Fault Detection and Diagnosis in HVAC System Based on Soft Computing Approach

A. Parvaresh, A. Hasanzade, S. M. A. Mohammadi, A. Gharaveisi

Abstract: The fault detection and diagnosis (FDD) play an important role in the monitoring, repairing and maintaining of technical systems. In this paper, we presented a new method based on soft computing approach for FDD in a special type of HVAC system namely unitary system. In the proposed method, the feature vectors are extracted by applying wavelet transform to output signals of model. Then, a Takagi-Sugeno (T-S) fuzzy classifier detects and diagnoses the faults by use of extracted feature vectors, if the faults exist. The T-S fuzzy classifier needs to be trained. With inspiration from training formulation of support vector machine (SVM), the training process has been stated as an optimization problem. For solving the mentioned optimization problem, a reliable evolutionary algorithm namely differential evolution (DE) is used. One of the important types of faults in the unitary HVAC system is refrigerant leakage. FDD of refrigerant leakage is highlighted in the presented paper. The simulation has been done in MATLAB-Simulink and the efficacy of the proposed method is demonstrated based on the experimental results.

Index Terms: Differential Evolution Algorithm, Fault Detection and Diagnosis, Takagi-Sugeno Fuzzy Classifier, Unitary HVAC System, Wavelet Transform

I. INTRODUCTION

One of the important equipments in each modern building is Heating, Ventilating, and Air Conditioning (HVAC) system. Today, the HVAC system designer must consider more issues than keeping temperatures comfortable. It is due to the complexity of the requirements. In recent decades, HVAC technology has developed due to the alliance of science and engineering. Despite the great advances in HVAC, there are several active research fields in this area [1]. A critical issue in this area is the Fault Detection and Diagnosis (FDD). An early FDD can help to avoid inappropriate performance, major damage caused by machinery on itself and the financial damages. During the recent decades, experimental and theoretical researches have shown the new ways for FDD [2]. Examples of research works on FDD of HVAC system based on artificial neural network and wavelet analysis can be found in [3-7]. Liang and Du [8] have proposed a model-based FDD of HVAC systems using Support Vector Machine (SVM). Also, Lo and colleagues [9] have used a fuzzy-genetic algorithm for automatic fault detection in HVAC systems.

In this paper, we proposed a new method based on soft computing approach for FDD in HVAC system. The schematic of the proposed method is depicted in Figure 1. As the figure suggests, the suitable feature vectors that are as inputs of Takagi-Sugeno (T-S) fuzzy classifier are calculated by applying the wavelet transform to the output signals and Reduction of redundant wavelet coefficients. Finally, the T-S fuzzy classifier that is tuned off-line by Differential Evolution algorithm detects and diagnoses the faults (if exist). The simulation has been done in MATLAB-Simulink.

II. HVAC SYSTEM

HVAC systems that are used for different zones can be divided into four categories, namely, All-air systems, Air-water systems, All-water systems and Unitary or refrigerant-based systems. In the last category, vapor compression cycles are mostly used. Many of vapor compression cycles have been consisted of four components that are as follow

Compressor: Commonly referred as the heart of system. It is responsible for compressing and transferring refrigerant gas.

Condenser: Is the area in which heat dissipation occurs. The condenser is designed to radiate the heat. As hot compressed gas is entered into the top of the condenser, it is cooled off. As the gas cools in condenses, it exits from the bottom of condenser as a high pressure liquid.

Evaporator: the evaporator serves as the heat absorption component. Its primary duty is to remove the heat from the zone. A secondary benefit is dehumidification. Refrigerant enters the bottom of the evaporator as a low pressure liquid. The warm air passing through the evaporator fins causes the refrigerant to boil. As the refrigerant begins to boil, it can absorb large amount of heat.

Electronic Expansion valve (EEV): Is a device that allows a controlled amount of liquid refrigerant to enter into the evaporator from the condenser.

