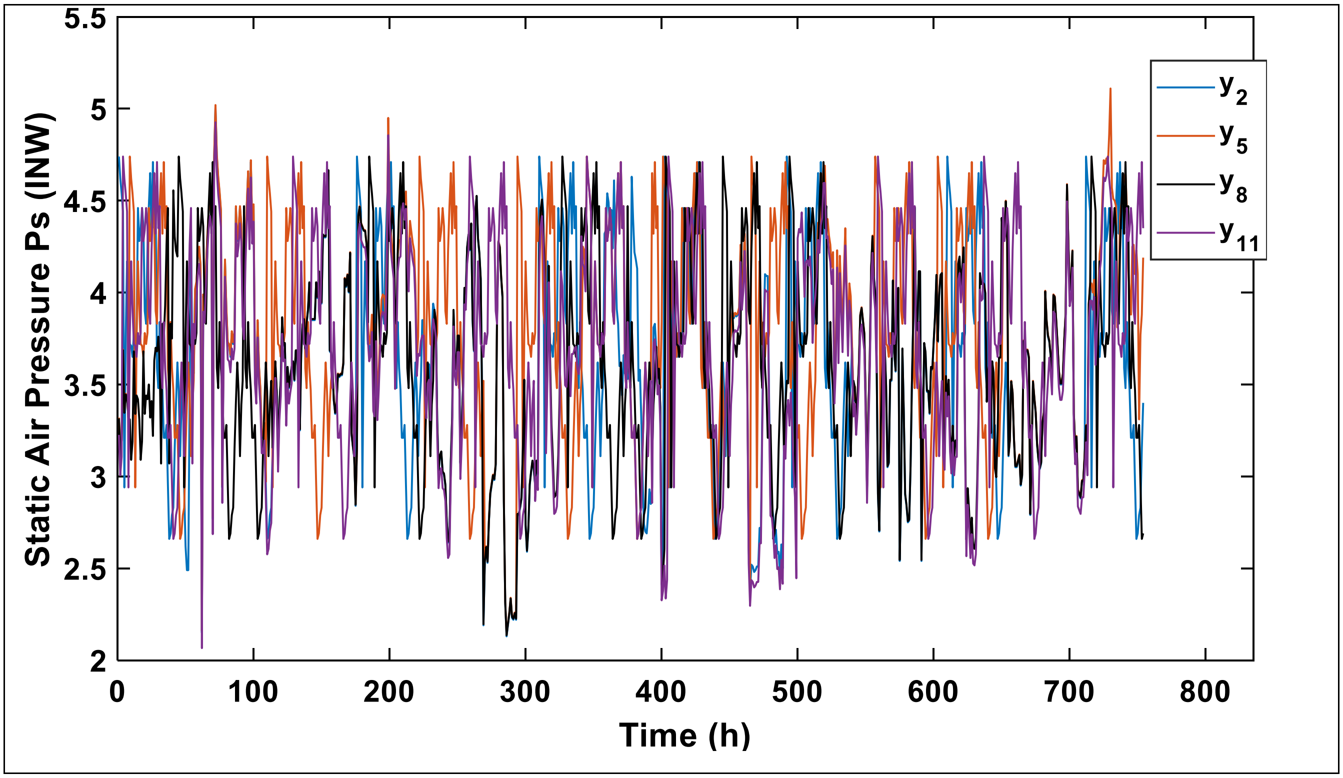

Figure 2.20 Static air pressure of AHUs

System disturbances (w) can occur with changes to wind speed/direction and outside temperature. These changes are recorded in the IDA-ICE software and the input/output signal data series organized through MATLAB. The ordering of the data is imperative before moving onto the next stage, which is system identification using the System Identification (SI) Toolbox. Every individual data set is cut in two: one half represents estimation data, while the other half represents validation data.

Data from the first half (Data 1) are organized as input/output sets using MATLAB. The inputs are arranged into 12 columns, with every column relating to a specific input signal. Note that the number of rows is equal to the number of simulation period hours. Similarly, the outputs are also arranged into 12 columns, with every column relating to a specific output signal and the number of rows being equal to the number of input arrays. In these calculations, both the estimation and validation data have a 90-day time frame. Figures 21, 22 and 23 show some of the time plots of this data for estimation. The CO_2 level of AHU_3, static air pressure of AHU_2 and zone temperature of AHU_1 are shown the output is the upper plot and the input is the lower plot.

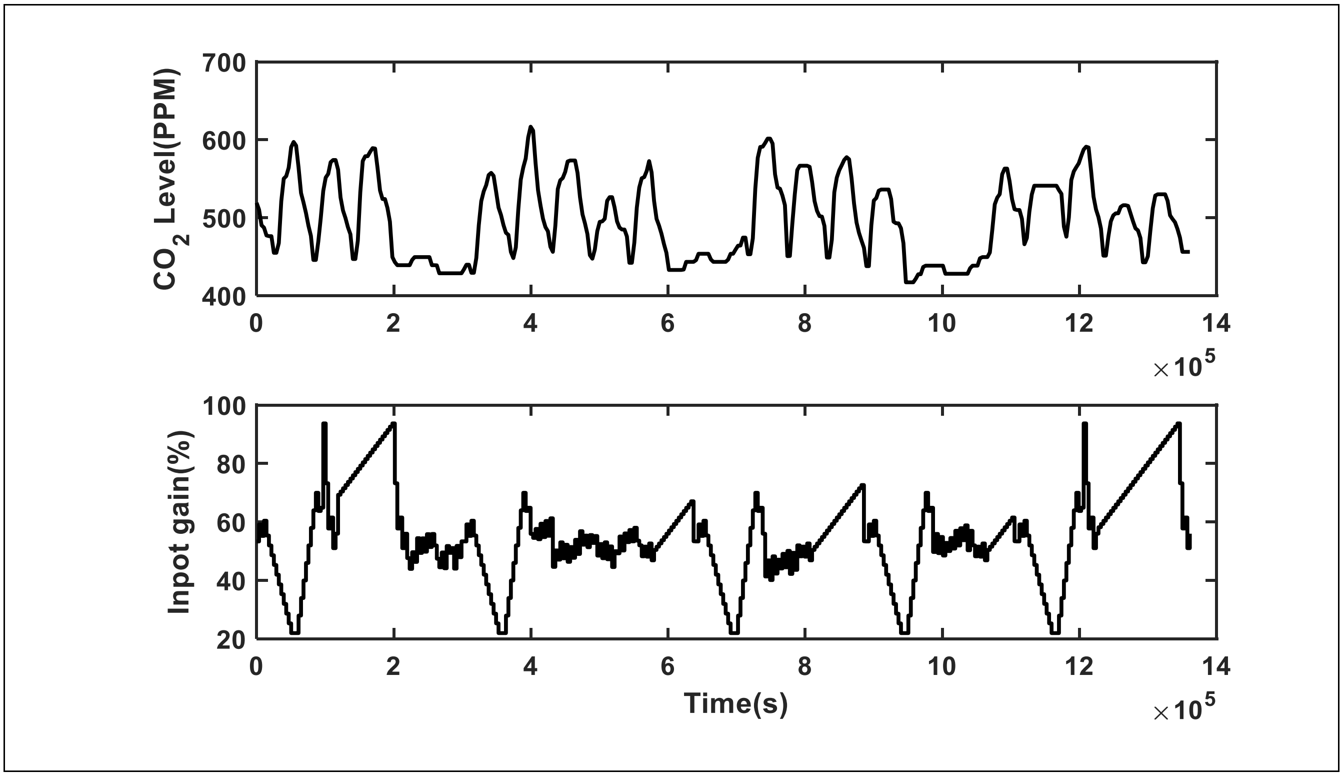

Figure 2.21 Input and output signals of CO_2 level of AHU_3 (U9)(%)

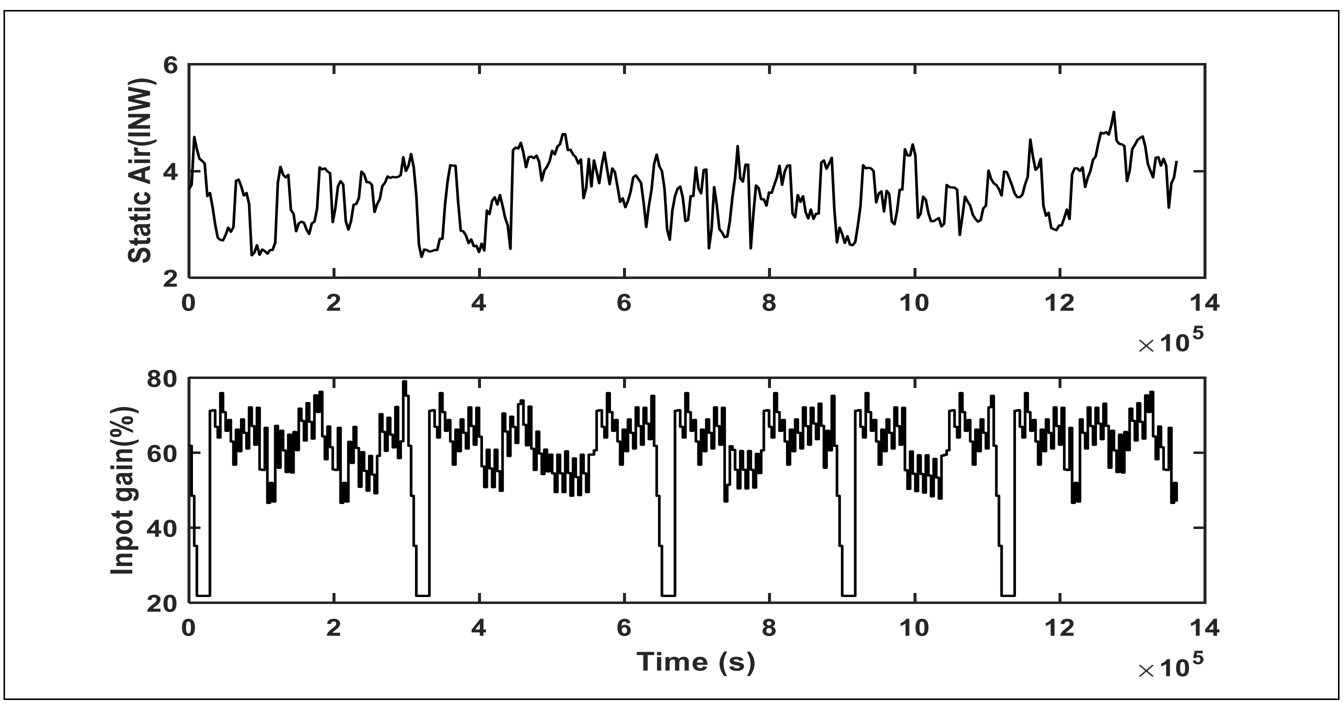

Figure 2.22 Input and output signals of the static air pressure of AHU_2

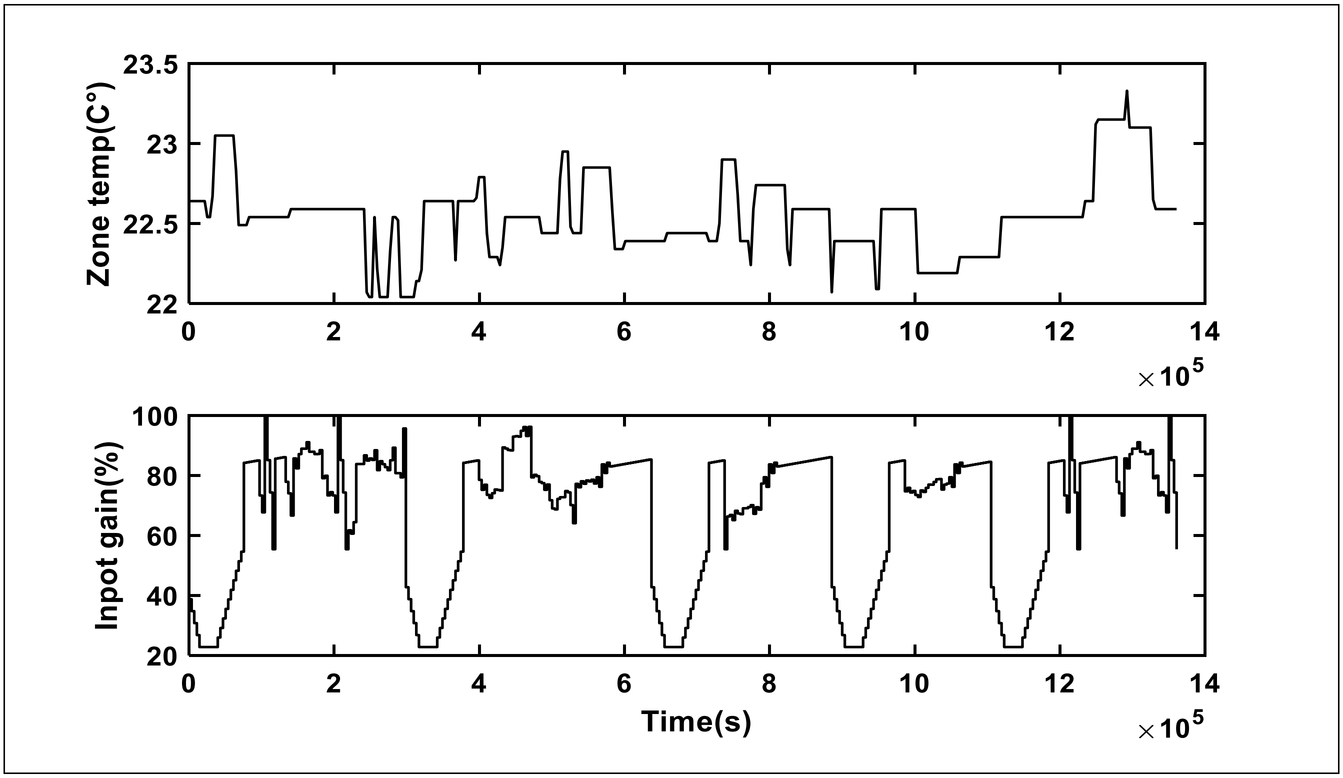

Figure 2.23 Input and output signals of zone temperature of AHU_1

Figure 2.24 shows the output of the model that follows the temperature of a zone in AHU_1 with the same output as the real system. The agreement between these graphs can be seen as a percentage of the error. Ideally, this result is 87%. Also, Figure 2.25 shows that the system performance percentage for the estimated model and the actual system of CO_2 level of zone 3 in AHU_3 was 84%. Also, the percentage of the estimation model of the static air pressure the simulated or predicted model output is shown together with the measured validation data in Figure 2.26.

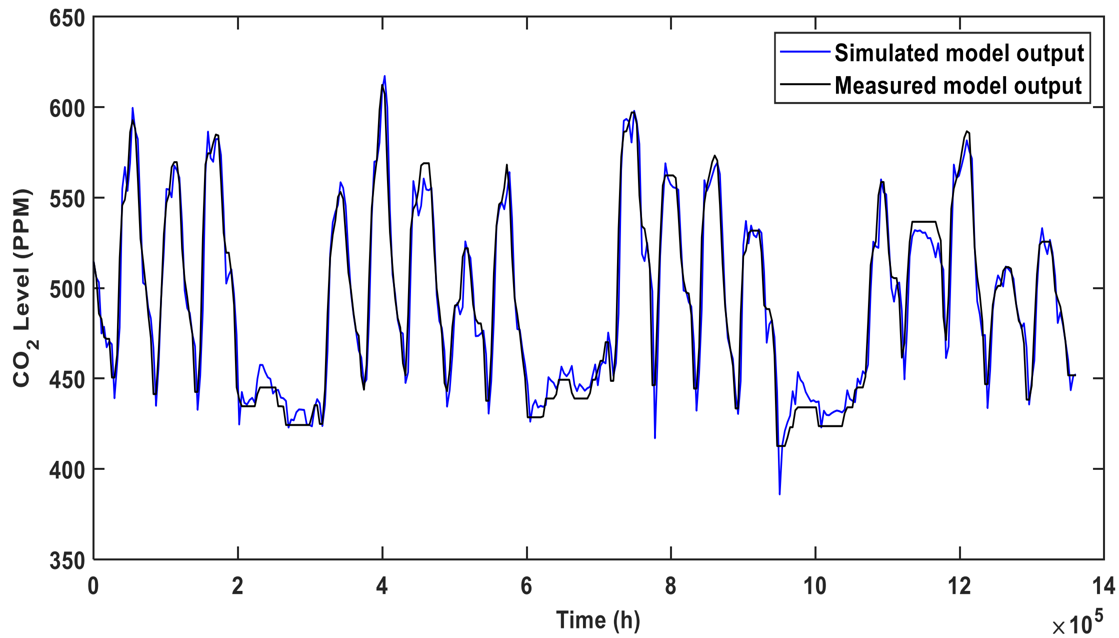

Figure 2.24 Validation of real measurements and outputs of CO_2 level model fit 87%.

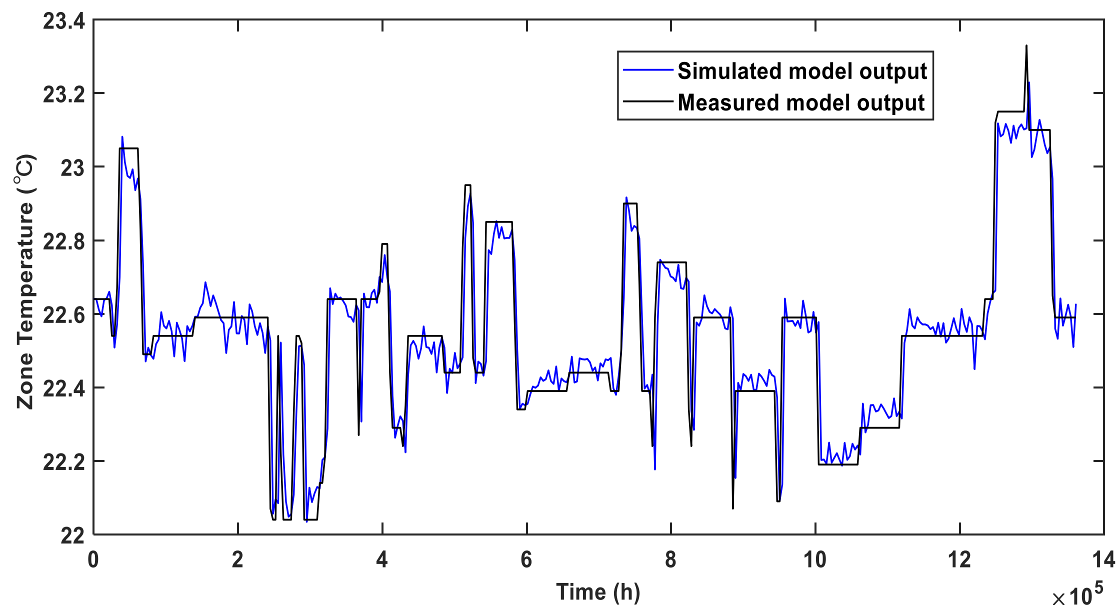

Figure 2.25 Validation of real measurements and outputs of zone temperature model fit 81%.

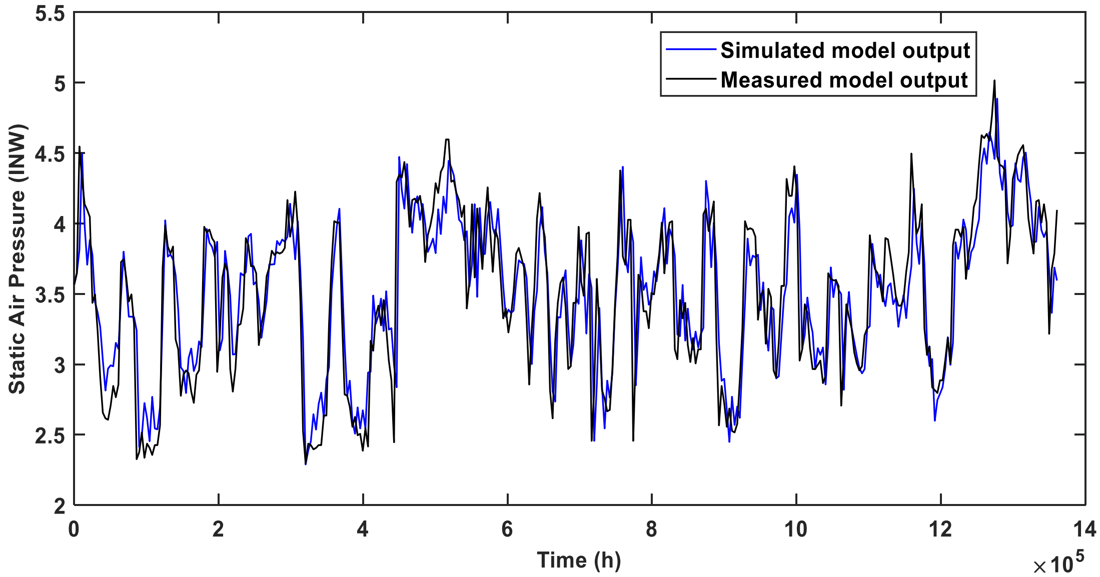

Figure 2.26 Validation of real measurements and outputs of the static air pressure model fit 80%.

The part of the system data that the model could not describe is called the residuals [28]-[30]. They contain important information about the quality of the estimated model. The cross-correlation between residuals and the correct model does not exceed the confidence level [28]. If this is the case, the original model has captured the underlying properties of the system. The remaining autocorrelation indicates whether the error pattern is accurate. Standard process models do not evaluate the error model and unknown interference is not in the original model, thus the remaining runtime is not used for model verification. Figures 2.27, 2.28 and 2.29 show plots of the autocorrelation and cross-correlation of system responses to inputs. It is clear from the cross-correlation diagram of these figures that the estimated model is very similar to the responses of the system to the inputs; the correlation curves lie between the dashed lines.

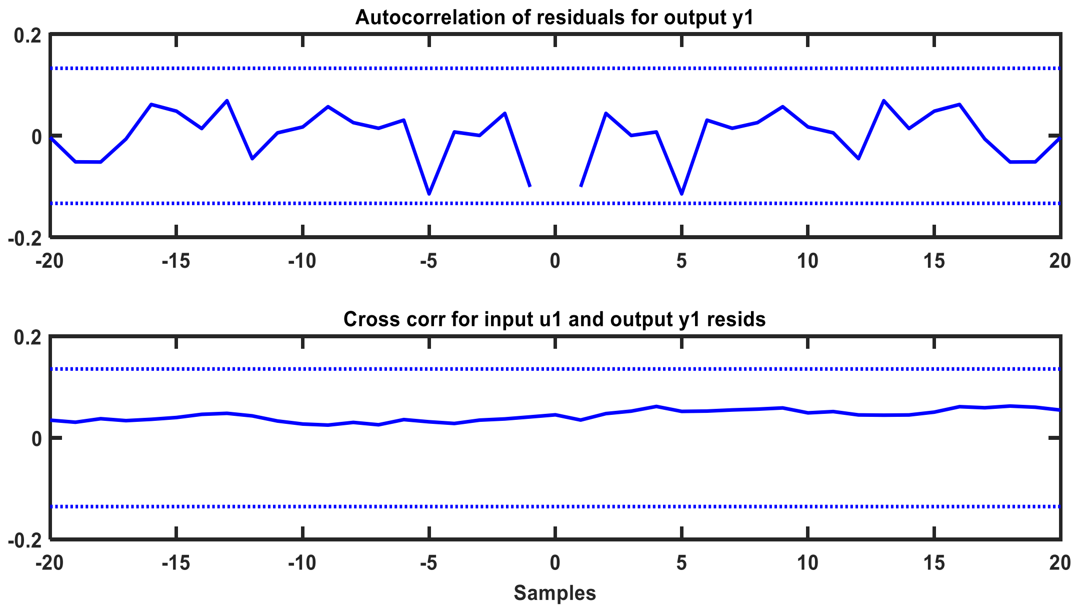

Figure 2.27 Autocorrelation y1 and cross-correlation of system response u1 & y1

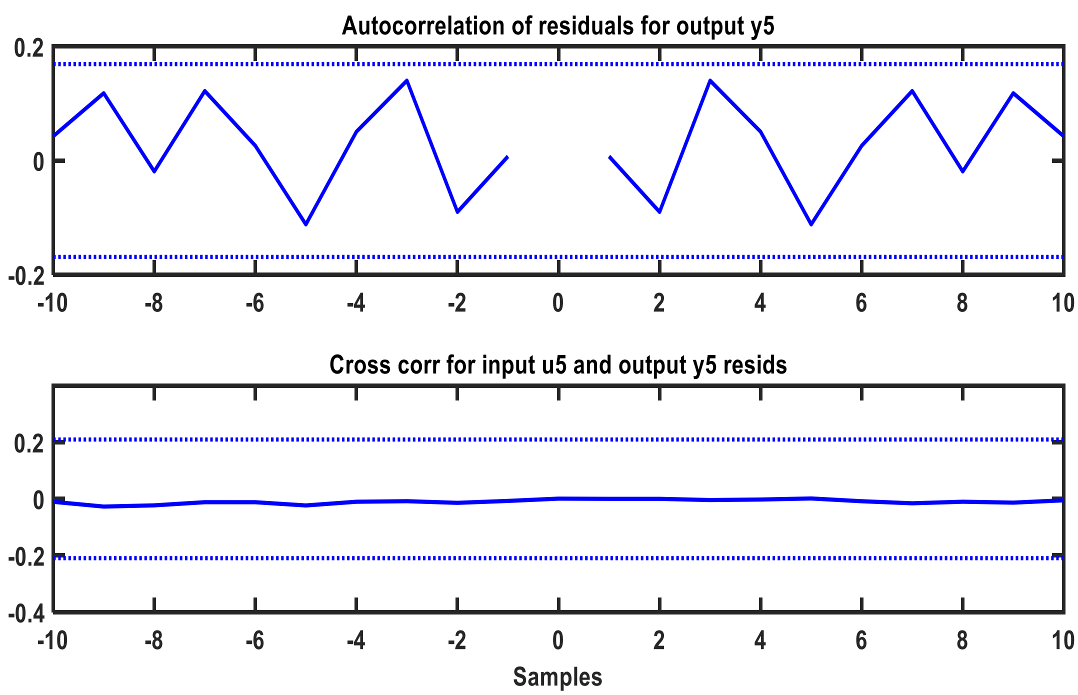

Figure 2.28 Autocorrelation y5 and cross-correlation of system response u5 & y5

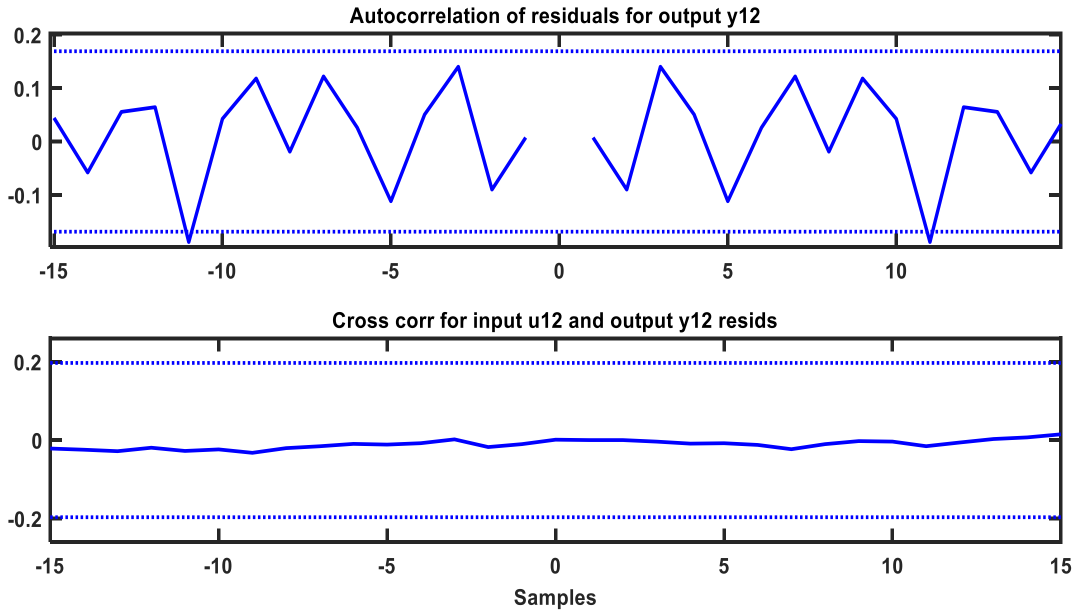

Figure 2.29 Autocorrelation y12 and cross-correlation of system response u12 & y12

Every state-space model is estimated in the SI Toolbox. The models undergo a comparison based on the degree of accuracy between the validation data sets estimated and measured (i.e., real) outputs. In the comparison, the estimated and real outputs are plotted for every model, after which a numerical value is allotted regarding the model's 'fit.' Using the SI Tool, the estimated outputs for numerous models are able to be plotted quickly and at the same time, with the model showing the highest value (i.e., the best 'fit') deemed to have the greatest reliability. As an outcome of the process, we can obtain state-space models for Data 1 data groups and compare models across different seasons. For detrending the data, there are no alterations made to any relative differences among inputs and outputs.

To determine model settings for the system, a linear parametric model can be estimated from a state-space structure. In general, the state-space model discrete-time settings generally feature the following structure:

$$X\ (t\ + Ts)\ =\ Ax(t) + Bu(t) + Ke(t)$$

$$Y\ (t)\ =\ Cx(t) + Du(t) + e(t) \tag{2.1}$$

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 Ts is the sampling time of the system.

For modeling multi-input/multi-output (MIMO) systems, state-space models have proven to be the most popular option, likely because the state-space method is relatively straightforward [31]. For the system used in the present work (twelve inputs and twelve outputs), the discrete-time state-space model for order 12 (sampled as Ts = 3600 s) and the A, C and K matrices are as following:

$$\mathbf{A} = \begin{bmatrix} 1.018596 & 0.024987 & -0.09841 & -0.01809 & 0.029826 & 0.011551 & 0.122706 & -0.09652 & -0.02257 & -0.03334 & 0.021134 & 0.044136 \\ -0.04802 & 0.953931 & -0.18782 & -0.10913 & 0.017903 & 0.012705 & 0.02266 & 0.044524 & -0.00967 & -0.02612 & -0.00755 & 0.013065 \\ 0.006735 & 0.161472 & 1.00175 & 0.153348 & -0.17807 & -0.0057 & -0.07445 & 0.089848 & -0.18638 & -0.04874 & -0.0658 & -0.09062 \\ 0.102572 & 0.106159 & 0.015012 & 0.876272 & -0.05667 & 0.040026 & 0.034899 & 0.063895 & 0.046081 & -0.0318 & 0.058022 & 0.151734 \\ -0.01012 & 0.119388 & 0.032058 & 0.193805 & 0.875773 & 0.105007 & 0.06194 & -0.11106 & -0.27665 & 0.118682 & -0.04009 & -0.12357 \\ 0.034182 & 0.001981 & 0.218893 & -0.06499 & 0.003683 & 0.698464 & -0.15637 & 0.16687 & -0.06375 & 0.068068 & -0.1383 & 0.073127 \\ -0.06088 & -0.03718 & 0.018276 & 0.026644 & 0.006168 & -0.00484 & 0.700056 & 0.134608 & 0.025221 & -0.05818 & 0.065294 & -0.06174 \\ 0.128313 & -0.04206 & -0.25685 & -0.11438 & 0.260537 & -0.27507 & 0.000851 & 0.632401 & 0.220702 & -0.20081 & 0.253606 & 0.220525 \\ -0.01409 & 0.071827 & 0.152001 & -0.06185 & 0.079589 & 0.449275 & 0.220342 & 0.126901 & 0.679172 & 0.092466 & 0.145962 & 0.114791 \\ 0.029159 & -0.04508 & -0.12238 & 0.073543 & 0.029797 & -0.28537 & -0.13111 & 0.07257 & -0.04701 & 0.726139 & -0.02971 & 0.136616 \\ 0.147829 & -0.16104 & -0.06659 & -0.35556 & 0.222772 & -0.21727 & -0.0814 & -0.01191 & 0.091189 & 0.117558 & 0.900431 & 0.262343 \\ 0.018322 & 0.124913 & 0.198312 & -0.06154 & 0.143552 & -0.17269 & 0.228241 & -0.13141 & 0.238771 & -0.21135 & -0.01898 & 0.833612 \end{bmatrix}$$

$$\mathbf{C} = \begin{bmatrix} -32.3819 & 3.032522 & 0.850361 & 1.320461 & 1.654051 & 0.228377 & -1.25475 & 0.711672 & -1.12264 & 0.011717 & -0.98978 & 0.435679 \\ -4.96281 & 4.825874 & 2.834766 & 1.076908 & 2.428522 & -0.77537 & 1.650816 & 0.829984 & 1.838859 & -1.4162 & -1.79384 & 0.42955 \\ -789.668 & 315.0027 & -248.299 & 258.1054 & 147.2952 & -161.542 & -225.011 & 100.9488 & 120.8973 & 83.13542 & -194.598 & -118.225 \\ -32.582 & 3.739006 & 1.189215 & 0.456838 & 2.628477 & -0.97674 & 0.321862 & -0.63062 & -1.01303 & 0.477141 & -0.11792 & 0.126173 \\ -7.89485 & 3.602045 & 0.534273 & 0.073331 & -0.29611 & 0.260542 & 2.093179 & 0.593547 & 0.695332 & -0.01057 & 2.583058 & -3.38128 \\ -596.62 & 338.8736 & 128.9263 & -51.9804 & -268.546 & -222.936 & -531.204 & -263.779 & 58.86106 & 194.4376 & 142.4278 & -27.9924 \\ -32.5222 & 3.375469 & 0.211781 & -0.90622 & 2.133119 & -0.3489 & -0.90599 & -0.03896 & -1.00358 & 0.530528 & -0.06908 & -0.21883 \\ -5.4587 & 1.758807 & 1.588113 & 0.661421 & 1.924165 & -2.58504 & 1.562919 & 2.286861 & 1.189903 & -0.49241 & -0.05558 & 0.912613 \\ -928.097 & 287.0009 & -266.691 & 428.3191 & 393.2388 & -234.874 & -209.795 & 90.12368 & -223.088 & -365.806 & 31.59467 & -280.605 \\ -32.443 & 3.893139 & -0.18864 & 3.345291 & 3.703252 & -0.71339 & -0.36698 & 0.15893 & 0.455992 & -0.00349 & 0.598077 & 1.910353 \\ -6.3736 & 0.362166 & 1.90677 & 3.073253 & 2.246129 & -1.03295 & 0.390075 & -1.42084 & 1.838677 & 0.77659 & -1.90933 & 1.183602 \\ -736.847 & 466.1483 & -328.719 & 73.65842 & 118.4599 & -142.761 & -464.838 & 183.0777 & -43.4737 & -86.4524 & -281.692 & -65.8117 \end{bmatrix}$$

$$
\mathbf{K} = \begin{bmatrix}
-0.02247 & 0.002415 & -0.00017 & 0.006293 & -0.00173 & 0 & -0.00404 & -0.00078 & -0.00012 & 0.006362 & 0.00369 & 0.000173 \\
-0.03766 & 0.008826 & 0.000201 & 0.019432 & 0.012113 & 0 & 0.006975 & -0.00743 & 0 & 0.012768 & -0.01539 & 0.000242 \\
0.033593 & 0.016611 & 0 & 0.004704 & 0.002891 & 0.000146 & -0.01335 & -0.00477 & -0.00877 & -0.02582 & 0.004979 & -0.00043 \\
0.03453 & -0.00396 & 0.000281 & -0.01639 & 0.002948 & 0.000201 & -0.05972 & 0.003692 & 0.000146 & 0.040423 & 0.001516 & 0.003516 \\
-0.03892 & 0.023262 & -0.00018 & 0.037843 & -0.00404 & -0.00028 & 0.00469 & -0.01357 & 0 & -0.01751 & 0.014066 & 0 \\
0.051835 & 0.000717 & -0.00015 & -0.03922 & -0.00076 & -0.00837 & -0.00337 & -0.01172 & 0 & -0.00887 & 0.006588 & -0.00045 \\
-0.02582 & 0.005204 & 0.000455 & 0.030462 & 0.009431 & -0.00026 & 0.011997 & 0.002781 & 0.000145 & 0.00114 & -0.02152 & -0.0003 \\
-0.01015 & -0.01334 & 0 & -0.04976 & 0.014821 & -0.00084 & 0.001932 & 0.016727 & 0 & 0.036388 & -0.02471 & 0 \\
-0.01445 & 0.018199 & 0.000477 & -0.02753 & 0.006731 & 0.000156 & 0.001845 & -0.00527 & -0.00022 & 0.030758 & 0.010523 & 0.000299 \\
-0.03034 & -0.00941 & 0.000446 & 0.010668 & 0.006548 & 0 & 0.021502 & 0.01097 & -0.00015 & -0.01222 & -0.0214 & -0.00045 \\
-0.01857 & -0.02641 & 0 & -0.04546 & 0.014413 & -0.00011 & 0.01149 & 0.013894 & 0.000132 & 0.034855 & -0.01938 & -0.00053 \\
0.01201 & 0.001892 & -0.00049 & 0.008802 & -0.02405 & 0 & -0.06658 & 0.00417 & -0.00037 & 0.067378 & 0.02137 & 0.000465
\end{bmatrix}
$$

2.8. Conclusions

In this paper, the S.J. Carew building was modeled using the IDA-ICE software using all details of HVAC system and instructions of the building. This model provides good approximations comparing the consumption of hot water and electricity with the measured data for a full year (2016). It also compares the average of the outside temperature of the weather file of IDA-ICE software and the measured data. All system inputs and outputs were selected, and a linear state-space model was identified describing the thermal response of the system. The dynamic model is required to design and test system controllers before actual implementation. The model was derived using MATLAB's System Identification Toolbox (SI). The model has twelve state variables, twelve inputs, and twelve outputs. The model responses when compared with actual data are within the allowed range. Validation data, autocorrelation function for the residuals as well as the cross-correlation function between input and residuals computed and presented.

2.9. References

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Chapter 3

3. Modeling, Analysis, and State Feedback Control Design of a Multi-zone HVAC System

Preface

A version of this manuscript has been published in the Hindawi Journal of Energy. I am the primary author of this paper. Along with the co-authors, Tariq Iqbal and Kevin Pope we gauge the usefulness of SI in identifying climate control dynamics when employing samples of one-hour discrete time data and we investigate the validity of a state feedback controller using a state space model. I completed the first version of the manuscript and further revised according to the suggestions of co-authors and reviewers. Tariq Iqbal helped to identify the research topic and scope. Keven Pope reviewed the manuscript and provided revision suggestions.

Abstract

A HVAC system is modeled by applying a state space MIMO (multi-input/multioutput) system method for control system design and analysis. State space model of the system are developed using the simulation program IDA Indoor Climate and Energy. The building has four floors in total, with separate air-handling units (AHUs) on each floor. The system's eight main input data are hot water and the energy usage for each AHU, while the eight main outputs are returned airflow temperature and CO_2 levels for AHUs. The factors of wind direction and velocity are also applied as disturbances. By comparing usage data on simulated power consumption versus measured data for the three months of October, November, and December 2016, good agreement was achieved with simulated data. The main aim is to develop a state feedback controller and then apply it toward the optimal functionality of a control system. After utilizing the MATLAB identification toolbox, a MIMO system-based state space model is developed.

Keywords: State space model, HVAC system, energy consumption system identification, state feedback controller,

3.1. Introduction

The main aim in developing an optimal HVAC (heating, ventilation, and air-conditioning) system is to create a comfortable environment for occupants with reduced energy inputs [1]. However, heating and cooling loads typically change according to the exterior environment, as well as with the specific needs of the users. HVAC systems require a control system to keep the comfort level and air quality relatively constant with variable conditions. Furthermore, power usage can be greatly decreased if the system is suitably controlled.

A method that is based solely on measured data is one possible means for obtaining a mathematical interpretation of the system. The model can be used to determine system parameters in cases where input and output variables are already available. This modeling method is useful if the system is constructed and data related to performance can be readily obtained. Compared to forwarding models, those that are data-driven can identify system approaches that can prove to be both easier to use and better performance predictors. Modeling methods that primarily use data are classified as “system identification” (ASHRAE 2005).

A wide range of research over the past few decades supports the suitability of applying the system identification approach in energy simulation and in determining and analyzing the moisture, cooling and heating environments in buildings. Applying data gathered from a building management system, Lowry and Lee (2004) studied the outcome of using a data-driven model to gauge thermal response [2]. A few years earlier, Madsen and Holst (1995) utilized nearly the same system identification approach to determine a structure’s heating dynamics obtained from data on discrete time performance [3]. Cunningham (2001) applied system identification methods to find moisture release rates in a structure based on psychometric data [4], and Mechaqrane and Zouak (2004) incorporated system identification in their investigations on the prediction of interior air temperature in residential structures [5]. A few studies have also focused on comparing test approach models with theoretical predictions using simulation software like TRNSYS. Peippo, K., P. Kauranen, and P. D. Lund (1991) determined the dynamics of a structure according to discrete time results obtained from simulation software using a one-hour time step [6].

Despite the approach's clear potential, there are numerous obstacles to the simulation of a structure's dynamic response when applying simulation software. Currently, simulation software can be significantly time-consuming, and the results are often missing important information on the fast dynamic behavior of a structure (i.e., in the order of seconds), as the majority of available software utilizes a discrete time step that is typically set at one hour. Problems arise when, for instance, data is needed on fast dynamic behavior for a control strategy (e.g., on/off), but it cannot be obtained because it is situated within the time step.

This paper presents a simulation of an entire structure, applying the simulation program IDA Indoor Climate and Energy 4.7. In the simulation, the energy usage (including the heating and cooling) of the S. J Carew Building of Memorial University of Newfoundland, and also investigate a 3-D model, a heat model based on variable parameters, and typical IDA ICE model library parts. Established in 1998, the IDA Indoor Climate and Energy program can investigate separate thermal climate zones [9]. There are four main objectives of the present work:

1. Use real data to create the entire structure and then validate the results.
2. Determine the viability of using system identification in decreasing the time required for calculating the simulation of complex structures.
3. Determine the viability of using system identification for identifying the dynamics of climate control design in a structure when using discrete time data of one-hour sample time.
4. Use state feedback (classical) control by applying a state space model.

3.2. Building thermal simulation

3.2.1. Building structure

For analysis purposes, we use a building on the Memorial University campus in St. John's, Newfoundland, and Labrador, S. J. Carew Building, which accommodates Memorial's Faculty of Engineering and Applied Science. There are more than 300 zones in the S. J. Carew building, which measures approximately 25,142 m^2 and comprises a cafeteria, teaching rooms, staff rooms, and research labs. Table 3.1 provides a description of the structure's amenities and Fig. 3.1 illustrates the structure.

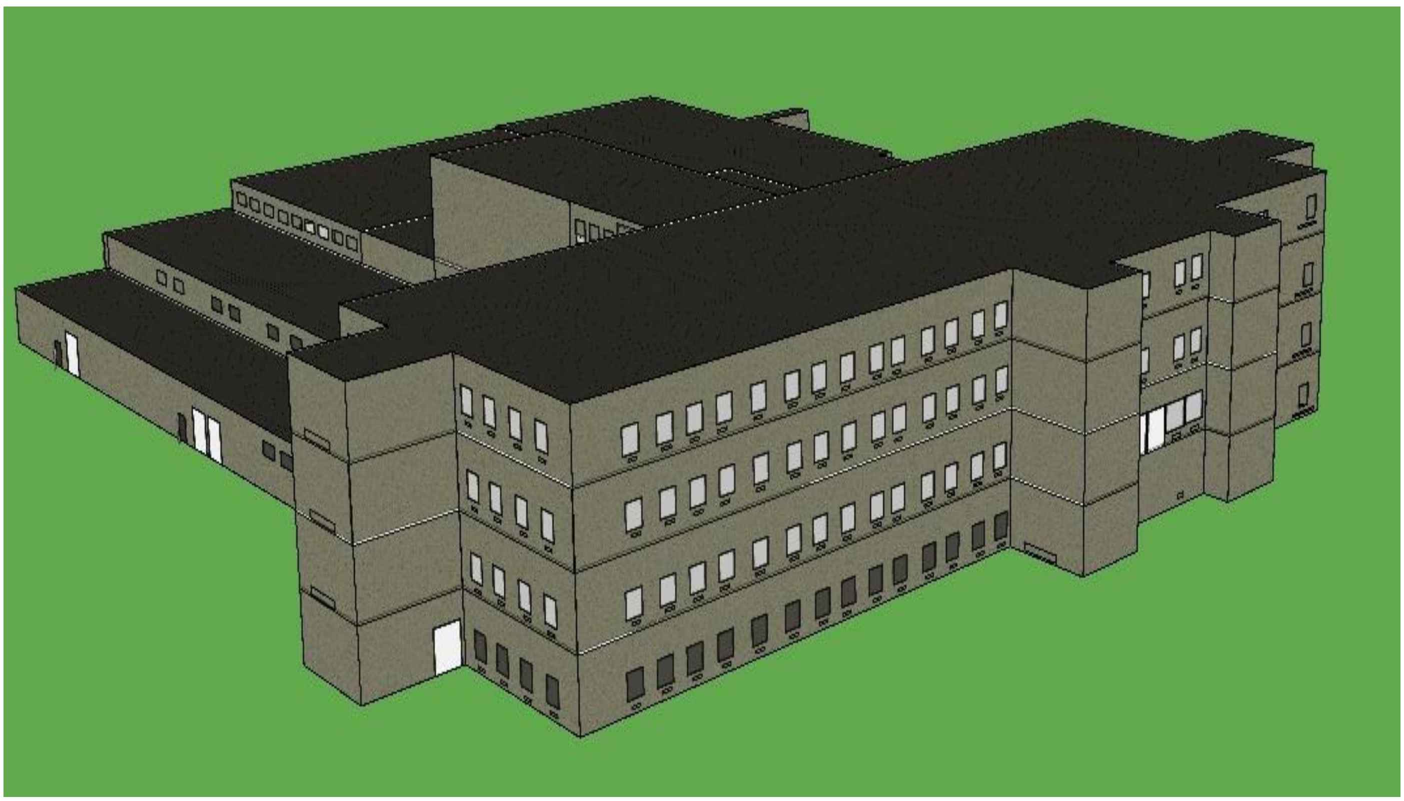

Figure 3.1 3D model of the S. J. Carew building.

