CMAC Neural Network Application on Fault Diagnosis of Water Circulation System

Chin-pao Hung
Department of Electrical Engineering , National Chin-Yi Institute of Technology Taichung , Taiwan , R.O.C.

Yi-shin Lin
Institute of Information and Electrical Energy, National Chin-Yi Institute of Technology ,Taichung , Taiwan , R.O.C.

Wei-ging Liu
Department of Electrical Engineering , National Chin-Yi Institute of Technology Taichung , Taiwan , R.O.C.

Abstract: - In this paper, a CMAC (cerebellar model articulation controller) neural network application on fault diagnosis for water circulation system is proposed. Firstly, we build a CMAC neural network based diagnosis system depending on the fault types. Secondly, the fault patterns, obtained from the China scholar's technical data, would be employed to train the CMAC neural network off-line. Thirdly, the learning algorithm was developed to guarantee the learning convergence. Finally, combining the MATLAB program the trained neural network can be used to diagnose the possible fault types of water circulation system. Comparing with the traditional schemes, following advantages are obtained at least:(1)Eliminate the weights interference between different fault type patterns.(2) Improve the noise rejection ability.(3) Alleviate the dependency to expert's expertise.(4) Memory size can be reduced by new excited addresses coding technique . (5) High learning and diagnosis speed.

Keywords: water circulation system, neural network, fault diagnosis, CMAC

1 Introduction

Water circulation system is important equipment in industry application, including chemical engineering, refrigerator and air condition engineering and other like. Generally, water circulation system contains cooling water tower, filter, pump, motor sets, pipeline and spray tower. More than hundred of components effect the system operation. The maintenance of water circulation equipment strong depends on the expert's experience.

In past decade, many researchers used intelligent theorem to diagnose the incipient fault of mechanical and electrical equipments. Such as the fault diagnosis of power transformer using fuzzy logic [2-5], the expert system [6-7], and the neural network [8-11]. Also, the fault diagnosis of air-conditioning system and power system used the neural network theorem and had been demonstrated with better performance [12]. In the field of water circulation system, the scholars of mainland China proposed the multiple layer neural network schemes to diagnose the possible faults [1]. Some test results are obtained and it indeed demonstrated the intelligent scheme can replace the human judgment. However, the local minimum problem, slower leaning speed and the weights interference between different fault patterns are its major drawbacks.

In order to solve the drawbacks described above, in this paper a novel CMAC neural network based methodology is presented to solve the fault diagnosis problem of water circulation system. Depending on the known fault types, the CMAC neural network (CMAC NN) diagnosis structure is built first. Next, we use the known fault patterns as the training data to train CMAC NN. Finally, the trained neural network can be used for to diagnose the fault types of water circulation system. The characteristics of association and generalization make the CMAC NN based diagnosis scheme a powerful, straightforward and accurate fault diagnosis.

2 The CMAC fault diagnosis system of water circulation system

Figure 1 shows the schematic of water circulation system and Fig. 2 shows the main measure signals which reflected the fault type of water circulation system. In accordance with the research of Dr. Feng [1], there are three major fault types about water circulation system, i.e. pump oppilation, machinery fault and pipeline oppilation. The fault patterns of [1] are list in Table 1. Based on previous researches [12] and Table 1, the configuration of proposed diagnosis system is shown in Fig. 3. In Table 1, x_{n1} denotes the normalized inlet pressure, x_{n2} the outlet pressure, x_{n3} the flow rate, x_{n4} the motor current, and x_{n5} the bearing temperature between pump and motor. Also, there are three major fault types, pump oppilation, machinery fault and pipeline oppilation, denote as T_{n1}, T_{n2} and T_{n3}, respectively.

