

A Lean Model for Improving HVAC Predictive Maintenance Performance

by

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Modèle Lean pour améliorer les performances de la maintenance prédictive du système HVAC

Matti Tehrani

RÉSUMÉ

L'objectif de ce projet est d'évaluer et ultimement d'améliorer les techniques de maintenance prédictive du filtre de chauffage, ventilation et climatisation (HVAC). Le filtre est un sous-composant crucial pour le bon fonctionnement du système HVAC. Le colmatage et d'autres dysfonctionnements du filtre compromettent la qualité de l'air et peuvent entraîner des dommages coûteux au système HVAC dans son ensemble. La maintenance prédictive (PdM), dans laquelle le filtre est remplacé selon un calendrier planifié avant que le colmatage du filtre ne se produise, est nécessaire pour éviter de tels résultats. La majorité des programmes PdM de filtres HVAC ont échoué dans leur implantation. Par conséquent, des recherches sont nécessaires pour évaluer et explorer l'utilisation des techniques actuelles et nouvelles pour prédire les modèles de défaillance des filtres HVAC.

La première étape de ma recherche vise à évaluer cinq techniques prédictives actuellement utilisées pour les PdM de filtres HVAC : la régression des réseaux de neurones, la régression linéaire, la régression des réseaux bayésiens, l'arbre de régression boosté et la forêt de décision. Une étude de cas a été utilisée pour comparer les résultats de ces techniques prédictives au modèle de défaillance réel d'un filtre installé dans le système HVAC de l'École de Technologie Supérieure. Une approche multicritère a été utilisée pour évaluer les techniques prédictives en fonction de la précision prédictive et de l'opinion d'experts.

Une meilleure compréhension de la cause du colmatage du filtre est nécessaire pour prédire la défaillance du filtre. Par conséquent, la deuxième partie de ma recherche porte sur quatre paramètres relatifs au colmatage du filtre : la vitesse du ventilateur, la température de l'air de reprise, la température de mélange (reprise et air neuf) et la position du registre de mélange. Une étude de cas a été développée pour examiner dans quelle mesure chaque paramètre affecte les performances du filtre. Des capteurs installés à l'intérieur de l'unité HVAC UTA-104 de l'ÉTS ont recueilli des données sur ces paramètres et les performances des filtres sur une période de six mois. Les données expérimentales recueillies ont été intégrées à la dernière partie de ma recherche : un modèle de dynamique des fluides computationnelle (CFD) d'un système HVAC.

La troisième partie de mes recherches a été consacrée au développement d'un modèle CFD fonctionnel utilisant ANSYS FLUENT pour simuler le flux d'air dans l'unité de filtrage du système HVAC. Ce modèle CFD intègre la meilleure technique prédictive telle que déterminée par la première partie de ma recherche, ainsi que les données expérimentales recueillies dans la deuxième partie de ma recherche. S'il est combiné à un algorithme qui associe les données

VIII

en temps réel recueillies à partir d'un filtre HVAC et de son environnement, ce modèle CFD pourrait théoriquement être utilisé pour évaluer de manière fiable l'état du filtre et prescrire des procédures de maintenance.

Mots clés: HVAC, maintenance Prédictive, CFD, filtre

A Lean model for improving HVAC predictive maintenance performance

Matti Tehrani

ABSTRACT

The objective of this project is to evaluate and ultimately improve predictive maintenance techniques for the heating, ventilation and air conditioning (HVAC) filter. The filter is a crucial subcomponent to the proper function of the HVAC system. Clogging and other filter malfunctions compromise air quality and can result in costly damages to the HVAC system as a whole. Predictive maintenance (PdM), whereby the filter is replaced on a pre-planned schedule before filter-clogging occurs, is needed in order to avoid such outcomes. The majority of HVAC filter PdM programs have failed in their implantation. Therefore, research is needed to evaluate and explore the use of current and new techniques for predicting HVAC filter failure patterns.

The first step of my research aims to evaluate five predictive techniques that are currently used for HVAC filter PdM: neural network regression, linear regression, bayesian networks regression, boosted regression tree, and decision forest. A case study was used to compare the results of these predictive techniques against the actual failure pattern of a filter installed within the HVAC system at Écoule de Technologie Supérieure. A multi-criteria approach was used to evaluate the predictive techniques according to predictive-accuracy and expert opinion.

A better understanding of why filter clogging occurs is needed to predict filter failure. Therefore, the second part of my research focuses on four parameters pertaining to filter-blockage: fan speed, return air temperature, mixed temperature (return and fresh air), and the position of the mixture damper. A case study was developed to examine the extent to which each parameter affects filter performance. Sensors installed within the UTA-104 HVAC unit at ÉTS collected data on these parameters and filter performance over a six-month period. The experimental data gathered was incorporated into the final part of my research: a computational fluid dynamic (CFD) model of an HVAC system.

The third part of my research was devoted to developing a working CFD model using ANSYS FLUENT to simulate airflow within the HVAC system's filter unit. This CFD model incorporates the best predictive technique as determined by the first part of my research, as well as the experimental data gathered in the second part of my research. If combined with an algorithm that pairs real-time data gathered from an HVAC filter and its environment, this CFD model could theoretically be used to reliably assess filter health and prescribe maintenance procedures.

Keywords: HVAC, Predictive maintenance, CFD, filter

TABLE OF CONTENTS

	Page
INTRODUCTION	1
CHAPITRE 1 LITERATURE REVIEW	15
CHAPITRE 2 MULTI-SCENARIO AND MULTI-CRITERIA APPROACH TO EVALUATE PREDICTION TECHNIQUES USED TO RECOGNIZE FAILURE PATTERNS (CASE STUDY: HVAC FILTER BLOCKAGE)	23
2.1 Introduction	24
2.2 Literature Review	26
2.3 Research Methodology	29
2.3.1 Prediction technique	31
2.3.1.1 Neural network regression.....	31
2.3.1.2 Linear regression	32
2.3.1.3 Bayesian networks regression	32
2.3.1.4 Boosted regression trees (BRT).....	33
2.3.1.5 Decision Forest regression.....	33
2.3.1.6 Full factorial design of experiment.....	34
2.3.1.7 Multiple criteria decision making method.....	35
2.4 Application of proposed methodology in the case study.....	37
2.4.1 Case study.....	37
2.4.2 Data description.....	38
2.4.3 Model application.....	39
2.4.3.1 Decision forest regression:	41
2.4.3.2 Neural network regression:.....	41
2.4.3.3 Bayesian linear regression:	41
2.4.3.4 Boosted decision tree regression:	41
2.4.3.5 Linear regression method:	41
2.4.4 Prediction model output analysis.....	42
2.5 Prediction technique comparison results	44
2.6 MCDM tools to rank the prediction techniques	52
2.7 Conclusion	53
2.8 Recommendation and future works	54

2.9	ACKNOWLEDGMENT	54
CHAPITRE 3 CORRELATION OF CRITICAL PARAMETERS THAT CONTRIBUTE TO HVAC FILTER AND PRE FILTER CLOGGING		
3.1	Introduction	55
3.2	Literature review.....	56
3.3	HVAC maintenance costs caused by filter blockage and clearing.....	58
3.4	Assumptions and Hypothesis.....	63
3.5	Experimental plan.....	63
3.6	Method of analysis.....	64
3.7	Results and discussion	66
3.7.1	Statistical analysis.....	66
CHAPITRE 4 ASSESSMENT OF HVAC SYSTEM FILTER PERFORMANCE USING COMPUTATIONAL FLUID DYNAMICS(CFD).....		
4.1	Introduction	71
4.2	Literature Review	72
4.3	Research Methodology	75
4.3.1	Data Description	75
4.3.2	Model Description	76
4.3.2.1	Assumptions & Givens.....	76
4.3.2.2	Geometry and Meshing.....	78
4.3.2.3	Boundary and Initial Conditions.....	79
4.3.2.4	Physics & Solver Setup	81
4.4	Results 82	
4.4.1	General Results.....	82
4.4.1.1	Pressure Contours	83
4.4.1.2	Velocity Contours.....	83
4.5	Discussion and Analysis	84
4.6	Conclusion	86
	DISCUSSION	89
	CONCLUSION	95

LIST OF REFERENCES 97

LIST OF TABLES

	Page
Table 2-1	Examples of data points 39
Table 2-2	Different scenarios for model prediction using different versions of edited data 48
Table 2-3	Result of performance measurement for all prediction techniques in all scenarios..... 50
Table 2-4	Pair-wise comparison of prediction methods..... 52
Table 2-5	Results of TOPSIS method for eight scenarios..... 52
Table 2-6	Results of TOPSIS method for scenario No9 53
Table 3-1	Costs of Major HVAC System Repair and Maintenance 59
Table 3-2	Experimental parameters used 64
Table 3-3	Model summary statistics for the responses studied..... 67
Table 3-4	Model summary of regression modes between Delta P (Filter) and Delta P (Pre-Filter)..... 69
Table 4-1	Assumption identification..... 76
Table 4-2	Assumption justifications and references 77
Table 4-3	Simulation Case Boundary Conditions..... 80
Table 4-4	Simulated and Experimental Pressure Drop across filter 85
Table 4-5	Simulated and Manufacturer’s Data for Pressure Drop across filter 85

LIST OF FIGURES

		Page
Figure 2-1	The flowchart of the proposed methodology	31
Figure 2-2	Schematics of ETS HVAC system	38
Figure 2-3	Exponentially weighted moving average.....	43
Figure 2-4	Moving range	44
Figure 2-5	Decision tree schematic block for actual out-of-control points	46
Figure 2-6	Factors and levels for investigating the performance of prediction methods using DOE	47
Figure 3-1	Life cycle costing formula	61
Figure 3-2	Optimum Final Pressure Drop	62
Figure 3-3	Pareto chart of (a) Delta P (Filter) and (b) Delta P (Pre-Filter) in Quadratic model.....	67
Figure 3-4	Pareto chart of (a) Delta P (Filter) and (b) Delta P (Pre-Filter) in quadratic model with only significant statistical elements	68
Figure 3-5	3D contour plot of (a) Delta P (filter) and (b) Delta P (Pre-Filter) at the fix levels of the opening valve (B) and Returned air Temperature (C)	68
Figure 3-6	Multiplicative Regression model between Delta P (Filter) and Delta P (Pre-Filter).....	69
Figure 4-1	HVAC System Schematic.....	78
Figure 4-2	HVAC System Fluid-Domain Mesh.....	79
Figure 4-3	HVAC System Model Named Selections (blue inlet, red outlet)	80
Figure 4-4	Residuals convergence for case 1 (left), case 2 (mid), case 3 (right)	82
Figure 4-5	Mass flow rate convergence for case 1 to 3 (left to right)	82
Figure 4-6	Pressure contour of flow across filter for case 1 to 3 (left to right)	83

Figure 4-7 Velocity contours of flow across filter for case 1 to 3 (left to right) 84

LIST OF ABBREVIATIONS

HVAC	Heating, Ventilating and Air-Conditioning
SBS	Sick Building Syndrome
CFD	Computational fluid dynamics
FDD	fault detection and diagnosis
PWM	Pulse-width modulation
PSTC	Predictive smart thermostat controller
MPC	Model predictive controller
CAD	Computer aided design
DES	Detached Eddy Simulation
ETS	École de Technologie Supérieure
SA	Spalart-Allmaras
LES	Large Eddy Simulation
r	Correlation Coefficient
R ²	Correlation of Determination
HVAC	Heating Ventilation and Air conditioning
ETS	École de technologie supérieure
ANOVA	Analysis of variance
ANOM	Analysis of means
RSM	Response surface methodology

INTRODUCTION

Heating, ventilation, and air conditioning (HVAC) systems provide thermal comfort by heating or cooling buildings based on internal and external environmental conditions, and maintain acceptable air quality by introducing, filtering, and disseminating air throughout buildings (Noris, Siegel et al. 2009) (Biada and Gray 2010). Properly functioning HVAC systems are crucial to building infrastructure (Thompson, Gao et al. 2018). Yet it is often the case that HVAC systems operate under faulty conditions. While incorrect installations and other human maintenance errors are sometimes to blame for faulty HVAC operation, many HVAC system failures are the result of subcomponent malfunctions that current predictive maintenance models (PdM) fail to anticipate (Rosato, Guarino et al. 2020) (Robb 2015) (Perez, Zimmerman et al. 2006) (Mowris, Jones et al. 2012). Behavioral rules, such proper training and oversight for HVAC maintenance workers and installations or measures to improve indoor air pollution, can generally correct HVAC malfunctions stemming from human error; designing and implementing reliable PdM is a more challenging and potentially more impactful measure to ensure optimal HVAC operation. (Biada and Gray 2010) (Robb 2015) (Rosato, Guarino et al. 2020) (Roy 2006) (Duncan 2019). HVAC systems cannot reliably provide thermal comfort and acceptable air quality until more effective PdM models are developed.

My research focuses on PdM for the HVAC filter. While the failure of any single HVAC subsystem component has consequences for the system as a whole, the filter is of particular concern when it comes to optimal HVAC function. At best, a filter malfunction compromises the HVAC system's optimal efficiency; filter clogging can compromise airflow and temperature regulation, which can ultimately lead to the HVAC system to operate at an energy increase of up to 15% (Richardson 2019, November 20). At worst, filter-blockages can lead to major system failures stemming from related subcomponent malfunctions including frozen evaporator coils, furnace failure, fan motor damage, and ductwork uncleanliness (Richardson 2019, November 20). The goal of PdM is to avoid these outcomes by prescribing maintenance procedures for the HVAC filter on a pre-planned schedule (Biswal, Americas et al. 2010). In

order to design an effective PdM model, techniques for reliably assessing the failure mode of the filter must be developed and implemented.

My research also focuses on applying the concept of a lean model to HVAC filter PdM. A lean model endeavors to streamline PdM by removing non value-added techniques, data, models, and maintenance procedures within its framework. A lean HVAC filter PdM model therefore becomes more efficient as more research and data pertaining to HVAC filter function is gathered.

Motivation and Challenges

Finding effective techniques for assessing the lifespan of the HVAC filter has always presented a challenge (Heidrich et al., 2018). Each available predictive model to date provides different outputs and so far, none have proven to be entirely reliable. The majority of predictive techniques in current use have been designed purely on the basis of mathematics and do not take experimental data, the opinion of experts, or practical application into account (Lennox, Montague et al. 2001). Furthermore, much of the current literature and many of the current models devoted to HVAC filter maintenance focuses on reducing energy-consumption rather than determining filter health and predicting filter failure. If more reliable predictive techniques could be developed and implemented, the resulting HVAC filter PdM models could yield a wide array of economic, environmental, and public health benefits.

HVAC filter blockage can create several problems for a maintenance team. The HVAC (Heating, Ventilation, and Air Conditioning) system relies on a clean and unobstructed filter to function effectively. When the filter becomes blocked, it can lead to various issues, including:

- 1) **Reduced airflow:** A blocked filter restricts the airflow through the HVAC system. This can result in decreased air circulation and poor ventilation throughout the building. Insufficient airflow can cause discomfort for occupants, uneven temperature distribution, and reduced indoor air quality.

- 2) **Decreased energy efficiency:** An obstructed filter forces the HVAC system to work harder to maintain the desired temperature. This increased strain on the system leads to higher energy consumption and utility costs. Inefficient operation can also contribute to premature wear and tear on HVAC components, reducing their lifespan.
- 3) **Impaired heating or cooling performance:** A clogged filter impedes the system's ability to heat or cool effectively. With reduced airflow, the HVAC system may struggle to reach the desired temperature, resulting in discomfort for occupants. In extreme cases, the system may fail to provide any heating or cooling at all.
- 4) **Increased maintenance and repair needs:** A blocked filter can lead to additional maintenance and repair requirements. The restricted airflow can cause components like the blower motor and evaporator coil to overheat, leading to their failure. Furthermore, contaminants bypassing the filter can accumulate on sensitive components, causing damage and reducing the system's reliability.
- 5) **Decreased indoor air quality:** HVAC filters play a crucial role in trapping dust, pollen, allergens, and other airborne particles, preventing them from circulating in the indoor environment. When the filter is blocked, these contaminants can bypass the filter and enter the occupied spaces, negatively affecting indoor air quality. This can lead to respiratory issues, allergies, and discomfort for occupants.

For the maintenance team, a filter blockage means increased workload and maintenance tasks. They will need to regularly check and replace filters, clean affected components, and address any issues arising from the blockage. Failure to address a filter blockage promptly can result in more extensive and costly repairs, compromised system performance, and occupant dissatisfaction. Therefore, it is essential for the maintenance team to proactively monitor and address HVAC filter blockages to ensure the system operates efficiently and maintains optimal indoor air quality.

Reliable HVAC filter PdM could improve the economic efficiency and stability of institutions and organizations across the world. All commercial, public, and nonprofit organizations aim to deliver goods and services on predictable schedule and at an optimal cost. In the absence of

effective PdM for the HVAC filter, institutions cannot reliably project the overhead costs associated with HVAC maintenance; the potential for a costly and unexpected HVAC system failure related to filter-blockage is always present. Replacing the filter on an accurate and predetermined schedule is much more cost-effective than paying for repairs associated with a filter-clogging. HVAC system failures stemming from filter-blockages can burden institutions with excessive maintenance fees, a shortened HVAC unit lifespan, extra costs associated with replacing HVAC subcomponents, and any number of indirect financial damages that come with disrupting the daily operations of an organization (Heinemeier, Hunt et al. 2012). Energy inefficient operation due to filter blockages also results in inflated utility bills that significantly increase the cost of running the HVAC system (Rosato, Guarino et al. 2020) (Robb 2015). Inadequate PdM can also financially drain institutions with maintenance practices that call for the filter to be replaced too early or too often. A lean PdM HVAC filter model that seeks to minimize repairs by continually improving its efficiency and removing non-value added maintenance procedures will economically benefit organizations that rely on HVAC function. Given the global ubiquity of HVAC systems in building infrastructure, improved filter PdM models could boost the economic productivity of a vast array of public and private institutions worldwide.

In addition to potential economic benefits, improved techniques for predicting HVAC filter failures could prove environmentally advantageous. Filter-clogging makes the entire HVAC system less energy efficient to operate (Richardson 2019, November 20). Filter-blockages reduce the HVAC unit's operational lifetime (Heinemeier, Hunt et al. 2012), thereby contributing to the extra waste and energy-consumption associated with discarding and replacing a prematurely-dysfunctional HVAC system with a new one. HVAC systems account for 40 to 60% of energy consumption within the building sector (Solano, Caamaño-Martín, Olivieri & Almedia-Galárraga, 2021); the building sector itself accounts for 40% of energy consumption and 30% of greenhouse gas emissions worldwide (Zhai & Helman, 2019). Energy-inefficient HVAC operation resulting from poor filter-performance therefore contributes to climate change by producing more potentially-avoidable greenhouse gas

emissions. Ironically, as global temperatures rise, properly-functioning HVAC systems will be more crucial than ever; beyond maintaining thermal comfort, organizations will increasingly rely on HVAC systems to regulate dangerously hot environments. Designs and solutions for HVAC systems will need to account and adjust for the realities of climate change in order to ensure optimal functionality and efficiency in the future (De Rubeis, Falasca, Curci, Paoletti & Ambrosini, 2021). As HVAC designs adjust to changes in climate, it will be necessary for predictive maintenance techniques for the HVAC filter to adjust as well. Extreme heat conditions will become more common as global temperatures rise, thereby placing more strain on the air conditioning component of HVAC systems including the filter unit. Improved PdM methods for the HVAC filter could help break this feedback loop between filter malfunctions contributing to climate change, and climate change contributing to increasing strain on the HVAC filter.

Improved PdM for the HVAC filter could yield significant public health benefits. Filter-clogging compromises air flow within the HVAC system, which can in turn lead to sick building syndrome (SBS): health and discomfort effects associated with time spent in a building, including dizziness and nausea, headaches, dry cough, and irritation of the eyes, nose or throat (EPA, 1991). Problems associated with SBS can result in diminished worker productivity and satisfaction (Perez, Zimmerman et al. 2006). As previously mentioned, the air conditioning component of HVAC systems will likely play an increasingly vital public-health role as global temperatures rise; potentially-avoidable system failures could put the lives of building occupants at risk during heat waves. The emergence of COVID 19 reveals another crucial reason to improve PdM for HVAC filters. According to the American Society of Heating, Refrigerating, and Air-Conditioning Engineers, some actions related to HVAC function (with a particular focus on the filter and its function in regulating air quality) may affect the indoor spread of COVID 19 (ASHRAE, 2021). These actions include increasing outdoor air ventilation, ensuring optimal air filtration through use of MERV 13 filters (or the highest quality filters available for a given unit), limiting air bypass by sealing the edges of the filter, and keeping HVAC systems running 24/7 (ASHRAE, 2021). Improved filter PdM would

allow HVAC systems to perform these functions more reliably, thereby helping institutions like schools and businesses safely resume their in-person operations.

Research Objectives

I have developed a three-part strategy for obtaining research that could be used to improve a lean HVAC filter PdM. My research will aim to achieve the following objectives:

- Evaluate current predictive techniques based on accuracy and practical application
- Study and assess the critical parameters that lead to filter-clogging
- Integrate the best predictive technique from objective 1. and data gathered from objective 2. into a 3D computational fluid dynamics (CFD) model that could theoretically be used to assess filter-health and predict the next filter-failure.

The first goal of my research is to assess which current predictive technique provides the most accurate and practical maintenance procedures. Testing the failure-modes of predictive models against the actual failure-mode of the HVAC filter would reveal which model provides the most accurate assessment of filter health. In turn, this research would also reveal non value-added predictive techniques that could be eliminated from a lean PdM model. Comparing predicted failure modes against the actual failure mode of the HVAC filter requires experimental data to be gathered from a working HVAC unit. Expert opinions must be taken into account in order to assess the practical viability of predictive techniques. An ideal PdM model should provide maintenance recommendations that are both accurate and financially practical, relatively undistruptive to organizations in proximity to the HVAC system, and successfully implementable by HVAC maintenance workers in a real-world setting; a PdM model that burdens organizations with overly disruptive, expensive, or complicated maintenance recommendations is likely to be neglected or rejected in favour of more practically-implementable systems. No mathematical prediction technique is infallible, and sensors will inevitably misdiagnose filter issues from time to time. An HVAC expert must confirm the accuracy of the PdM filter diagnosis and act either according to or contrary to its recommendation. Therefore, an evaluation of predictive techniques for the HVAC filter must account for both accuracy and the opinions of experts.

