2013 European Control Conference (ECC)
July 17-19, 2013, Zürich, Switzerland.

Robust Fault Tolerant Application for HVAC System Based on Combination of online SVM and ANN Black Box Model

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Abstract— **Efficient heating, ventilation, and air-conditioning (HVAC) systems are one of the big challenges today around the world. The fault detection and isolation (FDI) play a significant role in the monitoring, repairing and maintaining of technical systems for the final destination of cost reduction. FDI makes it possible to reduce total cost effective of maintenance and thus increase the capacity utilization rates of equipment. Reduction of energy wasting in the system by on time fault detection is another goal. Therefore, this work proposes a new fault detector based on a black box Artificial Neural Network (ANN) model and online support vector machines (SVM) classifier which integrates a dimension reduction scheme to analyze the failure of air fan supply and dampers fault. The key advantage of this algorithm is to make robustness for SVM to recognize a faulty condition with unexpected sensors values. The ANN generates a high accurate model which is based reference for SVM classifier. Now by using this black box model we make possibility of robustness for SVM to increase detection probability. Finally, a series of faulty experimental data are applied to evaluate the effectiveness of the robust classifier. Final results show that online SVM can detect accurately the air supply fan fault and damper fault of a HVAC system with minimum usage data. It is also outperforms offline SVM on such energy systems for classification.**

I. Introduction

The extensive research that has gone into fault diagnosis of HVAC systems thus far has been motivated by several concerns, ranging from the need to reduce power consumption and energy costs, improving comfort levels in buildings, reducing wear on HVAC equipment, reducing the magnitude of greenhouse emission, to assisting in optimal building operation [1-3].

Some theories or methods in computational intelligence are applicable to this task, such as neural network, Wavelet Analysis, gray clustering, decision tree, Petri network, information fusion have been applied to fault diagnosis and produced some results[4-8]. Many methods, such as rough set theory [9], fuzzy clustering [10] and grey relation [11] were created to deal with the input samples.

But HVACs are complex system with uncertainty factors and information, and these methods have different shortage. For example, Petri network puts domain knowledge into a series of producing rules to solve fault diagnosis problems, but when new fault or new information is coming, it will lead to matching collision and combination blast. Neural networks method alone has some drawbacks in network structure selecting, cost solving in time and CPU, network training and enhancing network spread ability.

Recently, a new learning machine, named support vector machines (SVMs) [12], has attracted more attention in certain areas ranging from its initial implementation in pattern recognition to the extended application in regression estimation. This is brought about by its excellent characteristics such as good generalization performance, the globally optimal and unique solution, and sparse representation of solution. SVMs seek to minimize the upper bound of the generalization error based on the structural risk minimization (SRM) principal. Another key feature of SVMs is that training SVMs are equivalent to solving a linear constrained quadratic programming problem [13]. In recent years, SVMs have been applied to many real-world problems, such as pattern recognition, function approximation and time series forecast because of its greater generalization performance. Although it is still in high speed with light core of calculation compare to their similar algorithms but there are some drawbacks that it doesn't make enough robustness in case of lake training.

Since the available faults and information in HAVC diagnostics is not always accurate and measurable but rather uncertain and incomplete, SVM doesn't effectively deal with vagueness and uncertainty information. In order to resolve those problems and make a robustness fault detector, a hybrid fault diagnosis model composed of Black Box Neural Network (BBNN) [14] and SVM [12] component is presented in this paper. Our proposal aims to make great use of the advantages of black box modeling as a healthy reference to make robustness to SVM approach. It may increase fault diagnosis system robustness and improve efficiency and accuracy in the fault system detection. Following to our research, this developed algorithm was tested on a laboratory scale of HVAC system and result shown the increasing of robustness on fault detection.