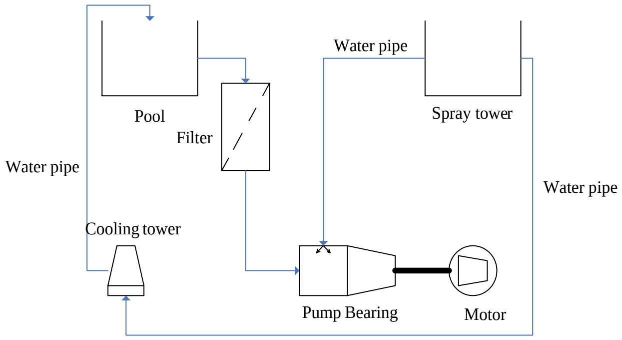

Figure 1. Schematic of water circulation system

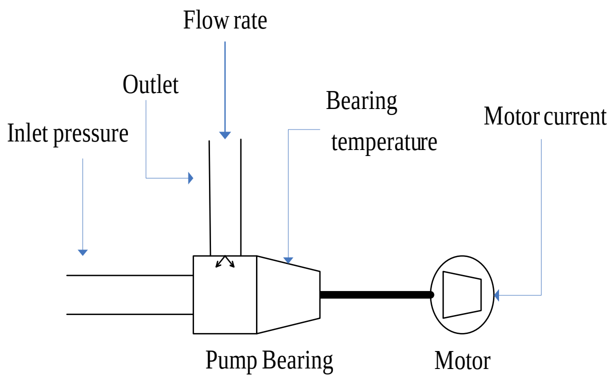

Figure 2. Schematic of pump operation for water circulation system

Table 1. The fault patterns of water circulation system

No.	Detected signals					Fault type(fault number
	x_{n1}	x_{n2}	x_{n3}	x_{n4}	x_{n5}	
1	0.83	0.66	0.83	0.78	0.76	pump oppilation
2	0.83	0.66	0.85	0.80	0.76	pump oppilation
3	0.83	0.55	0.80	0.80	0.76	pump oppilation
4	1.00	0.40	0.66	0.82	0.78	pump oppilation
5	0.66	0.30	0.60	0.82	0.78	pump oppilation
6	0.83	0.84	1.00	0.95	0.88	machinery fault
7	0.83	0.84	1.00	0.98	0.93	machinery fault
8	1.00	0.78	0.92	1.00	0.90	machinery fault
9	0.66	0.66	0.83	0.98	0.98	machinery fault
10	0.83	0.62	0.85	0.98	1.00	machinery fault
11	0.50	0.84	0.66	0.82	0.76	pipeline oppilation
12	0.20	0.66	0.60	0.84	0.78	pipeline oppilation
13	0.66	0.95	0.60	0.85	0.79	pipeline oppilation
14	0.66	1.00	0.50	0.90	0.78	pipeline oppilation
15	0.66	1.00	0.66	0.85	0.78	pipeline oppilation

Depending on the fault pattern of Table 1, the diagnosis structure of water circulation system is built as Fig. 3. The input layer with five input signals, memory layer with three parallel memory cells to memorize the individual fault characteristic, and three output nodes output the probability of each fault type. The operation steps include training mode, set the weight value to the memory cells via training; diagnosis mode, input the diagnosis data to diagnose the possible fault types. Details are illustrated as follows.