Table 3.1 Details of the building

EQUA SIMULATION TECHNOLOGY GROUP		**Delivered Energy Report**	
Project		**Building**	
		Model floor area	**25141.7 m^2**
Customer		**Model volume**	**128952.9 m^3**
Created by	**Almahdi Abdo-Allah**	**Model ground area**	**10544.5 m^2**
Location	**Newfoundland (St. John's Airport) _718010 (ASHRAE 2013)**	**Model envelope area**	**29440.0 m^2**
Climate file	**CAN_NF_St. Johns.718010_CWEC**	**Window/Envelope**	**2.40%**
Case	**building2017_AHU8.**	**Average U-value**	**0.3031 W/(m^2 K)**
Simulated	**2/13/2017 23:03**	**Envelope area per Volume**	**0.2283 m^2/m^3**

Initially, a section of the building is investigated using the simulation software IDA-ICE [9]. Data is applied on the weather for St. John's and also construction details (e.g., windows, doors and walls, as well as radiators, fans, and pumps) to obtain energy consumption information for the simulation. In addition, we apply AutoCAD files drawings for determining the dimensions of the building such as the height of the building, size, and positions of the windows and doors, as well as information on ventilation and heating systems.

3.2.2. IDA ICE simulation validation

Determining whether the model satisfies the requirements and whether the results are accurate is critical to developing a feasible model. In this study, data is obtained from the Department of Facilities Management at Memorial University and compared with the structure's hot water and power usage. Fig. 3.2 illustrates the power usage and Fig. 3.3 illustrates the hot water for the entire structure of the S. J. Carew building from April 2012 to May 2017.

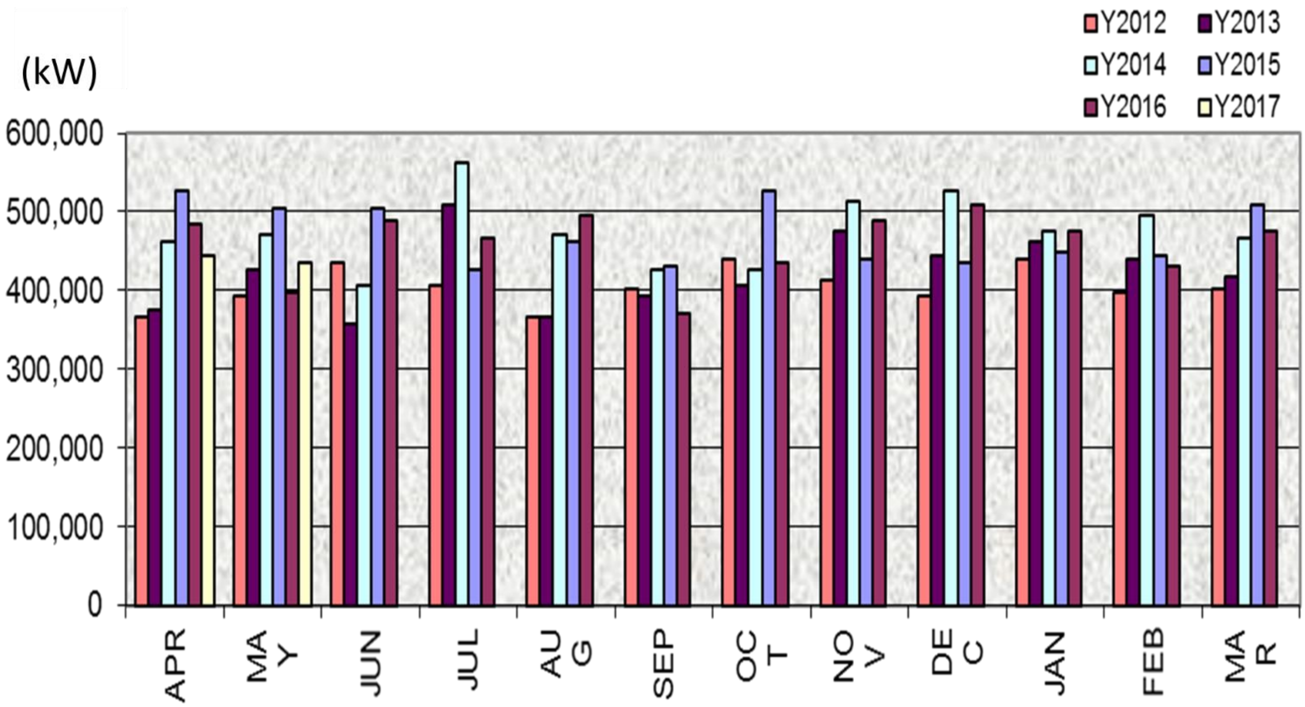

Figure 3.2 Power usage for the whole building

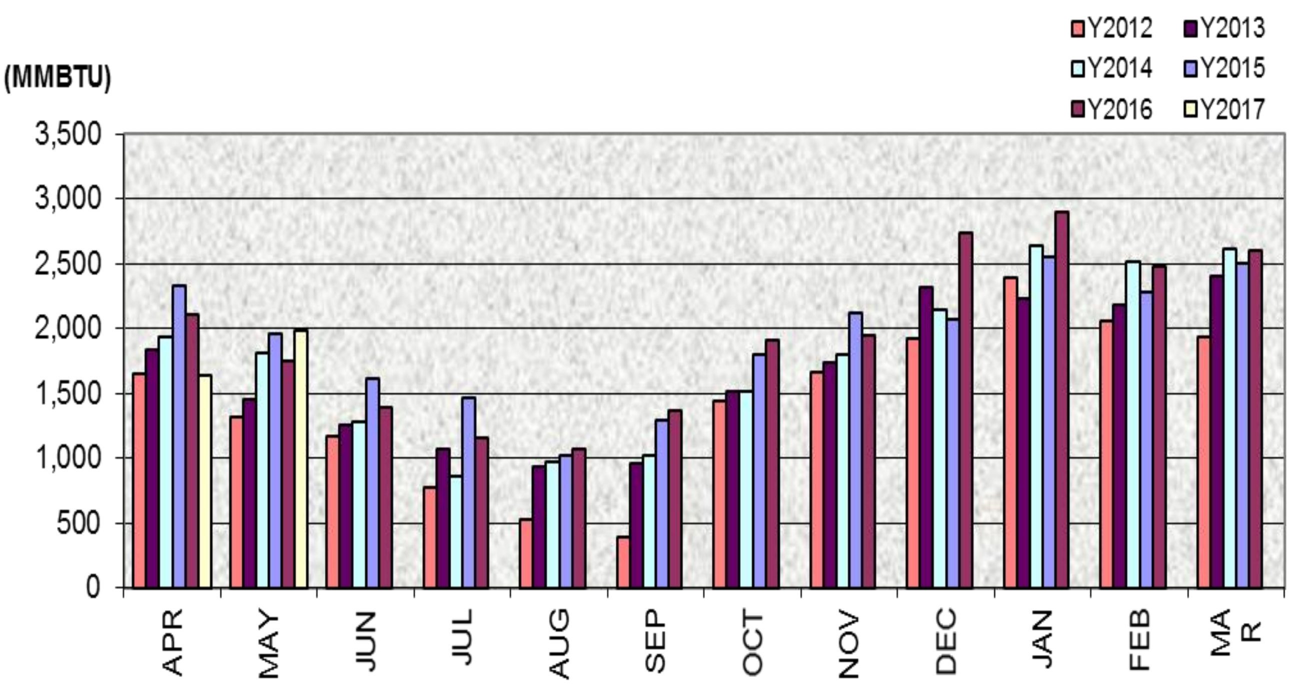

Figure 3.3 Hot water usage for the whole building

Table 3.2 and Fig. 3.4 illustrate the IDA ICE data for three months October to December 2016, including energy consumption in the building, from lighting, HVAC, and Equipment. Equipment tenant comprehends the electricity used for university hold purposes such as (Computers, TV, cookers, Fridge-freezer, etc.).

Table 3.2 IDA ICE data for three months

Month	Facility electric		Facility fuel (heating value)	Tenant electric
	Lighting, facility	HVAC aux	Domestic hot water	Equipment, tenant
	(kWh)	(kWh)	(kWh)	(kWh)
Oct	181016	98019	534558	135768
Nov	180769	152414	571011	135583
Dec	166544	174971	813670	139914
Total	528329	425404	1919239	411265

	Purchased energy		Peak demand
	kWh	kWh/m^2	kW
Lighting, facility	548329	21.8	251.1
HVAC aux	518404	20.6	460.2
Domestic hot water	1919239	76.1	2610
Equipment, tenant	411265	16.4	188.3

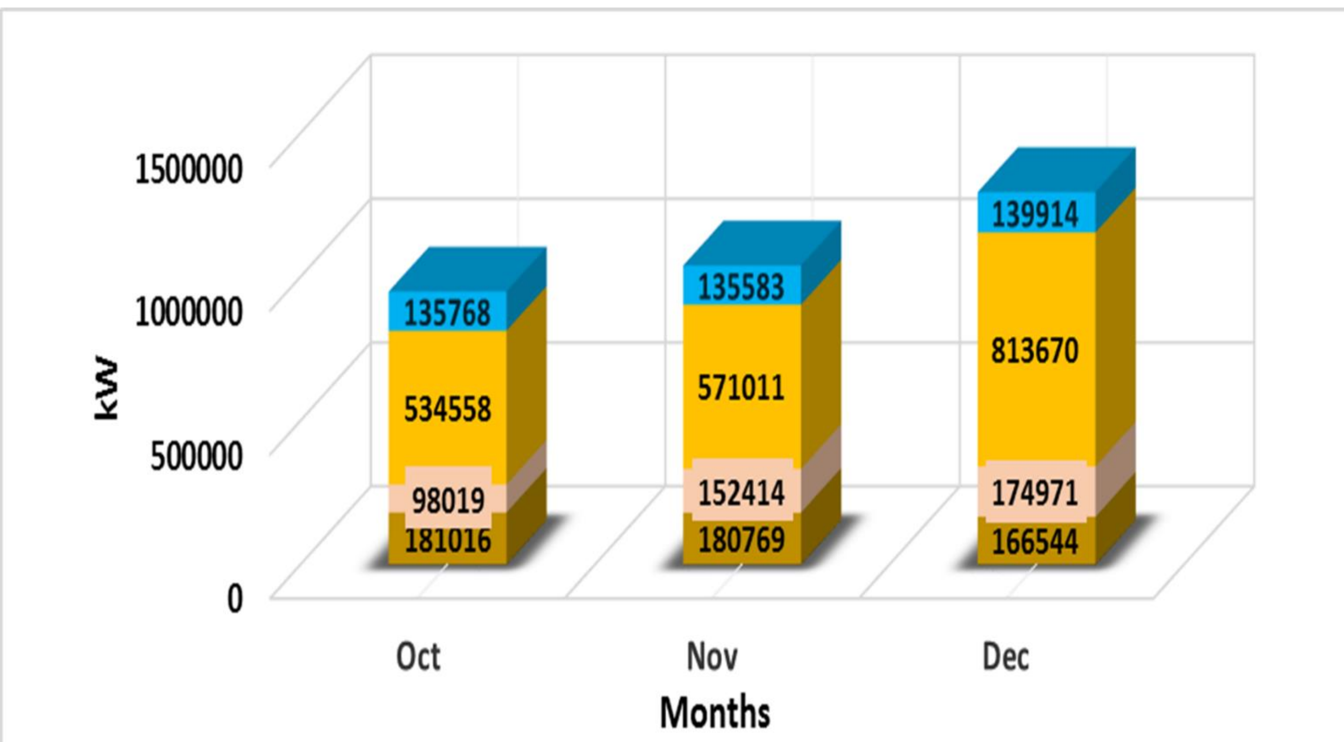

Figure 3.4 IDA ICE data for three months

The output variables of exterior temperature, hot water power usage, and power usage are compared with simulation data (three months' worth) from IDA ICE software, as follows:

3.2.2.1. Exterior temperature

Exterior temperature from the IDA ICE program and data weather files were compared with data from October to December 2016, using one-hour time samples, as shown in Fig. 3.5.

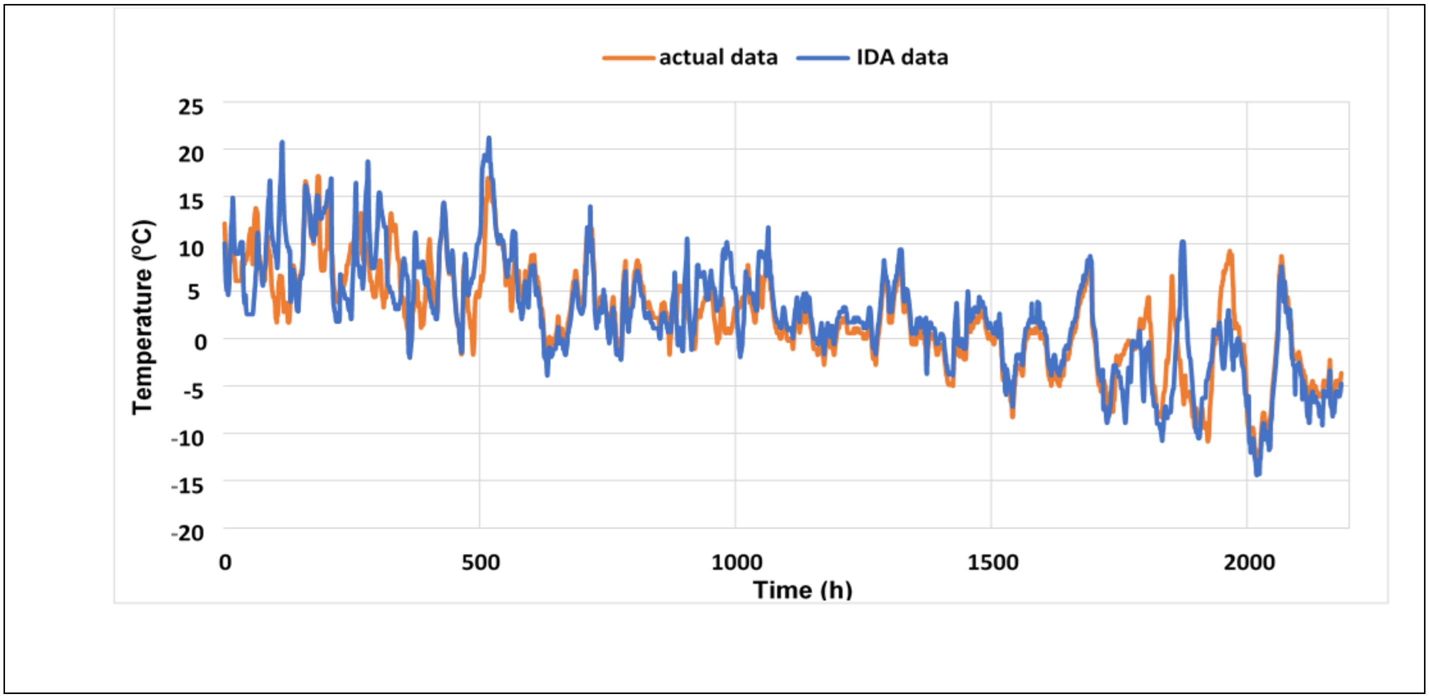

Figure 3.5 outdoor temperatures of IDA ICE and actual data

3.2.2.2. Power usage

The modeled data differs slightly from measured data for power usage. As illustrated in Fig. 3.6 the measured data slightly exceeds the modeled data, which is likely due to differences in laboratory equipment.

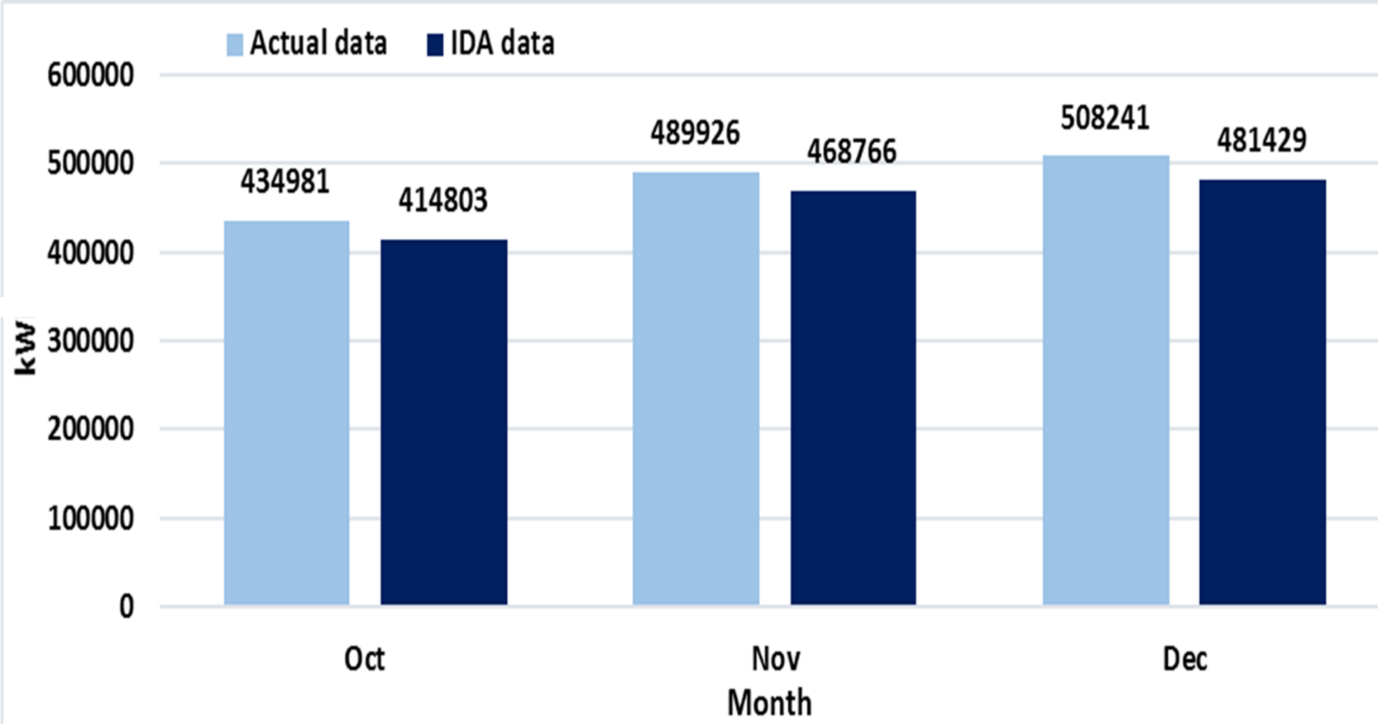

Figure 3.6 power usage of IDA ICE and actual data

3.2.2.3. Hot water power usage

As illustrated in Fig. 3.7, in October to December 2016 IDA ICE model, hot water power usage measured 6,583 MMBTU. Hot water usage in October for actual data was lower than IDA data, but in December was opposite and November was almost the same.

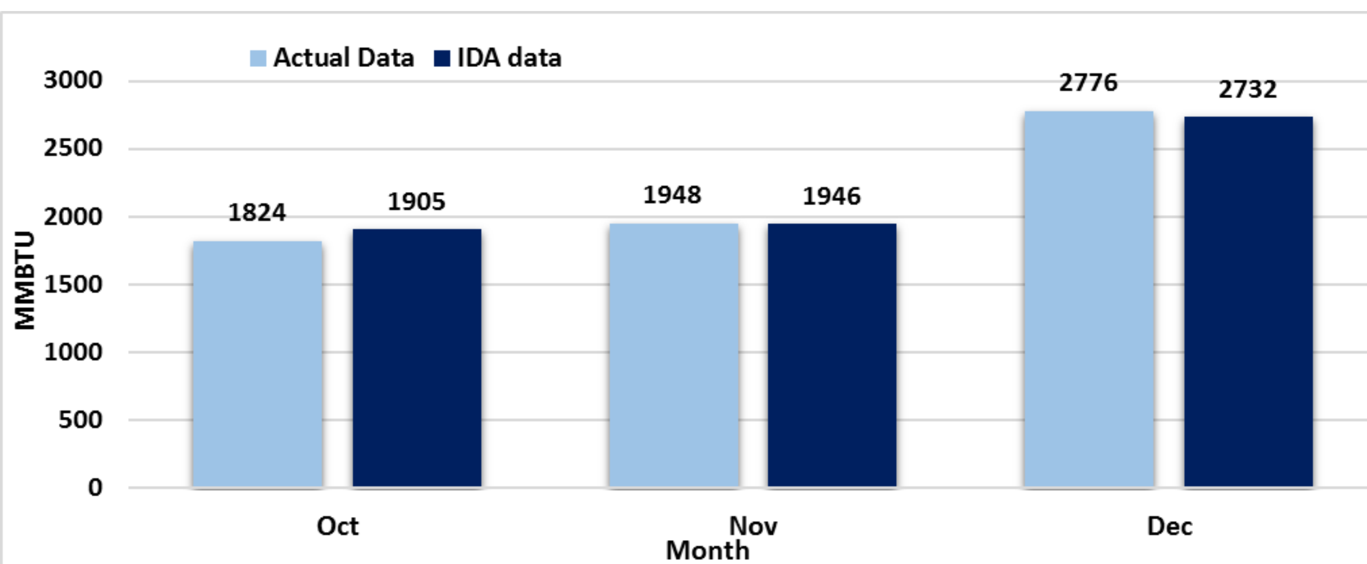

Figure 3.7 water power usage of IDA ICE and actual data

3.2.3. Simulation model

The IDA Indoor Climate and Energy 4.7 (IDA-ICE) simulation tool is used to make an assessment on both the energy performance and interior climate. The tool can model multiple-zoned structures housing HVAC and can also be used for assessing thermal comfort, interior air quality, dynamic simulation, and required energy. Figs. 3.9, 3.10 and 3.11 provided details on the zonal input and output data. This information is needed for the identification data and the reference model for modeling the building.

3.3. System identification

Three distinct stages can be defined when using system identification [7]:

1. Data gathering for identifying the model
2. Choosing a suitable model structure.
3. Developing a model which offers optimal system functionality.

The S. J. Carew building has four AHUs which are needed to identify the system's state space model. The system has eight inputs 1, 2, 3 and 4 represent the hot water power usage (kWh) and 5, 6, 7 and 8 represent the power usage (kWh) inputs of the system. For the outputs, 1, 2, 3 and 4 represent the level of CO_2 (PPM), While the 5, 6, 7 and 8 outputs represent the zone temperature (^oC), as shown in Fig. 3.8.

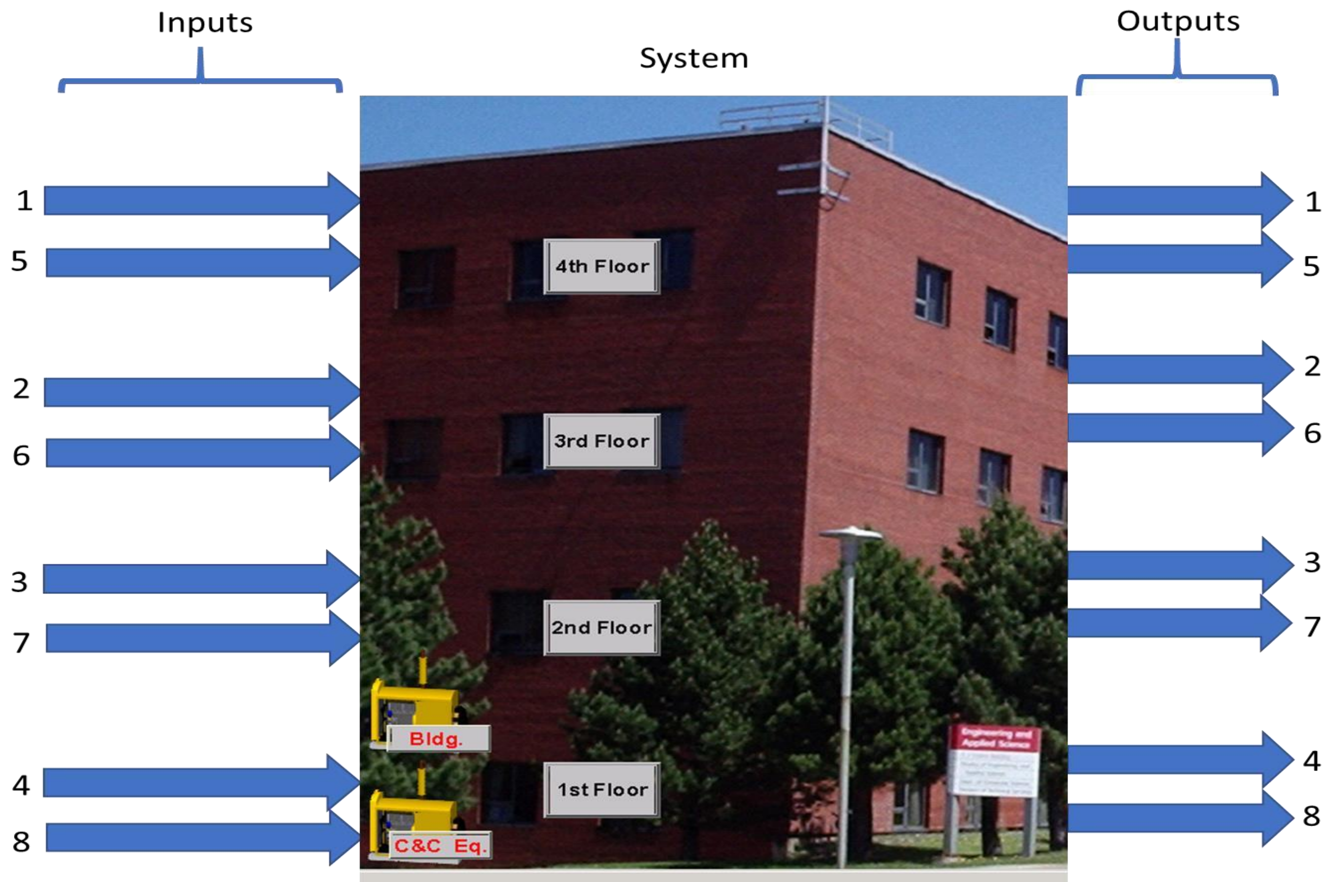

Figure 3.8 System with inputs and outputs

3.3.1. Input signals

A rise in airflow temperatures and radiator heat of the zonal temperature and hot water flow (minimum and maximum temperatures) is highly plausible. These form the zones' sole control variables. Thus identification system signals can be used as input signals. The system's power usage (PU) and hot water power usage (WPU) as a time function, for each AHU, are illustrated in Fig. 3.9.

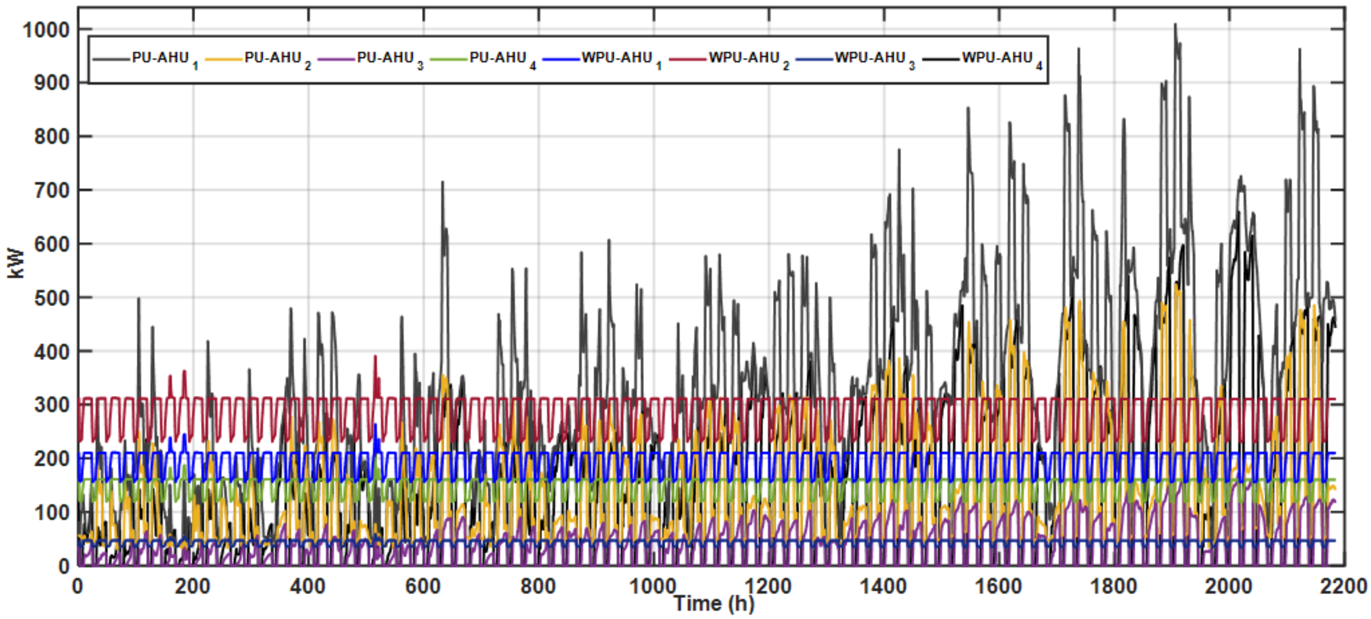

Figure 3.9 Actual data of power usage (PU) and water power usage (WPU).

3.3.2. Output signals

The system outputs are defined as the temperature and CO_2 level in the return air flow. Returned air CO_2 levels are shown in Fig. 3.10 and returned air temperature variations are shown in Fig. 3.11.

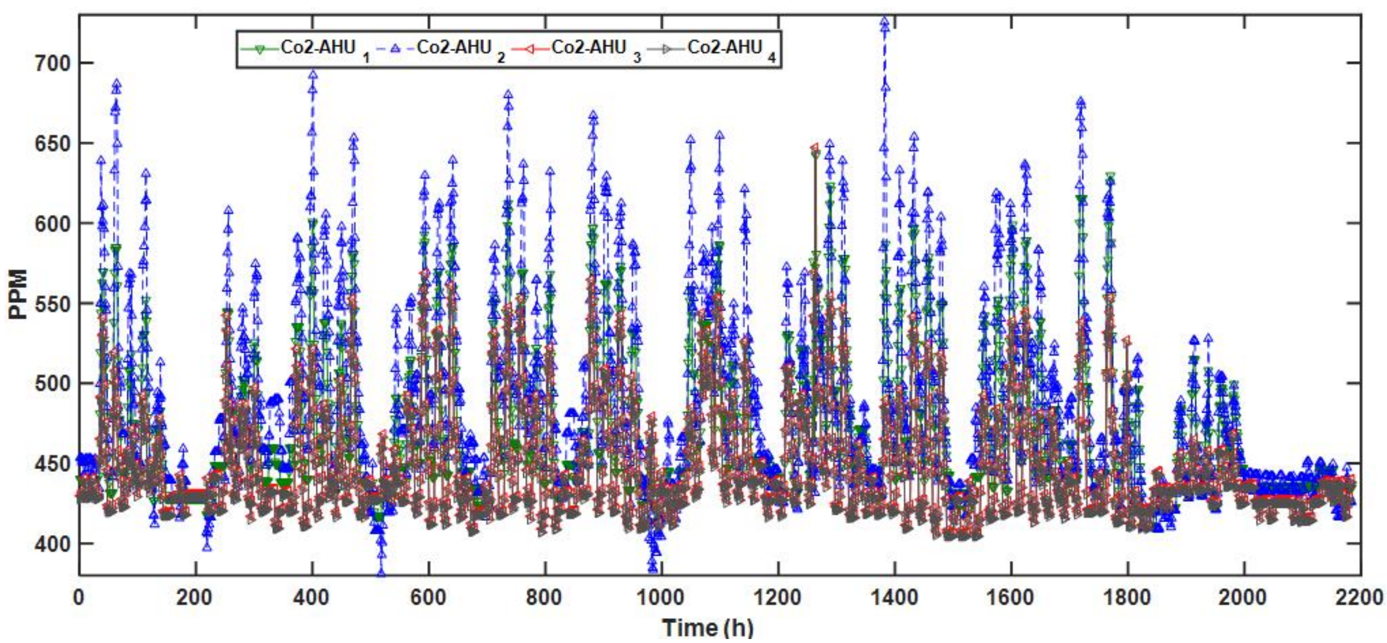

Figure 3.10 Actual data of return air CO_2 levels

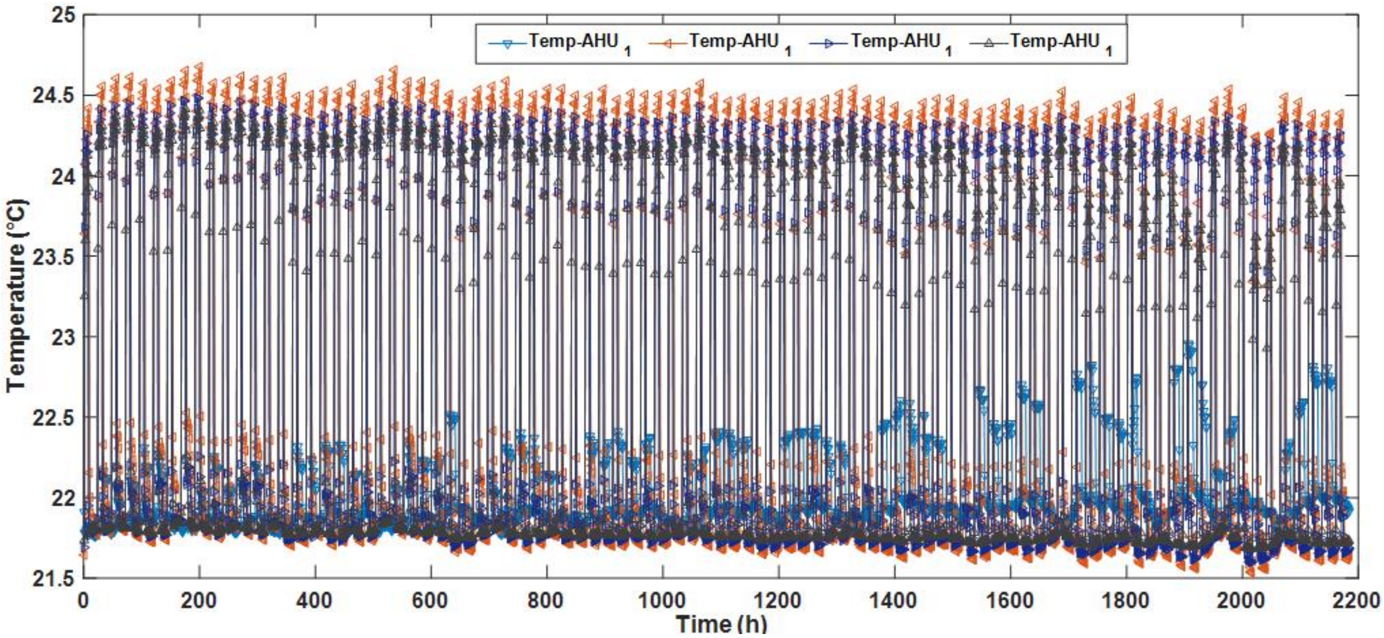

Figure 3.11 Actual data of return air temperature

3.3.3. Choosing a model structure

A model structure is selected from a range of structures which are roughly categorized as being either linear or nonlinear. However, because we are using a nonlinear system in this work, we choose the ARMAX model.

3.3.4. Identifying the model

For the identification decision process used in pre-processing the data, the decision process can be categorized into five stages [8]:

a. Deciding the optimal model structure (e.g. ARX, ARMAX, process models) for our purposes.
b. Deciding the model order.
c. Deciding the optimal estimation approach.
d. Launching the identification process.
e. Reviewing and validating the results.

3.3.5. State space model

The total quantity of the system's independent components is assumed to equal to the total number of the state variables, *n*. The system's total power and state time derivative variables set the system's power change rate, and the system's state variables at a time, *t*, give enough data for calculating the values of the system's variables for that time [10]. The multizone HVAC system was developed as a single system with 42 states and nine outputs [11], [12].

$$\dot{x} = Ax + Bu$$

$$y = Cx + Du$$

Matrix A_{8*8} and matrix B_{8*8} form the system's properties. Hence, the output variables impact the output equation matrices (C_{8*8} and D_{8*8}). The matrices are calculated by applying the MATLAB tool box for system identification.

Additionally, using MATLAB, we can formulate the system's dynamic behavior for an arbitrary input and *lsim (sys, u, t, xo)* function simulation. The system uses eight inputs, each depicted as *u*, while the time samples are given as *t vector* and x_o indicates the system's starting values. The system outputs response, in Fig. 3.12 shows the zonal temperatures, while Fig. 3.13 indicates the zonal level of CO_2.

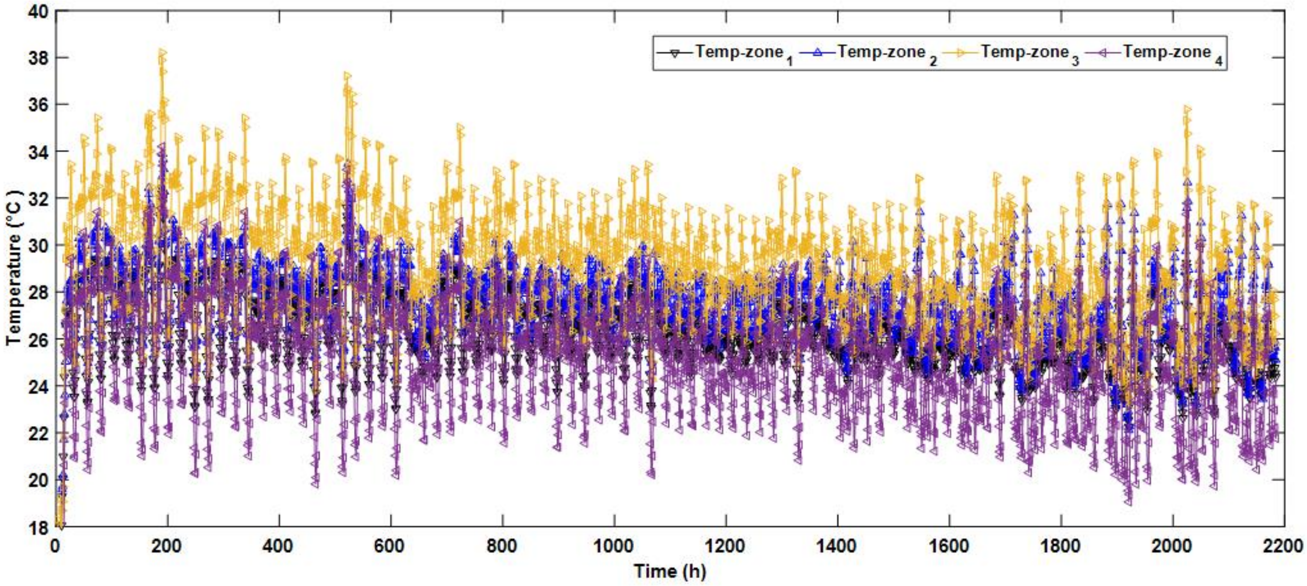

Figure 3.12 Temperatures using *lsim* function simulation.

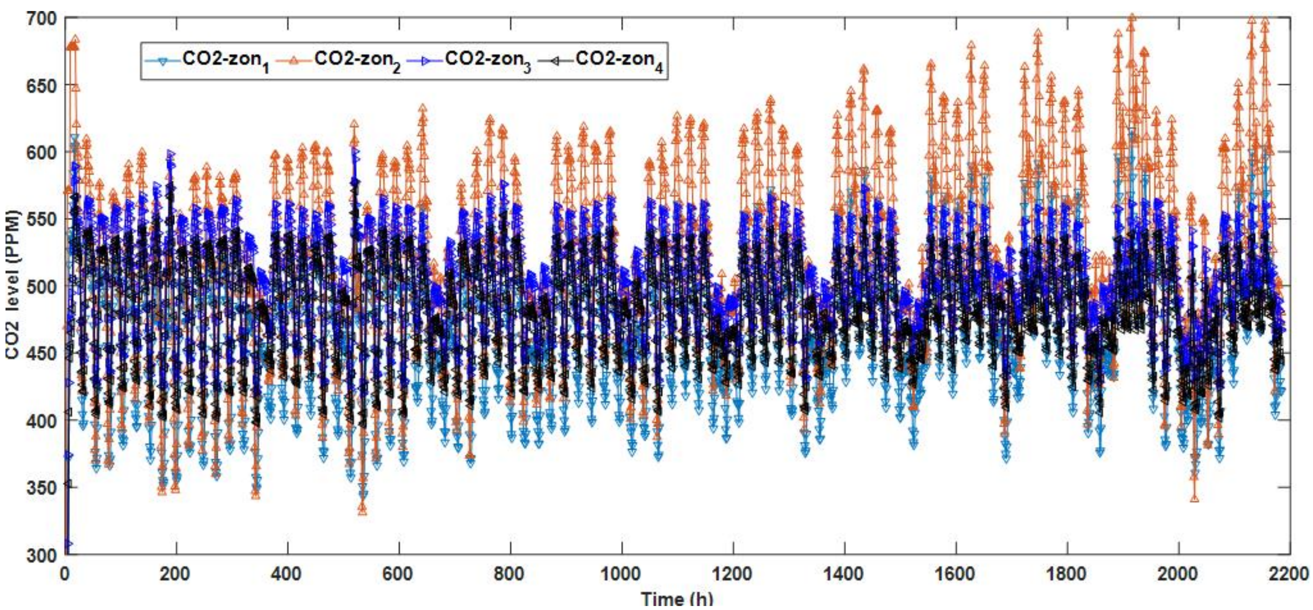

Figure 3.13 CO_2 level using *lsim* function simulation

As illustrated in Fig. 3.13, the system responses fall within the correct range if the starting transient is neglected.

3.4. Control strategies

HVAC systems control interior environmental factors such as room humidity and temperature in commercial or residential structures, with the overall aim of giving users a comfortable working and living environment. HVAC systems are so widely used that they comprise at least 50% of global power usage [13]–[16]. In addition to creating a comfortable working and living environment, HVAC controls typically need also to consider maximizing energy efficiency. System identification and state space model for one AHU of the S. J. Carew Building was presented without control [17]. In earlier studies, researchers investigated mainly humidity and temperature levels in modeling HVAC systems [18]-[22]. A nonlinear HVAC model was introduced [18] and [19] that involves a temperature/humidity ratio and an observer for determining approximate moisture and thermal loads. An adaptive fuzzy output feedback controller was developed [20] that can be premised on an HVAC system observer. Researchers proposed applying both a decentralized nonlinear adaptive controller [21]. And a back-stepping controller [22] on a model.

CO_2 concentrations are generally seen as having a notable impact on room comfort levels [23], [24]. Accordingly, some researchers are suggesting developing a hybrid HVAC system that can develop continuous temperature states, as well as CO_2 concentration as a discrete state [25], [26]. As these states can be highly interrelated, a more viable approach would be to integrate the presented discrete and continuous dynamics to form a model that assumes as states both CO_2 concentration and temperature.

A system's possible future development can be predicted by the state of a dynamical system; the latter is essentially a group of variables. The control system is used to bring the non-linear system into a stable state while achieving the control targets. For one AHU unit system design feedback linearization technique have been applied [29], the control of the cross-water heat exchanger [28] and feedback controller achieves global input_ output linearization of greenhouse environments [30]. In creating system dynamics by referring to state feedback, the multi-input system can be controlled as a linear state model. Hence, the feedback control can be devised through a step-by-step process that is based on putting closed-loop eigenvalues in specific places. Fig. 3.14 illustrates a control system that utilizes state feedback. The system features linear process dynamics, processes disturbances, d, reference input, r, and controller elements, K, is feedback gain and, K_r is input gain.

The feedback controller's main purpose is regulating the system output, y until it tracks the reference input during process dynamics uncertainty and disturbances.

Performance specifications are critical to controlling design, and the most important feature is stability. The aim is for the system's equilibrium point to stabilize asymptotically, but increasingly complex specifications can include obtaining the preferred properties from the system's step or frequency responses. Such desired specifications include rise times, overshoot and settling times of step responses. In optimizing functionality, the system's disturbance rejection properties can be analyzed to find the best way to handle disturbance inputs, *d*, while maintaining output, *y*, at the required value specifications.

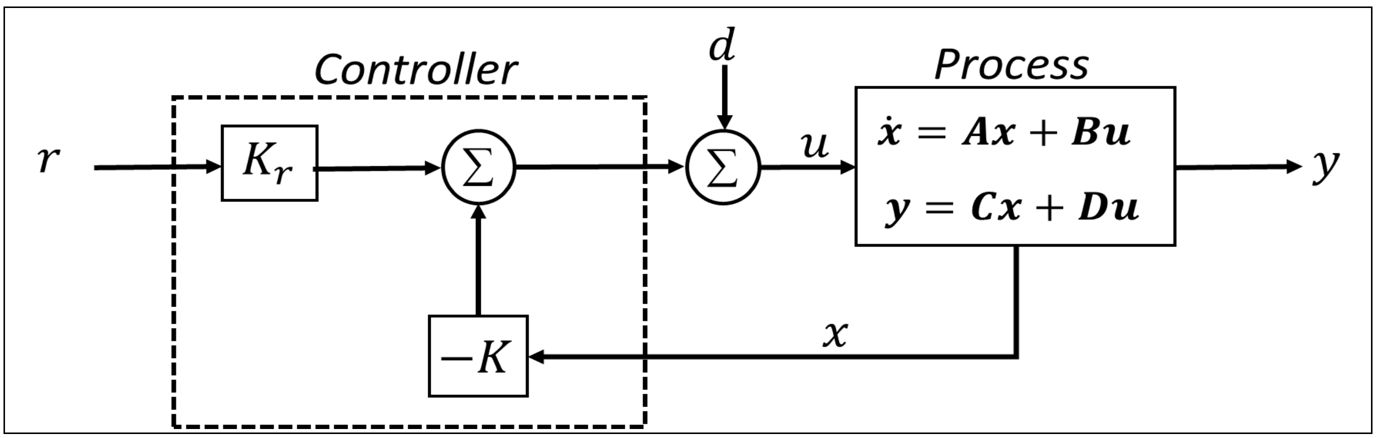

Figure 3.14 system with state feedback (K) and (K_r).

