Fault Diagnosis of an Air-Handling Unit System Using a Dynamic Fuzzy-Neural Approach

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Abstract. This paper presents a diagnostic tool to be used to assist building automation systems for sensor heath monitoring and fault diagnosis of an Air-Handling Unit (AHU). The tool employs fault detection and diagnosis (FDD) strategy based on an Efficient Adaptive Fuzzy Neural Network (EAFNN) method. EAFNN is a Takagi-Sugeno-Kang (TSK) type fuzzy model which is functionally equivalent to the Ellipsoidal Basis Function (EBF) neural network neurons. An EAFNN uses the combined pruning algorithm where both Error Reduction Ratio (ERR) method and a modified Optimal Brain Surgeon (OBS) technology are used to remove the unneeded hidden units. Simulation works show the proposed diagnosis algorithm is very efficient which can not only reduce the complexity of the network but also accelerate the learning speed.

Keywords: fuzzy neural network; fault diagnosis ; Air-handling unit.

1 Introduction

It is generally accepted that the performance of HVAC systems often falls short of expectations [1]. In order to investigate methods of FDD and evaluate the most suitable modeling approaches, the international research project entitled International Energy Agency (IEA) annex 25 and annex 34 has been made. A number of methodologies and procedures for optimizing real-time performances, automated fault detection and fault isolation were developed in the Annexes, which concentrated on computer-aided fault detection and diagnosis, [2].

Artificial intelligence methods, which using neural networks and fuzzy set theory, have undergone rapid development in fault diagnosis for HVAC systems [1]. Previous research has investigated the monitoring and diagnosis of HVAC systems using solely fuzzy logic theory or neural network algorithm [3]. However, in the above studies, the fuzzy system and neural network designs have limitations. These are difficult and time-consuming tasks. To improve the accuracy of single-algorithm applications, various fusions of fuzzy logic and neural

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networks, the so-called hybrid intelligent architecture, have been development for better performance in decision making systems [4]. However, very few fuzzy-neural approaches are utilized for diagnosis of HVAC systems, while such kind of approaches are very well developed for other application fields such as for nuclear power plants, marine and power systems.

In HVAC operation, AHU plays an essential role for supplying treated air with specified temperature to the conditioned space [5]. In this paper, an EAFNN approach is introduced to deal with the problem of faults diagnosis in data generated by a pilot variable air volume (VAV) AHU system. EAFNN has the salient features of no predetermination of fuzzy rules and data space clustering and automatic and simultaneous structure and parameters learning automatically and simultaneously by online hierarchical learning algorithm.

This paper is organized as follows. Section 2 gives a brief description of the AHU and the residuals used in the fault diagnosis. The four faults and domain residuals are then described. The description of EAFNN and its learning algorithm are presented in Section 3. Section 4 shows the simulation results and some comparative studies with other learning algorithms. Lastly, conclusions are drawn in Section 5.

2 System and Model Description

A VAV AHU pilot plant was built for experimental purpose. As shown in Fig. 1, number 1, 2, 3 and 4 indicate the components of computer controller, air-conditioning pilot plant, signal process board and signal transmission cables, respectively. All motors (fans, pumps and compressors) in the system are controlled by variable speed drives (VSD).

A simplified system lay out diagram of AHU is shown in Fig.2. It can be seen from the figure that air enters the AHU through the outdoor air damper then mix with air passing through the re-circulation air damper. Air exit the mixed air plenum passes through the cooling coils. After being conditioned in the coils, the air is then distributed to the zones through the supply air duct. The supply air temperature is measured downstream of the supply fan and a static pressure sensor is settled on the supply air duct to measure the main supply air pressure. The objectives of the AHU are to maintain the supply air temperature at a constant set point value of $17.5°C$ by controlling the water pump and the supply air pressure at a constant set point value of 160 Pa(1.0 in. of water) by controlling the rotational speed of the supply fan.

There are two types of faults, namely complete faults (or abrupt failures) and performance degradations. Complete failures are severe and abrupt faults. Performance degradation is gradually evolving faults. In [3], the authors used seven different equipment and instrumentation faults to represent complete failures of various components in the AHU. By the limitation of real pilot plant of AHU system, here we only choose four main faults: two equipment faults and two sensor faults. The faults are shown in Fig. 2.