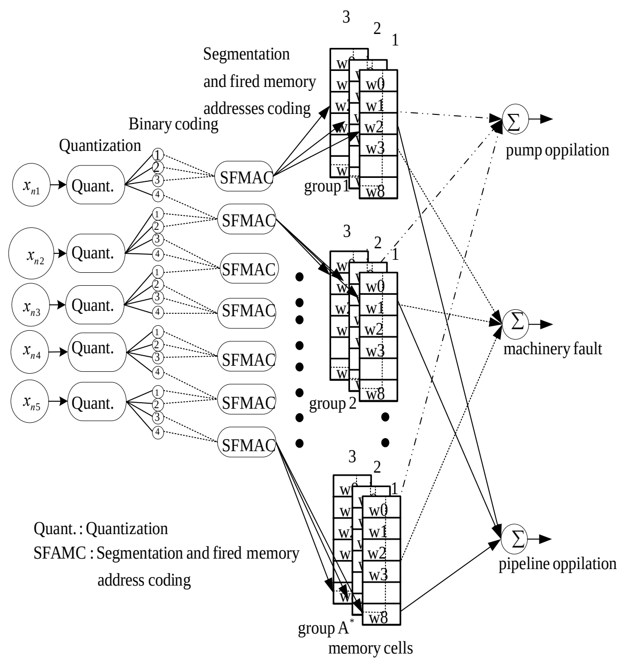

Figure 3. The configuration of water circulation diagnosis system using CMAC neural network

2.1 Training mode

As shown in Fig. 3, the three parallel memory layers are used to memorize the fault features. To avoid the learning interference, each memory layer just memorizes one fault characteristic. Therefore, in the beginning all the memory cells have zero weight value and we train it by learning rule in training mode.

In training mode, the patterns of fault type *i* (*i*=1,2,3), shown in Table 1, are used to train the memory layer *i* which memorizes the feature of fault type *i* only. Input the fault patterns to the diagnosis system, via a series of mappings, including quantization, binary coding, segmentation, fired memory addresses coding and summation of the fired memory addresses weights, the CMAC will produce an output value. All the mapping processes just want to satisfy the characteristic of CMAC neural network, i.e. similar input will excite the similar memory cells (similar excited memory address). Assuming the output value is trained equal to 1 to denote a specific fault type, that is the node output 1 confirms what fault type is. All the patterns of fault type *i* will input to the diagnosis system repeatedly to train the memory layer *i* until the learning convergence achieved. The mapping processes are summarized as follows.

2.1.1 Quantization

Firstly, the input signals are quantized to produce a quantization output. For example, Fig. 4 shows the input signal is quantized as 16 levels ($q_{max} = 16$) between the minimum value, x_{min}, and maximum value, x_{max}. I.e. every detected signal will be quantized as 0 to 15. In Table 1, x_{n1} with minimum value 0.2 and maximum value 1.0. and the quantization output of 0.83 will be quantized as 12.

2.1.2 Binary coding

As described above, the quantization output can be expressed in four digits binary code, such as 12 expressed as 1100b. In Table 1, the quantization outputs of first set of x_{n1} to x_{n5} are 12, 8, 10, 0, 0 respectively. Four digits binary expression is 1100b, 0100b, 1010b, 0000b, 0000b. Concatenate the five binary value, we have the following binary series.

11000100101000000000b

The most significant characteristic of CMAC NN is that similar inputs activate similar memory addresses. The fired memory addresses coding must satisfy this condition. Using the binary series is benefit to the following fired memory addresses coding and reduce the memory size. It is different to the traditional coding scheme.

2.1.3 Segmentation, fired addresses coding and output mapping

In segmentation operation, we take suitable bits as a segment (group) to generate the excited memory addresses. For example, take three bits as a segment and rewrite above series as follows.

<u>11</u>000<u>100</u>101<u>000</u>000<u>000</u>b

Then from LSB to MSB the excited memory address are coded as a1=000b=0, a2=000b=0, a3=000b=0, a4=101b=5, a5=100b=4, a6=000b=0, a7=11b=3. It implies the fired memory addresses number, A^*, is seven. The features of the specific fault type will be distributed on the seven fired memory addresses. To add the weights of excited memory addresses, $w_1^0, w_2^0, w_3^0, w_4^5, w_5^4, w_6^0, w_7^3$, will produce the CMAC output. The output of CMAC can be expressed as

$$y = \sum_{i=1}^{A^*} w_i^{ai}, \quad i=1,\ldots,A^* \tag{1}$$

where w_i^j denotes the *j*-th addresses of group *i*.

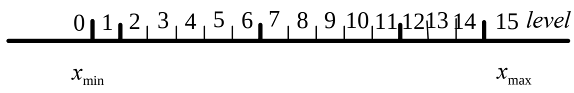

Fig.4. Quantization mapping diagram.

