RECURRENT NEURAL NETWORK (RNN) BASED BEARING FAULT CLASSIFICATION OF INDUCTION MOTOR EMPLOYED IN HOME WATER PUMP SYSTEM

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ABSTRACT

In home appliances, the water pump is used to supply the water from a room to the other rooms. Defects of the water pump are not distributing the water, inner stator winding short circuit, and bearing failure. In this paper, bearing fault detection of induction motor (IM) used in home water pump system is developed by using recurrent neural network (RNN) method. It is difficult to detect fault bearing of IM using a mathematical model. So that, a recurrent neural network (RNN) method is applied to solves this problem. These bearing faults classifications are based on IM stator current waveform. Bearing fault types are all normal (AN), front fault (FF), rear fault (RF), and all fault (AF). While, the detection process consist of three step. They are taking bearing fault data, features extraction, and RNN fault detection. The bearing fault data is taken from the stator currents of IM by using soundcard oscilloscope software. Second step is features extraction process to obtain more bearing fault signs. In this step, stator currents of IM is converted from time domain into frequency domain by using Fast Fourier Transform (FFT). Last stage is RNN model to clasify the bearing fault of IM. The effectiveness of proposed RNN method is clarified by using four bearing fault types.

Keywords: *water pump, bearing fault, recurrent neural network, fast Fourier transform.*

1. INTRODUCTION

In household life, water is utilized for bathing, washing and drinking. The water usually comes from shallow well. The water is distributed to all parts of the house using water pump. Water pump is used to easily supply the water from a lower pressure to a higher pressure or a lower place to a higher place. Water pump consist of pump unit and single phase induction motor (IM) as prime mover. The damage of water pump is not removing the water, winding short circuit, and bearing damage. The bearing is one of the important induction motor (IM) components which often fail in rotating machinery during operation. It has the important function to reduce the friction occur in shaft of IM, so that the rotor of IM can rotate. Bearing fault run by an induction motor (IM) cause a change in the stator current waveform [1,2]. However, the bearings must be created from strong metal to sustain the shaft and other engine components to function properly. Several tests of bearing condition have been discussed to detect the bearing fault of induction motor [3-4]. Nevertheless, it demands a complex mathematical model and high cost fault detection devices [3-5].

In this paper, fault detection of induction motor bearing is developed using artificial intelligent (AI) technique. There have been researches of AI applications to power electronics and motor drives [6-12]. AI method used in this bearing fault detection is recurrent neural network (RNN). Objective of this research is to know bearing fault types and early detection of bearing faults on home water pump system. The fault types are divided in four types such as all normal (AN), front fault (FF), rear fault (RF), and all fault (AF). The bearing fault detection process consists of three steps such as taking current of induction motor (IM), features extraction using Fast Fourier Transform (FFT), and RNN fault detection. First step, the data of IM currents are taken using soundcard oscilloscope software v.1.41 through audio line input of personal computer [2,13]. In second step, the IM currents are changed from time domain into frequency domain using FFT to obtain more bearing fault signs and than four types of IM currents data are extracted. In last step, RNN model is used to select and detect fault bearing of IM based on IM

current waveforms. The effectiveness of proposes RNN method is tested by simulation using MATLAB. The results of detection for four bearing fault types are shown.

2. RESEARCH METHODOLOGY

The research methodology employed to detect and classify bearing faults of induction motor (IM) employed in home water pump system can be seen in Figure 1. The bearing fault data employed in this paper is acquired from the current of induction motor (IM). Data of IM currents describe the bearing fault types.
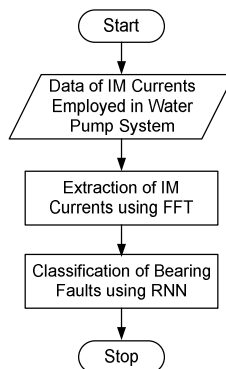

Figure 1. Methodology to classify the bearing fault of induction motor

Second stage is extraction process. In this stage, IM currents are extracted by using Fast Fourier Transform (FFT) to know the difference of four bearing fault types. Last stage is creating RNN model to detect four bearing faults of induction motor (IM).

