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A Predictive Preference Model for Maintenance of a Heating Ventilating and Air Conditioning System

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Abstract: Predicting next failure of the filter's differential pressure of heating ventilating and air conditioning (HVAC) system provides for a higher performance of the system. There exist various fluctuating parameters that contribute in this paramount prediction. In the current study, the traditional method of linear regression and artificial neural network are applied as means of prediction, and it is shown that the performance is improved when supplemented with a decision tree approach. The outcome reveals which one can more effectively predict trends and behavioral patterns as well as maintenance requirement of such systems with limited considered attributes. Hence, the empirical data is retrieved and a new method for predictive maintenance illustrated using HVAC system of École de technologie supérieure (ÉTS).

Keywords: Linear Regression, Neural Network, Predictive, Maintenance, HVAC system;

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1.INTRODUCTION

Predicting next failure of each component in a system effectively provides better performance of the system as a whole. Consequently it can enhance maintenance, services, monetary issues and many other desired issues related to the system's availability. The next failure can be predicted either by applying traditional Linear Regression model or a model of Artificial Neural Network; however, the result may not equally support the same desired options. Therefore, attempts are made to represent empirical preferences of these two models whereby the system is not considered very complicated with numerous features.

1.1 Review of Literature

Predictive analytic is an area of data mining that deals with extracting information from data and uses it to predict trends and behaviour patterns. Usually the unknown event of interest is in the future, but predictive analytics can be applied to systems with any type of unknown relationship among their components whether it exists in the past, present or future (Nyce and CPCU, 2007, Murphy, 2012).

Broadly speaking, there are two classes of predictive models: parametric and non-parametric. In addition, a third class, semi-parametric models, which includes both features. Parametric models make "specific assumptions with regard to one or more of the parameters that characterize the underlying distribution(s)" while non-parametric regressions "make fewer assumptions than their parametric counterparts" (Sheskin, 2011, Murphy, 2012).

Another classification for the approaches and techniques used to conduct predictive analytics can broadly be grouped into: A) Statistical methods and B) machine learning techniques. Furthermore, the following statistical methods are proper for diagnosis and decision making: 1)regression techniques, the mainstay of predictive analytics, by a mathematical equation as a model which represents the interactions between the different considered variables; (Freedman, 2009, Warner and Misra, 1996); 2) linear regression (Freedman, 2009); 3) discrete choice models, can properly analyse discrete ordered dependent variables instead of using multivariate regression (Flury, 1988, Press and Wilson, 1978) 4) logistic regression, proper for classified setting, to assign outcome probabilities to observations, transforms information of binary dependent variable into an unbounded continuous variable and estimates a regular multivariate model (Bishop, 2006, Hosmer Jr and Lemeshow, 2004, Press and Wilson, 1978, Studenmund, 2005); 5) multinomial logistic regression, an extension of the binary logit model to cases where the dependent variable has more than 2 categories and especially when they are not ordered (Menard, 2002, Raymond, 1990, Neter et al., 1996, Snedecor, 1956),6) probit regression, an alternative to logistic regression for modelling categorical dependent variables, their outcomes tend to be similar while the underlying distributions are different (Bollen, 1998);

7)time series models are applied to predict or forecast the future behaviour of variables, capable of considering internal structure among variables (such as autocorrelation

, trend or seasonal variation) (Gilbert, 1987, Wang, 2006), 8)Classification and regression tree, a generalization of optimal discriminant analysis may be used to identify the statistical model with maximum accuracy for predicting the value of a categorical dependent variable for a dataset consisting of categorical and continuous variables (Lior Rokach, 2008); 9)random multinomial logit, specifically applied to multivariate datasets through generalizing linear mixed model (Breiman, 2001);10) multivariate adaptive regression splines is a non- parametric technique that builds flexible models by fitting piecewise linear regressions (Friedman, 1991). The statistical techniques are classically used and have been commonly accepted as being very effective; while in less complicated cases (Razi and Athappilly, 2005).

On the other hand, machine-learning techniques emulate human cognition and learn from training examples to predict future events in more complex cases (Murphy, 2012, Mitchell, 1997), As a brief review of some of machine-learning methods the most commonly use are: 1) neural networks, nonlinear sophisticated modelling techniques that are able to model complex functions and to predict, classify or control future problems (Bansal et al., 2005, Taylor, 1996, Mehrotra et al., 1997, Fausett, 1994, Freeman, 1993, Lawrence, 1993, Smith, 1993, Hertz, 1991, White, 1992, Lippmann, 1987, Rumelhart et al., 1988); 2)Multilayer perceptron , consisting of an input and an output layer with one or more hidden layers of nonlinearly activated nodes or sigmoid nodes (Ruck et al., 1990); 3)Naïve Bayes assumes the predictors are statistically independent which makes it an effective classification tool that is easy to interpret (Panda and Patra, 2007). 4) K-nearest neighbours involves a training set of positive and negative values, a new sample is classified by calculating the distance to the nearest neighbouring training case. The sign of that point will determine the classification of the sample- (Denoeux, 1995).

