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DATA-DRIVEN ARTIFICIAL NEURAL NETWORK BASED PREDICTION OF FILTER CLOGGING IN BUILDING VENTILATION SYSTEM

Master's thesis

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TALLINNA TEHNIKAÜLIKOOL
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HOONE VENTILATSIOONI FILTRITE MUSTUMISE ENUSTAMINE TEHISNÄRVIVÕRKUDEGA

magistritöö

Juhendaja: Eduard Pentlenkov
Professor

Author’s declaration of originality

I hereby certify that I am the sole author of this thesis. All the used materials, references to the literature and the work of others have been referred to. This thesis has not been presented for examination anywhere else.

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Abstract

The issue of energy consumption in buildings is very significant. In this thesis, duct filter clogging was predicted and its relationship with the energy consumed by the building's ventilation system was presented. As duct filters become clogged, the pores of the air filters become blocked thereby obstructing the flow of air. The pressure drop across the filter subsequently increases as the filter becomes clogged. The pressure loss coefficient of the filters was calculated from the dataset available from four ventilation systems. The calculated pressure loss coefficient for each filter was used to develop a dynamic neural network predictive model that could predict the pressure loss coefficient. The training of the neural network was done in two methods: in the first method, two models were developed. The first model predicted the next day's pressure loss coefficient (K-values) with the output of the neural network at time t, t-1, t-2 and date as the neural network's inputs, while the second model predicted a two-week K-values with the output of the neural network at time t, t-1, t-14 and date as the neural network's inputs. It is, however, worthy to note that due to the inherent cyclic nature of the data which depicts seasonality, months, week of months, etc., the date which was one of the inputs to the neural network was split into position-in-month, number-in-days in a month and days-of-week respectively. These split quantities were transformed into two dimensions each and fed into the neural network in a bid to convey the data's cyclical nature to the model. The model accuracy and performance were evaluated using Mean Absolute Percentage Error (MAPE) and Mean Square Error (MSE) respectively. In method two, recurrent prediction using these models was presented to show the effect of longer predictions on the prediction models. The results obtained show that the models performed very well in predicting the pressure loss coefficient as evident by the MAPE and MSE values obtained while the result of the recurrent prediction showed that the longer prediction a prediction model does, the lower the accuracy of the model.

Finally, the relationship between the pressure loss coefficient of filters and energy consumed by the duct fan was presented.

Keywords: HVAC, Pressure loss coefficient, ANN, K-values, Mean Absolute Percentage Error (MAPE).

Annotatsioon

Hoone ventilatsiooni filtrite mustumise enustamine tehisnärvivõrkudega

Ehitiste energiatarbimise küsimus on väga oluline. Selles lõputöös ennustati kanalite filtrite ummistumist ja tutvustati selle seost hoone ventilatsioonisüsteemi tarbitava energiaga. Kanalifiltrite ummistumisel ummistuvad õhufiltrite poorid, takistades õhuvoolu. Seejärel suureneb rõhu langus filtril, kui filter ummistub. Filtrite rõhukao koefitsient arvutati neljast ventilatsioonisüsteemist saadava andmekogumi põhjal. Iga filtri arvutatud rõhukadude koefitsienti kasutati dünaamilise närvivõrgustiku ennustusmudeli väljatöötamiseks, mis võimaldaks rõhukao koefitsienti ennustada. Neuraalvõrgu väljaõpe toimus kahes etapis: esimeses etapis töötati välja kaks mudelit. Esimene mudel ennustas järgmise päeva rõhukao koefitsienti (K-väärtusi) koos närvivõrgu väljundiga ajahetkel t, t-1, t-2 ja kuupäevaga närvivõrgu sisenditeks, teine mudel ennustas kahenädalast K-väärtused koos närvivõrgu väljundiga ajahetkel t, t-1, t-14 ja kuupäevaga kui närvivõrgu sisenditega. Väärib märkimist, et hooajalisust, kuud, kuunädalat jne kirjeldavate andmete loomupärase tsüklilise iseloomu tõttu jagati kuupäev, mis oli üks närvivõrgu sisenditest, positsioonisisesesse vastavalt kuu, nädalate arv päevades ja nädalapäevad. Need jagatud kogused muudeti kaheks mõõtmeks ja juhiti närvivõrku, et edastada mudelile andmete tsüklilisus. Mudeli täpsust ja jõudlust hinnati vastavalt keskmise absoluutse protsendi vea (MAPE) ja keskmise ruutvea (MSE) abil. Teises etapis esitati korduv ennustamine neid mudeleid kasutades, et näidata pikemate ennustuste mõju ennustusmudelitele. Saadud tulemused näitavad, et mudelid toimisid rõhukao koefitsiendi ennustamisel väga hästi, nagu nähtuvad saadud MAPE ja MSE väärtustest, samas kui korduva ennustamise tulemus näitas, et mida pikem ennustus ennustusmudelil on, seda madalam on mudeli täpsus. Lõpuks tutvustati filtrite rõhukao koefitsiendi ja kanaliventilaatori tarbitud energia vahelist suhet.

Märksõnad: HVAC, rõhukao koefitsient, ANN, K-väärtused, keskmine absoluutprotsendi viga (MAPE).

List of abbreviations and terms

ANN	Artificial Neural Network
CI	Computational Intelligence
DNN	Dynamic Neural Network
IEEE	Institute of Electrical and Electronics Engineering
MLP	Multi-Layer perceptron
MPC	Model Predictive Control
MSE	Mean-Squared Error
SLP	Single-Layer Perceptron
HRV	Heat Recovery
HVAC	Heating, Ventilation and Air Conditioning
CSV	Comma-Separated Values
fpm	feet per minute
EMA	Exponential Moving Average
MAPE	Mean Absolute Percentage Error

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1 Introduction

1.1 Background

Buildings account for 40% of the total energy consumption in the European Union EU, thereby leading to more emission of carbon dioxide into the atmosphere which directly impacts on climate change [1]. Heating, Ventilation and Air Conditioning HVAC systems consume about 30% of energy in commercial buildings with about 12% for ventilation [2]. However, it is paramount that the efficiency of HVAC systems should be greatly considered to achieve a reduction in energy consumption in buildings. Therefore, efficient energy management is key to achieving conservation of energy and reducing its impact on the environment and, predicting energy consumption can be of immense value [3]. Furthermore, the HVAC system consists of several components like pumps, fans, dampers, etc. However, if the performance of the HVAC system in terms of energy consumption is to be established, it is necessary to consider these components.

The main goal of the HVAC system is to provide indoor environmental quality which includes thermal and acoustic comfort to occupants. Meanwhile, the heating and cooling effects of the HVAC system vary with the time of the day and year hence the need to closely monitor and control its components. The breakdown of these components could impact gravely to the overall energy consumption of the HVAC system, nevertheless, timely predicting the failure of these components and scheduling maintenance before failure could not only minimize energy consumption but also minimize cost.

There are several developed methods in the literature for improving energy efficiency, one of which is to predict energy consumption for a month which gives building managers prior knowledge on how to control energy consumption without tampering with the thermal comfort of occupants. Predictive methods are mainly divided into two categories: model-based predictive methods and data-driven methods (machine learning method).

1.2 Proposal of dissertation

This thesis aims to investigate and present a simplified energy prediction model of an HVAC system. The model uses an artificial neural network (ANN) to predict the pressure loss coefficient of duct filters with a direct relationship to the energy consumed by the duct fan. The neural network for better prediction uses as input, the output of previous time step, and input at the current time step to estimate the pressure loss coefficient which consequently shows a linear correlation with energy consumed by the duct fan.

1.3 Objective of the study

Buildings are the highest contributor to energy consumption worldwide and account for greenhouse gas emissions [4]. Consequently, this thesis sets out to define a modeling approach for estimating the energy consumption of HVAC systems. However, this work will show how HVAC energy consumption can be predicted to assist building engineers and planners to control energy consumption. This study will consider and deal with the development of a model to estimate the pressure loss of duct filters which has a direct relationship to the energy consumed by the HVAC system's duct fan.

1.4 Description of the tasks involved

The steps taken to develop a model capable of estimating the consumption of energy of an HVAC system are as shown below:

I. Data was collected from several HVAC systems in Finland as comma-separated values files (CSV).
II. The collected data were preprocessed
III. The pressure loss coefficient for each duct filter (return and supply) was calculated
IV. An artificial neural network was trained to predict the pressure loss coefficient for a month
V. Finally, the relationship between the pressure loss coefficient and energy consumed by the duct fan can show the estimated energy consumption of the HVAC system.

1.5 Thesis Structure

This report will consist of five (5) chapters as elucidated below.

Chapter 1 –presents the introduction and overview of the thesis. In this chapter, the thesis objectives and description of the tasks to be carried are also elucidated.

Chapter 2 – discusses a review of previous literature primarily different modeling techniques for predicting energy consumption in HVAC systems. Meanwhile, different methodologies employed were also identified.

Chapter 3 – presents holistically, the HVAC system: its different parts and functionalities

Chapter 4- development and implementation of an artificial neural network model for predicting the pressure drop coefficient. Before the model development, the pressure drop coefficient for each duct filter was calculated using the ventilation theory formulae. The relationship between pressure drop coefficient and duct fan energy consumption was also presented.

Chapter 5: Coalition of the result obtained, and its analysis was presented in this chapter.

Chapter 6: provides a conclusion and discussion on future works.

2 State-Of-The-Art

2.1 CI Algorithms

Computational intelligence (CI) was first proposed by Bezdek and was first used as a term by the Institute of Electrical and Electronics Engineers (IEEE) [5]. CI is a growing research field with several computation techniques as depicted by the figure below:

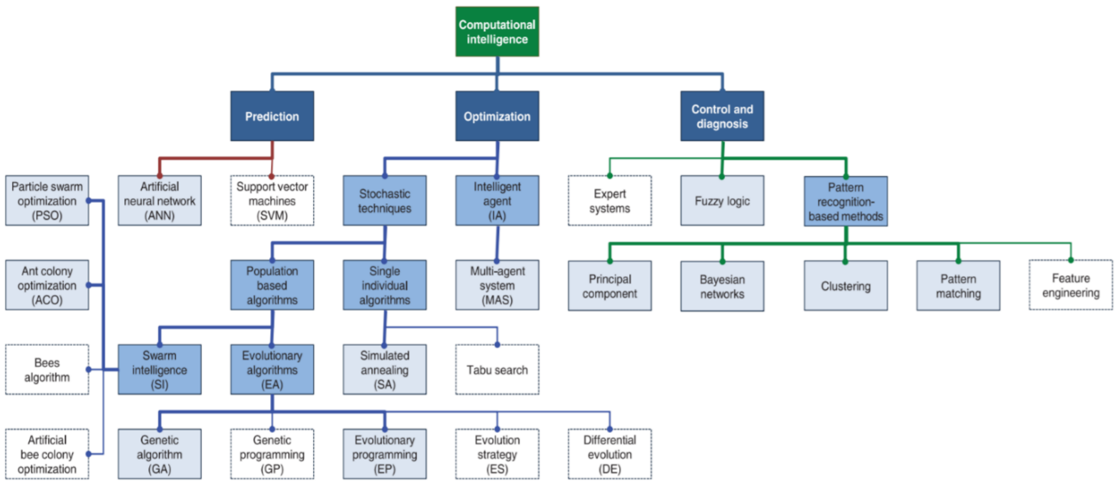

Figure 2.1. Classification of Computational Intelligence Techniques [5].

Meanwhile, several CI methods have been deployed to investigate the energy consumption of HVAC systems in terms of prediction, optimization, and control. This chapter tends to review the several CI methods as elucidated below.