The second goal of my research is to gather experimental data from a working HVAC unit in order to better understand the variables that lead to filter-clogging. This data could improve HVAC filter PdM by helping to determine why, how, and when filter-blockages occur in a real-world setting. Incorporating this experimental data into the design of PdM models themselves could result in more accurate techniques for predicting filter-blockage than those yielded by purely mathematical models. A PdM model tempered by experimental data would also have the advantages of flexibility and incremental improvement required by a lean model; maintenance procedures could be adjusted as more data pertaining to filter-blockage is collected from an increasing list of variables and environmental conditions. Data collected from a single HVAC system in real-time could help customize filter maintenance-procedures for that particular unit based on the demands of the climate and building infrastructure in which it operates; data collected and analyzed across thousands of HVAC systems could improve general PdM procedures, elucidating more parameters that contribute to filter blockage with increasing precision across a wider array of variables like air quality, climate and temperature fluctuations, the age and lifespan of the HVAC unit, etc.

The third objective of my research is to develop a CFD model in order to account for air-flow in a three-dimensional setting. This CFD model will integrate the best technique for predicting filter-clogging (objective 1.) with data pertaining to conditions that lead to filter-blockage (objective 2.) in order to arrive at more reliable diagnostics pertaining to HVAC filter health. Current numerical models used to predict filter-blockage are largely based on two-dimensional geometry simplifications. For example, most models that attempt to simulate pressure drops and the capture of air contaminants in HVAC filter media are 2D in nature. While some of these simulations establish reasonably viable 2D models (Justi, Cândido Da Silva et al. 2014) (Feng, Long et al. 2014), they cannot observe and account for airflow properties in a three-dimensional context. CFD models, when combined with experimental data, can better simulate airflow within an HVAC system and allow for more accurate aerodynamic predictions (Zhai et al.) (Barber, Hall 2006). CFD modelling has already been shown to improve thermal load predictions within HVAC systems by 10% (Chafi, Hallé 2011); the potential for CFD to

simulate airflow within HVAC systems thereby makes it a promising area of research for filter PdM. Current advances in CFD analysis of HVAC filters indicate that Detached Eddy Simulation (DES) models are more reliable and efficient in simulating pleated filter systems than two-dimensional mathematical models (Feng, Long et al. 2014). Despite its potential to improve PdM by way of more sophisticated analyses of flow conditions, CFD models have been largely underutilized and misunderstood due to the complexity of physics modeling. Three dimensional CFD modeling techniques, validated by experimental data and real-time monitoring obtained from HVAC systems, could prove useful to developing more reliable PdM for the HVAC filter.

If a CFD model proves successful, an algorithm could potentially pair the model with real-time data gathered from the HVAC filter and its environment in order to prescribe accurate maintenance procedures that are specific to each unit. Such a system would essentially act as a Digital Twin: an Industry 4.0 system that synchronizes a virtual simulation of reality (in this case, a CFD model) with a real-time operating scenario (a working HVAC unit) to facilitate sound decision making (Semeraro et al., 2021). By adapting and responding to real-time sensory data in concert with computer modeling, Digital Twins can be powerful forecasting tools for predictive maintenance (Liu et al., 2018).

Methodology

I designed and carried out a case study in order to determine which current prediction models perform best when it comes to anticipating the next HVAC filter blockage. My research compares the actual failure mode of the HVAC filter to that of the failure modes predicted by five more applicable techniques(based on literature review):

- Neural network regression
- Linear regression
- Bayesian linear regression
- Boosted regression tree (BRT)
- Decision forest

Based on the literature review and below references among different prediction technique 5 models have been selected which are more applicable for this specific case studies which is HVAC filter blockage .

Neural network :

In the case of HVAC filter blockages, a neural network can be trained to predict the likelihood of a filter being blocked based on various input variables .Cui, H., & Zhang, C. (2021).

Linear regression:

Linear regression is a simple, yet powerful statistical technique used to model the relationship between a dependent variable and one or more independent variables. It can be used to predict the probability of a filter blockage based on factors such as the age of the HVAC system, the frequency of filter changes, and the quality of the filters used. Sharma, A., & Bhatia, M. (2021).

Bayesian linear regression :

Bayesian linear regression is graphical models that can represent probabilistic relationships between variables. They can be used to predict the likelihood of a filter blockage based on various input variables, such as the type of HVAC system, the age of the system, and the frequency of filter changes. Song, J., & Gao, W. (2020)

Boosted regression.

Boosted regression is a machine learning technique that combines multiple regression models to improve prediction accuracy. It can be used to predict the probability of a filter blockage based on various input variables, such as the type of filter, the time elapsed since the last filter change, and the air quality index. Cai, W., & Cui, Y. (2019)

Decision forest regression:

Decision forest regression is a machine learning technique that builds multiple decision trees to make predictions. It can be used to predict the likelihood of a filter blockage based on various input variables, such as the age of the HVAC system, the type of filter, and the frequency of filter changes. Li, Y., Li, J., Huang, B., & Yu, Q. (2021)

Experimental data is needed to compare outcomes predicted by these techniques to that of a working HVAC unit. I chose the HVAC system installed at École de Technologie Supérieure (ÉTS), an engineering university in Montréal, Canada, for this purpose. This HVAC system consists of 25 separate units, with each unit serving one zone of the building. Each unit is controlled and monitored by Johnson Controls. Data for this study was gathered from the UTA-104 operational unit, which cycles air through the internal areas (zones) of building B. This particular unit was selected because it works the most hours and controls temperature in one of the main buildings (B) at ÉTS. The UTA-104 contains sensors that were used to gather data points on six parameters that are relevant to filter-blockage:

- Return air temperature
- Mixed temperature
- Damper-opening percentage
- Fan speed
- Pre-filter pressure
- Post-filter pressure.

Statistical control charts were used to compare the actual failure mode of the UTA-104 filter (as determined by data points gathered on the six parameters above) against those predicted by the five aforementioned techniques. The outcome of this comparison will reveal which predictive technique is best suited to accurately predicting filter-blockage. In order to account for practical implementation and human oversight, I included expert opinion within a multiple criteria decision making (MCDM) tool for evaluating HVAC filter PdM models.

I have developed another case study to examine the critical parameters that contribute to filter and pre-filter clogging. Experimental data collected from the UTA-104 operation unit at ÉTS was used for the purpose of this research. The system process of concern is the unit's air output. Air output includes the volume, flow, and quality of outputted air, as well as the energy consumed in the process of outputting air. There are four manageable process parameters that influence the UTA-104's air output: the fan speed, the return temperature, the mixed temperature (return and fresh air), and the position of the mixture damper. A model was developed to examine the relation between these variables and the process response, which include air filter and pre-filter blockage. Over a six month research period, an aggregate of 108 experiments were completed, and 34544 data points were collected and recorded using calibrated sensors installed within the UTA-104 at ÉTS. These data points were targeted on the basis of better understanding the unit's filter performance over the six month period. Statistical models are necessary to understand what the gathered data reveals about the impact of each parameter (Kilickap, 2010). In this case study, four statistical models were used to analyze the data gathered by the model developed in my research:

- Analysis of variance (ANOVA)
- Pareto analysis
- Analysis of means (ANOM)
- Response surface methodology (RSM).

Once analyzed through these statistical models, data gathered on the air output of the UTA-104 at ÉTS university could better our understanding of how, why, and over what time period filter blockages occur. This knowledge could in turn be used to prevent the unit's next filter blockage and maintain optimal HVAC system performance.

In order to fully utilize the research conducted in my two aforementioned case studies, my research aims to develop a CFD model that incorporates the data I have gathered on predictive techniques and parameters pertaining to filter-blockage. My research objectives in this area are threefold:

- Develop a Detached Eddy Simulation (DES) using ANSYS simulation software.
- Validate this model with experimental data gathered from the HVAC system.
- Explore the theoretical possibility and potential benefits of combining this model with real-time monitoring of a working filter system

The DES model developed in my research using ANSYS took some assumptions and givens pertaining to the physical properties of HVAC systems and filters into account. Primary assumptions taken into account by the model include the size and materials of the steel duct, the size, material and porosity of the air filter, and the maximum duct airflow speed. These assumptions were based on commonly used materials in ductwork for HVAC systems (Connecticut State Government, 2015), typical industrial HVAC system sizes including the one installed in building B of Ecole de Technologie Superieure (Terhani et., al.) (Camfil, 2021) (Mann Hummel Group, 2021), and a study of HVAC systems' pleated filters (Feng, Long et al. 2014). A working physics method was integrated into the CFD model using ANSYS's Design Modeler in order to account for meshing and geometry. A no-slip boundary condition was created using the enclosure method ANSYS's Design Modeler in order to simulate air flow within the HVAC aluminum duct (i.e. the housing of filter assembly) in the computational fluid domain. The DES model treats the filter as a porous zone under laminar flow conditions. The ANSYS FLUENT User Guide (ANSYS Inc., 2009) and experimental data of the synthetic filter (Tehrani, Beaugard et al. 2015) were used to set parameters for the viscous resistance coefficient in the direction of flow and the direction of the remaining axes normal to the flow direction, an inertial resistance coefficient, and fluid porosity of the HVAC filter within the DES model. A Detached Eddy Simulation – Spalart Allmaras model was used to anticipate transitional flow and pressure drop through the filter via time transient simulation. The ANSYS FLUENT solver, with preferences set to the SIMPLE algorithm, was employed to solve the primary fluid flow governing equations. If validated by experimental data, this 3D computational model could help diagnose filter health and lifespan for HVAC units.

It has been established that it is crucial to integrate and validate HVAC PdM models with experimental data in order to establish more effective predictive techniques. Thus, the DES

model developed in my research is guided in part by experimental-data gathered by (Feng, Long et al. 2014) and (Tehrani, Beauregard et al. 2015). The model also uses experimental data gathered from a working HVAC unit for validation and verification (V&V). This data was collected from the operation unit UTA 104 installed at Ecole de Technologie Superieure over a six-month time period at a rate of 34,544 data points every 30 minutes. The gathered experimental data was targeted toward the study of performance-based variables that influence filter operation. These variables include the fan speed (%), the damper position (%), and the mixed air and return air temperatures (°C). The data, which was processed by (Tehrani, Beauregard et al. 2015), was used to validate the CFD model developed. If the computational model proves valid, it could be paired with software that integrates real-time data gathered from the HVAC unit so that ANSYS can assess and account for filter pressure drop and account for environmental conditions. If this model and its potential accompanying software could be successfully implemented, filter-blockage percentage and could be approximated more accurately, thus avoiding the financial, environmental, and public health risks associated with filter clogging and related HVAC system failures.

Thesis Contribution

This thesis will contribute research necessary to improving HVAC filter PdM. The first contribution will take the form of evaluating five predictive models (neural network regression, linear regression, Bayesian networks regression, boosted regression tree, decision forest) for filter failure. Experimental data gathered in my case study and the opinions of experts will be used for this evaluation. The second contribution will be to study and to determine which factors contribute most to filter-blockage. The third contribution will be to develop a DES model that simulates filter-blockage. The DES simulations are validated by experimental data that could theoretically be used in concert with experimental data to predict filter blockages in HVAC systems.

Thesis Outline

This thesis contains 5 chapters. Following in the introduction, CHAPTER 1 includes a literature review pertaining to the HVAC filter and PdM. CHAPTER 2 contains a case study to evaluate five models for predicting failure of the HVAC against experimental evidence and expert opinion. CHAPTER 3 includes a case study that aims to determine which factors contribute most significantly to filter-clogging. CHAPTER 4 outlines the DES model created to simulate filter blockage. This chapter also tests this simulation against experimental evidence for V&V. The DISCUSSION analyzes the results, validity and limitation of the research conducted, and suggests ideas for future research. The CONCLUSION summarizes the results of the research conducted.

CHAPITRE 1

LITERATURE REVIEW

Ineffective or ill-timed HVAC system maintenance results in a variety of system operation and health issues. For example, HVAC system failures can result in Sick Building Syndrome (SBS), which causes the occupants of a mechanically-ventilated building to experience symptoms ranging from headaches to respiratory problems, ultimately resulting in decreased worker productivity and satisfaction (Perez, Zimmerman et al. 2006). Poor maintenance practices also results in less energy-efficient and more costly HVAC operation (Heinemeir, Hunt et al. 2012, Robb 2015, Rosato Guarino et al. 2020).

Preventive maintenance, whereby HVAC subcomponent parts are replaced on a pre-planned schedule before they fail, is necessary to avoid problems associated with poor HVAC maintenance. Filter dust is a common problem for inefficient units; dust can result in higher levels of airborne fungal contamination that lead to SBS and other building-health problems (Perez, Zimmerman et al. 2006, Roy 2006). Filter media blocks airborne heavy metal, bacteria and fungi particles (Rossnagel 1997, Norris, Seigel et al. 2009). However, filters become ineffective as airflow reaches a certain threshold and as dust and other particles build up; therefore, timely replacement of the HVAC filter (including replacing the filter mesh) is particularly important to effective and efficient system operation (Rossnagel 1997, Norris, Siegel et al. 2009).

Understanding the life cycle of HVAC filters, which varies according to variables like system operation, environmental conditions, filter mesh size, and filter quality, is necessary to arrive at effective PdM for the HVAC filters. Most maintenance procedures focus on the complete unit models and controlling the output of a unit. This approach is useful for improving HVAC efficiency and reducing energy consumption, but does not effectively implement maintenance

procedures for the filter, and therefore does safeguard against common system failures associated with filter-clogging.

A thorough examination of literature relevant to HVAC filter predictive maintenance is necessary to guide this project. This literature review will examine current state of research pertaining to predictive techniques, the processes that impact HVAC filter-function, and HVAC system modelling techniques including Computational Fluid Dynamic (CFD) techniques.

Predictive techniques

Predictive maintenance for the HVAC is generally based on predictive techniques: mathematically-derived models used to find correlations between dependent and independent variables in order to predict future conditions (Nyce and CPCU 2007, Murphy 2012). Parametric models work from a large number of assumptions and a strong hypothesis pertaining to one or more parameters; non-parametric models use larger data sets and rely on fewer assumptions. Statistical models and machine learning are also used for predictive techniques (Murphy 2012, Sheskin 2011).

Regression is a key component of predictive analysis. Regression technique uses statistical methods to generate mathematical models that reproduce interactions among examined variables (Warner and Misra 1996, Freedman 2009). Historically, these techniques have been widely regarded as effective approaches to non-complicated operations (Razi and Athappilly 2005). Commonly used statistical techniques include:

1. Linear regression, which models the relationship between a response to one more variables (Freedman 2009)
2. Discrete choice models, which can be used to analyze ordered, discrete, dependent variables. This is often employed as an alternative to multivariate regression (Press and Wilson 1978, Flury 1988).

3. Logistic regression, which is used to pair observations with outcome probabilities, change information from a binary dependent variable into a one continuous variable, and act as a regular multivariate model (Press and Wilson 1978, Hosmer Jr and Meleshow 2004, Studemund 2005, Bishop 2006).
4. Multinomial logistic regression, which modifies and extends the binary logit model for cases concerning a dependent variable of more than two categories (Snedecor 1956, Raymond 1990, Neter Kutner et al. 1996, Menard 2002)
5. Probit regression, which models categorical dependent variables and can be used as a substitute for logistic regression for modelling categorical dependent variables (Bollen 1998).
6. Time series models, which take the internal structures of variables into account and can be used to predict the future behaviour of variables (Gilbert 1987, Wang 2006) \
7. Classification and regression tree, which can be used to identify the statistical model with the highest level of accuracy in order to forecast a categorical dependent variable value according to a dataset comprised of categorical and continuous variables (Lior Rokach 2008)
8. Random multinomial logit, which generalizes the linear mixed models when applied to multivariate datasets (Breiman 2001).
9. Multivariate adaptive regression splines, a non-parametric technique that generates flexible models (Friedman 1991).

Machine learning is another prominent method for predictions. These methods simulate potential scenarios and outcomes in order to forecast future possibilities in more consequential and complex cases (Mitchell 1997, Murphey 2012). Four machine learning techniques are particularly popular for these operations:

1. Neural networks, which encompasses a family of nonlinear methods used to model complex functions that must be accounted for when predicting, classifying or controlling future scenarios (Lippmann 1987, Rumelhart, Hinten et al. 1998, Hertz

1991, White 1992, Freeman 1993, Lawrence 1993, Smith 1993, Fausett 1994, Taylor 1996, Mehrotra, Mohan et al. 1997, Bansal, Evans et al. 2005).

2. Multilayer perception, which is comprised of three layers: input, output and one or more hidden layers comprised of a number of nonlinearly activated nodes or sigmoid nodes (Rucik, Rogers et al. 1990)
3. Naïve bayes, an effective classification tool and relatively easy-to-interpret method that treats predictors as statistically independent of each other (Panda and Patro 2007).
4. K-nearest neighbours algorithm uses a training set containing positive and negative samples, classifying a new sample according to its calculated distance from the nearest case in the neighbouring training set; the nearest case's sign therefore determines the sample case (Denoeux 1995).

Processes that impact HVAC filter function

Understanding the process of a system (i.e. the components it needs to function) is necessary to maintain the optimal function of that system (Tehrani, Beauregard et al. 2015). HVAC system components must be maintained properly and in a timely manner in order to avoid issues related to energy consumption and output-air quality (EPA. 2020, Friedman, 2020). Maintaining the air filter in order to prevent filter blockage is of particular concern in this regard. There are four main processes that affect HVAC filter function: fan speed, return air temperature, mixed air temperature and the damper positions (Tehrani, Beauregard et al. 2015).

The volumetric flow capacity of air across the fan increases with fan speed, with greater fan speed resulting in a greater volume of air passing through the system and filter (ToolBox 2003). As airflow carries dust particles, greater fan speed also correlates to more dust and other particles passing through the HVAC system. The filter, which blocks dust particles, may consequently clog quicker due to dust accumulation and blockage (Pro 2019, April 22). The filter may also be less effective at higher fan speeds if fewer particles are blocked when the incoming air velocity is too high; in other words, the momentum of particles at higher velocities

may pass through a filter more easily, particularly if the filter media is already compromised (Classroom 2014).

The temperature of air can affect filter blockage due to variations in air density, pressure, and speeds of air volumes. Variations in air temperature can also cause condensation near or on the filters (EPA, 2020, July 29). These variations may cause inconsistent filter performance, cause the filter to clog sooner, or prevent the filter from blocking dust. Return air temperature (air returning back into the HVAC system) and mixed air temperature (incoming outside air mixed with return air) each impact the HVAC function, resulting in poor performance if unregulated. Mixed air temperature is difficult to control because it is affected by return air temperature, outside air temperature, and airflow rates. This unpredictability makes reliable filter maintenance especially important for the function of the HVAC system.

The damper positions within the HVAC system duct separate airflow and send air to desired zones or areas. Their positions within the duct affect airflow rate, resulting in variations in the average speed of air fed into different zones. This in turn affects mixed air temperature, which can result in undesirable outcomes such as freezing evaporator coils when not enough air (or too much cool air) passes over them to remove condensation (Team. 2015, March 9).

In order to reliably predict filter blockage, a model must be developed to simulate conditions of the HVAC system with these four process parameters in mind. Although outside air temperature affects mixed air temperatures, it is unrealistic to include it in such a model (Tehrani, Beauregard et al. 2015).

HVAC system modelling

A model that simulates HVAC operation could be useful to designing effective PdM for the filter. Most literature pertaining to HVAC modelling has focused on improving energy efficiency. For example, (Soudari, Kaparin et al. 2018) studied an HVAC system's cooling

process and designed a thermal dynamic model that combines a model predictive controller (MPC), a proactive controller that provides prior information for HVAC operation, with the pulse-width modulation (PWM) technique. The resulting controller, called a predictive smart thermostat controller (PSTC), makes decisions based on the solution to a linear optimization problem solved through programming and simulations. In other words, PSTC makes on/off decisions to reduce HVAC energy consumption with no hardware modifications.

(Li, Vrabie et al.) identified two primary approaches used for HVAC system modeling. The first approach uses complete building energy software, while the second approach uses a semi-physical dynamic model like a thermal network model. Their research concluded that the former approach is difficult to implement given the amount of data needed to determine various thresholds for calibration and validations for the HVAC unit. They developed a simple, lower-order dynamic model using an MPC. The effectiveness of the MPC was verified through simulations and experiments. Li et al. developed HVAC models through a quasi-steady state approach, extrapolating values for model coefficients from test data of a working HVAC unit. Their modelling approach reduced total unit energy consumption by 17.5%.

While reducing energy for the HVAC unit is well-established in current literature, these models do not implement predictive techniques for effective maintenance for HVAC system filters, thereby leaving HVAC units vulnerable to system failures. Advances in computational fluid dynamics (CFD) within three-dimensional computer aided design (CAD) tools represent a promising path toward developing and evaluating predictive models for the HVAC unit filter (Yang, Philip et al. 2007).

Studies using CFD techniques to examine HVAC system operations are preliminary in nature. (Popovici et al. 2020) used CFD to analyze airflow in a theatre hall, using a 2D domain to determine the HVAC system's effectiveness. (Anghel, Popovici et al. 2020) developed an ANSYS simulation of airflow inside a hospital room to observe the airborne spread of the

novel SARS-CoV-2 coronavirus. These simulations examine airflow within a fixed control space and do not account for filter operation.

Models that account for the HVAC filter and try to simulate the capture of airborne particles in filter media or or pressure drop across the filter media are generally 2D in nature. (Justi, Cândido Da Silva et al. 2014) simulated a two-dimensional porous filter geometry through an experiment-based and pre-defined set of boundary conditions. (Feng, Long et al. 2014) examined 2D pleated filter geometries through several physics models, validating them against experimental evidence. While both of these simulations establish reasonable analogs to HVAC system filters, they cannot account for airflow in a 3D setting.

Three dimensional airflow is a crucial variable to the function of airflow within HVAC system filters; a model that accounts for airflow in a three-dimensional setting will be necessary to develop a simulation whereby HVAC filter performance can be effectively evaluated. My research will borrow from currently available CFD methods for 2D simulations to create a 3D filter assembly model that will be validated against an independent data set. This model will be used to explore the possibility of predictive simulation using ANSYS CFD simulation software to determine filter health. This research will ultimately aim to develop a Detached Eddy Simulation (DES) (an SA based model using ANSYS) in order to simulate filter filter operation and predict the next filter failure.

