Fault Diagnosis of Air-conditioning System Using CMAC Neural Network Approach

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Summary. In this paper, a CMAC neural network application on fault diagnosis of a large air-conditioning system is proposed. This novel fault diagnosis system contains an input layer, binary coding layer, and fired up memory addresses coding unit. Firstly, we construct the configuration of diagnosis system depending on the fault patterns. Secondly, the known fault patterns were used to train the neural network. Finally, the diagnosis system can be used to diagnose the fault type of air-conditioning system. By using the characteristic of self-learning, association and generalization, like the cerebellum of human being, the proposed CMAC neural network fault diagnosis scheme enables a powerful, straightforward, and efficient fault diagnosis. Furthermore, the following merits are obtained: 1) High accuracy. 2) High noise rejection ability. 3) Suit to multi-faults detection. 4) Memory size is reduced by new excited addresses coding technique.

Index Terms: fault diagnosis, air-conditioning system, neural network, CMAC.

1 Introduction

The fault diagnosis of a large air-conditioning system, however, is not an easy task. Traditional fault diagnosis schemes employed a look-up table, which recorded the mapping relation of the fault reasons and symptoms and supplied by equipment manufacturer[1]. A large system has a large amount of symptom detection points. The number of symptom code combinations is larger than the number of fault reasons (types), and "no match" may be indicated in the fault diagnosis. When the "no match" conditions exist, the fault diagnosis will become time-consuming and depend strong on the maintenance man's expertise. Long time failure of air-conditioning system may cause a break in suitable air supply and loss of profits. Therefore, it is of great importance to detect incipient failures in air-conditioning system as soon as possible, so that the people can maintain them quickly and improve the reliability of air-conditioning system.

In the past decade, various intelligent fault diagnosis techniques have been proposed. For example, the fault diagnosis of power transformer using the expert systems [2], neural network (NN) [3, 4]and fuzzy logic approaches [5, 6, 7]. Our recent work also developed a CMAC-based fault diagnosis scheme [8]. However, these researches consider fewer detection points and the fault symptoms are analog signals. When the fault signals are large amount binary value, the method described above can not diagnose them directly.

In this paper, a novel digital CMAC (Cerebellar Model Articulation controller) neural network methodology is presented for the fault diagnosis of air-conditioning system, especially for system with large amount symptom detection points. By using the fault type look-up table as the training data, the characteristic of association and generalization make the CMAC fault diagnosis scheme enables a powerful, straightforward, and efficient fault diagnosis. With application of this scheme to the training data and simulated data that adding noise or uncertainty, the diagnoses demonstrate the new scheme with high accuracy and high noise rejection abilities. Moreover, the results also proved the ability of multiple incipient faults detection.

The remainder of this paper is organized as follows. Section 2 is a brief description about the digital CMAC neural network. Section 3 is the configuration of proposed diagnosis system. It contains the training rule, learning performance evaluation, and the diagnosis algorithm. Section 4 shows the diagnosis results of training patterns and simulated data. Finally, the conclusion is stated in section 5.

2 Brief description of digital CMAC neural network

Figure 1 schematically depicts the digital CMAC networks [9,11], which like the models of the human memory to perform a reflexive processing. The CMAC, in a table look-up fashion, produced a vector output in response to a state vector input. The mapping processes include the segmentation, excited addresses coding, and summation of the excited memory weights. The characteristic of the mapping processes is that similar inputs activate similar memory addresses; restated, if the input states are close in input space, then their corresponding sets of association cells overlap. For example, if $x_1$and x_2 are similar (close), then x_1 activates the memory addressesa_1,a_2,a_3,a_4 ,and x_2 should activate the memory addresses a_2,a_3,a_4,a_5 or a_3,a_4,a_5,a_6. The inputs are said to be highly similar if two inputs activate the same memory addresses. Lower similarity outputs would activate fewer same memory addresses. Therefore, we can use the known training patterns to train the CMAC network. The CMAC will distribute the specific fault type feature on fired memory addresses. When the input signal is same as the training data, it will activate the same memory addresses and output exactly fault type. Non-training data input the CMAC will activate different memory addresses depending on the similarity degree with the training data. Therefore, the summation of fired memory weights diverges from the original output of training data fired. Assuming the output is trained to equal one to denote a specific fault type, that is the node output one confirms what fault type is. Then input the diagnosed data to the diagnosis system, the node output can express the possibility of the specific fault type.