2.1.4 Learning rule

Assuming the memory layer *i* (*i*=1,2,3) outputs 1 denotes the fault type *i* is confirmed, then 1 can be thought as the teacher and the supervised leaning algorithm can be described as [9,12]

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

where $w_{i(new)}^{a_i}$ are the new weight values after the weights tuning, $w_{i(old)}^{a_i}$ are the old weight values before weight tuning, and *ai* denotes the fired memory addresses, β the learning gain, $y_d = 1$ the desired output.

2.1.5 Learning convergence and performance evaluation

From [14], the convergence of a supervised learning algorithm can be guaranteed. Assuming the *i*-th (*i*=1,2,3) layer outputs one denotes the system has fault type *i*, and the number of training patterns is N_p. Let the performance index be

$$E = \sum_{j=1}^{N_p} (y_j - 1)^2, \tag{3}$$

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

2.2 Diagnosis mode

When the training mode is finished, the diagnosis system can be used to diagnose the fault type of water circulation system. Input the diagnosis data to the diagnosis system, the operations of CMAC NN are same as the training mode. But in diagnosis mode, the same fired memory addresses weights of every memory layer are summed up and each layer has one output value. If the input signal is same as the training patterns of fault type i, it will activate the same memory addresses of layer i and layer *i's* output near one denotes the exactly fault type. But other layer's output, generally, far away from 1 expresses low possibility of fault type *j* ($j \neq i$). Multiple layers output near one value expresses multiple fault types happened. Therefore, the proposed diagnosis scheme suits to multiple faults diagnosis naturally. The software program flowchart is shown as Fig. 5. Other features of the proposed scheme are described as follows.

2.2.1 High noise rejection

The noise rejection ability can be illustrated as follows. Assuming the first fault type coding has following error or deviation (bold type).

Original coding: 11000100101000000000b

Error coding: 110001001010000000**11**b

Then the fired up memory addresses, (a1,a2,a3,a4,a5, a6,a7) changed from (0,0,0,5,4,0,3) to (3,0,0,5,4,0,3), only the a1 is wrong. Since the fault feature is stored on eight different addresses, the output will preserve 85% feature at least and the noise rejection ability can be obtained.

2.2.2 Wrong diagnosis learning

If the diagnosis output is wrong, the detected data will be seem as a new pattern and the training mode describe above will be running again.

2.2.3 Memory reduction

The needed memory size is related to the bit number of segment (*m*), maximum quantization level (q_{max}) , the number of input signals(*k*), the total bit number of binary coding series(*n*) and the number of fault type (*F*).

It is easy to obtain the following relation.

$$n = k \cdot \mathrm{ceil}(\log_2(q_{max}+1)) \tag{4}$$

Therefore, the total memory addresses M_{total} is

$$M_{total} = A^* \cdot F \cdot 2^m = \mathrm{ceil}(n/m) \cdot F \cdot 2^m \tag{5}$$

and the optimal memory size (less) can be determined using following scheme.

$$\frac{\partial M_{total}}{\partial m} = (-n/m^2) \cdot f \cdot 2^m + \frac{n}{m} \cdot \ln 2 \cdot 2^m = 0 \tag{6}$$

Let $m = ceil(1/\ln 2)$ will have the least memory size. In fact, m=1 or 2 has the least memory size for the water circulation diagnosis system. This new fired memory address coding scheme reduces the memory size efficiently than the traditional method in [15]. However, an interesting phenomenon appears in our research, m is related to the convergence speed. More rigorous proof is still under studying.

2.3 Diagnosis algorithm

Based on the configuration of Fig.1, the diagnosis algorithms are summarized as follows.

2.3.1 Training mode

step 1 Build the configuration of CMAC fault diagnosis system. It includes 5 input signals, 3 parallel memory layers and 3 output nodes.

step 2 Input the training patterns, through quantization, 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 equation (2) to update the weight values.

step 4 Training performance evaluation. If $E < \varepsilon$, the training is finished. Save the memory weights. Otherwise, go to step 2.