CHAPITRE 2

MULTI-SCENARIO AND MULTI-CRITERIA APPROACH TO EVALUATE PREDICTION TECHNIQUES USED TO RECOGNIZE FAILURE PATTERNS

(CASE STUDY: HVAC FILTER BLOCKAGE)

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Abstract

Predicting the next failure of a specific component in a machine, results in higher performance of the equipment in terms of its reliability. The literature review reveals the existence of various prediction techniques used to forecast upcoming failures. Each of the current prediction methods can be applied under some particular circumstances. Finding the most efficient, applicable, and precise prediction method has always been a challenge because such a method needs to respond to the reality of concrete situations and to take into consideration the industrial criteria prevailing in the real world. This study examined the five most applicable prediction methods used to predict HVAC filter blockage. The prediction techniques assessed include neural network regression, Bayesian linear network, Boosted decision tree, linear regression, and decision tree regression. Considering different scenarios that use Design of Experiment (DOE), and based on numerous versions of edited data, diverse performance metrics are defined and calculated to compare the prediction methods. A multiple criteria decision making (MCDM) tool, known as TOPSIS, is utilized to compare the performance of each predictive technique according to their performance in various contexts. The results show that the performance of the system is improved when the best predictive method has been selected not only on the premises of a purely mathematical approach, but also when the solid mathematical

prediction is supplemented by the judgments of experts and edited data. In addition, the empirical data is retrieved, and a new method to evaluate the prediction techniques, based on the applications of DOE and MCDM tools, is illustrated. A case study of a Heating Ventilation and Air Conditioning (HVAC) system located at École de Technologie Supérieure (ÉTS) in Montreal, is investigated to show the applications and benefits of the proposed methodology.

Keywords: prediction techniques, predictive maintenance, multiple criteria decision making, design of experiment, heating ventilation and air conditioning system

2.1 Introduction

It has been proven in literature that an effective prediction of the next failure of every component in a system results in better performance and higher reliability of the whole system. Detection of the upcoming failure will prevent many other potential and random system failures, and, as an ultimate result, will enhance availability and reduce the cost of maintenance (Freire, Oliveira et al. 2008). Many models have been proposed to predict the next filter blockage (2007, 2012), but the majority of them use a purely mathematical technique. In the real industrial environment, when failure occurs, there are various criteria that should be taken into consideration in order to make a decision about prediction methods. These criteria could be technical, financial or management based principles.

Recent studies of several world-class companies that have predictive maintenance have revealed that the majority of predictive maintenance programs have failed in their implementation. The reasons that explain this failure is a lack of clear objectives and nonconformity with the real industrial and management and technical environment (Biswal, Americas et al. 2010).

The ultimate goal of predictive maintenance (PdM) is to timely undertake maintenance on a pre-planned schedule (2010). There are several prediction techniques used to predict the next failure of a part or the entirety of a system. Each prediction technique can work adequately under some specific circumstances to predict the failure pattern of one specific part. Finding

the best prediction method to outline the failure pattern of one particular part or an entire system has always been a challenge. For example, in the case study of the current research project, which is heating ventilation air conditioning (HVAC) filter blockage, each prediction technique provides different outputs, and the performance of each forecast method must be evaluated when its prediction is compared with reality. Moreover, both the review of the literature and a large number of practical industrial cases reveal that the majority predictive techniques have been selected purely on the basis of mathematics (Lennox, Montague et al. 2001, Wang, Ma et al. 2007). Nonetheless, expert judgment must also be taken into consideration besides rigid mathematical prediction techniques. Different criteria can be used to compare the performance of predictive techniques when the mathematical calculation is combined with the experts' opinions about the practical application of each technique.

In HVAC systems, any unexpected interruption brings about inconveniences and also ends up generating energy losses, incurring extra costs as a result of these energy losses, and creating the need for excessive maintenance work. Designing the most accurate predictive model will be a significant contribution to the performance of PdM. In consequence, the present research seeks to determine which of the prediction models tends to outperform the others when it comes to predicting the next failure of a component in the HVAC system of this case study.

In this study, the literature review served for the purpose of identifying the most applicable and well-matched (failure) prediction techniques for case study problems. These techniques include: 1) Neural network regression, 2) Linear regression, 3) Bayesian networks regression, 4) Boosted regression tree (BRT), and 5) Decision Forest. Each method is applied to the case problem in order to predict the next filter blockage. Different scenarios are developed based on the full factorial design of experiment (DOE) and on experts' judgment in order to identify the best prediction model using different edited versions of data. The results of each prediction method are evaluated through the application of statistical control charts that compare the actual failure mode with the predicted one. A multiple criteria decision making (MCDM) tool, called The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is applied to compare the performance of each prediction technique using different scenarios.

The next sections of this paper are organized as follows. A literature review of prediction methods is provided in section two. Section three presents the research methodology. The application of the proposed methodology in this case study is developed in Section four. The outputs of this case study are analysed in section five. Section six presents the application of MCDM to evaluate the prediction techniques. Finally, section seven draws useful conclusions and offers both recommendations and directions for future research studies.

2.2 Literature Review

Prediction techniques are mathematically-based methods used to find a correlation between dependent and independent variables and predict future conditions. Predictive analysis, an area in the field of database analysis, uses information mined from the system to predict trends and behaviour patterns while aiming to help companies perform better. Most of the time, fluctuations in production rates and equipment availability affect future plans. Predictive analytics is useful for problems of that nature, but can also be practical for any system containing unknown connections within their mechanism, regardless of the time-frame (Nyce and CPCU 2007, Murphy 2012).

Predictive models can generally be divided into two categories: 1) parametric models, and 2) non-parametric models. Parametric models propose a particularly large number of assumptions and stronger hypotheses regarding one or more underlying distribution parameters while non-parametric models presume fewer hypotheses and use large data sets. Statistical methods and machine learning are yet another way of classifying predictive techniques. (Murphy 2012, Sheskin 2011)

Moreover, regression technique uses statistical methods to properly undertake diagnosis practices and make decisions. Regression is the core of predictive analysis and generates mathematical relations (i.e. models) to reproduce interactions among the numerous variables being examined; (Warner and Misra 1996, Freedman 2009). Different types of these statistical techniques are applied in different prediction situations. Some of these techniques are: 1)

linear regression (Freedman 2009); 2) discrete choice models, which can be employed as an alternative to multivariate regression, in order to analyse in depth discrete ordered dependent variables (Press and Wilson 1978, Flury 1988); 3) logistic regression, which are well-suited for classified settings. This group of methods can be utilized to assign outcome probabilities to observations, convert a binary dependent variable's information to a continuous unbounded variable, and approximate a regular multivariate model (Press and Wilson 1978, Hosmer Jr and Lemeshow 2004, Studenmund 2005, Bishop 2006); 4) multinomial logistic regression, which indeed is a modified extension of the binary logit model used to cover cases wherein a dependent variable of more than two categories (particularly when they are not ordered) is concerned (Snedecor 1956, Raymond 1990, Neter, Kutner et al. 1996, Menard 2002); 5) probit regression, a possible substitute for logistic regression when it comes to the modelling of categorical dependent variables. Even though the two substitutes tend to produce similar outcomes, they are based on different underlying distributions (Bollen 1998); 6) time series models, which are applied to predict variables' future behaviour. These models can take into account internal structures among variables (such as trends or seasonal variations as well as autocorrelation) (Gilbert 1987, Wang 2006); 7) classification and regression tree, which represents a generalized version of optimal discriminant analysis model and can be used to identify the statistical model with the maximum possible level of accuracy, so as to predict a categorical dependent variable value based on a dataset composed of data on categorical and continuous variables (Lior Rokach 2008); 8) random multinomial logit, which applies specifically to multivariate datasets by generalizing the so-called linear mixed model (Breiman 2001); 9) multivariate adaptive regression splines, which fits piecewise linear regressions to generate models of a deal of flexibility because it is a non- parametric technique (Friedman 1991). These statistical techniques have traditionally been accepted as highly effective approaches when it comes to less complicated cases (Razi and Athappilly 2005).

From another perspective, machine-learning methods imitate human intellect. They use practice situations and examples to foresee future possibilities or results in more demanding situations and complex cases (Mitchell 1997, Murphy 2012). There are four machine learning

techniques that are particularly popular. The first machine learning technique is neural networks. Neural networks refer to a family of well-sophisticated nonlinear modelling methods developed to deal with the modelling of complex functions faced when one is to predict, classify or control future problems (Lippmann 1987, Rumelhart, Hinton et al. 1988, Hertz 1991, White 1992, Freeman 1993, Lawrence 1993, Smith 1993, Fausett 1994, Taylor 1996, Mehrotra, Mohan et al. 1997, Bansal, Evans et al. 2005). The second machine learning technique is multilayer perception, which is made up of minimally three layers: an input and an output layer as well as one or multiple hidden layers containing a number of nonlinearly activated nodes or what is referred to as sigmoid nodes (Ruck, Rogers et al. 1990). The third machine learning technique takes predictors as statistically independent of one another. Naïve Bayes represents an easy-to-interpret,

Effective classification tool (Panda and Patra 2007). With a training set containing both positive and negative values, the fourth method is K-nearest neighbours algorithm which classifies a new sample based on its calculated distance to the nearest case in the neighbouring training set; subsequently, the nearest case's sign will determine the sample class (Denoeux 1995).

In an analytical data context, model training and model testing are two distinct stages of the machine learning (ML) process.

Model training involves the use of a set of data to build a predictive model that can make accurate predictions on new data. During this stage, the ML algorithm is fed with a labeled dataset (i.e., data that has known outcomes) and learns how to map input features to the corresponding output. The model is trained to minimize the prediction error, also known as the "loss function." The objective is to build a model that generalizes well on new data and can accurately predict the outcome of new observations.

On the other hand, model testing is the process of evaluating the performance of the model on a new, unseen dataset. This data set is not used during the model training process and serves as a benchmark to assess the model's ability to generalize on new, real-world data. During the

testing phase, the model is applied to the test dataset to predict the outcome, and its performance is evaluated using different metrics such as accuracy, precision, recall, and F1-score. The testing phase aims to ensure that the model is not overfitting to the training dataset and can provide reliable predictions for new observations.

In summary, model training involves building a predictive model using a labeled dataset, while model testing evaluates the model's performance on new, unseen data. Both stages are crucial in the ML process to ensure that the model can make accurate predictions on new data and can be deployed in real-world scenarios.

A careful and thorough examination of the literature about predictive modelling confirms that regression is commonly utilized for less complex situations. Since our case study deals with a non-complex machine (HVAC), multiple regression methods have been used to demonstrate how to train and compare multiple regression models to select the most adequate technique to match with multi criteria decision making (MCDM) tools.

2.3 Research Methodology

As discussed in section two, a careful consideration of the previous studies and the understanding gained in terms of predictive modelling has resulted in regression technique being the most common prediction method used in less complex situations. The first step of the proposed research methodology for the current case study is to obtain the required data for the status of the filter in the HVAC machine. After obtaining the data, and in order to make such information meaningful for application, the raw data need to be edited. In this step, outliers, unnecessary, and missing numbers are removed from the data set. In order to create the prediction model, edited data need to be divided into training data and test data. Then, training data will be used to create the prediction model by means of different prediction tools. The predicted model will be tested using the test data, and the performance of the model will be evaluated applying different performance metrics. In this step, the prediction model will

also be evaluated with the help of the statistical process control chart to see if any data are predicted as out-of-control data. Therefore, for each out of control data, the configuration of the data points will be checked using the decision tree method, presented later. The clean data resulting from the decision tree technique will be used to predict the model again. In this step, and based on the decision tree, different scenarios will be created considering different versions of the data. Each scenario includes a data set that will be used by the prediction technique to generate the prediction models, and the performance measure will be calculated for each scenario. Afterwards, the performance measures of the scenarios will be considered as the input for ranking the prediction techniques using multiple criteria decision making methods.

The flowchart of the model is presented in Figure 1.

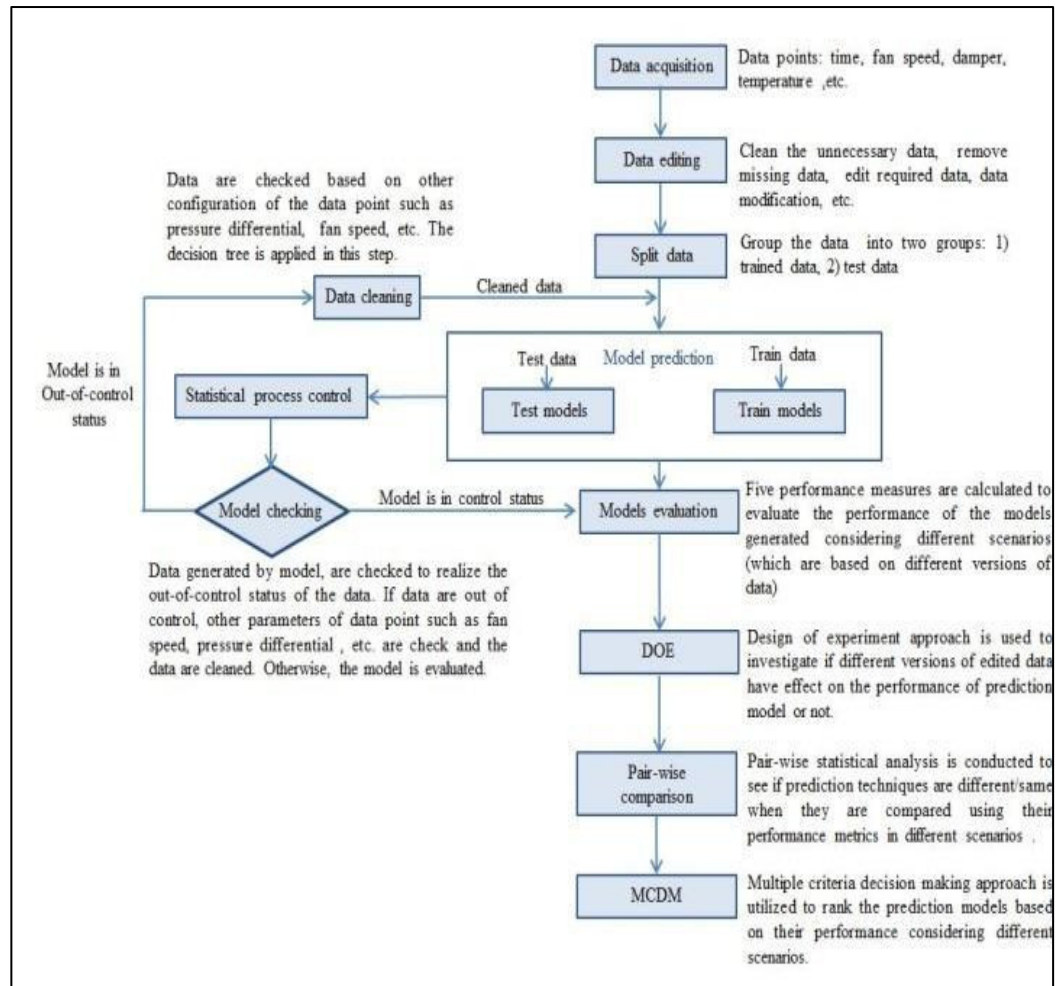


Figure 2-1 The flowchart of the proposed methodology

The prediction techniques, full factorial design of experiment, and MCDM model are presented as follows:

2.3.1 Prediction technique

2.3.1.1 Neural network regression

Neural network refers to a nonlinear modelling approach followed to model complex functions. It can be used to address prediction, classification or control problems in a wide

range of applications (Bansal, Evans et al. 2005). Neural network represents an efficient approach to detect faults within industrial environments (Bansal, Evans et al. 2005). Some researchers have proposed such networks as effective tools to successfully monitor industrial processes and control associated systems (Lennox, Montague et al. 2001). Neural networks are often implemented when one is faced with unknown relationships between input(s) and output(s). The key feature of any neural network is its ability to be trained in such a way as to learn the relationship between input(s) and output(s).

On the other hand, to be able to implement a real-time maintenance system, a neural network needs such a large deal of training data that it is practically impossible to generate one using only a production machine (Mazurowski 2008). In addition, when it is only employed to evaluate general performance of the trained package, the testing set may not be understood by any element of the neural network as the training process is running.(Islam, Yao et al. 2003)

2.3.1.2 Linear regression

A linear regression model is a tool to analyse how a response (or dependent variable) is related to independent or predictor variable(s). The model represents the relationship as a linear function of the predictor variables by which one can predict the response (Freedman 2009). Moreover the prediction, linear regression generally is used for describing the linear dependence from one variable on another one (Hoecker, Speckmayer et al. 2007). On the other hand when researchers seek to understand the direct relationship between a dependent variable and some independent variables, they often employ a method that is called Multiple Linear Regression (MLR).

2.3.1.3 Bayesian networks regression

Bayesian network is a graphical form model that can be used to encode probabilistic associations of considered variables. Bayesian networks may provide a number of data analysis-related benefits when coupled with statistical techniques. For example, encoding

dependencies among all variables, the model can be readily used to either address situations with missing data entries or learn causal relationships (in cases where experiments on the effects of further exposure are not to be conducted). In other words, it contributes to the understanding of the problem that is being investigated and predicts the consequences of error. (Heckerman 1998). In general, Bayesian networks are the approaches chosen for the application of directed cyclic graphs, which are used to evaluate inter-variable dependencies. In addition, in non-directed classification, the networks can build useful probabilistic models, on the basis of which one can end up predicting a subset of variables on the basis of a subset of any other variable(s) (Heckerman 1998) (Buntine 1991).

2.3.1.4 Boosted regression trees (BRT)

Boosted regression tree (BRT) has been proven to be a useful model when it comes to the application of statistical models to not just explain, but also forecast data (Elith, Leathwick et al. 2008). With contributions from both statistical and machine learning disciplines, BRT is fundamentally different from traditional regression methods because instead of returning a single ‘best’ model (which defines normal results of a regression approach) it follows a boosting approach to adaptively bring together a large number of simple tree models, so as to have enhanced forecast performance (P Anderson, Dudík et al. 2006) (Leathwick, Elith et al. 2006). Moreover, there is a need for techniques with enough flexibility to demonstrate typical features of data such as nonlinearities and interactions. BRTs deliver highlighted benefits of tree-based methods which are able to address numerous variants of predictor variables, and are capable of dealing with missing data. With no need for these steps as data transformation or outlier elimination, BRTs can fit complex nonlinear relationships and address interactive contributions from different predictors (Elith, Leathwick et al. 2008).

2.3.1.5 Decision Forest regression

In statistics, there is a technique which takes the results of more than one individual model and combines them to obtain a single forecasting model; the technique is called combining (or

ensemble or consensus) forecast (Bates and Granger 1969). The technique has its individual models usually established using either a neural network or a Decision Tree (Bunn 1987, Opitz and Shavlik 1996, Tong, Hong et al. 2003).

For most situations, individual models are built up on the basis of variables randomly taken from the original set of variables. For example, one may randomly split a dataset into a training subset (containing two-thirds of the entire dataset) and a testing subset (containing the remaining one-third of the entire dataset). Accordingly, one can confirm a model developed using the training subset only when it returns satisfactory prediction results for the testing subset. Launching over the procedure, a group of predictive models is created and can be combined whenever a new forecasting model is demanded. Furthermore, one can achieve the training subset following a more robust statistical approach.

2.3.1.6 Full factorial design of experiment

Full factorial design of experiment provides useful information about the input/output relationship in a process by optimizing the setting of an experiment with little knowledge about it.

The advantages deriving from the use of DOE are manifold. First of all, there is product or process quality improvement, in terms of reliability, with a contemporary diminishing of the design and execution costs. Secondly, there is a greater ability to optimize different factors at the same time (the method is mainly used to improve processes in which quality depends on a lot of variables). Finally, there is a higher possibility of taking into account the interaction between the parameters, the velocity of the test, and the analysis of residuals (Montgomery 2008). In a full factorial design (FFD) of experiment, all combinations of levels for all factors are considered in the analysis of experiment.

In other words, full factorial design of experiment is the most applicable, but most expensive, approach in designing and analyzing an experiment.

Full factorial design of experiment is based on the analysis of variance (ANOVA) which investigates if and how a different setting of a factor affects the response variable.

It also considered the interactions among factors, i.e. how multiple factors interact when they are both significant factors in an experiment.. Main effect and interaction plots are useful plots to show the main and interaction effects. (Montgomery 2008).

2.3.1.7 Multiple criteria decision making method

After obtaining the performance measures of the prediction techniques considering different scenarios, the prediction techniques will be ranked using multiple criteria decision making tools. In this case, the rank of each prediction technique, obtained from TOPSIS when considering different scenarios, will be considered as criteria. Then, the TOPSIS method will be applied, for the second time, to rank the prediction methods. The TOPSIS technique is presented as follows:

There are different MCDM methods in the decision making literature including TOPSIS, VIKOR, ELECTRE, etc. One of the most effective multiple criteria decision making methodologies is TOPSIS, introduced by (Hwang (1979))which stands for “technique of order preference similarity to the ideal solution”. The fundamental idea of TOPSIS is that the best alternative has the shortest distance to the ideal solution (known as the positive ideal solution, PIS), and the furthest distance from the anti-ideal solution (known as the negative ideal solution, NIS). The TOPSIS technique has been applied in different decision making processes in the literature(Mobin 2014, Salmon 2015) (BritishStandard Institution (BSI)). More specifically, and in the maintenance literature, TOPSIS has been applied to rank the criticality of maintenance for machines (Sachdeva 2009, December), to select the optimal maintenance strategy(Shyjith 2008, Momeni 2011), to investigate the condition-based maintenance policy of the electric power(YANG 2009), and to select the computerized maintenance management system (Uysal 2012).

TOPSIS methodology can be summarized in five computation steps as follows: Step 1) providing the criterion and alternatives, Step 2) normalizing the criteria, Step 3) weighting the normalized criteria, Step 4) find the distances of each alternative to the ideal and anti-ideal points, Step 5) find the closeness factor as the ratio of distances for each alternative (Lai 1994, Behzadian 2012, M. Tavana 2016). The listed steps are described as follows.