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II. BLACK BOX MODEL AND ANN ADVANTAGE

A black-box model is essentially an input-output model based on experimental data. There are different ways for model a process based on black box strategy. One way is the adaptive Auto-Regressive with eXogenous input (ARX) models [17] but one of the most common applicable methods is Artificial Neural Network (ANN) models [16]. Usually, the recursive ARX models can be used as adaptive observers [18], assuming there exists good persistently exciting conditions; dynamic properties of the processes, like static gain and bandwidth, can be computed from these models. But in nonlinear process the ANN models are commonly used as non-linear prediction in plants with nonlinear behavior. They normally require a set of input-output patterns in order to capture the dynamics of the process. An ANN is considering for black box modeling for non faulty reference in this research because of HVAC nonlinear dynamics due to changing of outdoor condition.

To overcome problems of using analytical models applied to real systems like robustness and nonlinear behavior, the neural networks can be use to both generate residuals and to detect and isolate faults [15]. One of the main features of neural networks is their ability to learn from examples [16]. They can be trained to represent relationships between past values of residual data and those identified with some known fault conditions. A typical scheme of two-layer feed-forward neural network configuration is shown in figure 1.

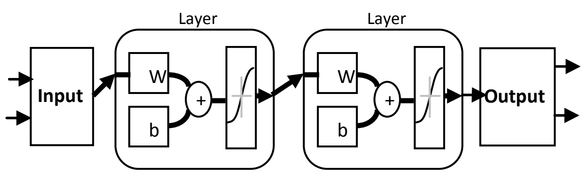

Figure 1 two layers feedforward neural network

Feed-forward neural networks (FFNN) are suitable structure for nonlinear separable input data. In FFNN model the neurons are organized in the form of layers. The neurons in a layer get input from the previous layer and feed their output to the next layer. In this type of networks connections to the neurons in the same or previous layers are not permitted. The back-propagation training algorithm is an iterative gradient algorithm designed to minimize the mean square error between the actual output of a multilayer fee-forward perceptron and the desired output

A combination of ANN model and SVM classification is present in figure 2. It is clearly illustrated a neural network (ANN) is used for model purpose and online SVM consider as a classifier to fault detection. A linear model is not suitable model structure for complicated systems such as HVAC system with a high nonlinearity and wide ranging dynamics. It is more efficient to use a non-linear model approaches (such as ANN modeling) for such systems.

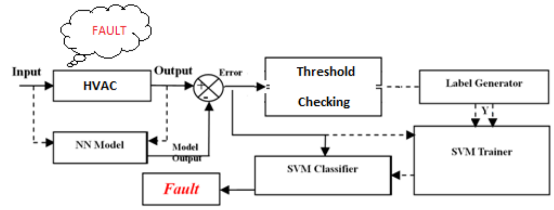

Figure 2 schematic diagram of black box ANN-SVM fault detector

In this study a wide range of ANN approaches applied with different range of training system and finally the beset response achieved from combination of a feed-forward ANN with back propagation training algorithm and consideration of time delay units. A HVAC system may included Cold box system, Heat box system, AHU and control system all together so it is possible to take inputs and outputs data set for a whole system or consider any part of system as a subsystem. It is clear richer data set can lead to accurate model then result more robustness in modeling. But robustness in fault detection is mainly delivered to fault detector algorithm. However, both views are considered in this study due to using combination method.

III. ONLINE SUPPORT VECTOR CLASSIFICATION

The main advantages of SVM include the usage of kernel trick (no need to know the non-linear mapping function), the global optimal solution (quadratic problem), and the generalization capability obtained by optimizing the margin [19]. However, for very large datasets, standard numeric techniques for Quadratic Program (QP) become infeasible. An on-line alternative, that formulates the (exact) solution for $\ell+1$ training data in terms of that for ℓ data and one new data point, is presented in online incremental method. Training an SVM incrementally on new data by discarding all previous data except their support vectors, gives only approximate results [20]. Cauwenberghs[21] consider incremental learning as an exact on-line method to construct the solution recursively, one point at a time. The key is to retain the Kuhn-Tucker (KT) conditions on all previous data, while adiabatically adding a new data point to the solution. Leave-one-out is a standard procedure in predicting the generalization power of a trained classifier, both from a theoretical and empirical perspective [22].