The system is represented by the following linear differential matrix equation:

$$\begin{aligned} \dot{x} &= Ax + Bu \\ y &= Cx + Du \end{aligned} \tag{3.1}$$

It is assumed that $D = 0$ while neglecting the disturbance signal, *d*. The aim is to give the output value, *r*. In this scenario, state vector components must first be calculated. Thus, as the state at the time, *t* already has the required data for predicting the system's behavior, the following time-invariant control law becomes both a state function and reference input:

$$u = \alpha(x, r) \tag{3.2}$$

The equation can be formulated as follows if the feedback is maintained linear:

$$u = -Kx + K_r r \tag{3.3}$$

In this equation, the reference value, r, has been deemed constant, which refers back to Fig. 3.14. Here, the negative sign works as an indicator of negative feedback being standard procedure. The closed-loop system we created after the feedback (3.1) has been applied to the system (3.3) can be calculated as:

$$\frac{dx}{dt} = (A - BK)x + BK_r r \tag{3.4}$$

To find feedback gain, K, to set the characteristic polynomial of the closed-loop system:

$$p(s) = s^n + p_1 s^{n-1} + \cdots + p_{n-1}s + p_n \tag{3.5}$$

This formulation is known as the "pole placement" or eigenvalue assignment problem. In the formulation, K_r input gain does not affect system stability (the latter is instead created by $A-BK$ eigenvalues) but does have an impact on the steady-state solution. Thus, we can set the equilibrium point and steady-state output as:

$$\begin{aligned} x_e &= -(A - BK)^{-1}BK_r r \\ y_e &= Cx_e \end{aligned} \tag{3.6}$$

In this formulation, K_r is the best choice, which then gives $y_e = r$, which is the required value. Furthermore, because K_r is scalar:

$$K_r = -1/(C(A - BK)^{-1}B) \tag{3.7}$$

The variable K_r represents the opposite of the closed looped system's zero-frequency gain. Therefore, by applying K_r input gain and K which is (8×8) feedback gain matrix, the dynamics of a closed loop system can be modified until the required specifications are achieved. In this paper, the state feedback gain matrix is

$$\begin{bmatrix} 102080.4 & -93791.2 & -729047 & 614999.7 & 350096.8 & 658615.9 & 202011.9 & 30447.25 \\ -1446580 & 596078 & -969369 & 776114.2 & 1646412 & 355322.9 & -393128 & -50502.8 \\ 645753.8 & -269577 & -1935998 & 1784298 & 589759.8 & 821055.8 & 623924.2 & 91440.54 \\ 388775.7 & -184664 & -601331 & 542196.5 & 197042 & 354662.3 & 191710.6 & 27060.44 \\ -30.043 & 25.90427 & 20.8471 & 0.886393 & 20.65468 & -3.9515 & -7.54395 & -0.83403 \\ -39.3176 & 33.88056 & 27.27797 & 1.154438 & 27.0208 & -5.17458 & -9.88601 & -1.0934 \\ -58.262 & 50.20904 & 40.42217 & 1.711219 & 40.04134 & -7.66779 & -14.6487 & -1.6203 \\ -8.83168 & 7.630466 & 6.129845 & 0.253818 & 6.062056 & -1.17064 & -2.24588 & -0.24996 \end{bmatrix}$$

3.5. Simulation results

3.5.1. Open loop system

The system has eight inputs and eight outputs. In this part, the system is presented by 64 transfer functions each relating one input to one output.

$$G_{11} = \frac{y1}{u1} = \frac{-0.024\,s^7 + 0.009\,s^6 - 0.03\,s^5 + 0.067\,s^4 - 0.107\,s^3 + 0.127\,s^2 - 0.08\,s + 0.027}{s^8 - 3.55\,s^7 + 6.323\,s^6 - 7.5\,s^5 + 6.66\,s^4 - 4.711\,s^3 + 2.635\,s^2 - 1.06\,s + 0.23}$$

$$G_{12} = \frac{y1}{u2} = \frac{-0.19\,s^7 + 0.47\,s^6 - 0.64\,s^5 + 0.54\,s^4 - 0.27\,s^3 + 0.095\,s^2 - 0.0154\,s - 0.0007}{s^8 - 3.555\,s^7 + 6.323\,s^6 - 7.5\,s^5 + 6.659\,s^4 - 4.711\,s^3 + 2.63\,s^2 - 1.06\,s + 0.23}$$

$$\vdots \qquad \vdots \qquad \qquad \vdots$$

$$G_{87} = \frac{y8}{u7} = \frac{5.6e5\,s^7 - 1.5e6\,s^6 + 2.6e6\,s^5 - 2.9e6\,s^4 + 2.6e6\,s^3 - 1.59e6\,s^2 + 6.7e5\,s - 8.5e4}{s^8 - 3.5\,s^7 + 6.323\,s^6 - 7.5\,s^5 + 6.659\,s^4 - 4.711\,s^3 + 2.635\,s^2 - 1.06\,s + 0.23}$$

$$G_{88} = \frac{y8}{u8} = \frac{6.68e5\,s^7 - 1.15e6\,s^6 + 1.6e6\,s^5 - 2.02e6\,s^4 + 2.3e6\,s^3 - 1.6e6\,s^2 + 7.9e5\,s - 1.4e5}{s^8 - 3.55\,s^7 + 6.323\,s^6 - 7.5\,s^5 + 6.659\,s^4 - 4.71\,s^3 + 2.635\,s^2 - 1.06\,s + 0.23}$$

Fig. 3.15 illustrates the steps response of the open loop system with sampling time (3600 s). In this paper, 8 responses are simulated, instead of 64 responses (such as G_{11}, G_{22}, G_{33}, G_{44}, G_{55}, G_{66}, G_{77}, and G_{88}).

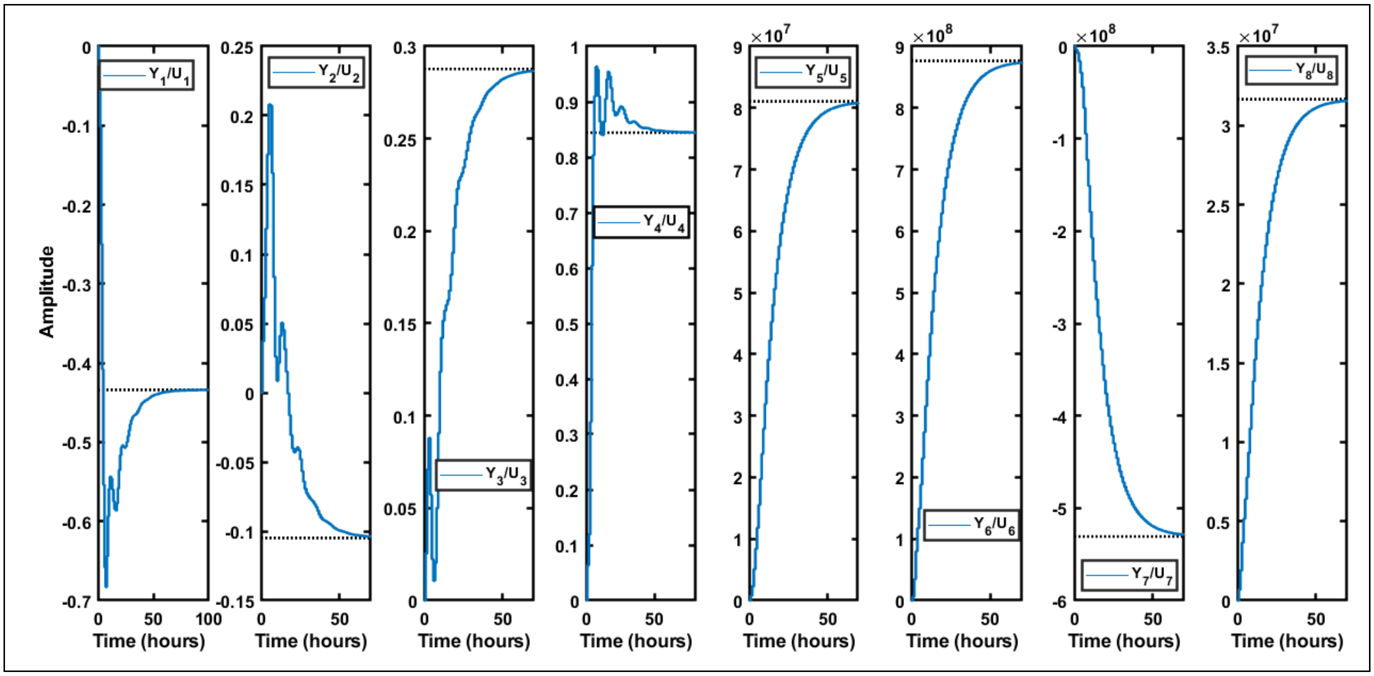

Figure 3.15 Steps response of the open loop system

3.5.2. Steady-state tracking

It has been shown in this paper how state feedback control laws affect the transient response characteristics of a system, including the definition of freedom, specifying their curves for a controllable equation of state, and how the eigenvalues affect the transient response. It has been demonstrated that by adjusting the gain matrix K, only some of the transient parameters can be appropriately adjusted, but there is no control over the steady-state value of the system. Next, the requirement forsteady-state monitoring for reference inputs is investigated. Such control systems are commonly referred to as servomechanisms.

Two approaches are described:

- input gain, the addition of an input gain to the state control law
- integral, including an overall follow-up measure

3.5.3. Input Gain

For the input gain K_r, presented in Equation (3.7), the input gain controller is introduced to eliminate the stationary error associated with the complete status feedback controller for each constant input. The control law is designed such that the output, y(t) follows the reference input, r(t). The controller maintains tracking in the steady state only if the reference inputs are stage inputs. The gain, K, is outside the feedback loop and makes the overall system sensitive to noise and disturbances. However, this is not "robust" since any change to the system parameter causes a nonzero error.

3.5.4. Integral action

The technique of integral control is another type of technique of placing the poles. It is also known as a tracking controller when it needs an output to track the input control signal. The output feedback is transferred to the controlled system via the integrator. The integrator, also called integral action, is used to increase the system type, and reduce finite errors to become zero [27].

The configuration of the integrated control technique is shown in Fig. 16. The introduction of the input integrator causes the controller to have a pole at S = 0, which helps to eliminate the constant reference and improve the robustness of the system. However, Fig. 3.16 shows the block diagram of a system with state feedback and integral control using Matlab Simulink. Simulations are performed for a controller structure where a unit's step input is [465 459 453 471 23.9 22.9 21.9 24.9], and signals are used as the reference signal. To accomplish one of the design requirements, the output signals should follow the given reference signals. Through simulation, mathematical modeling for the system is verified, and the performances for the controller structures are analyzed. Also, the initial state, X_0, of the system for concentrations and indoor temperatures are taken from measured data at 6:00 AM when the system just starts.

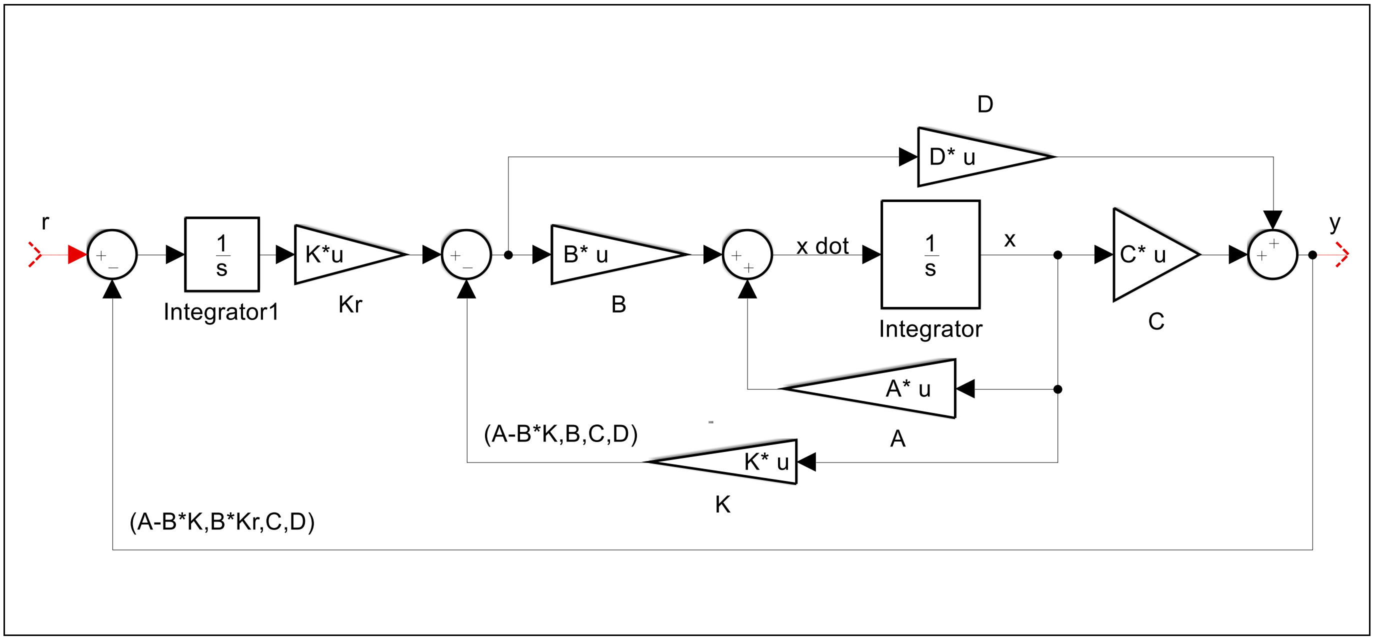

Figure 3.16 Block diagram using Matlab Simulink.

Simulation results of the system with a measured initial condition of CO_2 level is X_0= [446.4 440.6 435.44 453.4], and change for set points in different time investigate the system's responses with state feedback control and integral action. The responses of the CO_2 level for the zones are illustrated in Fig. 3.17.

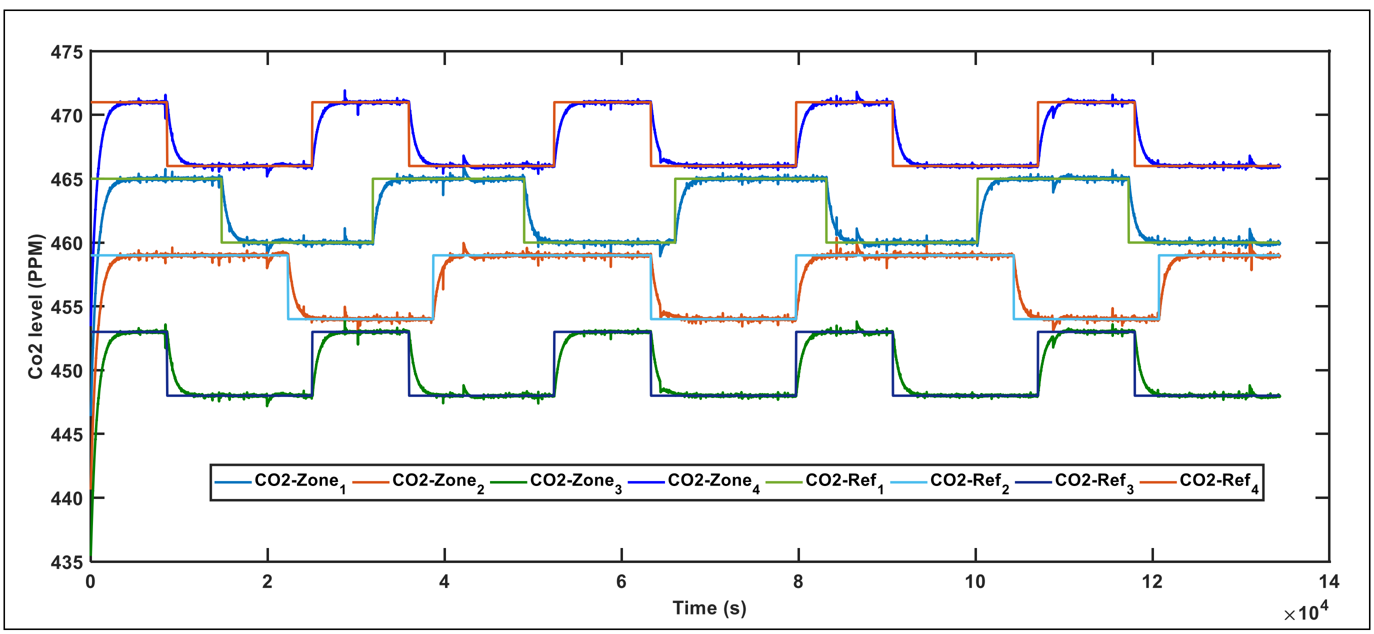

Figure 3.17 Outputs response of the CO_2 level of zones

Fig. 3.18 shows the responses of the zones temperature with measured initial condition of the zone temperatures, X_0= [21.21 20.35 19.39 22.13].

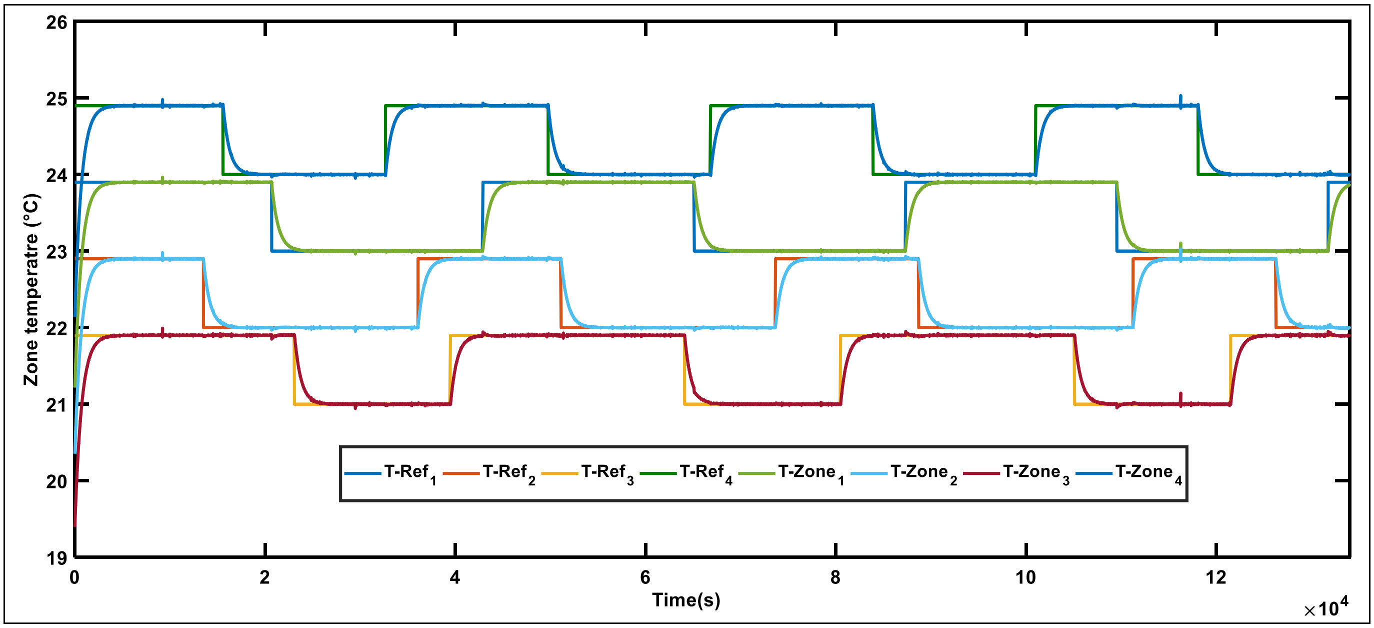

Figure 3.18 The outputs response of the zone's temperature T-Zones with steps references T-Refs

For full state feedback controller, K, with input gain, K_r, and integral action, the steady-state error is zero. Fig. 3.19 illustrates the controller action (steady-state error) of CO_2 level responses (CO_2-Er-Zones).

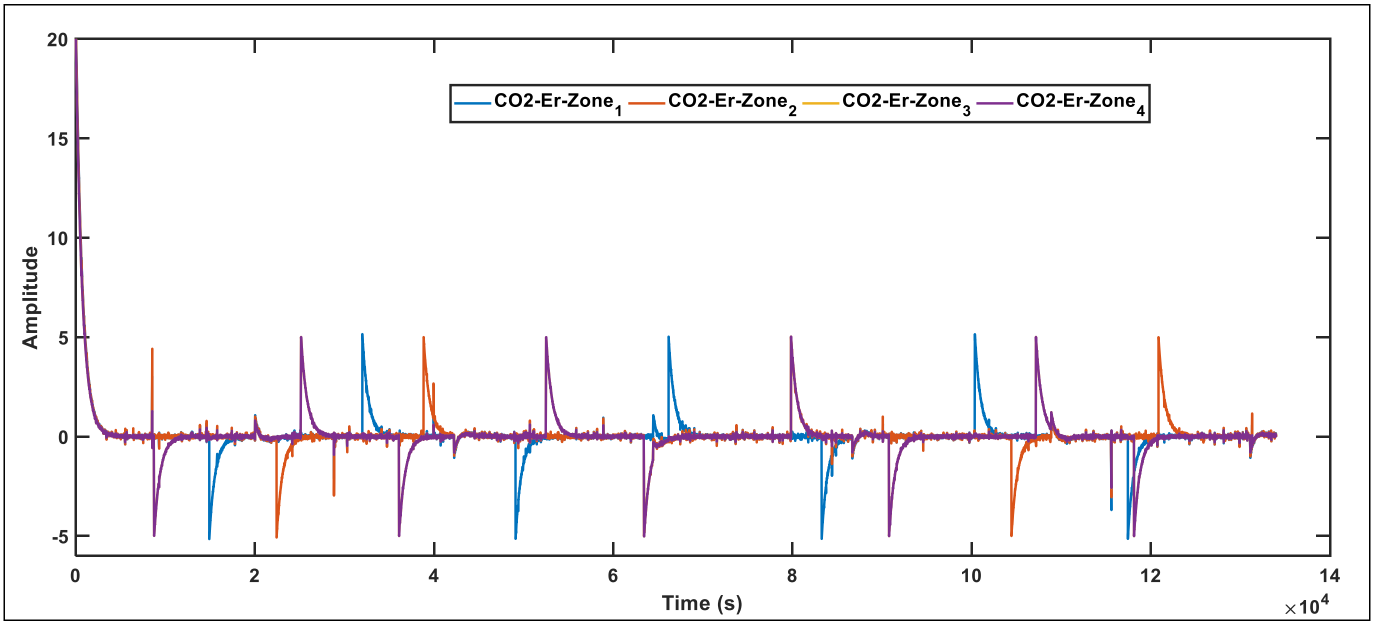

Figure 3.19 Controller action (steady-state error) of CO_2 level responses for each zone CO_2-Er-Zones.

Fig. 3.20 shows controller action (steady-state error) of zones temperature responses (T-Er-Zones).

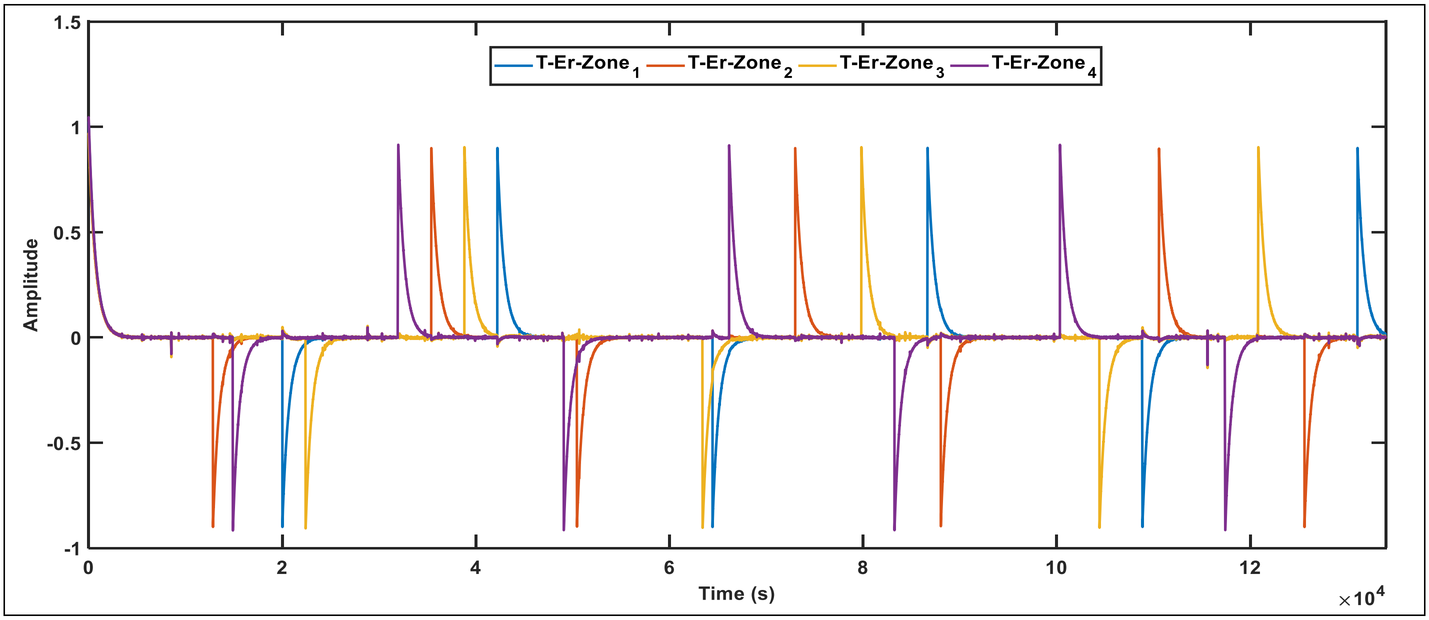

Figure 3.20 Controller action (steady-state error) of temperature responses for each zone T-Er-Zones.

3.6. Conclusion

In this paper, the HVAC system of the S. J. Carew building was modeled using the IDE ICE program. This model provides good approximation results in which hot water consumption and electricity consumption are compared with actual data. Also, the outside temperature for the program and the measured data are compared for three months as the first part of the process. In the second part, the system identification toolbox was used to obtain the state space model of the multi-input and multi-output system MIMO. The model has eight status variables, eight inputs, and eight outputs, and model responses are within the permissible range. In the third part, a novel HVAC system model was developed that considers temperature and CO_2 concentration as the quantitative indices of comfort in a building. In applying an input-output feedback linearization method to linearize the HVAC system, one type of linear controller, pole placement controller with input gain and integral action were able to regulate the linearized HVAC system at the desired set point without steady-state error. Simulation results validated the proposed HVAC model, demonstrating its effectiveness in maintaining comfortable conditions.

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Chapter 4

4. Modeling, Analysis, and Design of a Fuzzy Logic Controller for an AHU in the S. J. Carew Building at Memorial University

Preface

A version of this manuscript has been published in Hindawi the Journal of Energy. I am the primary author of this paper. Along with the co-authors, Tariq Iqbal and Kevin Pope. I build fuzzy logic controller structures with six inputs and three outputs and then apply these structures as controllers for the AHU_1 state space model. I completed the first version of the manuscript and further revised according to the suggestions of co-authors. Tariq Iqbal helped to identify the research topic and scope. Also helped in choosing the appropriate optimization method, programming and running the simulation, reviewing and correcting the achieved results, and contributed in preparing, reviewing and revising the manuscript. Keven Pope reviewed the manuscript and provided revision suggestions.

Abstract

Proper functioning of heating, ventilation and air conditioning (HVAC) systems is important for efficient thermal management, as well as operational costs. Most of these systems use nonlinear time variances to handle disturbances, along with controllers which try to balance rise times and stability. The latest generation of fuzzy logic controllers (FLC) are algorithm-based and used to control indoor temperatures, CO_2 concentrations in air handling units (AHUs) and fan speeds. These types of controllers work through the manipulation of dampers, fans, and valves to adjust flow rates of water and air. In this paper, modulating equal percentage globe valves, fans speed and dampers position have been modeled according to exact flow rates of hot water and air into the building, and a new approach to adapting FLC through the modification of fuzzy rules surface is presented. The novel system is a redesign of an FLC using Simulink, with the results showing an enhancement in thermal comfort levels.

Keywords: State space model, AHU modeling and simulation, HVAC, Fuzzy logic controller, system identification.

4.1. Introduction

Heating, ventilation, and air conditioning (HVAC) systems are installed in millions of commercial and non-commercial buildings as a means to provide the desired thermal comfort standards at an affordable cost and with minimal maintenance requirements. The HVAC approach to heating and cooling has become much more complicated, with the latest HVAC components using control algorithms, sensing technology, and artificial intelligence [1].

Energy saving is a key feature of HVAC systems and is increasing in importance [2], [3]. As the housing and business needs of the developed world generally include buildings that require HVAC systems, the percentage contribution of the total energy consumption of these buildings has increased from 20% to 40% in Western countries [4], [5]. Typically, an HVAC system requires more energy per building than any other system, given that optimal comfort in the home and work environments. However, there is a rising demand for costs to remain reasonable but efficiency to be high without sacrificing comfort levels. Recent research indicates that intelligent control might be a viable method of achieving optimal comfort levels at high energy efficiency. Intelligently controlled HVAC systems have been shown to reduce energy consumption by up to 30% [6] or higher [7]. Due to the potential these systems have for future energy needs, this paper proposes identifying advanced novel HVAC system models that employ intelligent control algorithms to produce energy savings without sacrificing comfort levels. Modeling HVAC systems and components mathematically have been demonstrated in the literature to be a viable approach for designing controls and detecting faults.

Earlier research in the field reveals modeling strategies that fall into two distinct categories: grey box and a black box. The grey box approach depends on the existence of physical knowledge, while the black box method requires no previous knowledge. In the literature, the black box is more common due in large part to issues related to thermodynamic modeling. Some black box options used in modeling HVAC systems include linear parametric models, such as OE, BJ, ARMAX, and ARX. However, this approach does consider a system's physical characteristics, which can be a drawback in the practical application of designs.

Chi-Man Yiu et al. [8] investigated black box identity in an air conditioning system. They compared a Single-input single-output system (SISO) ARMAX model with a multiple-input and multiple-output system (MIMO) ARMAX model, the latter which they devised using parameters obtained from the Recursive Extended Least Squares (RELS) technique. Mustafaraj et al. [9], investigated humidity and temperature models (OE, BJ, ARMAX, and ARX) to be applied in an office environment, identifying them with a black box strategy. This research was extended by Mustafaraj et al. [10], where they explored nonlinear auto-regressive models with eXogenous (NNARX) inputs. Using this approach, they estimated humidity and temperature and compared the performance of these models with linear ARX models. Mustafaraj et al. [10], also investigated carbon dioxide concentrations impact on the models, as there is a direct relationship between CO_2 and occupancy levels.

In other studies, Qi and Deng [11] reviewed a MIMO control strategy in air conditioning systems for modulating humidity and temperature indoors, using an air conditioning model that was based on principles of mass and energy conservation. Maasoumy [12] researched temperature models applicable to a three-room suite, designing a suitable HVAC control algorithm for the system using an analog of electric circuits along with the thermal circuit technique. More recently, Wu and Sun devised a room temperature model for an office building using a linear parametric model which was physics-based, the researchers used thermodynamics equations to develop structure and order in the linear regression model. The outcome indicated that the physics-based ARMAX (pbARMAX) model showed improved functioning over black-box models [13]. Finally, in [14], and based on physical dynamic systems, the researchers developed MISO ARMAX models to investigate humidity, temperature, and CO_2 levels in a standard bedroom. This model also makes allowances for the impact of room occupants, as occupants were deemed a 'disturbance' in the room temperature pbARMAX model designed in.

The present study develops a simulation for a whole building, using IDA Indoor Climate and Energy 4.7 as a simulation program. The IDA Indoor Climate and Energy program was founded in 1998 to study thermal climate zones [15]. The simulation will test the energy consumption (heating and cooling) at Memorial University's S. J. Carew Building in Newfoundland, Canada. It will investigate a heat model that is dependent on a range of parameters, a three-dimensional (3-D) model, and IDA ICE model library components. The present work will also examine results from [16], [17] which used real data as a basis for developing whole structures.

There are three primary aims in this study. Our first aim is to test system identification viability as a means for shortening the calculation times needed to simulate more complicated structures in Air Handling Unit One (AHU_1). Our second aim is to test the usefulness of system identification in the dynamics identification for structural climate control design when applying discrete time data for one-hour samples. Our third aim is to develop fuzzy logic controller structures that feature six inputs and three outputs and use this to develop a controller in an AHU_1 state space model.

4.2. Description of system

4.2.1. Building structure

Our analysis will use the S. J. Carew Building at Memorial University in St. John's, Newfoundland. The Carew Building measures approximately 25,142 m^2 and houses the university's Faculty of Engineering and Applied Science, as well as teaching rooms, research labs, and a cafeteria.

From a structural perspective, the building houses four AHUs across 300 zones. A more detailed description of the structure and amenities of the Carew Building can be found in earlier studies [16], [17]. As the building's HVAC system is based on the IDE ICE program, good approximation results can be obtained from the model regarding power and hot water data, which can then be compared to real data.

4.2.2. AHU₁ structure

Fig. 4.1 illustrates an AHU1 with a variable air volume (VAV) system. There are valves, hot water pumps, heating and cooling coils, supply and return fans, and fresh air dampers. To maintain a constant point of internal air quality (IAQ), the building employs fresh air control dampers. An economizer mixes outdoor air with recycled building air, while a supply fan funnels the air mixture into cold-deck and hot-deck ducts. The fan, which keeps the ducts set at fixed pressure points, also alternates the fan speed as a means to balance any duct system resistance changes caused by opening/closing dampers located at VAV terminal units.

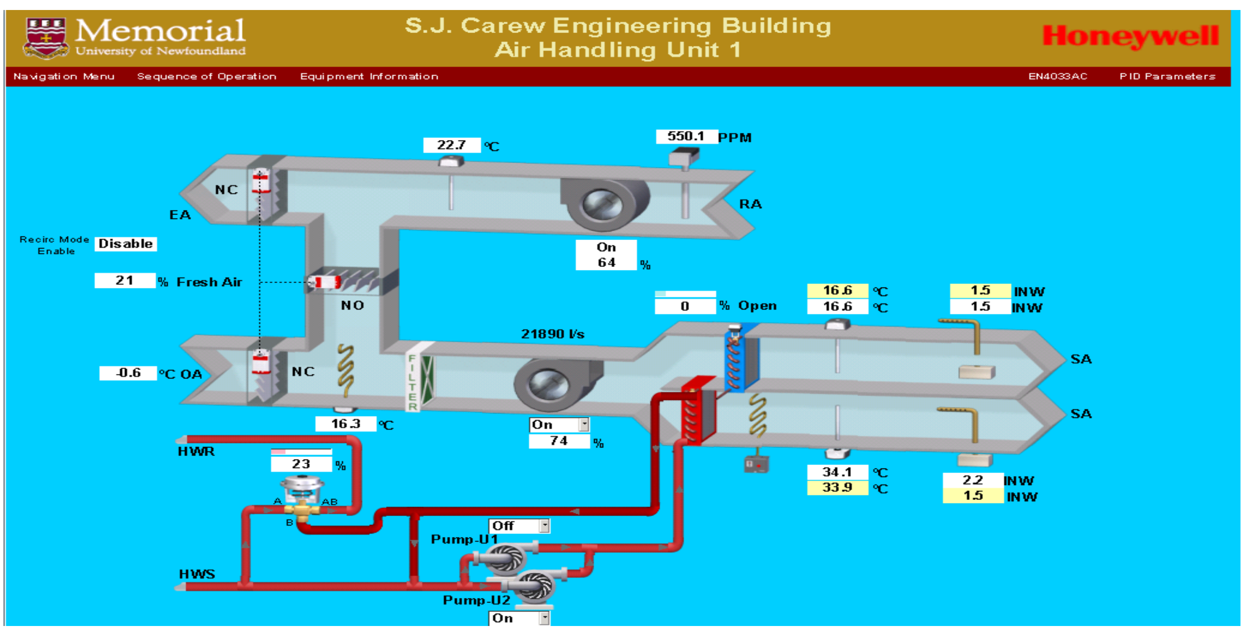

Figure 4.1 AHU₁ for S.J. Carew building

Fig. 4.2 depicts Room 347 at the Carew Building. The return fan located in the room's return duct is approximately 10% slower than the supply fan. Controllers are employed in the heat exchanger for keeping zonal temperatures set at fixed points through the use of modulating control valves. During the cold season (October to May), the heating system is turned on, and the cold system is turned off. The present study used data from October to December 2016, so the cold system was off, as illustrated in Fig. 4.1.

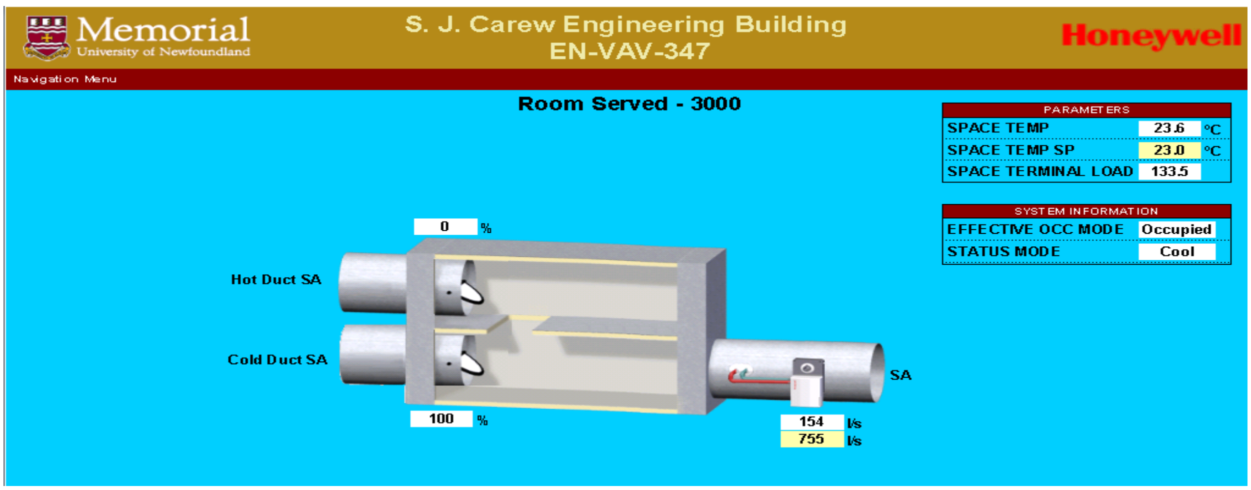

Figure 4.2 VAV terminal units of room 347 at the Carew Building.

4.2.3. Simulation model

The IDA Indoor Climate and Energy 4.7 simulation tool are used for assessing the indoor climate and energy performance. This simulation tool is suitable for modeling HVAC systems located in multiple-zoned structures, such as the S. J. Carew Building. The tool can assess IAQ, dynamic simulation, required energy, and overall thermal comfort. For the real system, a hot water valve (Fig. 4.1) provides data on hot water usage for the heating coil, as the system has a single valve for the building's entire hot water generation. However, with the IDA-ICE software, the hot water valve is divided into four valves, such that every AHU can have its own valve. Hence, every AHU includes three inputs and three outputs. This information will be used as a reference model and identification data when modeling the AHU_1.

4.3. System identification

System identification features three separate steps:

a. data gathering
b. choosing the model structure
c. building a model that provides the highest system functionality

AHUs are useful in system identification. There are three inputs to the AHU: 1) hot water valve for the heating coil/zones, 2) supply fan speed, and 3) fresh air from outdoors. The outputs show data for three different system elements: 1) return air temperature (degree celsius ^{o}C) for controlling the valve aperture of hot water, 2) static air pressure, P_S (inches of water INW) in ducts for controlling supply fan speed, and 3) CO_2 levels (parts per million PPM) for controlling fresh air dampers.

4.4. Inputs and outputs signals

Figure 4.3 shows the inputs of the AHU_1 as percentage of the hot water valve aperture, supply fan speed, and fresh air dampers position. As illustrated in Fig. 4.4, an output is zone temperature. The second output is static air pressure (Fig. 4.5), and the third output is CO_2 quantity (Fig. 4.6).