There are n alternatives a each with m criteria i presented in a decision matrix $X = (x_{ia})$, where $i = 1, \dots, m$, and $a = 1, \dots, n$. The values of x_{ia} need to be normalized in order to be able to compare the criteria on different units. There are several normalization methods in the MCDM literature, including the ideal normalization and the distributed normalization. The ideal normalization requires dividing each x_{ia} by the highest value for each criterion, if the criterion is the positive one; and the lowest value, otherwise. The distributed normalization can be calculated as Eq. 1.

$$r_{ia} = \frac{x_{ia}}{\sqrt{\sum_{a=1}^n x_{ia}^2}} \text{ for } a = 1, \dots, n \text{ and } i = 1, \dots, m \quad (2.1)$$

After obtaining the normalized x_{ia} , i.e., r_{ia} , the weighted normalized decision matrix can be generated by multiplying scores r_{ai} by their corresponding weight w_i , as follows: $v_{ai} = w_i \cdot r_{ai}$. Then, the weighted score will be used to be compared with the ideal A^+ and anti-ideal A^- values. A^+ and A^- can be obtained as follows: $A^+ = (v_1^+, \dots, v_m^+)$ and $A^- = (v_1^-, \dots, v_m^-)$, where $v_i^+ = \max_a(v_{ai})$ if criterion i is to be maximized, and $v_i^- = \min_a(v_{ai})$, otherwise. After obtaining the ideal and anti-ideal points, the distances from ideal and anti-ideal are calculated as Eq. 2 and Eq.3:

$$d_a^+ = \sqrt{\sum_i (v_i^+ - v_{ai})^2}, a = 1, \dots, m \quad (2.2)$$

$$d_a^- = \sqrt{\sum_i (v_i^- - v_{ai})^2}, a = 1, \dots, m \quad (2.3)$$

Finally, the relative closeness coefficient can be calculated using Eq. 4. The alternative with the closest value of C_a to one is the preferred alternative.

$$C_a = \frac{d_a^-}{d_a^+ + d_a^-} \quad (2.4)$$

2.4 Application of proposed methodology in the case study

2.4.1 Case study

There are regions where people spend most of their time indoors. In those places, people normally use HVAC systems. This equipment was fabricated for two main purposes. The first one is to create a pleasant environment for those inside facilities that need a mechanism to control the temperature of the place. The second purpose is to meet the criteria for indoor air quality. In this paper, the École de Technologie Supérieure (ÉTS) HVAC system was selected as a case study. The HVAC is located in one of the biggest universities in Montreal, Canada. Among 25 HVAC machines, unit number UTA-104 was selected. This selection was done taking into account the fact that this unit works more hours and is more loaded because it controls the temperature in one of the main buildings (B) at ÉTS University. The schematic of ETS HVAC is presented in Figure 3. In the schematic, the fresh air (outside air) after passing two steps filtration (pre filter and filter), goes to the heat exchanger. Depending on the indoor desired temperature, air is blown to the building by the suction compressor. The HVAC machine is a closed system and tries to control the temperature and remove carbon dioxide and unpleasant smells in the building.

In the HVAC system there are many sensors to control the performance of the machine for the purpose of proper operation and maintenance conditions. Figure 3 illustrates our case study (filter blockage) with data points measured by sensors represented by numbers. Number 1 is return temperature, number 2 is mixed temperature, number 3 is damper opening percentage, number 4 is fan speed, and numbers 5 and 6 are pre and post filter pressure, respectively.

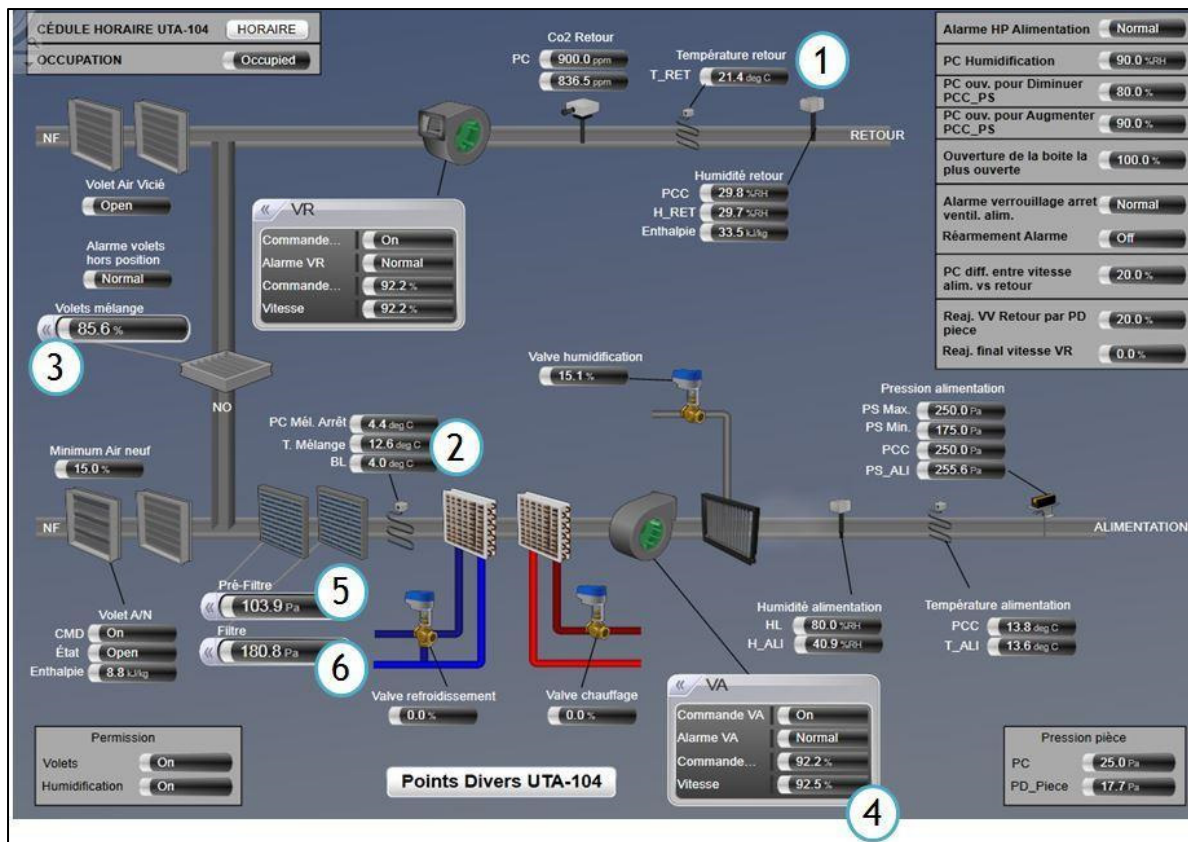


Figure 2-2 Schematics of ETS HVAC system

2.4.2 Data description

The acquired data represented the “filter” performance within the HVAC system. In an HVAC system, filter blockage both has an adverse impact on energy consumption properties and contributes to reduced quality and volume of the output air. As such, the model was developed on the basis of four attributes, namely fan speed (0 – 100)(%), returned air temperature (18 – 25)(°C), mix (returned and fresh) air temperature (16 – 25)(°C), and the position of mixture damper (0 – 100)(%). The information is obtained from HVAC systems that have been used for twenty seven (27) months. The period of data acquisition belongs to 2013-08-01 till 2015-01-31(18 months) and also nine months from 2015-06-10 to 2016-03-05. The dataset contained

39268 data points recorded every 30 minutes by a set of calibrated sensors. Some of the data points are shown in Table 1 for illustration purposes.

Table 2-1 Examples of data points

Data point	Time	Return temperature	Mixed temperature	Fan speed	Pre-filter deferential pressure	Damper position
1	2/1/2014 7:00:00 AM	22.093	14.43	20.6	0.443	41
2	2/1/2014 7:30:00 AM	21.734	16.04	61.28	0.554	71
3	2/1/2014 8:00:00 AM	21.609	14.67	66.18	0.574	71.5
4	2/1/2014 8:30:00 AM	21.531	14.46	72.06	0.717	72.5
5	2/1/2014 9:00:00 AM	21.484	13.82	69.06	0.752	75.2

2.4.3 Model application

All unnecessary data associated with the sensor readings when the HVAC system was not in service (i.e. during night time) are removed and the data are edited as inputs for the model. Considering McQuiston's findings (McQuiston, Parker et al. 2010) about taking into account the comments from HVAC specialists, four factors affecting the rise in differential pressure (which is the singe of filter blockage) were selected to be studied. These factors were fan speed, returned air temperature, mix (returned and fresh) air temperature, and position of the mixture damper. In addition, the condition of outside air, which represents one of the most significant factors contributing to filter blockage, should be taken into consideration. However, since it is unlikely to be controllable, this factor is not regarded in the present study but from a predictive standpoint this would be appropriate for future work.

The literature review revealed that regression is the most widely used statistical method. Therefore, this was the method employed to analyse the database with the help of Microsoft Azure ML® software and Statgraphics Centurion XVI.II®, respectively.

Among various applications, Microsoft provides data scientists with a template (which is, indeed, a component of Azure Machine Learning) framework to develop and adapt a predictive solution. With its emphasis on the approaches to be followed to forecast failure time of an operating machine, the template contributes to prompt planning for the maintenance of the machine. It comes with a series of preset machine learning modules and with custom R scripts incorporated into a module called Execute R Script. The purpose of these elements is to provide an overarching solution covering all issues from the data processing phase to the phase where the machine-learning model is deployed. In addition, it has to be noted that in order to analyse and recognize the relation between data, Statgraphics Centurion XVI.II, a powerful data analysis software, was utilized. This software program allows for better data visualization.

The five most applicable regression techniques are selected in order to build and compare performance of the selected predictive models. The five predictive regression techniques include 1) Bayesian linear regression, 2) neural network regression, 3) boosted decision tree regression, 4) linear regression and 5) decision forest regression. These techniques are applied to predict the next failure of filter blockage in the HVAC machine.

After conducting the data mining in step two of figure1 (a process of identification of unusual data records and investigation of the relationships between variables), five regression techniques that conceptually matched for predicting the failure pattern are obtained through a comprehensive literature review. These prediction techniques are adopted to solve the problems in this case study and their performances are evaluated and validated.

The result of each prediction technique is evaluated based on the application of a statistical control chart aimed at comparing the actual failure mode with the predicted one. By considering different combinations of levels for factors, different scenarios are generated using DOE to see how each prediction method performs in different edited versions of data. Afterward, a multiple criteria decision making (MCDM) tool, called TOPSIS, is applied in this step to compare the performance of each predictive technique in different scenarios.

It has to be mentioned that after cleaning the data, the used dataset was split into two sections, namely the training set and the testing set. Half of the data is configured with the training set, which means each set (training, test) has 50% of the data. The four selected attributes are taken as the models inputs, with their output being the differential pressure to be predicted by each model separately. For each technique, the detailed conditions are described below.

2.4.3.1 Decision forest regression:

The bagging resampling method is considered. A single parameter is selected for the training mode; the number of decision tree is set at 8. The maximum depth of the decision trees is 32 and the number of random splits per node selected is 128.

2.4.3.2 Neural network regression:

The number of the hidden node is set at 100, the learning rate is 0.005, the number of learning iteration is 100, the initial learning weight is 0.1.

2.4.3.3 Bayesian linear regression:

Regularization weight is set at 1one.

2.4.3.4 Boosted decision tree regression:

trainer mode is single parameter, maximum number of leaves per tree is 20; learning rate is 0.2, total number of trees constructed is 100.

2.4.3.5 Linear regression method:

A stepwise technique is utilized to recognize attributes contributing to differential pressure. For this purpose, the four variables used in the present study were subject to linear regression

analysis wherein the filter's differential pressure (Saeedpoor) was taken as the dependent variable, with the four selected attributes treated as independent variables. In addition, ordinary least squares is selected as the solution method and also L2 regularization weight is selected 0.001. It should be noted that L2 regularization is a technique that can be used by machine learning (ML) training algorithms to reduce model overfitting. Eliminating overfitting leads to a model that makes better predictions. The model output represents fitted results of a multiple linear regression model which can approximate how filter DP relates to the four independent variables. The fitted model follows this mathematical form $Y = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_p X_{ip} + \varepsilon_i$, where "Y" refers to filter DP, X_{i1} denotes returned air temperature, X_{i2} is mixed air temperature, X_{i3} represents the position of mixture damper, and X_{i4} is fan speed.

2.4.4 Prediction model output analysis

This section presents the efforts made to evaluate the generated output of each prediction method. Indeed, the output from Azure ML was fed into Statgraphics which serves as an analyser toolbox. Then two control charts were developed using the results of each of the methods separately. The charts were named "exponentially-weighted moving average" (EWMA) (see Figures 3 – 8) and "moving range" (see Figures 9-13), for either of the predicted values and residuals (the difference between the observed (actual) and the predicted values) (Montgomery 2007)

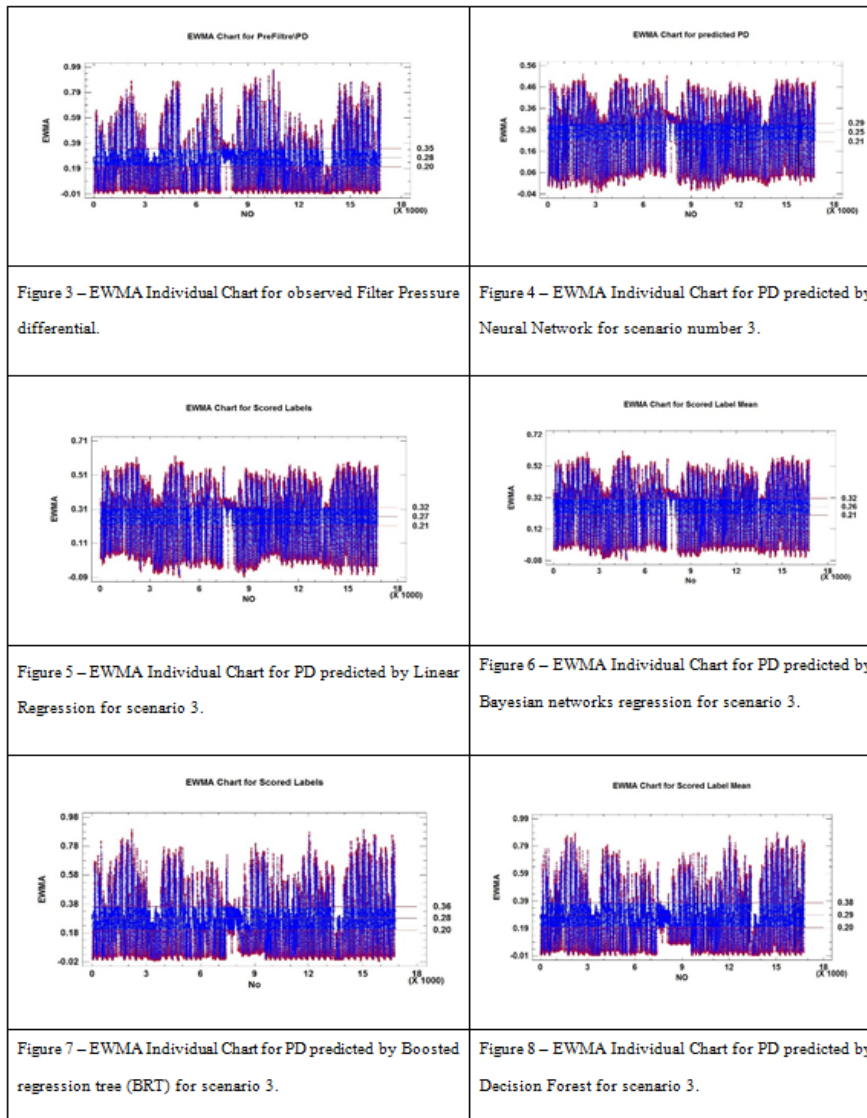


Figure 2-3 Exponentially weighted moving average

As shown in Figures 3 – 8 (as an example for scenario number 3), major portions of each observed or predicted point were not controllable. As such, one should carry out some analyses to find the cause for such a situation; and once the cause is found, it must be corrected and removed from the dataset before recalculating the control limits. The next section reports an in depth description of such out of control points.

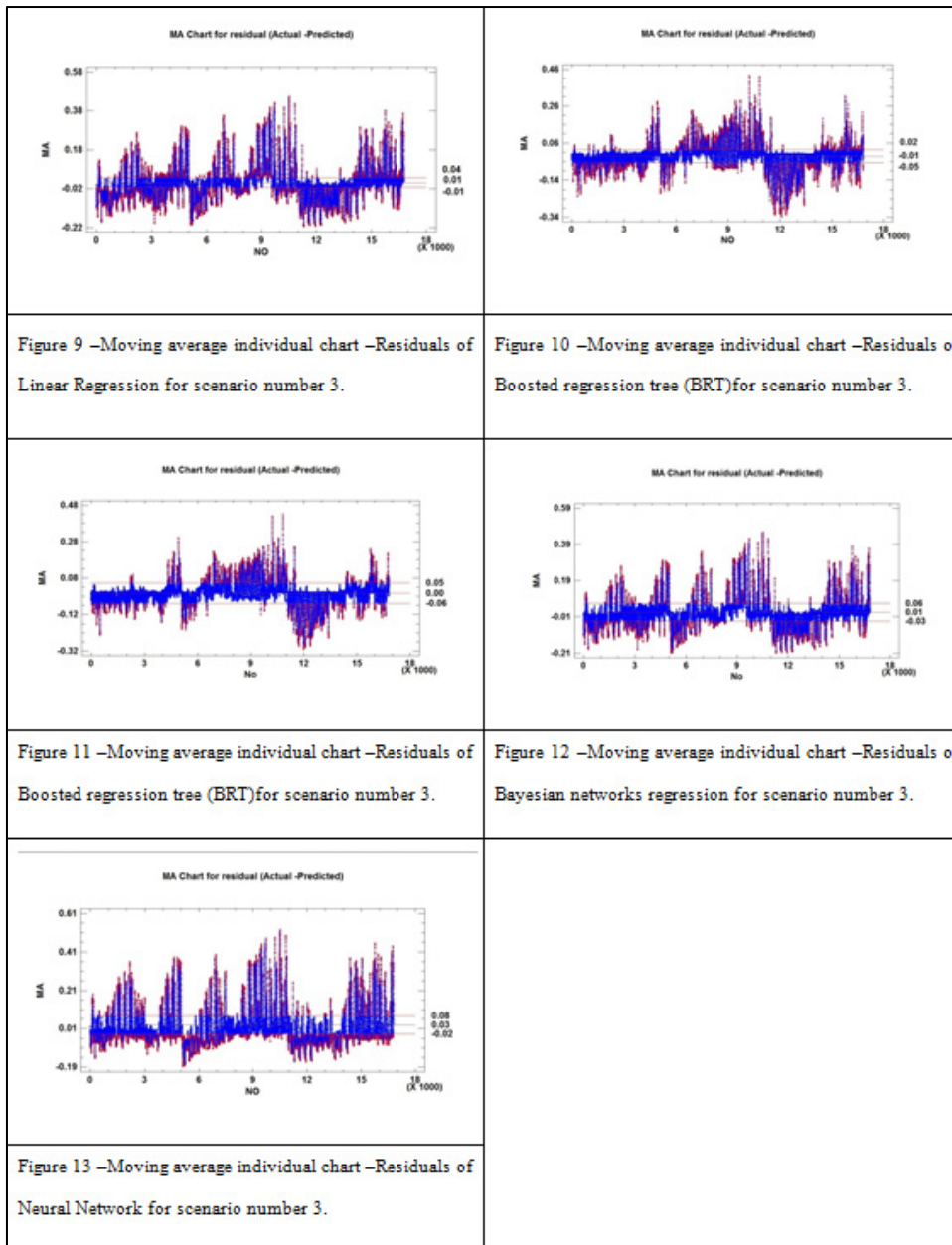


Figure 2-4 Moving range

2.5 Prediction technique comparison results

Considering the results of the EWMA charts, a large number of out-of-control errors were attributed to the high speed of the HVAC system’s fan, without resulting in filter blockage. In

fact, fan speed and supplied air volumes are known to significantly affect pressure drop (McQuiston, Parker et al. 2010); i.e. ΔP is likely to undergo a rise as either of the two parameters increases. Consequently, all of out-of-control points resulting from high fan speed and supplied air volume were eliminated, so as to come with real out-of-control points caused solely by the filter blockage. Subsequently, and in order to distinguish different scenarios, a decision tree approach was applied to identify the truly problematic situations that occurred while the HVAC system was operating.

Considering the uncertain nature of sequential decision problems, one can follow a decision tree approach, as discussed earlier. Such an approach generates a graphical illustration of probable events that may occur in the future, the corresponding optimal decisions that accompany the events, and the associated consequences for the combination of decisions and events (Baird 1989).

Hence, the associated following conditions are taken into consideration to remove data points (Figure 14):

- Differential pressure (ΔP): higher than the upper boundary, as computed by Statgraphics;
- Fan speed: below X% under normal operational conditions, as obtained from an analysis of the observed data;
- Return damper: higher than Y %, as evaluated according to the experiences of the main author as well as observed data analysis.

Once all unnecessary data was removed, the originally large dataset containing unrealistic out-of-control points was reduced to one (for example for linear regression including only 45 instances in which the ΔP was actually caused by filter blockage). Figure 8 shows the decision tree developed to remove out-of-control points.

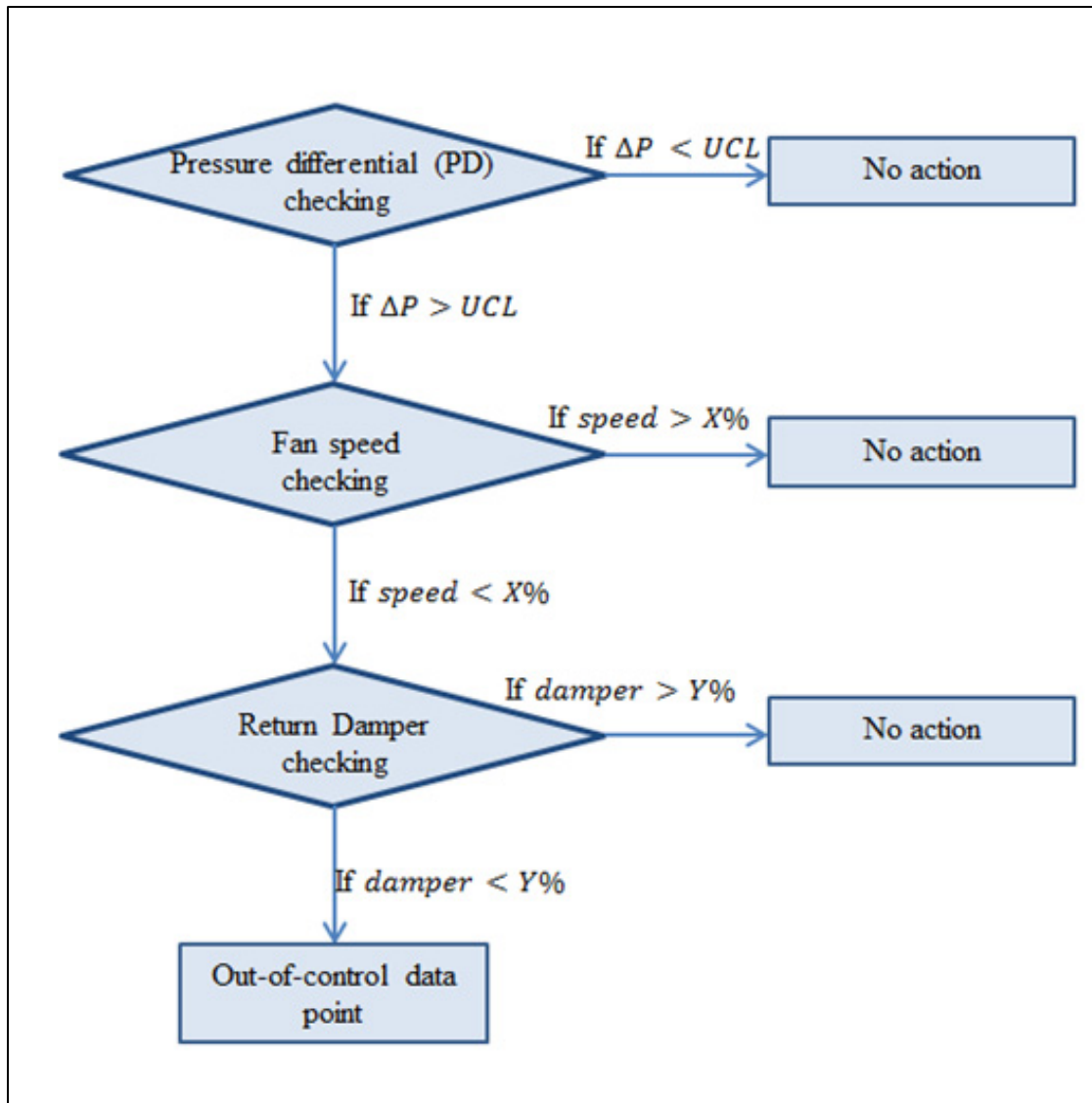


Figure 2-5 Decision tree schematic block for actual out-of-control points

Based on the thresholds considered for pressure differential, fan speed ($X\%$), and return damper ($Y\%$), different scenarios are provided using DOE, bearing in mind these factors, each with two levels. The factors and levels are presented in Figure 2.6.