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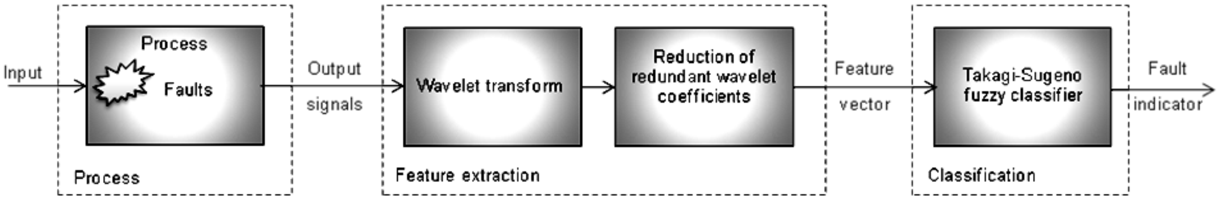

Fig. 1. Schematic of the proposed method

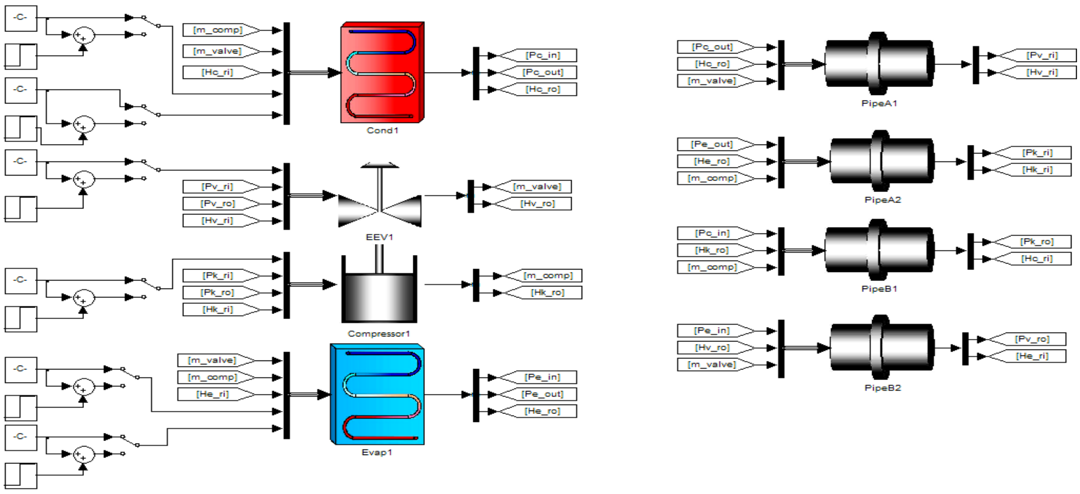

Fig. 2. Simulink model of HVAC system

TABLE I. HVAC SYSTEM FAULT CATEGORIES

Fault class	Fault code	Description of faults
Refrigerant Leakage	F_1	In the condenser
	F_2	In the evaporator
	F_3	In the compressor
	F_4	In the electrical expansion valve
	F_5	In the pipeA1(pipe between condenser and EEV)
	F_6	In the pipeA2(pipe between compressor and evaporator)
	F_7	In the pipeB1(pipe between condenser and compressor)
	F_8	In the pipeB2(pipe between EEV and evaporator)
Evaporator fan fault	F_9	If input-output temperature of evaporator has no noticeable difference.
Condenser fan fault	F_{10}	If input-output temperature of condenser has no noticeable difference.
EEV fault	F_{11}	If input-output pressure of evaporator has no noticeable difference.

In this paper we have simulated a simple unitary system as a model of an actual system. We have used MATLAB-Simulink with Thermosys Toolbox, originally developed at the University of Illinois at Urbana-Champaign as a tool for simulating the transient performance of sub-critical and trans-critical vapor compression systems [10]. Proposed model has been shown in figure 2.

We have considered six inputs to system that are listed in below: compressor speed, valve open command, condenser air mass flow rate, evaporator air mass flow rate, condenser air inlet temperature and evaporator air inlet temperature.

Important parameters that are considered as outputs in proposed system are condenser pressure, condenser air outlet temperature, evaporator pressure, evaporator air outlet temperature and evaporator refrigerant outlet temperature. Existence of fault in this system could affect the output parameters.

A. HVAC System Faults

In the vapor compression systems many faults may occur. One of them that it is very important fault is refrigerant leakage. This fault may appear in all over the system. We have focused to detection and diagnostic of this fault. Furthermore, we have considered some other faults that are shown in table1.