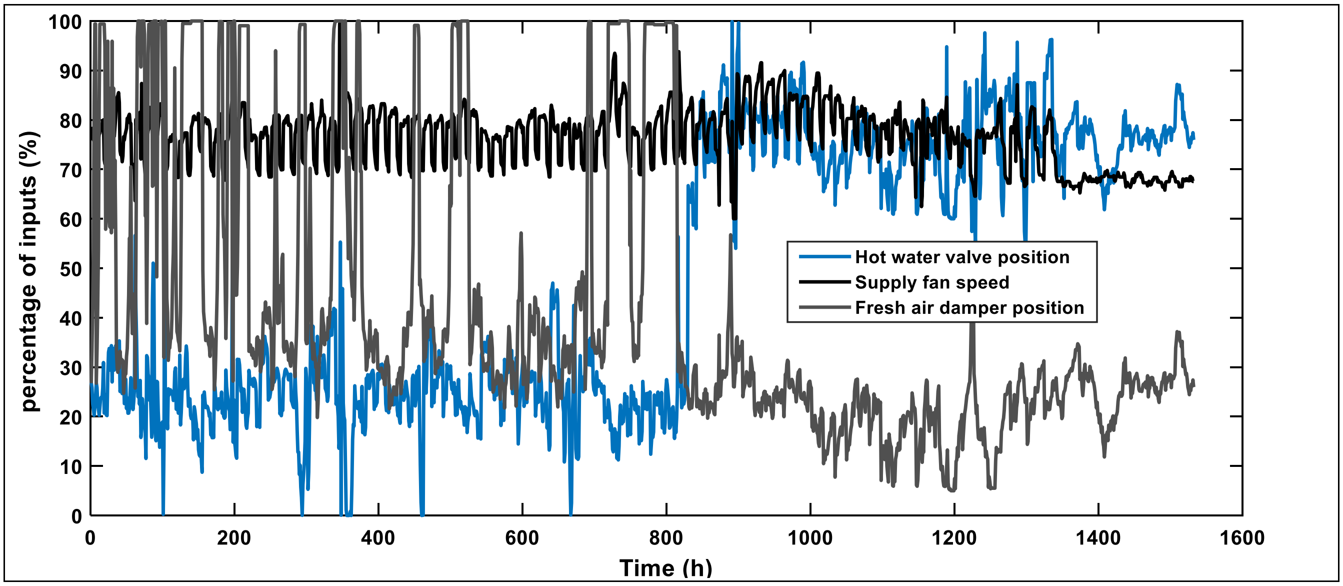

Figure 4.3 Inputs of AHU_1 as a percentage (%)

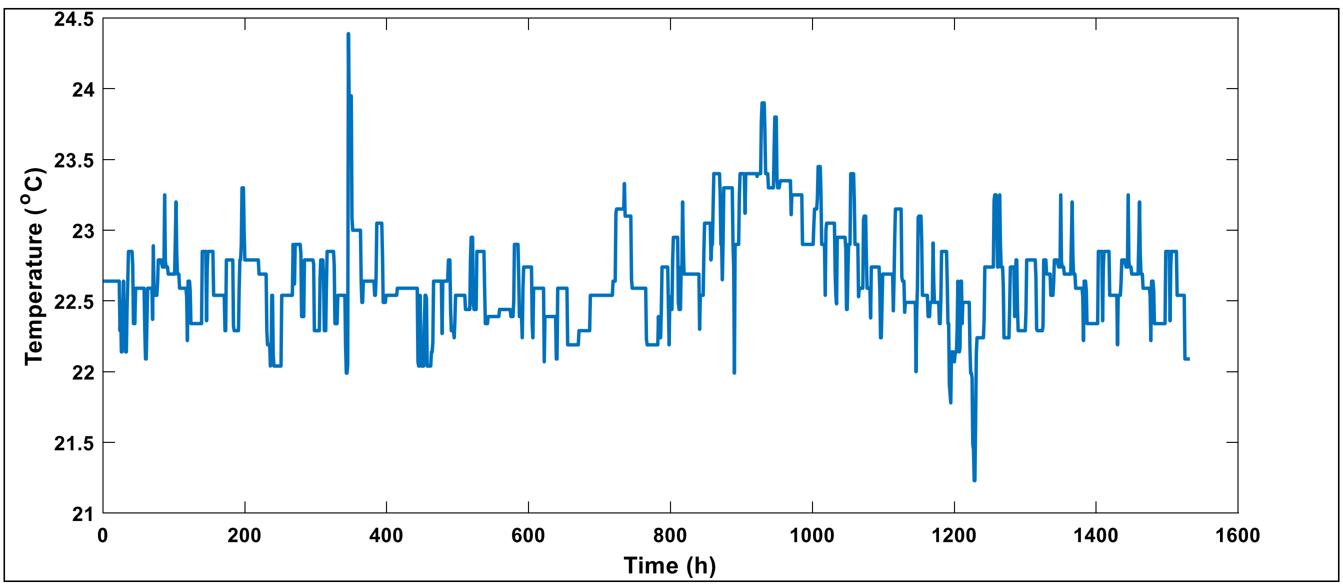

Figure 4.4 Zone temperature (in ^oC)

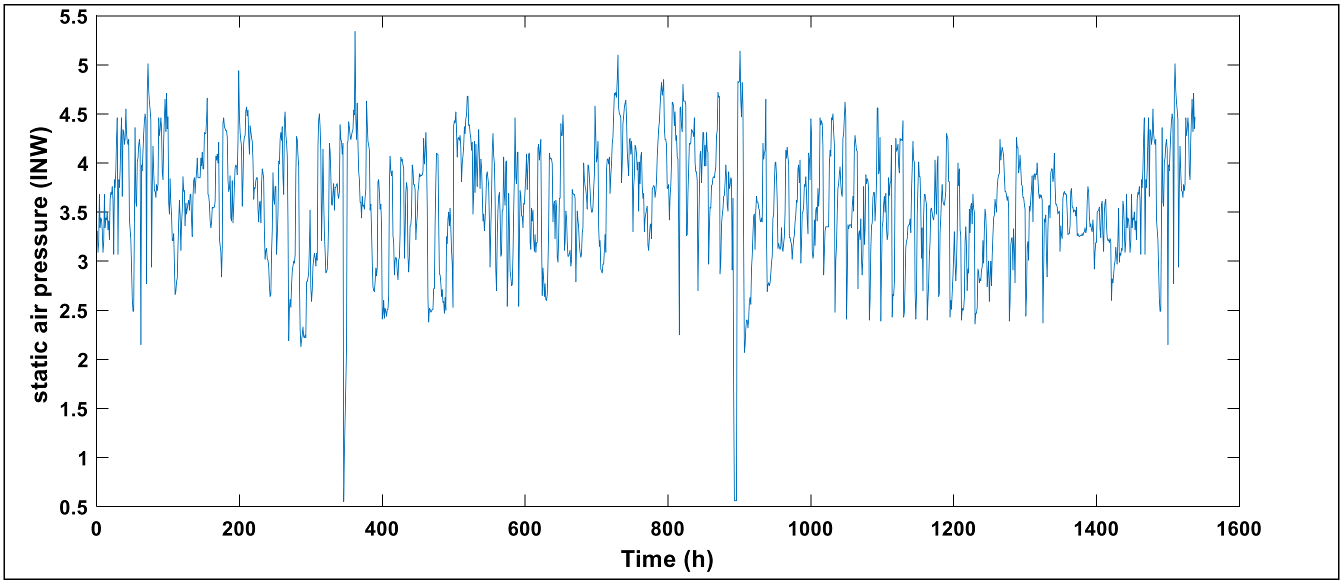

Figure 4.5 Static Air Pressure P_S (INW)

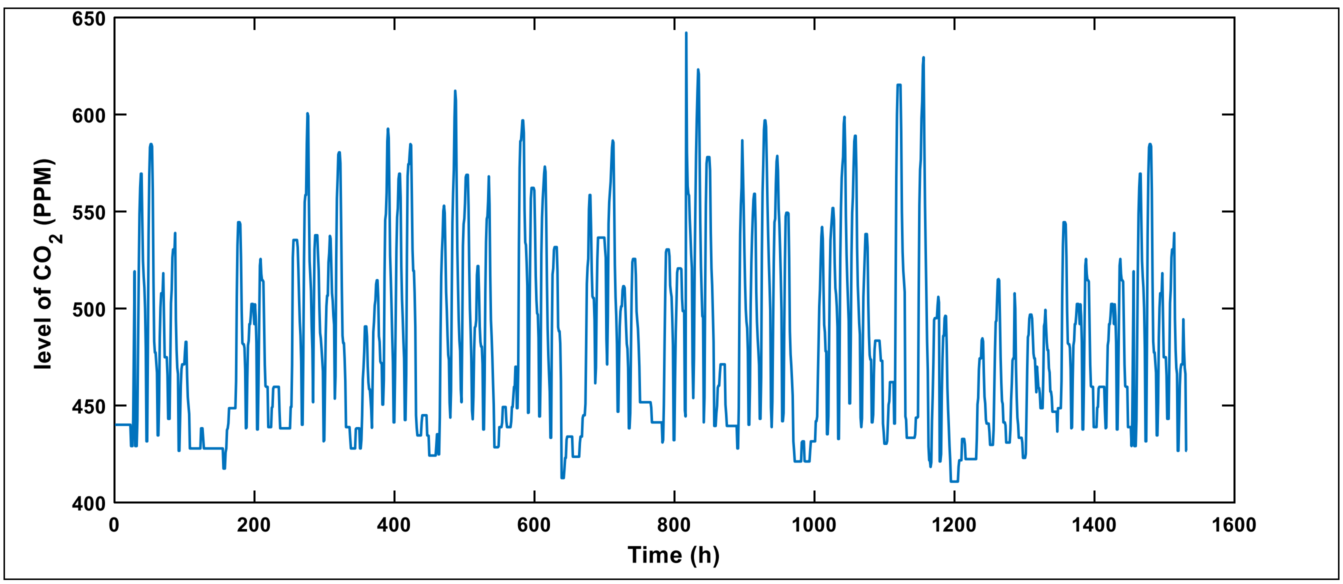

Figure 4.6 level of CO_2 (in PPM)

A model structure is selected from a range of structures which are roughly categorized as being either linear or nonlinear. The Identification Tool Box of Matlab is used in pre-processing the data. The decision process can be categorized into a few steps of optimal model structure (e.g., ARX, ARMAX, and process models), model order, optimal estimation approach and launching the identification process.

4.5. Control strategies

4.5.1. Fuzzy logic controller

Comfort levels and energy savings are the two main driving forces that have led researchers to create intelligent systems (i.e., Building Intelligent Energy Management Systems: BIEMS) as a means to manage energy use in buildings. BIEMS are usually employed only in large structures, such as commercial buildings, office towers, and hotels. These systems can control and monitor a building's environmental parameters, creating a comfortable microclimate while reducing energy consumption and operational costs.

Fuzzy techniques have been used in BIEMS, giving significantly better outcomes than traditional control systems. Practical applications employing fuzzy and neural control in HVAC systems are also being used, with the overall aim of lowering energy consumption and costs [18]-[22].

In traditional control methods, mathematical models of the building's operations are needed, but when using intelligent systems (i.e., model-free automatic controllers), mathematical modeling is unnecessary. Hence, through the introduction of higher-level comfort variables in intelligent controllers, such as PMV [23], comfort can be managed without the need to regulate lower-level variables such as humidity, air speed, and temperature. Users participating in intelligent systems are able to choose their preferred comfort levels with optimized fuzzy controllers which employ genetic algorithms and adaptive control strategies. Fuzzy logic control is already being applied in the latest furnace controllers, using adaptive heating control as a means to optimize comfort and energy efficiency in domestic heating systems [24]. Fuzzy controllers are also used to control natural ventilation, visual comfort, and thermal comfort; there are notable results in these subsystems [25], [26].

4.5.2. Design of fuzzy logic controller

There are several approaches for applying fuzzy logic for closed-loop control. The most common technique is the fuzzy PI controller [27], [28] which uses process-derived measurement signals as fuzzy logic controller inputs and outputs to operate the actuators. A fuzzy PI controller represents an incremental controller. A traditional fuzzy PI controller can be expressed as in Eq. (4.1), with fuzzy rules are determining the output [29].

$$u(k + 1) = u(k) + \Delta u(k) \tag{4.1}$$

where k is the sampling instance, and Δu(k) is the incremental change in the controller.

The present study uses a traditional fuzzy PI controller for the AHU_1 model. The proportional (P) and integral (I) actions are combined to benefit from the inherent stability, which is a feature in proportional controllers, as well as to benefit from the integral controllers' offset elimination feature. Incremental controllers are most suitable for use in situations where a valve or motor serve as actuators. Additionally, it can be beneficial when controller output is derived from an integrator due to its ease in handling noise and wind up. As shown in Fig. 4.7, a fuzzy PI controller applies error signals and change of error as inputs.

Another benefit in using a fuzzy PI controller is its lack of operational or set point. A rule-driven control strategy weighs differences between a set point and measured values, measuring any modifications to these differences as a means to determine if increments or decrements should be applied to a building's control variables. While a fuzzy logic controller is able to perform nonlinear control strategies, applying a fuzzy logic technique in real applications must be done in the three-step process shown below [30].

- *Step 1: Fuzzification* changes crisp/classical data into membership functions (MFs) or fuzzy data.

- *Step 2:* In the *Fuzzy Inference process*, MFs are added to control rules to obtain the required fuzzy output.
- *Step 3: Defuzzification* employs a variety of strategies as a means to formulate every associated output, to place them within a table framework, and to choose the output in a look-up table in accordance with the current input obtained for the specific application being performed.

As it is illustrated in Fig. 4.7, fuzzy controller is assigned to control zone temperature, static air pressure, and CO_2 level. Error signals and its changes are fed to a fuzzy controller. The output of fuzzy controllers is assigned as inputs of the system. The system outputs are sent to the fuzzy controller to make a closed-loop controller.

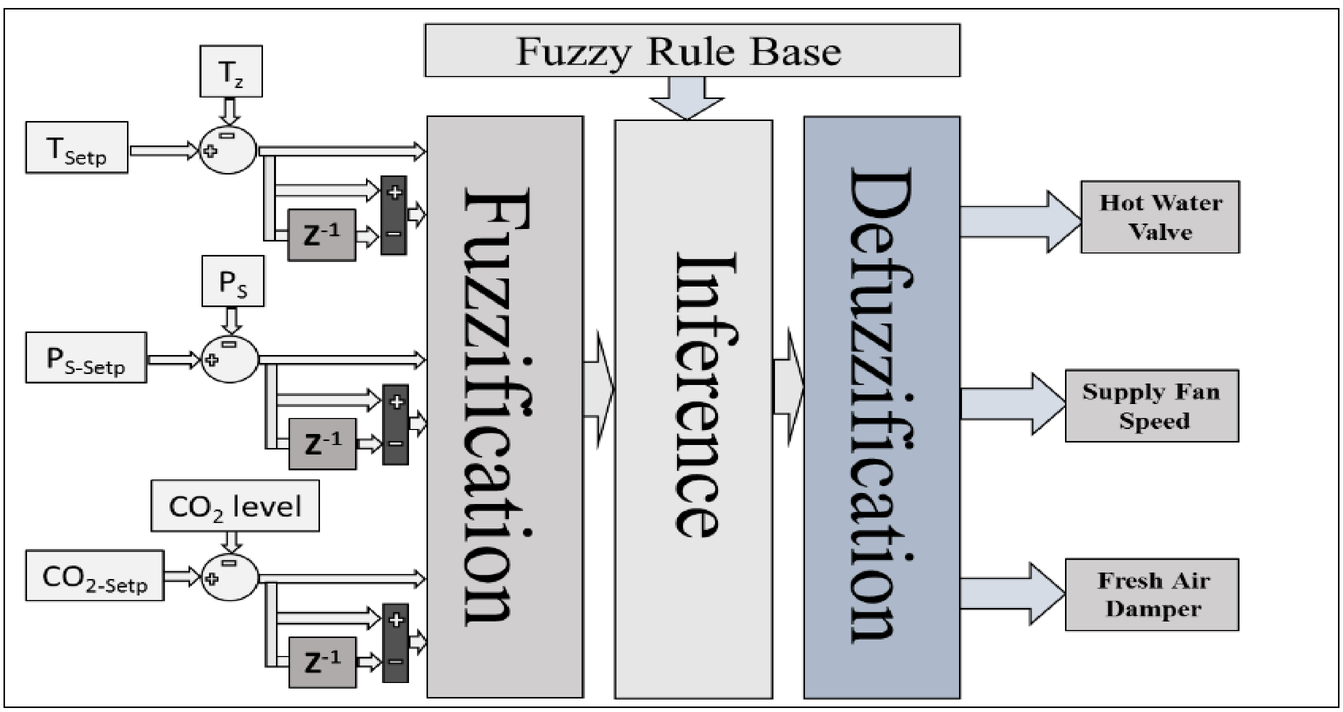

Figure 4.7 Structure of Fuzzy logic controller

Fuzzy Logic Designer App of the system is shown in Fig. 4.8, with this App the FLC can be designed to add or remove input or output, fuzzy membership function, IF-Then rules, and select fuzzy inference functions.

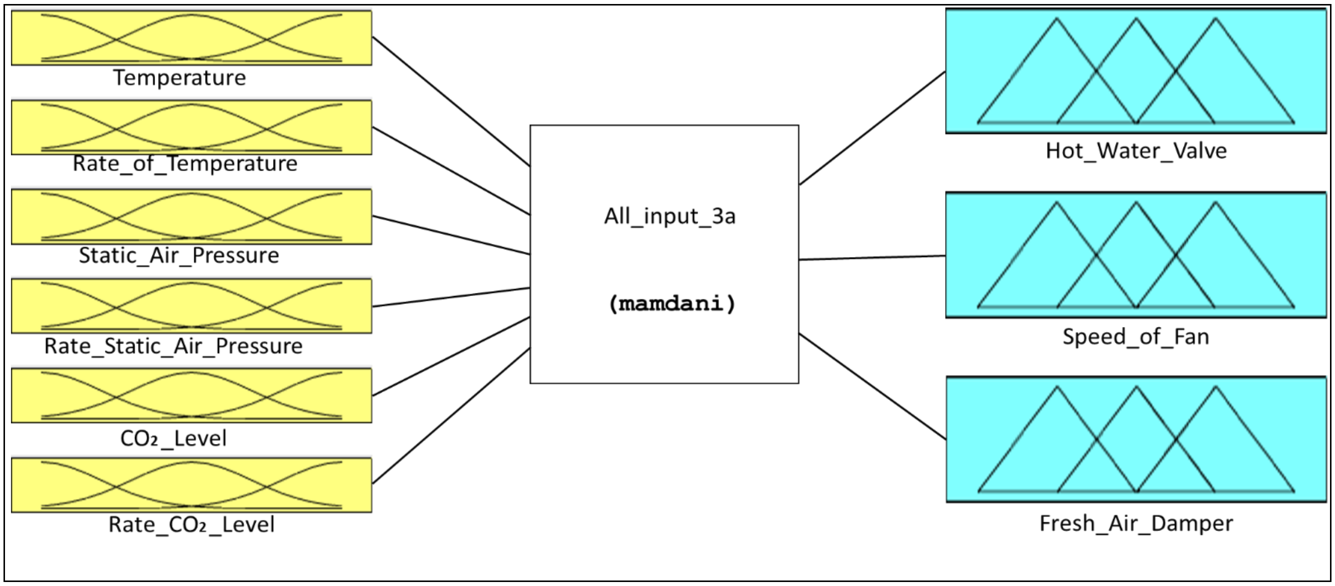

Figure 4.8 Fuzzy Logic Designer App

4.5.3. Fuzzy membership function

The MFs editor is used in unpacking the fuzzy tool box, which is applied in shape-defining any MFs that are related to variables in the membership. Fig. 4.7 illustrates the AHU_1 control system, indicating three outputs and six inputs. Brief definitions of the MFs for the input and output variables are presented in Sections 3.1 and 3.2.

4.5.3.1. Input variables

1. *Temperature differences (ΔT)*

Fig. 4.2 depicts the received current zone temperature of return air as recorded by an electronic sensor. Eq. (4.2) Expresses differences between setpoint (T_{setp}) and current zone temperature (T_z) for time (k), while Fig. 4.9 and Table 4.1 show the 5 MFs of V-Hot, Hot, Okay, Cold and V-Cold.

$$\Delta T(k) = Tsetp\ (k)\ -\ Tz\ (k) \qquad (°C) \tag{4.2}$$

Table 4.1 MFs of zone temperature difference

Input field	Range	Fuzzy set
Temperature Difference (ΔT)	[-10.52 -8.48 -1.222 -1]	V-Cold
	[-1.222 -1 -0.268 0]	Cold
	[-0.268 0 0.2714]	Optimal
	[0 0.268 1.02 1.563]	Hot
	[1.159 1.465 3.549 13.26]	V-Hot

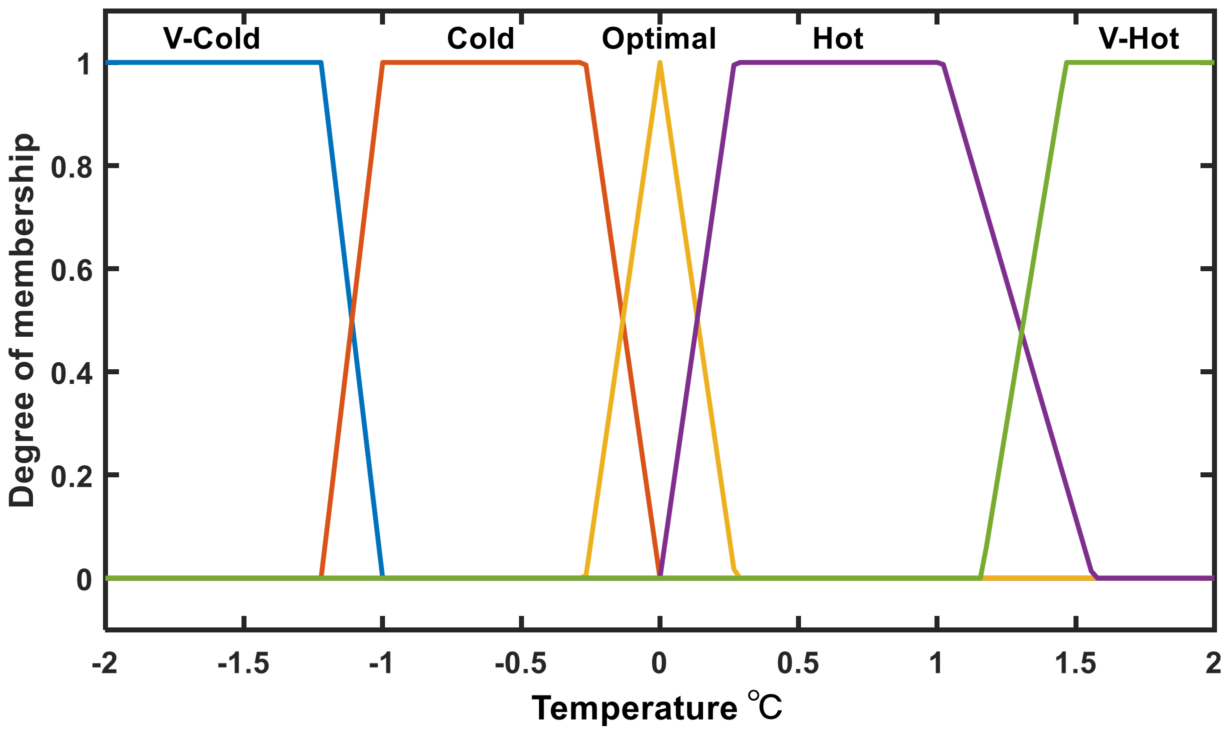

Figure 4.9 MFs of zone temperature difference

2. *Change in ΔT ($d\,\Delta T$)*

Error input variables related to changes in temperature are formulated through finding the ratio for the difference of past and present temperature error values in relation to sampling time (Δt), as expressed in Eq. (4.3). The building's real system, Honeywell Software, gives a system sampling time of 3 seconds (Department of Facilities Management and Honeywell Offices at Memorial University).

As shown in Fig. 4.10 and Table 4.2, three membership functions can be used to define error variable changes: Positive (*P*), Negative (*N*), and Zero (*Z*).

$$(d\Delta T) = (\Delta T(k) - \Delta T(k-1))/\Delta t \qquad (°C\,/s) \tag{4.3}$$

Table 4.2 MFs of change in ΔT

Input field	Range	Fuzzy set
Change of temperature error	**[-0.118 -0.1031 -0.05 -0.01]**	**N**
	[-0.05 -0.01 0.01 0.05]	**Z**
	[0.01 0.05 0.1534 0.1794]	**P**

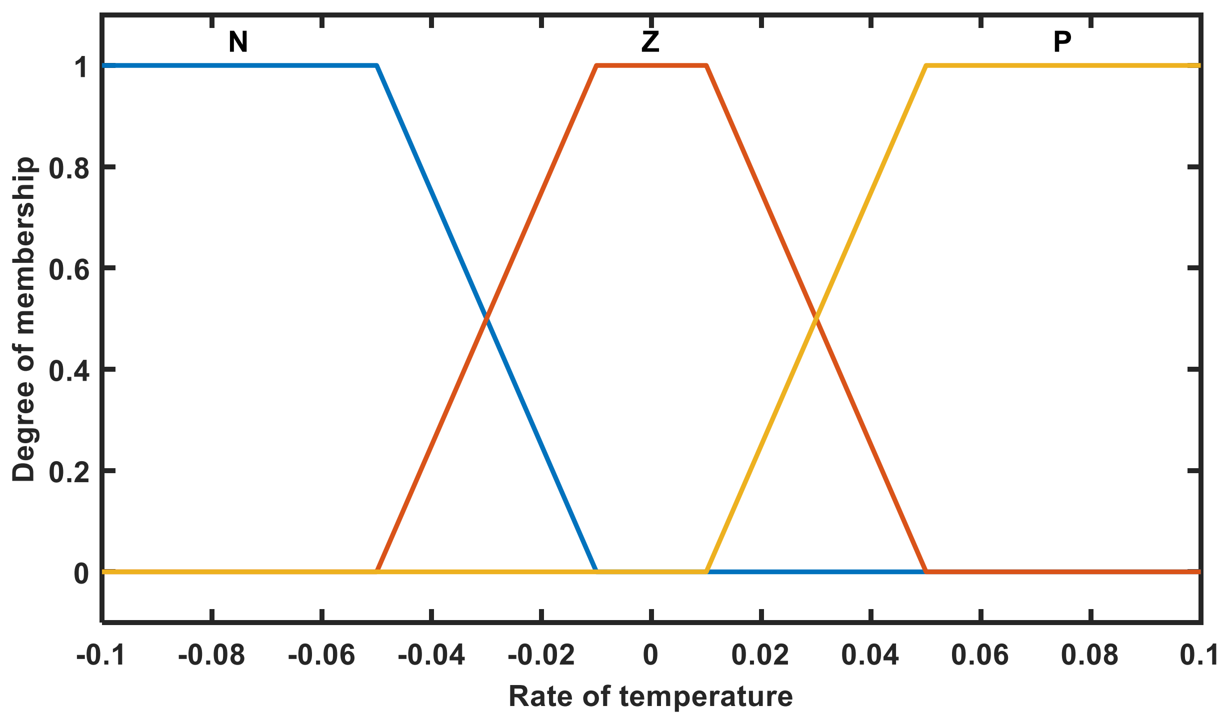

Figure 4.10 MFs of Change in ΔT

3. *Static Air Pressure P_S differences (ΔP_S)*

Fig. 4.10 illustrates changes in present duct P_S; these differences were noted by sensors located in both cold- and hot-deck ducts. As can be seen, the static pressure $P_{S\text{-}setp}$ setpoints occur for time (k), given in Eq. (4.4). Fig. 4.11 and Table 4.3 present five membership functions of V-High, High, Optimal, Low and V-Low.

$$\Delta P_S\,(k) = P_{S\text{-}setp} - P_S\,(k) \qquad \text{(INW)} \qquad (4.4)$$

Table 4.3 MFs of static pressure difference (ΔP_S)

Input field	Range	Fuzzy set
Static Air Pressure Difference ΔP_S	**[-0.8213 -0.1584 -0.08317 -0.06853]**	**V-Low**
	[-0.0826 -0.0668 -0.00836 0]	**Low**
	[-0.00771 0 0.00956]	**Optimal**
	[0 0.00836 0.071 0.0816]	**High**
	[0.07052 0.08278 0.1399 1.239]	**V-High**

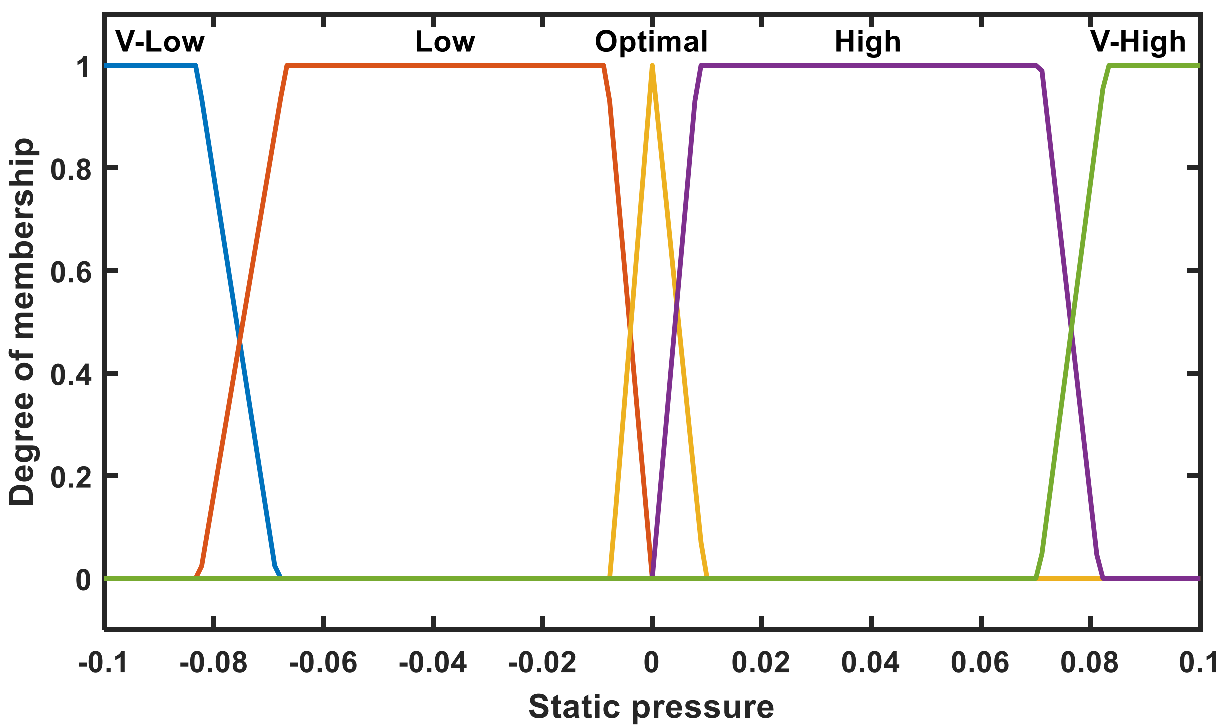

Figure 4.11 MFs of static air pressure difference

4. *Change in ΔP_S ($d\Delta P_S$)*

As expressed in Eq. (4.5), any alterations in the P_S error input variable are formulated using ratios for differences between present and past P_S error values in relation to sampling time (Δt). Fig. 4.12 and Table 4.4 illustrate three of the membership functions which indicate changes in error variables, expressed as Positive (*P*), Negative (*N*), and Zero (*Z*).

$$d\Delta P_s\,(k) = (\Delta P_s\,(k) - \Delta P_s\,(k\text{-}1))/\Delta t \qquad \text{(INW/s)} \tag{4.5}$$

Table 4.4 MFs of change in ΔP_S

Input field	Range	Fuzzy set
Change of P_s error (d ΔP_s)	[-0.005433 -0.005032 -0.002833 -0.001478]	N
	[-0.002833 -0.001478 0.001478 0.002833]	Z
	[0.001478 0.002833 0.005835 0.005935]	P

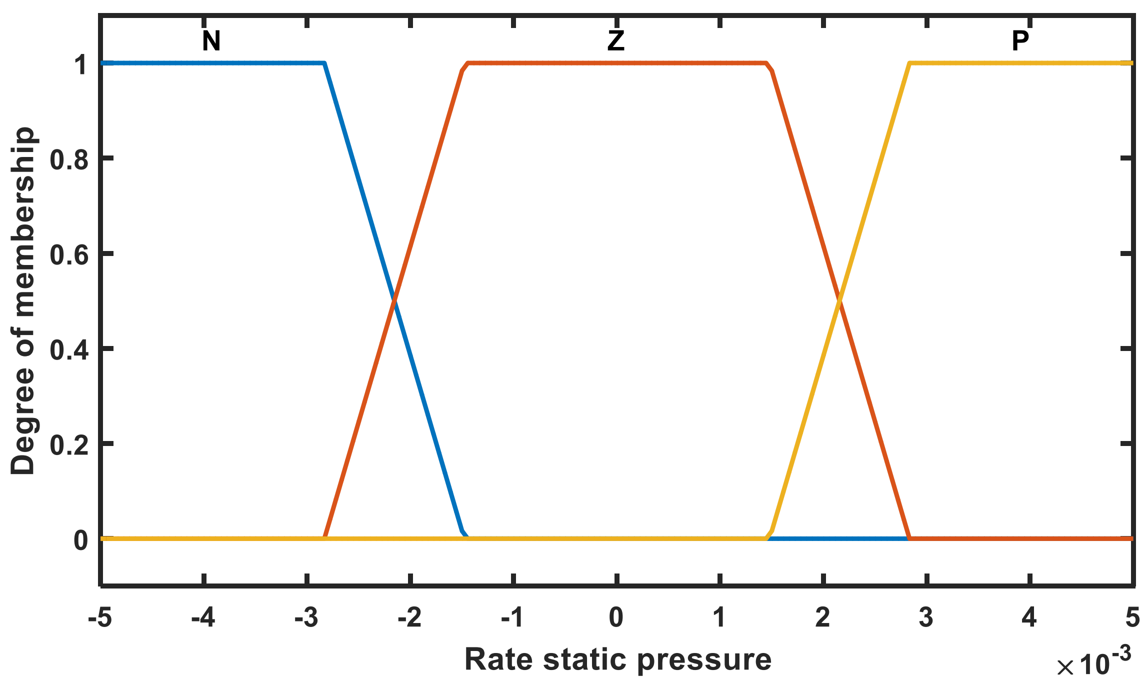

Figure 4.12 MFs of change in ΔP_S

5. Differences in CO_2 Levels (ΔCO_2)

As shown in Fig. 4.1, this is the difference between the present CO_2 level in the return air from the sensor in the AHU_1 return duct and the CO_2 level $CO_{2\text{-S-setp}}$ set point, as recorded at the time (k) and expressed by Eq. (4.6). The 5 MFs of V-High, High, Optimal, Low and V-Low are shown in Fig. 4.13 and Table 4.5.

$$\Delta CO_2\ (k) = CO_{2\text{-setp}} - CO_2\ (k) \qquad \text{(PPM)} \tag{4.6}$$

Table 4.5 MFs of CO_2 level difference (ΔCO_2)

Input field	Range	Fuzzy set
Level of CO_2 Difference (ΔCO_2)	**[-25.9 -20.19 -16.43 -14.2]**	**V-Low**
	[-16.47 -14.03 -2.92 0]	**Low**
	[-1.92 0 1.92]	**Optimal**
	[0 2.92 8.84 12.33]	**High**
	[8.39 12.1 120 178]	**V-High**

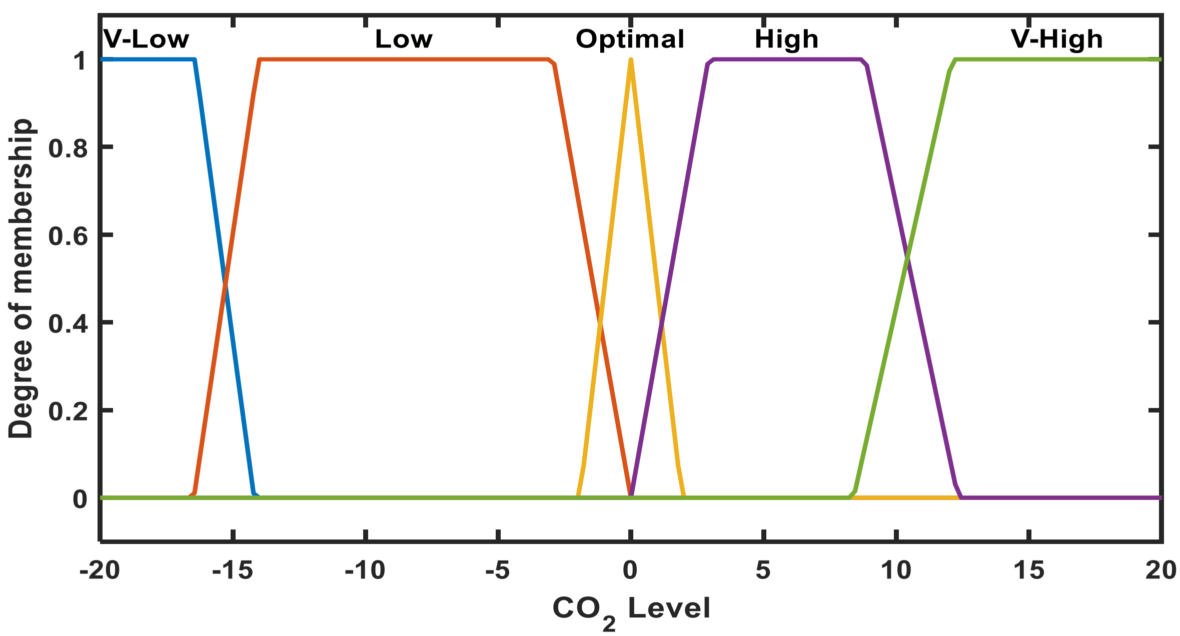

Figure 4.13 MFs of CO_2 level difference (ΔCO_2)

6. *Change in ΔCO_2 ($d\,\Delta CO_2$)*

As expressed in Eq. (4.7), CO_2 error input variable changes can be formulated through finding the ratio for the difference between the present and past CO_2 error values in relation to sampling time (Δt). Fig. 4.14 and Table 4.6 show the three MFs error variable changes as sets labeled Positive (*P*), Negative (*N*), and Zero (*Z*).

$$d\Delta CO_2\,(k) = (\Delta CO_2\,(k)-\Delta CO_2\,(k-1))/\Delta t \quad (PPM/s) \tag{4.7}$$

Table 4.6 MFs of change in ΔCO_2

Input field	Range	Fuzzy set
Change of CO_2 error ($d\,\Delta CO_2$)	**[-2.1 -1 -0.5 -0.3]**	**N**
	[-0.5 -0.3 0.3 0.5]	**Z**
	[0.298 0.498 0.998 1.1]	**P**

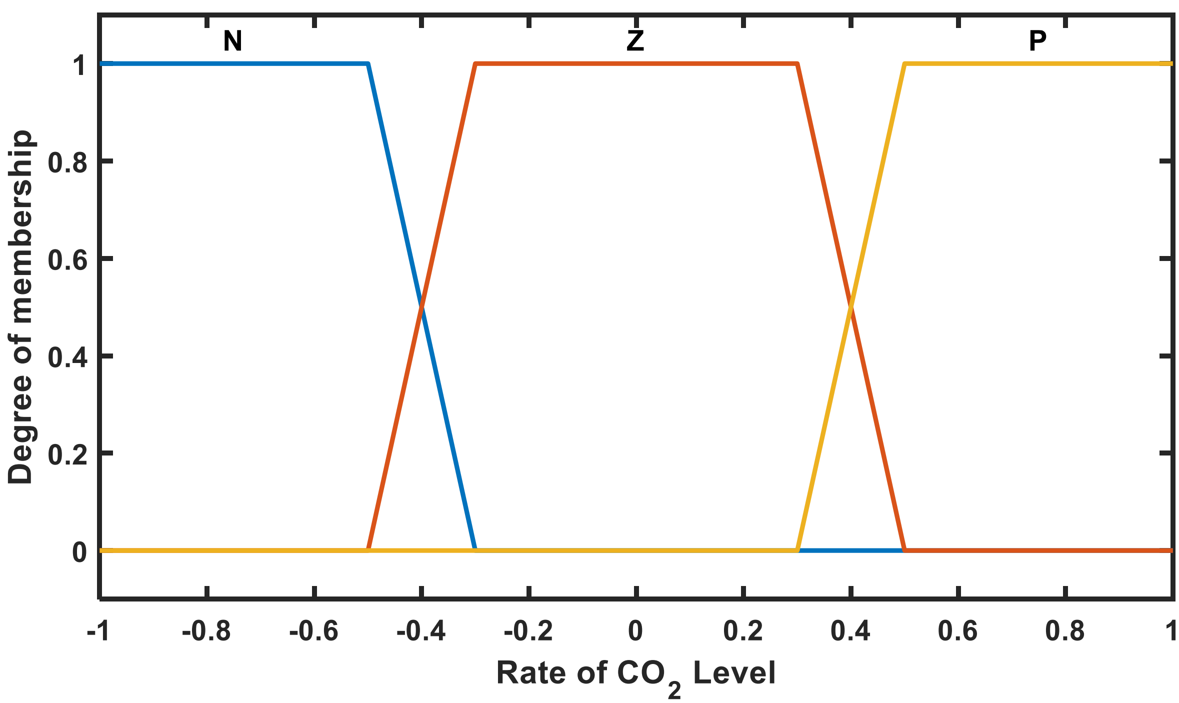

Figure 4.14 MFs of change in ΔCO_2

4.5.3.2. Output variables

The three inputs of AHU_1 (fresh air, air flow, and hot water) serve as FLC outputs. The values are introduced as gains to the system in order to move system responses towards a stability state. As a means to increase output gains, PI controller tuning can be used, as detailed in the following subsections.

1. *Aperture on the hot water valve*

The process involving the hot water valve's opening and closing is indicated through the 5 MFs for the fuzzy controller output in order to find the zone temperature setpoint (T_{setp}). Fig. 4.15 depicts MFs using MATLAB Fig, while Table 4.7 shows MFs and the related valve operation percentages.

Table 4.7 MFs of the first output

Output field	Range	Corresponding	Fuzzy set
Hot water valve temperature	**[-1320 -10000 -7894 -5060]**	**0%-20%**	**Close-Fast**
	[-7264 -5570 -1580 0]	**20%-40%**	**Close**
	[-689 0 768]	**40%-60%**	**NO-Change**
	[0 1580 5100 6594]	**60%-80%**	**Open**
	[5067 6607 10220 10260]	**80%-100%**	**Open-Fast**

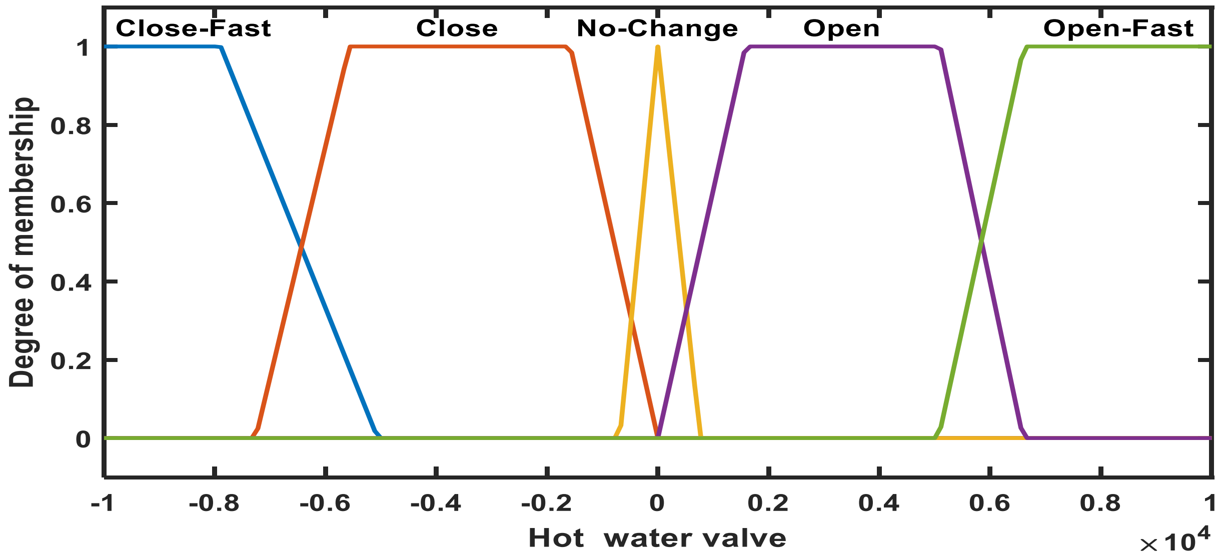

Figure 4.15 MFs of the first output

2. *Supply fan speed*

The FLC's second output serves as the speed control for the supply fan in order to reach the ducts' static air pressure set point. Fig. 4.16 and Table 4.8 show the five MFs for this process.

Table 4.8 MFs of the second output

Output field	Range	Corresponding	Fuzzy set
Supply fan speed	**[-1060 -913.1 -601 -371]**	**0%-20%**	**V-Slow**
	[-527.9 -449 -105 50]	**20%-40%**	**Slow**
	[-105.3 50 205.4]	**40%-60%**	**No-Change**
	[46.3 201 661 800]	**60%-80%**	**Fast**
	[658 811 1002 1010]	**80%-100%**	**V-Fast**

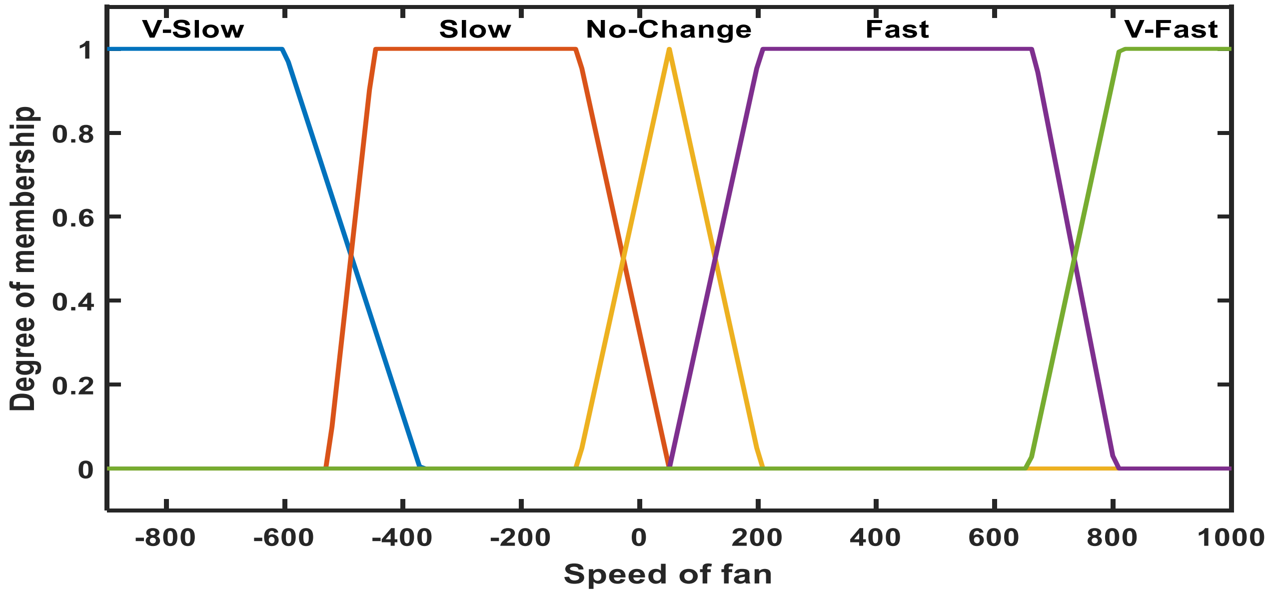

Figure 4.16 MFs of the second output

3. *Fresh air dampers position*

Five MFs of the fuzzy controller output for opening and closing operation of the fresh air dampers to obtain on the zone CO_2 level set point, the range of MFs are presented in Table 4.9 and Fig. 4.17.

Table 4.9 MFs of the third output

Output field	**Range**	**Corresponding**	**Fuzzy set**
Fresh air dampers position	**[-5200 -5028 -3910 -2980]**	**0%-20%**	**Close-Fast**
	[-4056 -2860 -1140 -250]	**20%-40%**	**Close**
	[-1139 -250 641.6]	**40%-60%**	**No-Change**
	[-250 642 1610 2677]	**60%-80%**	**Open**
	[1860 2660 4509 4810]	**80%-100%**	**Open-Fast**

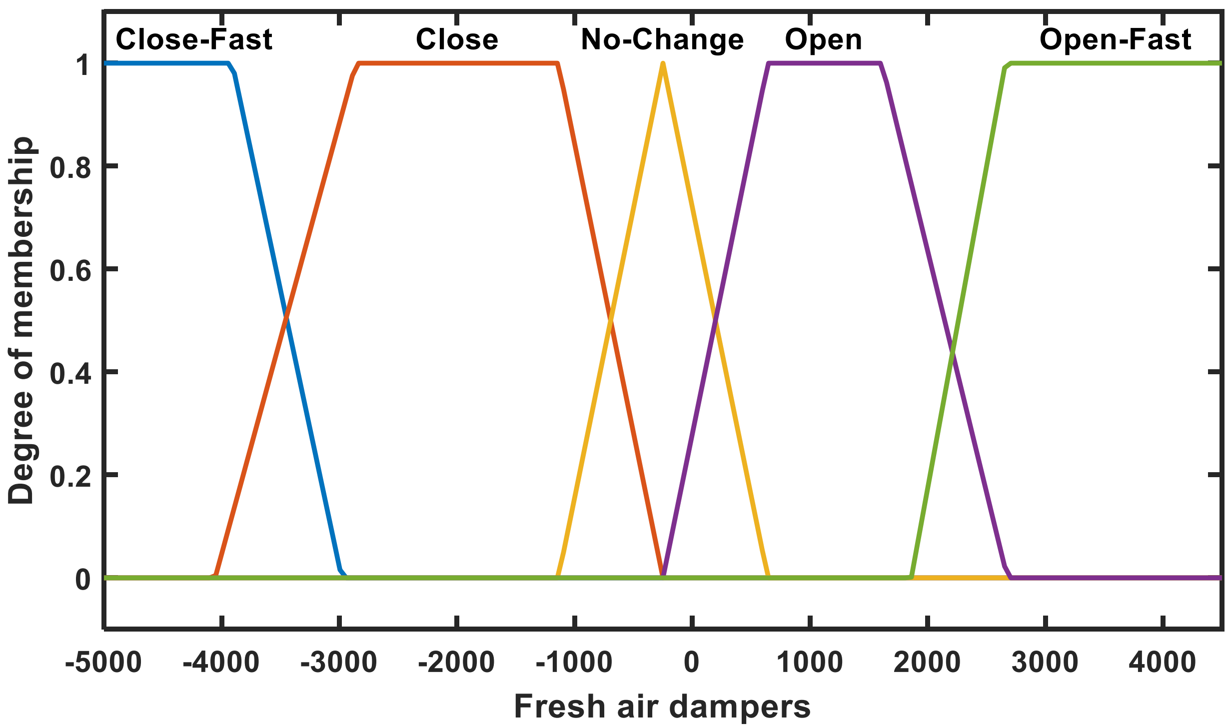

Figure 4.17 MFs of the third output

4.5.4. Fuzzy Rule Base

The rule base controls output variables as the most crucial part of the fuzzy inference system. In simplified terms, a fuzzy rule is represented as a basic IF-THEN rule which includes a condition and conclusion. The fuzzy membership functions can first be applied for converting both the input errors (ΔT, ΔP_S, ΔCO_2) and the error changes ($d\Delta T$, $d\Delta P_S$, $d\Delta CO_2$) to their fuzzy values. Furthermore, in every output (damper position, fan speed, and hot water valve) the control action is represented by fuzzy rules in different error/change of error values. In every control signal output, the fuzzy default rule is 5×3, thus indicating 45 rules for system control [31].