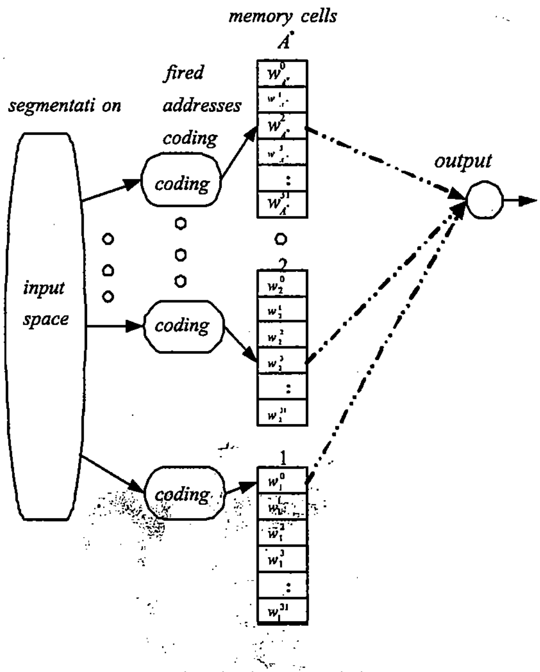

Fig. 1. Functional schematic of digital CMAC

3 The configuration of proposed fault diagnosis system

Extending from the Fig. 1 and using Table 1 as training patterns, Figure 2 is the proposed fault diagnosis configuration of air-conditioning system. We obtained Table 1 from Industrial Technology Research Institute-Energy & Resources Laboratories (in Taiwan). Some books refer to similar fault table also, such as P.C. Koelet's book[12]. Table 1 shows the air-conditioning system has 44 fault types and 40 symptom detection points. Therefore we construct the network with 40 symptom detection points, 44 parallel memory layers, and 44 output nodes. The operation of the proposed diagnosis system illustrated as follows.

3.1 Segmentation and fired addresses coding

As shown in Table 1, the binary code of first fault type is

0010100100110011000100000000000000000000

Take five digits as a segment (group), then from LSB to MSB the excited memory addresses are coded as $a_1 = a_2 = a_3 = a_4 = 00000B = 0$, $a_5 = 1001B = 17$, $a_6 = 11001B = 25$, $a_7 = 00100B = 4$, $a_8 = 00101B = 5$. Assuming all the initial memory

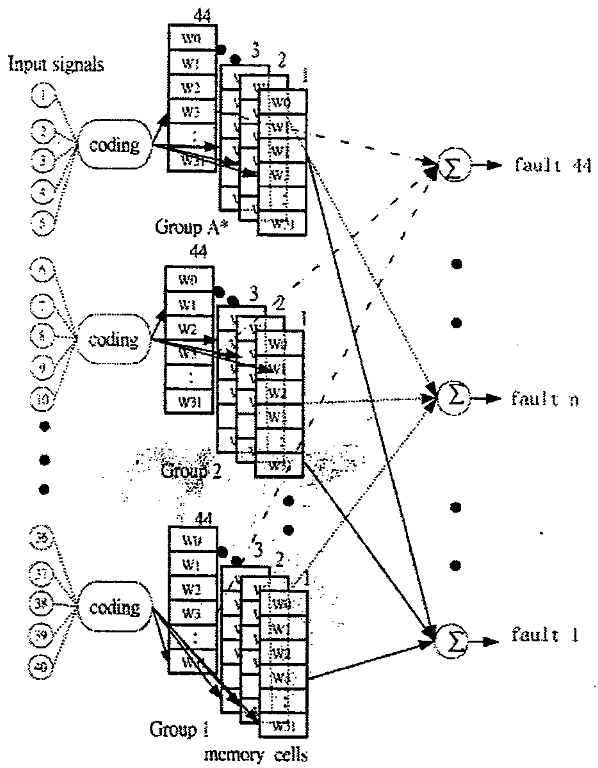

Fig. 2. The configuration of CMAC NN fault diagnosis system of air-conditioning system

weights are zero, then the summation of the fired up memory addresses w_1^0, w_2^0, w_3^0, w_4^0, w_5^{17}, w_6^{25}, w_7^4, w_8^5 are zero. The output of CMAC can be expressed as

$$y = \sum_{i=1}^{A^*} w_i^{ai},\ A^* : \text{the number of fired up memory cells} \qquad (1)$$