Daniel et al. believe that for filter blockage and predict the next failure, referring to linear regression is proper technique (Daniel, 2011) on the other hand, there are some preferences for the application of ANN models specifically in filters. For instant, Delgrange et al. developed an ANN model for ultrafiltration fouling (Delgrange et al., 1998).

Regarding to these two last point of views, the aim of current study is to represent which method can perform better for prediction of next filter blockage in the HVAC system. The paper is organized into following sections: Methodology, Model development,Model output analysis; Result and discussion; Recommendation and future works; Acknowledgment ;References .

2.METHODOLOGY

2.1 Study Area

HVAC system installed at École de Technologie Supérieure (ÉTS) is the area of focus of the study reported in the current paper. ETS is one of the biggest engineering university in Canada. The system totally consists of 25 separate units that are controlled and monitored by Johnson Controls. Each unit separately serves one zone of the university. More specifically the main focused in this paper is the operational unit UTA-104 which provides air volume to internal areas of the building B.

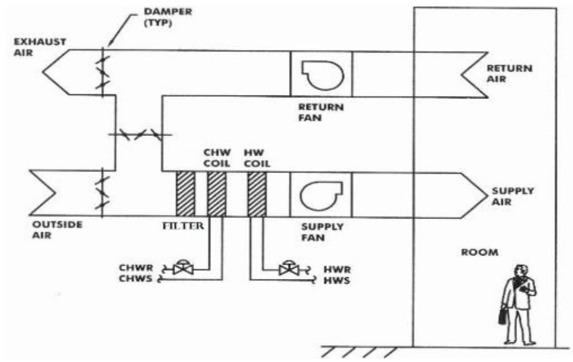

Figure 1 –HVAC systems schematic

2.2 Research question

The ultimate goal of predictive maintenance (PdM) is to accomplish maintenance at a pre-planned and on- time schedule(Biswal et al., 2010). In HVAC system, any unexpected interruption not only results in inconveniences, but also generates energy waste issues, imposes extra cost and requires unnecessary maintenance work. On the other hand, selecting the appropriate predictive model can critically enhance PdM performance. Regarding previous practices in the field of predictive modelling and proposed achievement (see review of literature) linear regression, a type of statistical techniques, and neural networks, a subdivision of machine learning techniques, are applied at less complicated and complex situation. Hence, the study is seeking to reveal which of the models can better predict the next failure of a component in the ÉTS HVAC system.

2.3 Data Description

Data is retrieved based on "filter" performance in the HVAC system. Filter blockage in the HVAC system critically affects the energy consumption and the quality of output air volume. Therefore, fan's speed (from 0% to 100%), return temperature (from 18°C to 25°C), mix temperature (return and fresh air from 16°C to 25°C), and mixture damper's position (from 0% to 100%) are four attributes according to which the model is developed in order to predict next filter blockage.

The retrieved information belongs to a six-month operation of HVAC system including 34544 data recorded by calibrated sensors every 30 minutes.

3. MODEL DEVELOPMENT

Large volume of data collected for model development is initially considered as row-data that requires to be organized and cleaned. Hence, in the first step the collected data is cleaned to be prepared for being analysed by models. As a result, all unnecessary data recorded by sensors when the system is out of service is removed (i.e. during night time). According to McQuiston as well as the HVAC specialists' judgment, four factors involved in differential pressure rise are selected (McQuiston et al., 2010). These are fan speed, return temperature, mix temperature (return and fresh air), and mixture damper's position. It should be noted that outside air condition is one of the most important factor affecting the filter blockage. However, in this study, it is not taken into consideration due to the fact that this factor is unlikely to be controlled (not in statistical sense but in reality).

According to the literature review accomplished in this paper, Neural Network method and Linear Regression method as two most commonly used methods are applied in database. Next, the methods are analysed respectively by Rapid Miner 5.3.005 and Statgraphics Centurion XVI.II.

3.1 Neural Network Approach

Neural networks are nonlinear sophisticated modelling techniques that are able to model complex functions. They can be applied to problems of prediction, classification or control in a wide variety of fields (Bansal et al., 2005).

Artificial Neural networks are used when the exact nature of the relationship between inputs and output is not known. Thus, fan's speed ,return temperature, mix temperature, and mixture damper's position are taken into account as the four selected attributes i.e. model's input and the output will be the differential pressure predicted by the model. Figure 2 illustrates the designed model using the neural network approach.

