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System Level Fault Detection in Building HVAC Systems

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SYSTEM LEVEL FAULT DETECTION IN BUILDING HVAC SYSTEMS

by

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A thesis submitted in partial satisfaction of the
requirements for the degree of
Master of Science

in

Mechanical Engineering

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ABSTRACT

Heating, ventilation and air conditioning (HVAC) is a mechanical system that provides thermal comfort and acceptable indoor air quality. The HVAC system takes a dominant portion of overall building energy consumption and accounts for 50% of the energy used in the U.S. commercial and residential buildings in 2012. The performance and energy saving of building HVAC systems can be significantly improved by the implementation of better fault detection strategies.

Motivated by these goals, this thesis presents a scaled-up system level fault detection application based top and cross level fault detection schemes. Using top level and cross level schemes, energy consumption of devices at different levels and at the same level, is compared using principal component and correlation analysis respectively. Through these strategies, anomalies in energy consumption, which are indicators of faults are revealed. Moreover, energy consumption models are established for each type of device inside the system. These models are based on thermal and potential energy balances. This fault detection scheme forms the foundation of a fault detection program implemented in MATLAB that is easily adaptable to different types of HVAC systems.

Additionally, this thesis presents a methodology for organizing the data. The organizational structure of the data reflects the physical structure of the HVAC system. This structure facilitates data retrieval and application of spatial and temporal partitioning schemes.

In this thesis, all the data processing, models, and implementation of the fault detection program are based on extensive data measurements collected from an office building on the campus of the University of California, Merced.

Chapter 1

INTRODUCTION

1.1 Overview of Building HVAC and Fault Detection

Since the 2nd half of the 20th century almost all large buildings have been equipped with heating ventilation and air conditioning (HVAC) systems to maintain occupancy comfort levels. Building HVAC systems span a wide range, from small window mounted units that condition a few rooms to large roof mounted units that condition a multi-story building. They consists of many components, based on the design of the system. All HVAC systems have an air handling unit. This can range from a small window based units to large roof mounted units. AHU is responsible for heating and cooling the air ventilating the building. Basic sub-components of an AHU are fans, filters, heating coils, cooling coils and dampers. The number of which depends on the model of the AHU. The fans are intended to circulate the air. Usually there is a fan for returning the air and supplying it. Filters clean dirt and debris from the circulating air. Air is heated or heated cooled by separate heat exchangers, based on the requirements of the building. Cooling is often accomplished by a refrigeration unit built inside the AHU, other large systems utilize chilled water from a central plant. The central plant will have large refrigeration units known as chillers circulating chilled water throughout a building complex. Similarly, heating will be accomplished by a hot air furnace or electric heater built into the AHU or from hot water boilers supplied by a central facility. The duct arrangement for HVAC systems ranges from constant volume systems to single or double duct VAV systems. In a constant volume system (CAV), the AHU directly supplies and conditions all spaces. In a variable air volume system, downstream of the AHU a device known as a VAV modulates and conditions air being delivered to a space. VAV systems are considered more efficient than CAV systems since they can modulate the air flow into a space. However, VAV systems are more complex. Single duct systems condition the incoming air with a heater or cooling coil built into the VAV terminal. Some VAVs have both a cooling and heating coil some only have one or the other. The heating can be accomplished by an electric heater or a hot water line. Double duct systems utilize two ducts for air conditioning one duct contains hot air and the other cool air. Before the air enters the space the ducts converge and the air mixes providing the required temperature for the space. One advantage of a double duct VAV system is that the system has less parts that can fail such as a cooling coil or a heating coil. Also, if the VAV has a water line feeding the heating or cooling requirements, associated problems exist such as a water leak or fouling of the heating or cooling coil. This discussion is not exhaustive, as many HVAC systems are designed for specialized work such as conditioning laboratory spaces where hazardous materials are used.

With many different components incorporated into an HVAC system, the overall complexity of the system increases with size. The complexities inherent in HVAC systems presents a breeding ground for problems. Mechanical and electromechanical parts such as valves and motors break or burn out. Heat exchangers can foul, reducing heat transfer. Sensors can fail and give faulty readings to the control system. Faults in the form of installation errors during the commissioning of the building also occur. A fault in the system does not necessarily result in a shut down or even discomfort to occupants. More often, faults will result in excess energy use and go unnoticed. HVAC acounts for 50% of a buildings energy consumption, while faults account for 1.5% to 2.5% of a buildings energy consumption [1, 2].

Faults will usually go unnoticed and are usually detected when the building management receives a complaint from an occupant. After a complaint, management will consult the real time trends displayed form the building management software (BMS) to confirm a fault. Fault detection and diagnostic (FDD) in HVAC systems is a relatively new field despite being long established in safety critical areas such as automobiles and industrial process control. Interest in fault detection for HVAC has only become an active research topic in the mid-1990s [3].

1.2 Review of Fault Detection Methods

Common research areas for HVAC fault detection are commonly classified into qualitative, quantitative, and data driven methods. Regardless of the method, some methodologies are combined. As an example, one will use a data driven method to detect abnormal behavior then use a rule based method to confirm the fault. The three FDD methods will be elaborated on in the following sections. A map of different FDD methods is shown in Figure 1.1

1.2.1 Quantitative Method

Quantitative models are based on physics. These are often referred to as white box models. In these approaches, mathematical models completely describe the internal workings of the system. Some of these models take the form of lump parameter models. On the other hand, a more descriptive approach would utilize the governing differential equations taken from heat transfer and fluids. The latter is computationally expensive considering the HVAC system consists of many components, many of which contain complicated fluid flows in their normal operation.

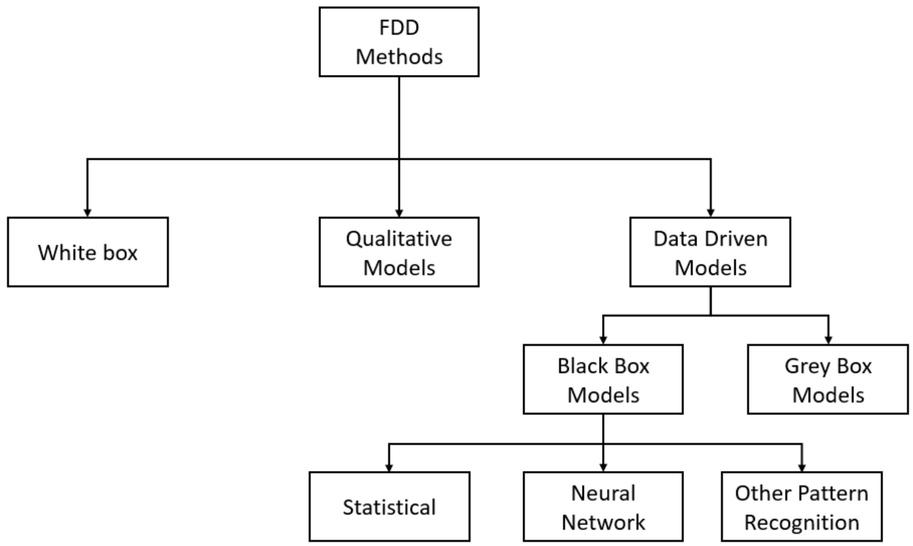


Figure 1.1: Tree for different fault detection methods.

1.2.2 Qualitative Methods

Qualitative models also known as expert rule methods are based on prior experience from manual fault detection of an HVAC system and models. The rules can be hard coded into a computer program These expert rules often have a built-in tolerance as to what constitutes a fault. This tolerance is to prevent false positive readings due to sensor noise [4, 5]. One such algorithm utilizes a combination of 28 different rules to detect various fault [4]. This method applies AHU utilized in both single duct variable air volume VAV systems and constant volume systems. The rules are based on comparing various temperature values to one another. Rule based methods apply to a specific type of system or component. Rule based methods are combined with data driven methods as an additional way of confirming faults. Expert rules based methods have clear logic and are easy to implement but are often specific to the system [6].

1.2.3 Data Driven Methods

Data driven or processed based methods depend a previous history of the system. These methodologies leverage the potential of sensors commmonly found inside a HVAC system. These sensors are common because they are needed for automated control of the HVAC system. In addition, the adoption has been facilitated by the decrease in sensor and computing cost over the years. Large HVAC systems are now equipped with more sensors and ability to store data. Data driven are methods split between black box and grey box models. Grey box models are based on a simple physical model with parameters incorporated to enhance accuracy. These parameters are determined from data gathered from the system. Unlike grey box models, black box models do not have any built prior knowledge about the internal mechanics of the system, they are entirely based on input and output data. Some classes of black box models include artificial neural networks (ANN), statistical methods, and other methods for pattern recognition such as support vector machine (SVM) and Support Vector Data Description (SVDD). Principal component analysis (PCA) is a statistical method commonly used in pattern recognition algorithms for data driven fault detection. Principal component analysis is a data reduction technique which finds the eigenvectors of a system. The largest i.e. most prominent eigenvector best describes the dynamics of the system.A method first developed for FDD in an AHU used PCA to obtain an approximation to measured data using the dominant principal components . The residual is computed between measured values and the dominant principal components. Prior training with simulation data established a threshold to which the residual was compared [7]. Another type of method is used is support vector machine method. SVM is a pattern recognition algorithm that generates features from using training data. Another relatively new method is support vector data description (SVDD) which was utilized for diagnosing chiller plant faults [8]. Unlike SVM the faulty training data is not required. Its claimed advantages over PCA is that it does not require the data to be Gaussian. Therefore, one can have fewer data points. Also, the data does not need to be linear. These are known restrictions on basic principal component analysis [8]. A genetic algorithm has been used to diagnose sensor faults in a chiller plant [9]. Genetic algorithm is an optimization tool originally developed for imitating evolution. It has been applied to many engineering problems such as designing an antenna. Support vector machines and artificial neural networks have been applied to diagnosing faults in supply fan and dampers of for a AHU in a laboratory setting [10]. New research is going into the field of deep learning. Deep learning is a new type of data driven method made popular in the late 2000s. It is a multilayered neural network. Recently researchers are beginning to apply these methods to HVAC FDD. A Deep belief network (DBN) which is a subclass of deep learning algorithm was used to diagnose faults in a HVAC system [11]. The DBN is trained using a simulation created using Modelica. They apply this method to detecting faults associated with fans, dampers and heat exchangers inside an AHU. As of 2017, different methods of feature extraction and deep learning algorithms have been applied toward cooling load predictions [12].

1.2.4 System Level Fault Detection

Most of these methods are not employed at the system level but rather look at a specific component such as a chiller plant [8]. In one instance the expert rule method is only applied to AHUs [4]. There are various schemes proposed over the years for system level fault detection. One method compares energy consumption at different levels to narrow down faults to a group of devices and then cross checks among similar devices at the same level [13]. Another method provides a system level fault detection scheme that utilizes PCA and expert rules to narrow down the fault . Three PCA models are used, one for a system level, and two for local level detection. Further fault detection is achieved using expert rules [14].

1.3 Summary of Current Work

In this work the top down fault detection methodogy is scaled up and applied to a large multipurpose building. This methodology was previously applied to a VAV system consisting of offices [13]. This work aims to generalize this method to apply to three types of systems. VAV, CAV and SAV spanning an entire building. Unlike many mechanical systems which are usually the same. HVAC systems all consists of similar components but the overall structure of the system is tailored to the building. This is due to architectural parameters, outdoor environment and building use. This work was developed on the Science and Engineering 2 building on the UC Merced campus. This building serves as an office building, and a lab facility. It contains a VAV and CAV system for the offices, and a SAV system for the lab. There is also a wealth of data available for the HVAC system in this building. All the work was applied to data gathered from the building management system. The fault detection program to the perform the work done in this thesis was implemented in the MATLAB programming environment.

1.3.1 Data Retrieval and Pre-Processing

A script for automatically retrieving data from the WebCrtl server is developed. The data is downloaded from the server in the form of CSVs for each specific device and contains data pertaining to a sensor located inside the device known as a trend. This script also reflects how the data is stored inside the WebCrtl server, by creating seperate folders for zone and device type Aside from this basic structure of the CSV there is no other structure to this data

In Chapter 5 a method for pre-processing the data is also developed. The data received is never clean, there is always missing or erroneous values due to sensor malfunctions. Therefore, in pre-processing the data is cleaned by simply removing erroneous values . In addition to cleaning, the data is partitioned by time and space. In pre-processing temporal partitioning is carried out from the year to day of the week. Spatial partitioning takes into account sun exposure, architectural parameters and the function of the space.

1.3.2 Feature Calculation

Data features allow a compact way of describing a complicated set of data. Power consumption is natural candidate to describe the operation of a thermal fluid system such as a HVAC system, so it forms a common metric for which all devices can be related. Power consumption of each component is computed rather than volumetric energy. The reason for this is that using power consumption voids the need for the geometry of each room which can become cumbersome if there are a large amount of rooms. Either way, feature calculation requires implmeneting models to compute power consumption and locating the the trends required for the models. Following practice by other researchers a pressure balance model was also implmeneted [8]. This essentially neglects the power consumption due to thermal effects and focuses on power consumption involing fluid flow such as pressure drops and the required to move air.This can aide in detecting faulty components that utilize pressure measurement for their control such as dampers. Implmenting the feature calculation scheme programatically required developing a system to locate trends in different devices. In many cases models require the supply variable such as temperature from an upstream device and often there are multiple upstream devices of different types.

1.3.3 Fault Detection

In this work there are two stages to fault detection, referred to as top level and cross level fault detection. These methods form a top down approach to detecting faults [13]. Top level fault detection essentially compares performance of two types of devices at different levels with an absolute measure. In this work the absolute measure is taken to be outside temperature. Device levels consist of a top level which is the AHU and a bank of lower devices which can be VAVs if the zone is so equipped. Cross level fault detection involves comparing devices of the same type at the same level in the same subgroup.Ideally, Top level and cross level detection are meant to be implmented in series where the top level is done first and points to which device type is causing problems. In practice, it was found that for some of the zones the HVAC structure precludes this. Therefore, programmatically, each method can be implmented independently by the user.

1.3.4 Outline

This thesis is organized into 7 chapters. Chapter 2 describes the SE2 building, in which the research for this work was conducted. The data partitioning strategy is discussed in Chapter 3 A description of the data feature used in fault detection is given in Chapter 4. Chapter 5 describes the process of gathering data and how it is organized based on the data partitioning strategy. The process of locating and retrieving the processed data to be used in the models is given in Chapter 6. Finally, Chapter 7 describes the methodologies that utilize the power data feature in the fault detection. The first two chapters present preliminary material such as the introduction and the overview of the SE2 building in which this research is conducted. Chapter 3 and 4 introduces the theory on which this work is based.

Chapters 5, 6, and 7 are application oriented and describe the implementation of the scheme programatically.

Chapter 2

BUILDING DESCRIPTION

2.1 Introduction

Merced is located in California's central valley. its climate is hot and dry in the summer and cool and wet during the winter. In the fall and spring merced experiences mild weather with occasional thunderstorms. As expected, the HVAC experiences heavy use during summer and winter. This research was tested on data gathered from the HVAC system in the Science and Engineering 2 (SE2) building on the UC Merced campus. SE2 is a multi-use research facility, contain many offices, conference rooms and research labs. The building can be divided into two major areas: short bar and long bar. Long bar contains most of the building's lab spaces, as well as several offices and two conference rooms. Short bar contains mostly administrative offices and conference rooms as well as the main lobby. Four AHUs service much of the building's occupied areas. The SE2 building is divided into four zones number 1, 2, 3 and 4. Zones 1 and 2 are considered one zone and is referred to as Zone 12 since the same two air handling units (AHU) supply the same duct. There are other AHU's called AHU 6 and 7 that service a small portion of the SE 2 building and consist of a single zone, these are ignored in this research.

2.2 Central Plant

Heating and cooling is accomplished indirectly by the central cooling plant. The central plant supplies hot water via natural gas boilers. Cold water is supplied by vapor-compression absorption chillers. The cold water is generated during off peak hours at midnight and stored in a tank at 37C°. Hot and cold water is supplied by the central plant to each campus building such as SE2. The hot and cold water connection between the central plant and any one of the campus buildings is known as a bridge. The hot and cold water flowing through this bridge supplies the AHU, VAV, and SAVs giving them the ability to condition the air. A graphical representation of hot and cold water flow from the central plant to the Science and Engineering 2 building is found in Figure 2.1.

2.3 Zone 1 & 2

AHU's 1 & 2 service what will be known as Zone 12, which consists of wet and dry lab areas. Most of these areas are located in long bar and are ventilated 24 hours

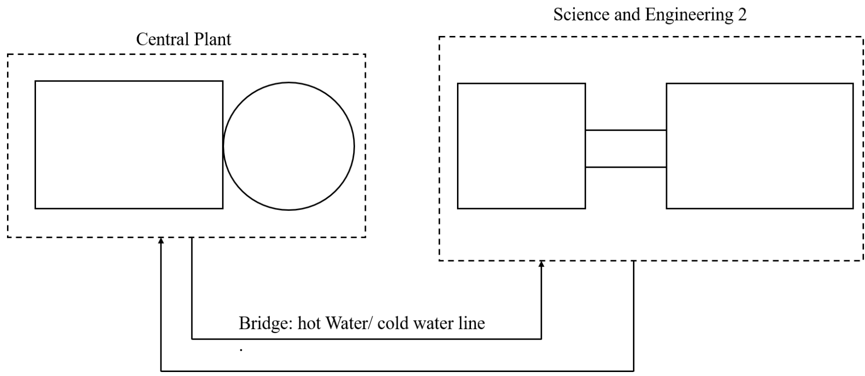


Figure 2.1: The relationship between SE2 and the central plant. All HVAC hot and cold water is supplied by the central plant through the bridge.

a day. AHU's 1 and 2 are single duct units that provide 100% outside air directly to each lab space, which are regulated by Seimens ventilation units, called SAV's. AHU's 1 and 2 work together both service Zone 12 and feed a common line as shown in Figure 2.3 .Using a plunger-like valve, the SAV can regulate airflow much like a damper. Each SAV also contains large cooling and heating coils, which use hot and chilled water to condition the supply air. All spaces served by SAVs also include an exhaust unit that can modulate air flow with the same type of damper.The SAV system is depicted in Figure 2.4. Since Zone 12 does not recycle air, it is by far the largest consumer of chilled water, while AHU's 1 and 2 are constantly operating to maintain the sensitive temperature conditions required in many of these spaces. Zone 12 is unique in the sense that AHU 1 and 2 do not condition the air. There is a slight change of air temperature across AHU 1 & 2 due to a heat exchanger that recovers energy from the exhaust air.