Fung [6] et al reviewed an ANN-based model predictive control (MPC) system for residential buildings paying more attention to lowering the operating cost of HVAC systems while predicting the cost of heating rather than minimization of energy consumption. Several scientific domains have been explored with a view to better design and model energy performances of buildings thereby enabling house engineers to better manage energy consumption. Foucquier [7] et al reviewed several domains which include physical (white box) models, black-box modeling, and the hybrid (grey box) modeling approach for predicting energy consumption, heating/cooling demand, and indoor temperature. Jun-young Kwak [8] et al presented a novel model for predicting HVAC energy consumption in commercial buildings using multi-agent systems. The model simulates energy behavior based on energy consumption prediction. The prediction was done on a daily, weekly, and monthly basis. The result obtained shows a 7.8 to 22.2% variation of the root mean square error while the ventilation energy consumption was predicted at higher accuracies (over 99%) and the cooling energy consumption accounts for most of the inaccuracies and variations in the total energy consumption prediction. Kalogirou [9] et al trained an ANN to learn to predict the required heating load of the building using the building's area of walls, the building space, design room temperature, areas of windows as input into the neural network while the output is the heating load. One drawback of this work is that the heating load is also affected by the external environmental condition, which was not considered as an input parameter during training of the neural network. Kreider et al [10] presented results of a recurrent neural network on hourly data to predict heating and cooling loads with weather and timestamp as variables. Meanwhile, Kusiak [11] et al presented a non-linear model developed to minimize the total energy consumption of the HVAC system. A multi-perceptron algorithm used to model a chiller, a pump, and the supply and return fans. The computational results showed energy consumed reduced by almost 23%.

Yuce [12] et al demonstrated an ANN approach to predicting the energy consumption of a specific HVAC system. A calibrated simulation model was used to generate the dataset using in the training of the ANN using the Levenberg-Marquardt algorithm which was compared against the conjugate-based training algorithm.

ANN learns from the dataset fed into it by mapping the relationship between the input and output data. This mapping relationship is established by a process called training. These training methods are divided into two parts, mainly supervised and unsupervised learning [5]. In supervised learning, both the input and output (otherwise known as a label) are known to the network so that if a new data is fed into the ANN, it can be used to predict the output for that data. While for unsupervised learning, only the input is known while the output is not. During the training process, the ANN tries to model the hidden structure in the dataset to learn about the data using different techniques.

3 HVAC System

3.1 Introduction to HVAC system

The main goal of the HVAC system is to create and maintain comfortable environmental conditions for occupants in a building [12]. Although, HVAC systems are classified into various types, but the mode of operation is the same. Outdoor air is drawn into the buildings through air ducts and is either heated or cooled before it is distributed into the occupied spaces. The exhaust air, which is of higher temperature from the occupied spaces, is either sent outside or it is used to heat-up the incoming outdoor air [13]. One of the criteria for the choice of the type of HVAC system to use is dependent on some factors which are not limited to climate, building, available resources, etc. [14]. HVAC systems can be classified according to the necessary processes and distribution processes [15] like heating, ventilation, cooling, humidification, and dehumidification processes. The HVAC system's effective functionality is supported by a system that distributes the conditioned air into the building. The distribution system mainly varies according to the complexity of the system which should include air handling units, duct fans, duct filters, dampers, etc. [13].

3.2 Types of hvac systems

There are different types of HVAC systems which are categorically group into four (4) types namely:

3.2.1 Heating and cooling split systems:

These are mostly the common types of HVAC systems, the split systems. They are found in a large portion of residential houses [16]. These include both indoor and outdoor parts, it houses the condenser and compressor in an outdoor cabinet while another indoor cabinet contains the evaporator coil and an air handler that pushes cool air through the duct network. A series of copper tubes connect both the indoor and outdoor components-moves the air to the house.

Figure 3.1. Diagram of Split HVAC System [17]

3.2.2 Hybrid split system

These are like the standard split system but have a distinct feature. This distinct feature lies in the way they are powered. However, this system gives the user the option of switching their heat pumps (One unit providing both heating and cooling) to be electrically fueled instead of using gas. Consequently, one important advantage of the hybrid split system includes saving money and energy with the option to switch fueling sources.

3.2.3 Duct – free system

As the name suggests, these types of HVAC systems are ductless. Duct-free systems are installed in areas where ducts are not necessary and can be installed individually in a room thereby offering several advantages which include allowing individual room temperatures and conditions to be controlled and also, it offers the advantage of energy conservation, in other words, rooms that are not occupied or not in use, the HVAC system for that room can be switched off consequently conserving energy [18].

3.2.4 Packaged heating and air system

A packaged system is one that has all the major components in one large cabinet. They contain an air conditioner/heat pump combination, evaporator and fan coil along with a thermostat. They are mostly installed in homes without basements likewise installed outdoors [18], [19].

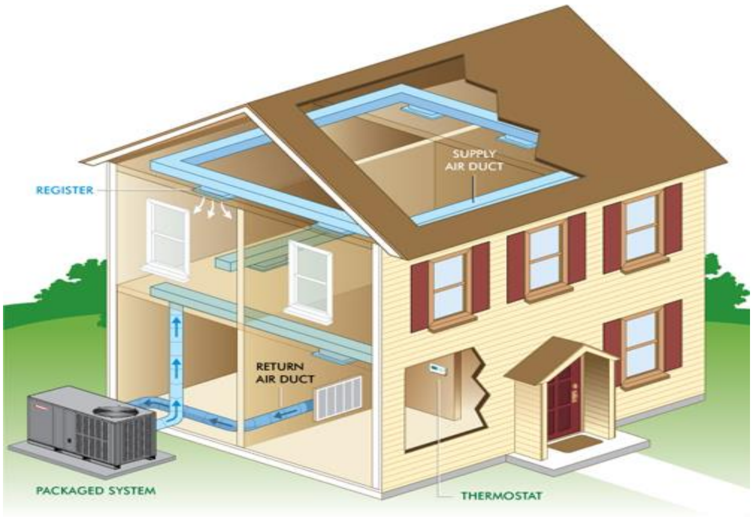

Figure 3.2. Diagram of Packaged HVAC systems [20]

3.3 Classification of hvac systems

A central structure and a localized or local network are the main grouping of HVAC systems. Types of a device depend on the postion of the primary equipment to be consolidated as conditioning the entire building as a single unit or localized as conditioning separately a different zone as part of a building [14]. Centralized systems are characterized by central refrigeration systems and chilled-water distribution [21]. De-centralized systems can be one or more individual HVAC units with an integral refrigeration cycle, heating source, and direct or indirect outdoor air ventilation. De-centralized systems are more advantageous than centralized HVAC systems in buildings particularly those with multiple tenants with different HVAC needs.

3.4 Components of hvac systems

3.4.1 Ventilation heat recovery system (HRV)

Buildings environmental conditions need to be conditioned to a comfortable temperature and relative humidity for human occupancy. Heating can account for over 50% of annual energy consumption in buildings. Since traditional ventilation systems introduce unconditioned outdoor and exhaust conditioned indoor air, there is potential for energy savings by integrating heat transfer between the two air streams. It will work both in winter when warm exhaust air preheats the intake air and in summer when colder, air-conditioned exhaust air precools the intake air [22].

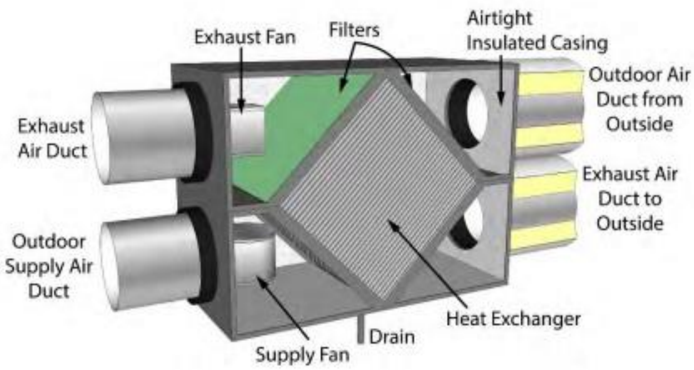

Figure 3.3. A typical Heat Recovery Ventilator [23]

The HRVs main goal is to reduce heating thereby reducing energy consumption while providing a balanced ventilation system. The outdoor air gets to the HRV and moves through the heat exchanger where heat is transferred from the outgoing exhaust air pre-heats it. This outdoor air is then delivered to the building through the supply fan and air ducts inside the system. A separate ductwork system and fan (exhaust) pulls the outgoing air from the house into the HRV while the exhaust air is pushed into the heat exchanger, there is a heat transfer from the exhaust air to the supply air stream as it is exhausted outside. These processes occur simultaneously thereby creating a balanced system with equal supply and exhaust airflows. In other words, the warm stale exhaust air is extracted from wet rooms like a toilet, bathroom, or kitchen. It is not advisable to connect a kitchen hood to such a ventilation system because there is a risk of air ducts becoming contaminated with impurities coming from cooking [24], [25].

The temperature efficiency describes the effect of heat recovery of the ventilation system. The temperature ratio (efficiency) η_{temp} is defined as [21] , [26]:

$$\eta_{\mathrm{temp}} = \frac{\overline{t_{\mathrm{sup}}} - t_{\mathrm{out}}}{t_{\mathrm{exh}} - t_{\mathrm{out}}} \tag{3.1}$$

Where t_{out} is the outdoor air temperature and t_{exh} is the exhaust air temperature. The time-averaged value of the supply air temperature $\overline{t_{\mathrm{sup}}}$ of ventilation units is given by [24]:

$$\overline{t_{sup}} = \frac{1}{\tau}\int_{t=0}^{t=\tau} t_{sup}(t) \cdot dt \quad (3.2)$$

Where t, is the time and τ is the semi-period, which means the duration of the supply or extract process. In the case of the recuperative HEX, the process is in a steady state [24]:

$$tsup(t) \ = \ const \quad (3.3)$$

And the temperature ratio (efficiency) η_{temp} is defined as:

$$\eta_{temp} = \frac{t_{sup} - t_{out}}{t_{exh} - t_{out}} \quad (3.4)$$

To define the temperature ratio (efficiency) η_{temp} of HEX of the ventilation unit, the temperature ratio η_{temp} in equal air mass flow is used:

$$\eta_{temp} = \frac{L_{m,sup} * (t_{sup} - t_{out})}{L_{m,min}(t_{exh} - t_{out})} \quad (3.5)$$

t_{out} is the outside air temperature, t_{exh} is the temperature of the extract air, $L_{m,sup}$ is the inlet mass flow rate, and $L_{m,min}$ is the minimum of inlet and outlet mass flows.

The temperature ratio η_{temp} of HEX can also be calculated using the exhaust air temperature t_{ex}. Then the η_{temp} can be calculated with the equation:

$$\eta_{temp} = \frac{(t_{exh} - t_{ex})}{(t_{exh} - t_{out})} \quad (3.6)$$

3.4.2 Air filtration system

Air filters are components within the HVAC system whose primary goal is to capture particles and prevent them from entering the conditioned air stream [27]. The HVAC system's overall performance depends heavily on the filtration system. Air filters tend to keep fans, ducts, and coils clean and avoid increased pressure drop and malfunctions [28]. Filters in HVAC systems are usually classified into two (2): supply filters and return filters. The supply filter has the potential to reduce the outdoor pollutants that is, filter out the outdoor air before it is delivered into the conditioned space. While the return filter removes particles from the return air; exhaust air from the conditioned space.