Refrigerant leaks are relatively simple to model within the Thermosys modeling framework. As an example, the leak at the inlet of electrical expansion valve could be introduced by abstracting the mass flow of the leak from the valve mass flow input to model.

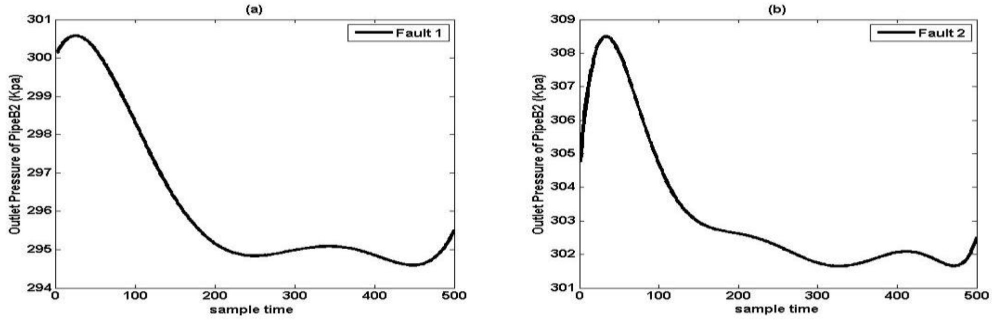

Fig. 3. A typical time domain output signal in the HVAC systems for two different faults

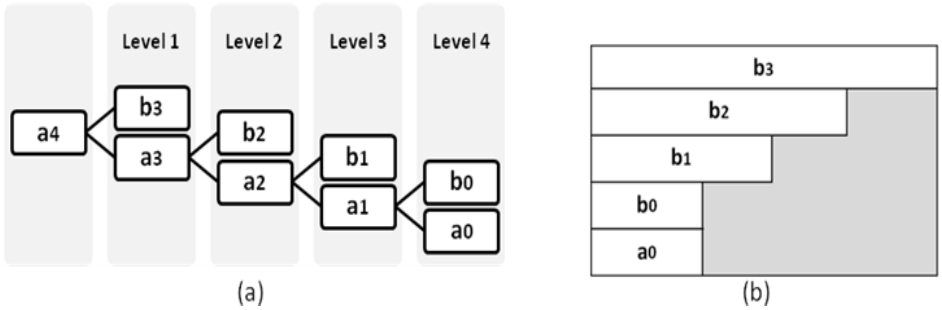

Fig. 4. a) The decomposition process b) The matrix of wavelet coefficients

III. PROPOSED METHOD FOR FDD IN HVAC SYSTEMS

A. Feature extraction

In general, elimination of the irrelevant data from the training data leads to create an appropriate classifier and decreases the training time [9]. So, the selection of relevant features that can best characterize the data is an important step to an effective classification task. A typical time domain output signal, outlet pressure of pipe B2, in the HVAC systems for two different faults is shown in figure 3(a) and (b). According to this figure, in spite of some differences, there is no or little obvious indicator to distinguish between two signals (faults).

Static signals in the time domain are sometimes insufficient to characterize the data [11]. Fourier transform (FT) is a common technique to overcome the mentioned problem. However, the FT gives only the frequency domain information of a signal and the time domain information, that is often critical, is lost when a FT is performed.

Wavelet transform (WT) with its time-frequency localization property is perhaps the most suitable technique for the feature extraction of the measured signals [12]. Feature extraction based on the WT is presented in the following section.

B. Wavelet transform

There are several wavelet families available such as Haar wavelets, Daubechies wavelets, Meyer wavelets and Gaussian wavelets. The Haar family wavelets, created by Alfred Haar, are one of the oldest families [13]. In the Fourier analysis, signals can be represented by a combination of sine and cosine signals. Same as the Fourier analysis in the wavelet theory, signals are represented by a combination of the scaling function Φ (father wavelet) and the wavelet function Ψ (mother wavelet). In the case of Haar wavelet [14], Φ and Ψ are defined as:

$$\Phi(t)=\begin{cases}1 & if\, 0\le t<1\\ 0 & otherwise\end{cases} \tag{1}$$

$$\Psi(t)=\begin{cases}1 & if\, 0\le t<1/2\\ -1 & if\, 1/2\le t<1\\ 0 & otherwise\end{cases} \tag{2}$$

Where $\Phi(t)$ and $\Psi(t)$ are orthogonal to each other.