Assuming the i layer ($i = 1, \cdots, 44$) outputs one denotes the fault type i is confirmed, then one can be thought as the teacher and the supervised leaning algorithm can be described as[8, 11]

$$w_{i(new)}^{ai} \leftarrow w_{i(new)}^{ai} + \beta \frac{y_d - y}{A^*}, i = 1, 2, \ldots, A^* \qquad (2)$$

where $w^{ai}_{i(new)}$ are the new weight values after the weights tuning, $w^{ai}_{i(new)}$ are the old weight values before weight tuning, and ai denotes the fired memory addresses, β the learning gain, y_d the desired output. Using the well known learning algorithm, the convergence can be guaranteed[10].

3.2 Noise rejection

The noise rejection ability can be illustrated as follows. Assuming the first fault type coding has following error.

Original coding: 001010010011001100010000000000000000000

Error coding: 001010010011001100010000000000000000011

Then the fired up memory addresses coding $(a_1, a_2, a_3, a_4, a_5, a_6, a_7, a_8)$ changed from $(0,0,0,0,17,25,4,5)$ to $(3,0,0,0,17,25,4,5)$, only the a_1 is wrong. Since the fault features are stored on eight different addresses, the output will preserve 87% features at least and the noise rejection ability can be obtained.

3.3 Learning performance evaluation

Assuming the i-th (i=1,...,44) layer outputs one denotes the system has fault type i, and the number of training pattern for fault type i is d. Let the performance index be

$$E = \sum_{i=1}^{d} (y_i - 1)^2 \tag{3}$$

when $E < \varepsilon$ the training process will stop. (ε is a small positive constant).

3.4 Wrong diagnosis learning

If the diagnosis output is wrong, the following modified learning rule is used to update the memory weights on line.

$$w^{ai}_{i(new)} \leftarrow w^{ai}_{i(new)} + \alpha \frac{\eta - y_{err}}{A^*}, i = 1,2,\ldots,A^* \tag{4}$$

where η is the threshold value, y_{err} the error output value, and α learning gain. Since the nodes outputs denote the possibility of fault type, the learning law merely modifies the memory weights to lead the error output nodes smaller or higher than threshold value.

3.5 Diagnosis algorithm

Based on the configuration of Fig. 2, the diagnosis algorithms are summarized as follows.

Off-line mode

Step 1 Build the configuration of CMAC fault diagnosis system. It includes 40 binary input signals, 44 parallel memory layers and 44 output nodes.
Step 2 Input the training patterns, through segmentation, fired memory addresses coding, and summation of fired memory addresses weights to produce the node output.
Step 3 Calculating the difference of actual output and the desired output ($y_d = 1$) and using Eq. (2) to update the weight values.
Step 4 Does the training finished? Yes, next step. Otherwise, go to **step 2.**
Step 5 Training performance evaluation. If , the training is finished. Save the memory weights. Otherwise, go to **step 2.**

On-line mode

When the training is finished, the diagnosis system can be used to the diagnosis of air-conditioning system. The diagnosis steps are described as follows.

Step 6 Load the up to date memory weights from the saved file.
Step 7 Input the diagnosed data.
Step 8 Segmentation, fired memory address coding, and summation of the fired memory weights using Eq. (1).
Step 9 Does the diagnosis correct? Yes, go to **step 10.** Otherwise, go to **step 11.**
Step 10 Does the next data to be diagnosed? Yes, go to **step 7.** Otherwise, go to **step 12.**
Step 11 Update the fired memory weights using Eq. (4).
Step 12 Save the up to date memory weights to file.