2.1 Taking Stator Currents of Induction Motor (IM)

Taking stator currents of induction motor are shown in Figure 2. Stator current of induction motor (IM) is taken by using current transformer (CT), probe circuit and personal computer (PC). Current transformer is used to record singgle phase induction motor (IM) employed in home water pump system. Output terminal of CT is connected to audio input of PC through probe circuit. Currents of IM are read through line audio input of PC and saved using soundcard oscilloscope software version 1.41 [2]. Next steps, the stator currents of IM are processed to detect the bearing faults of IM.
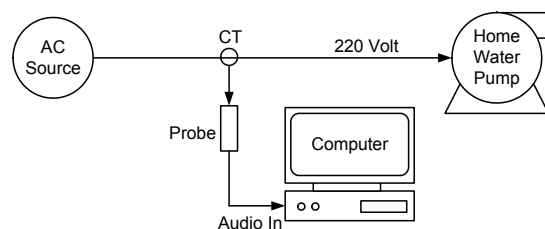

Figure 2. Taking stator currents of IM.

2.2 Bearing Faults of Induction Motor (IM)

The elements of home water pump system are single phase induction motor (IM), impeller, pipe and foot valve. In the IM, the critical element is bearing. Bearing function is to support a shaft of IM, so that it can rotate without experiencing excessive friction. Bearing must be strong to allow the IM shaft and other IM elements to work properly. Bearing faults are usually caused by over load, over heat and corrotion [3,4]. Bearing faults also impact a change in stator current waveform of IM [1]. Figure 3 show the construction of bearing.
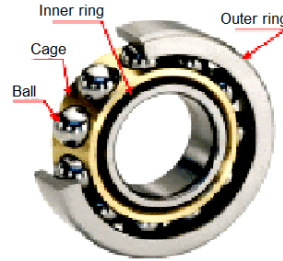
Figure 3. The construction of bearing.

2.3 Fast Faurier Transform (FFT)

Frequency domain analysis requires Fast Fourier Transform (FFT) method to change from time domain into frequency domain. Frequency domain is applied to show the frequency componets of a stator currents signal of induction motor. However, a time domain signal only shows its time componets. Formula of FFT for a signal *f(t)* can be described in Equation (1) [2,3,13].

$$f(t) = \sum_{n=1}^{\infty} C_n e^{inx}$$

(1)

where C_n is magnitude of the nth Fourier series component. The FFT method is used to convert the IM stator currents from time domain into frequency domain to yield more bearing fault signs.

2.4 Recurrent Neural Network Bearing Faults Detection

Recurrent neural network (RNN) architecture is similar to feed forward neural network (FFNN), but the fact that it contains the tapped delays (D). RNN architecture is shown in Figure 4. By this tapped delays (D), RNN can represent dynamic input output mapping and have ability to store information for next processes. Hence, the RNN is very appropriate to be applied to dynamic systems than FFNN [7,14].
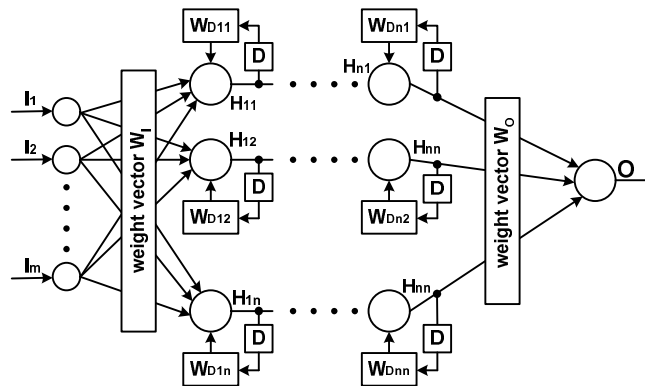

Figure 4. Architeture of Recurrent Neural Network

Block diagram of recurrent neural network (RNN) for bearing fault classification can be seen in Figure 5. In this paper, input signal of RNN is magnitude of the nth Fourier series component (C_n) obtained from extraction process of stator current signals using FFT technique. However, output of RNN is bearing fault classification of IM used in home water pump system.
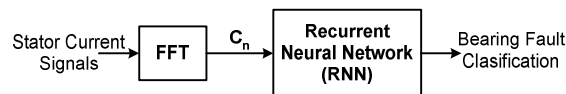

Figure 5. Block diagram of RNN bearing fault classification

3. RESULT AND ANALISIS

Experimental setup of induction motor (IM) bearing fault classification employed in house water pump system by can be seen in Figure 6. Thereafter, results of experiment setup are obtained to test the RNN model of IM bearing fault classification using software MATLAB. Parameters of IM are shown in Table 1.
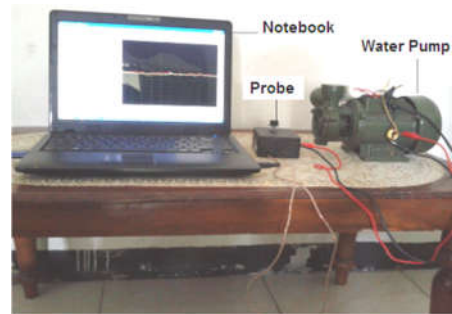

Figure 6. Experiment of IM bearing fault [2].