2.4 Zone 3

The HVAC system in Zone 3 is shown in Figure 2.5 and is located in long bar is supplied by AHU 3. Zone 3 consists of two rows of south-facing offices on the second and third floor. This zone is a constant volume system, meaning that the supply air provided by the unit is uniform throughout these areas. AHU 3 is equipped with an economizer that supplies air to each office. All offices are equipped with a special diffuser known thermafuser unit (THR) which is capable of regulating air flow through a valve built into the unit. The valve only shuts off air flow when the windows open it does not modulate air flow in the same sense as an SAV or VAV. It is also equipped with sensors to measure, airflow, supply air temperature, zone temperature, and occupancy. Zone 3 is occupied generally from 6 am to 11

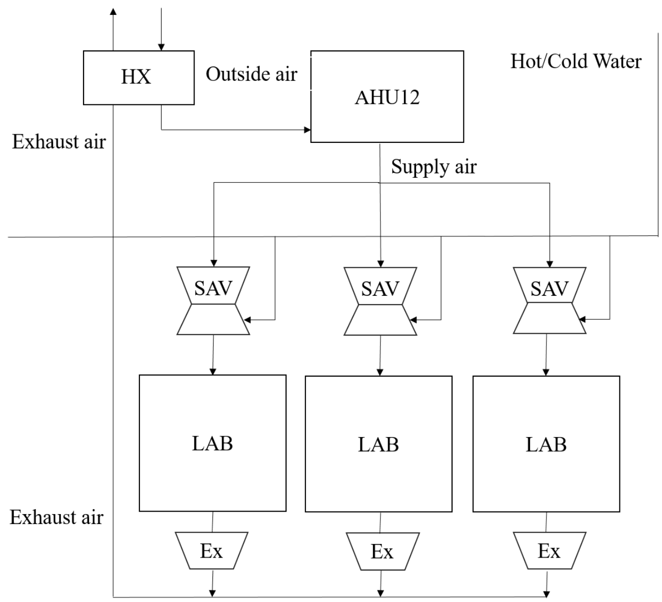


Figure 2.2: Layout of the HVAC system in Zone 12. AHUs 1 and 2 are not equipped with economizer, rather the exhaust air stream exchanges heat with an air water heat exchanger to heat up the incoming air stream.

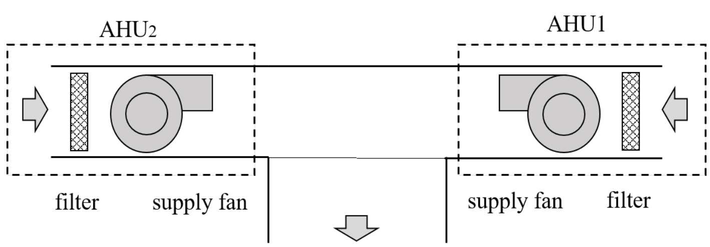


Figure 2.3: Schematic showing the relationship between AHU 1 and 2.

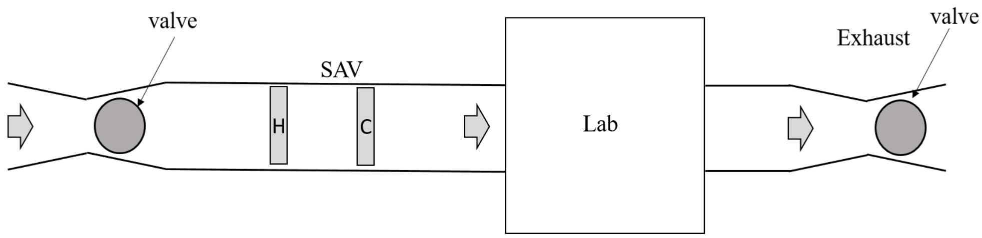


Figure 2.4: A simplified schematic of an SAV with the corresponding exhaust unit serving a lab space.

pm and allows each individual occupant to send a cooling or heating request to the AHU via the thermostat in the space. The AHU then aggregates the requests to determine if the system will go into heating or cooling mode.

2.5 Zone 4

AHU 4 services Zone 4 which contains the entirety of short bar, as well as the bridge(not the hot water and cold water bridge) connecting both regions. It consists primarily of offices and conference rooms and houses the main entrance lobby, which doubles as a common study area for students. AHU 4 is also a dual duct economizer unit supplying conditioned air to VAV units. Downstream from the AHU, Zone 4 consists of a single duct pressure dependent VAV system with hydronic reheat and cooling. Most of the VAVs inside Zone 4 feed into a number of thermafusers, a few of them however, feed directly into a building. A schematic depicting the interrelationship between devices in Zone 4 is shown in 2.6.

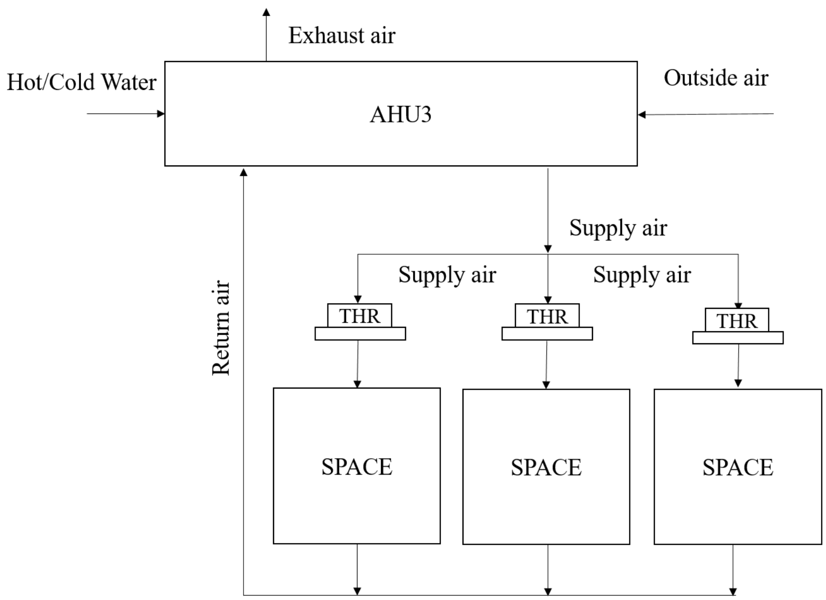


Figure 2.5: Layout of the HVAC system in Zone 3.

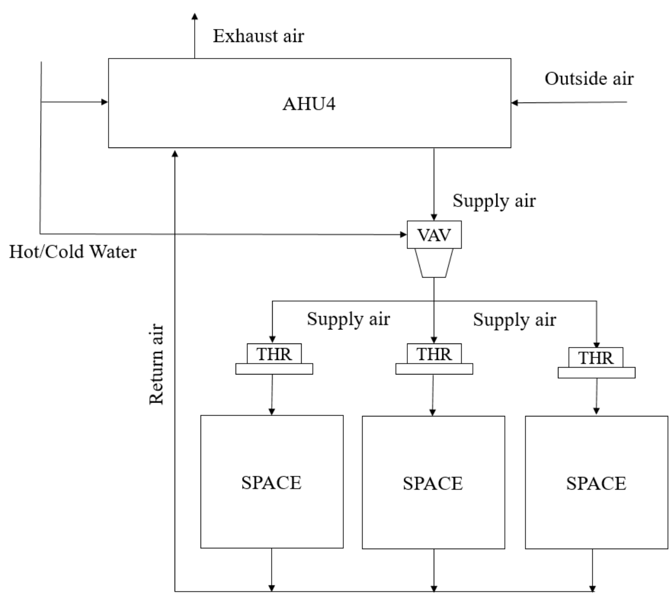


Figure 2.6: Layout of the HVAC system in Zone 4.

Chapter 3

DATA PARTITIONING STRATEGY

3.1 Organization

To detect faults more effectively, data must be organized in an appropriate manner. This means that data must be grouped based on time, spatial characteristics and operating conditions. Ultimately these partitions are due to two factors: weather and occupancy. Other factors that are important are architectural parameters and ventilation requirements depending on the type of space. Generally devices of the same type that have similar power consumption patterns are grouped. Once the clean data is obtained, the data can be organized based on its temporal and spatial components. The data breakdown based on time and space is depicted in 3.1. The temporal and spatial components are explained in greater detail in the following sections.

3.2 Temporal Partitioning

With regard to time, data is organized by year, season, time of the week, and time of the day. First, season and year are important because the weather is different depending on the season and may even change over the years for the same season. The time of the week is important because the air conditioning system runs at reduced capacity during the weekend due to smaller occupancy. Parititioning between day and night is required because varying occupency and sun exposure over the course of a day. Figure 3.2 illustrates how much the temperature can fluctuate over the course of a typical summer day. The delimeters between day and night do not necessarily correspond to sunset and sunrise, but rather they must also take into consideration of the operational schedule of the HVAC system. Some areas have different business hours such as offices and class rooms and occupency will therefore vary depending on the use of the building and vary within the same zone among the same type of devices. In addition, the temperature especially during the summer does not drop significantly after sunset. The above discussion results in a compromise of 1- 5am for temporal partitioning.

3.3 Spatial Partitioning

The data needs to be classified by zone. This decision comes naturally since the building HVAC was designed with different zones. These zones which differ in

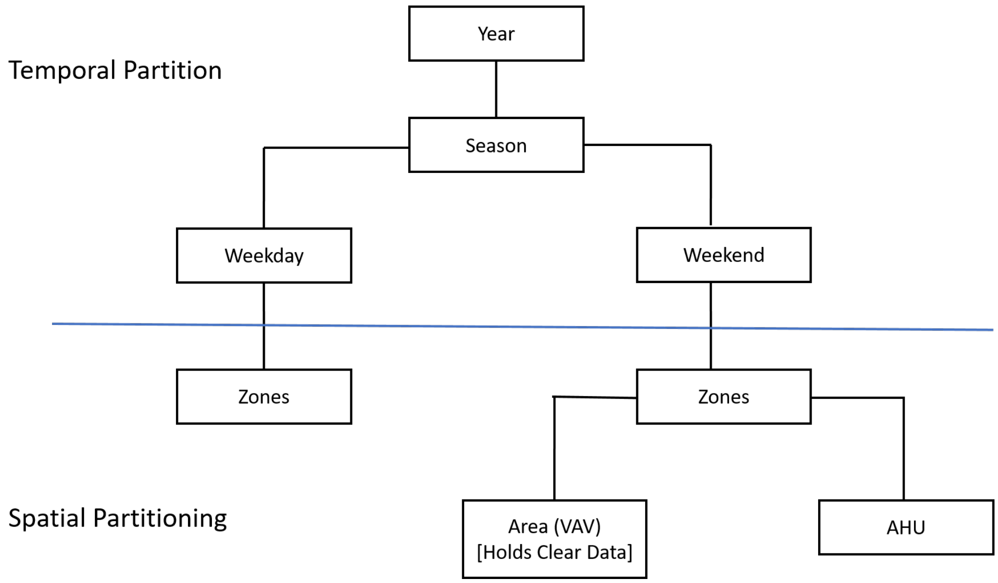


Figure 3.1: The file structure which represents the basic temporal and spatial partitioning scheme and also reflects the basic file structure for the program. VAV and AHUs are labeled in diagram as an example, but this file structure extends to other devices.

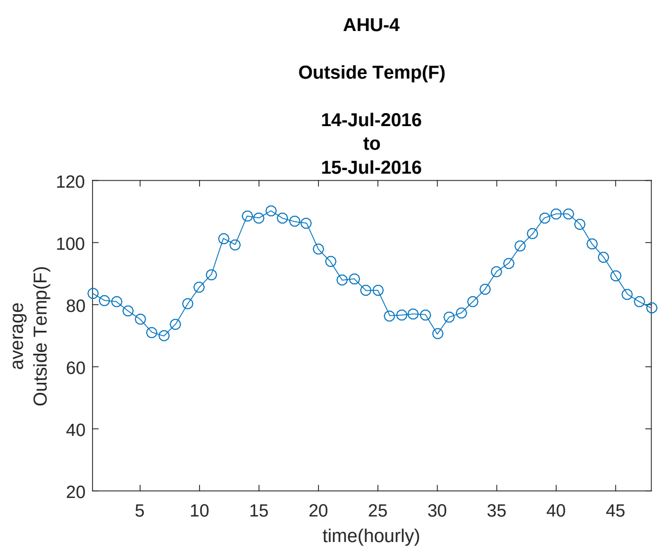


Figure 3.2: Average daily temperature.

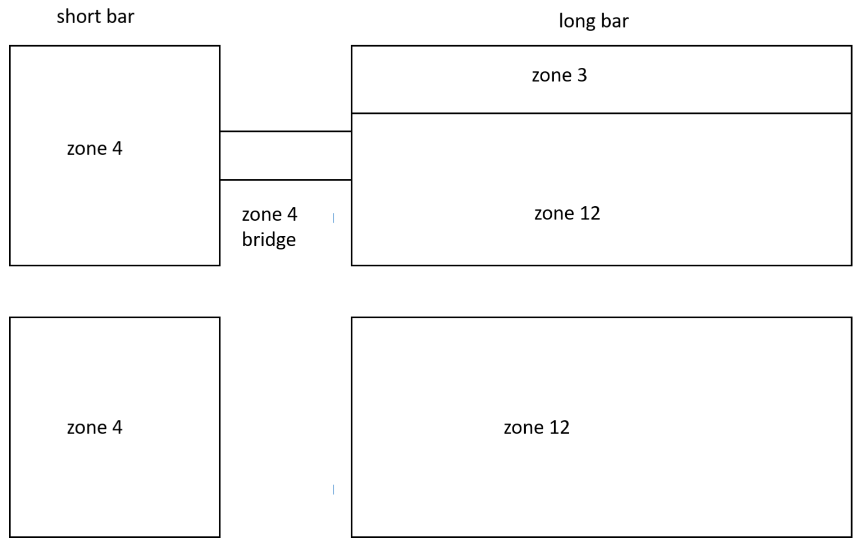


Figure 3.3: Outline of each zone with respect to the outline of the SE2 building.The bottom diagram depicts the first floor whereas the top diagram depicts the second and third floors.

purpose and structure are chosen based on the demands of the spaces that comprise them. Generally, zones consist of spaces with similar heating and cooling loads and ventilation requirements. For example, Zone 12 consist of labs and Zone 3 consists of offices all on the west side of the building with windows. These spaces are very different. For instance, a lab does not recirculate air, but a zone consisting offices does. There are also differing cooling loads due to geometrical factors such as where the space is located with respect to the sun and whether it is an interior or exterior room due to sun exposure. For instance, an adjacent building near a window will influence the load certain time of the day. A general layout of each zone in SE2 is shown in Figure 3.3.

A zone will have a certain number of AHUs attributed to it along with a certain number of lower level devices such as VAV terminal boxes. A VAV terminal box will be assigned to a group of spaces or one space with similar air condition requirements. Comparing energy consumption from different zones does not make sense since they have different demands, and structural differences which means they are expected to have different power consumption patterns.

The power consumption of the air handling unit is highly correlated to the outside temperatures during winter and summer days. This is expected since a significant amount of outside air is conditioned even on hot summer days due to state mechanical codes. The fact that the air conditioner is equipped with an economizer

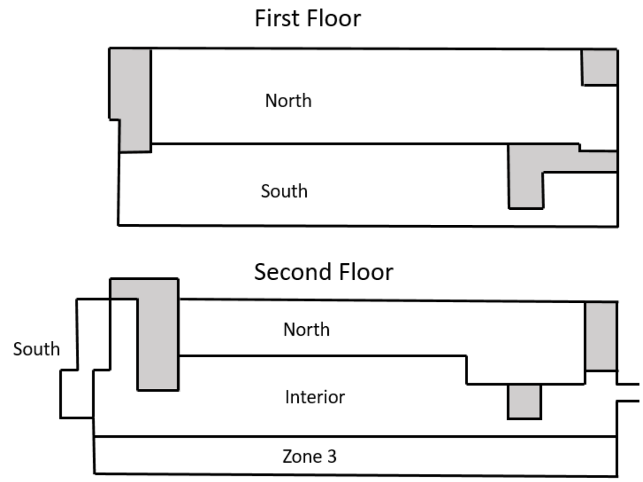


Figure 3.4: Zone 12 and Zone 3 spatial partioning for the SE2 building. Only the first and second floor are shown since the 3rd floor is virtually identical to the 2nd floor. Also, the basement is treated as one group so it is not shown.

that recycles the return air lowers the correlation between the outside temperature and lower temperature. This is because cool recycled air is mixed with the outside air. An introduction to the spatial partitioning scheme to each zone of the SE2 building is provided in the following sections. As expected, there is a lower correlation between the AHU energy consumption with outside temperature on days with mild weather. The conditioning requirments during these periods would be dominated by occupency and minmimum requirements set by state mechanical codes. In subsequent sections, the spatial partitioning pertinent to each zone is discussed.