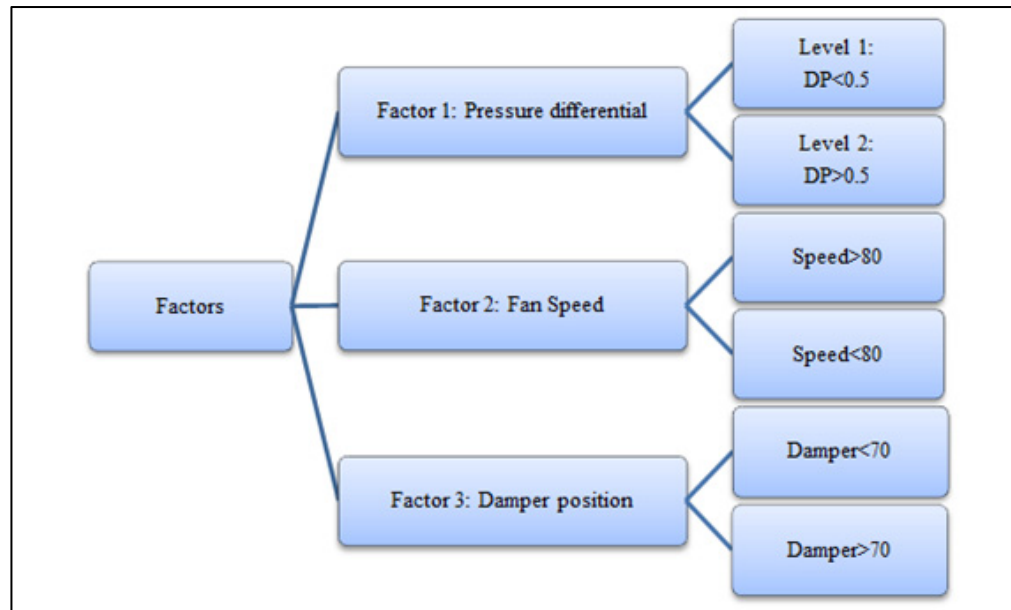


Figure 2-6 Factors and levels for investigating the performance of prediction methods using DOE

Based on the defined factors and levels which are obtained based on expert judgment and also the case study HVAC troubleshooting manual , 8 scenarios are considered which are presented in Table 2. In addition to these 8 scenarios, there is another scenario that is considered in our investigation. This scenario (scenario number 9) includes the data without any edition, i.e., original data.

For each scenario the generated data is applied and run with Azure ML® application by varying the levels for factors to see how each prediction method performs.

Based on the defined factors and levels which are obtained based on expert judgment and also the case study HVAC troubleshooting manual , 8 scenarios are considered which are presented in Table 2. In addition to these 8 scenarios, there is another scenario that is considered in our investigation. This scenario (scenario number 9) includes the data without any edition, i.e., original data.

For each scenario the generated data is applied and run with Azure ML® application by varying the levels for factors to see how each prediction method performs.

Table 2-2 Different scenarios for model prediction using different versions of edited data

		Factor 2			
		Level 1		Level 2	
		Factor 3		Factor 3	
Factor 1	Level 1	Level 1	Level 2	Level 1	Level 2
	Level 2	Scenario 1	Scenario 2	Scenario 3	Scenario 4
	Scenario 6	Scenario 7	Scenario 8		

Different performance metrics are calculated to evaluate the performance of the predictive models. The model output is statistically predicted using five statistical indices, namely Mean Absolute Error (MSE), Relative Absolute Error (RAE), Relative Squared Error (RSE) and Root Mean Square Error (RMSD) (Twomey and Smith 1997), (Yang, Greenwood et al. 2000), (Shamshiry, Mokhtar et al. 2014).

$$MSE = \frac{1}{n} \sum_{i=1}^n |Y_i - \hat{Y}_i| \tag{2.5}$$

$$RAE = \frac{\sum_{i=1}^N |y_i - \hat{y}_i|}{\sum_{i=1}^N |y - y_i|} \tag{2.6}$$

$$RSE = \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y - y_i)^2} \tag{2.7}$$

$$RMSD = \sqrt{\frac{1}{n} \sum_{i=1}^n |Y_i - \hat{Y}_i|} \tag{2.8}$$

$$R^2 = \frac{SSR}{SST} \tag{2.9}$$

(SSR: Sum of Square Regression and SST: Sum of Square Total)

Coefficient of determination (which is commonly written as R² or r² and pronounced “R squared”) is a statistical parameter and measure of data fitness for a statistical model – a line

or a curve, for example. Indeed, the regression line may perfectly fit the data when R^2 is equal to 1, with absolutely no fitness when the parameter is measured at 0. A zero R^2 may be arisen by either non-linearity of the data to an extent further than what is allowed by the curve, or by random nature of data. The higher the amount of R^2 , the better the model will fit the data.

Moreover, R^2 may deal with non-linear functions of data (Colin Cameron (1997)), in which cases, the average value of the data (based on this specific criterion), rather than the fitted function values, may be a better measure to fit the outcomes, (Imdadullah).

Root-mean-square deviation (RMSD) or root-mean-square error (RMSE) is performance metric commonly used and measures how different predicted results are formed. (Hyndman (2006)).

Mean absolute error (MAE) is a criterion which measures the deviation between forecasts or predictions and the corresponding final outcomes.

Relative absolute error (REA) is much like the relative squared error (RSE) since it also refers to something relative to a simple predictor, i.e. simple average of the actual values. Being two distinct types of error, absolute and relative errors should be well distinguished. Relative error refers to the goodness of a measurement with reference to the measured performance metric size, while absolute error simply denotes the magnitude of physical measurement error.

Table 3 reports performance evaluation results for all scenarios as computed in terms of the five statistical indices. (The five compared prediction techniques are : 1- Bayesian linear regression, 2- Neural network regression, 3- Boosted decision tree regression, 4- linear regression and 5- Decision forest regression respectively .Moreover the five performance metrics are 1-Mean Absolute Error, 2- Root Mean Squared Error, 3- Relative Absolute Error, 4- Relative Squared Error and 5-Coefficient of Determination).

Table 2-3 Result of performance measurement for all prediction techniques in all scenarios

Prediction technique	Performance metrics				
	1	2	3	4	5
	Scenario 1				
1	0.037067021	0.052751915	0.804854751	0.827169086	0.172830914
2	0.028467621	0.044597618	0.659355676	0.605503926	0.394496074
3	0.042511936	0.056195535	0.878060850	0.861384807	0.168615193
4	0.032048119	0.051745209	0.773901737	0.780284272	0.197157281
5	0.046069763	0.058762526	0.894918249	0.87750995	0.152490052
	Scenario 2				
1	0.032318596	0.041463391	0.801346996	0.677351946	0.322648054
2	0.025076697	0.032259169	0.581705165	0.565284755	0.434715245
3	0.030815111	0.038104294	0.774153323	0.654949227	0.345050773
4	0.026273810	0.035565914	0.600064346	0.570594686	0.429405314
5	0.031094879	0.040587486	0.798216195	0.669184936	0.339184936
	Scenario 3				
1	0.010381813	0.021290868	0.073805358	0.023085795	0.866914205
2	0.012705099	0.022304498	0.101776336	0.026123572	0.853876428
3	0.012833060	0.023066278	0.102801383	0.027696566	0.842303434
4	0.008865875	0.019635922	0.071021582	0.020246510	0.879753490
5	0.016031461	0.027211446	0.118422716	0.030882207	0.838117793
	Scenario 4				
1	0.020300168	0.029556421	0.347177789	0.170606959	0.829393041
2	0.052468824	0.064663043	0.897332994	0.81659241	0.183407592
3	0.026314066	0.035905658	0.415824329	0.211462923	0.788537077
4	0.022726419	0.030339111	0.353898604	0.180087432	0.820991253
5	0.023912639	0.031111082	0.391856828	0.189026761	0.810973239
	Scenario 5				
1	0.048171067	0.086995783	0.699266573	0.612624069	0.387375931
2	0.076022845	0.11205467	1.103571862	1.016383434	0.016383434
3	0.057589545	0.102866615	0.835988198	0.856537833	0.143462167
4	0.070845604	0.111096168	1.02841738	0.999069759	0.120930241
5	0.057008859	0.102722823	0.827558781	0.854144902	0.145855098
	Scenario 6				
1	0.034240818	0.047527552	0.694501582	0.516414247	0.483585753
2	0.046501707	0.062845464	0.943187437	0.902932326	0.097067674
3	0.035466104	0.048762553	0.719353888	0.543600944	0.456399056
4	0.027757728	0.037991874	0.563006012	0.329980861	0.670019139
5	0.048130255	0.064768263	0.976219032	0.959029203	0.040970797
	Scenario 7				
1	0.058135642	0.066199579	0.942527051	1.00326106	0.034261055
2	0.058278558	0.066282821	0.946059239	1.00475340	0.023753395
3	0.050785745	0.091676713	0.75885137	0.70822664	0.291773362
4	0.059860384	0.066797102	0.966863525	1.01938989	0.019389891
5	0.049171067	0.089995783	0.709266573	0.68621930	0.313780702
	Scenario 8				
1	0.033336476	0.042443015	0.478510902	0.289387893	0.710612107
2	0.032468842	0.041490391	0.466056912	0.276543172	0.723456831
3	0.068076383	0.081161634	0.977166618	1.058204147	0.058204151
4	0.035782125	0.044051954	0.513615681	0.311744107	0.688255893
5	0.063486346	0.078028680	0.911281334	0.978084599	0.021915401

A full factorial design (FFD) of experiment is conducted to investigate if a factor (and its interactions) has an effect on the performance measures or not. Results of the analysis of the full factorial experiment using MINITAB software show that all factors (and therefore their interactions) have an effect on the performance of the prediction techniques. It means that considering different edited versions of data for prediction methods will add value to the results of the prediction methods, in terms of improving the performance measure of the prediction techniques.

Statistical analysis, based on the pair t-test, is also used to investigate if prediction methods are different when they are compared based on their performance metrics in different scenarios. Pair t-test is a tool for comparing the mean of groups of a population to see if the means are significantly different or not. Results of analysis are presented in Table 4. Numbers in the table represent the P-value of the statistical test. Each column represents the P-value of the t-test when two corresponding prediction techniques (presented in the first column) are compared based on the performance metrics.

Since all P-values are greater than 0.05 (alpha), all prediction techniques are different based on the corresponding performance measure.

Table 2-4 Pair-wise comparison of prediction methods

Prediction techniques	Performance measures				
	1	2	3	4	5
1 versus 2	0.592	0.504	0.671	0.363	0.918
1 versus 3	0.685	0.558	0.630	0.293	0.804
1 versus 4	0.955	0.953	0.995	0.982	0.954
1 versus 5	0.668	0.548	0.652	0.335	0.806
2 versus 3	0.872	0.897	0.957	0.911	0.878
2 versus 4	0.627	0.540	0.666	0.371	0.870
2 versus 5	0.889	0.902	0.981	0.983	0.881
3 versus 4	0.726	0.599	0.625	0.299	0.756
3 versus 5	0.981	0.994	0.976	0.926	0.995
4 versus 5	0.708	0.589	0.647	0.342	0.757

2.6 MCDM tools to rank the prediction techniques

Considering each performance measure as a criterion, the TOPSIS method is used to rank the prediction techniques in each scenario based on all performance metrics. Using the procedure presented in section 3.2, the rank of each prediction technique is obtained in each scenario. The results of the TOPSIS method are provided in Table 5.

Table 2-5 Results of TOPSIS method for eight scenarios

Scenarios	The rank of prediction techniques				
	Bayesian linear regression	Neural network regression	Boosted decision tree regression	linear regression	Decision forest regression
1	3	1	4	2	5
2	5	1	3	2	4
3	2	3	4	1	5
4	1	5	4	2	3
5	1	5	3	4	2
6	2	4	3	1	5
7	3	4	2	5	1
8	2	1	5	3	4
Average of the ranks	2.4	3	3.5	2.5	3.6

In summary, considering all scenarios and all criteria, prediction technique number 1 (Bayesian linear regression) outperforms other techniques.

As explained before to understand the behaviour of data without any filtration, in addition to above 8 scenarios, there is another scenario (as an optional scenario), that is performed with original data (without any edition) .Following table is the result of prediction technique for scenario number 9.

Table 2-6 Results of TOPSIS method for scenario No9

Scenarios	The rank of prediction techniques				
	Bayesian linear regression	Neural network regression	Boosted decision tree regression	linear regression	Decision forest regression
9	3	5	1	4	2

With the above result we can see preference of the prediction techniques between filtered data (based on expert scenarios)and non-filtered data .

2.7 Conclusion

Predicting the next failure of the HVAC filter blockage is the main focus of the present study. The condition of the filter is crucial to guarantee the healthy functioning of an HVAC indoor machine. Moreover, the issue of a growing concern for more efficient energy consumption mechanisms has become the centre of attention for both industrial managers and researchers. This justifies the need to investigate matters such as filter blockage in the HVAC system.

Contribution of this paper is applying different failure prediction techniques in filter blockage of the HVAC system and comparing the performance of each technique based on different scenarios and different performance metrics by using Statistical control chart, decision making tree and multiple criteria decision making to rank the prediction techniques.

This paper applies different regression prediction techniques to predict the filter blockage of the HVAC system. Five prediction techniques including: 1) Bayesian linear regression, 2) Neural network regression, 3) Boosted decision tree regression, 4) linear regression and 5) Decision forest regression are used to predict the filter blockage when different versions of

edited data are used in each prediction technique. Based on the statistical control chart, the observed data are compared with the predicted data and a decision making tree is provided to edit the data considering differential pressure, fan speed and the damper position of the HVAC system. In this stage, different scenarios are provided using the design of experiment which considers three factors, each with two levels. Based on the results of running prediction methods using design of experiment and also calculating five performance measures, a full factorial design of experiment analysis is conducted to see if factors and their interactions have a significant effect on the performance measures or not. In addition, a comprehensive pair-wise comparison analysis is conducted to compare the prediction techniques based on five performance metrics in each scenario. In addition, the TOPSIS ranking technique is used to rank the prediction techniques considering all performance metrics simultaneously.

2.8 Recommendation and future works

The methodology conducted in this study compared the five most commonly used predictive techniques for the purpose of maintenance. The study also examined the notion that using a decision tree method, pair-wise statistical comparison and MCDM, can greatly reduce the occurrence of false out-of-control situations. For future studies to have a better comprehension of prediction techniques, it will be necessary to assess some of the other components that make up any HVAC system such as compressors, refrigerants, evaporators, and condenser coil sections. Moreover, future research may choose to concentrate on a prediction model followed by a discrete event simulation and other machine learning techniques. Financial scenarios are also recommended for future consideration when evaluating predictive techniques.

2.9 ACKNOWLEDGMENT

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CHAPITRE 3

Correlation of critical parameters that contribute to HVAC filter and pre filter clogging

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Abstract

The principal objective of this research is to present a methodology to evaluate the correlation between main manageable process parameters in a HVAC system which could cause the filter blockage.

In this case, the process of the system is the output of the air, and there exist four primary process parameters influencing the results. These include: the fan speed, the return temperature, the mixed temperature (return and fresh air), and the position of the mixture damper. To further examine the relation between the variables and the process response (including the air filter and the pre-filter blockage), a statistical model was developed to evaluate the individual each main parameter.

Keywords: Heating Ventilation and Air conditioning System, filter blockage, preventive maintenance

3.1 Introduction

Improving the functionality or performance and efficiency of a system fundamentally requires comprehending the influence of its critical components and necessitates the understanding of all processes or processing factors within the system. As such, the maintenance and system availability can be enhanced, and any service or financial issues can be eliminated (IFAC). Essentially, all organizations, either commercial, public, or non-profit, seek to improve their

services and deliver their products on schedule and at a low and optimum cost. However, to achieve such objectives, the organizations use various mechanical, electrical, and structural equipment, all of which require proper maintenance for efficiency improvement.

It is known that HVAC systems or heating, ventilating and air-condition systems, are often used to maintain thermal comfort for occupants of a building, by circulating air throughout it. However, research suggests that these systems are prone to failure due to maintenance issues which manifest themselves in the form of sick-building symptoms (22). Hence, the maintenance of HVAC systems plays an important role in all industries.

This paper focuses on studying the HVAC system installed at ETS university to gain a better understanding of the system and ensure proper system functionality. Overall, the system consists of 25 separate units, controlled, and monitored by Johnson Controls, and each unit serves one zone of the building. For this study, the primary unit of concern is the UTA-104 operational unit, which provides air to the internal areas (zone) of building B.

It is noted that the filter blockage in the HVAC system critically affects the energy consumption of the system and the quality of output air volume. In this case, the process of the system is the output of the air, and there exist four primary process parameters influencing the results. These include: the fan speed, the return temperature, the mixed temperature (return and fresh air), and the position of the mixture damper. To further examine the relation between the variables and the process response (including the air filter and the pre-filter blockage), a model was developed. Using this model over a six-month research and HVAC system operation, information of about 34,544 data points was retrieved and recorded by calibrated sensors every 30 minutes.

3.2 Literature review

To improve the performance of a system, the processes of the system, including the function of critical components partaking in its workflow must be understood. In doing so, the maintenance capability of the system can be enhanced, whereby the system can be optimized

to function most efficiently (Tehrani, Beauregard et al. 2015). Fundamentally, for HVAC systems, it is important to ensure the system components are properly maintained as any issues critically affect energy consumption and quality of supplied air (EPA. 2020, July 29, Friedman September 08, 2020). Specifically, maintaining the air filter (preventing filter blockage) to function optimally is always crucial to saving energy costs and supplying quality air. In doing so, the risk of system failure is reduced, by which, additional operational costs are saved (Team. 2015, March 9). It has been determined that four main processes, occurring within the system, largely impact the filter function. These include the fan speed, return air temperature, the mixed air temperature, and the damper positions (Tehrani, Beauregard et al. 2015).

Indeed, based on fan affinity laws, the volumetric flow capacity of air across the fan is increased with fan speed. As such, a greater fan speed translates to a greater volume of air entering the system and filter (ToolBox 2003). Moreover, since the airflow carries dust particles, the filter would be fed with a greater number of dust or with other particles suspended in the air. Accordingly, the filter may initially and effectively block more dust. But, it may quickly become ineffective due to dust accumulation and blockage (Pro 2019, April 22). However, another issue may arise at higher fan speeds; less particulates can be blocked if the incoming air velocity is too high. This suggests that particles can easily pass through an improper filter due to their higher momentum at larger velocities (Classroom 2014). As such, the fan speed plays a critical role in filter blockage.

Additionally, the temperature of the air also affects the filter blockage. This occurs because changes in temperature not only trigger density variation and change the pressure and speeds of the air volumes, but they also may cause condensation near or on the filters (EPA. 2020, July 29). Consequently, filters may clog much quicker, or may not stop dust at all. Thus, the return air temperature (for air returning from each zone that is fed to by the HVAC system), and the mixed air temperature (i.e., of incoming outside air mixed with return air), directly affect the system equipment and may cause adverse effects if not regulated. Moreover, because the mixed air temperature is dependent on the return air temperature, outside air temperature

and the corresponding air flow rates, it is much harder to control (Richardson 2019, November 20). Hence, the maintenance of the filter becomes even more essential.

Furthermore, the damper positions inside the duct of the HVAC system function to separate the airflow and redirect it to specific zones or areas. As a result, their orientation and positions inside the duct directly affect the air flow rate which translates to variation in the average speed of air being fed to different zones. Subsequently, this affects the mixed air temperature which enters the equipment and as such, it may cause undesirable effects including the freezing of evaporator coils when not enough air (or cool air) passes over them to remove condensation occurring during cooling (Team. 2015, March 9).

Ultimately, the main process of the system of outputting air is affected by four fundamental process parameters including the fan speed, the return and mixed air temperatures, and the position of the mixture dampers. Therefore, it is important to properly maintain the HVAC system filter so as to ensure the proper functioning of the system, as each of the process parameters cause the filters to clog, which in turn, reduces the effectiveness of the system to cool or heat a zone and thereby increases the cost of operation.

Conclusively, model development to simulate the conditions of the HVAC system to predict the next filter blockage is an important method in the maintenance of the system. However, such modelling is highly complex, and it is unrealistic to include the outside air conditions although they directly affect the mixed air temperatures (Tehrani, Beauregard et al. 2015). This suggests that accurate model development is difficult but can largely improve maintenance capabilities of the system by which its performance efficiency can be maximized.