Table 1. Parameters of IM

Parameters	Values
Nominal Voltage (volt)	220
Frequency (Hz)	50
Nominal Power (W)	125
Total Head (meter)	33
Max. Capacity (liter/minutes)	42

3.1 Stator Currents of Induction Motor (IM)

Data of induction motor currents are taken using soundcard oscilloscope software version 1.4 for all normal (AN), front fault (FF), rear fault (RF), and all fault (AF). Figure 7 show the current waveforms of IM for four bearing fault types.
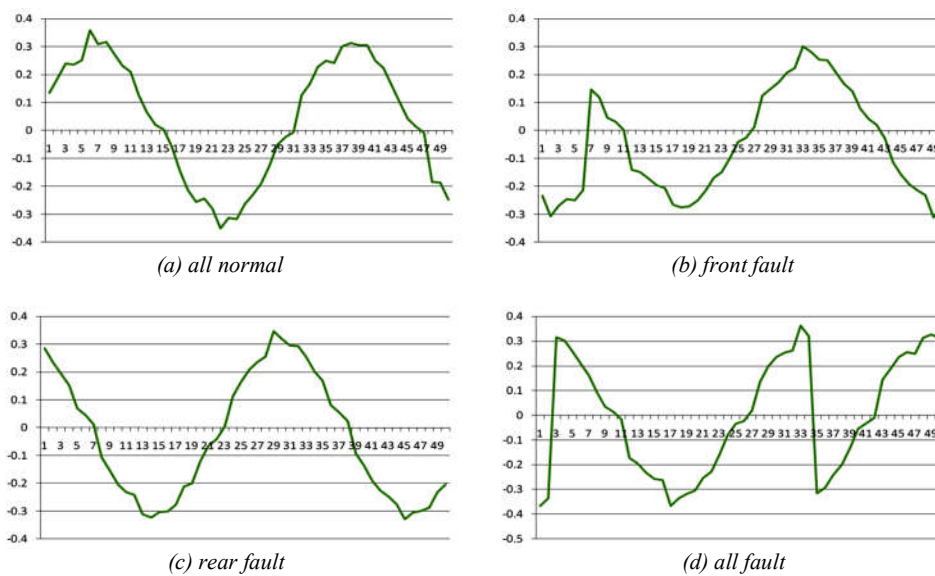

(a) all normal

(b) front fault

(c) rear fault

(d) all fault

Figure 7. *Stator current waveform of IM for bearing fault types [2]*

3.2 Stator Current Extraction Process.

Extraction process is done to change the stator current signal in time domain to frequency domain. Stator current extractions of IM for bearing fault types are carried out by using Fast Fourier Transform (FFT). Stator current extractions of IM refer to Equation (1) and yield the magnitude of the nth component FFT (C_n). The magnitude of the nth component FFT (C_n) for all bearing fault types can be seen in Table 2.

Table 2. Magnitude of the nth component FFT (C_n) [2]

n^{th} component of FFT	Fault Types			
	All Normal (AN)	Front Fault (FF)	Rear Fault (RF)	All Fault (AF)
1	2.953	0.188	0.878	1.832
2	1.038	1.971	1.833	1.34
3	0.212	0.928	0.742	0.516
4	0.218	0.601	0.633	0.197
5	0.080	0.601	0.342	0.382
6	0.024	0.316	0.355	0.281
7	0.161	0.370	0.324	0.076
8	0.056	0.254	0.308	0.194
9	0.056	0.254	0.308	0.194
10	0.161	0.370	0.324	0.076

3.3 Classification of Bearing Fault using Recurrent Neural Network (RNN)

Design of RNN for IM bearing faults classification consists of ten inputs and an output. Ten inputs are the components of FFT from extraction of stator currents. An output of RNN is target values which represent each fault types. Parameters and target values of RNN can be seen in Table 3 and Table 4.