Air filters consume energy and like any other energy-consuming appliance or component are directly responsible for global climate change. The correct design and good maintenance of air filters is important to minimize the energy consumption without affecting the removal of efficiency. Energy consumption is proportional to the pressure drop across a filter. About 80% of filters environmental load is from the energy to overcome the air resistance in operation.

Figure 3.4. HVAC Filter [29]

3.4.3 Fan system

The fan system is divided broadly into two (2) parts: the supply and return fans. The fan supplies the energy needed to move the air through the device. Air reaches a cylindrical collection of spinning blades inside the centrifugal fan, and is centrifuged, thrusting radially outward into a scroll shell. This fan is a very common option because of its ability to produce substantial pressure without unnecessary noise. While within the axial fan, the air passes through a rotating set of blades, which pushes the air along [30]. The total amount of pressure generated by a fan has two components: velocity and static pressures. The former is due to the momentum of the air as it moves axially through the duct while the latter is due to the perpendicular outward push of the air against the duct walls. However, the sum of both pressures is called the total pressure. The build-up of static pressure results in a decreased air velocity and thus a decrease in the fan airflow.

The fan efficiency is the ratio of power transmitted to airflow and the power the fan uses. The fan efficiency is independent of the air density. This can be expressed as:

$$\eta = P_t * \frac{Q}{P} \tag{3.7}$$

η =Fan Efficiency in %

P_t = Total pressure in Pascal

Q = Air volume delivered by the fan (m3/s)

P = Power used by the fan in Watts.

Figure 3.5. A DUCT FAN [31]

3.4.4 Duct system

Air ducts are channels through with conditioned air passes to spaces where it is needed. A primary problem is the trade-off between the initial expense of the duct system and the air distribution system's energy expense; wider ducts result in lower energy costs for fans. A duct system is a network of circular or rectangular tubes usually made of sheet metal, fiberglass or a versatile combination of plastic and wire. It is usually located within the walls, floors, and ceilings. The primary goal of the duct system is to transmit air from the central air source to the air diffusers [32].

The duct system's application, velocity, and pressure determine its classification. There are three (3) categories:

- Low-Velocity Duct systems (Air velocities in the range of 400 to 2000 feet per minute, (fpm)).
- Medium Velocity Duct systems (Air velocities in the range of 2000 to 2500 feet per minute, (fpm)).
- High-Velocity Duct systems (Air velocities in the range of 2500 to 3500 feet per minute, (fpm)).

It is worthy of note that of the three duct system classifications, the low-Velocity duct system is very significant for energy efficiency in air distribution systems. Efficient duct system design is paramount for minimizing the energy consumption of the HVAC system. Energy loss can be through leakages of heated air into and out of the ducts through accidental holes in the ducts or through open spaces between poorly connected sections of ductwork thereby causing depressurization of the entire system. However, energy loss can result from poor insulation of the duct network and through infiltration: pressure imbalances caused by faulty ducts causing air to leak through cracks in the duct system [33].

Figure 3.6. A Duct System [34]

3.4.5 Heat exchanger

The heat exchanger is one of the most important components of the HVAC system. It is a heat transfer device that is used for the transfer of internal thermal energy between two or more liquids or gases available at different temperatures. There are two types of heat exchangers: Indirect, where the fluid streams are physically separated from each other by a solid surface while direct heat exchangers are heat exchangers where the two streams get in contact with one another. The rate of heat transfer in a heat exchanger is larger than the heat losses to the environment. However, the energy balance for the heat transfer rate is:

$$Q = \dot{C}_c(\dot{T}_{co} - T_{c\imath}) = \dot{C}_h(T_{ho} - T_{hi}) \tag{3.8}$$

Where heat capacitance rate is $C = \dot{m} * c_p$

$\dot{m}$ - Mass flow rate

c_p - Specific heat at constant pressure.

$T_{co} - T_{ci}$, the temperature difference between internal and outside temperature [35].

3.4.6 Zone system

Zoning in HVAC systems is very paramount for energy efficiency. However, zoning grouping of spaces with similar thermal characteristics together such that the HVAC system may control and maintain approximate levels of prescribed conditions inside. In a building, there are different types of spaces that have varied load variations and operational patterns. Identifying these spaces and grouping them into clusters based on common characteristics of cooling would allow a limited number of thermal equipment to meet the space-conditioning requirements [32]. Several zones are controlled by installing a thermostat (a device that activates either cooling or heating in the required space when the thermal characteristics of the given space is below its set point), and dampers: mechanical devices that can open or close the air ducts thereby increasing or reducing the flow of air into the zoned spaces.

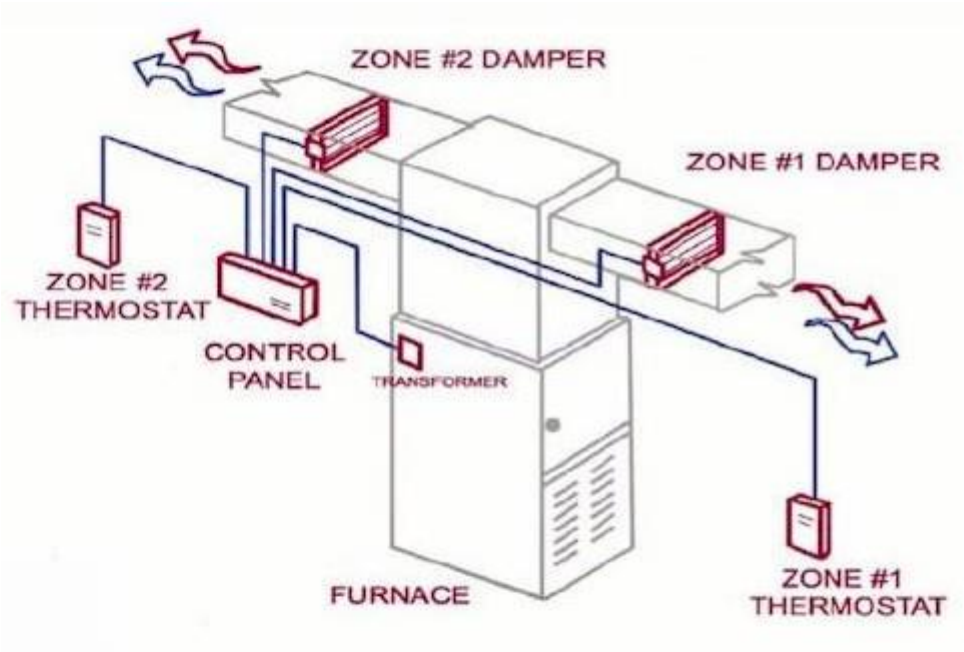

Figure 3.7. Typical Zoning System [36]

4 Methodology

The main aim of this thesis is to create a model that has the capability of predicting the K-value of filters in HVAC systems using data collected from the ventilation system. This chapter presents the experimental procedure followed towards creating the appropriate model.

Three (3) ventilation units were evaluated where each unit has two (2) filters named Supply and Return filters respectively. The K-values for each filter was calculated using parameters of the ventilation unit for which the filter belongs to. The data collected were pre-processed before been fed into a dynamic neural network for prediction.

The prediction was done in two stages and the results compared. In Stage one two predictions were made, one prediction was a short term prediction (one day prediction) with inputs to the neural network been the date, the output of the neural network at time t, t-1, and t-2 while the second prediction was a long term prediction (14 days) with inputs to the model been date, output of the network at time t, t-1 and t-14. The performance of the neural network under these three stages is evaluated. However, in stage two, recurrent predictions were made using the models obtained in stage one for 14- and 28-day predictions respectively.

Finally, the relationship between K-values and Electricity consumption was also presented using scattered diagram, however, giving building managers a rough idea of how energy consumption might look like within the period under prediction.

4.1 Data collection and preprocessing

Data from three (3) ventilation units were collected in a .csv format. The ventilation units were named 1740, 1741, and 1742 respectively. For each unit, the .csv file contains data for all the parameters of the ventilation unit which includes: Heating state_COIL_HEATING, Efficiency_HEATRECOVERY, Return air temperature, etc. Each .csv file contained at least 19,032 samples where each sample was collected at an interval of 15mins for each day.

The .csv files contain parameters for both the return and supply filters amongst other parameters. The parameters needed for calculating the K-values for the filters were extracted. In order to obtain a more distinct values from the data collected, each day's data were averaged to obtain a more unified and distinct value for each day.

4.2 Data smoothing

Smoothing data removes random variation and shows trends and cyclic components [37]. In this work, due to the seasonality and the cyclic component embedded into the data, the data had to be smoothed with the sole intention of exposing the underlying pattern, seasonal and cyclic components more clearly. There are several smoothing methods available for data smoothening, hence in this work, the Exponential moving average was used because of its sensitivity to changes in data.

4.2.1 Exponential moving average

The exponential moving average (EMA) is a type of moving average technique. In EMA, the lagging in the simple moving average (SMA) was compensated for by applying more weight to recent data relative to older data. The weighting applied to the most recent data depends on the specified period of the moving average. The shorter the EMA's period, the more the weight that will be applied to the most recent data. It is therefore worthy to note that EMA puts more weight on most recent data as such reacts quicker to recent data changes than a simple moving average. The formula for EMA is as shown below:

$$\mathrm{EMA}\ (\mathrm{C}) = \left(\lfloor \mathrm{Data}(\mathrm{c}) - \mathrm{EMA}(\mathrm{P}) \rfloor \times \mathrm{Multiplier} \right) + \mathrm{EMA}(\mathrm{P}) \tag{4.1}$$

Multiplier is equal to $\frac{2}{(1+\mathrm{N})}$

where: N is the specified number of periods; P is Previous while C is Current.

4.2.2 Filter clogging

An air filter is a gadget made from sinewy materials that remove strong particulates, such as dust, and microbes from the air. The air filter does not allow particulate matter from its air source which is the outside (atmosphere) from entering the ventilation system and subsequently into the space within a building [38]. However, this helps to keep the air within the ventilation system and the building clean thereby preventing corrosion of the ventilation vents and keeping the occupants of the building safe.

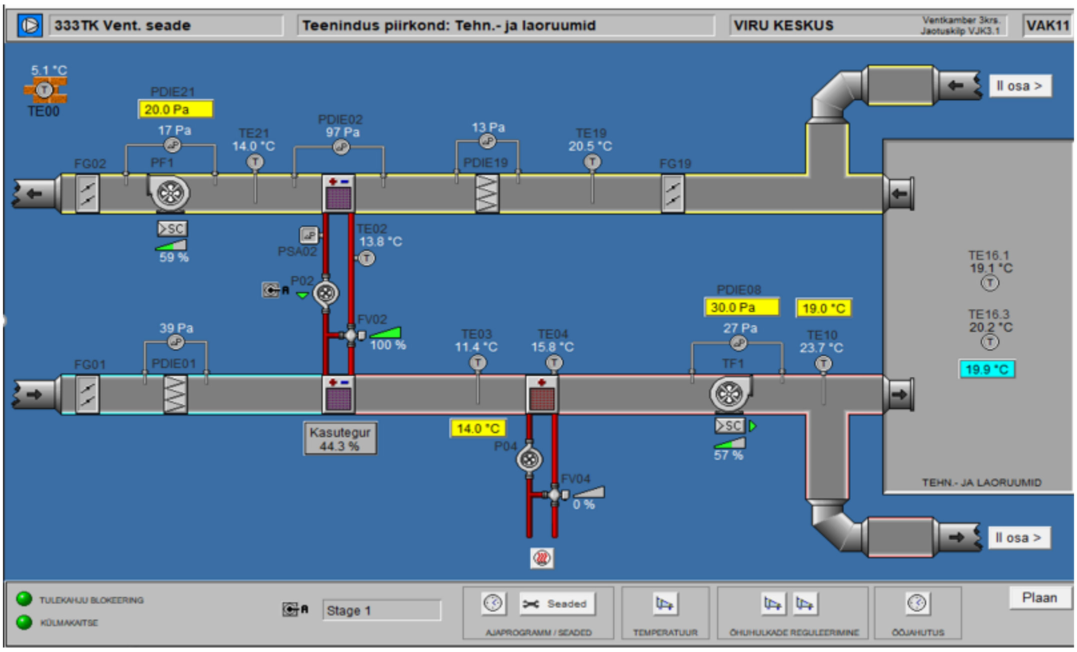

Figure 4.1.Ventilation system overview (Screenshot from a building information system)

Air from the outside reaches the spaces within the building via some devices within the ventilation system duct. Examples of some of the devices include a fan, heaters, coolers, dampers, etc. However, in this work, the focus will be mostly on the fans and filters. As the air passes through the filter, a differential pressure is created. The difference between the pressures on both sides of the filter is called a pressure drop. The pressure drop across the filter increases as the filter becomes clogged, thereby increase the power consumed by the fan to push the air through the filters.