4.5.5. Defuzzification

In the process of defuzzification, fuzzy set form results convert into crisp ones. This process is required for hardware applications that exchange crisp data. Generally, defuzzified output has to be the most appropriate solution. The two mechanisms are the maxima method, which looks for the highest pack, and the centroid method, which relies on determining a property's balance point. The present study uses the centroid approach.

In Fig. 4.18, the control surface for MFs implemented using zone temperature error values, as well as a fuzzy rule-implemented change of error values is presented. The values for the control output are associated with every potential input combination for controlling hot water valve processes.

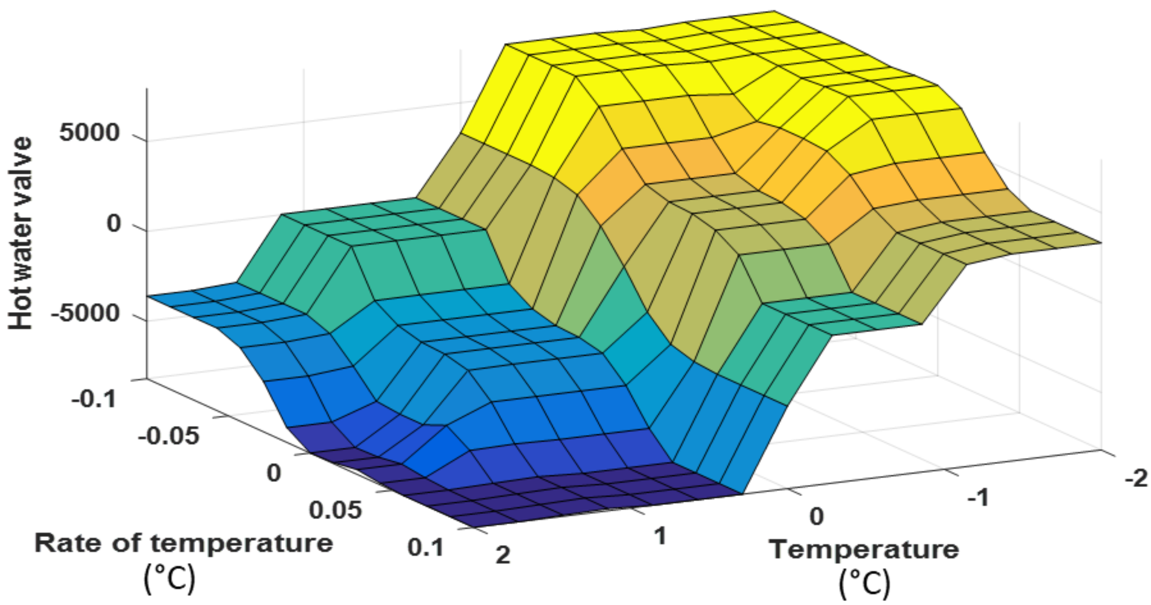

Figure 4.18 Control surface of the first output

Fig. 4.19 shows the control surface for implementing MFs for static air pressure error values as well as a fuzzy rule-implemented change of error values. The values for the control output are associated with every potential input combination for controlling the supply fan speed in order to obtain static air pressure setpoints for the ducts.

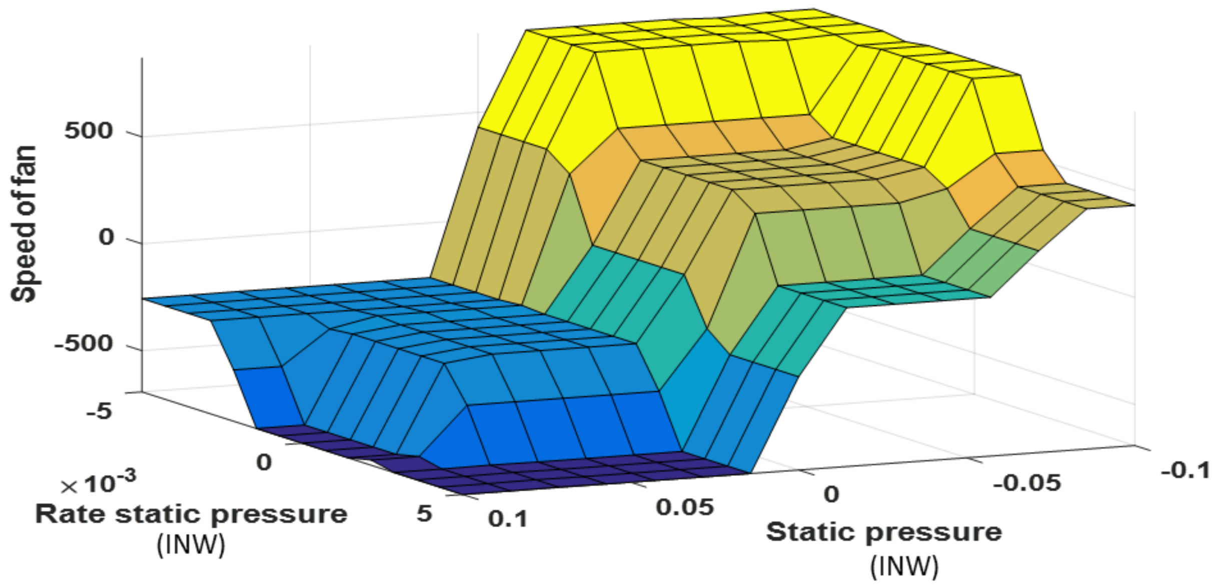

Figure 4.19 Control surface of the second output

Fig. 4.20 illustrates the control surface for error/change of error values for MFs related to CO_2 levels. Fuzzy rules are applied for controlling output values for every potential input combination to achieve the CO_2 set point.

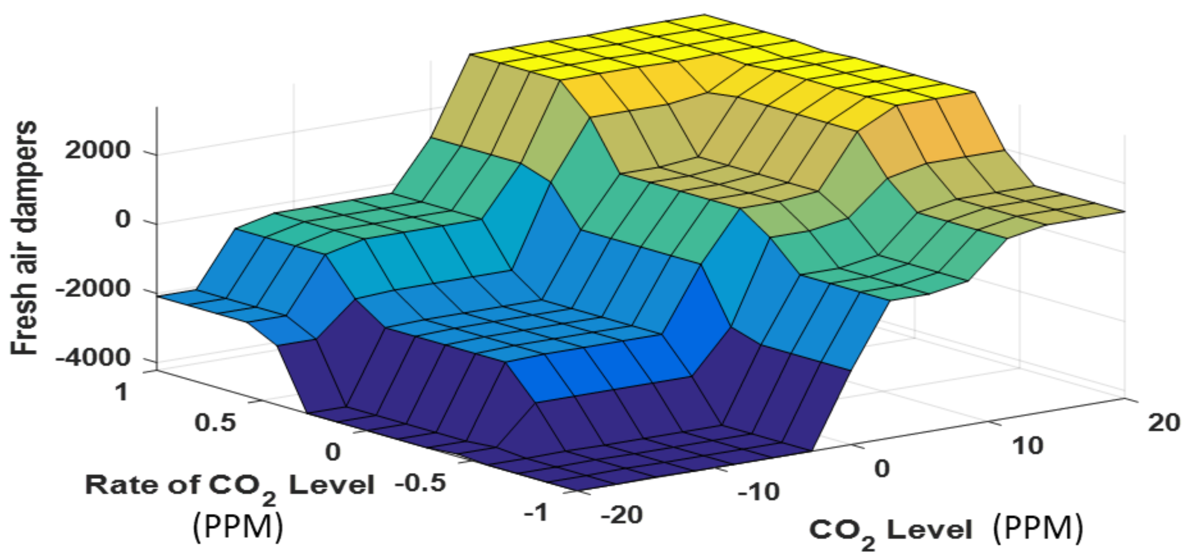

Figure 4.20 Control surface of the third output

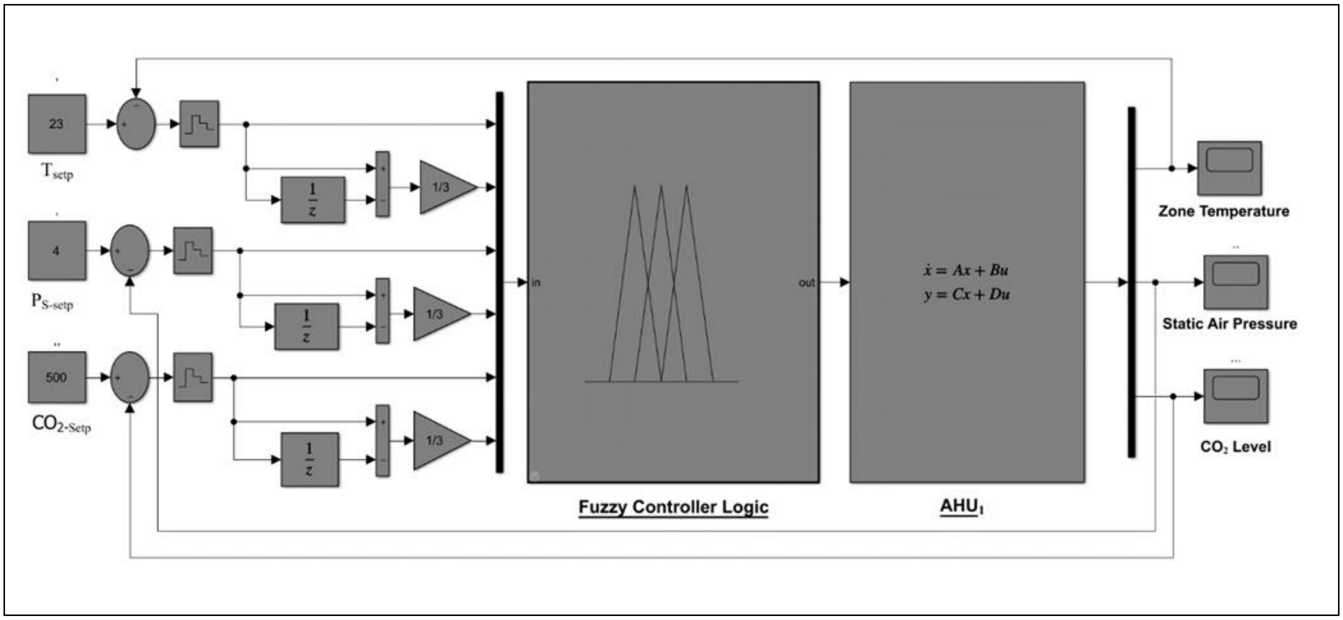

Figure 4.21 Block diagram for the AHU_1 state space model with controller

4.6. Simulation model and results

The Simulink model and simulation results are presented in this section. Fig. 4.21 shows a block diagram for the AHU_1 state space model for a fuzzy controller with the Simulink. The initial conditions selected for temperature, air pressure, and CO_2 levels are 20.7 ^oC, 3.62 INW and 374.2 MMP, respectively. The sampling time is three seconds for the control action, which is the same as for the real system. Furthermore, the real system's indoor air quality set points are a zone temperature of 23 ^oC, air pressure of 4 INW, and a CO_2 level of 500 MMP. A fuzzy-PI type adaptive controller controls the AHU_1 system, with T_{setp}, $P_{S\text{-}setp}$, and $CO_{2\text{-}Setp}$ as input references for temperature, air pressure, and CO_2 level, respectively. Control signals are obtained from FLC to reduce error as well as error change. The control signals can alter the system inputs, which include fresh air, air flow rate, and hot water to achieve the reference set points.

Three of the system's output responses that demonstrate the system's stability. As illustrated in Fig. 4.22, zone temperature T_z achieves the set point of 23 ^oC at a rise time of only 10.83 minutes and no overshoot. Fig. 4.23 depicts the response of static pressure, with a rise time of 6.71 minutes and no overshoot. Fig. 4.24 shows the CO_2 level response, achieving the set point, again with no overshoot, at a rise time of 14.13 minutes.

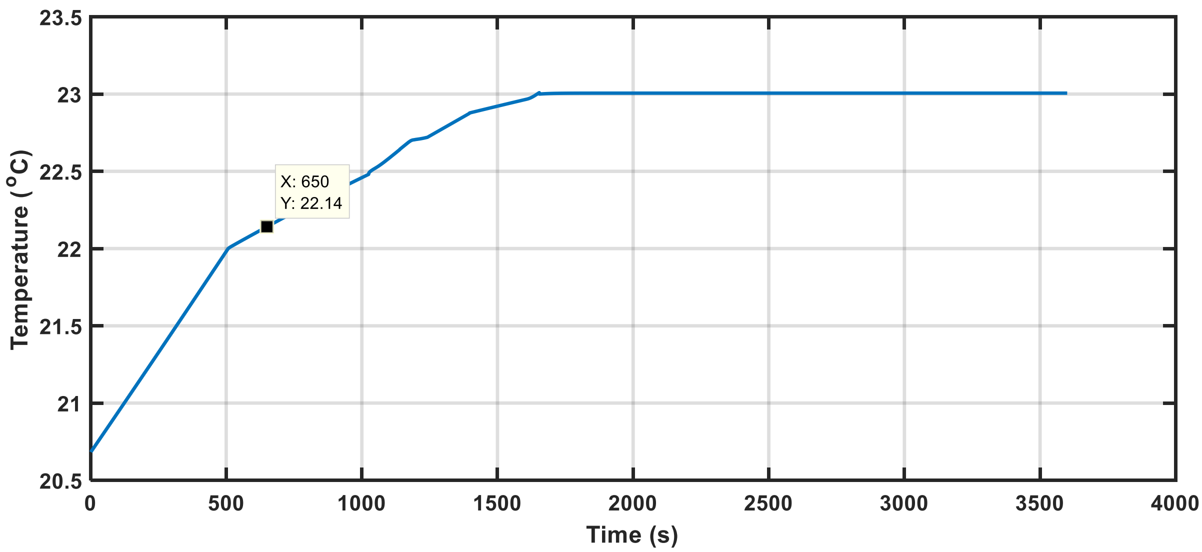

Figure 4.22 Zone temperature T_z response

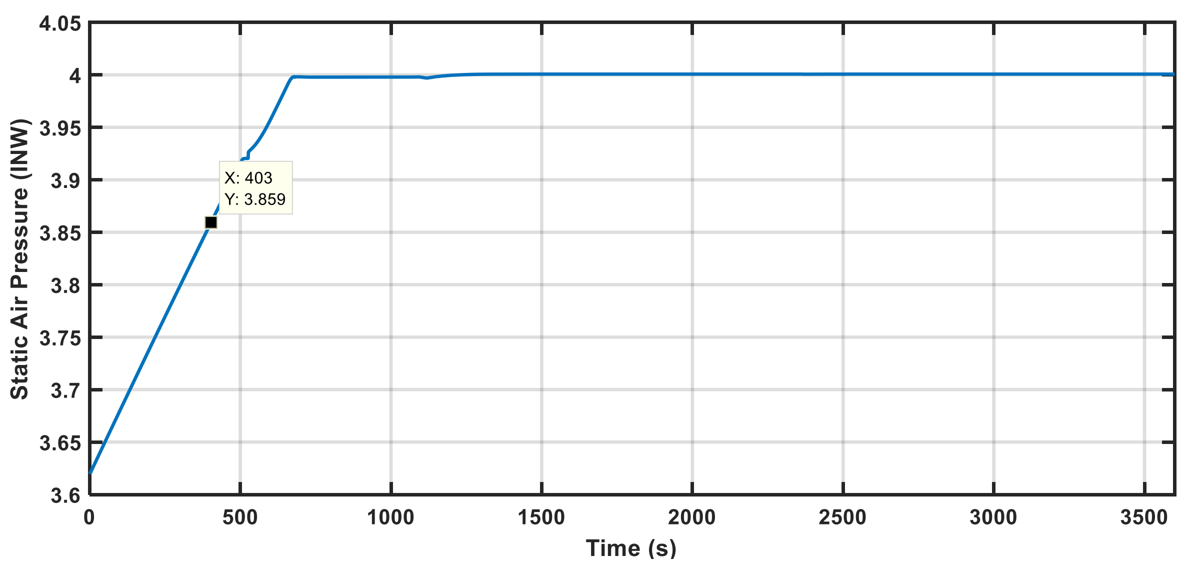

Figure 4.23 Static pressure P_s response

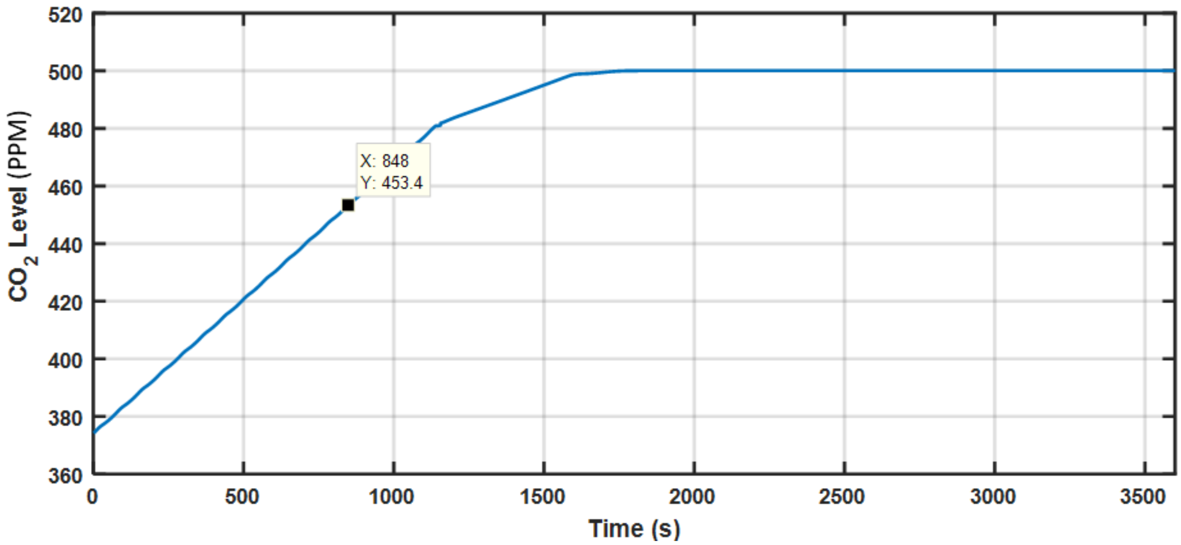

Figure 4.24 CO_2 level response

4.7. Conclusion

This research paper presented a simulation of the S. J. Carew Building's AHU_1 system using MATLAB's system identification toolbox along with real data and results from the IDE ICE program to formulate system parameters for both inputs and outputs. A fuzzy logic controller modulated the three AHU_1 inputs (fresh air, air flow, and hot water), while FLC was implemented in the multi-input / multi-output system state space model for the AHU_1. The results indicate that the fuzzy expert controller performance exceeded that of traditional algorithms, such that sufficient control was obtained from the fuzzy controller HVAC system. We can see that clearly in figures 3.17 and 3.18 of the responses of the system in Chapter 3, the model with feedback controller in that figures of internal temperatures and CO2 levels of the building have zero steady-state error at 3000 seconds approximately. There is some overshoot in the responses. Compare with the responses of the system with the fuzzy logic controller, the responses have zero steady-state error at 1700 seconds approximately, and all the responses do not have any overshoot. That means the system's responses to a fuzzy logic controller are faster than the system with a feedback controller. Also, the responses with

FLC has faster Rise Time without overshoot. Furthermore, across all lab conditions, the FLC algorithm gave a stable response and could deal better with several different parameters, including steadying errors, response time, and overshoot.

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Chapter 5

5. Supervisor Fuzzy Logic Controller for HVAC System of S.J. Carew Building at Memorial University

Preface

A version of this manuscript has been submitted to the Journal of Control Science and Engineering Hindawi. I am the primary author of this paper. Along with the co-authors, Tariq Iqbal and Kevin Pope. I developed supervisor fuzzy logic controller for the whole building, and this controller is able to control energy savings towards the building's overall performance levels of heating and cooling, with the individual demands of every floor being considered in the performance evaluation. I completed the first version of the manuscript and further revised according to the suggestions of co-authors. Tariq Iqbal helped to identify the research topic, and it is scope. Also, Tariq Iqbal helped in choosing the appropriate optimization method, programming and running the simulation, reviewing and correcting the achieved results, and contributed in preparing, reviewing and revising the manuscript. Keven Pope reviewed the manuscript and provided revision suggestions.

Abstract

One of the most important characteristics contributing to the thermal management efficiency of commercial, industrial, institutional or home environments is the optimal functioning of HVAC (heating, ventilation, air conditioning) systems. In addition to using supervisor controllers for balancing comfort level in a building, the majority of today's HVAC employ nonlinear time variance controllers when dealing with a variety of disturbances. This paper investigates both current and potential HVAC systems at Memorial University's S. J. Carew building, St. John's, Newfoundland. The study investigates the viability of algorithm-based supervisor fuzzy logic controllers (SFLC) for the control of the building's four air-handling units (AHUs) used to manage the interior environment. Along with temperature, the SFLCs also control the AHUs' fan speeds and CO_2 concentrations modifying hot water and air flow rates. This work presents models of

damper positions, fan speeds and globe valves that have been built in accordance with current rates of air and hot water flow in the S. J. Carew building. Based on these specifications, a novel method of SFLC adaptation using fuzzy rules has been devised. The novel system aims to better balance the performance level of the Carew building's HVAC system on a floor-by-floor basis. The overall results indicate better overall thermal comfort levels and enhanced cost-effectiveness when using the SFLC redesign.

Keywords: Modeling and simulation, HVAC system, IDA-ICC program, system identification, state space model, fuzzy logic, SFLC.

5.1. Introduction

The purpose of HVAC systems is to create comfortable and cost-efficient internal environments within structures. However, these systems must also be able to deal with constantly changing variables affecting their performance level. To accomplish this task, appropriate control systems are required, such as mathematics-based HVAC controllers. These approaches, which use input/output variable data to determine the parameters of individual systems, are able to refine and enhance HVAC systems through the process of system identification (SI) (ASHRAE, 2005) [1].

The thermal management efficiency of commercial, industrial, institutional and home environments relies, to a large extent, on the optimal functioning of their respective HVAC (heating, ventilation, air conditioning) systems. Air quality and thermal comfort levels are nearly entirely dependent on HVACs, and these systems also have a major role in a building's operational costs. In commercial or industrial structures, up to 50% of the building's overall energy use is contingent on how well the installed HVAC system is functioning [2]- [4]. In developed countries, mitigating pollution levels is almost equally as important as cost-effectiveness when it comes to heating and cooling systems, so there has been a recent surge in research that investigates combining renewable energy production with state-of-the-art HVAC systems [5].

A driving force behind the development of building intelligent energy management systems (BIEMS) in larger structures such as hotels and office buildings is the smart management of thermal comfort levels and the smart management of power costs. BIEMS enables buildings to essentially manage their own energy use by constant intelligent monitoring of the building's macroclimate. Based on the data, the operational parameters are then adjusted to suit the needs of the building's several microclimates. In research, as well as in practical application, BIEMS that use fuzzy techniques has consistently outperformed traditional control systems [6]-[8].

The main difference between intelligent systems (i.e., automatic controllers) and traditional control methods is that intelligent systems do not require a mathematical model to monitor and control a building's operations. Instead, intelligent systems, like PMV [9], use optimized fuzzy controllers based on adaptive control strategies and genetic algorithms. Fuzzy logic control is already being used for state-of-the-art furnace controllers in select homes. These controllers employ adaptive heating control to determine the best use of the available energy to achieve the desired comfort level [10]. Also, fuzzy controllers are currently being tested in real-life ventilation and thermal subsystems, giving promising results [11], [12].

Over the past thirty years, numerous HVAC experts have developed operational and control methods for specific applications. During the same timeframe, numerous research studies, textbooks and journal articles have also investigated various issues of HVAC operation and control, including the supervisor control technique (e.g., Honeywell [13]; Levenhagen and Spethmann [14] ; Wang and Jin [15]; Zaheer-Uddin and Zheng [16]; Hordeski [17]; Haines and Hittle [18]; Nassif et al. [19]; Wang [20]; etc.). They classify the primary supervisory control approaches that are employed in HVAC systems into four different types of supervisory control methods: 1) model-based, 2) model-free, 3) performance map-based, and 4) hybrid [21].

In a study conducted by Kanagaraj, Sivashanmugam, and Paramasivam [22], the researchers investigated the tuning of input scaling factors for direct expert controllers by applying error and process input parameters for closed-loop systems. Their aim was developing improved controller performance in relation to load disturbances and set-point changes. In general, the on-line tuning strategy involves significantly decreased levels of operator input and dependency, while improving the performance of the controller across a broad operational spectrum. The approach, which is a form of hierarchical control, comprises the input of an intelligent upper-level supervisory fuzzy controller in tandem with a lower-level direct fuzzy controller. The task of the upper-level controller is to introduce applicable mechanisms for the system's primary goals, while the task of the lower-level controller is to provide solutions for specific problems.

A few years later, Soyguder, Servet, Karakose, and Alli [23], used the Simulink, to model expert HVAC systems that had variable flow-rates. They used fuzzy adaptive controllers that were self-tuning PIDs to demonstrate PID parameters for kp, ki, and kd. The outcome of their tests showed that their novel control algorithm performed comparably to traditional PID, as well as fuzzy-PD type controllers.

Shepherd and Batty [24], conducted experiments that employed a high-level fuzzy supervisor for control decisions. They aimed to obtain the optimal quality for indoor environments by using a modified fuzzy supervisor. Their approach also considered how issues around cost and energy efficiency could ultimately impact the decisions. From the outcomes of their simulation tests, the researchers determined that systems operation could be enhanced by applying their approach.

Lianzhong and Zaheeruddin [25], built a non-linear dynamic model for water heating HWDH systems. Their work also included intelligent fuzzy logic-based hybrid control methods. The researchers' simulation results suggest that fuzzy logic-based PI provides enhanced control and regulation of return temperature of water, particularly, when combined with IATP strategies for controlling air temperature within a specific zone. The researchers noted a 17% improvement in energy savings through reduced consumption.

Hussain, Sajid, and Gabbar [26] attempted to improve energy consumption outcomes by tuning an FLC via GAs. Using a novel air conditioner, the researchers succeed in saving approximately 15% compared to strategies that simply employ an ON-OFF control method. They noted no increase either in the discomfort index/dissatisfaction levels but instead recorded a significant reduction, falling to 62% from a high of 91%. Meanwhile, in [27], dual-level controllers (lower-level and higher-level) are presented and tested. The lower level controller comprises a traditional PID-type controller, whereas the higher-level controller comprises a fuzzy controller which acts over the low-level controller's parameters.

Using these and other research outcomes as an inspiration for the present research, this work investigates a fuzzy level control method that controls outputs for four AHUs to maintain CO_2 concentrations, static air pressure, and zonal temperatures. The aim is to determine the best approach for fuzzy control methods to perform the desired actions required for each parameter, on a parameter-by-parameter basis. The proposed fuzzy supervisor will be able to decide whether a certain desired action is or is not in the best interest of the entire system (in terms of overall performance). The fuzzy supervisor might also be given control over aspects of energy savings that better balance a building's overall heating and cooling system's performance levels, taking the needs of each floor into consideration.

5.2. Case study

The present paper employs as a case study the S. J. Carew building, which is located on the campus of Memorial University, St. John's, Newfoundland. The building is currently used to house the Faculty of Engineering and Applied Science at Memorial and is divided into numerous lecture rooms and labs. There is also a large cafeteria space. Interiorly, the Carew building measures approximately 25,142 m^2 and features four individual air-handling units for the building's 300+ zones. Table 2.1 lists an energy report for the Carew building, while Figure 5.1 depicts a 3D model.

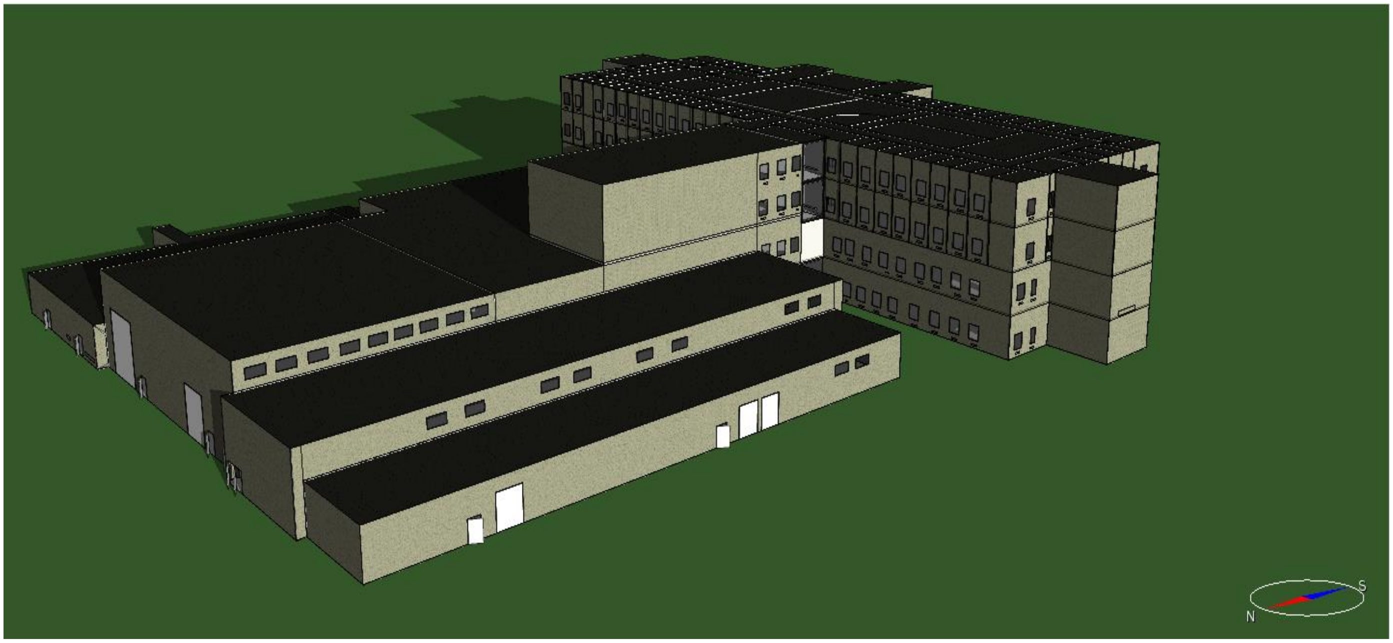

Figure 5.1 3D model for the system

5.3. Simulation Tool

The Carew building's multifaceted interior climate and energy use is modeled by the IDA-ICE 4.7 simulation tool. This tool can easily model multiple-zone HVAC systems like those existing within the Carew. Through dynamic simulations based on the monitoring and measuring of internal air quality (IAQ), the IDA-ICE 4.7 can gauge desirable thermal comfort levels for the structure. For instance, to maintain individual zonal temperatures, the heat exchanger employs controllers that are set to fixed points through control valve modulation. Figure 5.2 illustrates how a hot water valve gathers pertinent data on the water which has been warmed via direct contact with a heating coil. As shown in the figure, the building's system has only one valve to produce hot water, but the IDA-ICE tool creates four sub-valves to allow every air-handling unit its own valve [28], [29].

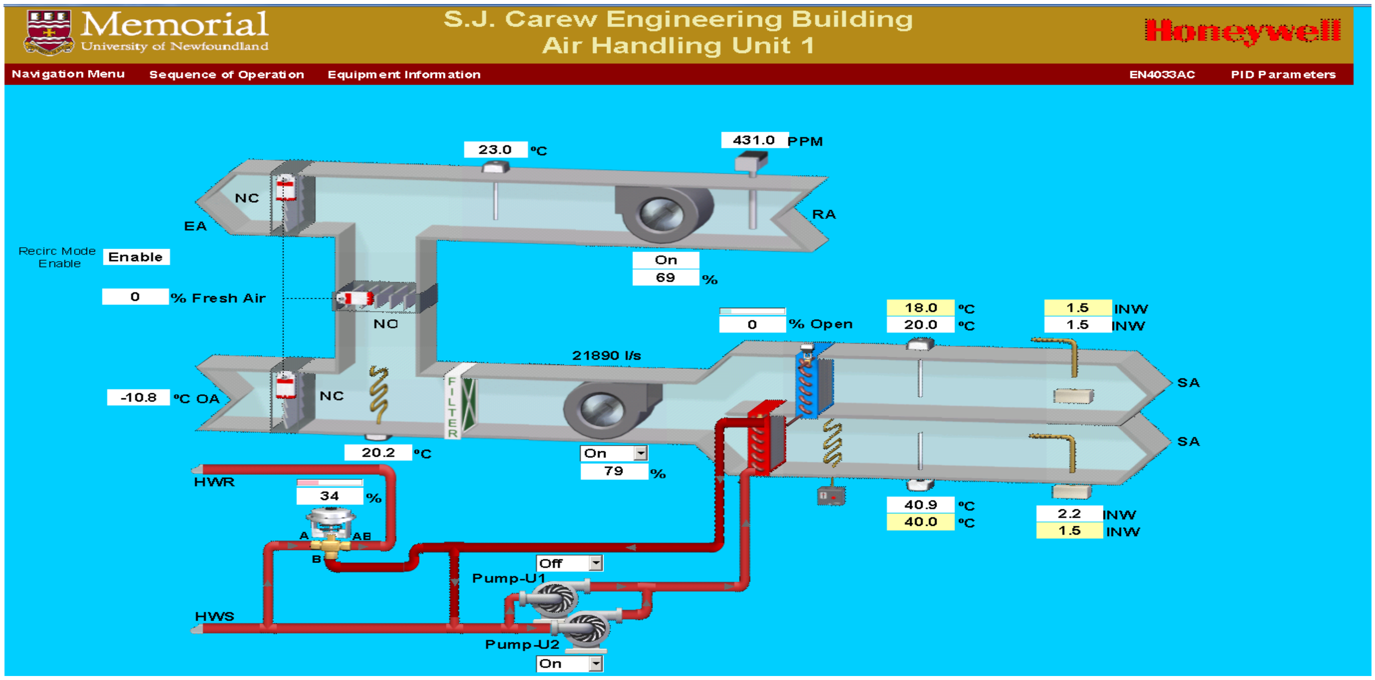

Figure 5.2 AHU$_1$ of the building

5.4. Simulation validation for IDA-ICE

Two key features that are necessary to form a viable model are the model's ease in satisfying specifications and the model's accuracy. Figure 5.3 depicts the Carew building's Jan-Dec/2016 hot water usage as modeled in IDA-ICE. The figure shows hot water energy consumption exceeding 800,000 kWh per month in winter and nearly 300,000 kWh per month for July and August. Real (i.e., measured) data for the building's annual power consumption shows lower hot water usage in some months compared to others, but the overall consumption levels for both the real and modeled data are nearly the same. Electrical power use data for both the IDA-ICE model and real consumption are shown in Figure 5.4. The real data is somewhat higher than the simulation data, which could be a result of uncontrolled lighting and equipment in the building.

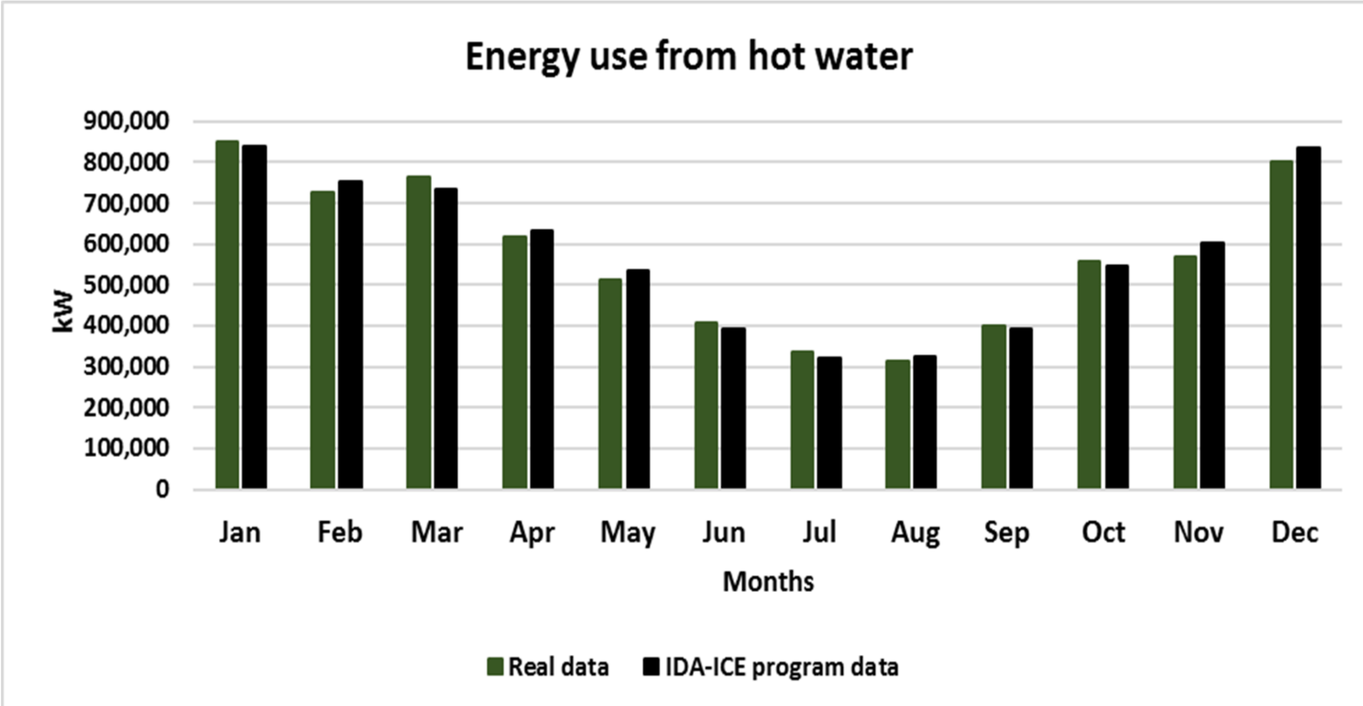

Figure 5.3 Energy use from hot water

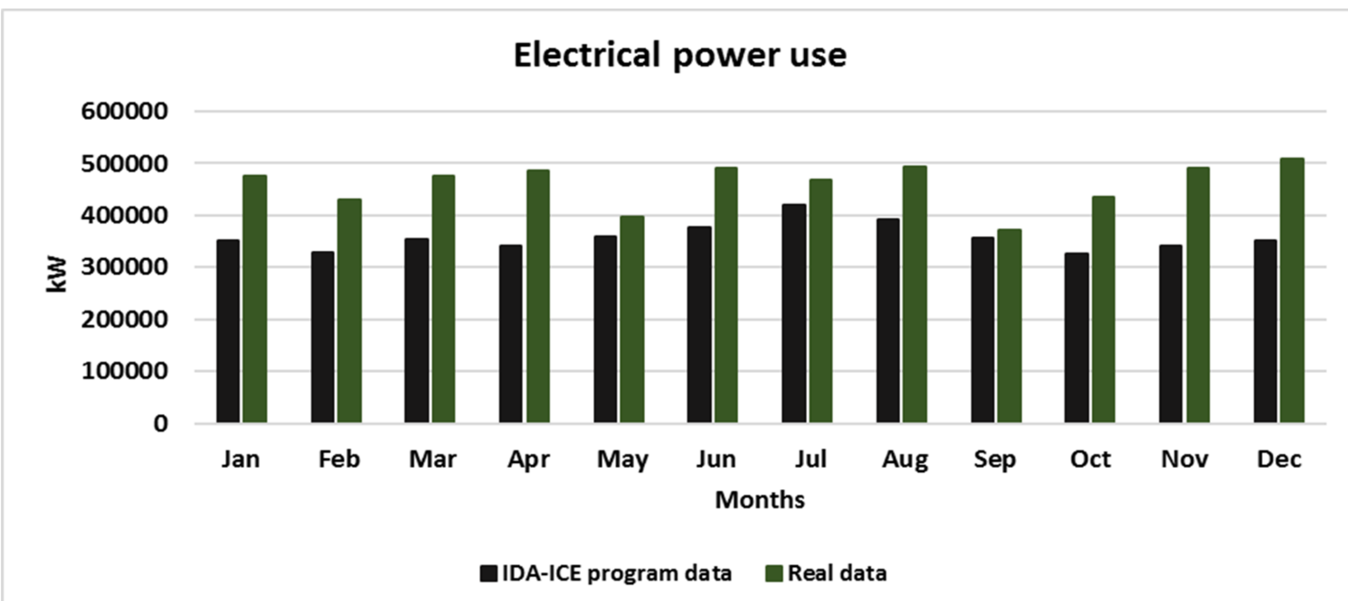

Figure 5.4 Electrical power use

5.5. System Identification

The present study employed the simulation tool IDA-ICE 4.7 to model the internal environment and energy performance of the S. J. Carew building on the Memorial University campus, St. John's, Newfoundland. IDA-ICE software can easily simulate & model HVAC systems that have multi-zonal features. The simulation tool can also measure a range of other important parameters, such as power requirement, thermal comfort levels, and interior air quality (IAQ). To model the building, the identification data must have zonal inputs and outputs. System identification occurs over three consecutive steps, as listed below [30], [31]:

i. Data collection towards the identification of the appropriate model.

ii. Choice of most suitable model structure.

iii. Construction of optimal model that satisfies required specifications and provides accurate results.

The main focus, when following through on each of the above steps, should be on choosing and then optimizing a model to reflect the real-life needs of the system. In this study, the Carew building has four AHUs, so the state space model was deemed most appropriate. Moreover, because our data employed for system identification were sourced in the winter (November to April), the chiller was not operational during that time frame. As the Carew building features four AHUs over four floors, there are 12 inputs and 12 outputs (i.e., 3 inputs $[U]$ and 3 outputs $[Y]$ for each AHU). Each AHU inputs are:

1. hot water valve for the heating coil/zones radiators
2. supply fan speed
3. fresh air from outdoors

The system controlled outputs for each AHU are:

1. Return air temperature (unit is degree Celsius, ^{o}C) for controlling the valve aperture of hot water.
2. Static Air Pressure P_S (unit is an inch in water, INW) in ducts for controlling supply fan speed.

3. CO_2 levels (unit is parts per million, PPM) for controlling fresh air dampers.

A detailed state space model used for controller design for AHU_1 was presented in [29].

5.6. Control Strategies

The simulation results of the fuzzy control methods developed in this research work suggest enhanced comfort levels and energy efficiency across the entire system. The outcome of these improvements would therefore also indicate improved cost efficiencies. Overall, we can assert that fuzzy logic can work with partial truth values along the same lines as humans process ideas and in this way have certain advantages in comparison to traditional controllers, such as:

i. Fuzzy controllers can work with control process models that are imperfect or incomplete (i.e., they do not require mathematical precision).

ii. Employing fuzzy modeling conditions and parameters expands the application of successful control strategies due to the flexibility of the model.

iii. We can successfully model non-linear processes, which are applicable to HVAC systems because these systems are nonlinear.

iv. Fuzzy controller systems can perform the function of approximate decision-making and reasoning, just like human thought processes.

v. In a fuzzy controller, multi-input / multi-output parameter strategies are controllable.

A number of different methods have been successfully used to employ fuzzy logic in a closed-loop control system, but the fuzzy PI controller is currently the most popular approach [32],[33]. In this strategy, fuzzy logic controller inputs and outputs are used to work the actuators, with fuzzy PI controllers serving as incremental controllers. Equation (1) expresses the formulation of a traditional fuzzy PI controller, with the output determined by fuzzy rules [34].

$$u\,(k\,+\,1)\,=\,u\,(k)\,+\,\Delta u\,(k) \tag{5.1}$$

Where k indicates sampling instance and Δu (k) denotes the controller's incremental change. K was selected as 3s

For the AHU model, this case study utilizes a traditional fuzzy PI controller. Combining the proportional (P) and integral (I) actions enhances the inherent stability that is characteristic of proportional controllers. When a motor or valve is the actuators, incremental controllers are the appropriate choice. Fuzzy PI controllers are also suitable if the controller output comes mainly from an integrator, as these types of controllers are easily able to mitigate issues such as wind-up and noise.