Giving n data, $S = \{x_i, y_i\}$ and $y_i \in \{-1, +1\}$ where x_i represents the condition attributes, y_i is the class label (correct label is +1 and faulty label is -1), and i is the number of data for train. The decision hyperplane of SVM can be defined as (w,b), where w is a weight vector and b a bias. Let w_0 and b_0 denote the optimal values of the weight vector and bias. Correspondingly, the optimal hyperplane can be written as:

$$w_0^T + b_0 = 0 \qquad (1)$$

To find the optimum values of w and b, it is required to solve the following optimization problem:

$$min_{w,b,\xi} \quad \frac{1}{2}w^T w + C\sum_i \xi_i \qquad (2)$$

Subject to $y_i(w^T\varphi(x_i)+b) \geq 1-\xi_i$

Where ξ is the slack variable, C is the user-specified penalty parameter of the error term (C>0), and φ is the kernel function and i is the number of data for train. If the training data is not linearly separable, there is no straight hyperplane that can separate the classes. In order to learn a nonlinear function in that case, linear SVM must be extended to nonlinear SVM for the classification of nonlinearly separable data.

The process of finding classification functions using nonlinear SVCMs consists of two steps. First, the input vectors are transformed into high-dimensional feature vectors where the training data can be linearly separated. Then, SVCMs are used to find the hyperplane of maximal margin in the new feature space. The separating hyperplane becomes a linear function in the transformed feature space but a nonlinear function in the original input space.

Note that, the kernel function is a kind of similarity function between two vectors where the function output is maximized when the two vectors become equivalent. Because of this, SVM can learn a function from any shapes of data beyond vectors (such as trees or graphs) as long as we can compute a similarity function between any pairs of data objects. Two regular kernel functions for classification problems are Radial Basis Function (RBF) and Gaussian function regard to nonlinearity consideration.

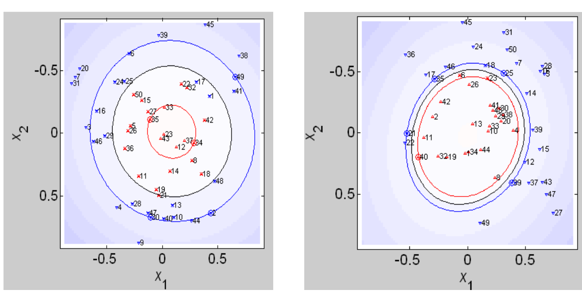

Figure 3 SVM classification result on a series of random numbers based on circle condition on two dimensions

Figure 3 shows the result of our coding for online SVM based on incremental algorithm that was explained. Purpose is separating inside and outside of a circle for testing the code and algorithm. 50 random number between (1) and (-1) was generating as X_1 and X_2 then terms of y was labeled based on circle equation($X_1^2+X_2^2=0.25$). y is labeled healthy (with sign of 1) for all X1 and X2 which working with $X_1^2+X_2^2<0.25$ condition and labeled faulty (with sign of -1) for $X_1^2+X_2^2>0.25$. We train the algorithm with this 50 point and then test it on whole page including 10000 points. The points are indicated on this figure are those which are useful for training and specified as vectors. Black circle is present separator line and distance between red and blue circle is margin. Margin can be change by defining of the penalty factor (C) in the program. Coding and simulation is done in MATLAB and SIMULINK environment (version 2010b) software.

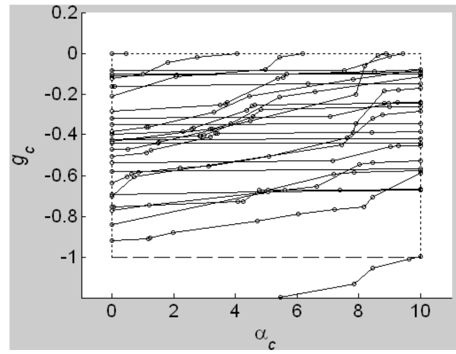

Figure 4 margin vector coefficients change against weight during each incremental step

According to figure 4 the margin vector coefficients change value during each incremental step to keep all elements in equilibrium. i.e., keep their KT conditions satisfied. It is naturally implemented by decremental unlearning, adiabatic reversal of incremental learning, on each of the training data from the full trained solution. Incremental learning and, in particular, decremental unlearning offer a simple and computationally efficient scheme for on-line SVM training.