Fig. 1. Pilot Plant of VAV AHU

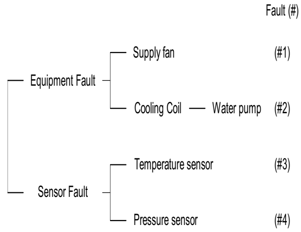

Fig. 2. Main faults in AHU

3 Algorithm of EAFNN

3.1 Structure of EAFNN

EAFNN is a multi-input multi-output (MIMO) system which has inputs and outputs. With the structure based on the EBF neural network, it is functionally equivalent to the TSK model-based fuzzy system.

Layer 1: Each node in layer 1 represents an input linguistic variable.

Layer 2: Each node in layer 2 represents a membership function (MF), which is governed by a Gaussian function.

$$\mu_{ij}(x_i) = exp\left[-\frac{(x_i - c_{ij})^2}{2\sigma_{ij}^2}\right] \tag{1}$$

where $i = 1, 2 \cdots r$, $j = 1, 2 \cdots u$ and μ_{ij} is the jth membership function of the ith input variable x_i, c_{ij} is the center of the jth Gaussian membership of x_i, σ_{ij} is the width of the jth Gaussian membership of x_i.

Layer 3: Each node in layer 3 represents a possible IF-part for fuzzy rules. For the jth rule, its output is given by

$$\phi_j(x_1, x_2, ..., x_r) = exp\left[-\sum_{i=1}^{r}\frac{(x_i - c_{ij})^2}{2\sigma_{ij}^2}\right] = exp[-md^2(j)] \\ j = 1, 2, ..., u \tag{2}$$

where md can be regarded as a function of regularized Mahalanobis distance (M-distance).

Layer 4: Each node in layer 4 represents the output variable as a weighted summation of incoming signals and is given by

$$y(x_1, x_2, \cdots, x_r) = \sum_{j=1}^{u}\omega_j \cdot \phi_j \tag{3}$$

where y is the value of an output variable and ω_j is the THEN-part (consequent parameters) or connection weight of the jth rule.

Equation (3) can be rewritten as follows in a more compact form

$$Y = W\phi \tag{4}$$

3.2 Learning Algorithm of EAFNN

I. Adding a Fuzzy Rule

EAFNN begins with no fuzzy rules. Two criteria are used in order to generate a new rule, namely system errors and ε-Completeness.

For each observation (X_k, t_k), $k = 1, 2, \cdots, n$, where n is the number of total training data, X_k is the kth desired output, compute the overall dynamic EAFNN output y_k of the existing structure using Equation (3). If

$$\|e_k\| = \|t_k - y_k\| > k_e \tag{5}$$

a new rule should be considered. Here, k_e is a predefined threshold that decays during the learning process.

The second criterion is ε-Completeness of fuzzy rules. When an observation (X_k, d_k), $\quad k = 1, 2, \cdots, n$,enters the system, we calculate the M-distance $md_k(j)$ between X_k and the center $C_j \quad (j = 1, 2, \cdots, n)$ of the existing EBF units. If

$$md_{k,\min} = md_k(J) > k_d(md_k(j)) \tag{6}$$

where k_d is a prespecified threshold that decays during the learning process.This implies that the existing system is not satisfied with ε-Completeness and a new rule should be considered.

II. Parameter Adjustment

A new Gaussian membership function is allocated whose width and center is set as follows:

$$c_{i(u+1)} = x_i^k \tag{7}$$

$$\sigma_i = \frac{\max\{|c_i - c_{i-1}|, |c_i - c_{i+1}|\}}{\sqrt{\ln(1/\varepsilon)}} \quad i = 1, 2, \cdots, m \tag{8}$$

where c_{i-1} and c_{i+1} are the two centers of neighboring membership function of ith membership function.