3.3 HVAC maintenance costs caused by filter blockage and clearing

HVAC system maintenance costs can be divided into repair costs and preventative costs. The latter, preventative costs, are primarily for the filter cleaning and or replacement. Indeed, if the filter is maintained and cleaned regularly (time interval dependent on system grandeur, usage and type) filter blockage can be prevented and major system failures can be avoided. Servicing

an HVAC system filter depends on the type (disposable, pleated, etc.), and size of filter as well as the quality (or rating) and composition of the filter (Housh 2017, August 7). On average, a good quality, large (>6”) pleated filter lasts approximately 9-12 months, and costs between 50-100\$ (Housh 2019, April 19). So, for a safe estimate, the filter replacement can be set at the higher 100\$ annual cost.

On the other hand, actual HVAC system repair costs are much higher than the preventative ones. Most of these costs are presented due to major system failures or problems which mainly result from clogged filters. Indeed, as described in the previous section, filter blockage can lead to numerous adverse conditions including frozen evaporator coils, furnace failure, fan motor damage, ductwork uncleanliness, and inadequate heating/cooling which in turn also leads to a 15% increase in energy consumption(Richardson 2019, November 20). The costs to repair and resolve these issues are shown in Table 1.

Table 3-1 Costs of Major HVAC System Repair and Maintenance

Table 1: Costs of Major HVAC System Repair and Maintenance (Advisor 2010, HomeGuide 2010, HomeGuide 2010)	
Repair/Maintenance Description	Cost (\$ CAD)
Coil Replacement	\$600 – \$2,000
Repair/Replace Ductwork	\$500 – \$2,000
Duct Cleaning	\$250 – \$500
Installing New Fan Motor	\$100 – \$700
Compressor Replacement	\$1,350 – \$2,300
Furnace Replacement	\$1,795 – \$6,290
AC Replacement	\$3,350 – \$5,910

Clearly, the main maintenance and repair costs of the system are far greater than the preventative costs. From this data, it is recommended that the system be maintained in a preventative manner, by timely replacing the filters and only using good quality filters as well as cleaning them as required. As such, this would reduce overall operational and maintenance costs and ensure optimal functioning of the HVAC system.

A building's air filtration system has many benefits, including a cleaner, healthy environment and the safety of appliances, furniture, and procedures. ASHRAE published the “Report of the Presidential Ad Hoc Committee on Building Health and Safety in the Event of Extraordinary Incidents” in January (ASHRAE Standard 2003). HVAC air filtration has risen to prominence as a critical tool for defending a building from bioterrorism. The factors to consider when comparing air-filter results are:

- How well a filter removes particulates from the airstream.
- How much dust a filter can contain.
- How much resistance to airflow the filter presents?
- How often the filter must be replaced or cleaned.

In reaction to the current condition, many plant managers are updating or transitioning to higher stages of air filtration. Certain plant managers are unaware that optimising production at the expense of pressure drop results in dirtier air and increased energy consumption/cost.

Moreover, decreased airflow increases the likelihood of device failure, compromising overall HVAC system efficiency.

Initial investment and maintenance, energy use, and disposal are three major components of the life cycle costing formula (Figure 3.1) (Carlsson March 2001) We know the cost breakdown based on operational characteristics:

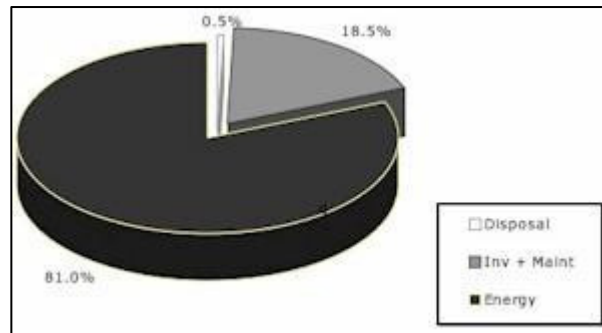


Figure 3-1 Life cycle costing formula

Due to the high cost of electricity and the reality that pressure drop is a key to energy usage, the two most critical considerations in delivering clean air are performance and pressure drop.

Even before a plant manager can decide the appropriate degree of cleanliness, they must assess the device's capacity. In terms of air filter resistance, the majority of large commercial HVAC systems are configured to handle pressure drops of one inch or greater. To ensure proper air filtration and exchange rates, it is critical to match the filter's original, final, and average resistance to the system. Additionally, instruments for measuring pressure drop, such as manometers or electronic pressure sensors, are needed.

After that, compare the pressure drops of different filter types and efficiencies to decide which one follows your specifications, or modify the filter bank or filter to improve the filter surface area and also reduce resistance (R.H. Avery 3rd Edition).

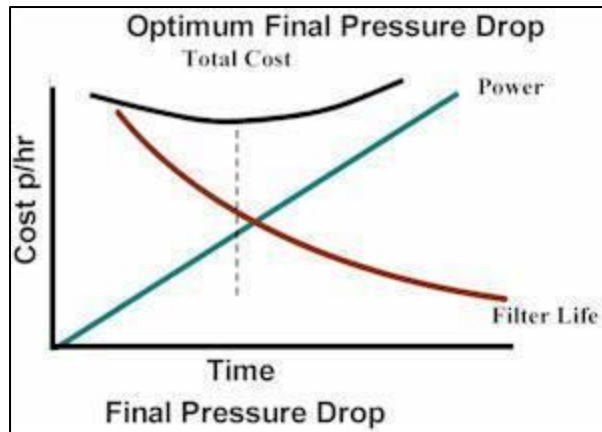


Figure 3-2 Optimum Final Pressure Drop

The following equation is used to calculate the optimal final pressure drop:

$$\text{Energy Consumption} \\ (\text{kWh}) = \frac{Q \cdot \Delta P \cdot t}{\eta \cdot 1000}$$

$$Q = \text{Air Flow (m}^3\text{/sec)} \\ \Delta P = \text{Avg. Pressure Loss} \\ t = \text{Time in Operation (hrs)} \\ \eta = \text{Fan Efficiency}$$

Using this formula, we will find filters with lower average pressure drops that use less electricity and have lower operating costs. It can assist in determining the best time to replace their filters.

The correct operation of the HVAC equipment depends on the system pressure. We can improve air filtration efficiency and provide additional security for systems but must also keep an eye on any additional device resistance. Air filters with increased media area or newer synthetic medias that have lower pressure drops will achieve the desired efficiencies and save energy. Pressure drop measurement instruments are used to calculate the optimal performance results and filter change-out frequency. The correct measurement and maintaining the HVAC air filter system would significantly assist the building's air filtration systems.

3.4 Assumptions and Hypothesis

Due to a large volume of data being collected, it was assumed that the data would require organizing before it could be used to further develop the model. Thus, this raw data was cleaned and prepared for the analysis; all unnecessary data recorded by the sensors when the system was out of service (i.e., during nighttime) was removed.

Additionally, the outside air condition was not considered in the model development, despite being one of the most critical factors affecting the filter blockage. This was because its condition cannot be controlled (realistically speaking). As such, and in accordance with the opinions of several HVAC experts, only four factors affecting differential pressure increase were chosen (McQuiston, Parker et al. 2010) . As described, these factors include fan speed, return temperature, mix temperature (return and fresh air), and mixture damper's position.

3.5 Experimental plan

The study uses a multilevel, full factorial design of the experiment ($3 \times 2 \times 2 \times 2$). The filter pressure for filter and pre-filter pressure were used as they have similar mechanical properties (see Table 2). The experimental factors and their corresponding levels are tabulated in Table 2. Among these, the parameters of fan speed and damper position were considered as qualitative factors, whereas all other factors were treated as quantitative. Overall, an aggregate of 108 experiments was completed, and 34544 data readings were collected (by calibrated sensors every 30 minutes) over a six-month operation of the HVAC system. The data was retrieved based on the 'filter' performance of the system, as filter blockage in the HVAC system is known to critically affect the energy consumption and the quality of output air.

As such, a model was developed to predict the next filter blockage to prevent issues and maintain system performance. This model was studied with four attributes including: the fan's speed (gauged between 0 and 100%), the return temperature (ranging between 18 and 25 °C), the mixture temperature (of return and fresh air, lying between 16 & 25 °C), and the mixture damper's position (gauged from 0 to 100%).

Table 3-2 Experimental parameters used

I D	Process Parameters	Units	Level		
			1	2	3
A :	Fan speed	percent age	14 ≤ <51	51 ≤ <88	88 ≤ <100
B :	Opening valve	percent age	0 ≤ <37	37 ≤ <75	75 ≤ <100
C :	Returned air Temperature	C	15.4 ≤ <18.2	18.2 ≤ <21.03	21.03 ≤ <24.8
D :	Mixed air Temperature	C	20.8 ≤ <21.6	21.6 ≤ <22.23	22.23 ≤ <25.3

3.6 Method of analysis

The use of statistical techniques is fundamental when analyzing the quality file parameters of machines or machined parts. Hence, for the study of the HVAC system, the following statistical methods were used:

- ANOVA: The analysis of variance (ANOVA) permits an examination of the most impacts of independent variables and their interaction impacts to decide their combined effects on the responses at 95% confidence interval (CI). For the purposes of data processing, the following mathematical terminology are used:
 - P-value: The probability that the outcomes of an analysis (or more extreme results) may have happened by chance (ranging from zero to one).
 - If P-value > 0.10, the variable is insignificant.
 - If $0.05 \leq P\text{-value} \leq 0.10$, The variable has a low level of significance.
 - If P-value < 0.05, The variable is crucial.
 - The coefficient of determination (R²) quantifies the observed reaction values' uncertainty and can be defined by the controllable variables and their interactions. If R² is greater than 75%, the projected model is considered to be responsive to process variable variance. Otherwise, the method is regarded as insignificant.

- R²adj models can be more useful in evaluating models of various numbers of independent variables. In comparison to R², R²adj increases only where the new term changes the model more than predicted. R²adj is often less than or equivalent to R² and may be negative.
- Pareto analysis: A Pareto map compares the relative value and statistical meaning of the method parameters' primary and interaction results. This chart describes influential causes that can be mitigated in order to reduce contribution.
- Analysis of means (ANOM) is used to evaluate the optimum HVAC filter blockage conditions by estimating the influence of each parameter on the response, as seen in the key effect plot diagram (Friedman September 08, 2020).
- Study of interaction results: Displays the interaction effects of method parameters. The subsequent parts of this study used a related form of study.
 - Statistical models are critical for analysing the impact of each particular element on the calculated responses [Kilickap., 2010]. The following statistical terminology are used in this study to refer to statistical research performed for STATGRAPHICS Centurion XV:
 - • Pareto analysis: A Pareto graph compares the relative value and statistical effects of the method parameters' primary and interaction results. This chart describes significant variables that influence contribution in order to reduce it.
 - • Analysis of Means (ANOM) is used to assess the optimum method parametric settings by calculating the key impact of each parameter, which is illustrated in the main effect plot diagram [Phadke., 1989].
 - • ANOVA: Analysis of variance (ANOVA) enables the examination of independent variables' key effects and their interactive results in order to know their overall effects on the response.
 - Response surface methodology (RSM): RSM is useful for modeling, analyzing, developing and optimizing engineering problems.

3.7 Results and discussion

3.7.1 Statistical analysis

Three design models are used to statistically analyse the influence of process parameters on the responses, which are Delta P (Filter) and Delta P (Pre-Filter). By considering the statistical R² and Adj. R² of design models for each response in Table 2, it is evident that variation of both responses is statistically significant, only in the quadratic models. In other words, the considerable difference between R² and Adj.R² in quadratic and linear, and 2 Factors interaction models exhibits that quadratic mode is the only statistically significant model that has R² of more than 0.75. This phenomenon means that the interaction effects of process parameters are also governing factors on the variation of both responses.

To better elaborate the effects of the experimental parameter on the responses, the Pareto chart of both responses were depicted in Figure. 1. According to Figure 1, the direct effects of fan speed (A) have the most significant effect on both responses. The grey colour of A with (+) sign in both graphs in Figure 1 means that higher levels of fan speed lead to higher recorded values of Delta P (Filter) and Delta P (Pre-Filter). The mixed air Temperature (D) is also another governing factor on both responses. The blue colour of D with (–) sign in the Pareto charts exhibits that higher levels of Mixed air Temperature (D) tend to decrease the Delta P (Filter) and Delta P (Pre-Filter). The Opening valve (B) is not a statistically significant element on both responses, while Returned air Temperature is only slightly significant on the Delta P (Filter). The interaction effects between the fan speeds (AA) and mixed air Temperature (DD) are other statistically significant factors on both responses. Figure 3 depicts both AA and DD and their effects on the responses.

To achieve a better understanding on the effects of experimental parameters on the responses, the non-significant elements depicted in Figure 1 were removed and the obtained results were depicted in Figure 2.

As shown in Figure 4, the resulting values of R2 and Adj. R2 in graph 2 are slightly less than the quadratic models of both responses. Knowing that the experimental parameters opening valve (B) and Returned air Temperature (C) are not considered as statistically significant elements, therefore, a 3D contour plot of both Delta P (filter) and Delta P (Pre-Filter) at the fixed levels of the opening valve (B) and Returned air Temperature (C) were presented in Figure 5. The non-straight mode of variation of both responses exhibits the intense effects of AA and DD, which are statistically significant elements on both responses (Figure 3).

Table 3-3 Model summary statistics for the responses studied

No	Response	Design Model	R2 %	Adj. R2 %
1	Delta P (Filter)	Linear	57.99	55.78
		2-Factor Interactions	70.91	66.74
		Quadratic	85.45	82.37
2	Delta P (Pre-Filter)	Linear	59.34	57.21
		2-Factor Interactions	72.51	68.58
		Quadratic	78.33	73.74

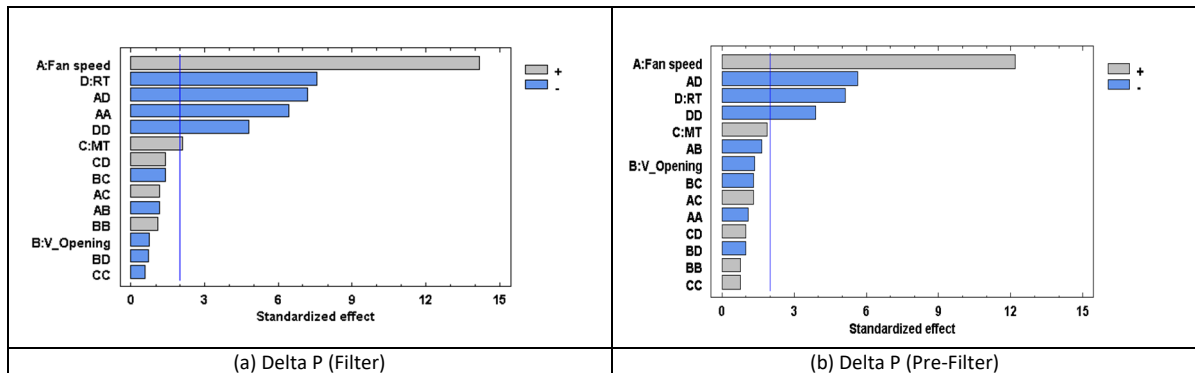


Figure 3-3 Pareto chart of (a) Delta P (Filter) and (b) Delta P (Pre-Filter) in Quadratic model

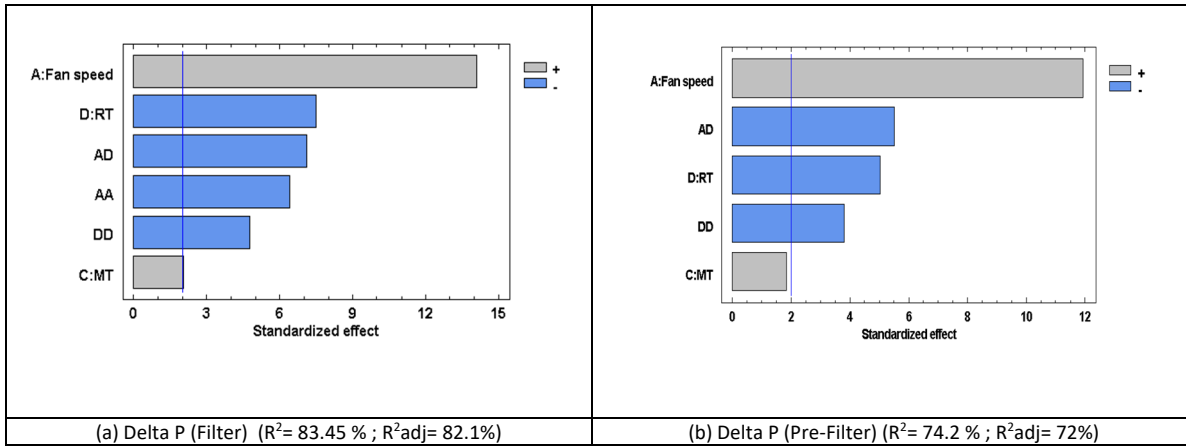


Figure 3-4 Pareto chart of (a) Delta P (Filter) and (b) Delta P (Pre-Filter) in quadratic model with only significant statistical elements

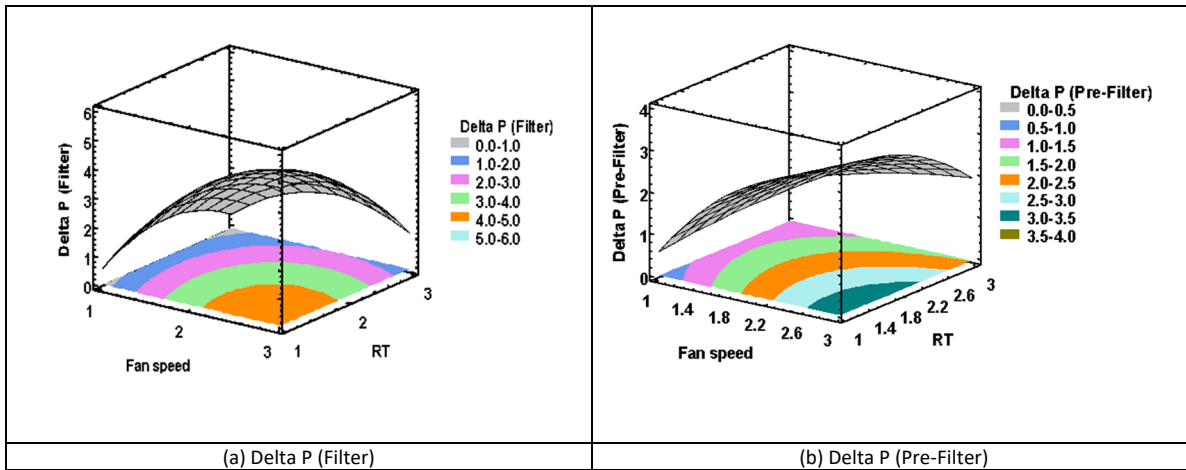


Figure 3-5 3D contour plot of (a) Delta P (filter) and (b) Delta P (Pre-Filter) at the fix levels of the opening valve (B) and Returned air Temperature (C)

Knowing that both responses are statistically affected by relatively similar parameters, it could be inferred that a significant correlation could be formulated between the resulting values of both responses under various experimental conditions. As shown in Table 4, three design models were formulated to assess the relationship between both responses. According to Table 3, it can be stated that under similar experimental conditions, Delta P (Filter) and Delta P (Pre-

Filter) can be presented as a function of each other with the maximum correlation rate ($r=0.962$) and correlation of determination ($R^2=92.49$) at multiplicative mode. In other words, by accurate measurement of one response, the other can be directly calculated by RSM mathematical models.

Table 3-4 Model summary of regression modes between Delta P (Filter) and Delta P (Pre-Filter)

No.	Design models	r	R2 %	F-ratio	P value
1	Linear	0.927	85.94	482.96	0
2	Exponential	0.893	79.85	313.14	0
3	Multiplicative	0.9617	92.49	973.4	0

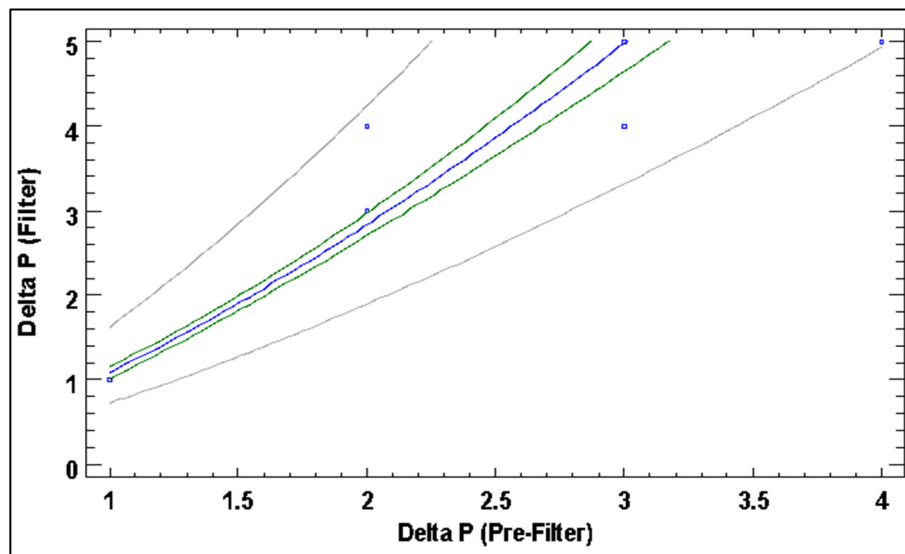


Figure 3-6 Multiplicative Regression model between Delta P (Filter) and Delta P (Pre-Filter)

CHAPITRE 4

ASSESSMENT OF HVAC SYSTEM FILTER PERFORMANCE USING COMPUTATIONAL FLUID DYNAMICS(CFD)

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Abstract

Since the introduction of Heating, Ventilation and Air Conditioning (HVAC) systems, manufacturers have repeatedly studied ways to improve the efficiency of such systems among which the analysis of filter performance has been widely encouraged. In fact, with developments in computer aided simulation, many studies have coupled this analysis with predictive filter maintenance using simulation software, with the goals of improving an HVAC system's operation whilst reducing adverse maintenance costs. As such, this paper explores the development of a simple Computational Fluid Dynamics (CFD) model using ANSYS FLUENT, to study the performance of a real-life HVAC system filter. The model uses the Spalart-Allmaras (SA) turbulence scheme, without consideration of filter dust accumulation, to simulate the pressure drop across the filter, which is successfully validated against independent studies conducted for the same HVAC filter at École de Technologie Supérieure (ETS) and by the filter manufacturer. The finalized model provides results accurate within 21.3% and 13.8% for the actual pressure drop values obtained from the experimental results of a dirty filter by the study at ETS and for a clean filter as suggested by the manufacturer, respectively, for airflow speeds of up to 1.5 m/s. Based on these results, suggestions have been made for future research to incorporate the collection of debris on the filter within the CFD model in conjunction with the coupling of a simple software to monitor and to predict the filter performance based on live and future air quality whereby the filter's end-of-life can be anticipated and maintenance can be addressed in a timely manner.