Table 3. Parameters of RNN

Parameters	Values
Number of Hidden Layer	1
Number of Neurons	5
Learning Rate	0.05
Maximum Error	0.001
Maximum Epoch	500

Table 4. Target Value of RNN

Bearing Fault Types	Targets
All Normal (AN)	0
Front Fault (FF)	0.333
Rear Fault (RF)	0.667
All Fault (AF)	1

The RNN should be trained before it is used to classify the bearing faults of IM. Learning process is carried out to obtain output error of RNN according to desired error. Figure 8 show the learning performance of RNN during the learning process and number of epochs is 15. The learning process produces the structure of RNN shown in Figure 9. The structure of RNN has 2 layers. Layer 1 and Layer 2 are hidden layer and output layer. Figure 10 show detail of each layers. Detail of layer 1 can be seen that one of input layer 1 comes from its output.
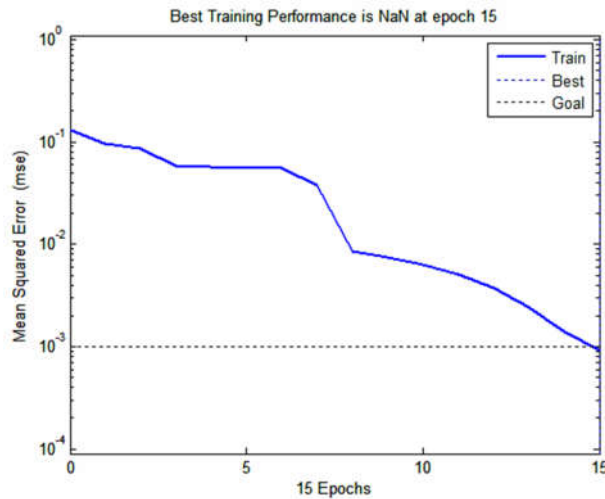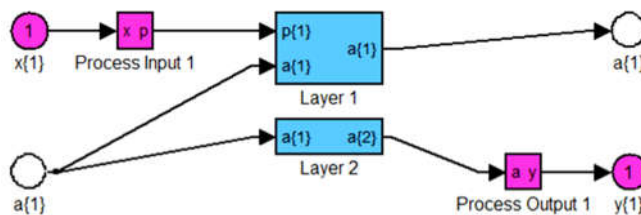
Figure 8. Learning Performance of RNN

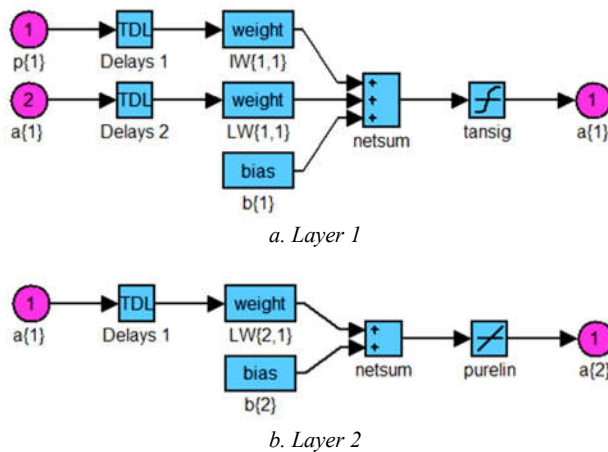*Figure 9. Structure of RNN*

a. Layer 1

b. Layer 2
Figure 10. Layer1 and Layer 2 of RNN

The proposed RNN method is tested to clarify its performances. Its performance is based on error value between design of RNN targets and test value of RNN output. Test of RNN method is done by using SIMULINK-MATLAB. Test of RNN method can be seen in Figure 11.
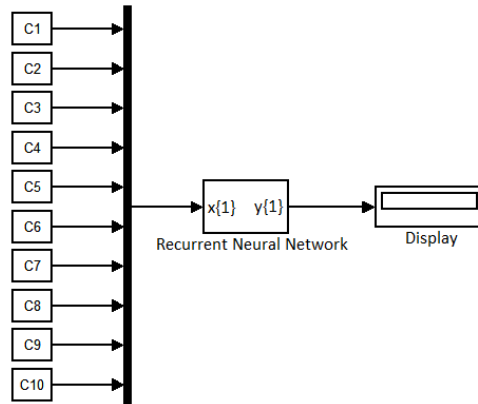
Figure 11. Test of RNN Bearing Fault Classification using MATLAB

Test results of proposed RNN method for each bearing fault types can be seen in Table 5. Test results of proposed RNN method are compared with target values of RNN output based on Table 4. Test results show that RNN method for IM bearing fault classification successfully work, because error values of RNN method are 0.1% - 0.2 % less than 5%.