4 Some test results

Using the training patterns of Table 1 to train the CMAC neural network, the weights distribution plot of group 1 memory layers is shown in Fig. 3. Input the training patterns to the CMAC again, Table 2 are the nodes output (partial results). As shown in Table 2, output value 1 denotes the fault type is confirmed. Input the simulated non-training patterns of Table 3 (that modify from Table 1, include noise and uncertainty), the node outputs are shown in Table 4. Of course, no outputs are exact equal to 1, but the outputs still denote the most possible fault reason. The maintenance man can obtain useful information from the table. For example, the first row indicates the most possible fault type is type 1 (87.5%) and the probability of fault type 11 is 62.5%. The third raw denotes the most possible fault types are 3 and 4 (75%), the multiple faults detection ability is proven. Assuming Table 3 is the new added patterns, the memory weights can be retraining. After the retraining processes, the up to date weights distribution plot is shown in Fig. 4. Input the patterns of Table 1 and Table 3 to the CMAC again, the nodes outputs are shown in Table 5 and Table

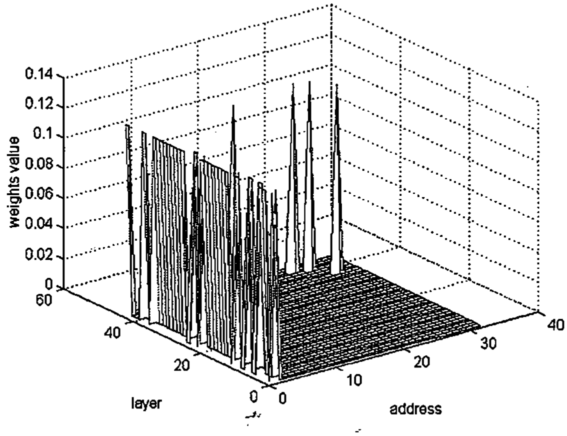

Fig. 3. Memory weights distribution plot after training

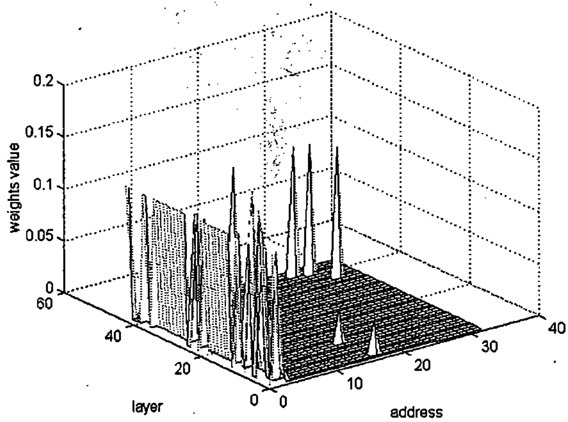

Fig. 4. Memory weights distribution plot after training

Table 1. Fault patterns of air-conditioning system

Fault reason	Symptoms detection coding(40digits)
1: shortage of refrigerant charge	0010100100110011000100000000000000000000
2: expansion value jammed	0000100100001011000000000001000000000001
3: expansion value closed fully	0000000100000001000000000000001000000000
4:membrane leakage of expansion value	0000000100000101000000000000001000000000
5: the hole of expansion value too small	0000100100001010000000000000000000000000
6: electromagnetic value cannot open	0000100100111011010000000001000000000001
7: filter valve blocked of liquid pipe	0000100000110011010000000001000000000001
8: output valve of container does not open fully	0000100000110011001000000000000000000000
9: liquid pipe blocked	0000100000000110101000000010000000000001
10 cooling water of condenser not enough	0101000000000000000000000000000000000001
11 cooling water of condenser too much	0010100100000001000000000000000000000000
12 air exist in the condenser	0101000000000000000000000000000000000000
13 water or air not enough on the evap. and cond.	0000000000000000000000000000000000000001
14 refrigerant too much	0100000001000000000100000000000000000000
15 expansion value stick on the open position	0000000001000100000000000000000000000000
16 expansion value with wrong adjustment	0000100101000110000000000000000000000000
17 pressure drop of steam pipe too large	0000000000000010000000000000000000000000
18 the capacity of evaporators too large	0001000100000000000000000001000000000000
19 load distribution of evaporator is not uniform	0000100001000010100000000000000000000000
20 the distribution of refrigerant is not uniform	0000100001000000100000000000000100000000
21 refrigerate oil gather in the evaporator	0000000000000010000001000000000000000000
22 refrigerant too much	0000000000000000000101000000000000000000
23 air return value of compressor blocked	0000100000000000000001000010000000000001
24 actuator overload	0000000000000000000000000000001000000000
25 low pressure control value too high	1000000000000000000000000001000000000001
26 high pressure control value too low	1000000000000000000000000001000000000001