Keywords: Predictive maintenance, Preventative maintenance, Heating, Ventilation and Air Condition system (HVAC), Computational Fluid Dynamics (CFD), Spalart-Allmaras (SA)

4.1 Introduction

Heating, Ventilation and Air-Conditioning (HVAC) systems are used to introduce and disseminate air throughout buildings, to cool or warm-up space, based on the internal and external environment conditions (Norris, Siegel et al. 2009, Biada and Gray 2010). In fact, HVAC systems have become a necessity for the operation of critical infrastructure (Thompson, Gao et al. 2018). However, it often occurs that HVAC units operate in faulty conditions, not only due to the failure of subsystem components as a result of incorrect installations, but also due to the lack of effective, preventative maintenance (Rosato, Guarino et al. 2020) (Robb 2015) (Perez, Zimmerman et al. 2006, Mowris, Jones et al. 2012). Hence, the importance of preventative maintenance is explored by observation of a key HVAC system component, the filter.

Numerous numerical models and methods exist to study the filter component and assembly of an HVAC system, using two-dimensional geometry simplifications, but there is less development of such assemblies using three-dimensional computational fluid dynamics (CFD) techniques. In fact, developing suitable models to simulate real-life flow conditions across filter media is largely misunderstood due to the complexity of the physics modelling. Yet, advances in CFD model analysis of HVAC filters by (Feng, Long et al. 2014), indicates that Detached Eddy Simulation (DES) models are most reliable and efficient to simulate pleated filter systems.

As such, the objective of this research are: (1) to establish a working HVAC system filter assembly model in 3D, using ANSYS, which is representative of an operating real-life HVAC system, (2) to validate the model with experimental data obtained from the HVAC system and (3) to theoretically explore the possibility of coupling the model with computer programming

for real-time monitoring of working filter systems whereby filter blockage may be predicted to maintain proactive predictive maintenance.

4.2 Literature Review

Due to improper and irregular HVAC system maintenance, a variety of problems arise, which include both, health, and system operation-related issues. Among those classified as health-problems, the Sick Building Syndrome (SBS) is observed among building occupants of mechanically ventilated buildings with concerns ranging from symptoms of headaches to upper respiratory problems (i.e., asthma) as well decreased worker productivity and satisfaction (Perez, Zimmerman et al. 2006). Veritably, this can be explained by poor maintenance practices and faulty system design and construction all of which allude to increased inefficient operation whereby the system consumes more energy thereby reducing its overall operational lifetime (Heinemeier, Hunt et al. 2012). As a result, the cost of running the HVAC system significantly increases (Robb 2015, Rosato, Guarino et al. 2020). Yet, there are ways to optimize the system functionality; these include managing the internal environment conditions by means of: adding occupancy sensors (to reduce lighting-heat loads), establishing occupant behavioral rules (to reduce indoor pollution), implementing fault detection and diagnosis (FDD) methods (to monitor the HVAC system component operation), using humidity control equipment and most importantly, adapting timely, preventative maintenance measures (Roy 2006, Biada and Gray 2010, Robb 2015, Duncan 2019, Rosato, Guarino et al. 2020). The latter technique is especially important when it comes to HVAC filter maintenance since filter dust is a primary source of an inefficient unit and as suggested by literature, filter dust contributes to elevated levels of airborne fungal contamination leading to SBS among other diseases (Perez, Zimmerman et al. 2006, Roy 2006). Veritably, filters effectively capture numerous heavy metals, bacteria and fungi, up to a threshold at which the resistance of air flow becomes significant, and therefore timely preventative filter maintenance (i.e., includes replacement of filter mesh) becomes a necessity (Rossnagel 1997, Noris, Siegel et al. 2009).

Preventative maintenance for HVAC filters requires understanding of its life cycle which varies according to system operation, environmental conditions, filter mesh size, and filter quality among other variables. However, the majority of maintenance measures for a HVAC system are devised based on complete unit models with major focus on controllability of the output or result of the unit. This approach is effective in improving HVAC efficiency by reducing energy consumption, but it lacks the implementation of maintenance which is a key aspect for any system's successful operation.

(Soudari, Kaparin et al. 2018), studied an HVAC system's cooling process and developed a model of thermal dynamics combining a model predictive controller (MPC) which is a proactive controller providing prior information for the HVAC operation, with the pulse-width modulation (PWM) technique. The resulting controller is referred to as the predictive smart thermostat controller (PSTC) whose decisions are based on the solution to a linear optimization problem solved via a programming and simulation approach. Simply, the PSTC uses an on/off approach to reduce energy consumption of the HVAC system and does not require hardware modification.

Similarly, (Li, Vrabie et al. 2015) studied building HVAC system modeling approaches and discovered that two primary approaches are used; one is to use complete building energy simulation software and the second involves a semi-physical dynamic model such as a thermal network model. Furthermore, in their literature, Li et al., concluded that the use of the previous approaches is quite difficult since a significant amount of data is required to determine various thresholds for calibration and validation thereafter. Hence, a simpler, lower-order dynamic model was developed using a MPC whose effectiveness was verified using simulations and experiments. In the literature, the HVAC models were founded using a quasi-steady state approach with values for coefficients (of the model) extrapolated from test data of the HVAC unit under study. As a result, the total energy consumption of the unit was reduced by 17.5%.

Though current literature is well established for reducing energy consumption, it does not employ maintenance (prediction) indications for effective maintenance of the HVAC system

filters which are the first of components that allow clean and efficient ventilation of buildings. Veritably, each model lacks the use of maintenance indications by which the risk of failure of the HVAC system due to maintenance issues remains the same. As such, this paper shifts focus toward possible predictive maintenance indications for the maintenance of filters whereby it uses the advances in computational fluid dynamics (CFD) and in three-dimensional computer aided design (CAD) tools as described by (Yang, Philip et al. 2007) for evaluating a model of an HVAC unit filter.

Though many studies have been conducted to better understand HVAC system filter operations, the studies using Computational Fluid Dynamic (CFD) techniques are preliminary in nature. For example, (Popovici and Valeriu Hudişteanu 2015) analysed the airflow of a theatre hall, defined using a 2D domain (shape) to observe the HVAC system effectiveness. Similarly, (Anghel, Popovici et al. 2020) observed the spread of the novel SARS-CoV-2 coronavirus via airborne transmission through HVAC systems, by developing an ANSYS simulation of the airflow inside a typical hospital room. Such simulations are simply limited to the airflow within a fixed control space and do not consider filter (or other HVAC components') operation. However, those that do model the filter assembly and attempt to simulate either the capture of air contaminants in fibrous filter media or the pressure drop across such filter media, are usually 2D in nature. For example, (Justi, Cândido Da Silva et al. 2014) simulated a two-dimensional porous filter geometry using a predefined experiment-based set of boundary conditions. Similarly, (Feng, Long et al. 2014) studied 2D pleated filter geometries using various physics models, validating them by comparison with an experimental setup. Clearly, these simulations establish working two-dimensional models reasonably comparable to HVAC system filter assemblies, but they lack the observation of airflow properties, in a three-dimensional setting which is highly important to better understand the true function of the flow across industrial-scale HVAC system filters whereby its performance can be effectively evaluated.

Thus, this research will extrapolate from current readily available CFD methodologies for 2D simulations, to create a 3D filter assembly model which will be validated against an

independent data set to observe the theoretical possibility of predictive simulation using ANSYS CFD simulation software for determining filter health (i.e., remaining life). Specifically, this research aims to develop a valid Detached Eddy Simulation (DES) – SA based model in ANSYS, to accurately estimate filter operation, such that future filter blockage can be predicted. The simulation will pave the way for future research whereby the model could be coupled with an algorithm for actively predicting filter blockage based on continuous monitoring and use of available environmental data, thereby ensuring proactive maintenance to reduce energy consumption costs.

The findings of this research are presented using this paper, sub divided into chronological sections of an introduction, a literature review, a methodology, results and analyses, a discussion, and a conclusion. Any literature used or referred-to is provided in the references section after the conclusion.

4.3 Research Methodology

4.3.1 Data Description

Unlike other predictive maintenance approaches focused on the entirety of the HVAC system, the primary objective of this study is to develop a working model for accurate prediction of the remaining life of a HVAC system filter under operation using CFD techniques. As such, this study will prioritise the development and validation of a HVAC system filter model using ANSYS simulation software. The validation and verification (V&V) will be conducted using data collected from the HVAC system installed at Ecole de Technologie Superieure (ETS), an engineering university in Montreal, Canada. The system at the university consists of multiple units serving different zones. However, the experimental data collected is for the operation of the unit UTA-104, for which the HVAC unit schematic is adapted from literature by (Tehrani, Beaugard et al. 2015) and shown in Figure 1.

The data retrieved is filter-performance-based, meaning the variables studied influence the filter operation; these include the fan speed (%), the mixture damper position (%), and the mixed air and return air temperatures ($^{\circ}C$). The data was collected over a six-month time period at a rate of 34,544 data points every 30 minutes. The data was primarily processed as part of the study by (Tehrani, Beauregard et al. 2015), and this study uses the pre-processed data to create a specific data set, for the research in-question, which is used to validate the model created.

4.3.2 Model Description

4.3.2.1 Assumptions & Givens

For the development of the model, some assumptions were considered alongside the given physical parameters from the experiment by (Tehrani, Beauregard et al. 2015). The primary assumptions summarized in Table 1 for which justifications or references are provided in Table 2, where applicable.

Table 4-1 Assumption identification

ID	Assumption
ASM-001	The duct is a galvanized steel duct
ASM-002	The duct is 24 x 24 inches in size
ASM-003	The air-filter is a synthetic, pleated filter with 10 pockets
ASM-004	The air-filter is 23.3 x 23.3 inches in size
ASM-005	The air-filter has a uniform thickness of 0.15 inch, spanning 22 inches
ASM-006	The maximum duct airflow speed is 500 fpm (2.54 m/s)
ASM-007	The air-filter porosity is 0.80.

Table 4-2 Assumption justifications and references

ID	Justification	References
ASM-001	Galvanized steel is the most commonly used material in ductwork for HVAC systems.	(2015)
ASM-002	This is based on the real HVAC system at ETS (Building B) and typical industrial HVAC system sizes.	(Tehrani et., al.) (2021)
ASM-003	See ASM-002	See ASM-002
ASM-004	See ASM-002	See ASM-002
ASM-005	This is derived from the reference of study conducted on HVAC systems' pleated filters.	(Feng, Long et al. 2014)
ASM-006	This is derived from the reference describing maximum airflow (across HVAC air filters) for best filter efficiency and based on the real HVAC system at ETS (building B).	(Carl 2021)
ASM-007	See ASM-002	See ASM-002

On the other hand, the given data corresponds to sensor output data obtained from the experiment by (Tehrani, Beauregard et al. 2015), which includes the time and date of collected data, the fan speed as a percentage, the pressure difference across the filter in inches of water, as well as the mix and return air temperatures as observed in Figure 1. The same data provided the inlet and outlet temperature conditions, as well as the airflow speeds for the simulation.

This data was also used to compare with the experimental results and is presented in the results section.

4.3.2.2 Geometry and Meshing

Indeed, as suggested by (Roychowdhury 2020), any CFD model requires a geometry, a properly refined mesh, a set of initial and boundary conditions and a working physics model (or method), to accurately predict the real system behavior, based on the physics of what occurs in a real environment. In this study of the filter assembly of the UTA-104 HVAC unit, the model is built to-scale in the Design Modeler of the ANSYS Software, as is seen in Figure 1.

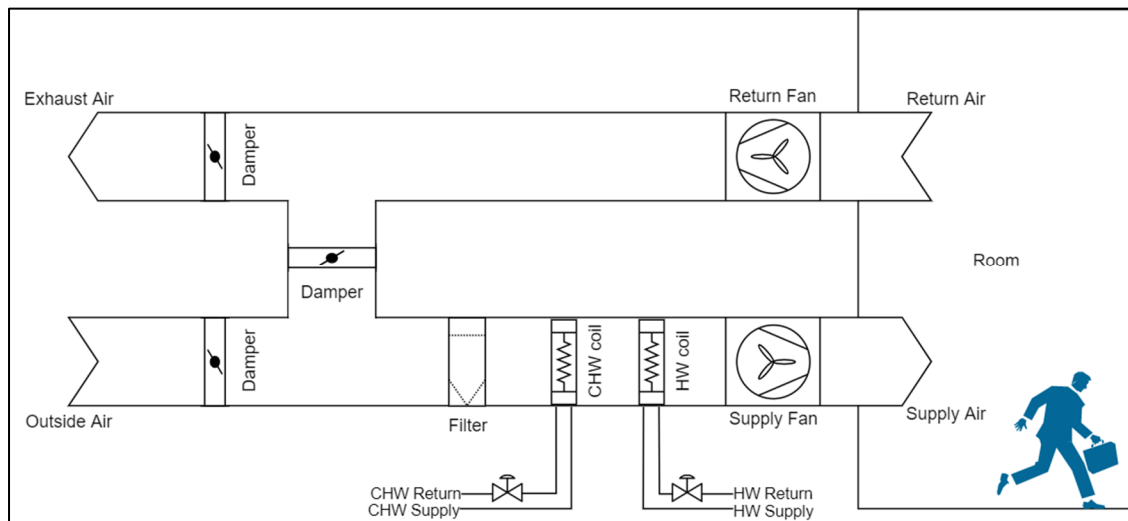


Figure 4-1 HVAC System Schematic

The domain is meshed using the MESHING feature in ANSYS, and the filter geometry is meshed with tetrahedrons, with refinements at the filter-wall boundary. This is observed in Figure 2.

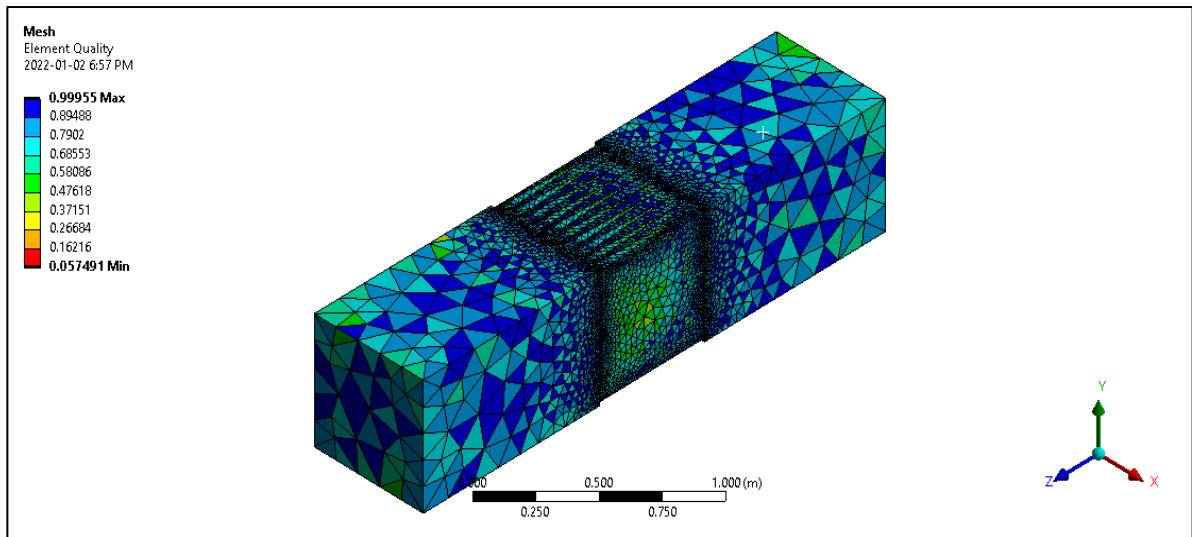


Figure 4-2 HVAC System Fluid-Domain Mesh

4.3.2.3 Boundary and Initial Conditions

The boundary of the computational fluid domain is the Aluminum duct (i.e., housing of filter assembly) within which the filter is secured. This is treated as a wall using the no-slip boundary condition and created using the enclosure method in the Design Modeler of the ANSYS Fluent software. The filter is treated as a porous zone under laminar flow conditions, with a viscous resistance coefficient of $2.78\text{E}+05 \text{ m}^{-2}$ in the direction of the flow ($-z$ axis) and $2.78\text{E}+10 \text{ m}^{-2}$ in the direction of the remaining axes normal to the flow direction, an inertial resistance coefficient of 0.048 m^{-1} for each axis, and a fluid porosity of 0.80. This is defined using the ANSYS FLUENT User Guide (Inc. 2009) and the experimental data of the synthetic filter tested in the study by (Tehrani, Beauregard et al. 2015).

The domain has one inlet and one outlet, in the direction of actual airflow. The inlet is defined as a velocity inlet with an initial airflow velocity which is based on the data provided from the baseline experiment for fan speed percentage and from the typical HVAC system airflow values (see ASM-006, Table 1 and Table 2). The outlet is defined as an outflow pressure outlet (with zero gauge pressure) such that the pressure drop and velocity of the flow may be studied.

As well, the initial airflow temperatures are set using the data of the experiment. This can be seen in Figure 3. The simulation is run three times, each with a different set of initial conditions based on the experiment, so as to validate the simulation by comparison with the experimental results. The boundary conditions of the inlet, for the three cases are tabulated in Table 3, which are the main conditions used to drive the simulation. It is noted however, that the outlet temperature is the same as the inlet temperature assuming an adiabatic process and considering changes of only pressure and velocity under an incompressible flow.

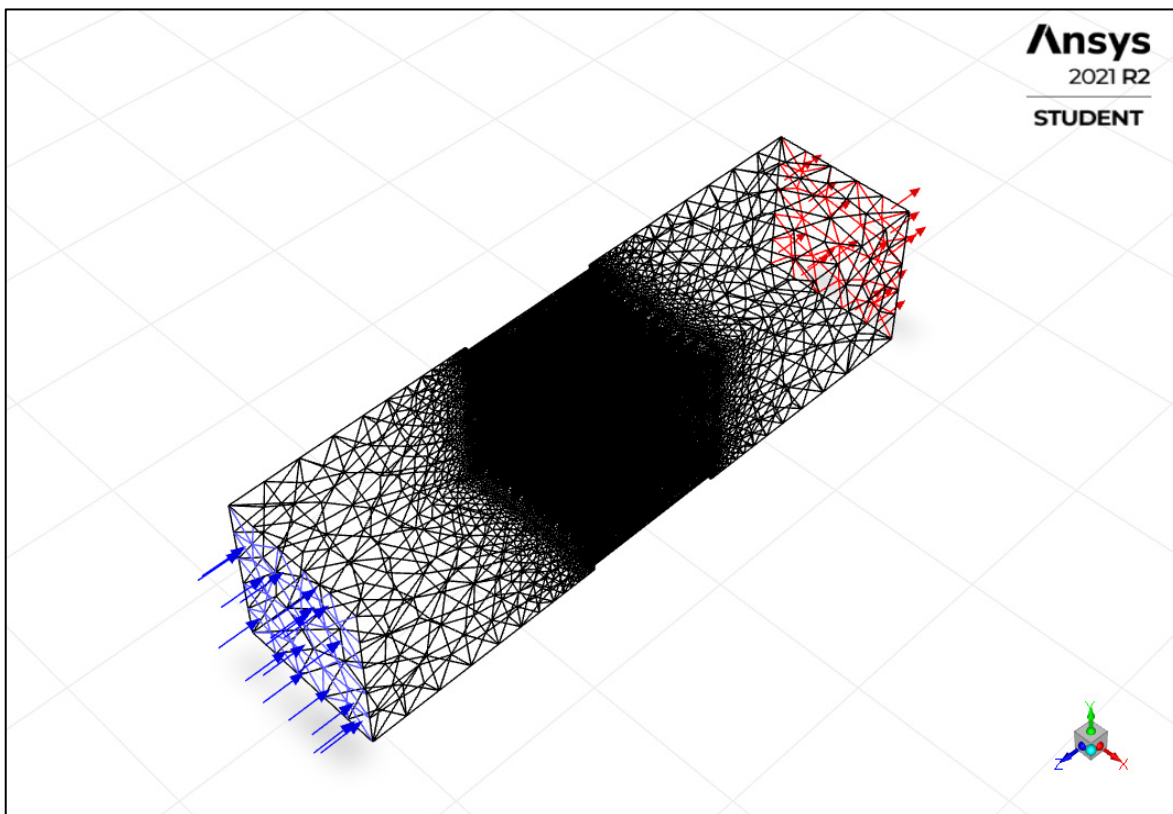


Figure 4-3 HVAC System Model Named Selections (blue inlet, red outlet)

Table 4-3 Simulation Case Boundary Conditions

Case Number	Inlet Velocity	Inlet Temperature
-------------	----------------	-------------------

#	m/s	K
1	1.410	289.041
2	1.140	289.098
3	1.051	288.921

4.3.2.4 Physics & Solver Setup

Generally, the flow is fully developed and turbulent in the HVAC duct prior to the filter in which case it transitions to laminar for a pleated filter, thereby suggesting complexity in flow physics. Thus, an advanced and accurate model such as the Detached Eddy Simulation (DES) – Spalart-Allmaras (SA) model is used to predict pressure drop and transitional flow through the filter, using a time-transient simulation, as is suggested by (Feng, Long et al. 2014). This is a hybrid approach combining the Large Eddy Simulation (LES) and Reynolds Averaged Navier-Stokes (RANS) models, which are respectively used to resolve turbulent and near-wall region flow fields.

The ANSYS FLUENT solver, solves the primary fluid flow governing equations, including the continuity (or mass conservation), and momentum conservation equations. The solver preference for the pressure equation correction is set to the SIMPLE algorithm, and all variable discretization schemes apply the second-order upwind method whereas the pressure discretization is performed using the standard or first-order upwind scheme, as suggested by (Feng, Long et al. 2014).

The solver is initialized using standard initialization from the inlet and the simulation is run at a time step of 0.001 s until convergence is observed when the residuals (RMS) approach $1e-05$ for the parameters of: energy, velocity (u, v, and w components).

4.4 Results

4.4.1 General Results

This section summarizes the results of the simulation for each of the three scenarios defined in section 3.2.3 Boundary and Initial Conditions. These include the simulation convergence of residuals and mass flow rate at the outlet suggesting a successful simulation, the streamline plots to observe the direction of the flow in three-dimensional geometrical space, and the flow-geometry contour plots for pressure and velocity for each case of boundary conditions. Figure 4 below, illustrates the simulation residuals comparison for each case.