2.3.2 Diagnosis mode

step 5 Load the up to date memory weights from the saved file.

step 6 Input the diagnosed data.

step 7 Quantization, segmentation, fired memory address coding, and summation of the fired memory weights using equation (1).

step 8 Does the diagnosis correct? Yes, go to step 9. Otherwise, go to step 2.

step 9 Does the next data to be diagnosed? Yes, go to step 6. Otherwise, go to step11.

step 10 Update the fired memory weights using equation (6). Go to step 9.

step 11 Stop and save the up to date memory weights to file.

3 Case study、discussions and diagnosis results

To demonstrate the effectiveness of the proposed scheme, Table 2 shows the training and diagnosis output using the patterns of Table 1. Undoubtedly, it appears high accuracy and the training times just 5. In Table 3, we added -30% to 30% noise to the original pattern as the diagnosis data (red bold type), high accuracy still obtained and the high noise rejection ability is guaranteed.

Fig. 6 shows the weights distribution plots of memory layers. Using CMAC scheme, the features of every fault type will be stored in memory cells just like the brain waves plot. In this study, we also try different bit number m, it related to the used memory size and the learning speed. Large memory size leads to fast learning speed. In real implementation, the engineer is easy to make decision depending on the system performance requirement. In on-line learning operation, the learning speed is the most significant factor and the larger memory size is inevitable; whereas in diagnosis apparatus design, the memory size affects the possibility of the proposed diagnosis algorithm and the engineer must evaluate the memory size first to match the chip device.

4 Conclusion and future work

This work presents a novel CMAC-based fault diagnosis system for water circulation 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 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. However, the CMAC diagnosis scheme can be applied to other systems also. There are many applications are under research, such as image pattern recognition, disease diagnosis, etc. They will be presented in near future. Moreover, we also developed portable diagnosis apparatus using PIC microcontroller. Because of the pages limitation, it will appear in other journals.

Acknowledgments

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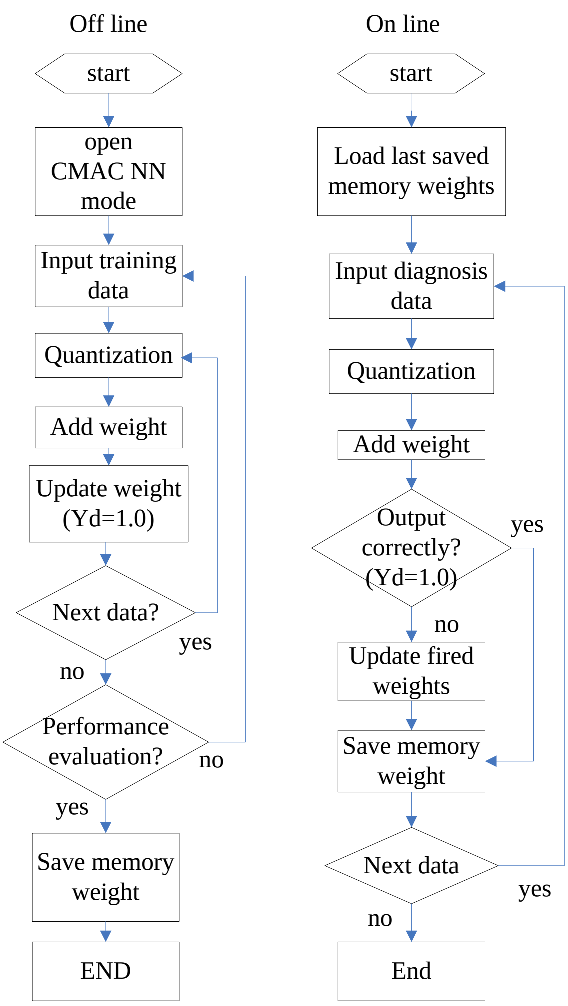

Figure 5. Software flowchart of diagnosis program.