However, the pressure drop across a filter cannot be used to determine how clogged a filter is because other parameters contribute like air temperature, atmospheric pressure, etc. Therefore, the need to use a holistic formula called the pressure loss coefficient (K-value) was used in this work.

4.2.3 Pressure loss coefficient

Pressure drop of a filter Δp is calculated based on the dynamic pressure P_d and pressure loss coefficient ξ:

$$\Delta p = p_d \cdot \xi \tag{4.2}$$

Dynamic pressure P_d is calculated as follows:

$$p_d = \frac{\rho \cdot v^2}{2} \tag{4.3}$$

The air velocity *v* is calculated as follows:

$$v = \frac{\dot{V}}{A} \tag{4.4}$$

The volumetric flow rate is calculated as follows:

$$\dot{V} = \frac{\dot{m}}{\rho} \tag{4.5}$$

The air density is calculated as follows:

$$\rho = \frac{p_{abs}}{R_{specific} \cdot T} \tag{4.6}$$

The absolute temperature is calculated as follows:

$$T = t + 273.15 \tag{4.7}$$

For this thesis, the absolute pressure P_{abs} was be assumed to be equal to standard atmospheric pressure P_{atm}.

The pressure loss coefficient of filters describes the state of the filters. When combining the previous formulas then the pressure loss coefficient can be calculated as follows:

$$\xi = \frac{2 \cdot \Delta p \cdot A^2 \cdot p_{atm}}{\dot{m}^2 \cdot R_{specific} \cdot (t + 273.15)} \tag{4.8}$$

If the supply and exhaust volumetric flow rates are controlled according to the pressure in the respective ducts and the ductwork is not manipulated or there is no airflow control, then the pressure loss coefficient should depend significantly only of the pressure drop Δp and air temperature t:

$$\xi = \frac{\Delta p}{(t + 273.15)} \cdot \frac{2 \cdot A^2 \cdot p_{atm}}{\dot{m}^2 \cdot R_{specific}} \tag{4.9}$$

4.2.4 Pressure loss coefficient calculation

From equation (16) above, the pressure loss coefficient (K-value) was calculated for each reading per filter. The area of the duct system was assumed to be 1squrared-meter.

Sequel to the pressure loss coefficient calculation, it was observed keenly that most of the readings captured and stored in the .csv files for each filter had some irregularities. These irregularities are as a result of either sensor malfunction or storage errors. These readings with irregularities were subsequently dropped as they form outliers within the data.

On the other hand, several readings were collected in a day with an interval of 15minutes averaging about 10-18 readings per day. Be that as it may, it was observed that the calculated K-value for each reading that make up a day did not change much. Sequel to this, the K-values for all the readings that make up a day were averaged to obtain a single K-value for one day.

4.2.5 Artificial neural network

An artificial neural network (ANN) is a type of human brain-inspired computation. It is composed of a set of interconnected artificial neurons that depend on the weights of the neural network. These neurons are arranged into layers within the network with its weight determining the impact of one neuron on another. The structure of ANNs is divided into three (3) layers: the input layer which contains neurons that receive the input data and transfer them to the second layer called the hidden layer through the weighted links. In the hidden layer, some mathematical processing is done on the dataset while the result is transferred to the neurons of the next layer, the output layer [39]. ANN’s structure can be narrowly categorized into two (2) groups, namely: Single Layer Perceptron (SLP) and Multi-Layer Perceptron (MLP). In SLP, the structure has only two layers: the input and output layer which are fully connected to the input layer, while in the MLP, and contains a hidden layer where all neurons are fully connected.

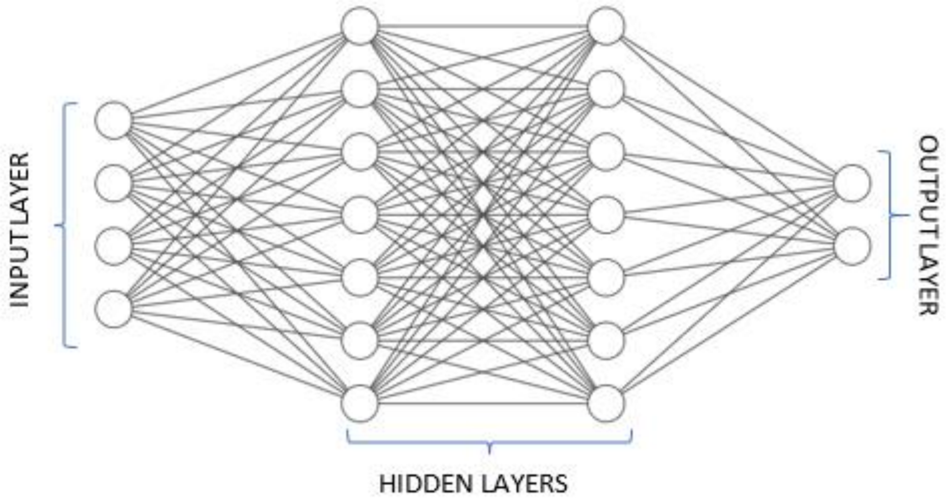

Figure 4.2. General Structure of an MLP neural network with two hidden layers

ANNs are best defined based on its architecture (the number of layers, number of neurons in each layer), the learning mechanism applied for updating the weights of the connections, and the activation functions used in various layers [39]. In this thesis, an MLP neural network was employed.

4.2.6 Dynamic neural network

In dynamic neural networks (DNN), the output of the network depends not only on the current input to the network but also on the current or previous inputs, outputs or states of the network [39]. In terms of information processing, the feedback signals involved in a DNN deal with some processing of the past knowledge and sore current information for future usage. Therefore, a DNN has its internal potential or internal state that is used to describe the dynamic characteristics of the network [40].

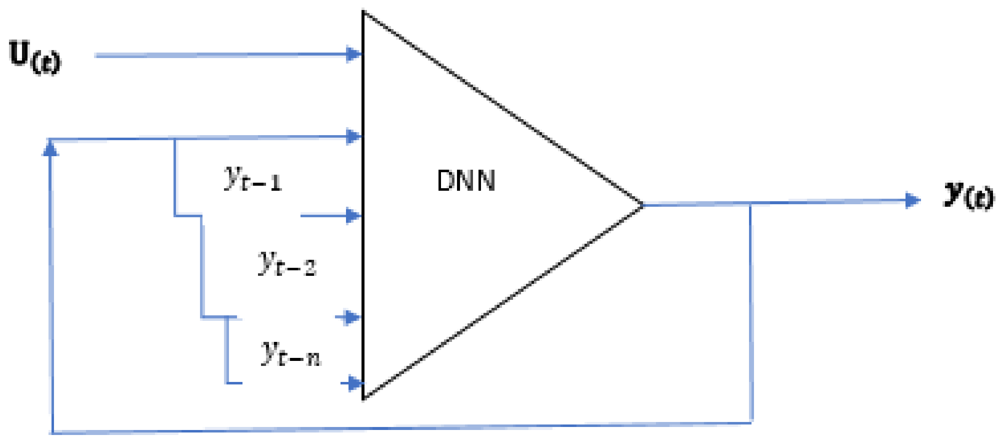

Figure 4.3. Symbolic representation of the DNN

In this work, a dynamic neural network was used to develop a predictive model for the pressure loss coefficient of filters. The input parameters for the DNN were the date/time, the current output of the neural network, and the two previous outputs of the network. The date/time input was treated as a cyclic continuous feature because of its inherent cyclic nature (month, day of week, and day-in-month).

4.2.7 Training process

There are two types of training processes otherwise known as the learning process in neural networks. They are supervised and unsupervised training. Both the inputs and outputs are given during supervised learning. The network processes the input and compares their resulting outputs to the necessary outputs. Errors are then propagated back through the network resulting in weights adjustments. This process is performed continuously until the acceptable level of error is achieved. However, in unsupervised learning, the network is provided with inputs but not with labels (outputs). The network must decide what feature it will use to group the input data. That is often called self-organization or adaptation [41].

In this work, supervised learning was employed where the inputs are as described above while the output was the calculated pressure loss coefficient (K-values).

The data set from each filter was divided into two parts: one part was used for training of the neural network called training set while the remaining part called the testing set was used for testing the performance of the trained network in the ratio of approximately 77% and 23% respectively. The training dataset was fed into the created dynamic neural network where it was subsequently trained. The training of the dynamic neural network was trained in two (2) stages as described above and the results presented in the next chapter.

4.2.8 Activation function

Activation functions are mathematical equations which determine a neural network output. An effect is attached to each neuron in the network and decides if it should be triggered or not, depending on whether each neuron's input is important to the prediction of the model. Activation functions also help normalize each neuron's output between 1 and 0 or -1 and 1 [42]. There are several activation functions used for neural network training such as purelin (Linear transfer function), tansig (tangent-sigmoid function), logsig (Logarithm-sigmoid function), etc.

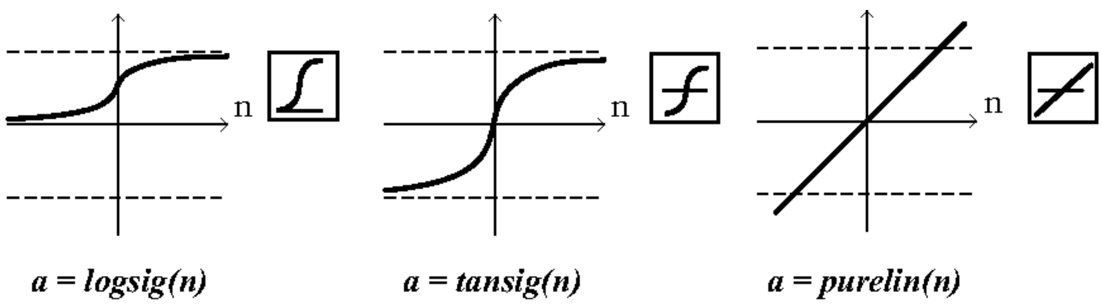

Figure 4.4. Graphical representation of activation functions [43]

For this thesis, several activation functions were tested until the best combination for each layer was established. For all layers in this work, the purelin (Linear activation function) was used.

The software used for this thesis work is MATLAB® 2018b.