3.4 Zone 1 & 2 Partitioning

For Zone 12, the rooms are grouped based on orientation and occupancy. Zone 12 consists almost entirely of labs but also contains a few offices. So all labs on the south end of the building are the same group.The six southwest side offices are lumped in with the "south" group since they all have windows facing south or southwest. All labs on the north end are the same because the north end of the building receives less sun than the south end because the SE1 building adjacent to the SE2 building blocks the sun as it lowers. All of the labs inside the basement are one group. Also the interior of the 2nd and 3rd floor constitute one group.

3.5 Zone 3 Partitioning

Zone 3 is treated as one zone and spans the second and third floor. This zone which is served by AHU 3 and lacks any intermediate conditioning from any devices downstream. The AHU directly conditions all the air supplied to the rooms and will adjust the temperature of all zones by polling the thermostats in each office. All rooms face the south and have windows as shown in Figure 3.4. The layout on both floors in this zone are identical. Taking the above reasons into consideration, it is appropriate to treat this as one group.

3.6 Zone 4 Partitioning

Zone 4 is divided into 3 sub areas defined as, exterior left, exterior right, interior. The left and right view is defined by the Figure 3.5. The exterior left side of the building faces south west. It is partially shielded from the sun by long bar and a metal lattice covered in solar panels. The exterior left side of Zone 4 consists of a lobby area and hallways. The exterior right of Zone 4 consists of offices and conference rooms. The interior contains most of the VAVs. It is expected that the energy consumption associated with the VAVs has little correlation with the outside temperature and more on occupancy and ventilation requirements of the space.

The exterior left side of the building faces south west. It is partially shielded from the sun by long bar and a metal lattice covered in solar panels called the breezeway and consists of a lobby area and hallways. The exterior right of Zone 4 consists of offices and conference rooms. The interior contains most of the VAVs which service offices and conference rooms. Hallways should be separated from rooms due to their varying occupancy, but there are not enough hallways in Zone 4 to justify having another group.

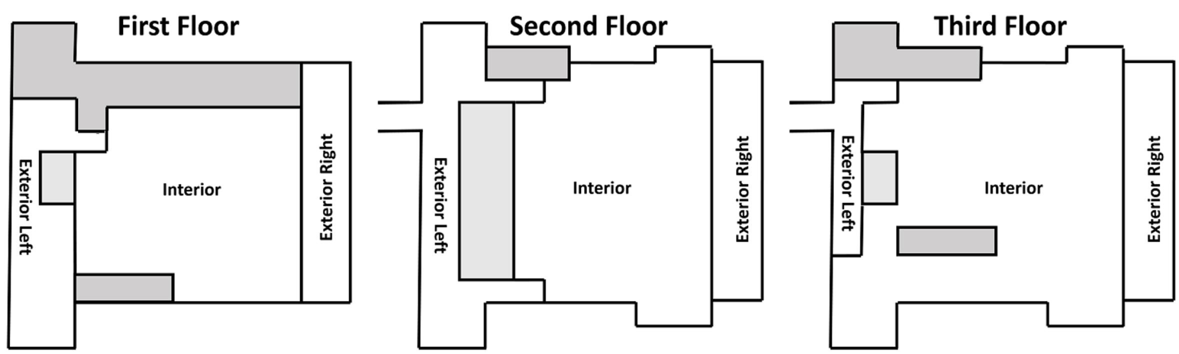


Figure 3.5: Zone 4 spatial partitioning. The zone comprises three user defined areas; exterior left, exterior right and interior. The gray areas are not conditioned by the HVAC system. There are also a small number of rooms in the basement that belong to Zone 4.

Chapter 4

ENERGY MODELS

4.1 Energy Description

Energy consumption in the form of power is selected as a data feature, this is because energy best captures the operating characteristics of the HVAC system. The various sensor inputs are utilized to compute the power consumption of each device. In this chapter, mass and energy balances are derived for each of the components. For this work two ways of describing energy consumption apply: thermal and potential energy model introduced in Sections 4.2 and 4.3 respectively. This follows the practice of other researchers [7]. Also, due to the necessity of using trends associated with multiple upstream devices in modeling a device downstream, a method for describing parameters from multiple upstream devices in a downstream device is formed. This is introduced in Section 4.4.

4.2 Thermal Energy

In this section, thermal energy models descrbing the components for each device are derived. This includes the AHU and the VAV. The thermal energy models account for the effects related to temperature changes. These are the main models used in this work.

4.2.1 AHU

The air handlers for Zone 4 and Zone 3 are shown in Figure 4.1. These AHUs also move air via two fans, supply and return. Heating and cooling is achieved with two coils which are fed by hot water and cold water streams respectively supplied by the central plant. When deriving the energy model, the only heating inputs are assumed to be from the cooling coil and heating cool. This neglects friction and electrical heating from the fans.

The power consumption for the air handling unit mainly consists of the heating and cooling requirements of the coil and the work done by the return and supply fan in moving the air. In calculating the thermal energy balance the energy from the supply and return fan is neglected.

A description of the thermal energy consumption of the air handling unit can be derived using conservation of mass and conservation of energy and is given by

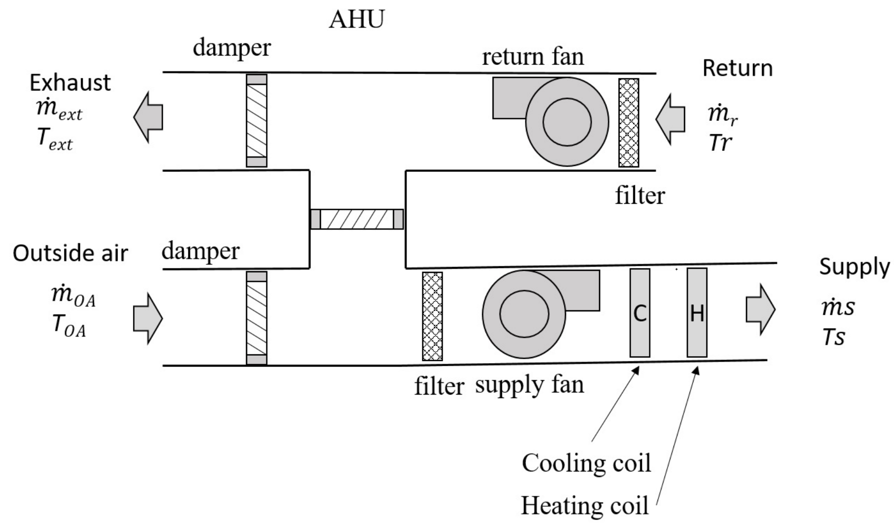


Figure 4.1: Simplified diagram of a single duct AHU equipped with an economizer. This is the type of AHU found in zones 3 and 4.

Equations (4.1) and (4.2) respectively. The incoming streams are the mass flowrates due to the outside air, and return air which are repsented by $\dot{m}_{OA}$ and $\dot{m}_{RA}$ respectively. Similarily, exiting flow rates are represented by the exhaust and supply air flow rates and are represented by $\dot{m}_{EA}$ and $\dot{m}_{SA}$ respectively. The return air term is included because this AHU uses an economizer, where some of the air from the space is mixed with the incoming outside air to reduce energy consumption. In this model, kinetic energy and potential energy effects are neglected, only the thermal effects represented by specific enthalpy h are considered. Note that the mass balance is used to solve for the unknown exhaust air flow rate because the AHU lacks exhaust flow rate sensors.

$$\dot{m}_{EA} = \dot{m}_{RA} - \dot{m}_{SA} + \dot{m}_{OA} \tag{4.1}$$

$$E = \dot{m}_{RA}h_{RA} + \dot{m}_{OA}h_{OA} - \dot{m}_{EA}h_{EA} - \dot{m}_{SA}h_{SA} \tag{4.2}$$

The enthalpy of air is given by Equation (4.3) and can be found in any standard thermodynamics text [15]. The first term represents the dry air enthalpy and since air is an ideal gas, enthalpy is related to temperature by specific heat at constant pressure, c_p. The second term represents the enthalpy of water vapor mixed with the air and is called the mixture enthalpy. ϕ represents the ratio of the mass of water to air and is known as the humidity ratio and h_g is the enthalpy of saturated

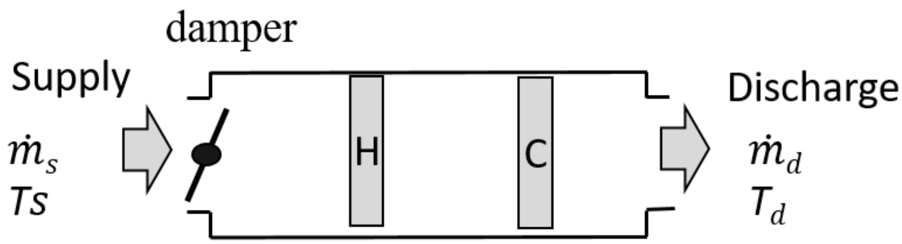


Figure 4.2: A schematic of a VAV, showing essential parts that are useful for deriving the model.

steam at a given temperature. In the SE2 building there are no humidity measurements. Merced is dry region especially during the summer so there is little moisture in the air. Therefore the mixture enthalpy in this work is neglected. However, this may cause issues in fault detection if there is process taking place inside a room that results in high humidity such as open boiling of large amounts of water. Aside from these concerns, the dry air portion of Equation (4.3) is applied to Equation (4.2) thus forming Equation (4.4) which is the one used in this work. Note that in Equation (4.4) volumetric flowrate q is used rather than mass flow rate, because sensors measure the latter. This is a simple solution because the density ρ is constant so it can be factored out of each energy term.

$$h = c_p T + \phi h_g \tag{4.3}$$

$$E = \rho c_p (q_{RA} T_{RA} + q_{OA} T_{OA} - q_{EA} T_{EA} - q_{SA} T_{SA}) \tag{4.4}$$

4.2.2 VAV

The VAV shown in 4.2 has only two flow inputs, supply air and discharge air. The incoming air is heated or cooled by the heating and cooling coil. Encapsulates the heat added or removed from the system by the heating and cooling coil respectively.

It is assumed that the supply air to the VAV is the same temperature as the air supplied by the AHU, that is there is negligible heat transfer in the air duct between the VAV and the air handling unit.

Since air is an ideal gas, Equation (4.5) applies.

$$E = q_{SA} \rho c_p (T_s - T_d) \tag{4.5}$$

4.3 Potential Energy

The AHU and VAV units are equipped with static pressure sensors. This allows one to compute the power associated with moving the fluid. Velocity pressure is not factored into this model This is because the velocity in the ducts is very low. Accounting for the effects of flow without regard for sensible energy allows one to detect faults associated with ventilation. Static pressure is a parameter used in the control system for the AHU when determining ventilation requirements. This also dictates how much the damper opens and closes. Sometimes spaces are overventillated thus wasting energy [16]. Also a frozen fan may be detected with this method. Other researchers take the approach of seperating pressure and thermal energy [7].

There are three pressure terms; they are static pressure, velocity pressure, and elevation pressure. Static pressure(thermodynamic pressure), p, is the internal energy of the fluid. Velocity pressure, $\rho\frac{v^2}{2}$, represents kinetic energy and is due to the speed of the fluid. Elevation pressure, gz, is the result of elevation changes where g is the local acceleration of gravity and z is the height. In this work, velocity pressure and elevation pressure are neglected. Also, the flow in an HVAC system is slow enough that compressibility effects may neglected. Therefore, the energy change between two points is given by Equation (4.6).

$$p_1 + \rho\frac{v_1^2}{2} + gz_1 - p_2 + \rho\frac{v_2^2}{2} + gz_2 = p_f - p_l \tag{4.6}$$

Assume velocity pressure $\rho\frac{v^2}{2}$ and elevation gz is negligible then Equation (4.6) reduces to Equation (4.7)

$$p_l - p_2 = p_f - p_l \tag{4.7}$$

The static pressure difference between points 1 and 2 is equal to the difference between the pressure rise across the supply fan p_f and the pressure drop from any losses in the system p_l. Some losses could be the damper throttling the air flow and friction in the duct work. The related energy rate transport can be calculated by multiplying across by the flow rate and is given by Equation (4.8) .

$$E = q(p_1 - p_2) = q(p_f - p_l) \tag{4.8}$$

4.4 Multiple Upstream Devices

There are cases in which there are two or more devces feeding a common line. The some of the models incorperated into this fault detection scheme utilize a parameter associated with the upstream device. In addition, there may be multiple upstream devices feeding a common line. There needs to be a methodology for describing the value used in the model of the downstream device. This case is

Table 4.1: Format for the csv containing listing the number of errors for each day.

Trend Type	Class
pressure	across
temperature	across
damper position	misc
power	through

encountered in Zone 12 where there are two AHUs feeding the same duct as seen in Figure 2.3. In this situation, the type of variable must be first be distinguished. Variables are classified into three types, "across", "through", or "miscellaneous". Examples, of an across variables are temperature and pressure. Through variables include mass and power. Variables that fall into the miscellaneous catagory would be chilled water valve and damper position. Currently no model in this work utilizes upstream trends that fall into the "miscellaneous" category. For "across" variables the duct is treated as a mixing chamber and trend x, used in the model of the downstream device, will be derived using Equation (4.9). If the tend is classified as "through" then the trend downstream of multiple devices is derived using Equation (4.10) where w is the "through" variable. This equation simply means their effect downstream is additive. A summary of trend types and the class they belong to are summarized in Table 4.1.

$$\bar{x} = \frac{\sum_{i=1}^{n} m_i x_i}{\sum_{i=1}^{n} m_i} \tag{4.9}$$

$$w = \sum_{i=1}^{n} w_i \tag{4.10}$$

Chapter 5

DATA RETRIEVAL AND PRE-PROCESSING

5.1 Introduction

Before fault detection, the first step is to retrieve and pre-process the data. Every data driven fault detection scheme has a pre-processing phase [3]. Data from sensor networks is noisy, and often contains missing and erroneous values. Often these values are obviously wrong and therefore physically unrealizable, however, this is not always the case. In this chapter, the methodology of data retrieval, cleaning, interpreting, and recording the faulty data is discussed. A system for retrieving and organizing the data before pre-processing is established. Pre-processing is then implemented to clean the data. This chapter ends with an outline of how the pre-processing scheme is implemented programmatically.

5.2 Control System

The control system in the SE2 building and many modern buildings equipped with an HVAC system utilize direct digital controls or DDC. DDC systems use a microprocessor that can programmed to implement different control strategies. These controllers are linked over a network like a computer network. There are different types of DDC protocols. One such protocol is BACNet, which is a standard protocol established by ASHRAE. Not all vendors follow this protocol completely and some do not follow it at all. The building automation systems (BAS) used on the UC Merced campus which includes SE2 is WebCtrl. This is BACNet compatible building automation system by developed by Automated Logic Control (ALC).

5.3 Data Retrieval and Organization

5.3.1 Data Retrieval

Data is stored on the WebCrtl server. WebCtrl works in coordination with all HVAC control modules, which then provide trend data through BACNet points. Each BACNet point has a certain name or address based on the control program it exists in. Each of these points commonly known as a trend represents a specific sensor output. For example the supply air temperature trend for AHU 4 is listed as *#ahu-4_0206/sa_temp* , while AHU 4's outside air damper position is listed as *#ahu-4_0206/oa_dmpr*. In order to successfully pull data via SOAP protocol, the program

Table 5.1: The format for the CSV that is used to tell the script what control points to use.

server	10.20.0.47
	10.20.0.47
	10.20.0.47
location	Science & Engineering 2: 0206
	Science & Engineering 2: 0206
	Science & Engineering 2: 0206
branch	First Floor
	First Floor
	First Floor
sub_branch	Short bar
	Short bar
	Short bar
control_program	1C1A
	1C1A
	1C1A
point	Air Flow Feedback
	clg setpt
	htg setpt
path	#1c1a_thermafuser/m073
	#1c1a_thermafuser/m135
	#1c1a_thermafuser/m134

must be provided appropriate trend addresses from all three zones. However, all areas can be classified by zone since each AHU is responsible for a specific part of the building. A global trend list provided by WebCrtl allows trends to be retrieved. The list of trend addresses is then saved into comma seperated value (CSV) files from which a Python script can refer. An excerpt of the trend list for Zone 4 is shown in Table 5.1. The identification of Zone 3, 4, or 12, gives one the ability to pull from the predetermined list of control programs. Their corresponding trends are then written to a CSV file for a specific date.

Raw data is gathered from ALC and stored CSV files. There are specific CSV files for each device in a zone. The name of the name of the specific device is the same name as the control program as shown in Table 5.3. For example, there is a CSV for the AHU 3 in Zone 3. The first column of the csv lists the timestamp which

Table 5.2: The format for the CSV that contains the data for each device.

TimeStamp	#vav-1-23/cl_stpt_tn	#vav-1-23/cw_valve	#vav-1-23/da_temp
6/30/2016 0:05	65	0	64
6/30/2016 0:10	65	0	64
6/30/2016 0:15	65	0	64
6/30/2016 0:20	65	0	64

gives the month day and specific time. All data is sampled at 5 minute intervals for an entire day hence each CSV contains 288 entries. For example, AHU-3 has 48 sensor outputs while a VAV in zone 4 has 10 sensor outputs. An example of a raw data csv is shown in Table 5.2, this particular one is for a VAV serving BreakOut 120J VAV. The naming format is such that *(Name)(Date).csv*. As a example the file name is *BreakOut120J VAV-1-23 2016-06-30.csv*. It must be noted that all raw data csv files follow this name and date format.