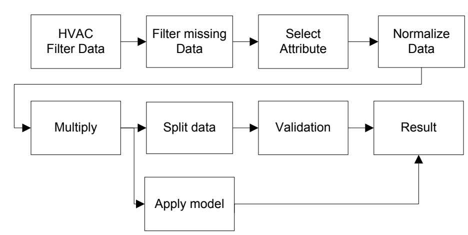

Figure 2-Nureal Network model

A key feature of neural networks is that they learn the relationship between inputs and outputs through training.

A neural network requires a large amount of training data, which is impractical to generate using a production machine for real-time predictive maintenance system.(Mazurowski, 2008) . Furthermore, the testing set is applied to assess the generalization performance of the trained package and is not meet by any particular neural networks while the training process is running.(Islam et al., 2003)

In this proposed model (Figure 2), the data used regarding for feedforward neural network method are specified into two sections. The first half of them is attached to network training set and the second half is applied for testing set. The model is organised with 4 input 1 hidden layer and 1 output. The output analysis is provided in section 4 of this paper.

3.2 Linear Regression Approach

The linear regression model analyses the relationship between the response or dependent variable and a set of independent or predictor variables. This relationship is expressed as an equation that predicts the response variable as a linear function of the parameters(Freedman, 2009). In this phase, the stepwise technique is applied to identify the considered attributes contributing to predict differential pressure. To achieve this objective, the four variables used in the study are exposed to linear regression analysis. Differential pressure of the filter is considered as a dependent variable comparing to the four attributes applied as independent variables.

The generated output represents the result of fitting a multiple linear regression model to describe the relationship between filter PD and 4 independent variables. The mathematical equation of the fitted model is:

$$Y = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip} + \varepsilon_i$$

Where "Y" is Filter PD, X_{i1} is return temperature, X_{i2} equals to mixed temperature, X_{i3} is mixture damper's position and X_{i4} reflects fan's speed. Therefore:

$$Y_i = -0.7838 + 0.02066X_{i1} + 0.00141X_{i2} - 0.0004005X_{i3} + 0.009279X_{i4}$$

Note: The values of β_o to β_4 are calculated by the statgraphics software .

4.MODEL OUTPUT ANALYSIS

In model output analysis, efforts are made to evaluate the output generated by Neural Network and linear regression methods. Therefore, the created output in Rapid miner software is exported to Statgraphics, which is an analyser software. Consequently, two control charts including "Exponentially- weighted moving average" (EWMA) (see figures 3, 4 and 5) and "Moving range" (see figures 6 and 7) for both predicted amount and residual are developed using the output of each separate method. The residuals are derived from subtracting the observed (actual) value from predicted amount. (Montgomery, 2007) .

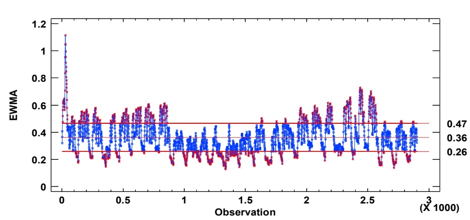

Figure 3 – EWMA Individual Chart for observed Filter PD

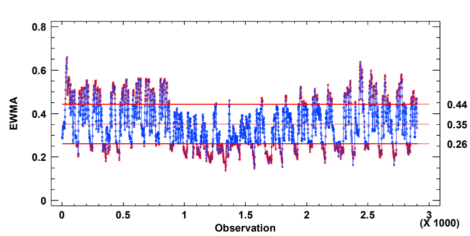

Figure 4 – EWMA Individual Chart for PD predicted by neural network

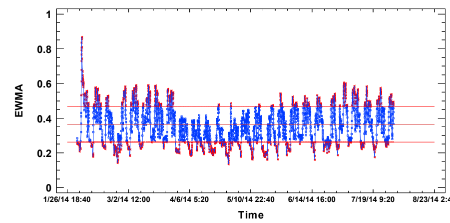

Figure 5 – EWMA Individual Chart for PD predicted by Regression

Refering to the graphs shown in figures 3-5, a large number of points, either observed or predicted, are out of control. They should be analysed to identify where they are originated from, and once their cause is found and corrected removed from the data points and the control limits recalculated. A detailed description of these out of control points is provided in the following section of this paper.