There are two main types of wavelet transforms: continuous wavelet transforms (CWT) and discrete wavelet transforms (DWT). In this paper, we used the DWT. It comes from the fact of output signals that are discrete signals. The Haar discrete wavelet transform (HDWT) is described as follows:

Suppose

$$f_j(t)=\sum_{k\in ¢} a_k^j \Phi(2^j t-k) \tag{3}$$

Then $f_j(t)$ can be decomposed as

$$f_j(t)=w_{j-1}(t)+f_{j-1}(t) \tag{4}$$

Where

$$w_{j-1}(t)=\sum_{k\in ¢} b_k^{j-1}\Psi(2^{j-1}t-k) \tag{5}$$

$$f_{j-1}(t)=\sum_{k\in ¢} a_k^{j-1}\Phi(2^{j-1}t-k) \tag{6}$$

With

$$b_k^{j-1}=\frac{a_{2k}^j-a_{2k+1}^j}{2} \tag{7}$$

$$a_k^{j-1}=\frac{a_{2k}^j+a_{2k+1}^j}{2}$$

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(8)

This process can be repeated when j is replaced by $j-1$ to decompose $f_{j-1}(t)$ as $w_{j-2}(t)$ and $f_{j-2}(t)$. Usually, each repetition is called one level of decomposition. Continuing in this way, we achieve the decomposition in the level j

$$f_j(t) = w_{j-1}(t) + w_{j-2}(t) + \ldots + w_0(t) + f_0(t) \quad (9)$$

It is noticeable to know that the first level of the decomposition, extracts the high frequency features. Subsequent decompositions extract lower and lower frequency features from the signal and finally we are left with an approximation of the original signal ($f_0(t)$) that is smoother than the original signal ($f_j(t)$).

C. Reduction of redundant wavelet coefficients

The decomposition process and the matrix of wavelet coefficients are depicted in figures 4(a) and 4(b), respectively. As is seen in figures 2 (a) and 2 (b), the wavelet decompositions generate a large number of coefficients. There are various methods for reduction of redundant wavelet coefficients same as method presented in [11]. In this paper, the Euclidean norm (or energy of signal) is used for reduction the data size. Euclidean norm is defined as:

$$\|x\|_2 = \sqrt{\sum_{i=1}^{m} x(i)^2} \quad (10)$$

For each output signal, the following occurs.

- HDWT is applied and the matrix of wavelet coefficients is constructed.
- Euclidean norm of each row vector of the wavelet coefficients matrix is calculated.

Consequently for each output signal, a feature vector is obtained that its length is equal to level of decomposition +1.

D. T-S fuzzy model

Takagi and Sugeno proposed the Takagi–Sugeno fuzzy model (T-S model) [14]. For simplicity, a system is assumed with multi-input and single-output [15]. Typical form of T-S model with r rules and n input variables represented as:

$$\begin{aligned} &R_i: \text{if } x_1 \text{is } A_{i1} \text{and } x_n \text{is } A_{in} \text{then} \\ &y_i = p_{i1}x_1 + \ldots + p_{in}x_n + p_{i(n+1)} \end{aligned} \quad (11)$$

Where R_i denotes the ith rule, x_j denotes the jth input variable; A_{ij} denotes the fuzzy membership function belong to ith rule and jth input variable ; y_i is the output of the ith rule and is usually represented as a polynomial; $p_{i1}, p_{i2}, \ldots, p_{i(n+1)}$ are the parameters of the polynomial (or consequent).