27 compressor value cracked	0011000000000000000000110000000100000000
28 leakage of low pressure value	0000000100000000000000000000000000000000
29 compressor bearing can not rotate	0000000000000000000000000001000010000000
30 compressor movable element can not action	0000000000000000000000000001000110000000
31 compressor oil pump damage	0000010000000000000000101000010100000000
32 compressor oil pipe blocked	0000001000000000000000011000000100000000
33 compressor capacity controller damage	1000000000000000000000001110000000000000
34 compressor over reduce load	0001000100000001000001000000000000000000
35 compressor piston or link damage	0011000000000000000000100000000000000000
36 power failure	0000000000000000000000000001000001000000
37 voltage supply too low	0000000000000000000000000001100010011100
38 fuse burn down	0000000000000000000000000001000001000000
39 short circuit of control board	0000000000000000000000000001000000000000
40 switch contact element burn out or dusty	0000000000000000000000000001000000001110
41 wire terminal loose	0000000000000000000000000000000000011010
42 motor coil burn out	0000000000000000000000000001000010011000
43 temperature control switch failure	0000000000000000000000000010001000000000
44 instrument damage	0111111000000000000000000000000001100000

4. It is clear the '1' output confirms what fault type is, and other outputs indicate the possibility of other fault type.

Note: Symptoms detection points contain the pressure normal, high pressure too high, high pressure too low, low pressure too high, low pressure too low, oil pressure too low, oil pressure too high, backflow tube temperature too high, backflow tube near the compressor temperature too high, backflow tube with cold sweat, refrigerant window with air bubble..., breaker fault, the switch junction with spark, the amount of refrigerant.

Table 2. Diagnosis output of training pattern (partial results

No.	1	2	3	4	5	6	7	8	9	10	11
1	1	0.375	0.5	0.5	0.625	0.375	0.375	0.625	0.25	0.375	0.75
2	0.375	1	0.5	0.5	0.625	0.75	0.625	0.375	0.625	0.375	0.375
3	0.5	0.5	1	0.875	0.5	0.375	0.25	0.375	0.25	0.375	0.5
4	0.5	0.5	0.875	1	0.5	0.375	0.25	0.375	0.25	0.25	0.5
5	0.625	0.625	0.5	0.5	1	0.5	0.375	0.625	0.375	0.5	0.75
6	0.375	0.75	0.375	0.375	0.5	1	0.75	0.375	0.625	0.375	0.375
7	0.375	0.625	0.25	0.25	0.375	0.75	1	0.625	0.75	0.5	0.25
8	0.625	0.375	0.375	0.375	0.625	0.375	0.625	1	0.5	0.5	0.5
9	0.25	0.625	0.25	0.25	0.375	0.625	0.75	0.5	1	0.375	0.375
10	0.375	0.375	0.375	0.25	0.25	0.375	0.5	0.5	0.5	1	0.5
11	0.75	0.375	0.5	0.5	0.75	0.375	0.25	0.5	0.375	0.5	1

Table 3. Simulated non-training patterns (include uncertainties or noise)

Fault reason	Symptoms detection coding(40digits)
1: shortage of refrigerant charge	0010100100110011000100000000000000000001
2: expansion value jammed	0000100100001011000000000001000000000010
3: expansion value closed fully	0000000100001001000000000000001000000000
4:membrane leakage of expansion value	0000000100000101000000111000010000000000
5: the hole of expansion value too small	0000100100011010000000000010000000000000
6: electromagnetic value cannot open	1000100100111011110000000001000000000011
7: filter valve blocked of liquid pipe	0000100000110011110000000001001000000001
8: output valve of container does not open fully	1000100000110011001000010000000000000001
9 liquid pipe blocked	0000100001000011010101000010000000000001
10 cooling water of condenser not enough	1101000000000000000000000000000000000000
11 cooling water of condenser too much	0010100100000001000000001100000000001111