Figure 5 illustrates how a fuzzy PI controller uses as inputs error and changes of error signals. An additional feature of fuzzy PI controllers is that they are not limited by operational set-points. In control methods that are rule-driven, any discrepancies between measured or set-point values are first discerned to determine whether it is appropriate to use increments or decrements for the control variables. However, in fuzzy logic controllers, non-linear control strategies can be performed by using fuzzy logic for actual applications, as follows [35]:

a) In Fuzzification, crisp data is turned into fuzzy data, which are also known as membership functions (MFs).
b) MFs are then included as part of the control rules to find the requested fuzzy output, a process which is termed fuzzy inference.
c) Finally, in the defuzzification step, several different approaches are employed in order, firstly, to incorporate all relevant outputs, secondly, to position them as in a table format, and thirdly, to find the output in a look-up table that matches the current input in the desired application.

Figure 5.5 shows the fuzzy controller being designated to control CO_2 levels, static air pressure, and zonal temperatures. As illustrated in the figure, the fuzzy controller is fed error signals and modifications, with the fuzzy controller outputs used as system inputs. The resulting outputs are then forwarded to the fuzzy controller, forming a closed-loop control system.

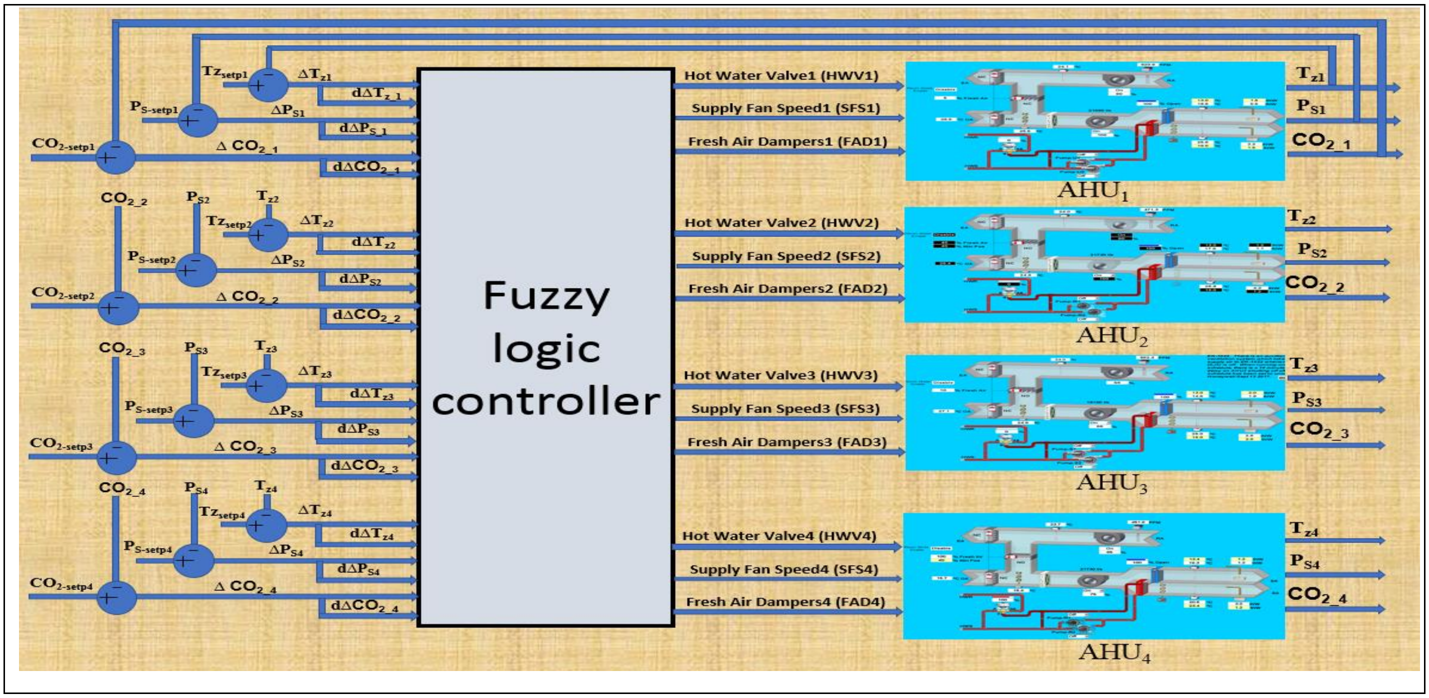

Figure 5.5 The SFLC with four AHUs.

Figure 5.6 depicts a fuzzy logic design in Matlab fuzzy logic toolbox according to system specifications (e.g., add/remove input/output, or select fuzzy inference operations could be done in Matlab toolbox).

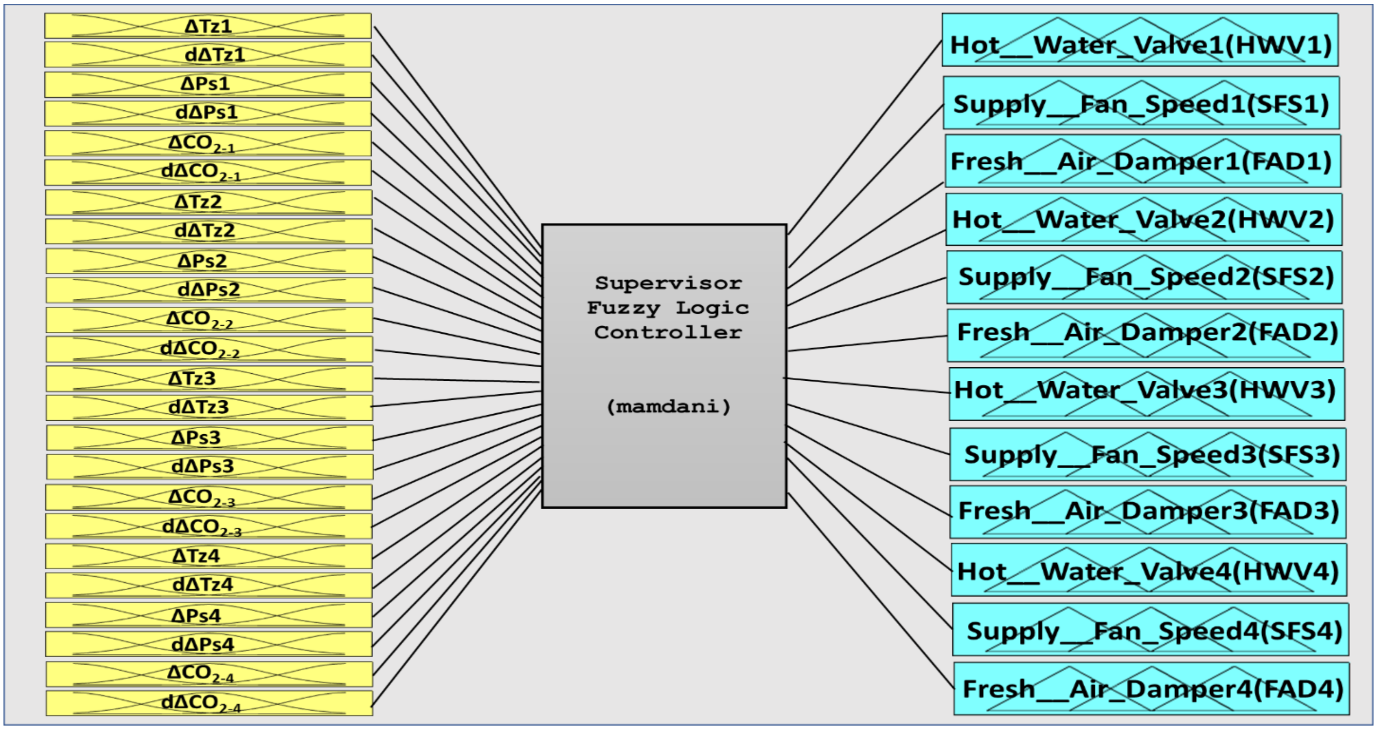

Figure 5.6 Application designer of SFLC

SFLC of the system has 24 inputs as following: 1) 8 inputs are temperature differences (ΔT) and the ratio for the difference ($d\Delta T$) of AHUs, 2) 8 inputs are static air pressure P_S differences (ΔP_S) and the ratio for the difference ($d\Delta P_S$), and 3) 8 inputs are differences in CO_2 Levels (ΔCO_2) and the ratio for the difference ($d\ \Delta CO_2$). There are 12 outputs of the SFLC; each AHU has three (fresh air, air flow, and hot water). The values are introduced as gains to the system to move system responses towards a stability state. As a means to increase output gains, PI controller tuning can be used.

5.7. Fuzzy Membership Function

The MFs editor is used to separate the fuzzy toolbox that is in the form defined by all membership variables for MFs. The final factors are assigned to the variable inputs and output variables as follows:

5.7.1. SFLC input variables

The control system has 6 inputs from each AHU. Three for the difference between setpoints and current values and three inputs are the ratio for response differences. The following data show inputs from AHU_1. Also, Tables 5.2 and 5.3 illustrate the details of all controller inputs.

a. *Temperature Differences of AHU_1 (ΔT_{z1}).* Zone temperature of return air as recorded by an electronic sensor as shown in Figure 5.2 that Eq. (5.2) expresses differences between setpoint (T_{setp1}) and current zone temperature (T_{z1}) for time (k). Figure 5.7 shows the five MFs of (V-High, High, Optimal, Low, and V-Low). Table 5.2 illustrate the details of this MFs.

$$\Delta T_{z1}\,(k) = T_{setp1}\,(k) - T_{z1}\,(k) \qquad (^{\circ}C) \tag{5.2}$$

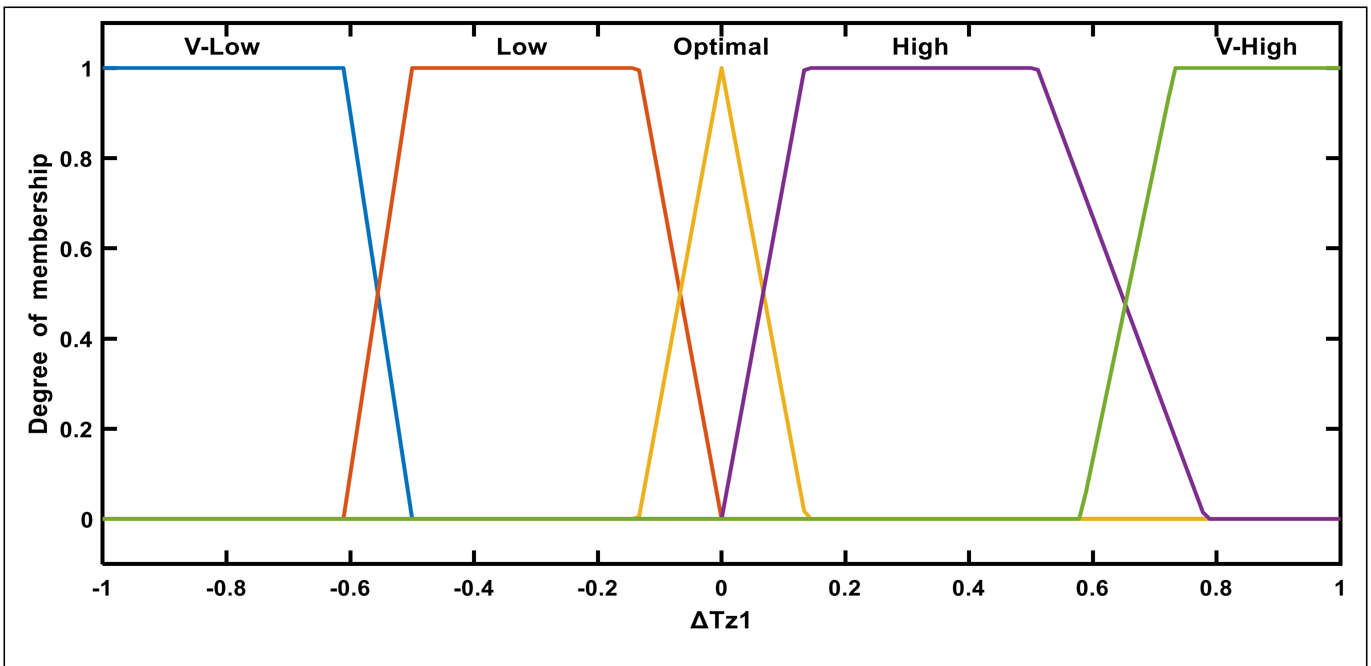

Figure 5.7 MFs differences between (T_{setp1}) and (T_{z1})

b. *Change in ΔT_{z1} in AHU_1 ($d\Delta T_{z1}$).* The variables for the error input in temperature changes are set by observing the difference ratio between current and actual temperature error values and the sampling time (Δt), as shown in Eq. (5.3). The building's real system gives a system sampling time of three seconds (Honeywell Offices and Department of Facilities Management and at Memorial University).

Figure 5.8 and Table 5.3 illustrate that three MFs used to define error variable changes: Positive (P), Negative (N), and Zero (Z).

$$(d\Delta T_{z1}) = \left(\Delta T_{z1}\,(k) - \Delta T_{z1}\,(k\ -\ 1)\right)/\,\Delta t \qquad (^{\circ}C/s) \tag{5.3}$$

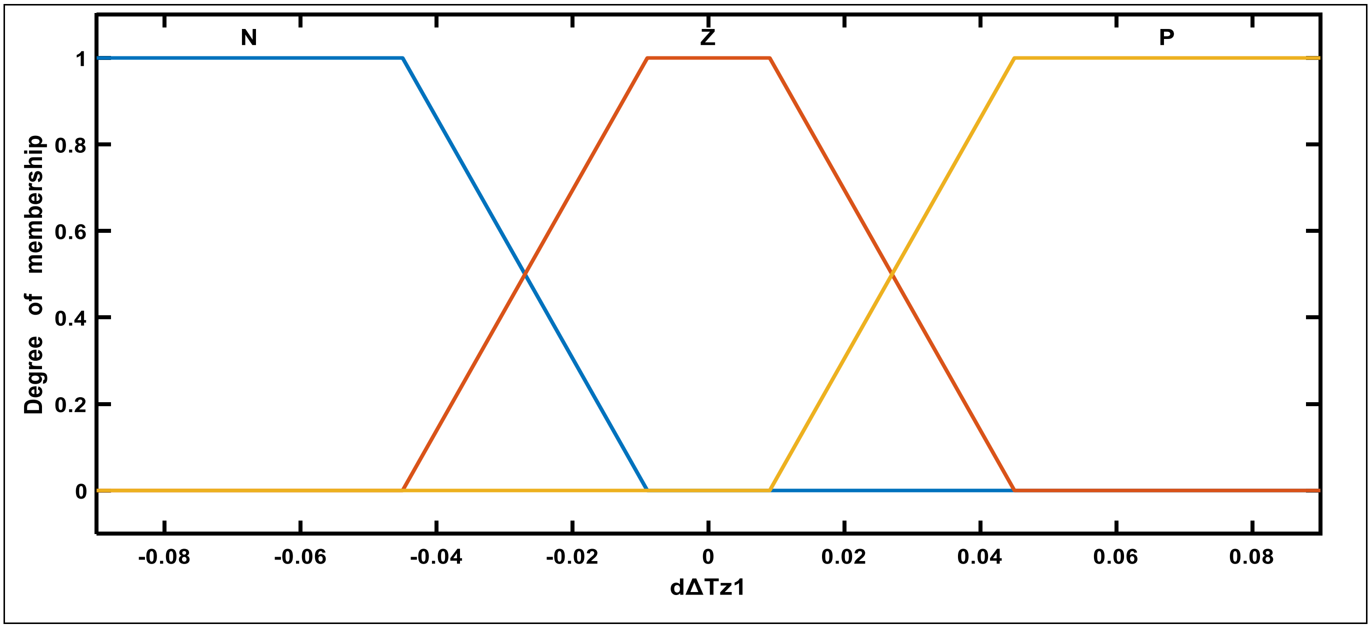

Figure 5.8 MFs ratio between the current and actual temperature

c. *Static Air Pressure Differences of AHU*$_1$ *(*P_{S1}*)*. Figure 5.2 illustrates changes in present duct P_S; these differences were noted by sensors located in both cold- and hot-deck ducts. As can be seen, the static pressure ($P_{S\text{-}setp1}$) setpoints occur for time (k), given in Eq. (5.4). Figure 5.9 and Table 5.2 present five MFs of (V-High, High, Optimal, Low, and V-Low).

$$\Delta P_{S1}\,(k)\ =\ \Delta P_{S-setp1}\ -\ P_{S1}\,(k) \qquad (INW) \tag{5.4}$$

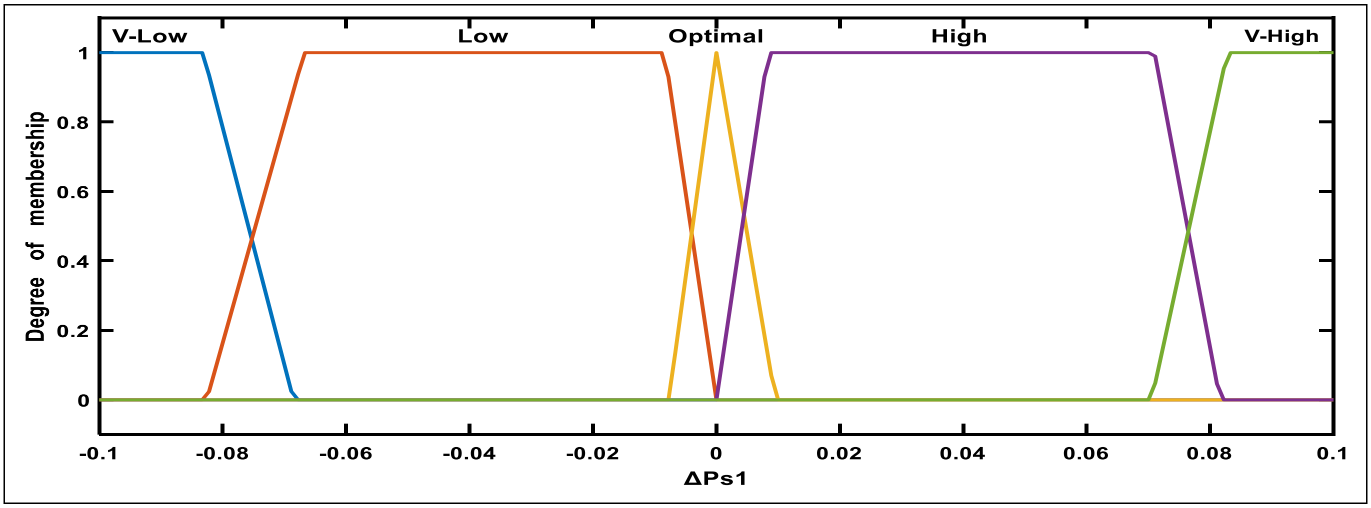

Figure 5.9 MFs of Static Air Pressure Differences

d. *Change in ΔP_{S1} ($d\Delta P_{S1}$) in AHU_1.* As expressed in Eq. (5.5), All changes of the (P_S) error input variables are made with ratios for the differences between current and actual (P_S) values depending on the sampling time (Δt). Figure 5.10 shows three MFs that show changes in the displayed error variables Positive (P), Negative (N), and Zero (Z).

$$d\Delta P_{S1}\,(k) = (\Delta P_{S1}\,(k) - \Delta P_{S1}\,(k-1))/\,\Delta t \qquad (INW/s) \qquad (5.5)$$

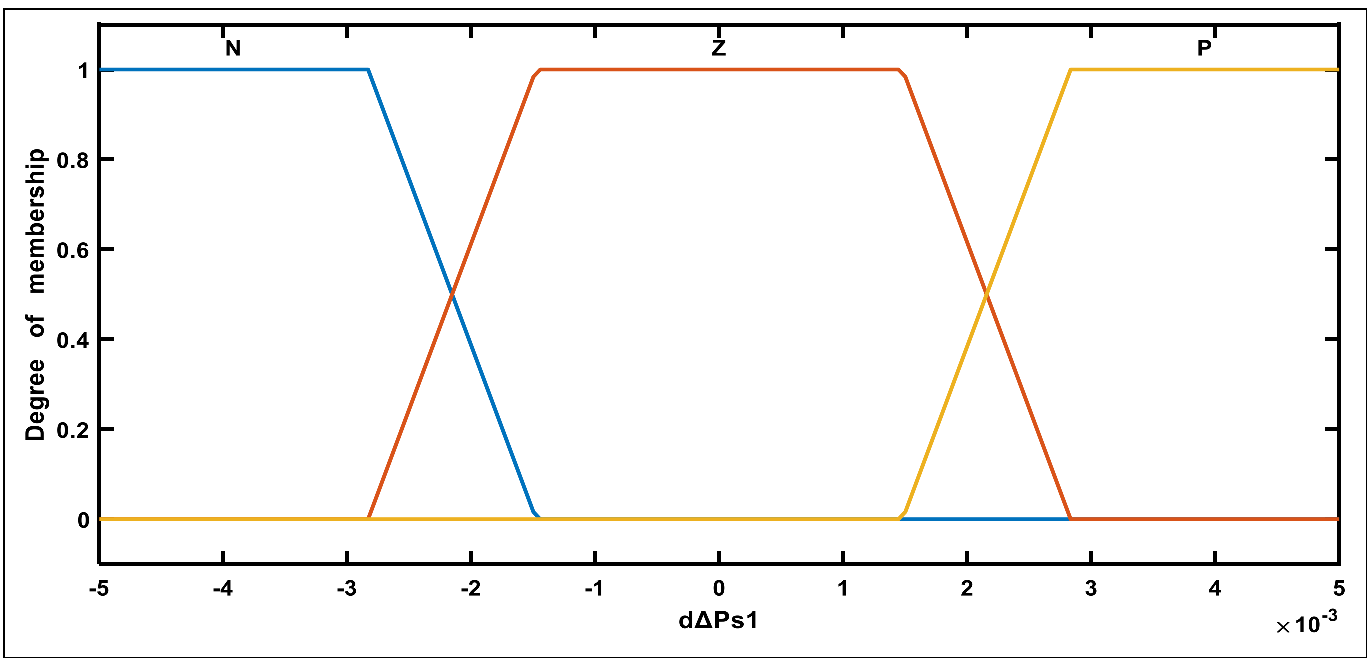

Figure 5.10 MFs of ratios for the differences between current and actual (P_S) values

e. *Differences in CO_2 Levels in AHU_1* ($\Delta CO_{2\text{-}1}$). As shown in Figure 5.2, this is the difference between the current $CO_{2\text{-}1}$ level in the return air from the sensor in the AHU_1 return duct and the CO_2 level of setpoint $CO_{2\text{-}setp1}$, as recorded at the time (k) and expressed by Eq. (5.6). The 5 MFs of (V-High, High, Optimal, Low, and V-Low) are shown in Figure 5.11.

$$\Delta CO_{2-1}\,(k) \; = CO_{2-setp1} \; - CO_{2-1}\,(k) \qquad (PPM) \tag{5.6}$$

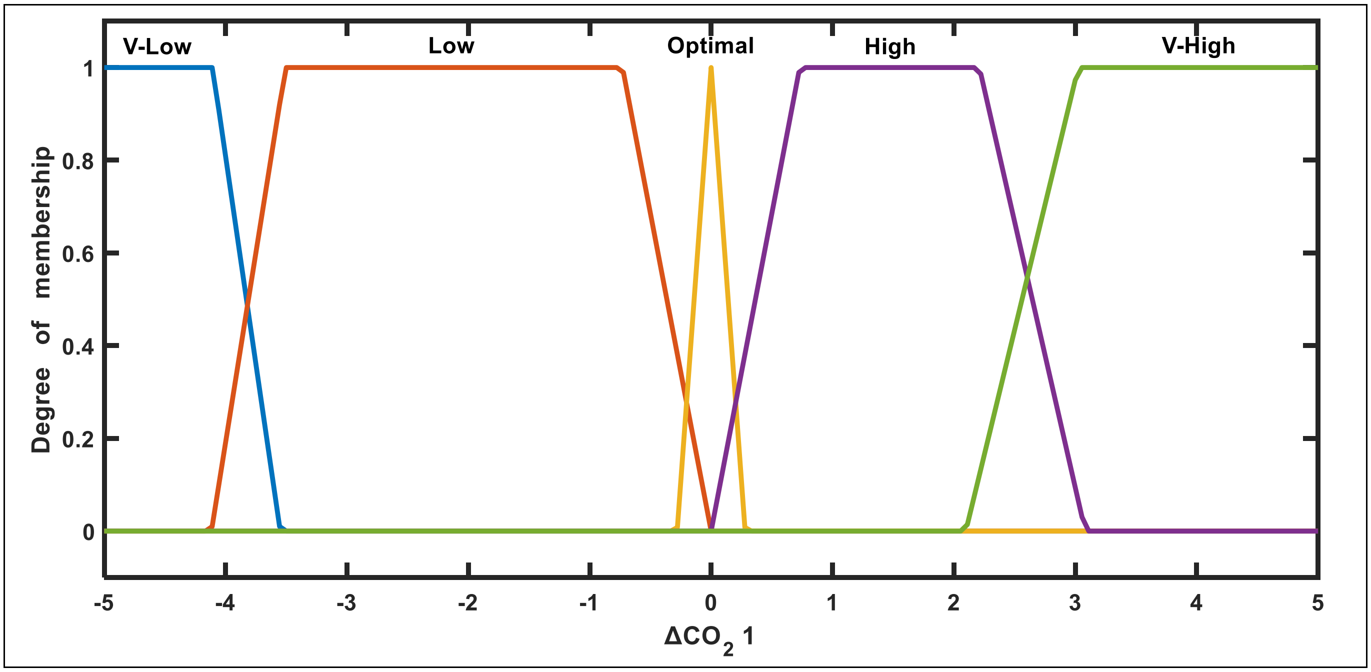

Figure 5.11 Difference between the current and setpoint of $CO_{2\text{-}1}$ level

f. *Change in* $\Delta CO_{2\text{-}1}$ ($d\Delta CO_{2\text{-}1}$). As indicated in Eq. (5.7), the input variable CO_2 error changes can be formed by observing the difference ratio between the current and previous CO_2 error values as a function of the sampling time (Δt). Figure 5.12 show the three MFs error variable changes as sets labelled Positive (P), Negative (N), and Zero (Z).

$$d\Delta CO_{2-1}\,(k) \; = \; (\Delta CO_{2-1}\,(k) \; - \; \Delta CO_{2-1}\,(k \; - \; 1))\,/\Delta t \quad (PPM/s) \tag{5.7}$$

Table 5.2 and Table 5.3 lists all limits of MFs used in Matlab fuzzy logic toolbox for all AHUs.

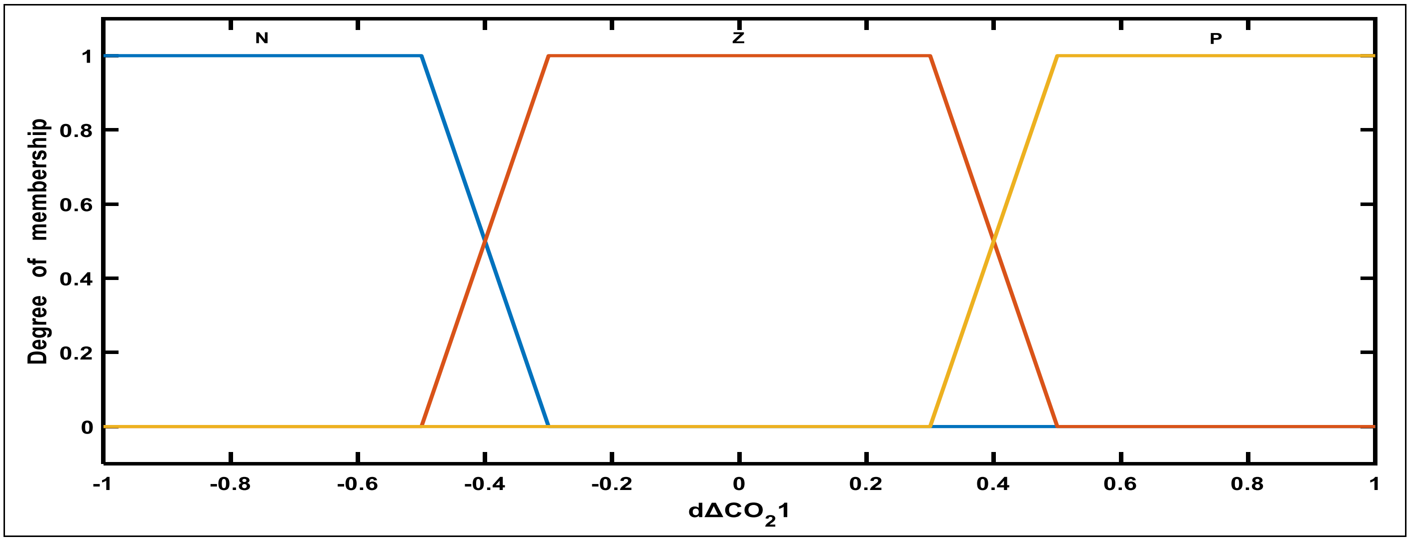

Figure 5.12 Difference ratio between current and previous CO_2 error values

Table 5.1 Difference between setpoints and current values of all inputs

Range / Inputs	V-Low	Low	Optimal	High	V-High
ΔT_{z1}	[-5.26 -4.24 -0.611 -0.5]	[-0.611 -0.5 -0.134 0]	[-0.134 0 0.1357]	[0 0.134 0.51 0.7817]	[0.5797 0.7323 1.774 9.13]
ΔP_{S1}	[-7 -0.15 -0.083- 0.068]	[-0.08 -0.06 -0.008 0]	[-0.007 0 0.0095]	[0 0.008 0.071 0.081]	[0.07052 0.08278 0.1399 9]
$\Delta CO_{2\text{-}1}$	[-62.73 -5.04 -4.1 -3.55]	[-4.117 -3.5 -0.73 0]	[-0.28 0 0.28]	[0 0.73 2.21 3.082]	[2.098 3.025 30 119.5]
ΔT_{z2}	[-8.76 -4.24 -0.611 -0.5]	[-0.611 -0.5 -0.134 0]	[-0.134 0 0.1357]	[0 0.134 0.51 0.7815]	[0.5795 0.7325 1.774 9.63]
ΔP_{S2}	[-5.6 -0.126 -0.06 -0.05]	[-0.07 -0.05 -0.007 0]	[-0.0061 0 0.007]	[0 0.006 0.056 0.065]	[0.05642 0.0662 0.1119 7.2]
$\Delta CO_{2\text{-}2}$	[-56.4 -5.04 -4.107 -3.5]	[-4.11 -3.507 -0.73 0]	[-0.18 0 0.18]	[0 0.73 2.21 3.082]	[2.098 3.025 30 119.5]
ΔT_{z3}	[-5.26 -4.24 -0.611 -0.5]	[-0.611 -0.5 -0.134 0]	[-0.134 0 0.1357]	[0 0.134 0.51 0.7815]	[0.5795 0.7325 1.774 9.63]
ΔP_{S3}	[-6.4 -0.12 -0.066 -0.05]	[-0.06 -0.05 -0.006 0]	[-0.0061 0 0.007]	[0 0.0067 0.057 0.06]	[0.05642 0.0662 0.1119 7.2]
$\Delta CO_{2\text{-}3}$	[-56.48 -5.048 -4.1 -3.5]	[-4.117 -3.51 -0.73 0]	[-0.28 0 0.28]	[0 0.73 2.21 3.082]	[2.098 3.025 30 119.5]
ΔT_{z4}	[-5.26 -4.24 -0.611 -0.5]	[-0.611 -0.5 -0.134 0]	[-0.134 0 0.1357]	[0 0.134 0.51 0.7815]	[0.5795 0.7325 1.774 9.63]
ΔP_{S4}	[-4.9 -0.12 -0.06 -0.048]	[-0.06 -0.04 -0.005 0]	[-0.005 0 0.0067]	[0 0.006 0.049 0.058]	[0.05 0.05795 0.09793 6.3]
$\Delta CO_{2\text{-}4}$	[-56.5 -5.04 -4.11 -3.55]	[-4.12 -3.507 -0.73 0]	[-0.288 0 0.288]	[0 0.73 2.21 3.082]	[2.098 3.025 30 119.5]

Table 5.2 Ratio between the current and previous values of all inputs

Range / Inputs	P	Z	N
$d\Delta T_{z1}$	[-0.1062 -0.09279 -0.045 -0.009]	[-0.04601 -0.009 0.01 0.04499]	[0.0109 0.0395 0.1381 0.175]
$d\Delta P_{S1}$	[-0.005533 -0.005 -0.003 -0.001469]	[-0.002833 -0.0014 0.001478 0.002833]	[0.00158 0.00293 0.00595 0.0065]
$d\Delta CO_{2\text{-}1}$	[-2.1 -1 -0.5 -0.3]	[-0.499 -0.3002 0.2993 0.5]	[0.3 0.5 1 1.091]
$d\Delta T_{z2}$	[-0.1062 -0.09279 -0.045 -0.009]	[-0.045 -0.009 0.009 0.045]	[0.009 0.045 0.1381 0.1615]
$d\Delta P_{S2}$	[-0.0053 -0.005 -0.0028 -0.00149]	[-0.002833 -0.0014 0.001478 0.002833]	[0.00148 0.003 0.00635 0.00635]
$d\Delta CO_{2\text{-}2}$	[-2.21 -1.1 -0.53 -0.323]	[-0.5 -0.3 0.3 0.5002]	[0.3005 0.501 1 1.1001]
$d\Delta T_{z3}$	[-0.1064 -0.09279 -0.045 -0.01]	[-0.045 -0.019 0.0101 0.045]	[0.009002 0.04502 0.139 0.162]
$d\Delta P_{S3}$	[-0.005433 -0.005 -0.00288 -0.00147]	[-0.002833 -0.0014 0.001478 0.002833]	[0.00148 0.00283 0.00585 0.0055]
$d\Delta CO_{2\text{-}3}$	[-2.21 -1.4 -0.555 -0.343]	[-0.5 -0.289 0.3 0.499]	[0.3 0.5005 1 1.0891]
$d\Delta T_{z4}$	[-0.1072 -0.09379 -0.04501 -0.01]	[-0.045 -0.009 0.009 0.045]	[0.01 0.045001 0.138 0.161501]
$d\Delta P_{S4}$	[-0.005433 -0.005 -0.0028 -0.001478]	[-0.002833 -0.0014 0.001478 0.002833]	[0.0025 0.00298 0.00585 0.0075]
$d\Delta CO_{2\text{-}4}$	[-2.103 -1 -0.501 -0.312]	[-0.5 -0.3 0.3 0.5]	[0.299 0.50035 1 1.1]

5.7.2. Output Variables.

The inlet of all ventilation units (hot water, fan speed, and fresh air) acts as an SFLC output. This means that SFLC has twelve output. Values are entered as a gain in the system to introduce system reactions into a steady state. To increase the output gain, the tuning of a PI controller can be used, as described the outputs of the first AHU_1 in the following subsections [29]. Also, table 5.4 illustrate all the details of MFs (Close-Fast, Close, No-Change, Open, and Open-Fast) and the related operation percentages of hot water valve's, fan speed and fresh air dampers of the whole system.

a. *Aperture on Hot Water Valve of AHU_1 (HWV_1)*. The 5 MFs indicates the output of the process controller to open and close the hot water valve to set the temperature range of the zone (T_{setp1}). Figure 5.13 depicts MFs using MATLAB/Fig.

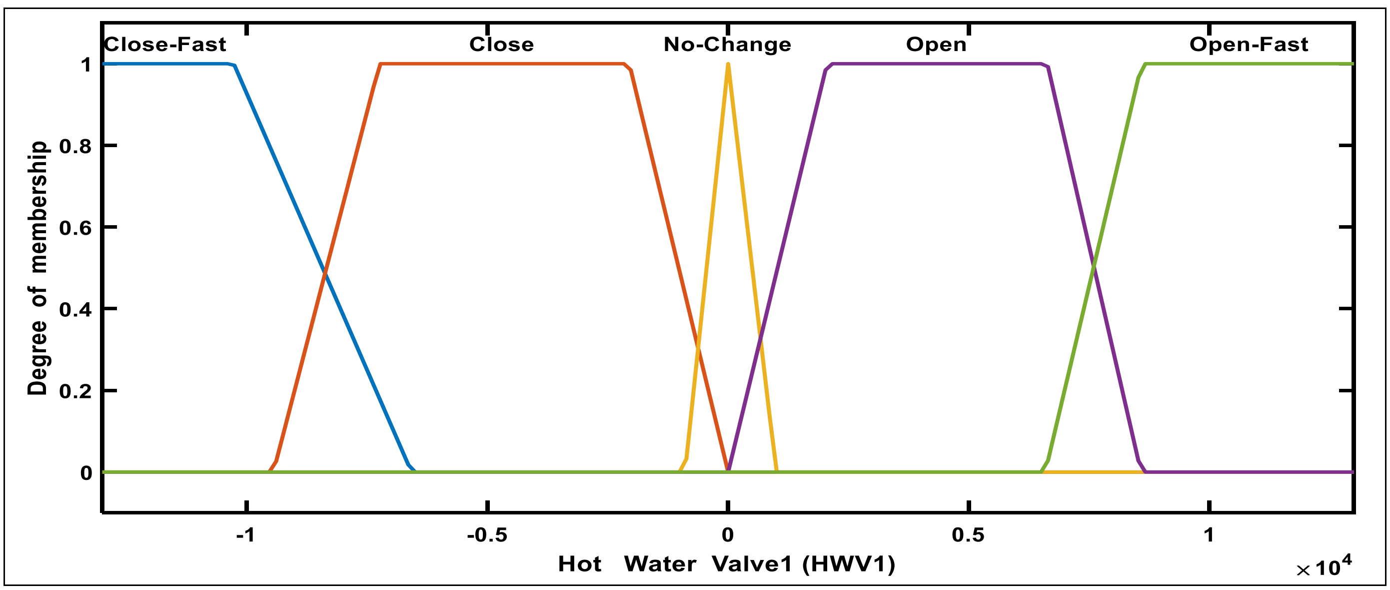

Figure 5.13 MFs of the first output of SFLC

b. *Supply Fan Speed of AHU_1(SFS_1)*. The second output of the SFLC is the speed control of the supply fan to reach the static air pressure setpoint ($P_{S\text{-}setp1}$) inside ducts. Figure 5.14 shows the five MFs for this process.

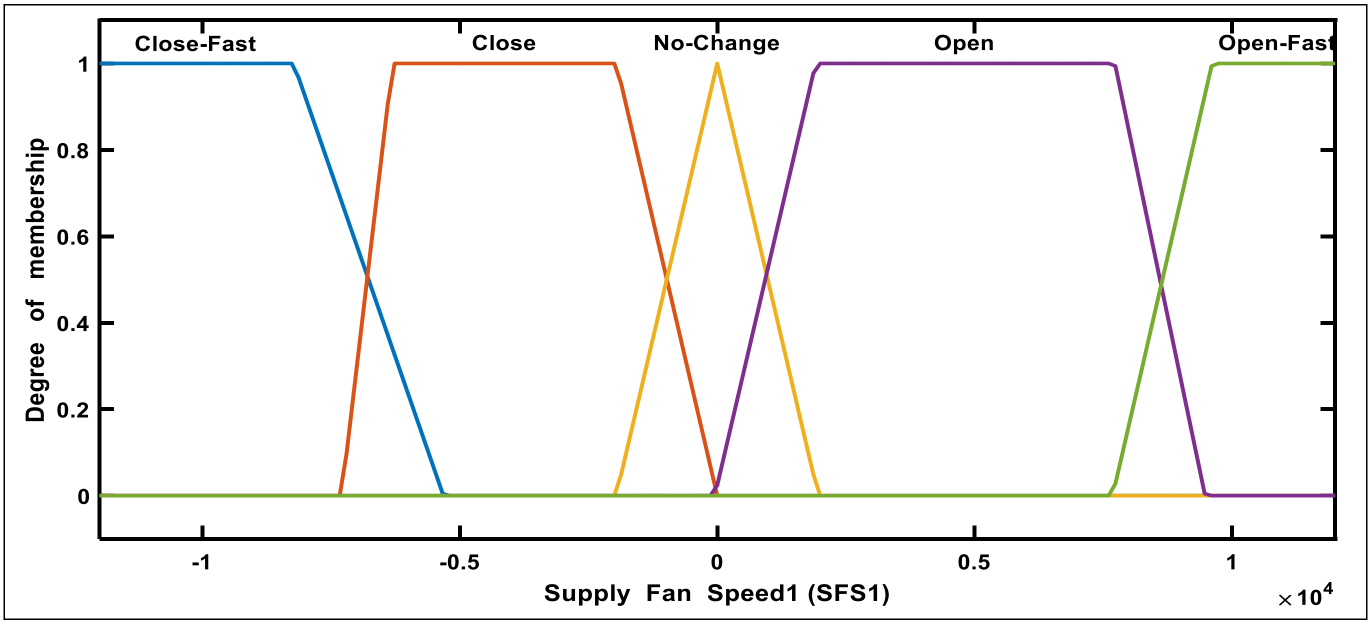

Figure 5.14 The second output of the SFLC

c. *Fresh Air Dampers Position of AHU$_1$ (FAD$_1$)*. Five MFs were used for the controller output to open and close the position of the fresh air dampers to determine the CO_2 concentration setpoint ($CO_{2\text{-setp1}}$), Figure 5.15 shows that. Table 5.4 provides a list of limits of output MFs of all AHUs.

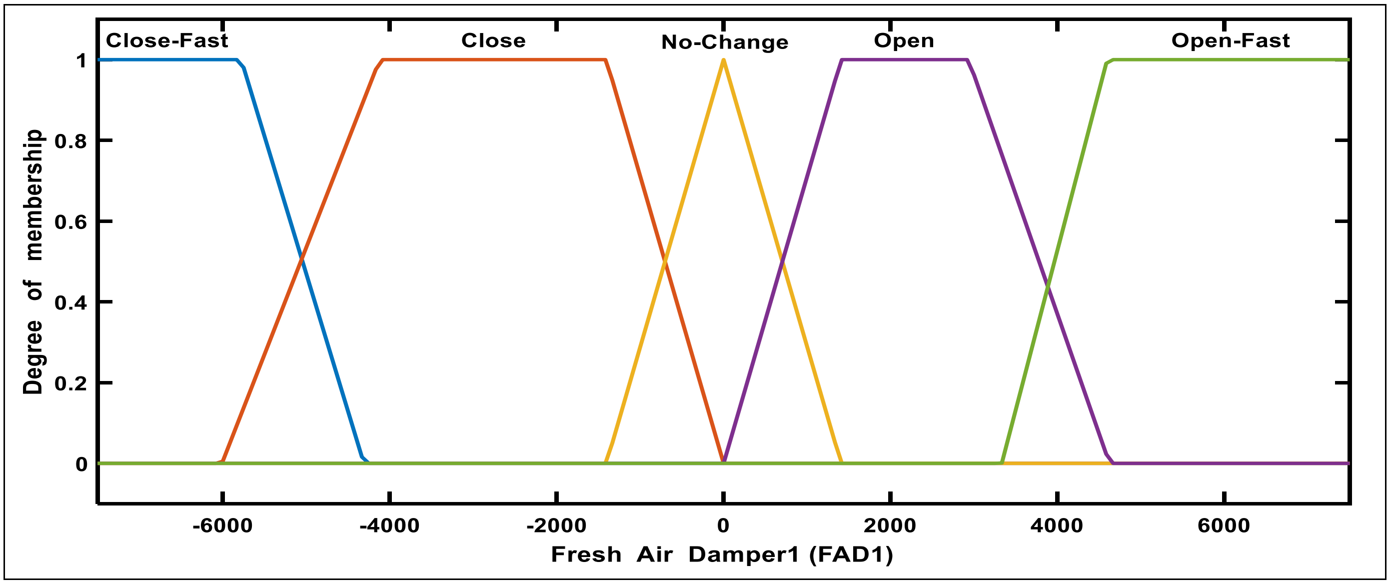

Figure 5.15 The third output of the SFLC

Table 5.3 All the outputs of SFLC

Corresponding	0% - 20%	20% - 40%	40% - 60%	60% - 80%	80% -100%
Range / Outputs	**Close-Fast**	**Close**	**No-Change**	**Open**	**Open-Fast**
HWV_1	[-17160 -13000 -10270 -6578]	[-9447 -7241 -2054 0]	[-895 0 998]	[0 2054 6630 8576]	[6588 8590 13280 13340]
SFS_1	[-14020 -12170 -8227 -5319]	[-7296 -6307 -1958 0]	[-1963 0 1963]	[0 1911 7723 9475]	[7680 9612 12020 12130]
FAD_1	[-7823 -7545 -5779 -4310]	[-6010 -4121 -1405 0]	[-1404 0 1407]	[0 1408 2936 4622]	[3332 4595 7515 7988]
HWV_2	[-15840 -12000 -9473 -6072]	[-8717 -6684 -1896 0]	[-826 0 921]	[0 1896 6120 7913]	[6081 7929 12260 12310]
SFS_2	[-8768 -7605 -5138 -3323]	[-4563 -3938 -1223 0]	[-1227 0 1227]	[0 1195 4827 5925]	[4800 6008 7515 7583]
FAD_2	[-11460 -11060 -8476 -6322]	[-8814 -6044 -2062 0]	[-2059 0 2065]	[0 2066 4307 6778]	[4886 6738 11020 11720]
HWV_3	[-11090 -8400 -6631 -4249]	[-6102 -4679 -1327 0]	[-578 0 645]	[0 1327 4284 5539]	[4257 5549 8585 8617]
SFS_3	[-7010 -6083 -4110 -2659]	[-3652 -3150 -979 0]	[-981 0 981]	[0 955.8 3862 4735]	[3840 4805 6014 6065]
FAD_3	[-9379 -9053 -6935 -5173]	[-7211 -4945 -1686 0]	[-1684 0 1689]	[0 1690 3524 5546]	[3998 5514 9017 9587]
HWV_4	[-11220 -8500 -6707 -4301]	[-6172 -4735 -1343 0]	[-585 0 652]	[0 1343 4335 5604]	[4307 5616 8686 8720]
SFS_4	[-31540 -27410 -18520 -11960]	[-16450 -14180 -4406 0]	[-2614 0 2614]	[0 4298 17360 21330]	[17280 21620 27050 27290]
FAD_4	[-17600 -17010 -13020 -9709]	[-13550 -9287 -3166 0]	[-1456 0 1469]	[0 3177 6616 10400]	[7505 10330 16930 18020]

5.7.3. Fuzzy Rules

In systems that operate using fuzzy inference, the output variables are controlled by fuzzy rules, which essentially are IF-THEN rules that contain both a condition and a conclusion. Fuzzy membership functions can alter input errors (ΔTz, ΔPS, ΔCO_2) as well as error changes ($d\Delta Tz$, $d\Delta PS$, $d\Delta CO_2$) in accordance with their appropriate fuzzy values. Additionally, for each output investigated in this paper (e.g., hot water valve, fan speed and damper position), fuzzy rules provide the control action for values of error and error changes [36]-[38]. Note that because each control signal output has 5 × 3 i.e. 15 rules. Ta,ble 5.5 illustrate the rules between first and second input (ΔTz_1 *and* $d\Delta Tz_1$) of the controller as the fuzzy default rule, there are three inputs in each AHU and four AHUs for the system, that mean the SFL controller has (15 × 3 × 4) 180 rules. Also, The SFLC can control aspects of energy saving that better the performance of the heating and cooling system of building, takingthe into account the needs of each floor, for that there is extra rules between floors.