5 Results and analysis

5.1 Data presentation

As described in the previous chapter, from the data collected, parameters for calculating the pressure loss coefficient (K-value) were extracted and subsequently calculated using the equation (8) as described above. The calculated K-values were smoothened as shown in the results below:

Data smoothing was subsequently done to remove noise so that the neural network can make predictions precisely. Below is the smoothened data using EMA with a span of 20:

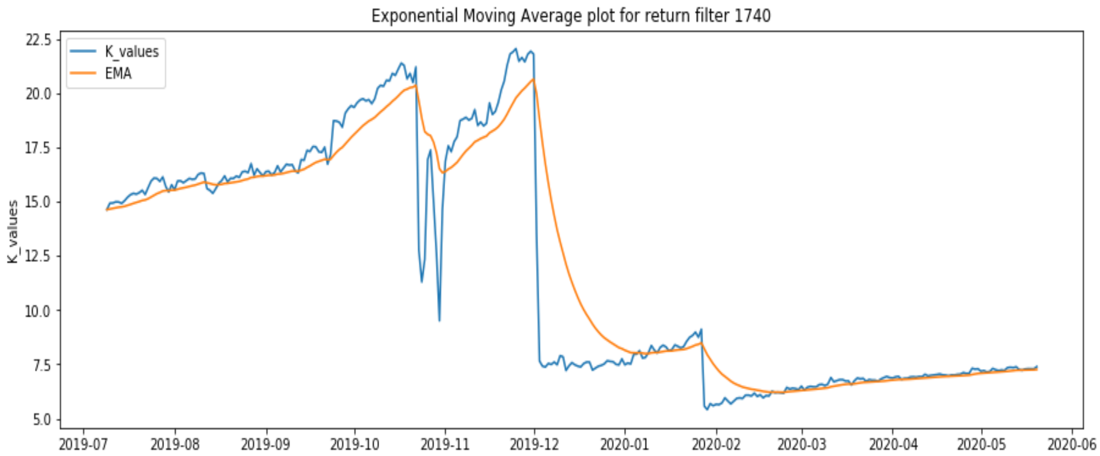

Figure 5.1 K-value plot and EMA of span 20 for return filter 1740

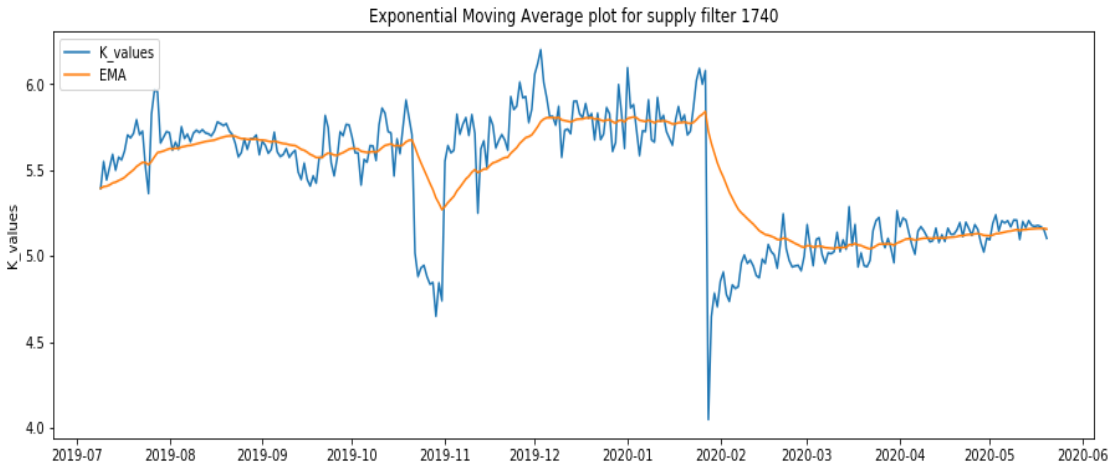

Figure 5.2 K-value plot and EMA of span 30 for supply filter 1740

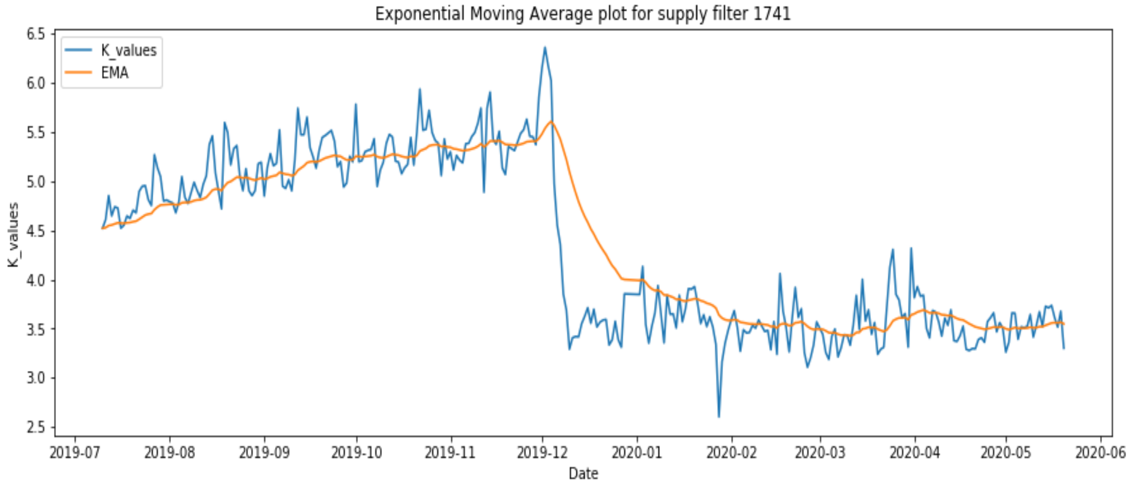

Figure 5.3 K-value plot and EMA of span 30 for supply filter 1740

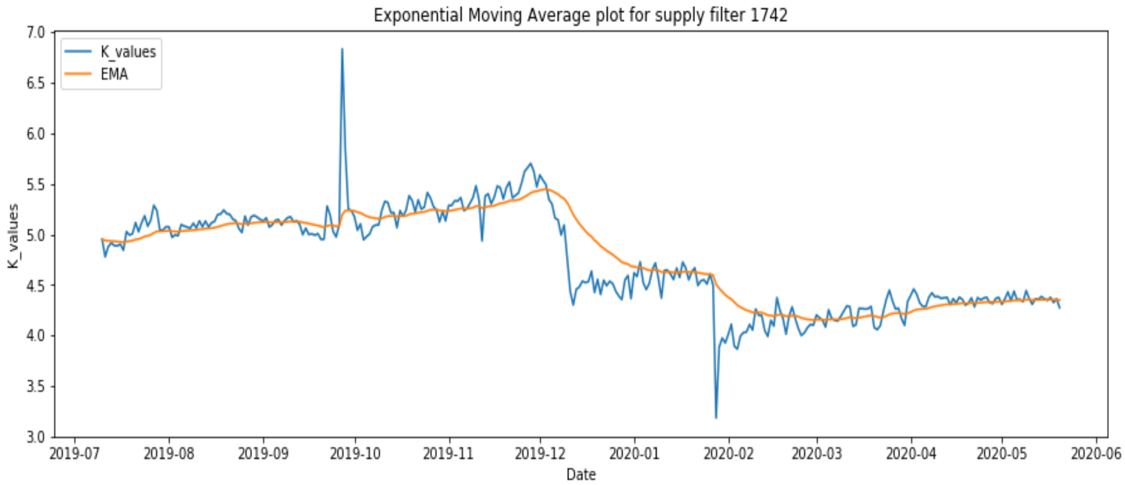

Figure 5.4 K-value plot and EMA of span 30 for supply filter 1742

This thesis aims to predict the pressure loss coefficient of filters before the filter change in the ventilation units. Therefore, the figures above show a period when filter change occurred in each ventilation unit. However, as filters begin to get clogged, there is an increase in the pressure drop across the filter hence a proportional increase in the pressure loss coefficient as depicted by the equation (8) above. Subsequently, when a filter is changed, the pressure drop across the filter drops so as the pressure loss coefficient.

Be that as it may, looking critically at the figures above, periods where filter change was performed, could be observed. However, the datasets used by the model for prediction in this work are those obtained before filter change in each filter of the ventilation units.

5.2 Dataset splitting

The dataset was split into training and testing datasets. The splitting for each filter was done in the ratio of 77% to 23% respectively. The training input and output data, as well as the testing input and output data, were also obtained from the training and testing datasets respectively. A total of 143 samples were used

5.3 Model evaluation

The model is a dynamic feedforward MLP neural network as described in the previous chapter. The number of hidden layers was set for each stage of training as well as the input-output number of neurons. To determine the number of hidden layers to use and the number of neurons in each layer, several experiments were conducted to obtain the best combinations. The neural network models were trained either with the Bayesian Regularization (trainbr) training algorithm (trainbr can train any network as long as its weight, net-input, and transfer functions have derivative functions. Bayesian regularization minimizes a linear combination of squared errors and weights. It also modifies the linear combination so that at the end of the training the resulting network has good generalization qualities [44]) or the Levenberg-Marquardt backpropagation algorithm (trainlm) while the network performance was evaluated using the Mean squared Error (MSE). The network was trained over 200 epochs. The best parameter combinations obtained for various stages are as shown in tables 5.1 and 5.2 below. Four (4) filters were considered taken from three (3) ventilation units as described in the previous chapter. Summary of the neural network is as shown in the table below:

Table 5.1. Neural network configuration for stage 1

Parameters (stage 1)	**Values**
First hidden layer	19 neurons
Second hidden layer	11 neurons
Third hidden layer	6 neurons
Output layer	4 neurons
Epoch	200
Training Algorithm	Trainlm
Activation function	Purelin

Table 5.2. Neural Network configuration for stage 2

Parameters (stage 2)	**Values**
First hidden layer	23 neurons
Second hidden layer	10 neurons
Third hidden layer	5 neurons
Output layer	4 neurons
Epoch	200
Training Algorithm	Trainbr
Activation function	Purelin

5.4 Network training

As described in the previous chapter, the neural network was trained in two stages:

5.4.1 Stage one:

The pressure loss coefficient (K-value) for time, t+1 was predicted while date, output of the neural network at time t, t-1 and t-2 served as input to the neural network, hence its dynamic nature. Figure 5.5 below depicts the input-output configuration of the model. The inputs from all the filters are fed into the neural network as vectors likewise the outputs from each filter. The figure below shows the input-output configuration used in stage 1 at time, t:

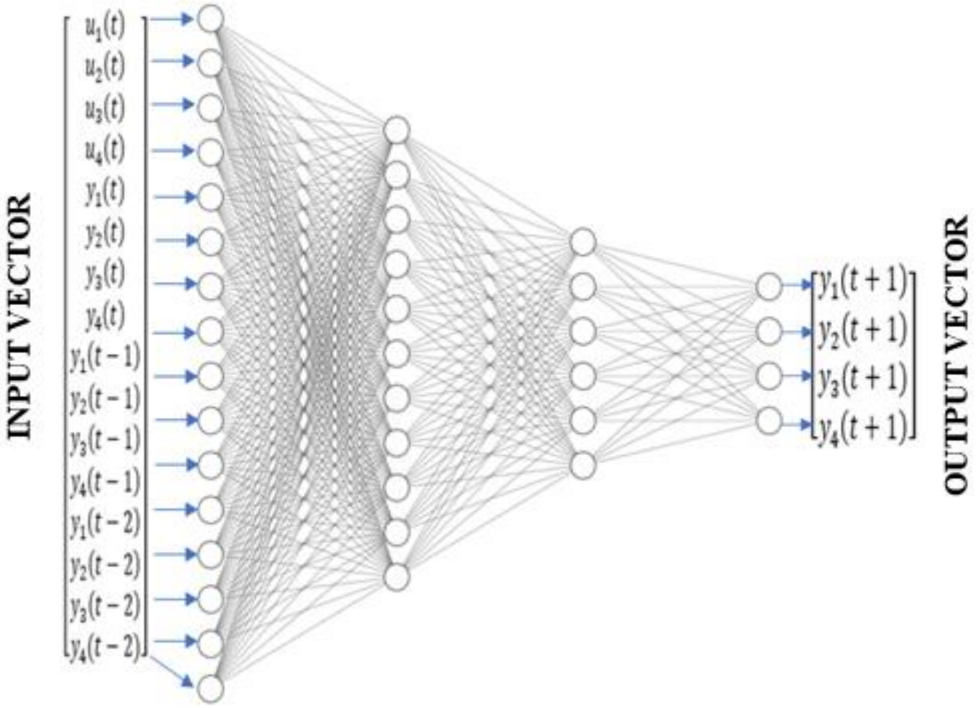

Figure 5.5: Input-Output configuration for stage 1

The U_1, U_2, U_3, and U_4 represent dates when the ventilation system data were read for each filter. These data gotten from the ventilation units are inherently cyclical hence encoding them to reflect their seasonality is paramount. Two new features were derived from the date parameter deriving a sine and cosine transform of the month of the year, days in a month, and day in a week respectively. The formulae used are shown below:

Month in a year:

$$\text{Sine transform} = \sin\left(\frac{\text{month} \times 2\pi}{12}\right) \tag{5.1}$$

$$\text{Cosine transform} = \cos\left(\frac{\text{month} \times 2\pi}{12}\right) \tag{5.2}$$

Day in a month:

$$\text{Sine transform} = \sin\left(\frac{\text{day} \times 2\pi}{31}\right) \tag{5.3}$$

$$\text{Cosine transform} = \cos\left(\frac{\text{day} \times 2\pi}{31}\right) \tag{5.4}$$

Day in a week:

$$\text{Sine transform} = \sin\left(\frac{\text{week} - \text{day} \;\times 2\pi}{7}\right) \tag{5.5}$$

$$\text{Cosine transform} = \cos\left(\frac{\text{week} - \text{day} \;\times 2\pi}{7}\right) \tag{5.6}$$

These sine and cosine transforms constitute inputs to the neural network U_1, U_2, U_3, and U_4 for the four (4) filters respectively.

$y_n(t-m)$ represents the output of the neural network (Pressure loss coefficient) where 'n' is the number of filters and m, shows the degree of recurrence of the network's output.

Table 5.3. Stage 1 Neural Network Training

Training Parameters	**Values**
Epoch	200
Performance	0.000324 (MSE)
Gradient	3.54e-06
Mu	1.00e-10
Training Algorithm	Levenberg-Marquardt

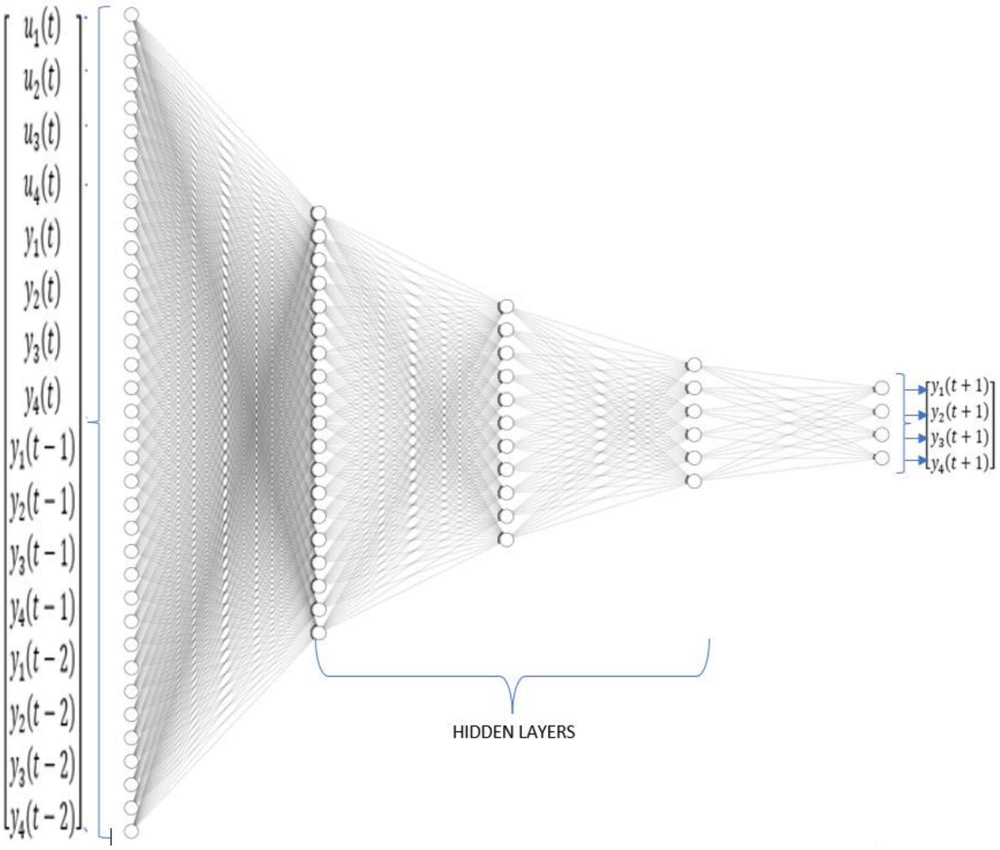

Figure 5.6: Stage 1 Neural network configuration

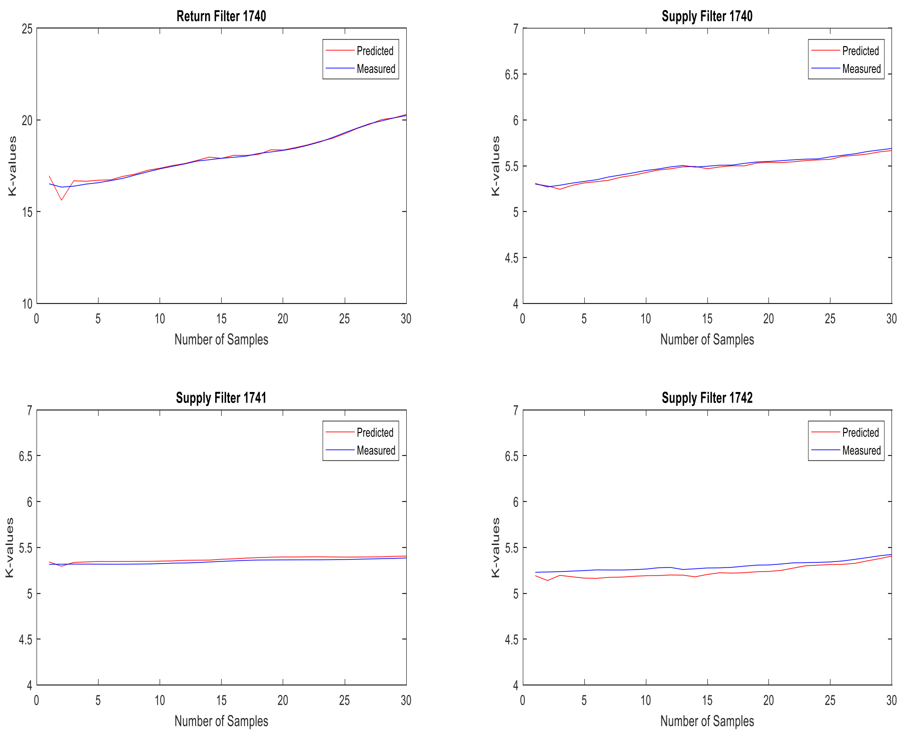

Figure 5.7: K-values prediction Results in Stage 1

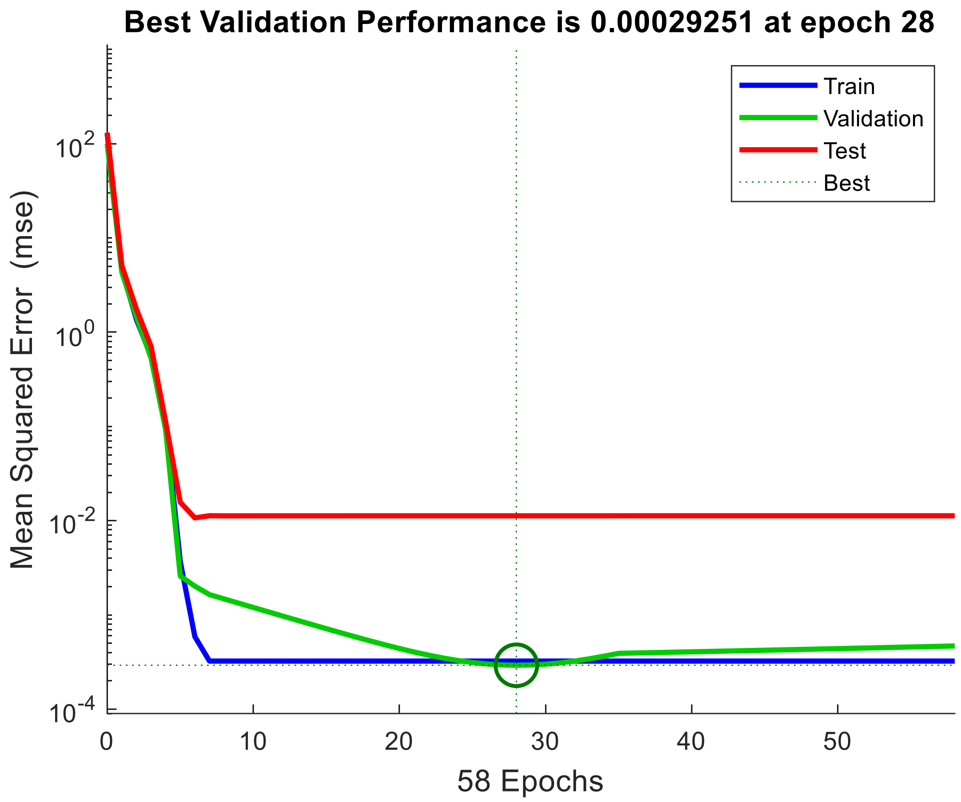

Figure 5.8: Stage 1 Neural Network Training Performance Plot (MSE)

5.4.2 Stage two

In this stage, a two (2) week prediction of the pressure loss coefficient was made as described in chapter four above. The inputs to the model are date, output of the model at time t, t-1 and t-14. The input-output configuration of the model is as shown in the figure below. The results obtained are as shown below:

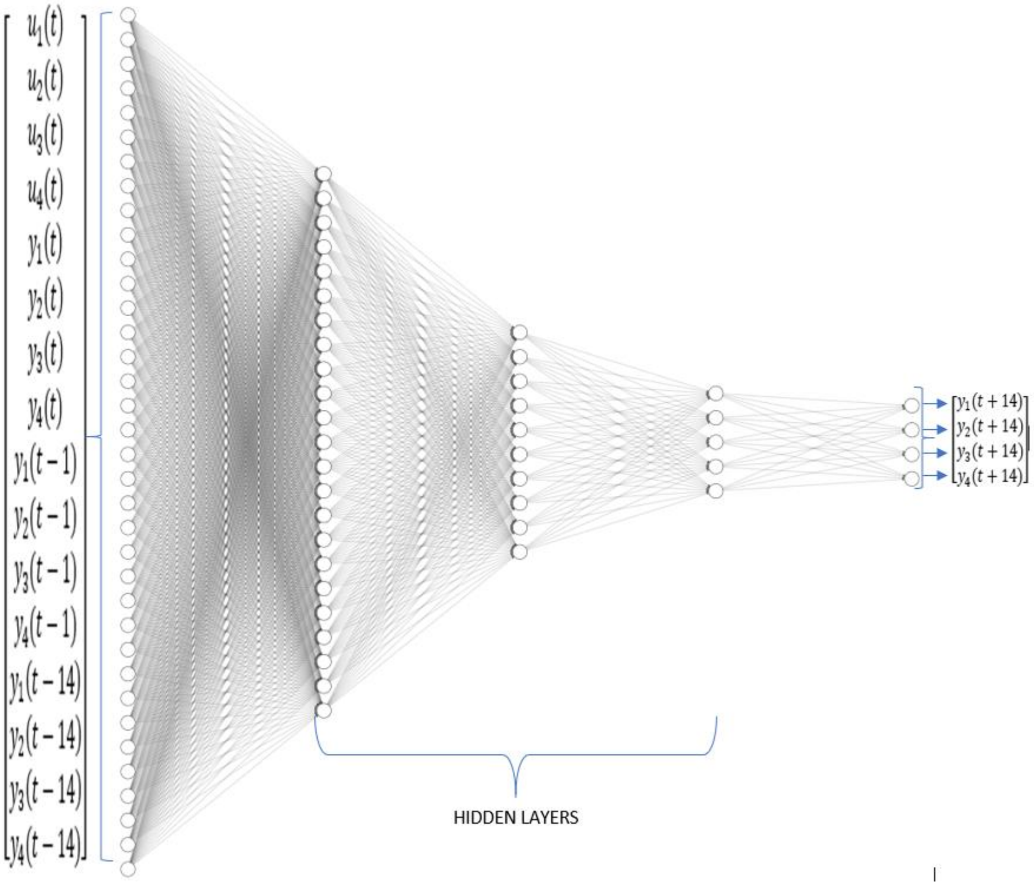

Figure 5.9: Stage 2 Neural network configuration

Table 5.4. Neural Network Training for stage 2

Training Parameters	Values
Epoch	200
Performance	0.00377 (MSE)
Gradient	0.000640
Mu	5.00e-05
Training Algorithm	Bayesian Regularization (trainbr)

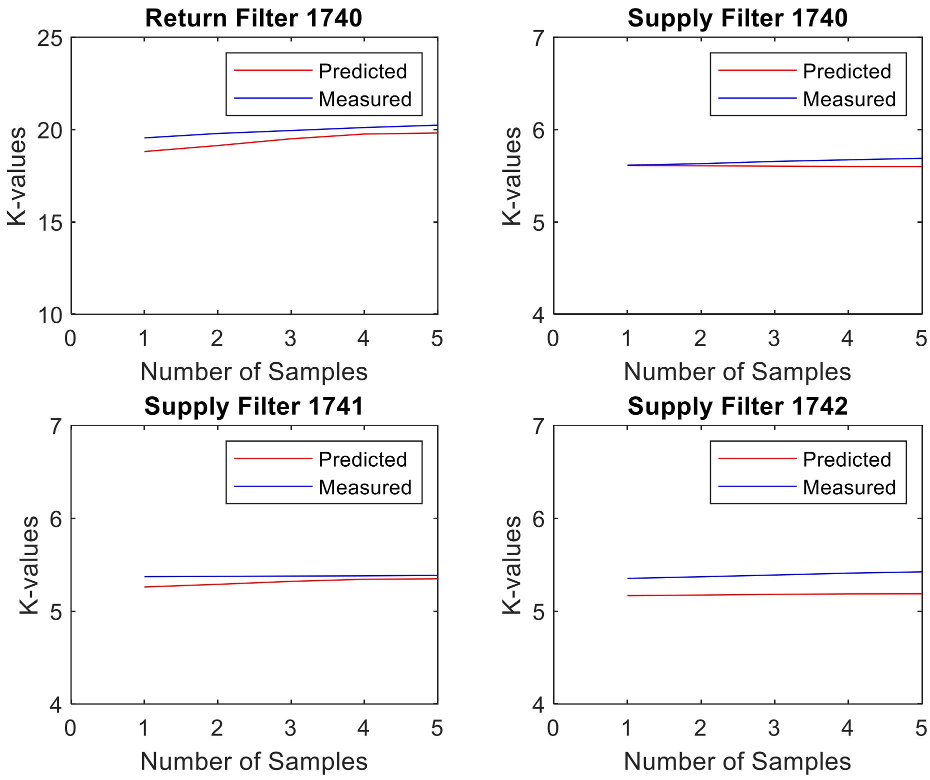

Figure 5.10: Two weeks K-values prediction Results

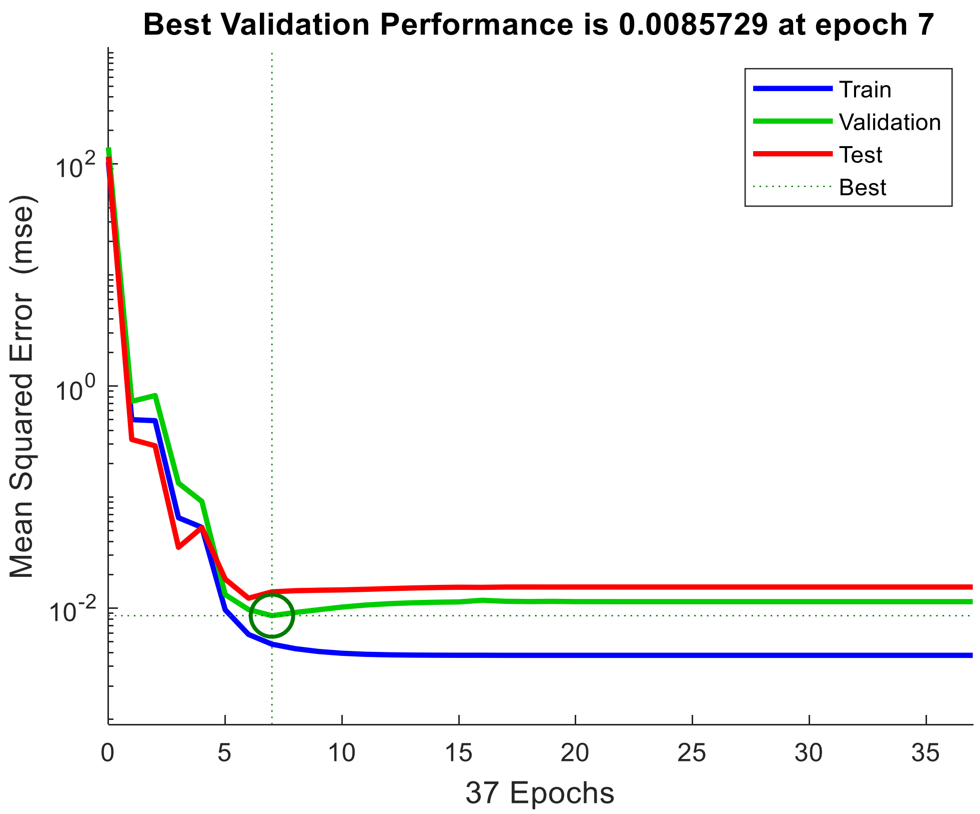

Figure 5.11: Neural Network Training Performance Plot (MSE) for stage 2.

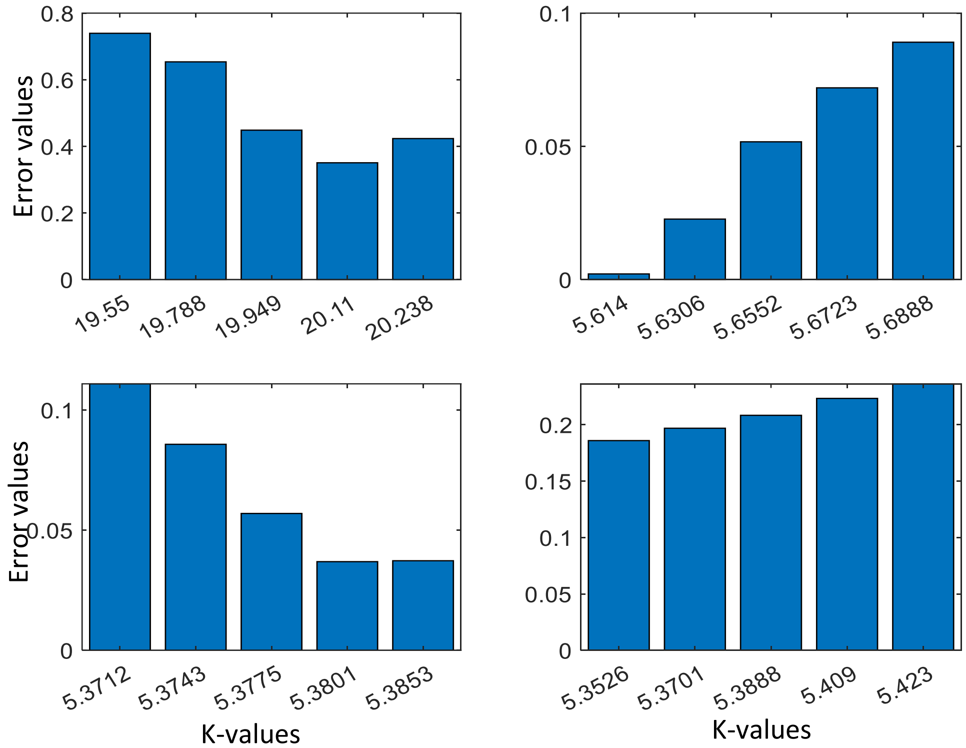

Figure 5.12: Error plot between Measured and Estimated K-values

5.5 Mean absolute percentage error

The Mean absolute percentage error (MAPE) is used to measure the accuracy of a prediction. The accuracy is measured as a percentage, in other words, it the average absolute percentage error minus the actual value divided by actual values. Mathematically, this can be expressed as shown below:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{5.7}$$

Where A_t and F_t are the actual and predicted values respectively.

However, to measure the accuracy of the predictions of the models developed in the work, MAPE was used. Below is a table that summaries the accuracy of the models.

Table 5.5. Prediction Accuracy

STAGE 1	MAPE			
	Return 1740 Filter	Supply 1740 Filter	Supply 1741 Filter	Supply 1742 Filter
1-day prediction	0.3738%	0.0093%	0.1435%	1.3874%
14-day prediction	1.9453%	0.8832%	0.2319%	4.1917%

Stage 1 was used to develop two models for a 1–day and 14-day predictions of K-values. From the table above, it can be observed that both models had a very good accuracy.