Suppose that u fuzzy rules are generated according to the two criteria stated above for n observation with r number of input variables, the outputs of the N nodes can be obtained according to Equation (3). Writing in matrix form:

$$W\phi = Y \tag{9}$$

where $W \in \Re^{u(r+1)}$, $\phi \in \Re^{u(r+1)\times n}$, $Y \in \Re^n$

Assume that the desired output is $T = (t_1, t_2, \cdots t_n) \in \Re^n$. The problem of determining the optimal parameters W^* can be formulated as a linear problem of minimizing $\|W\phi - T\|_2$ and W^* is determined by the pseudoinverse technique

$$W^* = T(\phi^T\phi)^{-1}\phi^T \tag{10}$$

III. Pruning a Fuzzy Rule

The performance of an EAFNN not only depends on the number and location (in the input space) of the centers but also depends on determination of the network weights. In this paper, Error reduction ratio method (ERR) and a modified Optimal Brain Surgeon (OBS) method are utilized as pruning strategy.

(1) Error Reduction Ratio Method

Given n input-output pairs $\{X(k), t(k), k = 1, 2, \cdots, n\}$, consider Equation (4) in the following compact form:

$$D = H\theta + E \tag{11}$$

where $D = T^T \in \Re^n$ is the desired output, $H = \phi^T = (h_1 \cdots h_v) \in \Re^{n\times v}$ are the regressors, with $v = u \times (r+1)$, $\theta = W^T \in \Re^v$ contains real parameters and $E \in \Re^n$ is the error vector that is assumed to be uncorrelated with the regressors $h_i (i = 1, 2, \cdots, v)$.

The matrix H can be transformed into a set of orthogonal basis vectors if its row number is larger than the column number. H is decomposed into

$$H = PN \tag{12}$$

where $P = (p_1, p_{2,} \cdots, p_v) \in \Re^{n\times v}$ has the same dimension as H with orthogonal columns and $N \in \Re^{n\times v}$ is an upper triangular matrix.

Substituting Equation (12) into Equation (11) yields

$$D = PN\theta + E = PG + E \tag{13}$$

The linear least square (LLS) solution of G is given by $G = (P^T P)^{-1} P^T D$

$$g_i = \frac{p_i^T D}{p_i^T p_i} \quad i = 1, 2, \ldots, v. \tag{14}$$

As p_i and p_j are orthogonal for $i \neq j$, the sum of squares of D is given as follows:

$$D^T D = \sum_{i=1}^{v} g_i^2 p_i^T p_i + E^T E \tag{15}$$

Substituting g_i by Equation (14), and ERR due to p_i is defined as

$$err_i = \frac{(p_i^T D)^2}{P_i^T p_i D^T D} \quad i = 1, 2, \ldots, v \tag{16}$$

The above equation offers a simple and effective means of seeking a subset of significant regressors. Define the ERR matrix $\Delta = (\rho_1, \rho_2, \ldots, \rho_u) \in \Re^{(r+1)\times u}$ whose elements are obtained from Equation 16 and the jth rule column of Δ as the total ERR corresponding to the jth rule. Furthermore, define

$$\eta_i = \sqrt{\frac{\rho_j^T \rho_j}{r+1}} \quad j = 1, 2, \ldots, u \tag{17}$$

then η_j represents the significance of the jth rule. If $\eta_j < k_{err}$, $j = 1, 2, \ldots, u$, where k_{err} is a prespecified threshold, then the jth rule is deleted.

(2) Modified OBS Pruning Method

In the learning process, the network reaches a local minimum in error and the third and all higher order terms can be ignored. The cost function ΔE of the system can be approximated simply as

$$\Delta E \approx \frac{1}{2} \Delta w^T H \Delta w \tag{18}$$

where Δw is the increase of weight, H is the Hessian matrix.The cost function also can be defined as the squared error as follows:

$$E(k) = \frac{1}{2} \sum_{i=1}^{n} [d(i) - p(i)^T \theta]^2 \tag{19}$$

where $p(i)^T = h_i$, $\theta = w$.

Then the Hessian matrix can be written as follows:

$$\frac{\partial^2 E}{\partial \theta^2} = H = \sum_{i=1}^{n} p(i) p^T(i) \tag{20}$$

Because the dimension of Hessian matrix is equal to the number of hidden units in the network, S_i can be computed through w_i as follows:

$$S_i = \frac{\bar{w}_i^2}{2[H^{-1}]_{i,i}} \tag{21}$$

$$\bar{w}_i = \frac{\sum_{j=1}^{m} w_{ij}}{m} \tag{22}$$

where m is the number of weights which connect with the ith unit. The smaller the value of the saliencies S, the less important is the neuron.