The margin vector coefficients change value during each incremental step to keep all elements in equilibrium. i.e., keep their KT conditions satisfied. It has also exact leave-one-out evaluation of the generalization performance on the training data.

IV. CASE STUDY

Simulation object is a laboratory scale of a HVAC system which is used for testing and implementation of new technology on the HVAC. This system is located in air conditioning laboratory at University of technology Sydney (UTS) and designed for study and research purposes. A schematic diagram of this system is also presented in figure 5 based on subsystems and single controllable room. The gross floor area of the room is 32 square meters and building height is 2.7 meters. The ground area to be occupied by the building has a rectangular shape. Also walls, windows, floor and roof are modeled according to ASHRAE [23] transfer function approach. This system was run for working hours of building during specific days between 8 a.m. to 10 p.m.

Lighting power density is 20 W/m^2 a common value used in practice for a commercial building. The heat gain from the lights is assumed to be 40% convective. The central cooling plant installed in the building consists of one water cooled chiller, one cooling tower, one air handling unit, two chilled water pumps and two condenser water pumps. The chiller has screw compressors, with a nominal capacity of 7 kW, and uses refrigerant R-407C. For the plate-type evaporator, the evaporator temperature is set to be 4°C. The temperature of the supply chilled water is taken at 7°C at design conditions. The chiller comprises two refrigeration circuits in parallel in which each circuit includes one thermostatic expansion valve and one screw compressor. The chiller can operate down to about 10% of its rated full load capacity via a modulating slide valve in the compressor.

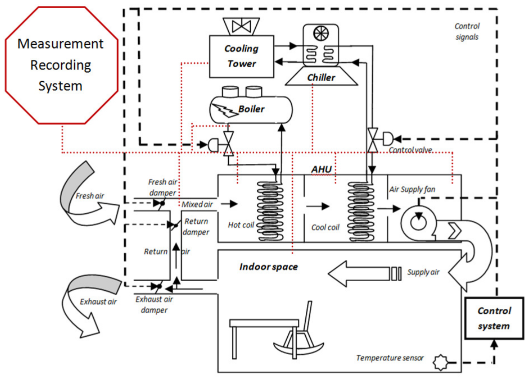

Figure 5 schematic diagram of UTS HVAC system

The design air flow rate and the electric power input of variable speed cooling tower fan at maximum air flow rate are 1700 m^3/h and 0.35 kW respectively. The design air flow rate of the air handling unit with variable air volume fan is 2500 m^3/h and its rated power input is 1.2kW. The design water flow rate and electric power of the chilled water pump is 2.1 m^3/h and 0.32 kW respectively. The design water flow of each condenser water pump is 2.5 m^3/h and their electric power is 0.15 kW. All circulator pumps operate at a constant speed. A photograph of AHU section of UTS HVAC system which is used for the case study is shown in Figure 6.

Figure 6 Air Handling Unit (AHU) of UTS laboratory

Room temperature(T_r), supply temperature(T_s), cooling coil temperature (T_c), room and supply moistures(r_r,r_s), chiller inlet and outlet water temperatures(T_{chi},T_{cho}) and chiller power consumption(P_{ch}) take as HVAC system output and chiller coldwater mass flow rate (m_{ch}) takes as HVAC system input for black box model. All mentioned parameters are regular parameters which are used in a HVAC control system. So customers are not force to take extra cost for new sensor installation. Test is run three times in similar outdoor condition for 14 hours from 8:00 am to 10:00 pm. first day of running data used for black box modeling of the HVAC system. The second day data was including artificial faults of supply fan which are spread during a full day at the times 10 am, 1 pm and 4 pm. third test is instruct based on return damper fault with same condition of second test. All tests are conducted during summer season with highest outdoor temperature between 34 to 35°C at afternoon time.

V. TEST AND RESPONSE

A. *Fault Definition*

HVAC system may suffer from many faults or malfunctions during operation. It is possible to apply this algorithm to whole system on a Building Management System (BMS) or as apart on a device, sensor or actuator. In our test we consider two commonly encountered faults due to some limitation for fault generation. These two faults are: Supply fan fault and Return damper fault.