5.6 Recurrent prediction

However, to show the effect of longer prediction on the prediction models, the models obtained in stages 1 and 2 were subjected to longer term prediction i.e. 14 and 28-day prediction respectively while the result obtained is shown below:

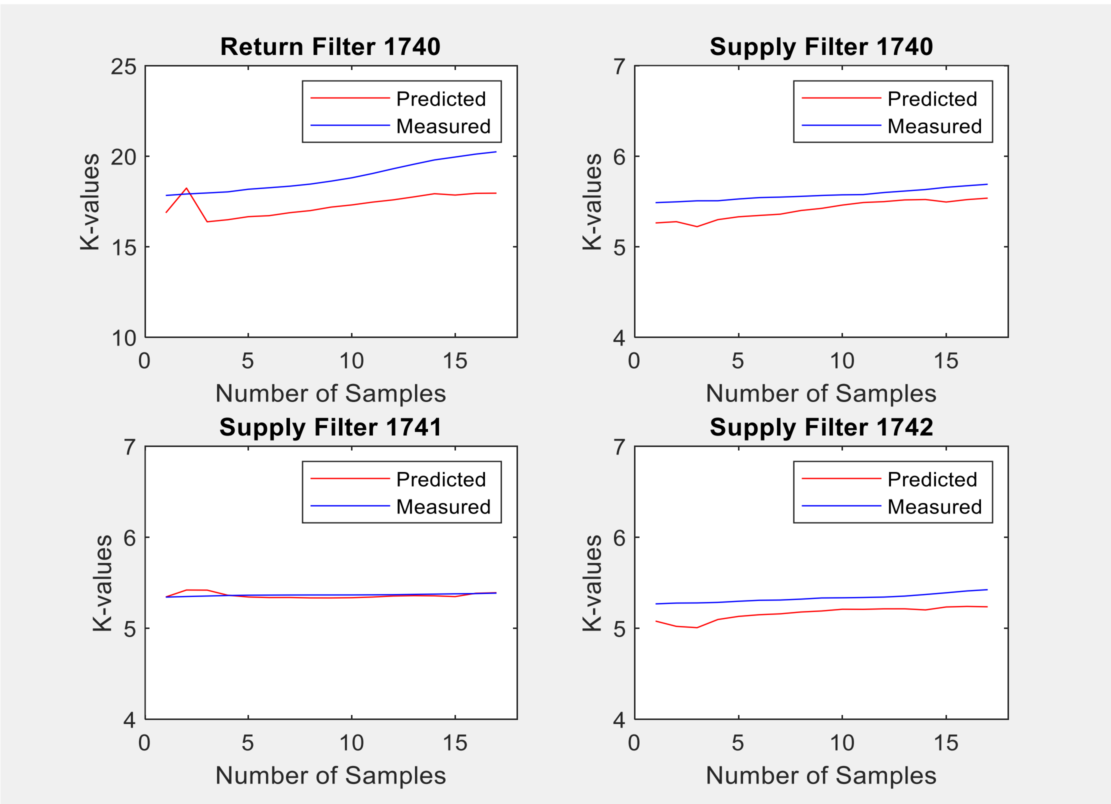

Figure 5.13: A 14-day prediction using model 1.

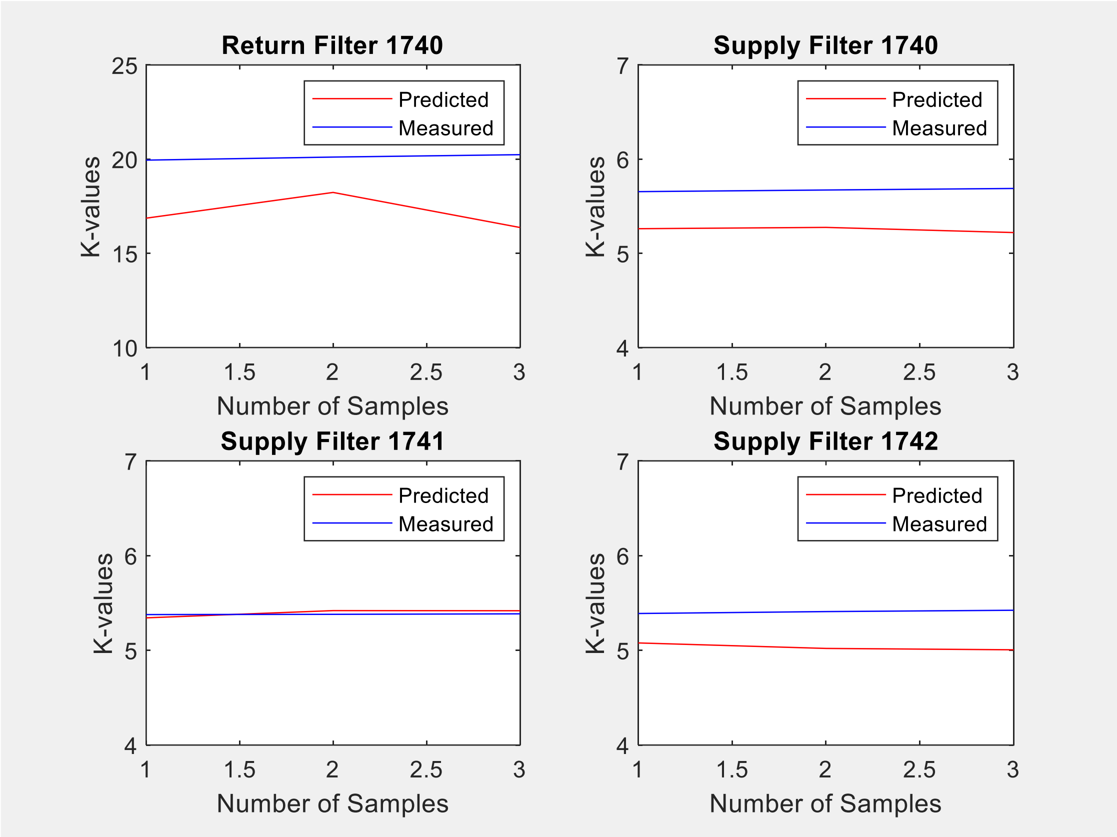

Figure 5.14: A 28 days K-values prediction using the model from stage 3.

The table below shows figures 5.13 and 5.14 prediction's accuracy using the MAPE:

Table 5.6. Recurrent Prediction Accuracy

Stage 2	**MAPE**			
	Return 1740 Filter	**Supply 1740 Filter**	**Supply 1741 Filter**	**Supply 1742 Filter**
Recurrent Prediction				
14 days prediction (model 1)	8.1053%	2.9587%	0.6343%	3.1729%
28 days prediction (model 2)	14.6277%	7.3953%	1.1280%	6.8843%

5.7 Summary

Tables 5.5 and 5.6 show the accuracy of the predictions in terms of MAPE. Table 5.5 shows a very good accuracy in terms of predicting the pressure loss coefficient by the trained models. However, table 5.6 shows how longer prediction can affect prediction models. Using model one from stage 1 (which was used for a day's prediction) to make a 14 days prediction, table 5.6 shows a reduction in the accuracy of the model. Meanwhile using model 2 from stage 1 to make a longer prediction (28 days) showed a reduction in the accuracy of the model. In conclusion, we can say that longer predictions reduces the accuracy of prediction models. However, it is paramount to make shorter predictions in order to get higher accuracies and performances of prediction models.

5.8 Electricity consumption and filter clogging

Pressure drop across filters increases as the filter becomes clogged. In a ventilation duct system, the duct fan pushes the air from either the outside environment in the case of a supply duct or from the inside space of a building in the case of return duct through the filters to the inside space and outside environment respectively. The filters on the duct act as a resistance to the flow of air which the fan duct must overcome to push the air to its destination. This resistance poised by the filters increases in 'strength' as the filters come clogged therefore increasing the work the duct fan must do in other to push the air to either the space within the building or to the outside environment. Therefore, the more work the duct fan has to do as the filter becomes clogged, the more the energy the duct fan consumes (electric energy) to push the air into or out of the building ventilation system. The relationship between electricity consumption and K-values are illustrated using the scatter plot diagram. A scatter plot diagram also known as a scatter plot shows the relationship between two quantitative (numerical) variables. These variables may be positively or negatively related or might not even be related at all. When two variables are positively related, it means that as one variable tends to increase, the other variable tends to increase also and vice-visa. However, two variables tend to be negatively related only if one variable increase or decreases while the other tends to do the opposite. The relationship between electricity consumption by duct fans and duct filters is shown using the data of ventilation unit 1740 return fan and filter respectively as shown below:

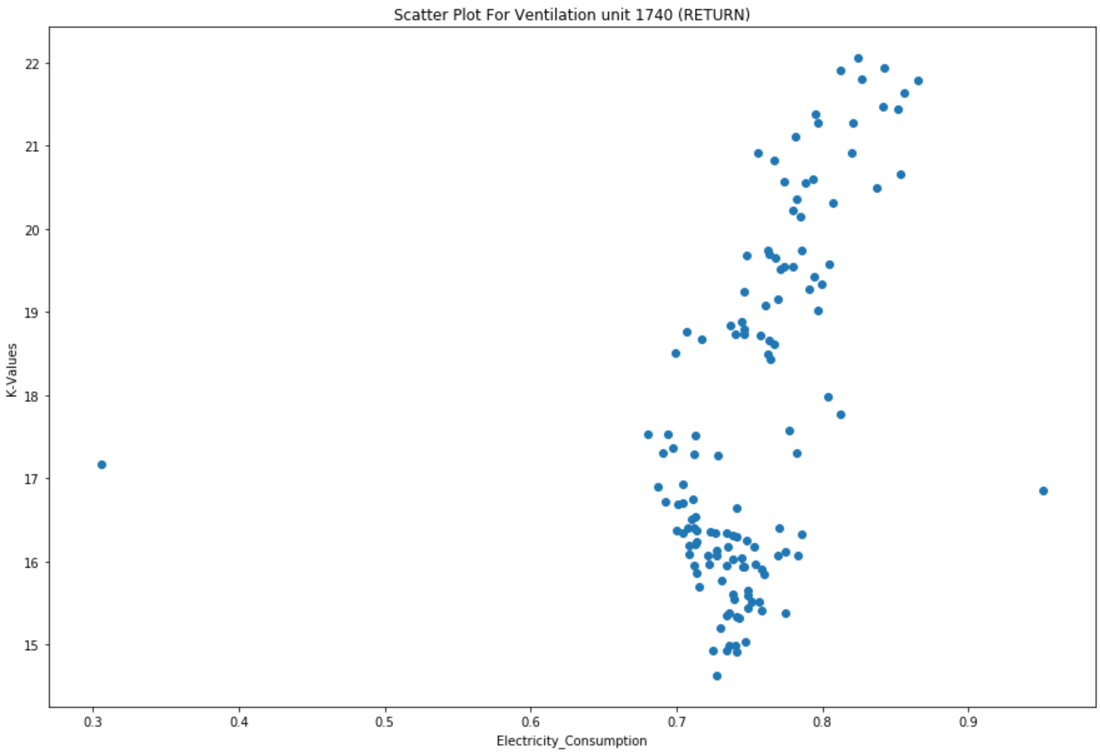

Figure 5.15: Relationship between K-values and Electricity consumption of duct filter scatter plot.

The general direction of the data points shown in figure 5.15 above is from the lower-left corner of the plot to the upper-right corner of the plot depicting that the two variables have a positive relationship.

6 Conclusion and future works

This chapter presents the last and concluding part of this thesis depicting the limitations and finally the future continuity of this work.

In this thesis, a data-driven artificial neural Network-based prediction model of filter clogging in building a ventilation system was presented. Meanwhile, the relationship between filter clogging in building ventilation systems and the power consumed by the duct fan was also presented. The uniqueness of this work points to the fact that a dynamic neural network was used for the prediction alongside unique input-output data.

The pressure loss coefficient prediction performance was measured using the MSE while its accuracy was measured using MAPE and the result obtained could help building managers Schedule filters change appropriately to minimize cost both in filter change scheduling and energy consumption costs.

6.1 Limitations and future work

One limitation of this work was the amount of dataset available. As discussed in chapter 4, data needed for the training of the Neural Network were taken from the total data gathered for each filter after a filter change was conducted, however, with larger dataset before filter change could improve the performance and accuracy of the models.

This research could furthermore be developed to estimate the actual cost (in monetary terms) filter clogging impacts on ventilation systems thereby quantifying its financial implication towards energy consumption in buildings.

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