Table 5.4 The rules between the first and second input of the controller

Δ inputs / dΔ inputs	V-Low	Low	Optimal	High	V-High
N	Open-Fast	Open-Fast	Open	No-Change	Close
Z	Open-Fast	Open	No-Change	Close	Close-Fast
P	Open	No-Change	Close	Close-Fast	Close-Fast

5.7.4. Defuzzification

Defuzzification changes fuzzy output variables into crisp variables in order to meet control objectives. The defuzzification step is used in hardware applications where crisp data are exchanged, and defuzzified output is deemed the best solution. The underlying mechanisms for this approach are the maxima strategy and the centroid strategy. The maxima approach actively seeks the highest pack, whereas the centroid approach seeks to find the balance point. In our case study of the S. J. Carew building, the centroid method is used. Figure 5.16 shows the control surface with the applied MFs. Error values for zonal temperatures along with the change of error values based on fuzzy rules have been used. The control output values derive from a range of input combinations in hot water valve functions.

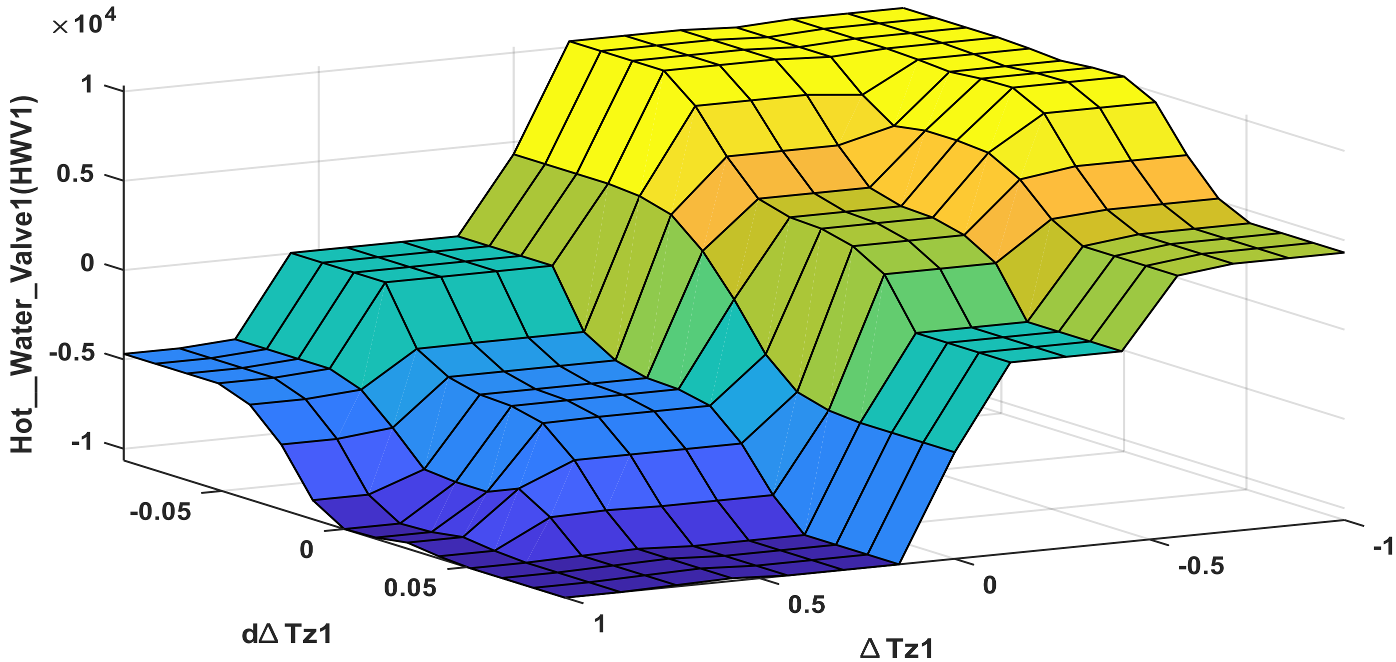

Figure 5.16 Control surface of ΔT_{z1} and $d\Delta T_{z1}$ based on fuzzy rules

In Figure 5.17, the control surface employed to implement static air pressure error value MFs and fuzzy rule-implemented change of error values is illustrated. In this case, the control output values derive from a range of input combinations for moderating supply fan speed as a means to determine the ducts' static air pressure set-points.

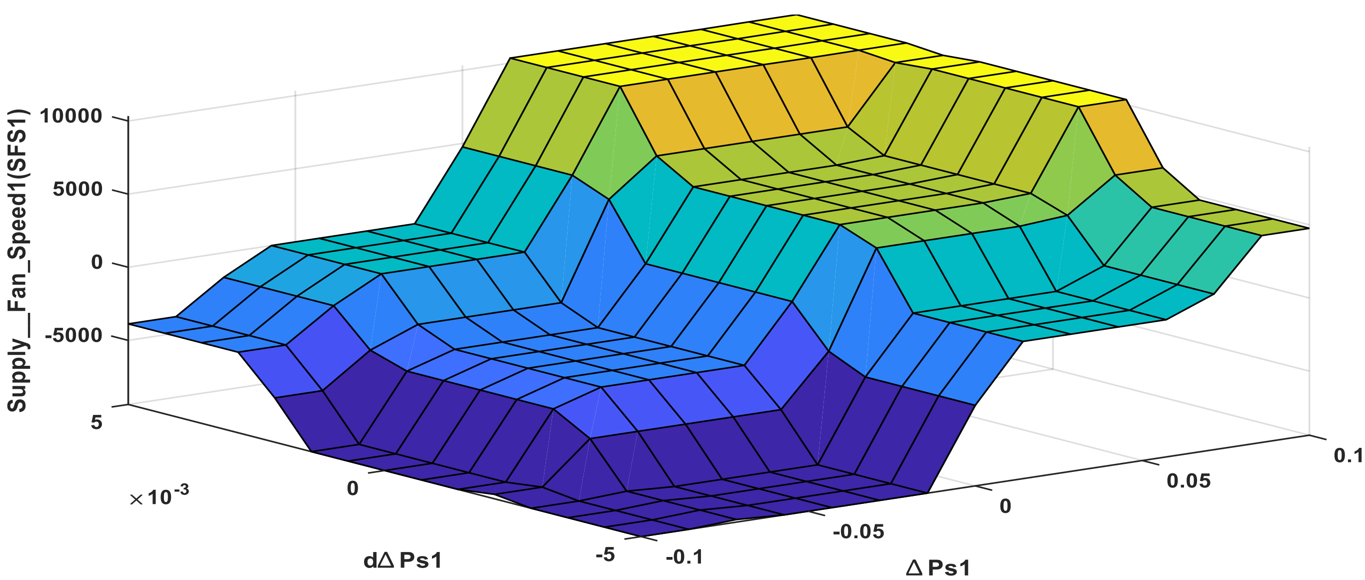

Figure 5.17 Control surface of ΔPs_1 and $d\Delta Ps_1$ based on fuzzy rules

The control surface for values of error and changes of error in MFs are measuring CO_2 levels is depicted in Figure 5.18. As shown, fuzzy rules have been used to control output values in order to determine the CO_2 set-point which is most appropriate.

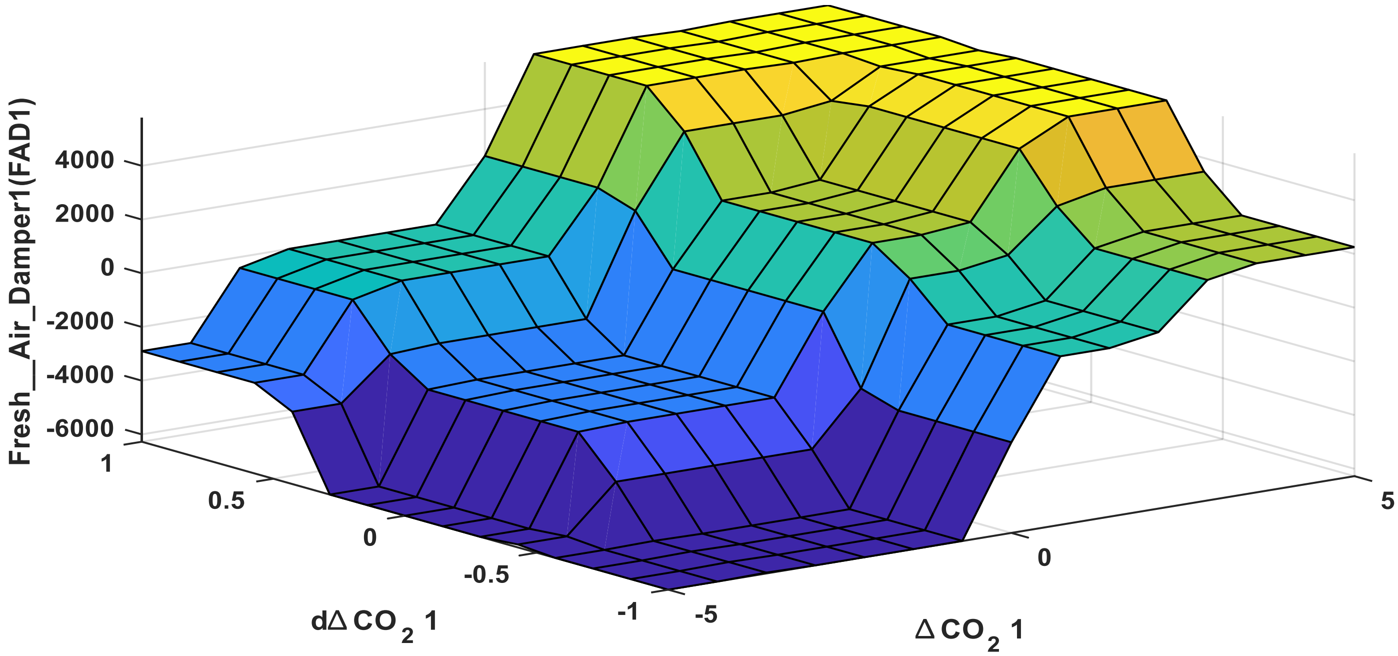

Figure 5.18 Control surface of $\Delta CO_{2\text{-}1}$ and $d\Delta CO_{2\text{-}1}$ based on fuzzy rules

For the extra rules between floors, Figure 5.19 shows the control surface between second and third-floor temperature differences for saving energy and better the performance of the hot water valve of AHU_2 (*HWV2*).

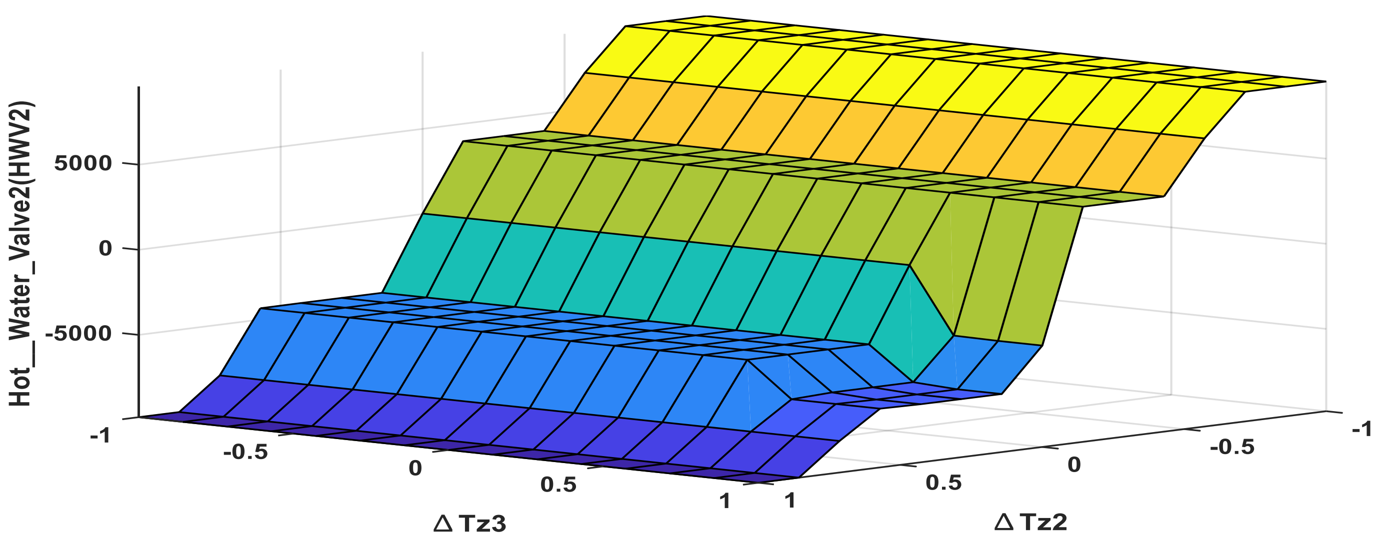

Figure 5.19 Control surface of ΔTz_2 and ΔTz_3 based on fuzzy rules

Figure 5.20 shows the control surface between the second and third floor Static Air Pressure Differences for saving energy and better the performance of supply fan speed of AHU_2 (*SFS2*).

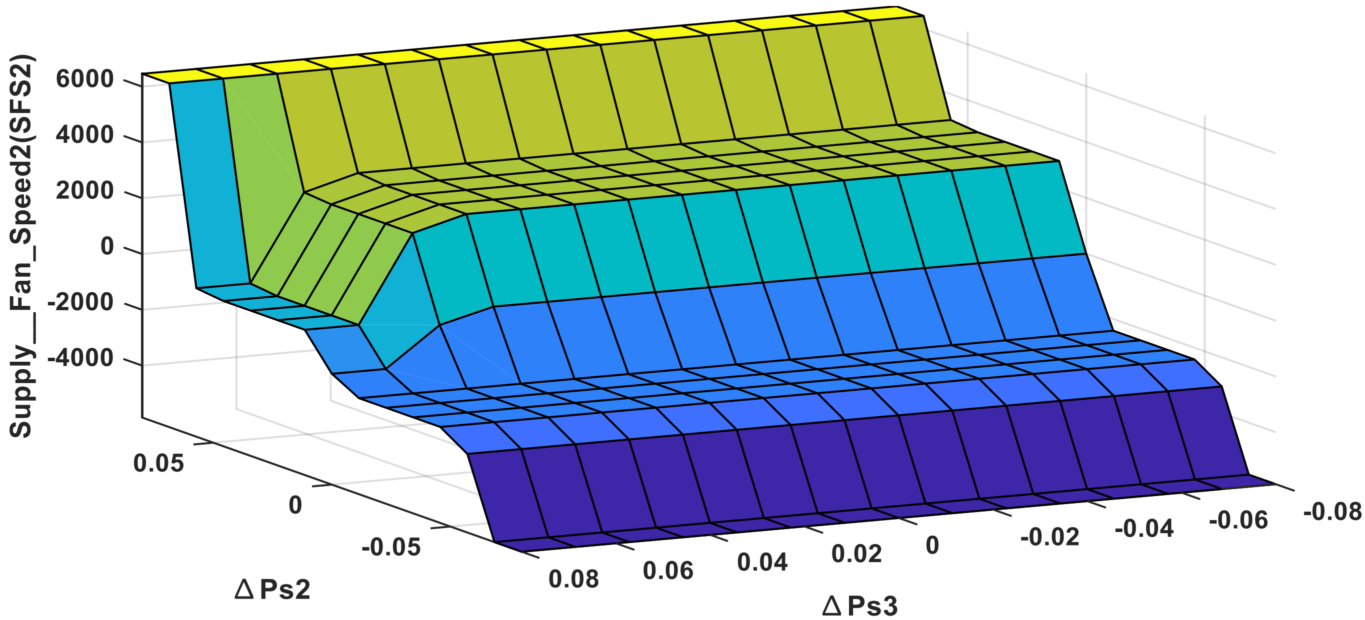

Figure 5.20 Control surface of ΔPs_2 and ΔPs_3 based on fuzzy rules

5.8. Simulation and Results

In this section, the simulation results and the Simulink model are presented. Figure 5.21 shows a block diagram for state space models of a whole building (four AHUs), supervisor fuzzy logic controller and all setpoints using the Simulink. There are four state space models; each AHU has one with three inputs and three outputs; the advantage of separate the system to four is to decrease the rules of the controller. Also, the sampling time was selected as 3 seconds of the control action the same as that for the real system [29]. Also, the initial conditions and setpoints are selected for a state space model of temperatures, air pressures, and CO_2 levels of AHUs of the system as follows:

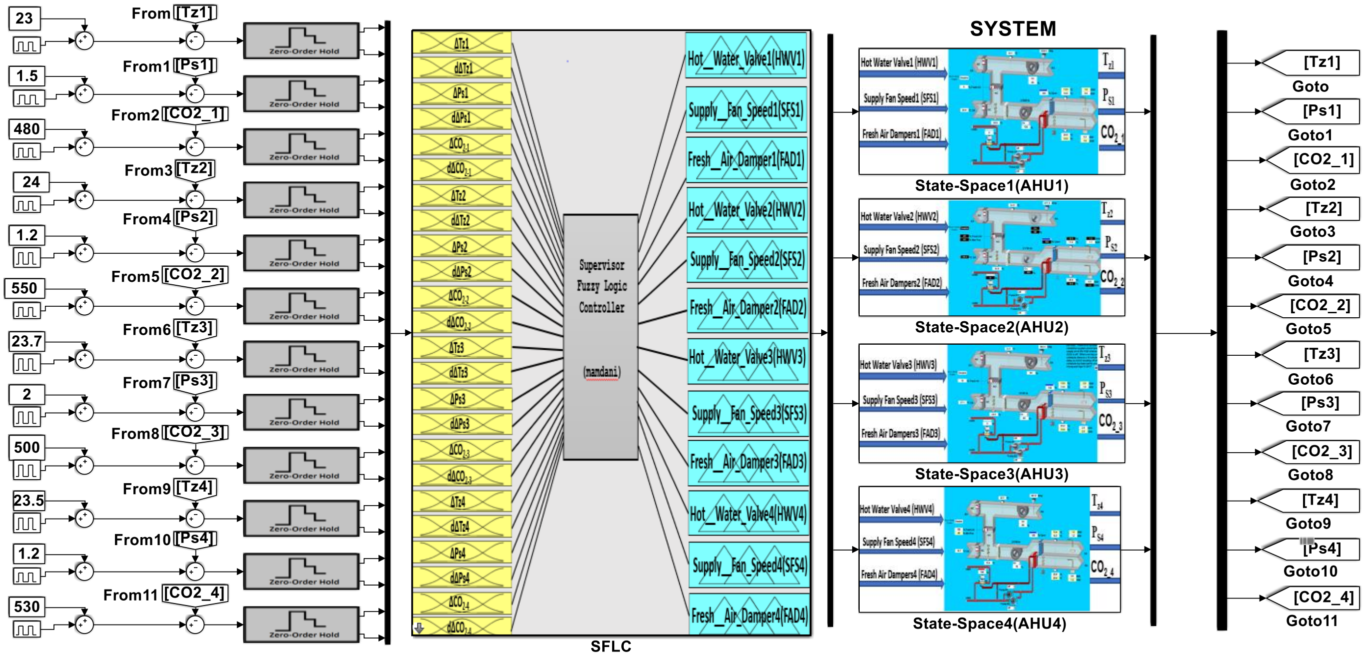

Figure 5.21 block diagram for state space models of the whole system with SFLC

i. 22.46 °C for temperature, 1.013 INW for air pressure, and 471 PPM for CO_2 levels of the AHU_1 initial conditions. Furthermore, the real system's indoor air quality setpoints are a zone temperature of 23 °C, air pressure of 1.5 INW, and a CO_2 level of 480 PPM.

ii. Initial conditions of AHU_2 it was 20.29 °C for temperature, 1.11 INW for static air pressure, and 502 PPM for CO_2 levels. Setpoints are 24 °C, 1.2 INW, and 550 PPM of zone temperature, air pressure, and CO_2 level, respectively.

iii. For the AHU_3 the initial conditions were 22.31 °C for temperature, 1.39 INW for static air pressure, and 469 PPM for CO_2 levels, the setpoints 23.7 °C, 2 INW, and 500 PPM of zone temperature, air pressure, and CO_2 level, respectively.

iv. AHU_4 has the initial condition of temperature 21.3 °C, static air pressure 1.01 INW, and CO_2 levels 486 PPM. Setpoints are 23.5 °C, 1.2 INW, and 530 PPM of zone temperature, air pressure, and CO_2 level, respectively.

SFLC control characters receive both errors and changes. System input control signals can be changed, including hot water, fresh air, and airflow gains to reach the reference points. Figure 5.22 shows the first of the system's output responses of each AHU that demonstrate the system's stability. Zones temperature (T_{z1}, T_{z2}, T_{z3}, and T_{z4}) achieves setpoints of 23 °C, 24 °C, 23.7 °C and 23.5 °C at good rise time and there is a small overshoot of some responses. Also, the setpoints of the system were changed to see the action of the controller; the figure shows good responses with this change.

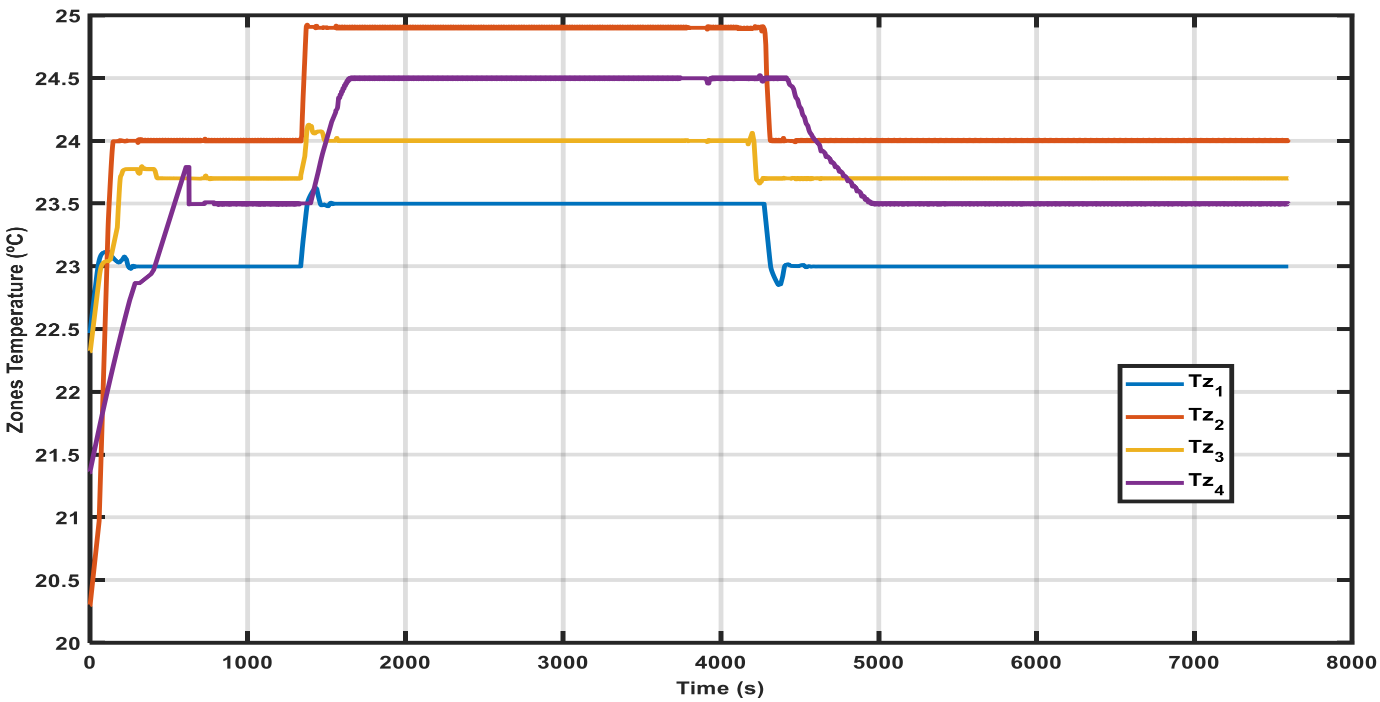

Figure 5.22 Zones temperature responses

Figure 5.23 depicts the second responses of static air pressure of AHUs (Ps_1, Ps_2, Ps_3, and Ps_4), with perfect rise time and some small overshoots of the responses. With the changing of the references of the system for a period of time, the responses have no study state error.

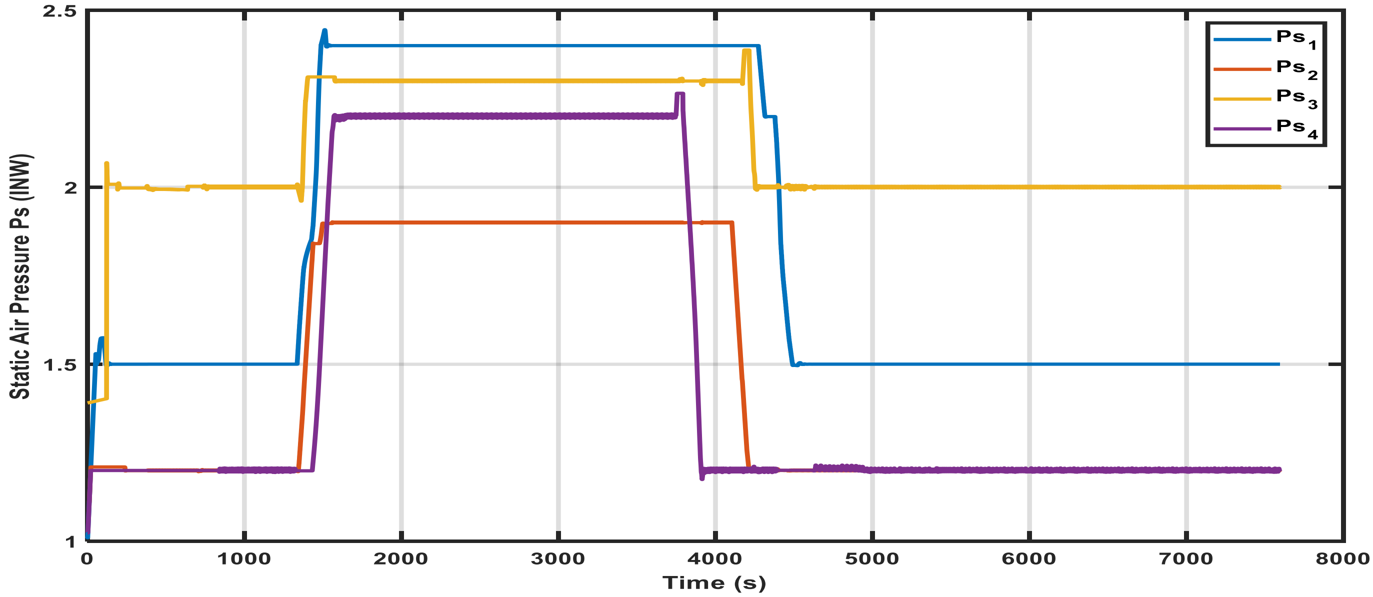

Figure 5.23 Responses of static air pressure of AHUs

Figure 5.24 shows the CO_2 level responses of AHUs (CO_{2-1}, CO_{2-2}, CO_{2-3}, and CO_{2-4}), achieving the setpoints of CO_2 level with good rise time and small overshoot of some responses. As before the setpoints were changed in a period of time, the next figure shows that.

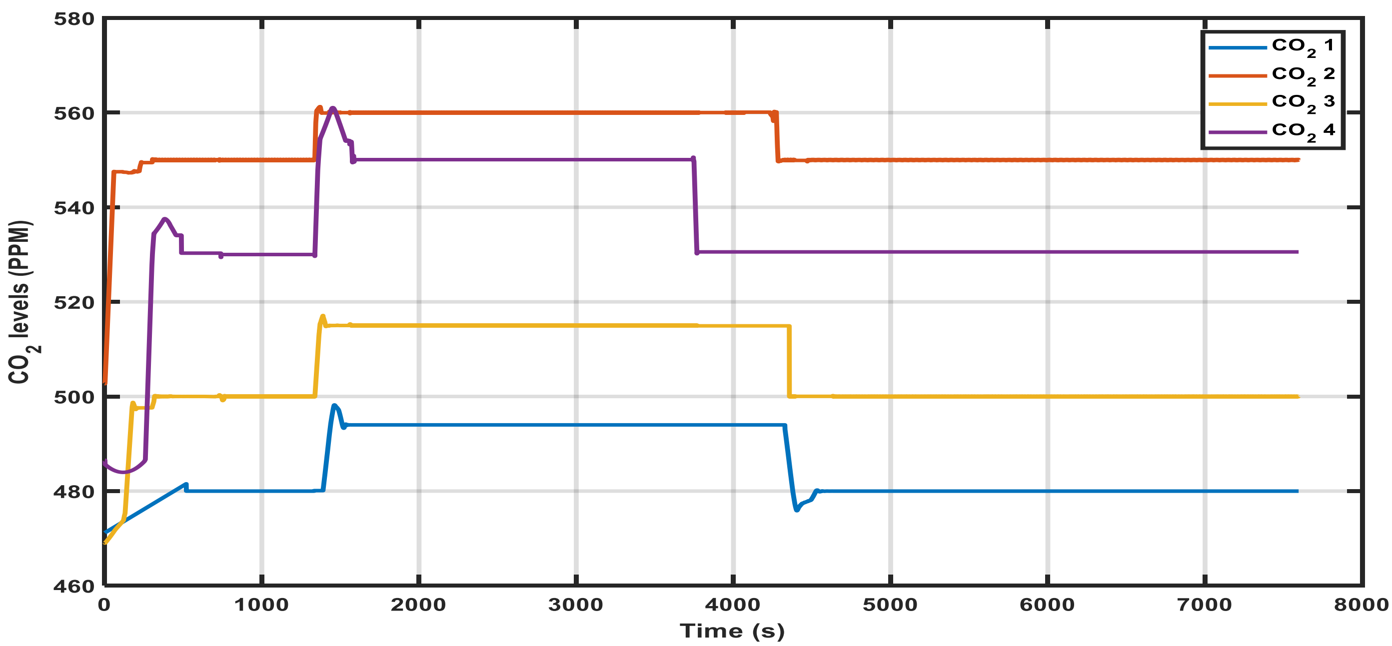

Figure 5.24 CO_2 level responses of AHUs

5.9. Conclusions

The simulation results covered the proposed HVAC model, which reflects its capability in maintaining comfort conditions. The S.J Carew building control system was simulated in MATLAB 2018a. The building's AHUs were modeled with the MATLAB System Identification Toolbox with real data and IDE-ICE results available to determine input and output system parameters. The designed supervisor fuzzy logic controller modulates the AHUs input (fresh air distributing air flow and hot water for each AHU) to achieve comfort level in the building. Modeling building each floor as a separate block results in four spatial models that offer the advantage that the rules of the supervisor controller are reduced to 180. The results show that the performance of the fuzzy controller was better compared to traditional algorithms and current controller used to control the HVAC system. Also, the SFLC algorithm responded systematically to all laboratory conditions and was able to handle a variety of parameters, including response time, steadying errors, and overshoot. By adding additional rules between the entry steps, the SFLC can control energy-saving features and results in an improved performance in the heating and cooling of buildings.

5.10. References

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Chapter 6

6. Summary

6.1. Conclusions

The first section of this research study employed an HVAC system model for the S. J. Carew Building that was formulated using the IDA-ICE software. In comparing the model's power and hot water consumption estimates with twelve consecutive months of measured data, the model was shown to obtain good approximations. As well, the model offered a comparison of the IDA-ICE software's external temperature estimations with measured data, during which the inputs/outputs of the system were selected, and the system's thermal responses identified. From this, a linear state-space model emerged with the assistance of MATLAB's System Identification (SI) tool. The new model featured twelve state variables (twelve inputs/twelve outputs) and showed good responses (i.e., in the acceptable range) compared to real-life data.

The second section of this research study applied the system identification tool in MATLAB to build a state-space model that featured a MIMO (multi-input/multi-output) system as a first scenario. The model, which had eight status variables (eight inputs/eight outputs), gave responses which were in the acceptable range. From this, a novel HVAC system model was constructed which used as quantitative indices the Carew Building's temperature and CO_2 concentrations to gauge comfort levels. In using an input-output feedback linearization approach for linearizing the HVAC system, the pole placement controller was able to control the linearized HVAC system without steady-state error and according to the designated set point. The rigorously obtained simulation results for the HVAC model showed system validation, thus indicating the method's ability to maintain optimal comfort levels.

In the third section of the research study, the building's AHU_1 system was simulated for a second scenario. Incorporating results from the IDE-ICE software and actual data, the MATLAB SI tool generated appropriate system parameters of the inputs and outputs. Meanwhile, a fuzzy logic controller (FLC) regulated three AHU_1 inputs (hot water, external-to-internal air, and general air flow) and also applied a MIMO system state space model to AHU_1. The test outcomes showed that the performance of the FLC surpassed all traditional algorithms, providing ample control for the HVAC system. Moreover, in every lab condition tested, the FLC algorithm demonstrated not only a stable response but enhanced ability to deal with various key parameters such as overshoot, response time, and steadying errors.

In the final section of the research study, the simulation results indicated that the novel HVAC model was able to provide the desired level of environmental comfort throughout the structure by employing a supervisor FLC to control the targeted AHUs. Specifically, every floor of the S. J. Carew Building was considered a fully unique block, thus giving four spatial models. The advantage of this separation approach was a reduction in the number of supervisor controller rules to 180. Even so, the outcomes demonstrated the FLC's superior performance in comparison to both conventional algorithms and the actual controller which is presently regulating the Carew Building's HVAC system. Furthermore, the SFLC algorithm responded appropriately under a broad range of laboratory conditions and easily satisfied key parameters (e.g., steadying errors and response time). With the addition of a few rules in the entry steps, the SFLC was able to regulate the power-saving features and provide enhanced performance of the Carew Building's heating and cooling system.

6.2. Research contributions

To date, our research results have indicated the following:

1. The S.J. Carew building was modeled using the IDA-ICE software using all details of HVAC system and instructions of the building for a whole year period, the model offers good approximation results, comparing power/hot water consumption levels with real data, measured data and exterior temperatures are also compared. Also, using the system identification toolbox, the state space model for a MIMO system was developed.

2. In using the input-output feedback linearization approach for HVAC system linearization, the pole placement controller (a form of the linear controller) with integral action and input gain successfully modulated the system. This was accomplished without any steady-state error and for the required set point and resulted in the maintenance of desired comfort levels for the indoor environment.
3. The fuzzy logic controller was able to control hot water, air flow and fresh air (i.e., the three AHU_1 inputs), and the FLC algorithm was used in the AHU_1 state space model of a MIMO multi-input/multi-output system.
4. The fuzzy expert controller outperformed conventional algorithms, and adequate control was achieved for the fuzzy controller HVAC system. As well, for every tested lab condition, the SFLC algorithm not only provided a stable response but was also able to better handle parameters such as overshoot and steadying errors. Anticipated outcomes for the present research study include building a state space model for the entire structure, using the supervisor's fuzzy controllers. It is expected that this approach will lead to an increase in response stability as well as the enhancement of key parameters such as overshoot and response time. The proposed fuzzy supervisor also controls the building's energy savings through providing options for improved balancing of the structure's cooling/heating systems, especially by considering the specific requirements of individual floors and areas. Also, the building separated to four state space systems, the advantage of this separation approach was a reduction in the number of supervisor controller rules, the number of rules ($15 \times 3 \times 4$) 180. Without this separation, the rules of the SFLC will be (15^4) 50625.

6.3. Future work

There are various directions to extend this work, which can be briefly outlined as follows:

- Modeling part of the HVAC system, in system identification can add more variables such lighting system and disturbances such as occupants the building, solar and the wind direction.

- The proposed control system could be implemented.
- Cost estimate for implementation could be done.
- Switching to another heating source could be studied.
- System simulation can include measured disturbance variable.
- Adapting the fuzzy logic controller can be used for HVAC control.
- For the FLC each floor model was determined and used in this study. A whole building model can also be used although that will need many more fuzzy rules.
- Sensitivity analysis of incorrect rules can be done.

6.4. List of publications

"Modeling and analysis of an HVAC system for the SJ Carew Building at Memorial University." Published in 2017 IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE), pp. 1-4. IEEE, 2017. Authors: Abdo-Allah, Almahdi, Tariq Iqbal, and Kevin Pope.

"Modeling, Analysis, and State Feedback Control Design of a Multizone HVAC System." Published in Journal of Energy 2018 (2018). Authors: Abdo-Allah, Almahdi, Tariq Iqbal, and Kevin Pope.

"Modeling, Analysis, and Design of a Fuzzy Logic Controller for an AHU in the SJ Carew Building at Memorial University." Published in Journal of Energy 2018 (2018). Authors: Abdo-Allah, Almahdi, Tariq Iqbal, and Kevin Pope.

"Energy Consumption Analysis of a Large Building at Memorial University." Submitted in Journal of Energy, Hindawi. Feb 14, 2019. Authors: Abdo-Allah, Almahdi, Tariq Iqbal, and Kevin Pope.

"Supervisor Fuzzy Logic Controller for HVAC System of S.J. Carew Building at Memorial University. " Submitted in Journal of Control Science and Engineering, Hindawi. Mar 8, 2019. Authors: Abdo-Allah, Almahdi, Tariq Iqbal, and Kevin Pope.

Appendix

7.1 Appendix I. IEEE Paper

2017 IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE)

Modeling and Analysis of an HVAC System for the S.J. Carew Building at Memorial University

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***Abstract*- In this paper, the HVAC System for the S.J. Carew Building at Memorial University is modeled using a state space multi-input and multi-output system (MIMO) approach for analyses and control system design. The IDA Indoor Climate and Energy ICE simulation program are used to develop the models. The system has three air-handling units and four floors. Supply air flow temperature and hot water temperature data are used as input data for the model. Environmental inputs of outdoor temperature, wind direction and velocity are used as disturbances. The temperature of the zones and humidity are used as output data. The simulated energy consumption for the first fifteen days of Dec 2015 is compared to measured data, and good agreement is achieved for the whole building. The main purpose of this paper is to obtain a state space model of a MIMO system using the Matlab system identification toolbox. Building data and details of the model are presented in the paper.**

Keywords: State space model, building modeling and simulation, HVAC, energy consumption, system identification.

I. INTRODUCTION

Over the past two decades, the demand for building energy has increased significantly, mainly due to economic growth in emerging markets. This has led to low fuel reserves and high pollution. To overcome these two problems, numerous studies are focusing on energy conservation and renewable energy generation [1]. For a building's heating, ventilation, and air conditioning system (HVAC), the design goal is to provide comfort to the occupants. Since the heating and cooling loads vary with time, a control system should supplement an HVAC system to maintain comfort in all conditions. Also, with proper control of the system, the energy consumption will be reduced. The HVAC system is also responsible for providing fresh outside air to the building. This paper represents a simulation of the whole building using the IDA Indoor Climate and Energy 4.7 simulation program. The performance of the detailed heating/cooling plant and energy consumption of the modeled plant consider the application of a recently developed three-dimensional model, the parameter-based heat model, and standard IDA ICE model library components. The IDA Indoor Climate and Energy program is a commercial program published in May 1998 that is aimed at studying the thermal climate of individual zones [4].

II. METHODS

1. The case study building

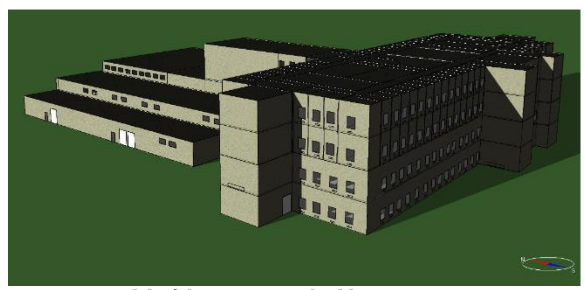


Fig. 1. 3D model of the S.J. Carew building

In this paper, the S.J. Carew Building at Memorial University's Faculty of Engineering and Applied Science is analyzed. This building consists of more than 300 zones, mainly classrooms, offices, and laboratories. Also, the building has a cafeteria. Overall, the studied building area is about 25,400 m^2. The building's details are presented in Table 1, and Figure 1 shows a 3D model of the building. First, a detailed area considered with the simulation software IDA-ICE [4] model simulation is developed. This high order nonlinear model is then used as the source of the identification data and the reference model for modeling the proposed structure.

The IDA ICE program's calculations offered for most types of buildings is represented [5]:

a. The thermal balance of the area, including solar radiation, light, occupants, furniture, air leaks, heating, and cooling appliances.
b. Solar radiation from windows considering shading devices and surrounding elements.
c. Air and surface temperatures.
d. Operating temperatures.
e. Indices of comfort: PMV, PPD and several occupants in arbitrarily chosen locations.
f. Level of daylight.
g. Humidity and CO2 levels. This provides information about the air flow system.
h. The wind and the flow caused by the buoyancy of the air through openings and leaks.
i. Airflow, CO2, pressure, and humidity in different areas of handling and distribution systems.
j. Heating power: heating and cooling units, equipment, occupants, light, solar radiation.
k. Total cost of energy using prices as a function of time.

TABLE I. DETAILS OF THE BUILDING

EQUA SIMULATION TECHNOLOGY GROUP		**Delivered Energy Report**	
Project		**Building**	
		Model floor area	25141.7 m^2
Customer		Model volume	128952.9 m^3
Created by	Almahdi Abdo-Allah	Model ground area	10544.5 m^2
Location	Newfoundland (St. John's Airport) _718010 (ASHRAE 2013)	Model envelope area	29440.0 m^2
Climate file	CAN_NF_St.Johns.718010_CWEC	Window/Envelope	2.4 %
Case	building2017_AHU8	Average U-value	0.3031 W/(m^2 K)
Simulated	12/18/2016 7:42:05 PM	Envelope area per Volume	0.2283 m^2/m^3

2. Validation of IDA ICE simulation

It is important to determine if the model meets the specifications and that the results are correct. The hot water and electrical consumption of the building are compared with actual data that was taken from the Department of Facilities Management at Memorial University. Figure 2 shows the Honeywell software log for the hot water consumption of the building. The following output variables were measured and compared with IDA ICE simulation data:

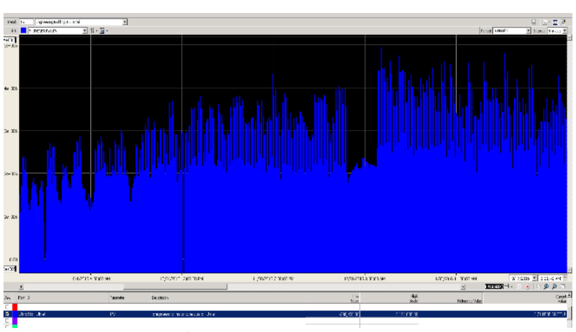
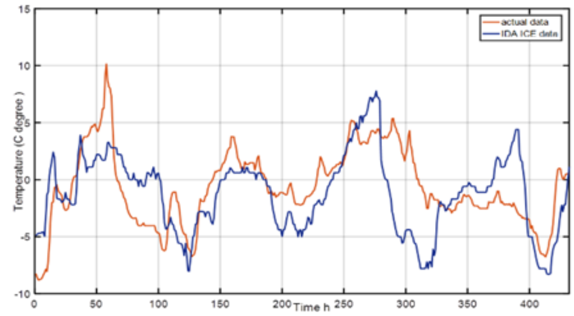


Fig 2: Honeywell software

2.1. Outdoor temperature

The first comparison was between the outdoor temperatures from the weather file in the IDA ICE



program and data was measured from the period from the 1st to the 18th of Dec 2015 by one hour of simple time. This is illustrated in Figure 3.

Fig. 3: Difference between outdoor temperatures of IDA ICE and actual data

2.2. Energy consumption from hot water

The energy consumption of hot water was 2,069.8 MBTU from IDE ICE program. However, the measured data showed 2,073 MBTU. Figure 4 shows the difference between these results for the whole December 2015.