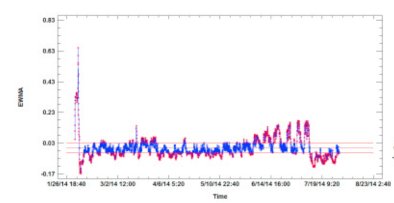

Figure 6 –Moving average individual chart –Residuals of Regression

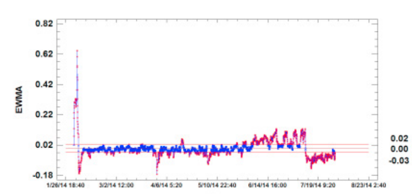

Figure 7 –Moving average individual chart –Residuals of Neural Network

Figure 6 and 7 illustrate moving average individual chart of residuals in which out of control points related to linear regression model are significantly more than those of Neural Network.

5. RESULTS AND DISCUSSION

Observing and analysing the result generated through EWMA charts, it is recognized that a considerable number of out-of-control errors are derived by high speed of fan but not due to the filter blockage. Speed of the fan and supplied air volumes impose a significant effect on pressure soaring (McQuiston et al., 2010); i.e. when these two parameters increase, differential pressure will raise . Thus, all these out-of-control points affected by fan's high speed and volume of supplied air should be cleared to achieve real out of control points associated with actual blockage in the filter. Consequently, a decision tree technique is applied as a post-processing step to provide the ability to distinguish true problematic situations in the operation of the HVAC system.

Due to uncertainty with sequential decision problems, a decision tree model can be applied as discussed previously. It graphically illustrates the future probable events, the appropriate decisions in case of occurring such events, and the consequences attached to decisions and events' combinations. (Baird, 1989).
Hence, only the data points associated with the following 'and' conditions are considered, see figure 8 below:
1) Differential pressure: more than upper limit calculated by Statgraphics;
2) Speed of the fan: less than 80% in normal operation condition and based on analysis of observed data;
3) Return damper more than 70 % based on the main author experience, and analysis from observed data.
Cleaning all unnecessary data, large amount of unreal out of control points were reduced to only 23 instances where the delta pressure actually belongs to a dirty filter situation. Figure 8 demonstrates the decision tree procedure created for the actual out of control points.

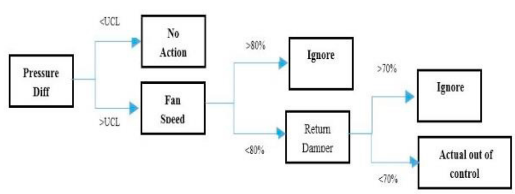

Figure 8 –Decision tree schematic block for actual out of control points

On the other hand, to evaluate the performance, in the first step the coefficient of determination (R squared) is calculated. Resulted values are 0.74 and 0.83 for Regression and Neural Network respectively. Afterward, the model output predictions are statistically calculated by three statistical indexes: Mean Absolute Percentage Error (MAPE), Mean Square Error (MSE), and Mean Absolute Deviation (MAD). (Twomey and Smith, 1997), (Yang et al., 2000), (Shamshiry et al., 2014). Table 1 illustrates the result of performance evaluation of both models subjected to three statistical indexes.

	MAD	MSE	MAP
Neural Network	0.0465	0.0046	13.55
Liner regression	0.0587	0.0055	15.80

Table 1: Result of performance measurement

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i-\hat{Y}_i}{Y_i}\right| * 100 \quad (1)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i-\hat{Y}_i)^2 \quad (2)$$

$$MAD = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i-\hat{Y}_i\right| \quad (3)$$

(Note: Y_i is observed data and $\hat{Y}_i$ is predicted amount)

Based on the result demonstrated in Table1, neural network approach performs relatively better than regression technique.

6. CONCLUSIONS

In brief, the study results suggest that neural networks take partial, but not significant, priority over linear regression techniques for uncomplicated systems like HVAC. Apparently, neural networks attract high performance expectation in literature, while the current study discovered no considerable improvement. Furthermore, the results also indicate that neural networks are typically more efficient than regression techniques for next failure prediction in uncomplicated systems; however, the performance improvement is marginally observable.

7. RECOMMENDATIONS AND FUTURE WORKS

Main focus in the current study is filter blockage as one of the HVAC maintenance issues. For enhanced understanding of model preferences, it is suggested that the prediction efficiency of these models will be examined using additional components of HVAC systems, adding for instances compressors (as heart of HVAC systems), refrigerant, evaporators and condensers coil sections. The literature review accomplished in this study compared neural network and linear regression as the two most commonly used predictive techniques in maintenance. We also showed how the use of a decision tree combined with both approaches can greatly reduce the occurrence of false out of control situations. Further studies using other techniques can also be made to compare and identify the preferred predictive approach for uncomplicated systems like HVAC.

Finally, the retrieved data used in the current study belongs to only the last six months of the year. It would be interesting to see how the HVAC system performs during a full year, with the huge changes in temperature and weather conditions that are characteristic of eastern Canada. (The dataset related to the second half of the year is already being investigated by the main authors).

8. AKNOWLEGMENT

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