5.3.2 Organization

The first stage of organization is done in the pre processing stage. The spatial and temporal partitioning scheme outlined in Chapter 3 is applied. The organization of the data is depicted in Figure 3.1. The data is first partitioned based on time from season to time of the week. Partitioning based on the time of the day is performed later in the fault detection phase because the HVAC system operating schedule can differ among devices within a zone. After temporal partioning the data is partitioned based on zone and organized based on device type found in the zone.

In this work, devices (known as control programs with respect to WebCrtl) with a group of trends in common is referred to as a device type. For example, although the air handler in Zone 3 and the and in Zone 1 & 2 are called air handlers, they are classified as two device types because the trends associated with them are much different. This also reflects the fact they are different mechanically due to their different duties. Inside the file structure, device types are given a three letter abbreviation. The abbreviations for devices in the SE2 building are listed in Table 5.3.

Device types in this work are, AHU's thermafusers, VAVs, SAVs and fans. The device type often but not always represent a separate device. For example, the AHU supply fan is inside the air conditioning unit but is classified as a different device because its power consumption is listed in a different directory as the trends for the AHU.

Table 5.3: Names of device types and their description.

Name	Abbreviation
Air handler	AHU
Air handler Fan	Fan
Variable air vol	VAV
Siemens air vol	SAV

5.4 Sensor Health

The raw data directly pulled from the server is far from being of any use. Any CSV will likely contain useless data, namely missing and erroneous values. Thus, before being used the data must be "cleaned". In addition, not all the sensor outputs stored in the CSVs are needed. Sensor outputs such as carbon dioxide and occupancy readings have no use in this stage of the research. Therefore, the goal of the of the pre-processing stage is to clean the data and to gather the necessary trends required for the models used to detect faults. In addition, the missing or erroneous values are not discarded. The time and locations of these values are recorded. This may have use in the future, where fault patterns may be extracted from the error logs. Therefore, a stage is included to check sensor health by finding and documenting unreasonable values. The following sections give an overview of some characteristics of these values encountered during the pre-processing phase.

5.4.1 Missing Values

The first stage of pre-processing is to check for dropped values, which are a result of communication errors and are represented in the raw data by a negative one value. Communication errors from the WebCrtl server may last days, hours or minutes. A communication drop lasting a day more will generate completely blank csv files or only consisting of a timestamp and header, but are filled with negative one values. Sporadic sequences of (-1) or single (-1) values are indicative of communication errors lasting minutes to hours.

5.4.2 Erroneous Values

Aside from missing values, the raw data can also be contaminated with erroneous values that are generated by faulty sensors. A value out of range will usually indicate a faulty sensor. Often these out of range values will be extremely large such as hundreds of orders of magnitude or extremely small as in 10^{-9}. Sometimes the errors are less obvious. A common sensor error that is not obvious is sensor bias.

Sensor bias can cause problems with control and manifests itself as a constant deviation from the correct value and is usually measure as a percent error. Bias can be a result of the degradation of sensor materials. Currently there is no methodology employed in the program to detect sensor bias.

There is a significant amount of research dedicated to sensor FDD. One such method utilizes PCA for sensor FDD in an AHU using squared prediction error [7]. The above principle is extended to sensor FDD for an entire VAV system [17].

5.5 Pre-Processing.

The first stage of preprocessing is to check for communication errors values in the CSV, which are a result of communication errors and are referred to as dropped values. A dropped value is represented in the raw data by a negative one value. Communication errors from the WebCrtl server may last days, hours or minutes. A communication drop lasting a day more will generate CSV files that are completely blank or consist of a timestamp and header, but are filled with negative one values. Sporadic sequences of (-1) or single (-1) values are indicative of communication errors lasting minutes to hours.

CSVs that are completely blank or filled with dropped values are completely ignored and replaced with a CSV equipped with the standard header and timestamp but with data fields filled in with NaN. This is necessary for indexing purposes. For small communication drops a more judicial procedure is applied. Generally, communication drops that last 5 – 30 minutes and are randomly distributed throughout the day are not an issue. These values are ignored, replaced with NaN and the remaining data in the CSV is still used. However, communication drops lasting many hours are flagged. More specifically, when more than 50 entries are missing from a CSV the entire trend for that day is effectively deleted by being replaced with NaN values.

Sensors are checked for obvious errors by comparing their readings to a range commonly found on properly functioning sensors. This range depends on the trend type and is summarized in Table 5.4.

5.5.1 Retrieving Trends

Not all of the trends listed in the raw CSV are needed and therefore do not need to be processed. The user must list the required trends for the models and store an excerpt of the WebCrtl address in a separate MATLAB file called *datalisting.m.* If the addresses do not change this only needs to be done once. The pre-processing script will read this file and output a CSV known as a trend listing file. An example of this file is shown in Figure 5.5. If this already exists the script will not rewrite

Table 5.4: The datatypes used in this research, along with their units and their valid ranges.

Trend Type	Range	Units
Pressure	0.1	inches of water
Temperature	30 - 90	Fahrenheit
Flow rate	0 - 50000	cubic feet per minute
Position	0 - 100	percent

Table 5.5: Partial trend listing for a VAV.

Name	Address	Column Number	DataType
HW_ValvePos(%)	hw_valve	8	position
CW_ValvePos(%)	cw_valve	2	position
Discharge_Temp(F)	da_temp	3	temperature
ZoneTemp(F)	m311	10	pressure

it, in order to add new trends, the user must delete the old one. This file has the format *(DeviceTypeName)TrendListing.csv*

This file has the following fields, “name”, “address”, “column number” and “data type”. The user specified name appears in the name field. The address field contains an abbreviation of the control point address specified in the WebCrtl server, an example of which is given in Table 5.1. The column number refers to the location of the trend in the raw data CSV. The data type is the classification of the data as listed in Table 5.4.

5.5.2 Filling in Missing Data Types

If the data is missing or obviously wrong, the next task is to establish a methodology for addressing it. Filling in missing data from sensor networks is an active research topic. Primitive methods of data imputation include filling in the missing points with the mean value of the entire dataset, or the value next to it. A reliable method of data imputation is known as hot deck imputation where data gathered under similar conditions from a different data set is substituted [18, 19]. In this research, list wise deletion is used due to its simplicity. This entails deleting every member of the same row. So if a particular trend is used in the model, then all the data in that row is deleted for that specific time. In many cases, simply deleting the erroneous data is undesireable because it reduces the sample size and introduces bias. The case where list wise deletion is valid is if the data is considered “missing completely at random” (MCAR). This means that the there is no underlying mechanism causing the data to be missing [18]. This type reflects the randomly dropped values found in the data. With regard to reducing the sample size, fortunately there is a wealth of data from the HVAC system. Also, parameters in HVAC such as temperature and pressure vary slowly (e.g. 30 minutes). Thus, significant quantities of data can be ignored in a day.

CSVs that are completely blank or filled with (-1) are completely ignored and are substituted with a CSV with the standard header and timestamp, but with data fields filled with NaN for indexing purposes. For small communication drops a more judicial procedure is applied. Generally, communication drops that last 5 – 30 minutes and are randomly distributed throughout the day are not an issue. These values are ignored, replaced with NaN and the remaining data in the CSV is still used. However, communication drops lasting many hours are flagged. More specifically, when more than 50 entries are missing from a CSV the entire trend for that day is effectively deleted by being replaced with NaN values. For data with obviouly bad sensor outputs, apply the same reasoning as that applied to dropped values. That is, a sensor whose output consists of more than 4 hours of erroneous readings will be deleted as the entire day is considered lost and replaced with NaN.

Deleting the the day after 4 hours is required because statistical measures such as mean and standard deviation are only useful metrics if the data can be represented by a Gaussian distribution. For the dataset to be considered Gaussian a rule of thumb is to have atleast 39 samples [20]. 4 hours of data consists 120 samples. We also need to take into account the data removed form the day during temporal partitioning. Thus, it is decided deleting the day after 4 hours offers a generous window for ensuring the Gaussian distribution. The assumption of a Gaussian distribution is a key assumption in principal component analysis (PCA) [21]. As discussed in Chapter 7, PCA is a key component of the fault detection scheme used in this work.

An example of a faulty sensor was detected in this stage by analyzing data from summer 2016 gathered from the SE2 building. In this case the fault is due to a temperature sensor located in a VAV box that supplies a group of offices in Zone 4. The sensor output was obviously unrealistic as shown in Table 5.6.

Table 5.6: Excerpt from the data CSV showing values representative of a sensor malfunction.

Time	Discharge Air Temperature(F)
7/23/2016 7:40	3.02×10^{21}
7/23/2016 7:45	$3.01\ \times10^{180}$
7/23/2016 7:50	2.29×10^{243}
7/23/2016 7:55	3.58×10^{160}
7/23/2016 8:00	$5.46\text{E}\times10^{242}$
7/23/2016 8:05	$1.07\text{E}\times10^{224}$
7/23/2016 8:10	6.94×10^{88}

Table 5.7: Format for the CSV containing listing the number of errors for each day.

Timestamp(day)	Trend 1	...	Trend n
-	0	-	1
-	0	-	0
-	5	-	0

5.5.3 Recording Erroneous Values

Once removed erroneous values detected in the raw data are not forgotten. These values which includes missing values and faulty values are noted. The sensor responsible and the time of their occurrence is recorded. The format for the CSV file reporting this information is shown in Table 5.7. This information may be useful for future fault detection research. After all, faulty sensor values, and missing data in and of themselves are faults. There may be a pattern hiding in seemingly random communication outages or sensor malfunctions. With deep learning these hidden patterns may be extracted. In short, for fault detection, missing or highly inaccurate information is still considered information about the system.

5.5.4 Process Flow

The entire processed disucssed here is summarized in a flow chart shown in Figure 5.1 which also describes the program implmented in Matlab. The output of this script develops the following file structure shown in Figure 5.2. This file structure is used as the input and output of the other script used for energy calculation and fault detection.

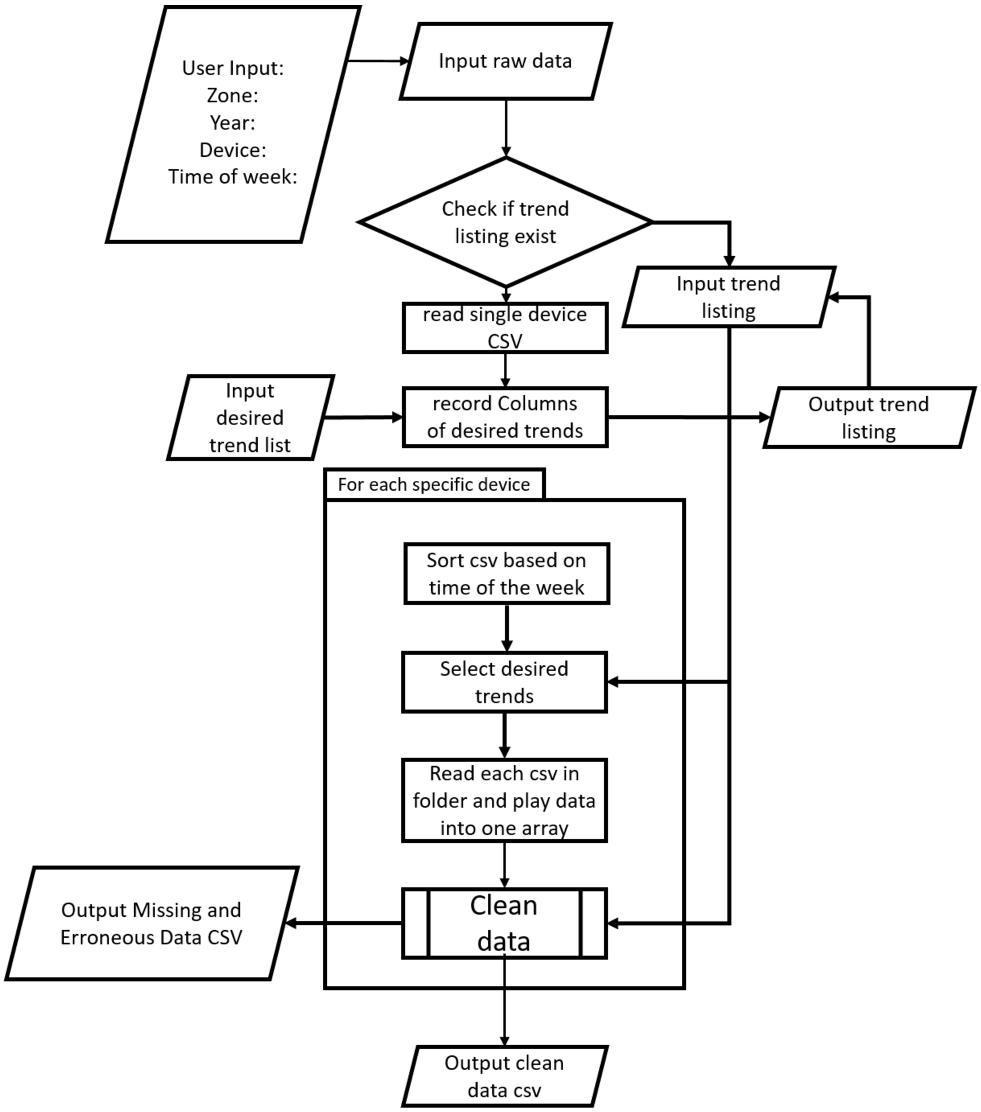


Figure 5.1: The pre-processing procedure

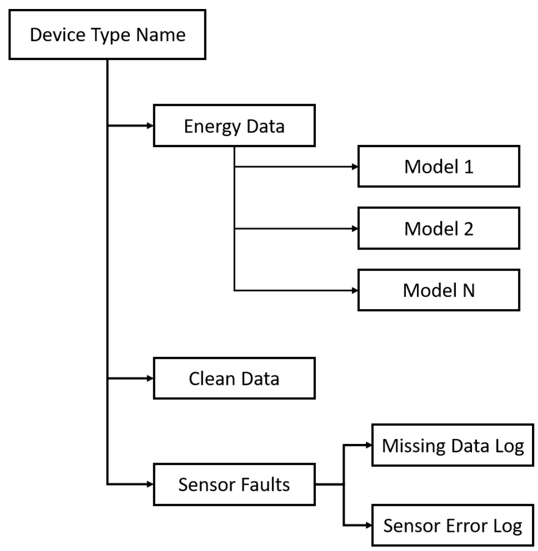


Figure 5.2: The output file structure generated during pre-processing.

Chapter 6

FEATURE CALCULATION

This chapter discusses the way power for each system component is calculated. Power is a data feature used to describe the operation of HVAC components such as AHUs and VAVs. The fault detection scheme utilized in this work relies on abnormal power consumption to detect faults. The energy models discussed in Chapter 4 are implemented. Also presented here, is a method used to represent the HVAC system structure. Energy models for a device require trends associated with other devices such as those upstream. Therefore, a method for modeling the structure of the system is necessary.

6.1 HVAC Structure

In this section an overview of the HVAC structure is given and how it is represented programatically. It is necessary to describe the structure of the system in order to locate trends required for the models. Often trends from different devices are required to model the energy consumption of a specific device because devices feed into one another.

6.1.1 Assumptions

In general, building HVAC systems involve complicated thermal fluid phenomena. However it is uneccessary to model this complexity for fault detection so here valid assumptions are introduced. These assumptions allow a simplified yet accurate representation of structure of the HVAC system.

1. Zones are independent.

2. Every zone has an AHU feeding directly or indirectly all devices in the zone and no other zone. If there are two devices then they feed the same pipe.

3. All intermediate devices are in parallel. An intermediate device cannot feed into an intermediate device.

4. There are no secondary loops. All air eventually returns to the air handler return air or exhausts to the atmosphere.

The above assumptions simplify analysis of the system and organization of the data. The first assumption guarantees that when we are analyzing a zone we do not need to access data from a device located in another zone. It is thus assume that the zones are thermally decoupled. Technically this does not reflect reality since the zones are in the same building. Air from different zones will eventually mix, technically making this assumption incorrect. This is compounded by the fact the air handlers are equipped with an air economizer which takes the mixed air from the building and reconditions it.

The second asumption is similar to the first assumption but makes it clear that no AHU services two zones at the same time. There can be two AHUs for one zone, i.e they share the same supply pipe. However there are no lines that branch off the AHU and send air to another zone served by another AHU.

The HVAC system is a thermal fluid network. It can be viewed as a pipe network, but unlike a pipe network there are no secondary loops. The entire system is one loop, all air supplied by the AHU is returned to the AHU and is exhausted or recirculated. The air stream moves in one direction only through all devices.

6.1.2 Accessing Data

Accessing data is controlled by reading CSV files that contains properties of all the devices of that specific type in the building as shown in Table 6.1. Therefore, there is a CSV file for each device type. These properties include the name of the specific device, name of the upstream device, upstream type, and the zone the device is in. These properties along with the naming convention of the files are sufficient to describe the structure of the HVAC system. That is, file contains enough information to describe the interrelationship between the components. The upstream field gives the exact name of each device that is directly connected and upstream of the current device. The field, "upstream type" lists the type of device is upstream. Inside the CSV each one of these properties forms a column. Each row is a specific device inside the building The structure of a HVAC system is specific to a building, so there is no underlying pattern for relating one device to another. Therefore, the CSV must be created by the user. Although labor intensive, this only needs to be done once for the life of the building unless the structure of the HVAC system is altered. This CSV is loaded into the script and converted into a struct with each field corresponding to a property.