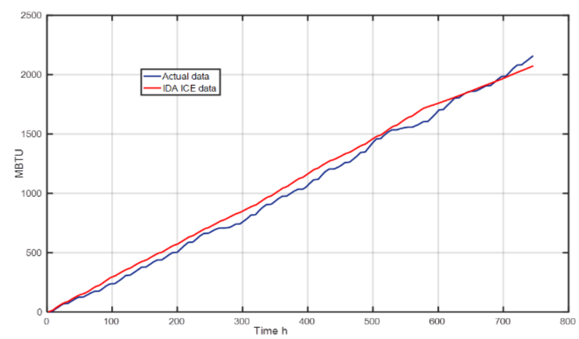
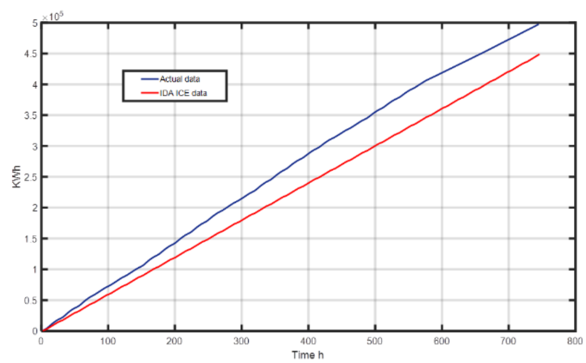


Fig. 4. Hot water consumption

2.3. Electricity consumption

Figure 5 shows the difference between the electrical power consumption for the measured and model data. The measured data is higher, which can likely be



attributed to the many different types of laboratory equipment that the model does not represent in the analysis.

Fig. 5. Electricity consumption

III. SYSTEM IDENTIFICATION

Three basic steps can be outlined when applying the system identification [2]:

i. Creation of data to be used for identification of the model.
ii. The choice of a model structure, namely a set of candidate models.
iii. Generate the model that best represents the system using a selection rule, for example, under the rule of selecting the least squares method or instrumental variables.

Precautions must be taken in each of these steps to obtain a model that can represent the real system. In this paper, the Air Handling Unit 1 (AHU1) is taken to identify the state space model of the system. Figure 6 shows the details of air handling unit 1.

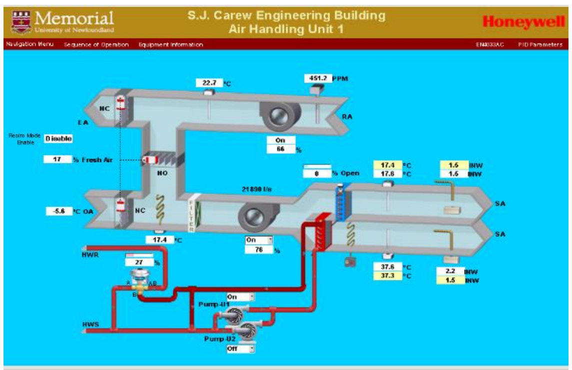


Fig. 6. Air handling unit 1.

A. *Choosing input signals*

It is expected that there will be an increase in the heat from radiators and air flow temperatures varying between the zone temperature and the current hot water as the minimum and maximum temperature for this component. This is the only control variable in the zones, and therefore the signals used for the identification system are input signals. Figures 7 and 8 show the supply of hot water and air flow to the system as a function of time.

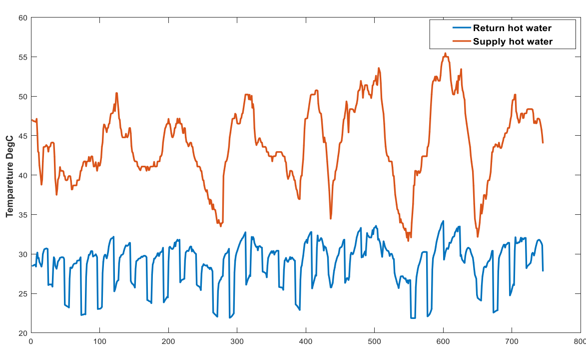


Fig. 7. Supply and return of hot water temperature.

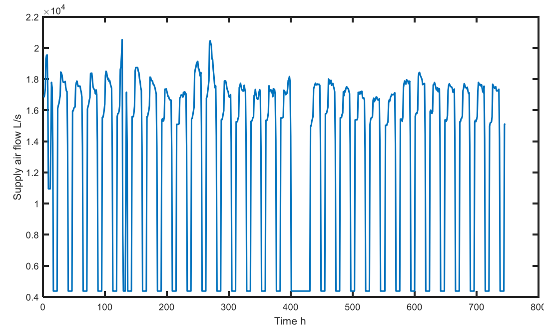


Fig. 8. Supply air flow (variation is due to damper operation)

B. *Choosing output signals*

The level of CO_2 and the temperature of the return air flow are taken as the system outputs. Figure 9 shows the CO_2 level in the return air and Figure 10 shows temperature variation of the return air.

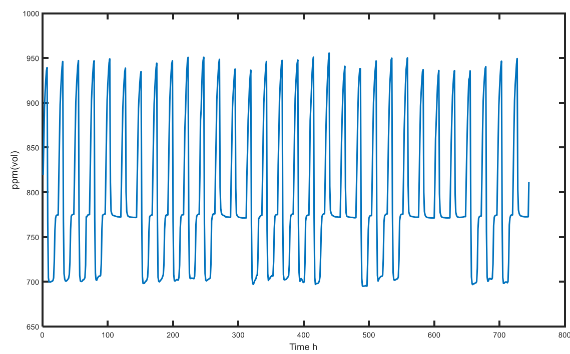


Fig. 9. Level of CO_2 in the return air.

Another output is taken as the return of the hot water temperature which is shown in Figure 7.

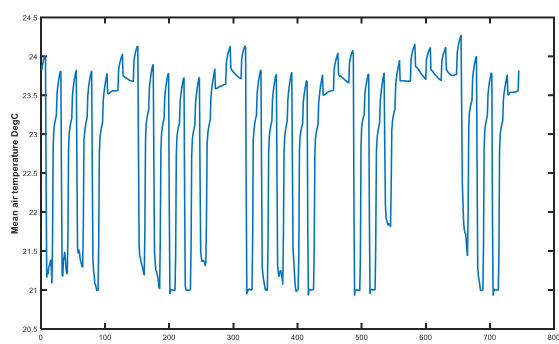


Fig. 10. Return air flow temperature

C. *Selecting a model structure*

There are several model structures that can be chosen. The model structures can be divided into two categories: linear and nonlinear. Since the system in this paper is nonlinear, the ARMAX-model is selected.

D. *Model identification*

In this section, the identification procedures that are considered for pre-processing the data set are presented. The procedure can be divided into the following steps [3]:

i. Choosing a model structure (e.g., ARX, ARMAX, process models).
ii. Choosing a model order.
iii. Choosing which estimation method to use (e.g., least square).
iv. Starting the identification procedure.
v. Checking and verifying the results.

E. *State space model*

The number of state variables, *n*, is the number of independent components of the system. The total energy of the system and the time derivatives of the state variables determine the rate of change in the energy of the system. Furthermore, the system state variables at any time, *t*, provide sufficient information to determine the values of all other variables in the system in that time [6].

$$\begin{aligned} \dot{\mathbf{x}} &= \mathbf{Ax} + \mathbf{Bu} \\ \mathbf{y} &= \mathbf{Cx} + \mathbf{Du}. \end{aligned}$$

The matrices A and B are properties of the system. The choice of output variables determines the output equation matrices C and D. The following matrices are obtained using the Matlab system identification tool box.

A =					B =		
	x1	x2	x3			u1	u2
x1	0.99786	0.03878	-0.0664		x1	-0.0011978	-3.27E-07
x2	-0.1429	0.79996	-0.3625		x2	-0.0049997	-6.01E-06
x3	0.22069	0.51922	0.9535		x3	-0.0015751	3.58E-06
C =					D =		
	x1	x2	x3			u1	u2
y1	-43.649	8.72573	3.5324		y1	0	0
y2	-30.577	8.60096	-14.41		y2	0	0
y3	-1673.1	102.417	185.65		y3	0	0

The dynamic behavior of the system is obtained for arbitrary input and simulated by the *lsim (sys,u,t,xo)* function in Matlab. The system has two inputs that are represented by *u*, which supply hot water and air flow to the system. Also, the *t* vector represents the time samples. Also, x_o is the initial values of the system. Figure 11 shows the outputs response of the system, the mean temperature of the zones, the return hot water and the quantity of CO_2.

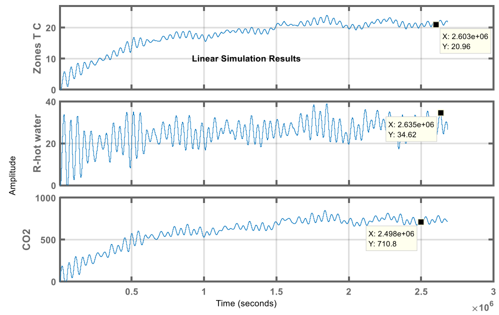


Fig. 11. Outputs of the system.

All responses of the system are in the correct range after ignoring the initial transient. Part one of Figure 11 illustrates the temperature of the zones the range between 21ºC to 23ºC in the steady state of the system. In part two the range of return hot water is between 20ºC to 38ºC. In part three the level of CO_2 is 700 ppm to 850 ppm.

IV. CONCLUSION

In this paper, the S.J. Carew building with a HVAC system has been modeled using the IDA ICE program. This model provides good approximation results in which the hot water and electrical consumption are compared with measured data. Also, the outdoor temperature for the program and measured data for a period are compared as the first step of the process. In the second step, the system identification tool box is applied to obtain the state space model of the multi-input and multi-output system. The model has three state variables, two inputs, and three outputs and the responses of the model are within an acceptable range.

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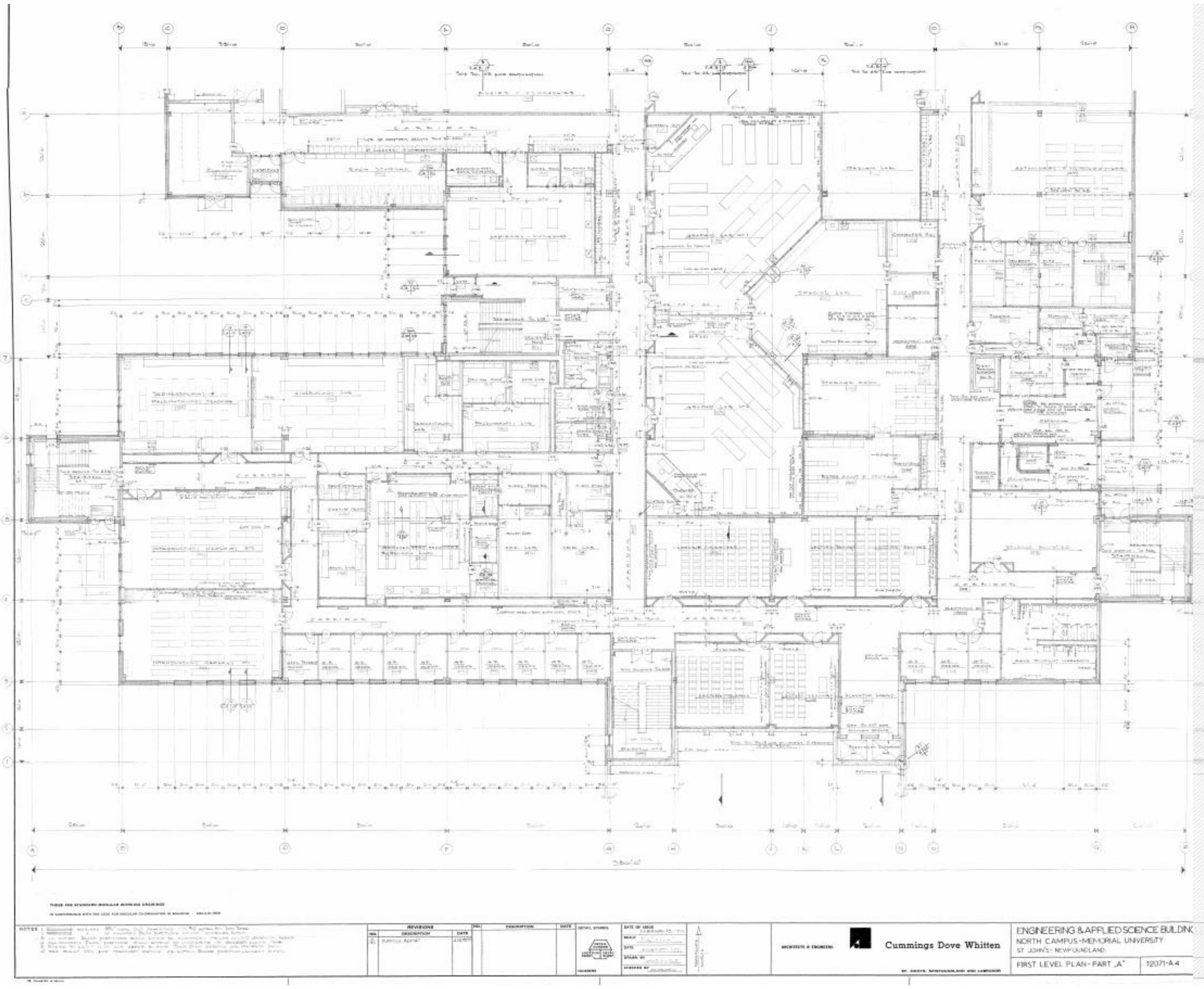
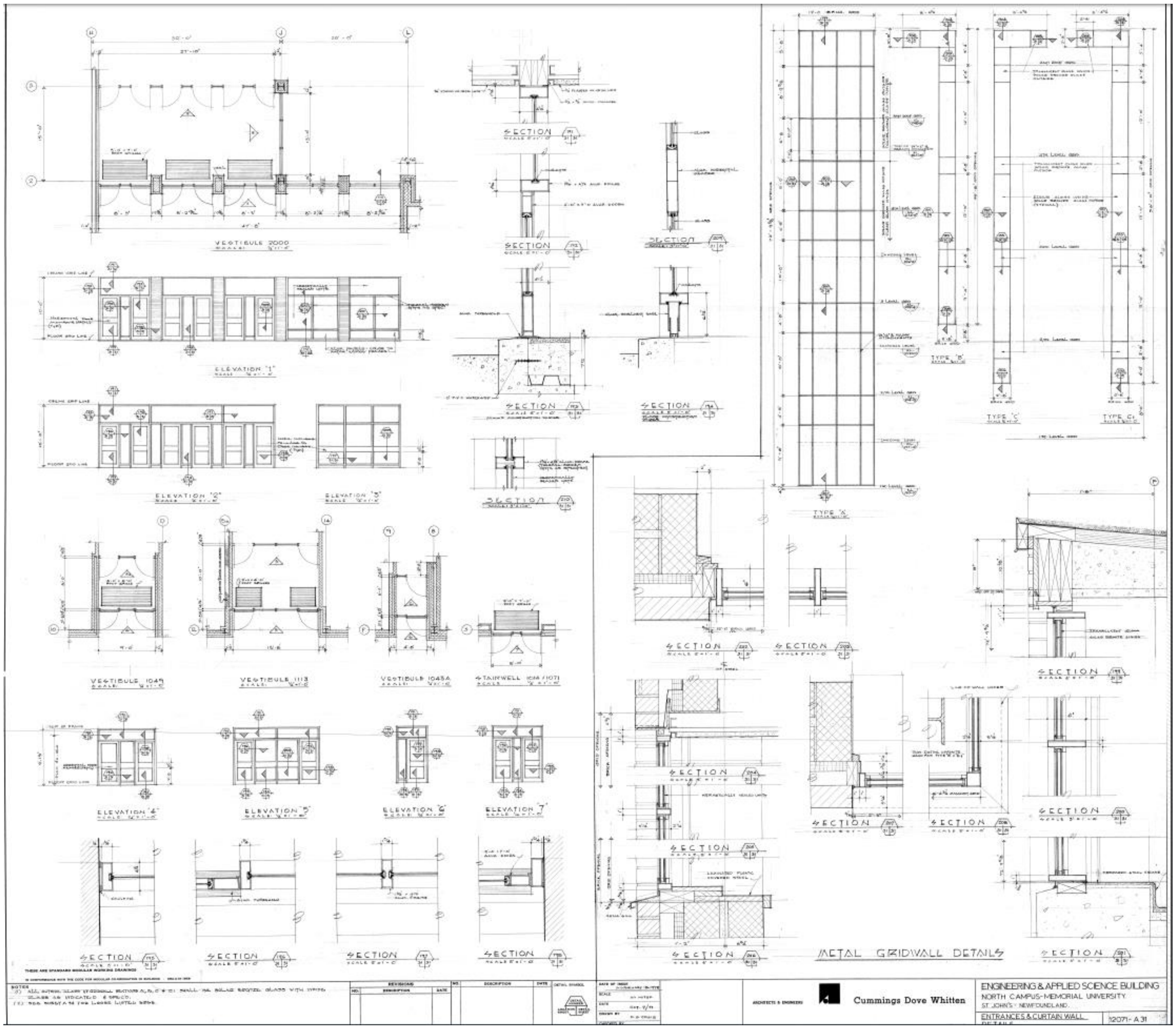
7.2 Appendix II. Construction Details

7.2.1 a02 Elevations

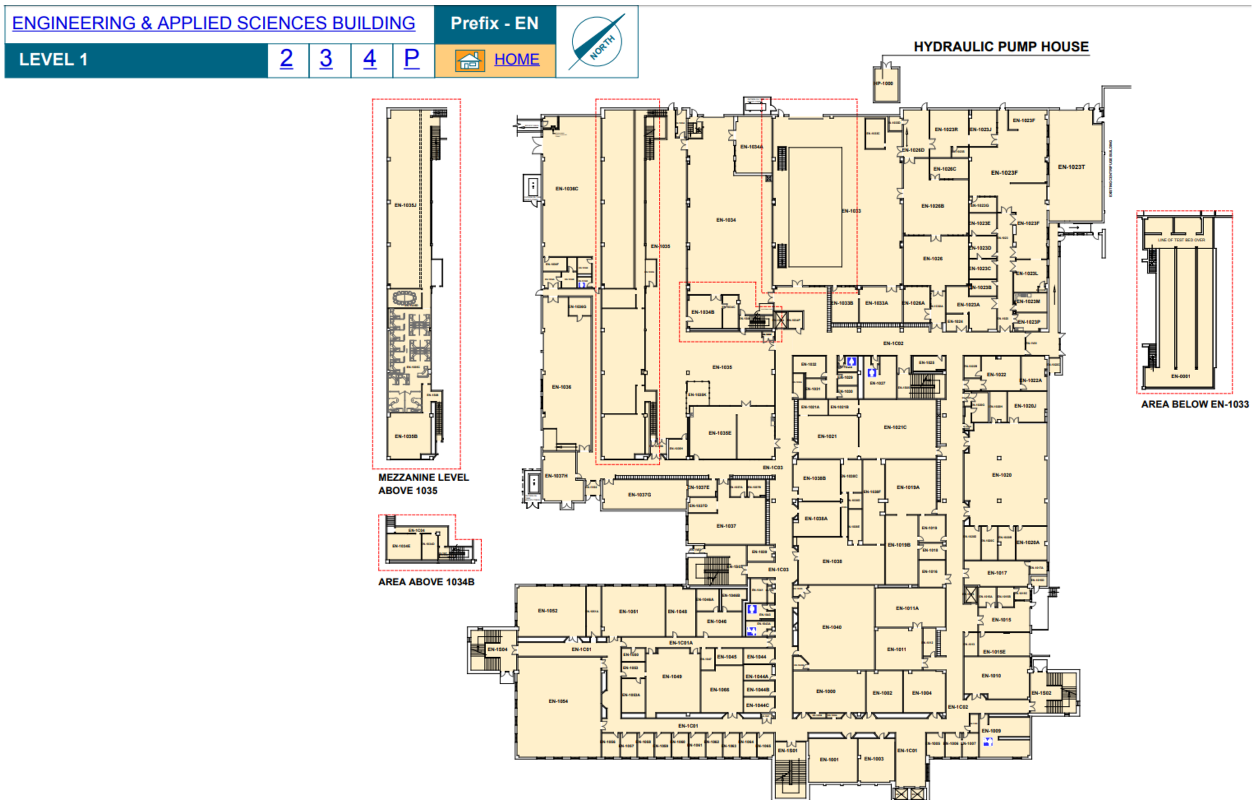
7.2.2 First Level Plan - Part A



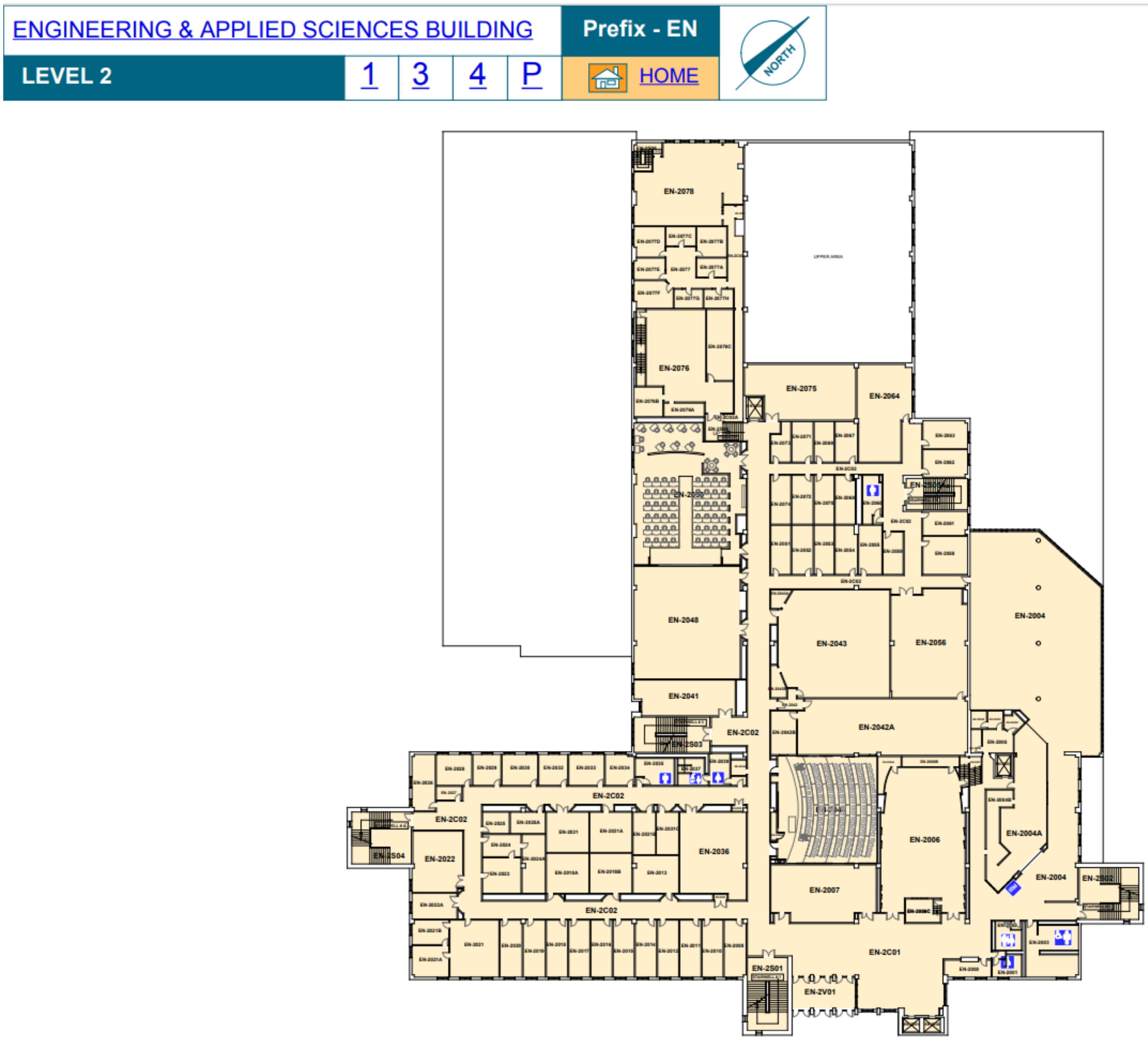
7.2.3 A31 Entrances and Curtain Wall Details



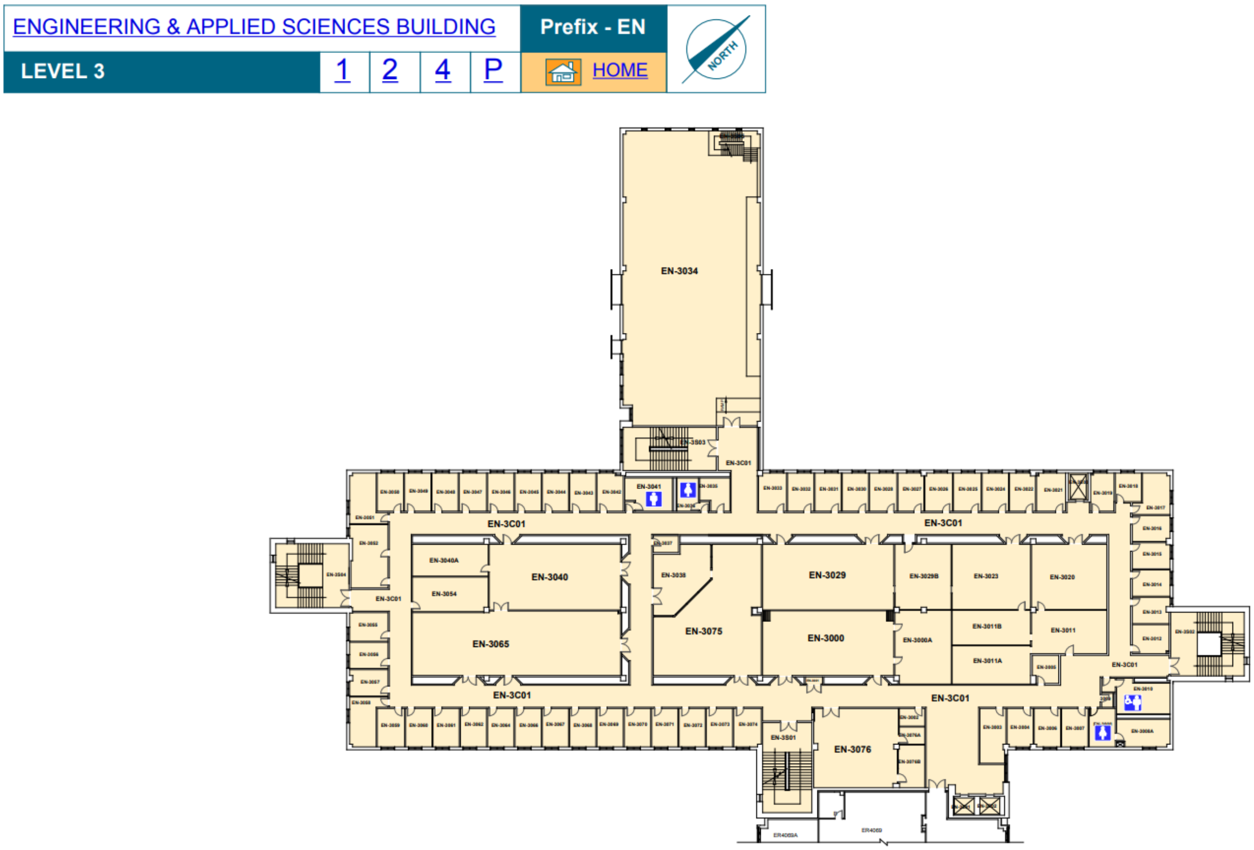
7.2.4 SJ Carew Level 1



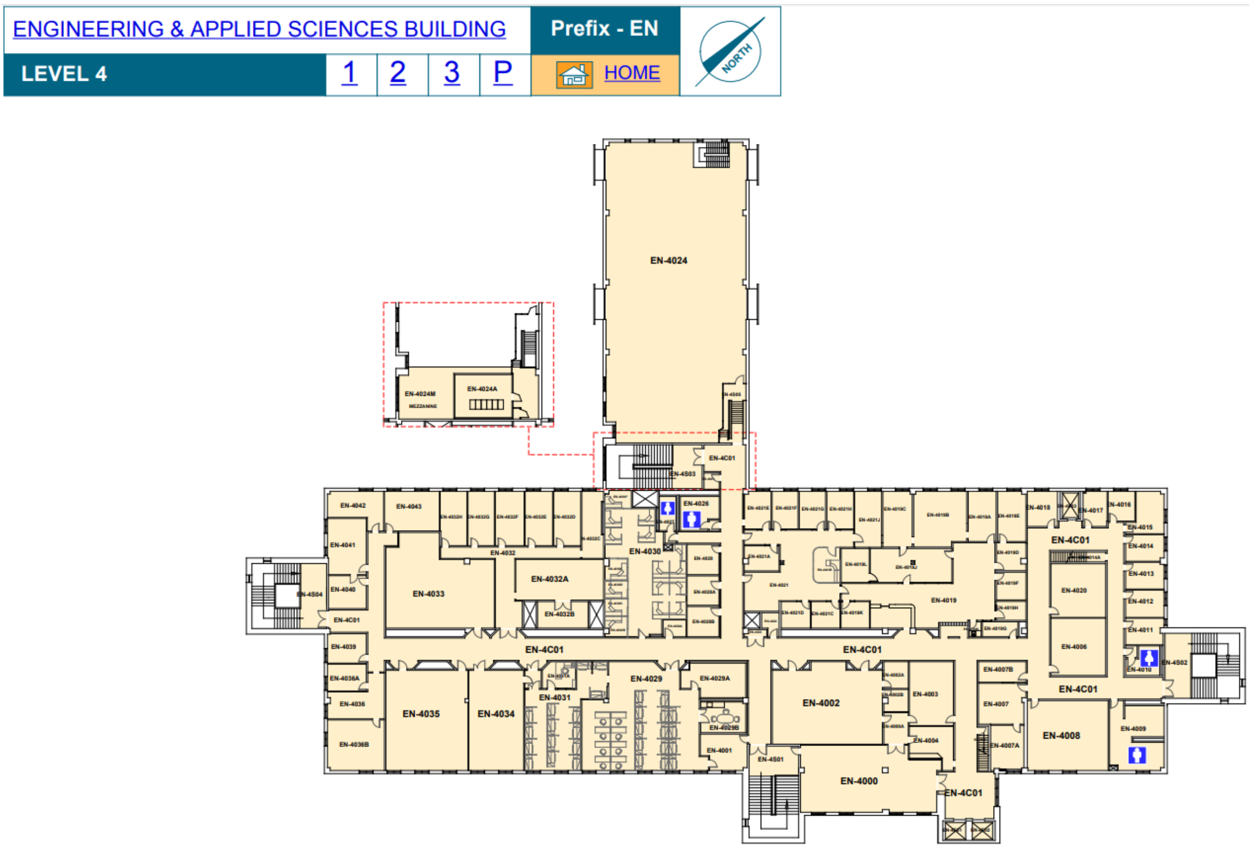
7.2.5 SJ Carew Level 2



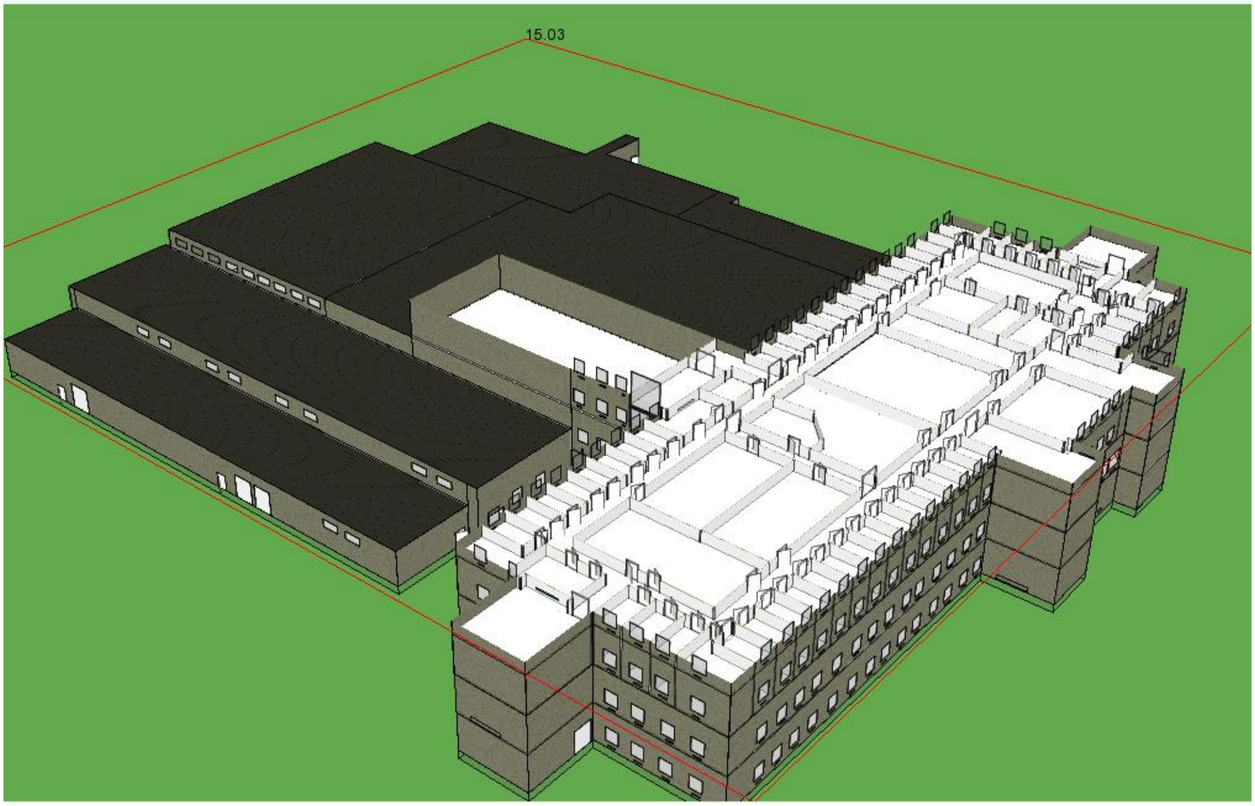
7.2.6 SJ Carew Level 3

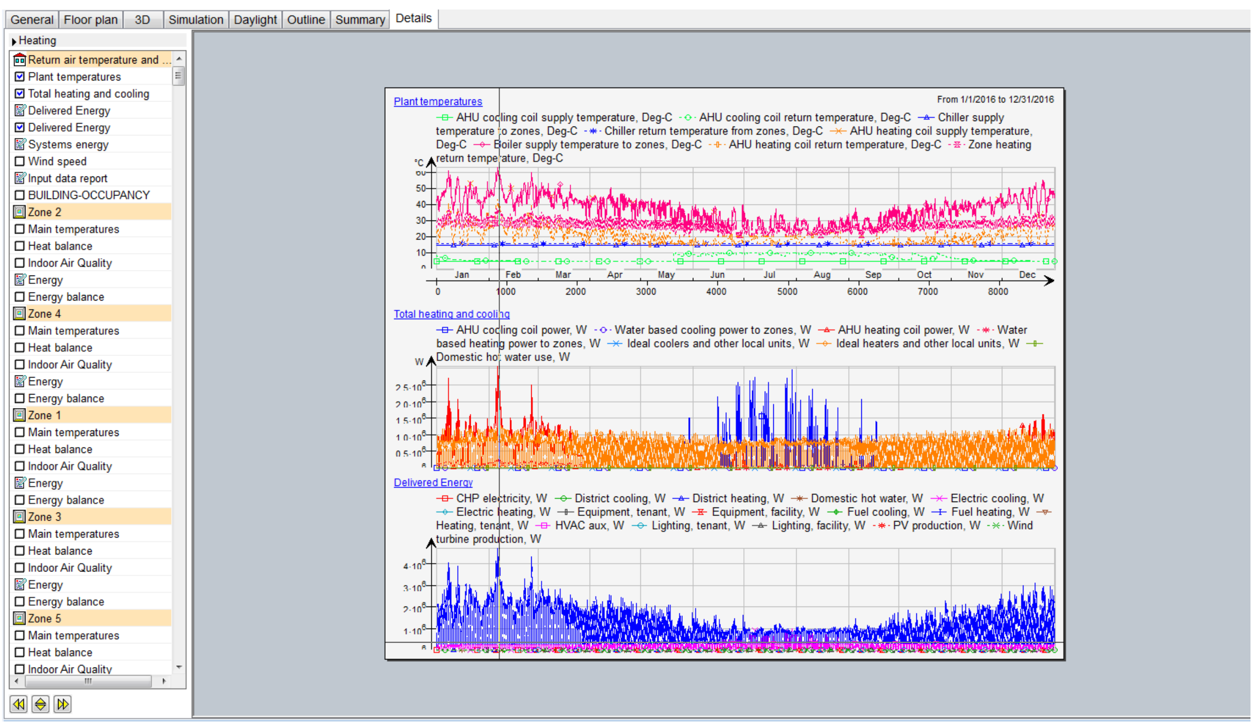


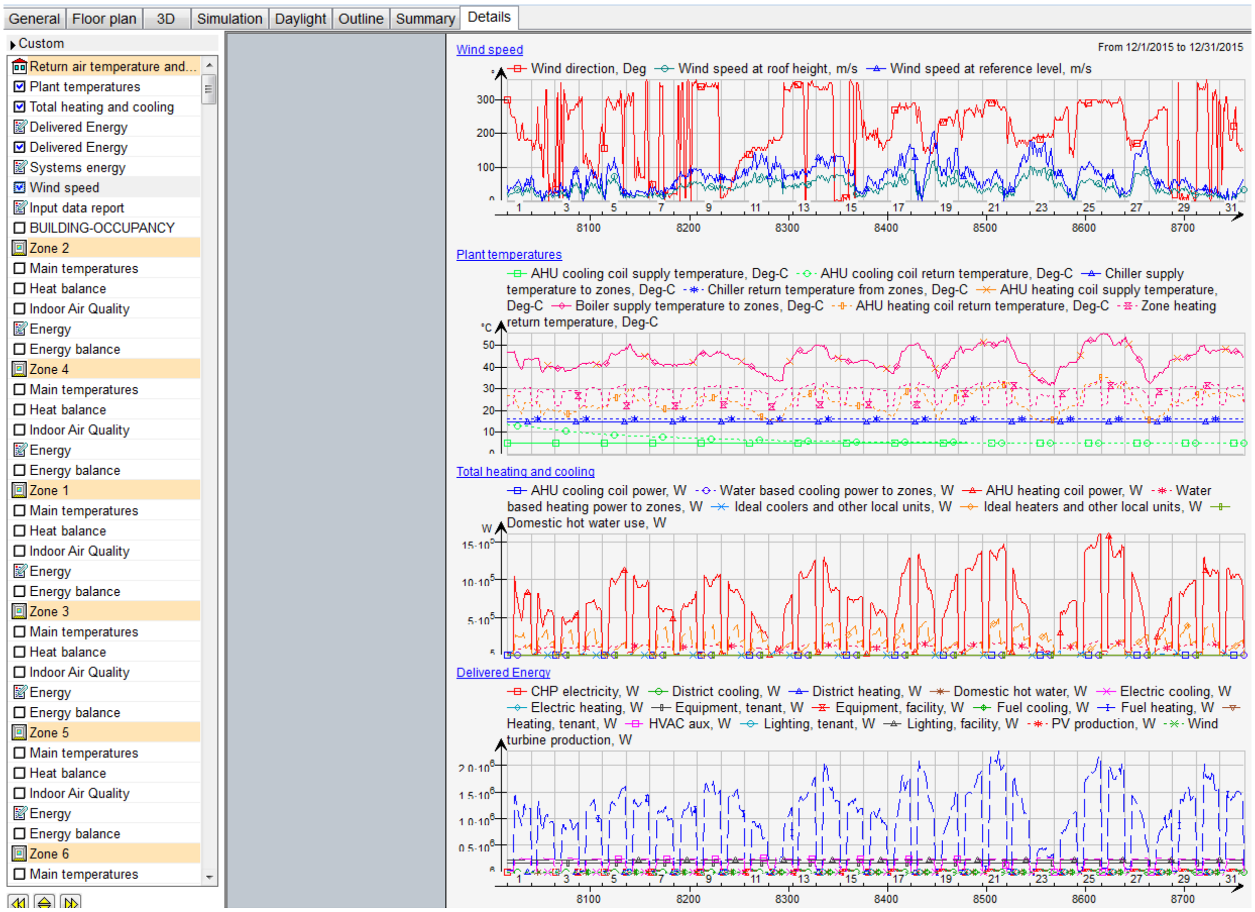
7.2.7 SJ Carew Level 4



7.3 Appendix III. IDA ICE Details






General
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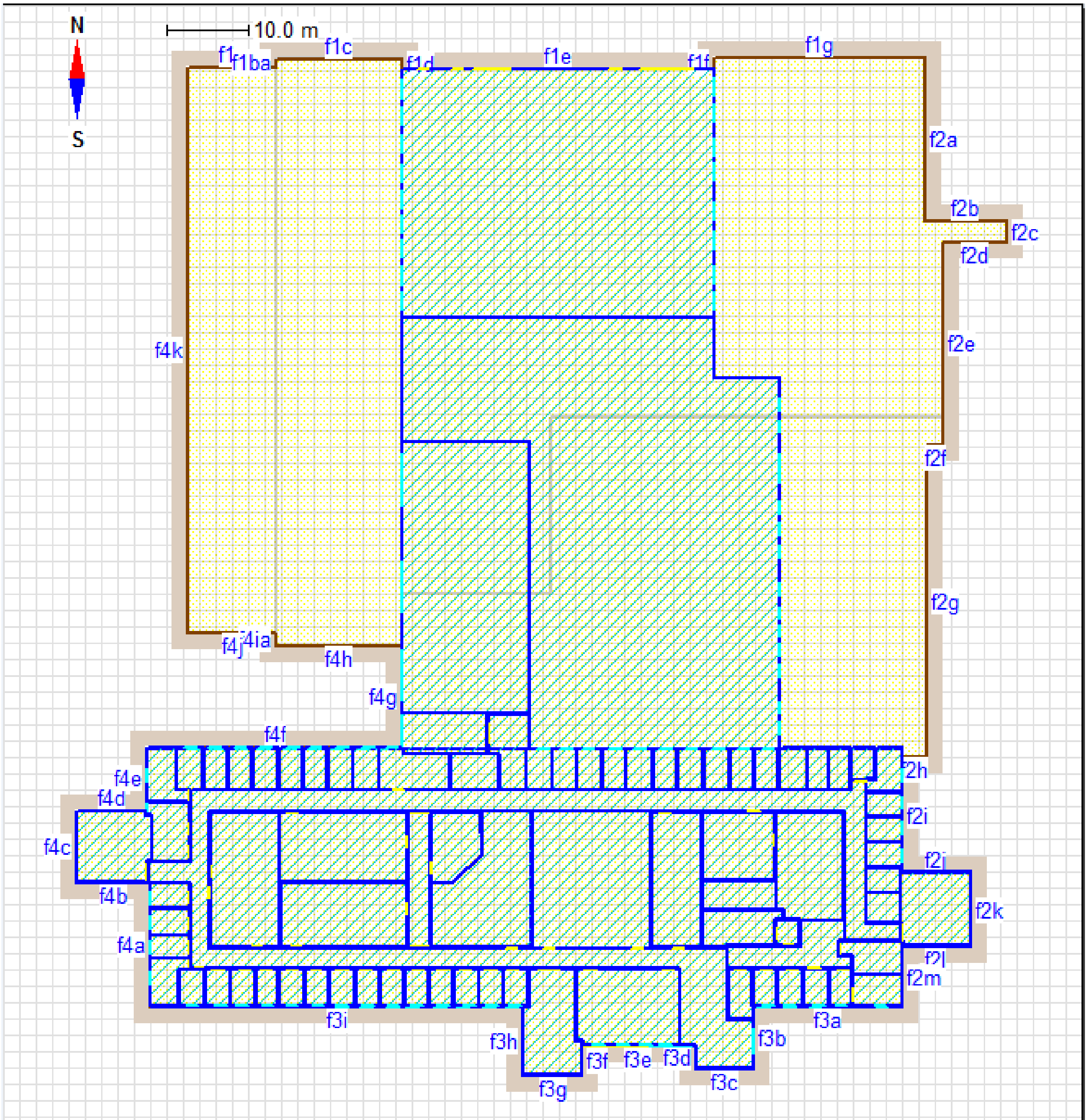
3D
Simulation
Daylight
Outline
Summary
Details
Custom
Return air temperature and...
Plant temperatures
Total heating and cooling
Delivered Energy
Delivered Energy
Systems energy
Wind speed
Input data report
BUILDING-OCCUPANCY
Zone 2
Main temperatures
Heat balance
Indoor Air Quality
Energy
Energy balance
Zone 4
Zone 1
Zone 3
Zone 5
Zone 6
Wind speed
From 12/1/2015 to 12/31/2015
Wind direction, Deg
Wind speed at roof height, m/s
Wind speed at reference level, m/s
Plant temperatures
AHU cooling coil supply temperature, Deg-C
AHU cooling coil return temperature, Deg-C
Chiller supply temperature to zones, Deg-C
Chiller return temperature from zones, Deg-C
AHU heating coil supply temperature, Deg-C
Boiler supply temperature to zones, Deg-C
AHU heating coil return temperature, Deg-C
Zone heating return temperature, Deg-C
Total heating and cooling
AHU cooling coil power, W
Water based cooling power to zones, W
AHU heating coil power, W
Water based heating power to zones, W
Ideal coolers and other local units, W
Ideal heaters and other local units, W
Domestic hot water use, W
Delivered Energy
CHP electricity, W
District cooling, W
District heating, W
Domestic hot water, W
Electric cooling, W
Electric heating, W
Equipment, tenant, W
Equipment, facility, W
Fuel cooling, W
Fuel heating, W
Heating, tenant, W
HVAC aux, W
Lighting, tenant, W
Lighting, facility, W
PV production, W
Wind turbine production, W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