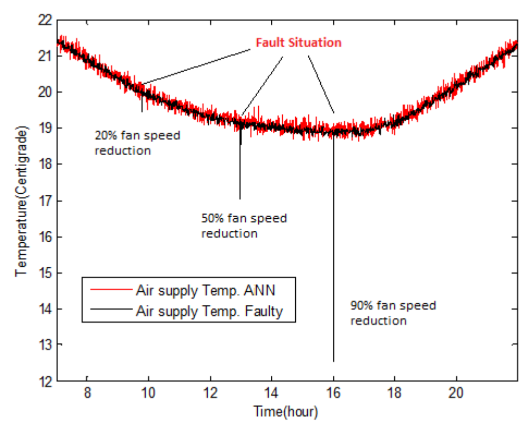

Figure 7 sensitivity of supply air temperature to supply fan fault

Air supply fan speed was forced to reduce for three times based on 20%, 50% and 90% of its nominal value. This reduction was three minutes for each time, to build the first artificial fault. Return air damper was closed for three times based on 30%, 50% and 70% of its normal work and this reduction was for 15 minutes each time to build the second artificial fault. Definition of these faults was based on our study among most common faults in the AHU part of HVAC system and these faults were used to test the performance of fault detector system. Our records shows measured variable are sensitive to different faults depend on type of the fault. For example supply air temperature (T_s) is strongly sensitive to supply fan fault as shown in figure 7.

Another good example is cooling coil temperature (T_c) which has a significant change to return damper fault that is presented in figure 8. A sensitivity analysis is established based on sensors respond to the different faults as we can see in figures 7 and 8. Then this analysis is sent to fault detector algorithm to automated detection base on its training.

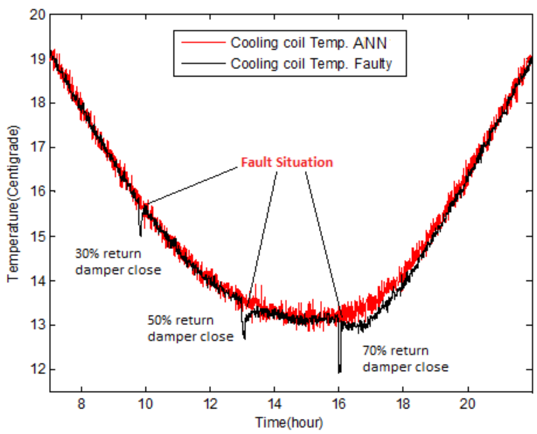

Figure 8 sensitivity of cooling coil temperature to supply fan fault

B. *Fault diagnosis approaches*

Sensors data are reading by an I/O card that is connected directly to a laptop. Data are stored by MATLAB software in version of 2010b which are installed on the laboratory laptop. The ANN Black box model is generated after finishing of first test in the first day. This model was used as the healthy reference (fault free model) for classifier during the second and third tests. Outdoor conditions for second and third tests were similar to the first test. An example of similar days is when day is sunny and the maximum outdoor temperature for afternoon times (between 2 to 3 pm) is 34 to 35℃.

Three range of fan speed reduction applied as an artificial fault for second test. So fan speed reduces three times when it was worked at its nominal value. Speed forced to reduce to 80% of nominal value at 10 am for around three minute and then it backs to nominal value. This faulty condition was applied at 1 pm just a difference for 50% reduction in nominal value for second time. A significant fault applied at 4 pm with reducing of speed to 90% of its nominal value for third time. The first fault has been used for training of SVM and two others applied to check the performance of detection area.