It is important to note that the data does not reside inside this structure. The structure only maps the relationship between the device. The names listed in the structure contain enough information for the script to locate the folder containing the relevant data. The script reads the device trend listing to acquire the known trends associated with each device. The structure is stored as a CSV file with the device name. The device CSV file has the same name as the folders that hold the

Table 6.1: The format for the device CSV. There is one of these files for each unique device type. This file reflects the structure of the HVAC system

Name	UpstrName	UpstrType	Zone
Breakout 120J VAV-1-23	AHU-4/AHU-4A Supply/...	AHU/Fan/...	4
CSE Break Out 213A VAV-2-34	AHU-4/AHU-4A Supply/...	AHU/Fan/...	4
CSE Lab 206 VAV-2-38	AHU-4/AHU-4A Supply/...	AHU/Fan/...	4

processed data for the device. This name is an abbreviation chosen by the user during pre-processing

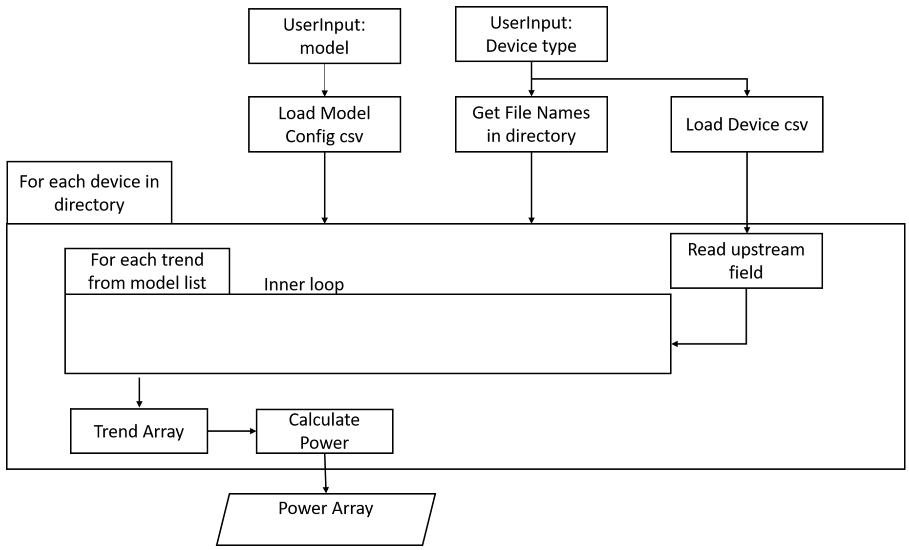
6.2 Power Calculation Process

An overview of the power calculation process is given in Figure 6.1 and how it is implemented is given in this section. The program takes the device type chosen by the user and retrieves the names of all specific devices of that type. Associated with these device types are different models. This program cycles through each specific device. Input files are the device, trend listing and model configuration file. The trend listing and device files were introduced in Chapter 5.

The model configuration file is a CSV file specific to a device type and energy. This tells the program what trends it needs to execute the model and compute energy. This file is shown in Table 6.2. The location of the trend is specified with respect to the current device. If the trend is associated with the device being evaluated then the trend is classified as "local" and if upstream, it is classified as "upstream".

As the program is cycling through the trends it must make certain decisions to reconcile the model with the structure of the HVAC system. This is discussed below. If the trend is associated with an upstream device the process is more involved. The program needs to know if there is more than one upstream device type feeding the current device. Then it needs to know which of those device types have the trend required by the model. Once this information is obtained, the next step is to determine what type trend type it is, whether it is "across" "through," or neither. This trend classification is explained in Chapter 4.

After all trends for the device model are retrieved, power is computed for the selected season and stored inside an array until energy for all devices of the selected type is calculated. The energy data is written to a CSV file where each column



.png

Figure 6.1: The overall process for calculating power.

represents the power consumption of a specific device at 5 minute intervals for the specified season.

6.2.1 Model File Structure

As introduced in 4, there are different models associated with different devices. these models are seperate functions stored along with model config file according to the file structure shown in 6.2.1. Every model has a CSV file that contains the following fields; “name”, “userdef”, “location” and is depicted in 6.2. The name field contains the hard-coded name of the trend which should never change. The field “userdef” contains the name as defined by the user. This is also the same name that is used in the data listing, this can change. Finally, the location field specifies where the trend is in relation to the device in question. Two possible values in this field are “upstream” or “local”. The term “upstream” means the trend is in the file associated with the upstream device whereas the “local” term means the trend is in the file associated with the current device.

6.2.2 Classification of Trend Types

As stated in Chapters 4 and 5, the trends are classified into general types to establish valid ranges when performing pre-processing. These trend types are further classified in order to aid in computing trends downstream of multiple devices.

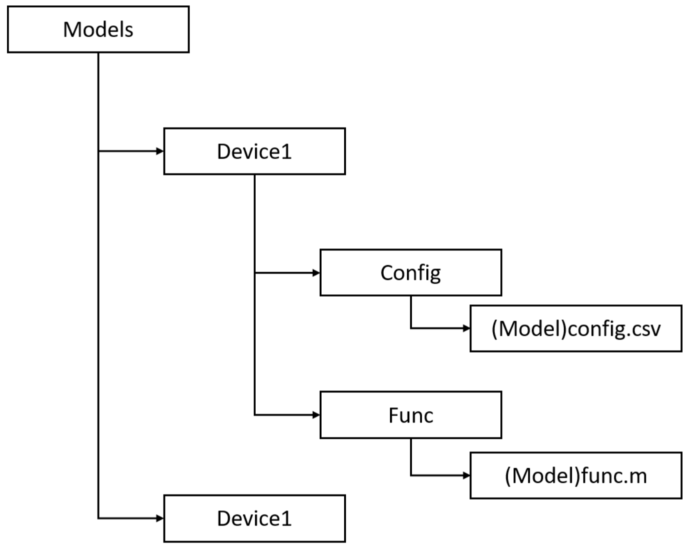


Figure 6.2: This shows the file structure for the models used in the power calculation process

Table 6.2: Model config file format, this particular one applies to a VAV. thermal model.

name	userdef	location
supply_temp	Supply_Temp(F)	upstream
exhaust_temp	Discharge_Temp(F)	local
airflow	AirFlowRate(cfm)	local

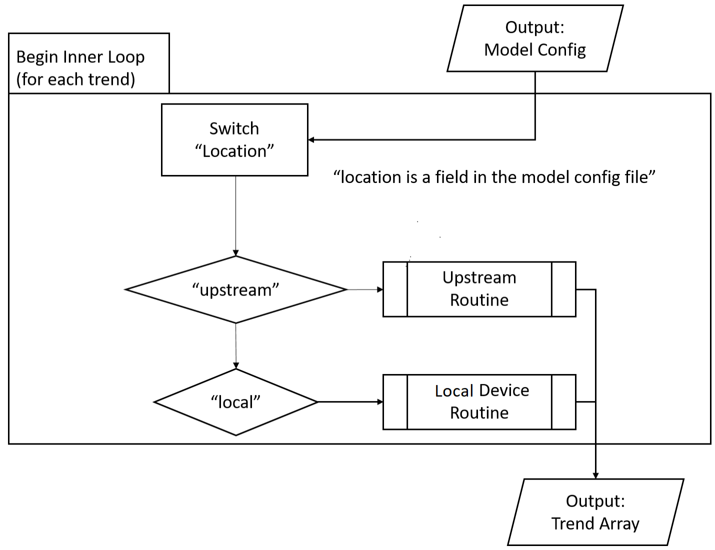


Figure 6.3: The inner loop of the power calculation process. The inner loop cycles through each trend listed in the model and executes a routine based on the location of the trend with respect to the current device.

Depending on if it is "across" or "through", a different procedure is required in order to calculate the trend fed downstream.

6.3 Retrieving Trend Data

As the program cycles through each trend listed in the model. It reads the field in the model configuration file which describes the trends location with respect to the current device. The field either lists the device as "local" or "upstream". This classification determines what routine will be executed in order to retrieve the current trend in the loop. These routines will be discussed below.

6.3.1 Local Routine

If the trend is local the procedure is simple. The program retrieves the trend listing associated with the current device type and pulls the required trend from its associated CSV in the clean data folder.

6.3.2 Upstream Routine

If there is more than one upstream device of the current device then the contribution from each upstream device needs to be considered when calculating energy through the current device. This in part, depends on the type of trend required by the model. The trend can either be "through", "across" or "miscellaneous".

The first part of the upstream routine involves identifying which device types the trend is found in. The program compiles a list of all the device type in which the trend is found. This involves identifying all the unique device types in the upstream field and reading their trend listing files. And searching for the current trend inside the trend listing files. If the trend is a found in a device type then all the number of specific devices of that type that are in the upstream field are logged. This is done for each unique device type. The number of occurrences of the trend in all specific upstream device types is summed up and is referred to as the frequency. Also, noted is the fact that different device types have different names for the same trend. Thus, there is a table that shows the equivalency between trends.

The frequency is the number of occurrences of the trend in all specific devices. Suppose there are 2 unique device types found upstream and of the of those types two specific devices belong to each of the types. So far in this discussion we have 4 devices upstream of the current device. If the trend is found in the trend listing of the two device types then a frequency of 4 will be noted by the program. This is number is used to determine the next action the program takes. If the frequency is 1 then the program executes what is called the single device routine, otherwise the “multiple device” routine is executed. The single device routine executes if there is a single specific device upstream. If there are multiple devices of the same type upstream as in two AHUs in Zone 12 then the multiple device routine will execute.

6.3.2.1 Single Device Routine

This routine will execute if there is exactly one device upstream of the current device. Programmatically, this means in the device csv there is only one device and device type listed in their corresponding fields.

6.3.2.2 Multiple Device Routine

If there are multiple devices upstream a number of inputs defined by the user are required. Each routine first involves identifying all device types upstream. If there are more than one device type then, the trends are grouped according to the device type and then the trends in each device type are matched. The script needs to consult a file listing all the equivalent trends because the same type of trend may have a different name for each device type. If this program is applied to a new building then the user must consult the control points and create a table listing all the equivalent trends between devices.

6.3.2.3 Through Routine Outline

Outlined below is the routine executed if the current trend is classified as “through”. These are trends such as power, and flow rate. This is a subroutine executed inside the multiple upstream device routine. This is only necessary if there is more than one upstream device in the device CSV.

1. Identify each unique upstream device type.

2. retrieve trend-listing for each unique device type.

3. Form the device type block (3d array) as in Figure 6.4.

4. Locate each current trend inside each upstream device type block.

5. Pull the relevant columns corresponding to current trend.

6. Form a 2D array consisting of each trend from each device in each device type block as in Figure 6.5

7. Sum up the rows of the array.

6.3.2.4 Across Routine Outline

In this section the procedure for evaluating an upstream trend that is classified as "across" is outlined. An across variable is analagous to voltage in an electric circuit. If the upstream trend is across the flow supplying the downstream device and the trend itself need to be retrieved. To compute the trend, upstream of the current device, the idea is to treat the common line as a mixing chamber as discussed in Chapter 4. This results in the following procedure.

An input specifically associated with the across routine is the definition of the primary flow rate for each device type encountered and logged is in a CSV. The primary flow rate is the flow that directly feeds the current device from the upstream device. So for example, consider a VAV downstream of the AHU, then the supply flow rate of the AHU is designated as the primary flow rate. Other flow rates associated with the AHU such as return air flow rate and exhaust flow rate are irrelevant since they do not feed the VAV. This can only be described by user input because devices and the structure of HVAC systems vary from building to building. Fortunately, this only needs to be defined once if the structure of the HVAC system does not change or the names of the control points do not change. The latter is more likely because management sometimes changes the names of the control points.

1. Outlined below is the routine executed if the current trend is classified as "across". These are trends such as power, and flow rate.

2. Group relevant trends based on the device type into a 3D array and call it the device type block.

3. Identify the current upstream trend in each device type block.

4. Identify the mass flowrate in each upstream device type block.

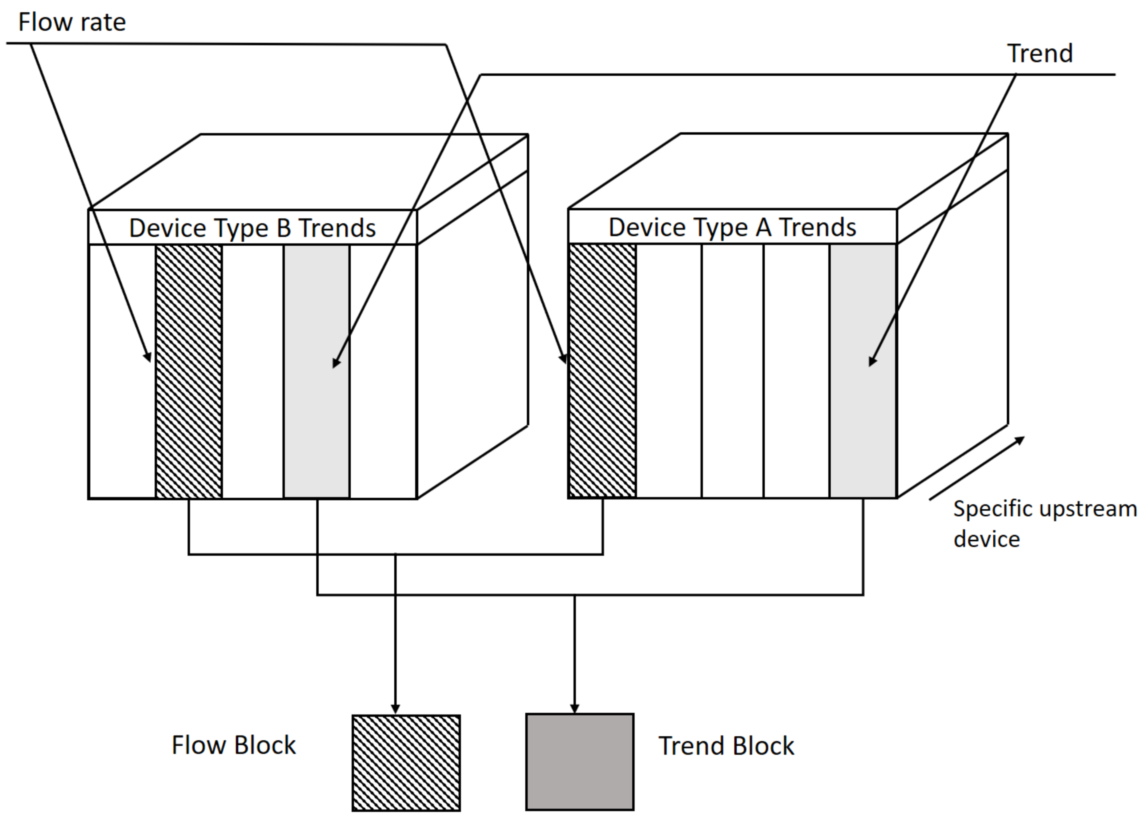


Figure 6.4: Illustration of how the data is organized in the subroutine that handles “across” trends.

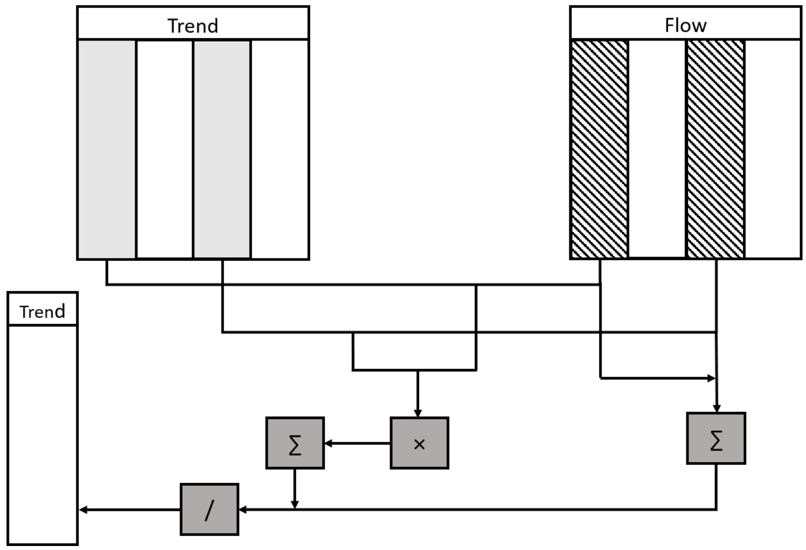


Figure 6.5: This is the second stage of the across routine. After each relevant trend is pulled out of the upstream device "blocks" they are reorganized into 2D arrays.

5. Group all current upstream trends into one block called the "trend block".
6. Group all flowrates into a block and call it the "flow block".
7. Match the corresponding trends and flows.

6.3.2.5 Misc Routine

If the trend is classified as misc, then each trend mut be stored seperately inside an array similar to that shown in Figure 6.5. Currently this is not implemented because models involving these types of trends are not used.

The power data is output is located in a file structure that reflects the user input. This means that the structure follows the data partitioning strategy outlined in Chapter 3 and displayed in Figure 3.1. There is one energy file associated with the model and the device type. The energy file is a CSV with the format shown in the Table 6.3. These energy files are organized according to Figure 5.2.

Table 6.3: The format for the power data.

TimeStamp	Breakout 120J VAV-1-23kW	CSE Break Out 213A VAV-2-34kW
6/28/2016 0:05	1.02E-01	1.18E-01
6/28/2016 0:10	6.39E-01	1.30E-01
6/18/2016 0:15	4.40E-01	6.58E-02
6/18/2016 0:20	2.77E-01	0

Chapter 7

FAULT DETECTION

7.1 Introduction

This chapter presents the structure of the program and the general fault detection procedure. Described here are two fault detection schemes top level and cross level and how they are implemented programatically.In addition, the mathematics behind each fault detection scheme is presented Since the zones are mechanically different, naturally the fault detection process differs between zones. Also, some examples of faults detected in the SE2 building with the procedure described here are presented.