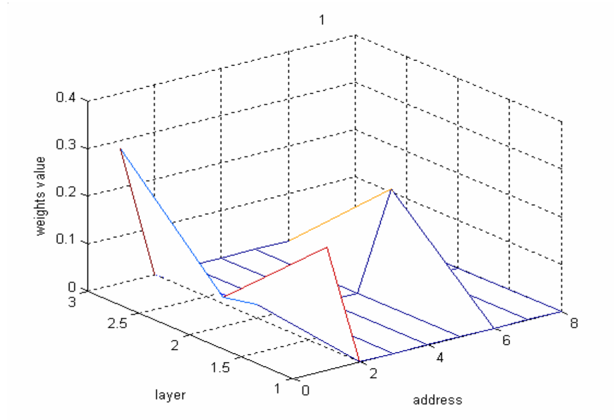

Figure 6. Weights distribution plot

Table 2. Diagnosis outputs of training pattern

NO.	Fault pattern					Node output			Real fault
	x_{n1}	x_{n2}	x_{n3}	x_{n4}	x_{n5}	T_{n1}	T_{n2}	T_{n3}	
1	0.83	0.66	0.83	0.78	0.76	1.0006	0.6471	0.6496	T_{n1}
2	0.83	0.66	0.85	0.80	0.76	1.0005	0.6471	0.6496	T_{n1}
3	0.83	0.55	0.80	0.80	0.76	0.9942	0.4426	0.5208	T_{n1}
4	1.00	0.40	0.66	0.82	0.78	1.070	0.4863	0.7360	T_{n1}
5	0.66	0.30	0.60	0.82	0.78	0.9999	0.3303	0.8811	T_{n1}
6	0.83	0.84	1.00	0.95	0.88	0.4498	1.0070	0.4089	T_{n2}
7	0.83	0.84	1.00	0.98	0.93	0.5784	0.9928	0.5472	T_{n2}
8	1.00	0.78	0.92	1.00	0.90	0.3343	1.0017	0.1818	T_{n2}
9	0.66	0.66	0.83	0.98	0.98	0.3495	1.0067	0.2993	T_{n2}
10	0.83	0.62	0.85	0.98	1.00	0.3685	0.9994	0.1175	T_{n2}
11	0.50	0.84	0.66	0.82	0.76	0.7649	0.4127	1.0011	T_{n3}
12	0.20	0.66	0.60	0.84	0.78	0.6837	0.3101	0.9948	T_{n3}
13	0.66	0.95	0.60	0.85	0.79	0.5360	0.3745	1.0592	T_{n3}
14	0.66	1.00	0.50	0.90	0.78	0.5338	0.2983	1.0197	T_{n3}
15	0.66	1.00	0.66	0.85	0.78	0.5208	0.3745	0.9956	T_{n3}

Table 3. Diagnosis output with -30%~~30% noise

No.	Fault pattern					node output			real fault
	x_{n1}	x_{n2}	x_{n3}	x_{n4}	x_{n5}	T_{n1}	T_{n2}	T_{n3}	
1	***0.83***	0.66	0.83	0.78	0.76	**0.9256**	0.6206	0.6023	T_{n1}
4	1.00	***0.40***	0.66	0.82	0.78	**1.0972**	0.4599	0.7001	T_{n1}
6	0.83	0.84	***1.00***	0.95	0.88	0.4498	**1.0078**	0.4089	T_{n2}
7	0.83	***0.84***	1.00	***0.98***	0.93	0.6658	**0.9663**	0.5113	T_{n2}
11	0.50	0.84	0.66	***0.82***	0.76	0.5806	0.4741	**0.9007**	T_{n3}
12	0.20	0.66	0.60	0.84	***0.78***	0.6837	0.3101	**0.9948**	T_{n3}
noise	10%	-10%	20%	30%	-30%				

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