Because the consequent of T–S model is linear, the process of the defuzzication is not necessary. So, the output of the system is represented as:

$$y = \frac{\sum_{i=1}^{r} w_i y_i}{\sum_{i=1}^{r} w_i} \quad (12)$$

Where w_i is the weight of the ith rule and is calculated as:

$$w_i = \prod_{j=1}^{n} \mu_{A_{ij}}(x_j) \quad (13)$$

And, where $\mu_{A_{ij}}(x_j)$ is the grade of the membership function (MF) of x_j [16]. There are many membership functions to calculate $\mu_{A_{ij}}(x_j)$ such as Gaussian function, bell function, Triangular function, Trapezoidal function etc. here $\mu_{A_{ij}}(x_j)$ calculated by a Gaussian function as:

$$\mu_{A_{ij}}(x_j) = \exp\left(-\frac{(x_j - c_{ij})^2}{2\sigma_{ij}^2}\right) \quad (14)$$

Where c_{ij} and σ_{ij} denote the centers and widths of the MFs.Figure 5 shows the typical form of T-S model. This figure illustrates the reasoning mechanism for a T-S model that has *r* rules, *n* input variables ($\overset{n}{X} = x_1, x_2, \ldots, x_n$) and one output.

In this paper, different output level ranges were considered for T-S model to indicate different faulty cases. For example, output levels in the ranges of 0.5 to 1.5, 1.5 to 2.5 and 2.5 to 3.5 are allocated to three faulty cases, respectively.

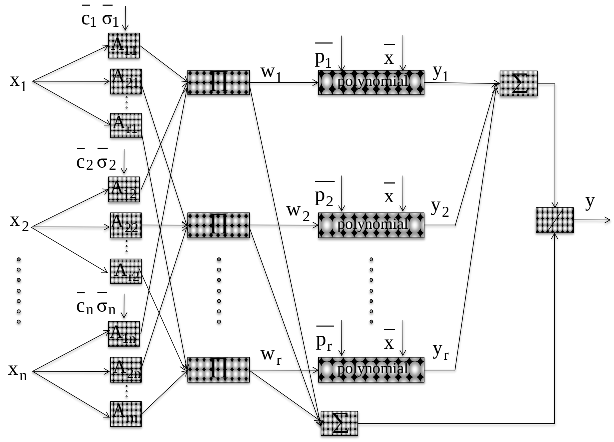

Fig. 5. The typical form of T-S model

E. Training the T-S fuzzy model

The purpose of the training process is tuning the parameters of the model So that the model becomes able to perform the desirable performance. The desirable performance for FDD is defined as: when a fault happens, the model sets the output in the predefined range of the related fault. So the necessary conditions to reach the desirable performance are written as:

$$\begin{cases} y_i - \hat{y}_i \le \varepsilon_i / 2 \\ \hat{y}_i - y_i \le \varepsilon_i / 2 \end{cases} \quad i = 1, 2, \ldots, m \quad (15)$$

Where m is the number of sample data, y_i is the model output, ε_i is the absolute

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length of the range of the related fault and y_i is the center of the range of the related fault.

The model may fail to satisfy the above constraints, so we change constraints as follows:

$$\begin{cases} y_i - \hat{y}_i \le \varepsilon_i / 2 + \xi_i \\ \hat{y}_i - y_i \le \varepsilon_i / 2 + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \end{cases} \quad i = 1, 2, \ldots, m \quad (16)$$

Where $\{\xi_i\}_{i=1,2,\ldots,m}$ and $\{\xi_i^*\}_{i=1,2,\ldots,m}$ are positive parameters. Now, the training process is equivalent to solve an optimization problem as:

Find, $\{c_i\}_{i=1,2,\ldots,n}$ $\{\sigma_i\}_{i=1,2,\ldots,n}$ and $\{p_i\}_{i=1,2,\ldots,n}$ to minimize $C\sum_{i=1}^{m}\left(\xi_i + \xi_i^*\right)$.

$$\begin{cases} y_i - \hat{y}_i \le \varepsilon_i / 2 + \xi_i \\ \hat{y}_i - y_i \le \varepsilon_i / 2 + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \end{cases} \quad i = 1, 2, \ldots, m \quad (17)$$

Where $\{c_i\}_{i=1,2,\ldots,n}$, $\{\sigma_i\}_{i=1,2,\ldots,n}$ and $\{p_i\}_{i=1,2,\ldots,n}$

It should be noted that the training method is inspired by training formulation of SVM [17-19]. An evolutionary optimization algorithm namely differential evolution (DE), described in followed section, is used to solve the above mentioned optimization problem.

F. Differential evolution algorithm

In this section we give some background on the DE algorithm. DE is a population-based stochastic method for global optimization over continuous spaces, which can also work with discrete variables. The original version of DE can be defined by the following constituents [20-25].