7.2 Building Summary

A detailed description of the SE2 building is given in Chapter 2 and a breif summary is given here. The SE2 building is split into three zones, labeled 1 2 and 3. Each zone is controlled by a different type of HVAC system. Zone 4, known as short bar, is a common single duct VAV system, equipped with hydronic reheat and cooling. It is also pressure dependent. Zone 3 is a simple constant volume system. The AHU controlling Zone 3 is also equipped with an economizer. Zone 12 is treated as a single zone. The AHU controlling both does not heat or cool air aside from a recuperator (energy recovery heat exchanger) that exchanges with the outgoing air. Zone 1 & 2 is a lab zone so ventilation requirements are different than the other two zones. AHU 1 and AHU 2 lack economizers, and all conditioning of air is performed downstream of the AHU in the SAV. The lab zones are also maintained at a negative pressure. From the summary, above, one can gather that the methodology for fault detection in each zone is going to be different. Due to these differences the zones have different sensors, therefore the data available to detect faults is different.

7.3 Program Structure

In this section, the program structure is explained which includes the preliminary conditioning of the data specific to the fault detection scheme. Some abstraction is introduced to aid in organizing the data and programmatically describe the structure of the HVAC system for fault detection. This abstraction aids in applying the fault detection schemes and is flexible and applicable to other HVAC systems

Table 7.1: User input specific to each fault detection method.

Top level	High device type
	Low device type
	Absolute measure
Cross level	Device group
	Device type

in other buildings. However, in this work it will be discussed in the context of the SE2 Building.

7.3.1 Preliminary

The output of the feature calculation stage, an example of which is given in Table 6.3, is a file whose columns represent specific device power consumption and rows represent power consumption at a specific 5 minute interval. The number of rows is equal to the number of 5 minute samples in the season. This data needs to be further processed before it is used in a fault detection scheme. First the data needs further screening. This is due to the fact that some devices consist entirely of bad data. This can be problematic because for both schemes the energy for all devices in a group or the entire zone is summed up. To be consistent, if data is missing for one device for a particular day then the data for all devices during that day are deleted when summed. Concievably, all the data can be deleted. To remedy this, a subroutine is introduced that screens each device column and removes the columns that have more than 50% of their data missing.

The data also needs to be partitioned further between day and night. temporal partitioning was implemented earlier in the pre-processing phase for year, season, and time of the week. Further partitioning is delayed to the fault detection stage, becuase some groups within zones have different operation schedules due to differing functions of the space such as whether it is an office or a lab.

All fault detection schemes have a standard user input.This input is essentailly required to navigate the file structure reflected by Figure 3.1 and retrieve the proper data. Further user input depends on the selected fault detection methodology. The script corresponding to a specific method will prompt the user for information specific to that methodology. The user input specific to each fault detection methodology used in this work is summarized in Table 7.1. All fault detection routines impliment the basic structure shown in Figure 7.1.

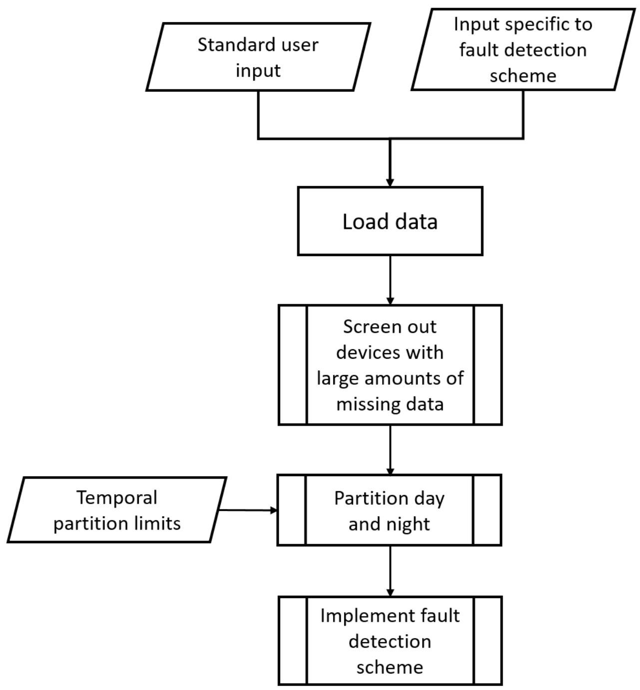


Figure 7.1: The process implemented before every fault detection scheme. Devices possesing large amounts of erroneous data are removed and the remaining device data is partitioned between day and night.

7.3.2 Device Hierarchy

To simplify the HVAC system to a point that a FDD scheme can be applied to a building consisting of different types of system some abstraction must be introduced. A classification scheme that applies to all systems must be established. It is observed that most HVAC systems resemble a tiered system consisting of a bridge that feeds all zones in the building. For each zone there is an AHU that feeds devices under it which in turn feed air to the rooms, directly feed the rooms. Thus, the methodology in this project asserts that there are three layers to the HVAC system. The top layer consists of the AHUs, which are known as upper devices. The VAVs, and SAVs are intermediate devices. All sensor inputs associated with the thermafusers or specific rooms are known as lower devices. All lower and upper devices have a supply variable for computing energy. Upper devices do not have a supply variable. The supply variable often comes from the data associated with the device upstream of the device in question and in reality they are physically connected by ductwork. High level devices serve at the zone level, intermediate devices serve the group level and low-level devices serve a small area. There may be multiple low-level devices for a large room. Also, some rooms may not have low level devices and some zones may not have intermediate devices. However, all zones have a high-level device, that is every zone has a AHU. See figure for the illustration. This organizational scheme is used in the fault detection phase. In this work the bridge is not considered and the highest level is taken to be the AHU.

7.3.3 Device Grouping Scheme

As stated in the chapter on spatial partitioning Chapter 3, an AHU will serve a large area with diverse architectural parameters, occupancy settings, and sun exposure. For this FDD scheme to be effective, spatial partitioning is required. Hence there needs to be an effective strategy to group areas based on location. Some areas are exposed to sun and some are not with different levels of occupancy. The grouping scheme is based on devices with similar loads. This there is a separate structure to contain the device groups. In the case of the SE2 building, grouping is necessary for Zone 4 and Zone 12. These are very large and have different zones. Grouping is unnecessary for Zone 3 and itself can be considered a single group. The device grouping scheme will be used during the fault detection phase of the program, it is not used during energy calculation. The grouping scheme is seperated from the HVAC structure file because the device grouping scheme is subject to change where as the structure CSV is not. The grouping scheme is not based on rigid connections between the system components but an abstraction created to group objects with similar loads. The grouping implies that there are sub groups of these devices in the same zone, the groups are formed by the considering the space the VAV serves. For example, all VAVs serving interior spaces would form a group and buildings on the left side of the building would form a group. It must be noted that this grouping scheme is flexible and subject to change. Groups based on both occupancy and sun exposure usually cannot be formed because forcing both conditions to form a group will result in a group that is too small. One must consider the season, for example, during summer time the building has low occupancy while sun exposure is a huge load. Therefore, when analyzing the building during the summer one should focus on grouping based on sun exposure.

7.4 Component Faults.

In literature, there are many documented hardware faults for HVAC systems. The ones that pertain to SE2 HVAC system are listed and their causes are summarized in this section. There are specific faults to each component. There are no documented faults for thermafuser or SAV in literature as these components are not widely used.Since most of their subcomponents are the same as those found in VAVs , it is assumed that they are susceptible to the same faults as VAVs. The only difference is that the SAV is much larger unit and it has two valves one for supply and exhaust to modulate the pressure inside the lab. The valve is plunger rather than a butterfly valve. AHUs 3 and 4 are mechanically similar. AHU 1 and 2 are atypical of air handling units since they do not have the ability to condition air and lack air economizers for reasonings pertaining to requirements for labs.

7.4.1 VAV

VAVs are diverse in their construction, so this discussion shall be restricted to the pressure dependent VAVs with single duct and hydronic reheat and cooling. Heating and cooling coils can foul, this means that inside the tube deposits can take place especially if the tube is using water to heat or cool the air. The fouling can either be on the air side or the water side of the heat exchanger. Fouling for the water side would be in the form of scale deposits on the inside of the tube. Deposition of dirt on the outside on the airstream is expected. Associated with the coil is the valve. Fouling occurs over time, whereas the valve is more likely to suffer catastrophic failure as it is a mechanical component that changes position constantly to modulate water flow in the coil. Stuck dampers are when the damper for the VAV stays in the same position for an unusually long time. This can be viewed in the trends as a constant flowrate or damper position for long period of time. This can be either indicative of a hardware failure, or a control system failure known as hunting. Hunting is where the valve oscillates around a certain position and is due to improper constants in the PI or PID controller [22].

7.4.2 Thermafuser

The thermafuser is a simple device consisting of sensors and a valve, thus all the faults that can be triggered with sensors can result in a thermafuser fault.

Also, the thermafuser can modulate air flow with a plunger valve and this can concievably suffer mechanical failure. Furthermore, the building management can lock the thermafuser valve so it does not move, so this may be another reason why a room may give faulty reading. Often times more than one thermafuser serves a space, so one can use cross checking among thermafusers to confirm faults.

7.4.3 SAV

The SAV contains many of the same components as a VAV such as a heating and cooling coil. The SAV differs because it has two plunger valves, one for intake and exhaust. These valves are also a possible failure point along with all the sensors that are located in the unit. Fault detection strategey for VAVs will be similar to VAVs since they are both classified as intermediate devices.

7.4.4 AHU

The AHU is single most fault prone component in the system since it is composed of the most moving parts and sensors. The AHU can be subject to frozen fans, stuck dampers, faulty heating coils, and faulty sensors. There is a sensor for the return, supply, outside air, and mixed air temperatures. There is a heating and cooling coil, 2 fans, and 4 dampers. Since the AHU is the top level device, often faults located downstream will be indicated as a fault in the AHU.

7.5 Mathematical Methods For Fault Detection

In this section, mathematical techniques utilized for fault detection are introduced and their relevancy is discussed. The methods used are PCA and correlation analysis.

7.5.1 Principal Component Analysis

PCA is a common data reduction technique fundamental to statistical analysis. The following discussion provides a brief overview of PCA. PCA changes the basis to reduce redundancy between two variables In general PCA creates a new basis from the existing vectors [23]

Consider a $m \times n$ matrix X where each column vector represents a variable with a n number of samples.

$$X = \begin{bmatrix} \vec{x}_1 & \cdots & \vec{x}_m \end{bmatrix} \tag{7.1}$$

Equation (7.2) is called the covariance matrix and is a symmetric $m \times m$ matrix. It encompasses all the interrelationships in the dataset.

$$Cov = \frac{1}{n-1} X X^T \tag{7.2}$$

The off-diagonal terms of the covariance matrix are called the covariances, and the diagonal terms are the variances.

Since the covariance matrix is symmetric the it can be decompose into two orthogonal matrices and a diagonal matrix. Assume there is some matrix Y such that the following is true.

$$Y = PX \tag{7.3}$$

$$Cov = \frac{1}{n-1} YY^T \tag{7.4}$$

It is shown without proof that the covariance matrix is diagonalized and the columns of the matrix P are the eigenvectors of the covariance matrix. This eigenvectors in the context of PCA are known as the principal components. These principal components represent a new basis that is a linear combination of the old basis. In the new basis the covariances are now as close to zero as possible and thus there is less redundancy in the data. Although versatile PCA is limited by the following assumptions [21].

1. The data fits a Gaussian distribution. That is, the variance and mean are sufficient statistics to describe the data.

2. The data sets are linearly related.

3. The larger variances are associated with more relevant dynamics. The lower variances are associated with noise.

4. The principal components are orthogonal.

In addition, PCA is related to the singular value decomposition (SVD). The SVD decomposes a matrix into two orthogonal matrices and a diagonal matrix of "singular values." The MATLAB implementation of PCA utilizes the SVD rather than the method discussed above.

The method applied in this current work utilizes PCA [13]. Previously it was mentioned that a limitation of PCA is the fact that it is based on the assumption that the variables are linearly related. Unfortunately this is far from the case with HVAC. However, one can still extract meaningful dynamics from the system using PCA. The relationships variables among the relevant variables in devices may be nonlinear. However, the energy consumption between the components at different levels is close to linear. That is the correlation coefficient between the energy consumption of the upper level devices and the sum of the lower level device is close to 1 [24]. In general prior knowledge of the dynamics of the system are incorporated into the model before performing PCA.

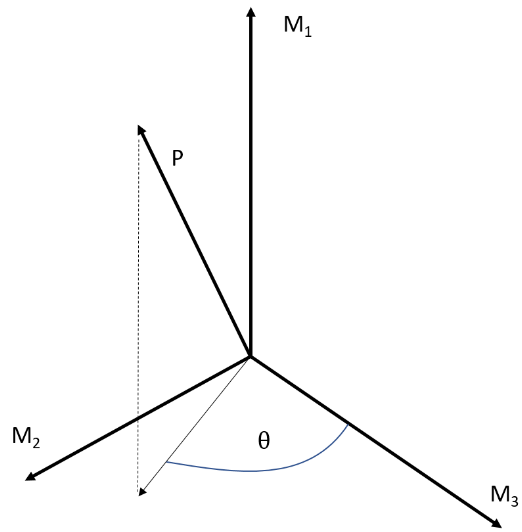


Figure 7.2: A graphical representation of the first principal component.

The first dominant eigenvector from a dataset selected. The first principal component which best describes the state of the system is projected on planes formed by each of the two measures. A properly functioning HVAC system is represented by a system vector whose projection lies in the first quadrant of all three planes as shown in figure 7.2.

The projection is given by Equation (7.5) [25]

$$proj = \frac{P_1^T A}{\parallel P_1^T A \parallel} \tag{7.5}$$

where A is a plane formed by two of the three measures and P_1 is the first principal component. The projection p is a 2 dimensional vector the angle can be found from finding the inverse tangent between the components of the vector.

7.5.2 Correlation Analysis.

For detection at the lower level correlation analysis is used. The correlation coefficient for two different measures X and Z are calculated for each day. The correlation coefficient is given by Equation (7.6) where σ is the standard deviation.

$$corr(x, y) = \frac{cov(X, Z)}{\sigma_x \sigma_z} \tag{7.6}$$

The diagnostic methodology for each zone is different due to structural differences. Zone 4 is a standard single duct VAV system. Zone 3 is a constant volume system. The majority of Zone 12 consists of labs. No conditioning of air is done at the AHU level in Zone 12. Most conditioning is done at the SAV level, with each SAV equipped with a heating and cooling coil. Zone 12 requires a different methodology for diagnostic than Zone 4 and 3.

7.6 Fault Detection

Currently this fault detection scheme utilizes two methods for fault detection referred to as top level and cross level fault detection [13]. Overall, they both constitute what is called top down system level fault detection. All implementations required a certain amount of user input which includes all the specifics associated with the temporal and spatial partitioning strategy discussed in Chapter 3 and specific inputs as required by the method chosen.

7.6.1 Top Level Fault Detection

The top level fault detection essentially compares the energy consumption between device types at different levels and an absolute measure which in this work is outside temperature. The device types must be at different levels. With respect to Zone 4, for example one could consider the energy consumption of the AHUs and the VAVs which are at lower levels. In general, there needs to be a group of high level devices and lower level devices. In the current stage of this work the "lower" devices is considered to be a device immediately downstream of the high level device. So, the lower level device in Zone 4 would be VAVs. In Zone 3 the lower level device would be the thermafuser. It must also be noted that the terminology high and low with respect to this fault detection methodology differs from the general classification of devices of high, intermediate, and low with respect to the topology of the HVAC system mentioned in 7.3.2. High and low in this sense are relative terms. Conceivably, the high device could be a VAV and the low devices are thermafusers directly connected to the VAV.

As introduced in Section 7.5.1, the foundation of this fault detection process is PCA. After pre-processing and calculating energy, the first stage of the fault detection process utilizes principal component analysis using three features of the dataset. These features consist of an absolute measure and relative measures comprising power consumption of both the high and low-level device. With these features an $n \times 3$ matrix is formed. This entire dataset usually corresponding to one season is split up into periods, which in this work is a day. The z-score is first taken for the entire dataset and then for each day period. Then principal component analysis is applied. Through PCA a 3×3 matrix is formed and the dominant principal component(eigenvector) is obtained. The principal component describes the operational characteristics of the system in terms of the three measures for the specified period. This dominant principal component is then projected onto each plane formed by a pair of measures. Finally, the angle between this projection and the basis vectors formed by the measures is used an indicator of faulty or proper operation. The entire process discussed here is implemented programmatically and the main functions that implement it are outlined in Figures 7.3 and 7.4. The Figure 7.4 outlines a subfunction of the function outlined in Figure 7.3. The average of the slopes for the entire season is computed along with the standard deviation. The mean and standard deviation are used to establish a “upper” and “lower” threshold for the slopes. Along with the slopes these thresholds are plotted. The output of this process is a graph consisting of daily slopes and thresholds, an example of which is shown in Figure 7.6.

To clarify the what the constitutes a measure, this topic is discussed in the context of Zone 4. The two relative measures would be power consumption of the AHU and VAV which are the measures associated with the high and low device respectively. The absolute measure is commonly taken to be the outside temperature since it is directly tied to the environment. However, implemented in this work one can choose any trend to be the absolute measure. It is unknown currently what purpose this may have in the future, but this feature is retained in the program for possible exploration.