4 Application of EAFNN to Fault Diagnosis

Faults in the AHU system are diagnosed by inputting vectors to the trained EAFNN. The training vectors are obtained by introducing faults in an AHU pilot plant and recording the subsequent response of the system. Data are calculated using system variables measured 150 seconds after the system begins running. In this study, 2047 data are used for training and testing of EAFNN. EAFNN is tested by using a jack-knife method [6]. In the jack-knife method, one half of the sample patterns are selected randomly from the database for training the EAFNN. Subsequently, the other half of the sample patterns is used for testing the trained EAFNN. Fig. 3 shows the growth of fuzzy rules. The assessment of the prediction performance of the different soft computing models was performed by quantifying the prediction obtained on an independent data set. The Root Mean

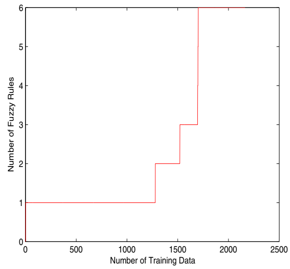

Fig. 3. Fuzzy rule generation

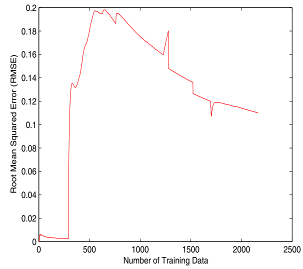

Fig. 4. The performance of DFNN

Square Error (RMSE) is used to evaluate the performance of fault diagnosis scheme. RMSE of EAFNN can be seen in Fig. 4.

$$RMSE = \sqrt{\frac{\sum_{k=1}^{n} (d(k) - y(k))^2}{n}} \tag{23}$$

To demonstrate the effectiveness of the novel algorithm, the results of the proposed method are compared with other earlier works, such as BP-based method, RBF-based method and GFNN method [7]. The number of hidden neurons and RBF function neurons need to be selected in advance for the BPNN and the RBFN separately. In this study, we choose the BPNN architecture as 4*10*5, corresponding to the number of inputs, the number of hidden neurons and the number of outputs respectively. A log- sigmoid activation function is used for both the hidden and output layers. The RBFN utilized in this research has 15 hidden neurons. Each of the 15 neurons in the hidden layer applies an activation function which is a function of the Euclidean distance between the input and prototype vector. Each hidden neuron contains its own prototype vector as a parameter. A comparison of information of fault diagnosis performances of BPNN, RBFNN, GFNN and EAFNN is shown in Table 1.

From Table 1, the GFNN and EAFNN have faster learning speed than the BPNN and RBFN because of the non-iterative learning. Moreover, The BPNN-based and RBFN-based methods need to predetermine the number of hidden layer neurons or the RBF neurons, while the GFNN and EAFNN can decide the system structure automatically without predetermination. The GFNN-based method and EAFNN-based method have less hidden neurons, which means they have better generalization ability and they can fit for different kinds of faults.

Table 1. Performance comparisons of different methods

	BPNN	RBFN	GFNN	EAFNN
Hidden layer neurons	10	15	4	6
Computing time (s)	679.453	390.156	98.453	101.345
Final RMSE	0.2585	0.1410	0.12	0.1101
Average RMSE	-	-	0.0634	0.0526

Finally, The RMSE of training and testing of the EAFNN are better than those of the other methods.

5 Conclusion

In this paper, the EAFNN is developed and applied to fault diagnosis in an AHU system. Firstly, four system variables which describe the dominant symptoms of fault modes of operation are chosen. Consequently, the proposed EAFNN is trained by dominant symptoms and the faults. The structure and parameter identification of EAFNN are done automatically and simultaneously without partitioning the input space and selecting initial parameters a priori. From the performance of the EAFNN in a real pilot, it is evident that the proposed EAFNN has high accuracy with a compact structure, and also has fast and efficient learning. The proposed approach can also be extended for on-line learning and can also be used to consider additional faults for more complex HVAC systems. We are currently developing EAFNN for AHU fault diagnosis in the condition of complex.

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