1) The population

$$\begin{cases} P_{x,g} = (X_{i,g}),\ i = 1, 2, \ldots, N_p \\ x_{i,g} = (x_{j,i,g}),\ j = 1, 2, \ldots, D \end{cases} \quad g = 1, 2, \ldots, g_{\max} \quad (18)$$

Where Np is the number of population vectors, g denotes the generation number, and D is the dimension of the problem, i.e. the number of parameters.

2) The initialization of the population

Each parameter of a population vector has a given domain defined by its lower and upper bounds: $x_{j,low}, x_{j,upp};\ j \in \{1, \ldots, D\}$. The uniform random initial population is selected between the lower ($x_{j,low}$) and upper ($x_{j,upp}$) as follow:

$$x_{j,i,1} = rand_j(0,1).(x_{j,upp} - x_{j,low}) + x_{j,low} \quad (19)$$

The random number generator, randj[0,1), returns a uniformly distributed random number from the range [0,1).

3) Mutation

By mutation for each population vector, a mutant vector $V_{i,g}$ is created. One of the most popular DE mutation strategies is “rand/1/bin” [25]:

$$V_{i,g} = x_{r_1,g} + F.(x_{r_2,g} - x_{r_3,g}) \quad (20)$$

Where the indexes r_1, r_2, r_3 are selected (once per each mutation) random and different integers in the range $[1, NP]$ and also different from index i. F is a scalar namely amplification factor within the range [0.5, 1.0].

4) Crossover

The crossover uses parameters of the mutation vector $V_{i,G}$ and the target vector $X_{i,G}$ in order to create the trial vector $u_{i,G}$. The most popular form of crossover is uniform and is defined as:

$$u_{i,g} = u_{j,i,g} = \begin{cases} v_{j,i,g} & if\,(rand_j(0,1) \le C_r or\ j = j) \\ x_{j,i,g} & otherwise \end{cases} \quad (21)$$

In Equation 21 ($\ldots$or $j = j_{rand}$) we are sure that at least one component is taken from the mutation vector $V_{i,G}$. C_i is a critical parameter in diversity enhancement.

5) Selection

The vector with the lowest objective function value survives at least in next generation.

$$x_{i,g+1} = \begin{cases} u_{i,g} & f(u_{i,g}) \le f(x_{i,g}) \\ x_{i,g} & otherwise \end{cases} \quad (22)$$

To reach termination condition, DE employs mutation, crossover and selection operations for each population vector.

G.Training T-S fuzzy classifier by means of DE

Figure 6 shows the training flowchart of the T-S classifier by means of DE. In the optimization process, DE generates the parameters $\{c_i\}_{i=1,2,\ldots,n}$, $\{\sigma_i\}_{i=1,2,\ldots,n}$, $\{p_i\}_{i=1,2,\ldots,n}$, $\bar{\xi}$ and $\bar{\xi}^*$. The parameters $\{c_i\}_{i=1,2,\ldots,n}$, $\{\sigma_i\}_{i=1,2,\ldots,n}$ and $\{p_i\}_{i=1,2,\ldots,n}$ are used by TS classifier to calculate outputs (or vector y) of the m training samples. The classification errors (vector e) are calculated by subtracting the approximated outputs than real outputs (vector y).

We defined a penalty function to handle the non equality constraints of Equation 16 as:

$$\begin{aligned} penalty(\bar{e}, \bar{\xi}, \bar{\xi}^*) = penfunc(\bar{e}, \bar{\xi}) + \\ penfunc(-\bar{e}, \bar{\xi}^*) \end{aligned} \quad (23)$$

Where the MATLAB-style pseudo-code of penfunc(.) is depicted in Figure 7.

In the process of optimization, DE tries to generate parameters that minimize the objective function value. This function is defined as:

$$Fitness(\bar{e},\bar{\xi},\bar{\xi}^{*}) = penalty(\bar{e},\bar{\xi},\bar{\xi}^{*}) + c_1 \sum_{i=1}^{m} (\bar{\xi}(i) + \bar{\xi}^{*}(i)) \quad (24)$$

Where c_1 is a scale factor. The first term of this Equation is related to constraints handling and its value will be increased when each constraint is violated. Also, the minimization of the second term causes decreasing of the error band.