Two faults in the hours of 13 and 16 have been detected with minimum delay(3 min later) and any error in detection as

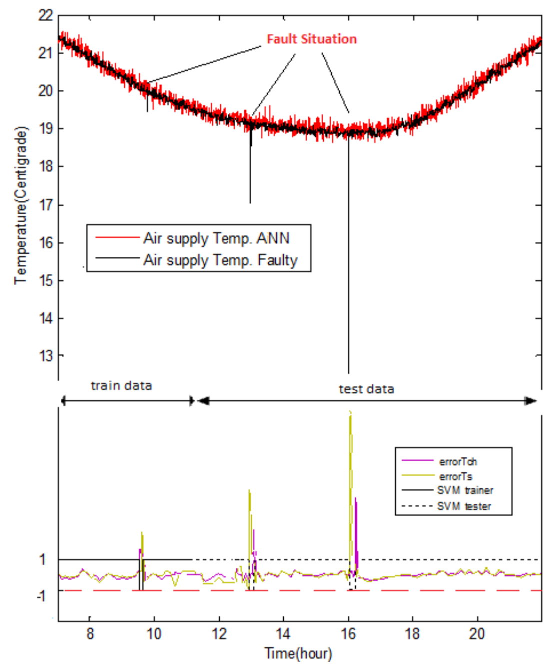

Figure 9 result of SVM fault detector for fan fault based on air supply temperature analysis (first fault used for training and two other following faults used for prediction)

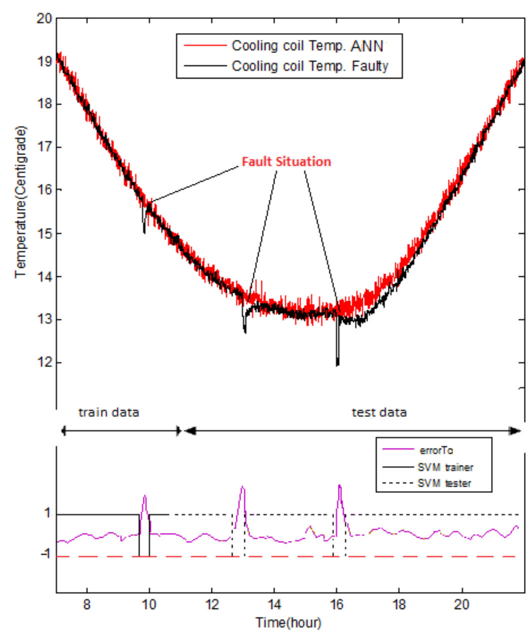

Figure 10 result of SVM fault detector for fan fault based on air cooling coil temperature analysis (first fault used for training and two other following faults used for prediction)

shown figure 9. It is clear HVAC system is a delay system due to inherently delays of temperature but this proposal based on combine ANN model and online SVM algorithm could detect the faults with minimum delay. It should be noted this delay consider as zero due to long terms delay on HVAC systems. This could be reached because of preparing a healthy reference (fault free reference) for SVM based on black box model. By this method we are now able to increase robustness in SVM for such a delayed system.

Another common fault for a HVAC system has been applied in the next step to increase the confidential of this algorithm. A series of artificial return damper's fault applied in the three fault stage with another similar day. Closing situation of the return damper was change between 30%, 50% and 70% during 10 am, 1 pm and 4 pm for 15 minutes for creating the second artificial fault. This faults return to normal working position after this 15 minutes. The result is shown in figure 10 for this type of fault during full day. First fault used to training and two others used for testing same as last procedure. The result increases our confidential for application of this algorithm as we expected. This fault has been detected in just first seconds of occurring and shows the robustness in higher level of achievement.

VI. CONCLUSION

This paper focuses on the robust fault detection of HVAC system under real time working conditions. An online SVM classifier combine with ANN black box model has been developed which can be trained during the operating of the HVAC system. Different with other algorithms, it is possible to detect any type of faults in HVAC system with minimum delay (few seconds or minutes) and error. Using minimal data for training and increasing SVM accuracy and reliability are now applicable by this combination algorithm. Furthermore, this approach can used as equipment monitoring to shows the device situation of the working. Our result shows detecting a fault by a healthy reference is more accurate compare to training with parameters. In addition, some working conditions such as speed or position can be detected by this algorithm to check the related sensors measurement. Moreover, the proposed algorithm can be implemented in a semi-unsupervised learning frame work due to using a healthy reference model in SVM. Simulation study indicates that the proposed approach can efficiently detect and isolate typical HVAC faults.

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