Table 5. Test Results of proposed RNN Method

Fault Types	Targets	Test Results	Errors (%)
All Normal (AN)	0	-0.001	0.1
Front Fault (FF)	0.333	0.329	0.1
Rear Fault (RF)	0.667	0.668	0.1
All Fault (AF)	1	0.998	0.2

4. CONCLUSION

Application of recurrent neural network (RNN) for bearing fault classification of induction motor (IM) has been shown. Recurrent neural network (RNN) method is employed to classify the bearing fault of IM used in home water pump system. The bearing fault types of IM are all normal (AN), front fault (FF), rear fault (RF), and all fault (AF), respectively. However, the bearing faults classification process is divided in three steps. They are reading stator currents of IM, stator current extractions using FFT, and bearing fault classification using RNN method. The proposed RNN method is tested to clarify its performances based on errors between target values of RNN output and test results of RNN. Test results show that RNN method successfully work to classify the bearing fault of IM with error values of 0.1% - 0.2%.

REFERENCES

[1] Sukhjeet Singh, Amit Kumar, and Navin Kumar. (2014). *Detection of Bearing Faults in Mechanical Systems Using Motor Current Signature and Acoustic Signatures,* The 21st International Congress on Sound and Vibration (ICSV 21), Beijing, China.

[2] Dwi Hendra Wicaksono and Bambang Purwahyudi. (2017). *Fuzzy Logic Based Fault Clasification of Induction Motor Bearing Used in Home Water Pump System.* International Conference of Technology and Applications (ICTA), pp. 157-164.

[3] Linggo Sumarno, Tjendro, Wiwien Widyastuti, and R.B. Dwiseno Wihadi. (2014). *Water Pump Mechanical Faults Display at Various Frequency Resolutions*, TELKOMNIKA, Vol. 12, No. 1, pp. 97-106.

[4] A. Brkkovic, D. Gajic, J. Gligorijevic, I.S. Gajic, O. Georgieva, and S.D. Gennaro. (2015). *Early fault detection and diagnosis in bearings based on logarithmic energy entropy and statistical pattern recognition.* 2nd International Electronic Conference on Entropy and Its Applications.

[5] A.R. Mohanty, P.K. Pradhan, N.P. Mahalik, and S.G. Dastidar. (2012). *Fault detection in a centrifugal pump using vibration and motor current signature analysis*. Int. J. Automation and Control, Vol. 6, Nos. 3/4, pp. 261-276.

[6] B. Purwahyudi, H. Suryoatmojo, M. Ashari, and T. Hiyama. (2011). *Feed-forward neural network for direct torque control of induction motor*. International Journal of Innovative Computing, Information & Control (IJICIC), Vol. 7, No. 11, pp. 6135-6145.

[7] Bambang Purwahyudi, Soebagio, and M. Ashari. (2011). *RNN based Rotor Flux and Speed Estimation of Induction Motor*. International Journal of Power Electronics and Drive Systems (IJPEDS), Vol. 1, No. 1, pp. 58-64.

[8] B. Purwahyudi, Soebagio, and M. Ashari. (2011). *Neural Network Technique for Direct Torque Control of Induction Motor Used in Electrically Driven Ship Propeller*. International Journal of Achademic Research (IJAR). Vol. 3, No. 5, pp. 358-364.

[9] B. Purwahyudi, K. Kuspijani, and A. Ahmadi. (2017). *SCNN based Electrically Characteristics of Solar Photovoltaic Cell Model*. International Journal of Electrical and Computer Engineering (IJECE). Vol. 7, No. 6, pp. 3198-3206.

[10] Bambang Purwahyudi, Saidah, and Hasti Afianti. (2013). *Fuzzy Logic Controller For Volts/Hz Induction Motor Control Used In Electrically Driven Marine Propeller*, Academic Research International, Vol. 4, No. 5, pp. 258-265.

[11] Bambang Purwahyudi, Saidah, and Hasti Afianti. (2014). *Self-Tuning Fuzzy-PI Controller in Volt/Hz Induction Motor Control for Electrically Driven Ship Propeller,* Academic Research International, Vol. 5, No. 5, pp. 86-94.

[12] Saidah, Bambang Purwahyudi, and Kuspijani. (2017). *Control Strategy for PWM Voltage Source Converter Using Fuzzy Logic for Adjustable Speed DC Motor,* International Journal of Power Electronics and Drive Systems (IJPEDS). Vol. 8, No. 1, pp. 51-58.

[13] C. Zeitnitz. (2011). *Manual for The Soundcard Oscilloscope V 1.41 beta*, User Manual, https://www.zeitnitz.eu/scope/manual_scope_v141beta.pdf.

[14] Chao Chee Ku, and Kwang Y. Lee. (1995). *Diagonal Recurrent Neural Networks for Dynamic Systems Control, IEEE Transactions on Neural Networks*, Vol. 6, No. 1, pp. 144-155.