Table 4. Diagnosis output of non-training data Table 3(partial results)

No.	1	2	3	4	5	6	7	8	9	10	11
1	0.875	0.5	0.375	0.375	0.5	0.5	0.5	0.5	0.375	0.5	0.625
2	0.375	0.875	0.5	0.5	0.625	0.625	0.5	0.375	0.5	0.25	0.375
3	0.375	0.5	0.75	0.75	0.375	0.375	0.25	0.25	0.25	0.25	0.375
4	0.375	0.375	0.75	0.875	0.375	0.25	0.125	0.25	0.125	0.125	0.375
5	0.5	0.5	0.5	0.5	0.75	0.5	0.375	0.5	0.375	0.375	0.625
6	0.375	0.5	0.375	0.375	0.375	0.625	0.375	0.5	0.375	0.25	0.375
7	0.375	0.5	0.25	0.25	0.375	0.5	0.75	0.625	0.625	0.5	0.25
8	0.375	0.25	0.125	0.125	0.25	0.25	0.5	0.625	0.375	0.5	0.25
9	0.125	0.375	0.25	0.25	0.125	0.375	0.375	0.125	0.625	0.25	0.25
10	0.5	0.25	0.5	0.375	0.625	0.25	0.375	0.625	0.375	0.75	0.625
11	0.5	0.25	0.25	0.25	0.5	0.25	0.125	0.25	0.25	0.375	0.75

Table 5. Diagnosis output of Table 1 data after retraining (partial results)

No.	1	2	3	4	5	6	7	8	9	10	11
1	1.109	0.421	0.593	0.546	0.75	0.515	0.468	0.765	0.296	0.5	0.875
2	0.437	1.109	0.625	0.546	0.75	0.937	0.75	0.462	0.765	0.437	0.437
3	0.546	0.562	1.187	0.968	0.625	0.515	0.312	0.421	0.343	0.5	0.562
4	0.546	0.562	1.062	1.109	0.625	0.515	0.312	0.421	0.343	0.343	0.562
5	0.687	0.703	0.593	0.546	1.187	0.640	0.468	0.718	0.421	0.656	0.875
6	0.437	0.828	0.468	0.406	0.625	1.234	0.875	0.468	0.765	0.437	0.25
7	0.437	0.687	0.312	0.265	0.468	0.890	1.187	0.812	0.890	0.593	0.281

Table 6. Diagnosis output of non-training data after retraining (partial results)

No.	1	2	3	4	5	6	7	8	9	10	11
1	1	0.546	0.468	0.406	0.593	0.640	0.625	0.687	0.468	0.593	0.75
2	0.421	1	0.625	0.546	0.75	0.812	0.593	0.421	0.593	0.312	0.437
3	0.421	0.562	1	0.828	0.468	0.515	0.312	0.296	0.343	0.312	0.437
4	0.406	0.421	0.906	1	0.468	0.343	0.156	0.296	0.218	0.187	0.437
5	0.546	0.562	0.593	0.546	1	0.640	0.468	0.546	0.421	0.5	0.718
6	0.421	0.562	0.468	0.406	0.468	1	0.468	0.343	0.462	0.312	0.437
7	0.437	0.546	0.312	0.265	0.468	0.640	1	0.812	0.718	0.593	0.281

5 Conclusion

This work presents a novel digital CMAC neural network fault diagnosis scheme of air-conditioning system. Using limited training patterns to train the CMAC neural network, like the brain of human being, each fault type feature is distributed and memorized on an assigned memory layer. When a diagnosed data input the CMAC, the diagnosis system will output the possibility of all fault types. It provides useful information to system fault diagnosis and maintenance. As the accumulation of training patterns and learning, the diagnosis system will become a more powerful and accurate diagnosis tool. The simulation results demonstrate the objectives of high diagnosis accuracy, multiple faults detection, suit to non-training data, and alleviate the dependency to expert's expertise are obtained.

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