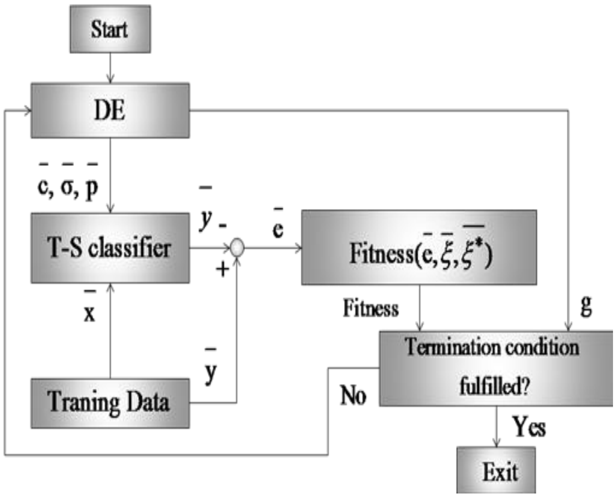

Fig. 6. The training flowchart of the T-S classifier by means of DE

```
function [out]=penfunc(e, ξ)
out=0;
for i=1:m
  if (e(i)> ε + ξ(i))
     out= out+c*(e(i)- ε - ξ(i));
  end
end
end
```

Fig. 7. The MATLAB-style pseudo-code of penfunc(.)

TABLE II. THE OUTPUT SIGNALS OF THE PROCESSES THAT ARE AS INPUTS OF FEATURE EXTRACTION STAGE

Label	Signal name	Label	Signal name
S_1	Refrigerant outlet temperature of condenser	S_6	pressure at pipeA2 outlet
S_2	the outlet temperature	S_7	pressure at pipeB1 inlet
S_3	pressure at pipeA1 inlet	S_8	pressure at pipeB1 outlet
S_4	pressure at pipeA1 outlet	S_9	pressure at pipeB2 inlet
S_5	pressure at pipeA2 inlet	S_{10}	outlet pressure of pipeB2

TABLE III. THE CONTROL PARAMETERS OF PROPOSED METHOD

Parameter	Manually picked value
Crossover control parameter in DE, Cr	0.95
amplification factor in DE, F	0.4
number of population vectors in DE, Np	50
Number of maximum generation in DE, G_{max}	1000
scale factor in fitness function, c_1	10
ε in fitness function	0
Rule number in T-S classifier, r	6
Level of decomposition in wavelet decomposition	3

TABLE IV. PROPOSED METHOD PERFORMANCE FOR EACH FAULT CATEGORY

Fault code	Efficiency (%)	Fault code	Efficiency (%)
F_1	92.5	F_7	95
F_2	90	F_8	92.5
F_3	95	F_9	87.5
F_4	90	F_{10}	85
F_5	87.5	F_{11}	90
F_6	87.5	*Average*	90.22

IV. SIMULATION RESULTS

This section presents the details of the development and test of the proposed method for FDD on HVAC systems. The output signals of the process that are as inputs of feature extraction stage are listed in table 2. Thirteen different data sets are generated through different simulation tests by using Simulink model presented in section 2. These consist of twelve data sets to represent

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for twelve faulty cases and one set to indicate normal and healthy operation.

A white Gaussian noise, having a level of 5% of the actual measurement level, has been added to each signal to infer as the probable measurement noise.

The total number of signal generated in each data set is 100. Among them, 60 signals are used for training and 40 signals are used for testing.

The Control parameters of the FDD system is listed in table 3. Note that, for simplicity it is assumed that two faults do not occur simultaneously. Table 4 shows the performance of the proposed method for each fault code (and normal operation).

V. CONCLUSION

In this paper, we proposed a new method based on soft computing approach for FDD. The proposed method is based on wavelet transform, T-S model and DE algorithm. The proposed method is applied for FDD in a special type of HVAC system namely unitary system. The simulation was done with Thermosys Toolbox in MATLAB-Simulink. The results of simulation show the efficiency of the proposed method. Future research will consider the extension of the proposed FDD scheme to a larger number of faults.

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