Proper operation of any component of the system, in theory, should manifest itself as a projection of the dominant daily principal component in the first quadrant at a 45-degree angle. This indicates a linear positive correlation which would be expected from these measures since one would expect energy consumption to rise with temperature during the summer. In practice, 45 degree angles are not realized so for normal operating conditions it is expected that the principal component projection lies within the first quadrant of the plane formed by the two measures. See this figure below. A projection of 45 degrees indicates a linear relationship between the two quantities.For example, a bad projection between for $AHUvVAV$ and $AHUvTOA$ would indicate a fault located in the AHU. A similar combination with energy consumption of the zones would indicate a fault located in one of the VAVs downstream of the AHU. Also, faults that have low impact on energy consumption may go undetected at this stage [24].

It must be noted that the top level fault detection in this current form is not applicable to all types of HVAC systems. An example of this is Zone 12 in the SE2 building. The air handling units which are the high devices are not equipped to condition the air, so it would not be expected for their energy consumption to have a high correlation with outside temperature. For this zone it is recommended to skip this step and move to the cross level detection scheme presented in the next section.

The basic top level fault detection procedure is outlined below.

1. Select a high level device.

2. Select a low level device.

3. Select an absolute measure.

4. Retrieve a data feature associated with the above devices (the current work uses power).

5. Form a $nx3$ matrix with the whose columns are data associated with the energy data and absolute measure.

6. Apply the method presented in Section 7.5.1.

7.6.2 Cross Level Fault Detection

In cross level detection, performance of device types at the same level are compared. A data feature is selected which in this work is taken to be power consumption. Devices at the same level in the same zone are grouped based on their spatial characteristics. The group and device type is selected by the user and the power consumption data is retrieved for devices of the same group. The next step is to compute the daily correlation coefficient of each power consumption of each device with respect to power consumption of the group. Also, the mean correlation coefficient along with the standard deviation for the entire data set is computed. The mean and standard deviation are used to establish upper and lower thresholds. The thresholds along with the daily correlation coefficient with respect to the group are plotted for each device. The entire process is outlined in Figure 7.5.

In general, correlation coefficient assumes a linear relationship between the two datasets. Therefore, a correlation coefficient of 1 would indicate a perfect linear positive relationship between the device and its group. In general, this is not reached because the spaces are not perfectly identical, but a correlation coefficient 0.8 or higher is a good indicator that the device operating properly. Also, if the device operates within the threshold this also may indicate proper operation but not necessarily. For example, a device can have bad data for the entire dataset that represents an entire seasons. This situation is given as an example in section 7.6.4.2 and shown in Figure 7.10. Another possiblity is that the device normall does not correlate with its respective group. Therefore the thresholds must be understood within a physical context. Also, note that cross level checking assumes that majority of the devices in the group are operating properly, this scheme will fail if all the devices in a selected group are performing poorly. Therefore, because of this along with statistical reasons, it is good practice to have large groups with many devices. Programmatically, the grouping is not hard-coded and is at the discretion of the user. This is due to the varying loads encountered by the HVAC system for different seasons.

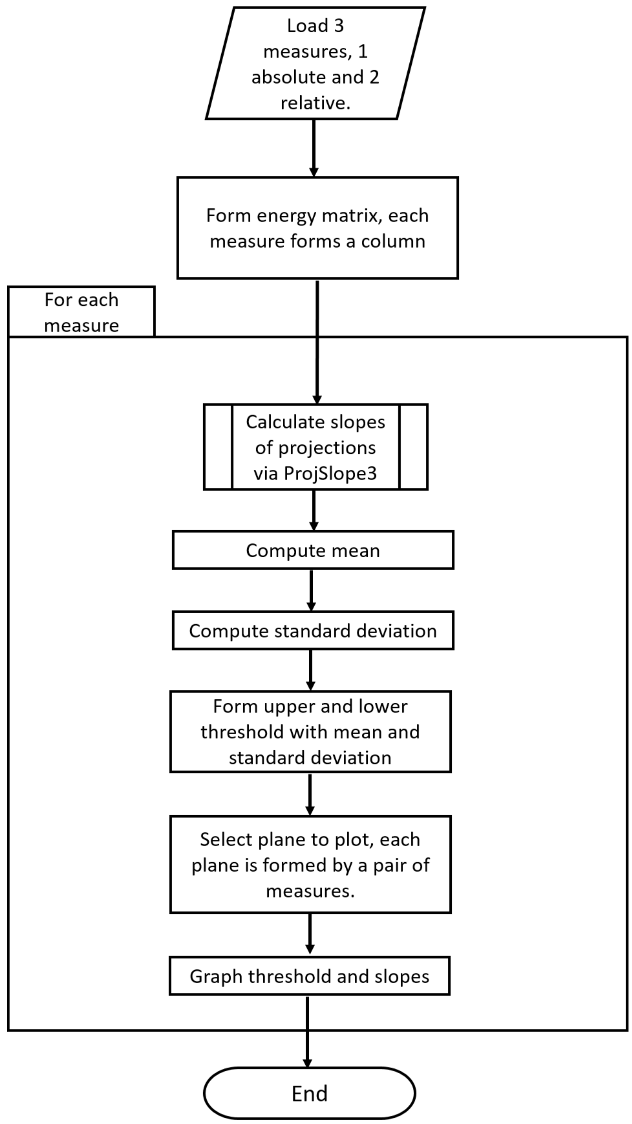


Figure 7.3: Main subfunction for the top level fault detection scheme.

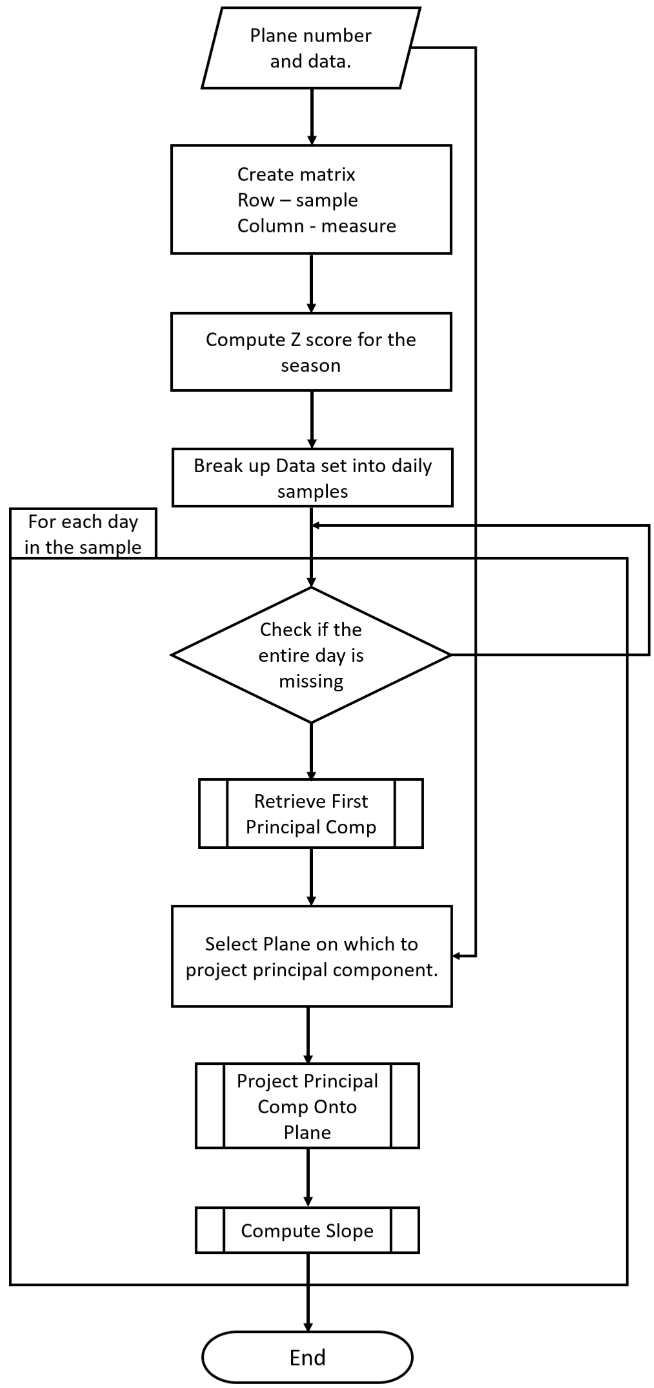


Figure 7.4: Subfunction of the function depicted in Figure 7.3. This function takes the data and computes the projection of the slopes onto each plane formed by each pair of measures.

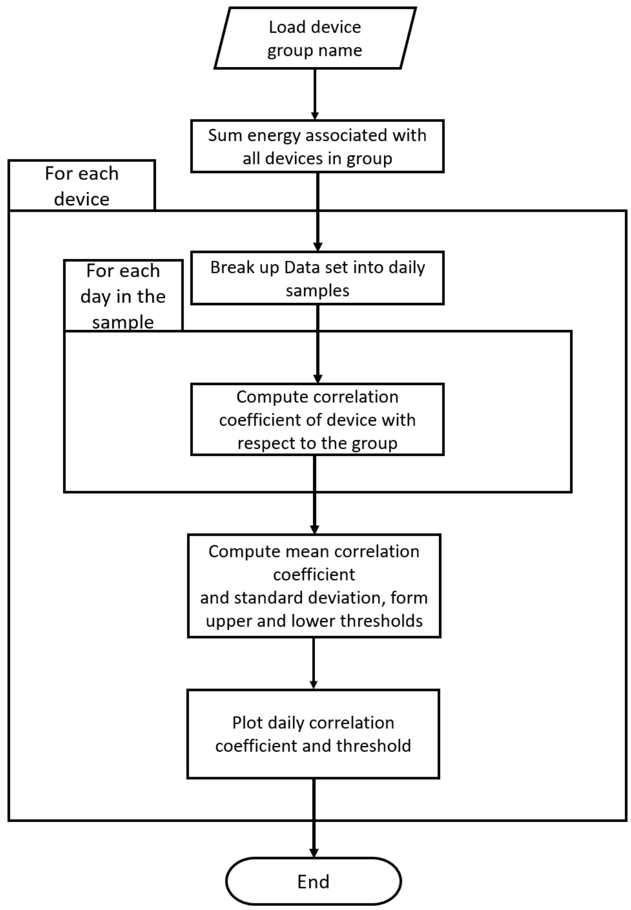


Figure 7.5: Process flow for cross level fault detection. It involves comparing the power consumption behavior of devices to their group.

The steps for cross-level fault detection are outlined below

1. Select a device.
2. Select a device group.
3. Retrieve a data feature associated the device and the sum of energies of the group it belongs to.
4. Compute the daily correlation coefficient between device and its group.

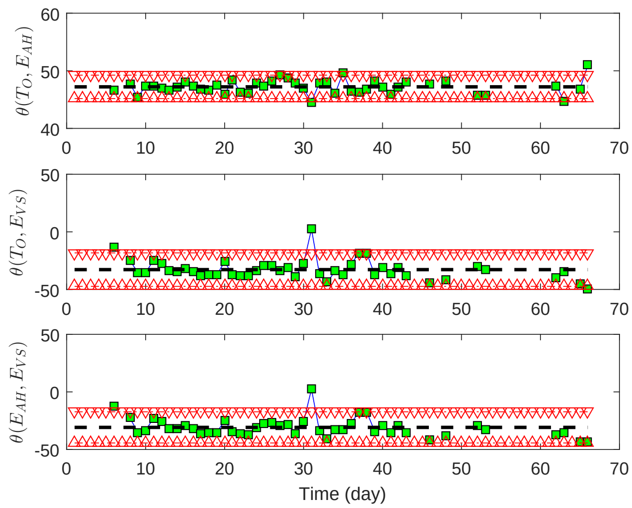


Figure 7.6: First stage of fault detection depicting the plot of the daily slopes. A slope of 45 degrees indicates a proper functioning system. In this case the AHU is working properly while the lower level VAVs are not. The period spans June 22nd to September 16th 2016.

7.6.3 Fault Detection Examples

In this section, an illustration of the fault detection process is given. The first example illustrates the first stage of fault detection which implements the PCA method. The other two examples occur at the intermediate device level and utilize the cross level detection using correlation analysis. The examples discussed below are derived from data that spans the time period from June 22nd to September 16th 2016.

7.6.4 First Stage of Fault Detection

An example of the top level detection graph is shown in 7.6. The angles between the AHU measures and the outside temperature measures are within the threshold and are in the first quadrant centered around 45 degrees. This is indicative of proper operation. On the other hand the VAV energy measure is negativly correlated with both the AHU and the outside temperature. This implies there are faults in the VAV system. Notice that since the VAV system is faulty for the entire period, all slopes related to the VAV are out of the first quadrant. In this case the thresholds are irrelevant.

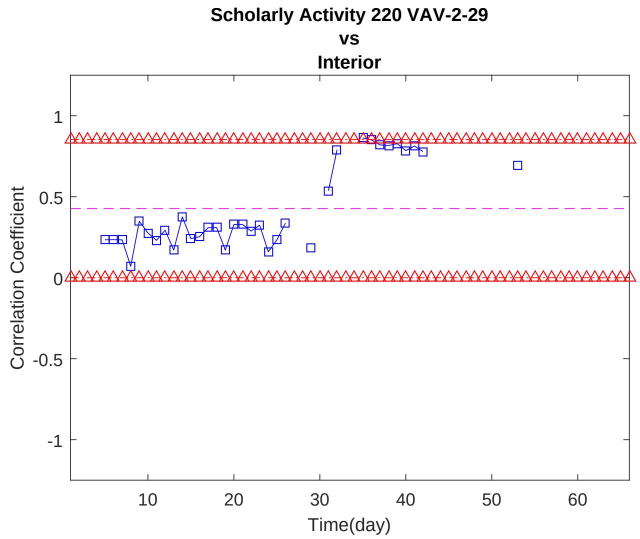


Figure 7.7: Daily correlation plot for VAV 2-29 spanning from June 22 to September 16th. The sudden change in the plot suggests a fault.

7.6.4.1 Stuck Heating Valve

An example of a stuck heating valve was found for VAV 2-29 which is a conference room located in interior portion of the short bar of the SE2 building. Some aspects of the graph displaying correlation coefficient are worth scrutinizing.

Observing Figure 7.7, as expected the energy consumption between VAV 2-29 is positively correlated with all days during the selected period. However, note that for most of the period the correlation coefficient is much lower and then experiences a sudden spike in late July. Since most of the days have a difference in correlation coefficient the threshold becomes very wide. There would be no fault if thresholds alone were used to detect a fault since all the correlation coefficients fall within the threshold.

To confirm this fault a plot of the hot water valve position is shown in Figure 7.8 and note that it is open for most of the summer and then suddenly drops to zero. This sudden drop in the hot water valve position corresponds to the rise in correlation coefficient in the correlation graph. The reason for this is simple, the fact that the VAV was in heating mode most of the summer is unusual since Merced experiences very hot summers often exceeding 100°F. This is observed in the correlation graph suggesting that the behavior of VAV2-29 is not like the behavior other VAVs in the group. The fault was eventually detected by building management after a complaint suggesting the room was too hot.

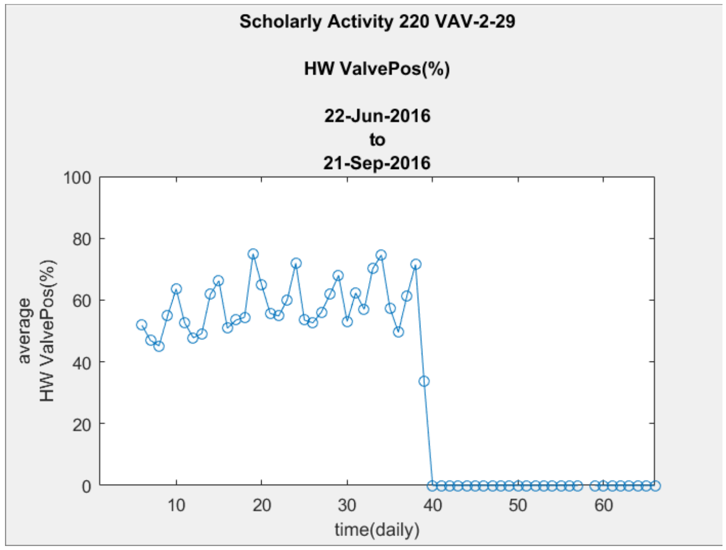


Figure 7.8: Plot of hot water valve position for VAV 2-29 for the summer season. The hot water valve is open which suggests a fault.

7.6.4.2 Stuck Damper

A stuck damper was discovered inside VAV 2-34 which is part of the group of VAVs that serve the interior of short bar . The correlation graph is shown in 7.9. Note that all the daily correlation coefficients fall within the threshold. However, the daily correlation coefficients are close to zero which implies that the behavior of the VAV does not march the behavior of the group.

After inspection of the correlation graph, trends pertaining to the energy model are scrutinized. Upon scrutinizing the trends, it is noticed the air flow for this VAV seems very low. This leads one to believe there is a stuck damper. A graph of hourly damper position for July 14-15 2016 is shown in the Figure 7.10. The damper position shows a flat trend for the rest of the day where it is near 20%. For comparison, graphs of the damper position for VAV 2-37 and VAV 2-33 are shown in are shown in Figures 7.11 and 7.12 respectively. These VAVs are of interest because they service spaces that are adajcent to the area served by VAV 2-34 and the areas they serve have similar functions, hence their trends should be similar. Also, VAVs 2-32 and 2-37 both correlate with the group in terms of energy consumption so it is expected that their damper position show normal behavior. It is expected from comparing the graphs of all three VAVs, that it is safe to assume that VAV 2-34 has a faulty damper.