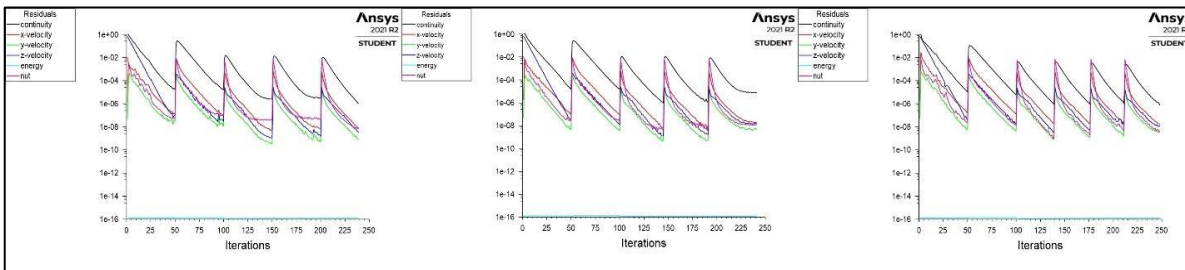


Figure 4-4 Residuals convergence for case 1 (left), case 2 (mid), case 3 (right)

Figure 5 below, illustrates the mass flow rate convergence comparisons for each case.

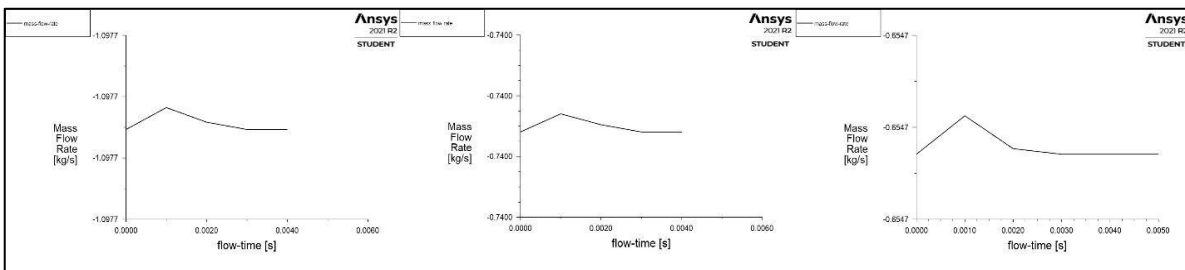


Figure 4-5 Mass flow rate convergence for case 1 to 3 (left to right)

Generally, each simulation scenario yielded acceptable flow streamline paths according to classical fluid mechanics theory of incompressible, subsonic, turbulent and laminar flow, presented in(Schobeiri 2010), which is practically observed in general wind tunnel experiments

conducted by (Verma and Baloni 2019). The flow characteristics are observed via the pressure and velocity contours (given for each case), which are presented and compared in the following sections.

4.4.1.1 Pressure Contours

For the airflow across the pleated filter with conditions of case 1, it was observed that the filter pressure drop had a maximum value of 176.199 Pa. Similar to case 1, case 2 demonstrated a pressure drop of 88.711 Pa, and case 3 yielded a pressure drop of 61.943 Pa across the filter. The fluid flow pressure contours for cases 1 to 3 are observed in Figure 6.

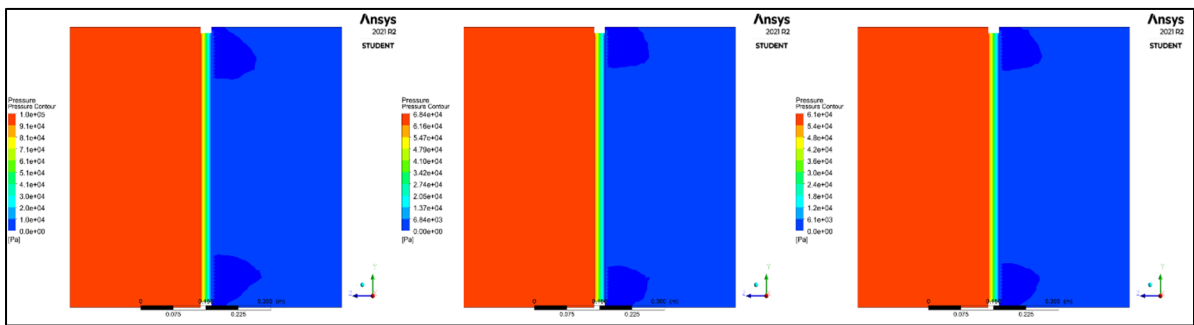


Figure 4-6 Pressure contour of flow across filter for case 1 to 3 (left to right)

4.4.1.2 Velocity Contours

For all cases (1 to 3) the velocity contours (shown in Figure 7), suggest that a constant average flow velocity is maintained, since the velocity magnitudes are mirrored across the filter. This average velocity is approximately 1.403, 1.137 and 1.050 m/s for cases 1 to 3, respectively. This is simply used for verification of convergence.

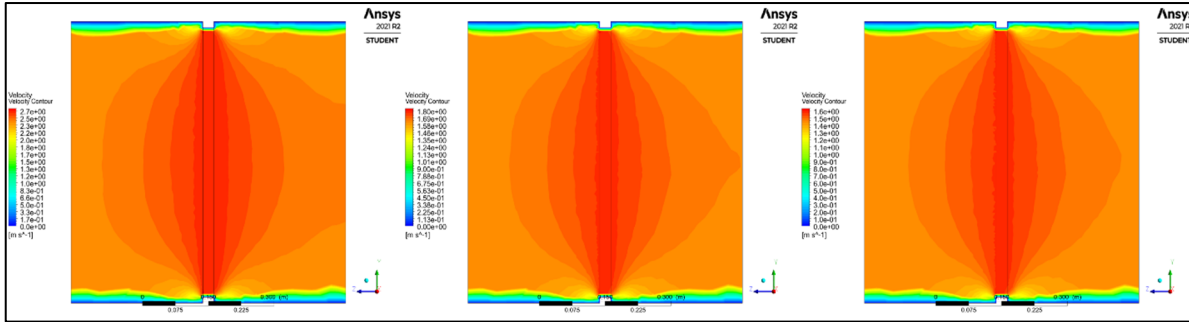


Figure 4-7 Velocity contours of flow across filter for case 1 to 3 (left to right)

4.5 Discussion and Analysis

This section discusses the results from Section 4. From Figure 4, it is observed that for all simulation cases, the fluid parameter residuals successfully converged to a value of $1e-05$ and/or lower. This type of convergence, within the provided set of iterations per time step for an extended number of iterations, is defined as periodic convergence, suggesting a successful simulation. Additionally, the stagnation of the mass flow rate at the outlet, for each case, as is illustrated in Figure 5, suggests that the conservation of mass or continuity equation is met, whereby the flow is a steady, real (i.e., true) flow, which is also observed from Figure 6, in which the flow streamlines presented are realizable.

Furthermore, observation of the pressure contours for case 1 through 3, suggests that a greater inlet speed yields a larger pressure loss across the filter, which is in accordance with both, the experiment from (Tehrani, Beauregard et al. 2015) and the theory of classical fluid mechanics relating the pressure as directly proportional to velocity. Additionally, the pressure losses simulated across the filter are similar to those obtained experimentally, evaluating at 176.199 Pa, 88.711 Pa and 61.943 Pa for cases 1, 2 and 3 respectively. As seen in Table 4, these values yielded a percent difference of 6.89%, 11.63% and 21.31% in comparison to the pressure drop data obtained from the experiment by Tehrani et., al. This discrepancy in results is primarily a consequence of the state of filter cleanliness for which the data is being compared. Indeed, the objective of the project was to create a simplified simulation to accurately predict filter performance which may be used for further studies. As such, the simulated results do not

consider accumulation of dust and debris on the filter whereby the pressure loss across it is affected. Hence, when comparing the simulated results (i.e., for the clean filter) to the experimental results of a slightly used (whose cleanliness status is not the same), the differences in pressure loss are observed.

Table 4-4 Simulated and Experimental Pressure Drop across filter

Case Number	Pressure Drop		Percent Difference
	Simulated	Experimental	
#	Pa	Pa	%
1	167.266	179.196	6.8866%
2	81.247	91.284	11.6347%
3	53.941	66.808	21.3122%

This makes it important to verify that the simulated results are valid. As such, Table 5 illustrates the comparison between the simulated results and the filter manufacturer's experimental data for the pressure loss across a clean filter. From this comparison, it can be extrapolated that the simulation is valid (i.e., the solver physics and boundary conditions are correct) for the given filter, as the percent errors in pressure drop for cases 1 through 3 are 13.81%, 8.78% and 5.20% respectively.

Table 4-5 Simulated and Manufacturer's Data for Pressure Drop across filter

Case Number	Pressure Drop		Percent Difference
	Simulated	Manufacturer's Data	
#	Pa	Pa	%
1	167.266	176.199	5.2017%
2	81.247	88.711	8.7838%
3	53.941	61.943	13.8101%

Clearly, this provides a better comparison than the former, whereby the existing or remaining differences in pressure drop can be explained by the assumptions used in the physics model. For example, the Spalart-Allmaras turbulence model used at the suggestion of (Feng, Long et al. 2014) is applicable to the given duct wall-bounded problem whereby it would provide good results for the pressure differences near the boundary layers of the filter pleats or pockets. Therefore, it becomes crucial for such regions to have proper mesh refinements whereby the computation can be made accurate. However, due to the lengthy computation time required to run a single case, the mesh was simplified such that the zone of proximity to the 3mm (0.15”) thick-porous filter was approximated by a single layer of a tetrahedrons mesh instead of a layered mesh with multiple smaller elemental domains to compute on. Hence, the computation of pressure at the interface of the filter and the duct fluid zone may not be accurate, whereby the remaining elemental computations foresee a truncation error. Additionally, the filter geometry was also simplified using a rigid non-curved interface spanning the 22” length of the filter. Yet, the true filter geometry is both flexible and curved which may affect the conditions of airflow and hence, the pressure drop across the filter. Together, these simplifications used in the simulation create the variation in the results for pressure drop, which are observed in comparison to the actual experimental data. Nonetheless, because the percent differences are acceptable, the simulation is regarded as acceptable.

4.6 Conclusion

In conclusion, the objectives of this research were accomplished as 1) a working CFD model of a real-life HVAC system was developed in ANSYS FLUENT, 2) the model was validated against experimental filter performance data obtained from an independent study on the ETS HVAC system and from the manufacturer of the filter and 3) the model’s successful validation provides a baseline configuration which can be enhanced to include dust accumulation on the filter which can be used for predictive maintenance. Indeed, in using the SA turbulence model, it was observed that the true filter pressure drop can be predicted within a maximum percent difference of 13.81% of the experimental values, for a clean filter and for speeds of up to 1.5 m/s. Although acceptable, the accuracy of these results can be improved by refining the mesh

surrounding the filter pockets and by considering the collection of debris on the filter, both of which can be implemented using ANSYS. In doing so, in a future continuation of this research, a new CFD model may be developed from the current one, which can first be verified against experimental data for a dusty filter, and then be coupled with a simple software such that the filter pressure drop can be assessed using simulation in ANSYS. In turn, the filter blockage percentage can be anticipated and given air quality conditions, the filter end-of-life can be approximated, such that maintenance delays are prevented, and associated maintenance costs are reduced.

DISCUSSION

The research objectives of this project were to evaluate predictive techniques for predicting HVAC filter blockage, to determine the extent to which four process parameters (fan speed, return air temperature, mixed air temperature, and damper positions) respectively correlate to filter-clogging, and to design a CFD model using ANSYS to simulate 3D airflow within an HVAC filter unit that could be used to predict the next filter-failure. All three research objectives were closely tied to one another. Data gathered on predictive techniques in the first paper was edited to account for factors like differential pressure, fan speed, and damper position. The second paper explored the extent to which those factors, namely mixed and return air temperature (which contributes to differential pressure), fan speed, and damper position, contribute to filter-clogging. The third paper outlines the development of a CFD model that incorporates data gathered in the previous papers pertaining to predictive techniques and process parameters that contribute to filter-clogging. This CFD model could potentially be used in concert with real-monitoring of a working HVAC system to predict filter blockage and prescribe maintenance procedures for the filter.

The contribution of the first paper is to evaluate predictive techniques for HVAC filter blockage. This research compares the performance of five progression predictive techniques (Bayesian linear regression, neural network regression, boosted decision tree regression, linear regression, and decision forest regression) for predicting filter blockage with different versions of edited data applied to each technique. A statistical control chart was used to compare observed data with predicted data, and a decision making tree was used to edit the data in order to account for differential pressure, fan speed, and the damper position in the HVAC system. Different scenarios were considered using a design of experiment that accounted for three factors (pressure differential, fan speed, and damper position), each with two levels. A full factorial design of experiment analysis was conducted to determine whether factors and their interactions had a significant effect on performance measures. The TOPSIS ranking technique was used to evaluate prediction techniques with all performance measures considered

simultaneously, with Bayesian linear regression ranking number one. Linear regression was within a 0.1 average ranking of Bayesian linear regression, which suggests that the scope of this research may have been too limited to definitively establish Bayesian linear regression as the superior technique for predicting filter-failure. More research on the scenarios considered, as well as research that considers additional scenarios (e.g. financial scenarios), would be useful for more precisely evaluating these techniques. When considering unfiltered data (not based on expert scenarios), Boosted decision tree regression was the top performing technique. This technique can be useful in concert with statistical comparison and MCDM to reduce false out-of-control situations.

The contribution of the second paper is to evaluate the extent to which four process parameters (fan speed, return air temperature, mixed air temperature, and damper positions) correlate to filter-clogging, as well as to establish a correlation between filter and pre-filter responses. Three design models were used to statistically analyze the influence of these process parameters on two responses, which are filter and pre-filter function. Variations in the two responses were only found to be statistically significant in the quadric statistical models. This suggests that the interaction effects of process parameters are governing factors for both responses. Fan speed was found to have the most significant effect on both responses, with higher levels of fan speed leading to higher values of Delta P (Filter) and Delta P (Pre-Filter). Mixed air temperature was also found to be a governing factor for both responses, with higher levels of mixed air temperature decreasing Delta P (Filter) and Delta P (Pre-Filter). The opening valve was not found to be a statistically significant response, and the returned air temperature was found to be only slightly significant to the filter response. Interactions between fan speeds and mixed air temperature were statistically significant to both responses. Non-significant elements (opening valve and returned air temperature) were removed in order to obtain results that better depict the effects of experimental parameters on the responses. Three design models were used to examine the relationship between filter and pre-filter conditions. They found that the two responses can be presented as a function of one another with a maximum correlation rate ($r=0.962$) and correlation of determination ($R^2=2.49$) at multiplicative mode. This

suggests that accurate measurement of one response allows for the other to be directly calculated via RSM mathematical models.

The contribution of the third paper is to develop and validate a working, 3D HVAC system filter assembly model using ANSYS in order to simulate filter function and predict filter clogging. Three simulations were run with a different set of initial conditions based on the experiment in order to allow validation by comparison with experimental results. A Detached Eddy Simulation – Spalart-Allmaras model was used to predict pressure drop and transitional flow through the filter with time-transient simulation. This approach was inspired by (Feng, Long et al. 2014). All three simulation scenarios resulted in acceptable flow streamline paths according to classical fluid mechanics theories of incompressible, subsonic, turbulent and laminar flow presented in (Schobeiri 2010) and observed via wind tunnel experiments carried out by (Verma and Baloni 2019). These flow characteristics were examined through pressure and velocity contours assigned to each simulation case.

Observing airflow across the peated filter with conditions of case 1, it was noted that the filter drop had a maximum value of 176.199 Pa. Under the conditions of case 2, a pressure drop of 88.711 Pa was observed. Case 3 resulted in a pressure drop of 61.943 across the filter. The velocity contours in all three cases suggested that an average velocity was maintained, with the velocity magnitude mirrored across the filter. The average velocities were approximately 1.403 m/s (case 1), 1.137 m/s (case 2), and 1.040 m/s (case 3). For all three simulation cases, the fluid parameter residuals successfully converged at a value of $1e-05$ or lower. This convergence suggests a successful simulation. The stagnation of the mass flow rate at the outlet for each case indicates that the conservation of mass (or continuity equation) is met, whereby the presented flow streamlines are realizable.

Observing the pressure contours for simulation cases 1 to 3 indicates that greater inlet speed results in larger pressure loss across the filter, which is validated against experimental results obtained by (Tehrani, Beauregard et al. 2015) and the theory of classical fluid mechanics

pertaining to pressure as directly proportional to velocity. Pressure losses across the filter yielded by the simulations (observed at 176.99 Pa, 88.711 Pa and 61.32 Pa in cases 1, 2 and 3, respectively) broadly correspond to experimental data. Compared to experimental results obtained by Tehrani et al., pressure loss values yielded a percentage difference of 6.89%, 11.63%, and 21.31%. The state of filter cleanliness explains this discrepancy in results; the simulations did not account for accumulation of dust and debris in the filter, while the experimental evidence gathered by Tehrani et al. observed a slightly used (i.e. slightly dirty) filter. The goal of this project is to create a simplified simulation to predict filter performance that could be used for and expanded upon in further research; not accounting for filter-cleanliness is therefore a limitation in the research conducted. The results of the simulations correlate more closely to the filter manufacturer's experimental data for pressure loss across a clean filter. By this comparison (errors in pressure drop for cases 1 through 3 are 13.81%, 8.78% and 5.20% respectively), the simulation is valid, meaning that the solver physics and boundary conditions are correct. Some of these remaining differences in pressure drop are a result of assumptions used in the physics model. Although the simulation is considered valid and acceptable within these percent differences, future research could expand upon this simplified model in order to arrive at simulations that use fewer assumptions and more closely track experimental data pertaining to pressure loss across the filter.

Future Research

Future research will be needed to evaluate predictive techniques for the HVAC filter with variables not taken into account by my research. For example, future works could include financial scenarios, air pollution, and experimental data gathered from different kinds of filters operating in the same HVAC system in addition to the nine scenarios and experimental data taken into account by my research. In order to improve PdM for the HVAC system overall, future research will also be needed to assess predictive techniques for other HVAC subcomponents including the compressors, refrigerants, evaporators, and condenser coil

sections. Discrete event simulation and other ML techniques could be used to further test predictive techniques.

My research on the parameters that lead to air filter and pre-filter blockage reveals that both responses are statistically affected by similar parameters. Future research could use this correlation to infer the values of both responses for future experimental conditions or simulations. If one response is accurately recorded, the other could be theoretically calculated by RSM mathematical models. This correlation, if validated by further research, could prove useful for designing experimental conditions and simulations for the HVAC filter. Future research into process parameters that affect other responses in the HVAC is also needed to better understand how the entire system functions; more research in this realm could then be used to improve PdM for other HVAC subcomponents.

The CFD model developed could be enhanced to account for dust accumulation on the filter within ANSYS. If validated by experimental data for a dusty filter, the improved CFD model could result in more realistic simulations of filter conditions and more accurate predictions for filter failure. The improved CFD model could also be coupled with simple software to assess filter pressure drop through a simulation in ANSYS. If successfully validated by experimental evidence, the simulation could be used to assess filter-blockage percentage, to anticipate filter end-of-life, and to prescribe accurate and timely maintenance procedures. Future research could also explore the use of CFD models for simulating and predicting failure modes for other subcomponents within the HVAC system.

A continuation of my research would need to explore how the findings of my three research objectives could be synthesized to improve a lean PdM model for the HVAC filter. In other words, further research could explore ways to combine Bayesian linear progression, more accumulated data pertaining to critical parameters that affect filter and pre-filter processes, and an improved version of the CFD model within a lean HVAC filter PdM model.

CONCLUSION

The goal of this thesis is to conduct research that could be used to improve accuracy and practical implantation of a lean HVAC filter PdM. The gathered research includes a study to rank five techniques for predicting failure of the HVAC filter within an MCDM tool called TOPSIS, a case study that gathers experimental data in order to establish the critical parameters that correlate to filter-blockage, and the development of a CFD model with ANSYS to simulate filter conditions within a three-dimensional context. This research also reveals non value-added predictive techniques for the HVAC filter and statistically-insignificant parameters for filter and prefilter blockage that could be eliminated from a lean HVAC filter PdM model.

Bayesian linear regression is the technique that performs best for predicting HVAC filter failure according to the data gathered in my research. The contribution of this research is to test predictive techniques against experimental data and the practical considerations of experts in order to arrive at a preferred technique and to determine which techniques are unsuitable for predicting HVAC filter failure. My case study compares the predicted failure modes of 5 techniques against the actual failure mode of a filter based on experimental data gathered from a working HVAC unit at ÉTS. An MCDM tool known as TOPSIS was used to rank the 5 techniques based on 9 scenarios and performance metrics including predictive accuracy and expert opinion. While Bayesian linear regression performs best on average, the technique does not significantly outperform Linear regression. My research also contributes to the development of a lean model of HVAC filter PdM by revealing that Decision forest regression and Boosted linear regression are outperformed by bayesian linear regression and linear regression by statistically significant margins; according to my research, Decision forest regression and Boosted linear regression are not value-added techniques and would therefore be eliminated from a lean HVAC filter PdM model. The results of my research also reveal Bayesian linear regression and Linear regression somewhat outperform Neural network regression.

Based on the three design models used to statistically analyze the influence of process parameters that lead to air filter and pre-filter blockage, fan speed is found to have the most significant effect. Higher levels of fan speed correlate to higher recorded values of air filter and pre-filter blockage. The mixed air temperature is a governing factor for both process responses (air filter and pre-filter blockage) as well; higher levels of mixed air temperature correlate to lower recorded levels of both process responses. The interaction effects of process parameters, particularly the interaction between fan speeds and mixed air temperature, also affect the variation of the process responses. The opening valve is not statistically significant to either process responses. The returned air temperature is slightly significant to the air filter response. My case study contributes to research by revealing that both responses are statistically affected by relatively similar parameters. This research also contributes knowledge needed to improve a lean model of PdM by revealing process parameters that are statistically insignificant to filter and pre-filter function; for example, my research suggests that data pertaining to the opening valve is statistically insignificant to filter and pre-filter function and would therefore be eliminated from a lean PdM model for the HVAC filter.

A working CFD model of a real-life HVAC system was successfully developed via ANSYS FLUENT in the course of my research. The CFD model was successfully validated by experimental filter-performance data from an independent study of the ÉTS HVAC filter, as well as data gathered from the filter manufacturer. The CFD model predicts true filter pressure drop of a clean within a maximum percent difference of 13.81% of experimental values for speeds of up to 1.5 m/s. This result is promising, but the model's predictive accuracy could theoretically be improved by refining the mesh around the filter pockets and taking debris collection into account within ANSYS.

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