The above examples both illustrate the advantages and limitations of the methodology as developed in this work. Therefore, this work is called fault detection

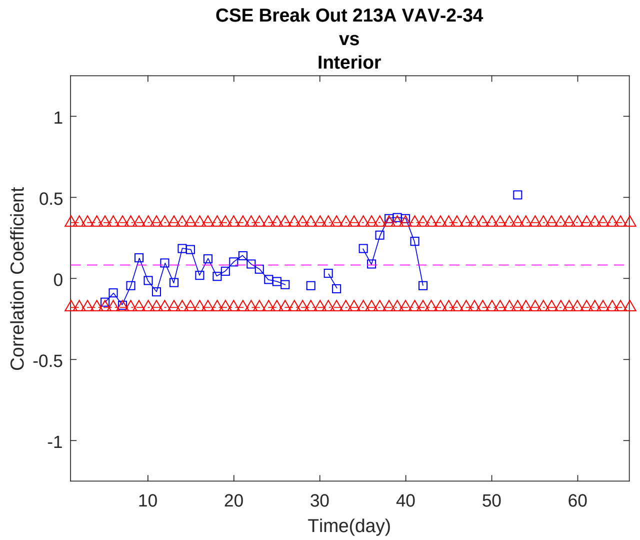


Figure 7.9: Daily correlation graph for VAV 2-34. This correlation graph suggests a fault.

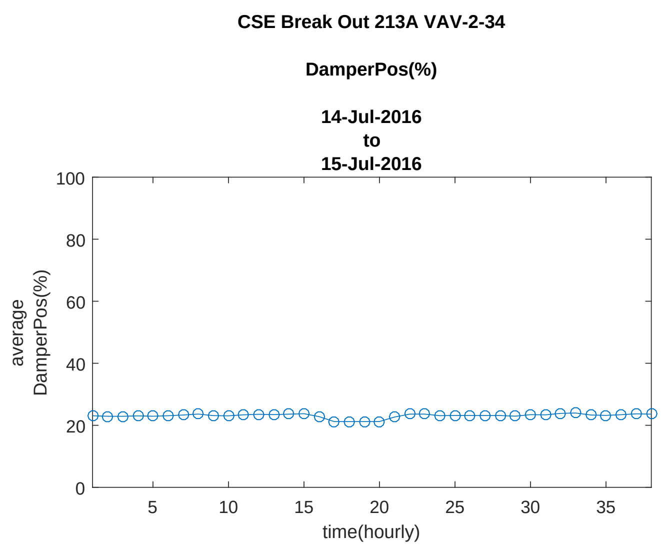


Figure 7.10: Plot of the damper position for VAV 2-34. The flat curve suggests a stuck damper.

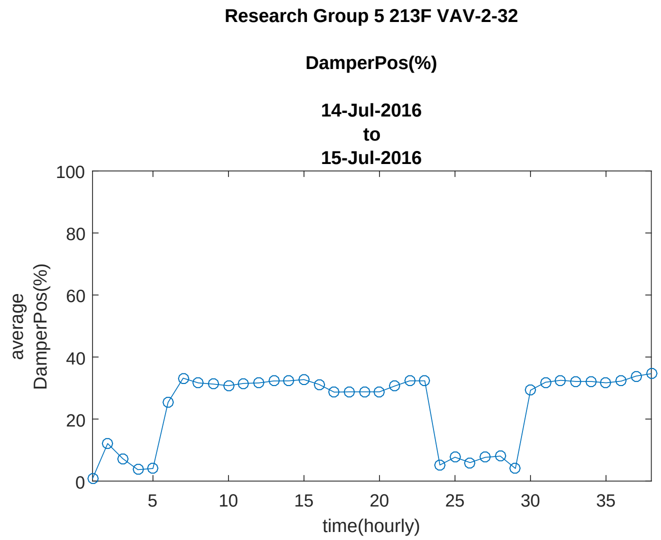


Figure 7.11: Plot of damper position for VAV 2-32. This curve represents a properly functioning damper.

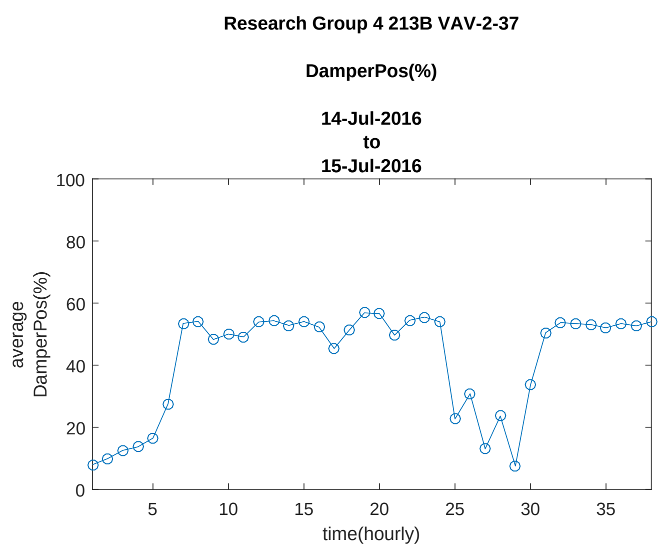


Figure 7.12: Plot of the damper position for VAV 2-37. This is a properly functioning damper.

and does not go the full extent of making a diagnosis. This work as it stands still requires expert diagnosis however it does reduce the work in detecting a fault.

Chapter 8

CONCLUSION FUTURE WORK

8.1 Concluding Remarks

A versatile system level fault detection scheme is created. The program that implements this scheme is split up into three modules; pre-processing, feature calculation, and fault detection. The interrelationship between the modules is shown in Figure 8.1

First, a pre-processing module that automatically collects data from the WebCrtl server was created. The script that collects data was implemented in python. This "raw" data is fed directly to the pre-processing module. In the pre-processing module the data is "cleaned" by removing obviously erroneous values. All erroneous and missing values are replaced with NaN and are logged for future reference.

Models applicable to specific device types are created for the system. There may be more than one model for the device but both calculate power. The models included in this work are the pressure balance model and temperature model. These models were created because some faults may exhibit themselves more clearly from using different variables in the model. For example, damper faults may be more prevelant if power using pressure drops instead of temperature drops is calculated.

Also included is a system to organize the devices. This device organization must reflect the physical structure of the HVAC systems by representing the interconnections between the devices. This aids in calculating the models by facilitating the data retrieval process. Integrated into the physical structure is the spatial and temporal partitioning schemes established by [13]. With respect to temporal partitioning, it is built into the scheme that trends be classified as based on year, season, and time of the week. Further temporal partitioning down to the time of the day is at the discretion of the user and can be changed. This is because HVAC systems have different operating schedules for different buildings. With respect to spatial partitioning, devices that serve specific areas such as VAV boxes are subjected to a partitioning scheme. High level devices such as AHUs are not subjected to this type of grouping. The grouping scheme applies to lower level devices because they are responsible for local conditioning of the air based the occupency and sun exposure of the space due to orientation and architectural parameters of the building. Architectural parameters includes effects such as overhangs and windows that can influence exposure.

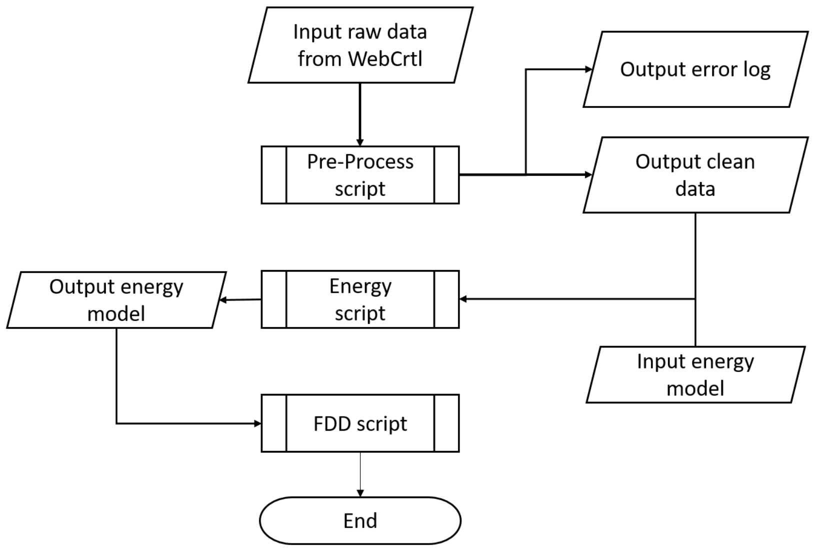


Figure 8.1: The structure of the fault detection program consisting of a pre-processing, feature calculation (energy script), and fault detection (FDD script) module.

Finally, fault detection is implemented on a building wide scale utilizing two fault detection schemes. These consist of top level and cross level. Top level consists of cross checking devices at different levels along with an absolute measure such as temperature. Ideally, the level at which a fault occurs can be isolated and then the one can proceed to cross level checking. In practice, however, this approach is not feasible due to the structure of the HVAC system (e.g. Zone 12.). Therefore, when implemented programmatically the user is able to skip the top level stage and proceed to the cross level stage.

8.2 Future Work

This application is workable in the sense it can used to detect faults. However, further improvements to the application described in this thesis can be made. Specific areas of improvement include pre-processing, user interface and fault detection models. Various short commings and improves are discussed below.

8.2.1 Pre-Processing

This work is equipped with a rudimentary cleaning process for removing bad data. This module can only detect obvious sensor faults. There needs to be an algorithm developed that can detect sensor faults that are less obvious such as bias.

The pre-processing module should be generalized such that different schemes for cleaning the data can be easily implemented.

In the current form, this program uses batch processing. The program operates on a large amount of data corresponding to a specific time e.g. one summer. This can be extended to operate daily, since the files correspond to one day. With little modification, this script can be modified to take in training data. Then operate on a CSV file as it comes in representing each day. Since parameters in HVAC operate slowly, monitoring the system daily is not a significant limitation. Faults in HVAC are generally not safety critical and this is evidenced by the fact that some faults persist for months on end without detection.

8.2.2 User Interface

For this to be a refined commercial product a more user-friendly interface must be created. Possibly a graphic of the system layout for each zone should be shown as an interface. If a faulty component is detected the graphic for that component in the layout changes to a different color. If the user clicks on each component in the layout diagram a box with the energy consumption trends appear.

8.2.3 Fault Detection

The work presented in this thesis leaves open the possibility of expansion in regards to fault detection to different HVAC systems and detecting different types of faults. Any future work should validate this by expanding the scheme to different types of HVAC systems.

It was understood from the beginning that HVAC systems are very diverse which is one of the reason data driven methods are very attractive for fault detection over other methods such as expert rules. This scheme can be extended different types of HVAC systems comprising a mixture of single duct and double duct VAVs. This was the rational for making the ability to add models to the script relatively easy. In the future, one can write new models for computing energy for these types of components to extend this fault detection strategy to these types of systems.

The UC Merced campus beyond the SE2 building contains buildings with different types of HVAC systems. For example, the classroom office building utilizes a mixture of double duct and single duct VAVs. It is possible to validate this methodology with these types of HVAC systems in the future. This scheme was developed with the intention that it be scaled up to different HVAC systems.

This scheme was only used to detect a few faults which were given as examples. There are faults that this system does not detect. Further extension of this program, will require the testing for different types of faults. For the current research, this presents a difficulty. It is difficult to test the script on something like a HVAC system due to the scale of such systems. Experimental setups are costly to model such systems. Detailed simulations are also difficult to implement. Thus, the most economical course of action is to apply the scheme to different buildings. Furthermore, the grouping scheme does not take into different types of devices at the same level. There are some systems that have different types of VAVs at the same level i.e. fed by the same AHU. Different types of devices in the system implies that these systems have different trends associated and hence energy consumption pattern. The grouping scheme spatial partition needs to account for this aspect of a system.

Again, this system is implemented with large HVAC systems in mind. The cross-level checking of components works much better when there are large amounts of devices. This methodology is not intended for small single zone systems such as those found inside residential dwellings or small businesses but rather large central air-conditioning systems serving large buildings.

This work only focuses on detection faults and not diagnosing them. An effective fault diagnostic scheme is necessary and one can possibly utilize machine learning techniques for this.

BIBLIOGRAPHY

[1] US Energy Information Administration annual energy outlook, Department of Energy (DoE) .

[2] M. Wiggins, J. Brodrick, HVAC fault detection, ASHRAE Journal 54 (2) (2012) 78–80.

[3] T. A. Reddy, Automated fault detection and diagnosis for hvacr systems: functional description and lessons learnt, in: Proceedings of the Second International Conference on Energy Sustainability, ES, Vol. 2009, 2008, pp. 589–599.

[4] J. Schein, S. T. Bushby, N. S. Castro, J. M. House, A rule-based fault detection method for air handling units, Energy and buildings 38 (12) (2006) 1485–1492.

[5] S. Katipamula, M. R. Brambley, L. Luskay, Automated proactive techniques for commissioning air-handling units, Journal of solar energy engineering 125 (3) (2003) 282–291.

[6] S. Katipamula, M. R. Brambley, Methods for fault detection, diagnostics, and prognostics for building systemsa review, part i, HVACR Research 11 (1) (2005) 3–25.

[7] S. Wang, F. Xiao, AHU sensor fault diagnosis using principal component analysis method, Energy and Buildings 36 (2) (2004) 147–160.

[8] Y. Zhao, S. Wang, F. Xiao, Pattern recognition-based chillers fault detection method using support vector data description (SVDD), Applied Energy 112 (2013) 1041–1048.

[9] S. Wang, J.B. Wang, Robust sensor fault diagnosis and validation in HVAC systems, Transactions of the Institute of Measurement and Control 24 (3) (2002) 231–262.

[10] D. Dehestani, S. Su, H. Nguyen, Y. Guo, Robust fault tolerant application for HVAC system based on combination of online svm and ann black box model, in: Control Conference (ECC), 2013 European, IEEE, 2013, pp. 2976–2981.

[11] D. Lee, B. Lee, J. W. Shin, Fault detection and diagnosis with modelica language using deep belief network, in: Proceedings of the 11th International Modelica Conference, Versailles, France, September 21-23, 2015, Linkping University Electronic Press, 2015, pp. 615–623.

[12] C. Fan, F. Xiao, Y. Zhao, A short-term building cooling load prediction method using deep learning algorithms, Applied Energy 195 (2017) 222–233.

[13] S. Wu, System level monitoring and diagnosis of building hvac system, Doctor of philosophy, University of California Merced (2013).

[14] Z. Du, X. Jin, Detection and diagnosis for multiple faults in vav systems, Energy and Buildings 39 (8) (2007) 923–934.

[15] M. J. Moran, H. N. Shapiro, Fundamentals of Engineering Thermodynamics, 4th Edition, John Wiley and Sons, New York, 2000.

[16] G. Shim, L. Song, G. Wang, Comparison of different fan control strategies on a variable air volume systems through simulations and experiments, Building and Environment 72 (2014) 212–222.

[17] S. Wang, Q. Zhou, F. Xiao, A system-level fault detection and diagnosis strategy for HVAC systems involving sensor faults, Energy and Buildings 42 (4) (2010) 477–490.

[18] T. A. Myers, Goodbye, listwise deletion: Presenting hot deck imputation as an easy and effective tool for handling missing data, Communication Methods and Measures 5 (4) (2011) 297–310.

[19] K. Lakshminarayan, S. A. Harp, T. Samad, Imputation of missing data in industrial databases, Applied Intelligence 11 (3) (1999) 259–275.

[20] A. J. Wheeler, A. R. Ganji, Introduction to Engineering Experimentation, 2nd Edition, Pearson Education, New Jersey, 2004.

[21] J. Shlens, A tutorial on principal component analysis, arXiv preprint arXiv:1404.1100 .

[22] M. R. Brambley, N. Fernandez, W. Wang, K. A. Cort, H. Cho, H. Ngo, J. K. Goddard, Final project report: Self-correcting controls for vav system faults filter/fan/coil and vav box sections, Tech. rep., Pacific Northwest National Laboratory (PNNL), Richland, WA (US) (2011).

[23] G. Strang, Computational Science and Engineering, 2nd Edition, Wellesley-Cambridge Press, Wellesley MA, 2012.

[24] S. Wu, J.Q. Sun, Cross-level fault detection and diagnosis of building HVAC systems, Building and Environment 46 (8) (2011) 1558–1566.

[25] G. Strang, Introduction to Linear Algebra 3rd Edition, Wellesley-Cambridge Press, 1998.

Appendix A

NOMENCLATURE

ϕ	humidity ratio
ρ	Air density (kgm^{-3})
σ	standard deviation
$\dot{m}$	Mass flow rate (kgs^{-1})
AHU	Air handling unit
CSV	Comma seperated value
c_p	Specific heat capacity of air at constant pressure ($kJkg^{-1}K^{-1}$)
CW	Cooling coil
p	Pressure (Nm^{-2})
g	Local gravitational acceleration (ms^{-2})
x	Generic across variable
w	Generic through variable
E	Power (kJs^{-1})
h	Specific enthalpy ($kJkg^{-1}$)
$HVAC$	Heating, ventilation, and air conditioning
A	plane formed by two measures
P	eigenvector matrix
P_1	projection of principal component
Cov	Covariance
THR	thermafuser
SAV	Siemens Aair Volume
CAV	Constant air Volume
FDD	Fault detection and diagnostic
T	Temperature (K)
VAV	Variable air volume unit
Subscripts	
EA	exhaust air
OA	outside air
RA	return air
SA	supply air
g	saturated steam