International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-9 Issue-4, February 2020

Neural Network Based Fault Diagnostics in Multi Phase Induction Machine

Balamurugan Annamalai, Sivakumaran Thangavel Swaminathan

Abstract*: This article proposes a new method for solving the diagnosis of faults in a multiphase induction motor using a least-squares filter (LMS) and a neural network. The proposed hybrid fault diagnosis method includes an efficient LMS-based feature extractor and an artificial neural network fault classifier. First, the LMS method is used to obtain efficient functions. The performance and efficiency of the presented neural network hybrid classifier is evaluated by testing a total of 600 samples, which are modeled on a failure model. The average correct classification is 96.17% for different fault signals, respectively. The result obtained from the simulation analysis shows the effectiveness of the proposed neural network for the diagnosis of faults in the multiphase induction motor.

Keywords* : Fault diagnosis, feature extraction, least mean square, multi layer perceptron neural network.

I. INTRODUCTION

The investigation and identification of faults in a multiphase induction motor are important in the diagnosis of products. Due to the design features of the engines and the theory of their operation, fault diagnosis processes and identification procedures have many characteristics [1]. A failure in an electric motor usually has many external symptoms, for example, as soon as the motor bus is broken, and many symptoms correlate with each other, for example, increment of shaking of the specimen, prolongation of the start time, fluctuation of the stator current, increase in slip, rotation speed and waviness of the twist moment, temperature shift, etc. [2].

Many changes in circumstances can cause a malfunction of the engine, for example, a change in load and other functionalities of the engine, which relate to all types of signs and symptoms; so the ratio is very complicated [3]. For this reason, it is difficult to determine the engine malfunction. Processes and several identification methods are obtained over a very long period of time, for example, current analysis, vibration estimation, thermal analysis, and hence further.

Revised Manuscript Received on February 28, 2020.
***** Correspondence Author
Balamurugan Annamalai*, Research Scholar, Dept. of EEE, Sathyabama Institute of Science and Technology, Tamil Nadu, India. Email: at.balamurugan@gmail.com
Sivakumaran Thangavel Swaminathan, Professor & Principal, Dept. of EEE, Sasurie College of Engineering, Tirupur, Tamil Nadu, India.

As soon as the bar is broken and the engine continues to run, the range of the broken bar will increase, the external signs become more and more noticeable, and the malfunction eventually becomes more and more acute; and finally, the motor is likely to soon be undoubtedly destroyed.

On the other hand, the same symptoms are caused by quite a few flaws. Some qualified fault identification strategies for a multiphase induction motor have been developed [4]. Investigation and identification of malfunctions is still a significant problem at present, since (a) the relationship between the cause of the malfunction and its symptom is quite complex; (b) the convenience of the fault identification procedure for a multiphase induction motor is rather limited; (c) the procedure for identifying artificial intelligence based on a fundamental discourse, you can find many questions, such as expression and gaining understanding, a fundamental lawsuit, etc. The procedure and the basic theory of fault identification of a multiphase induction motor are all discussed [5, 6]. Based on this study, the voltage of the motor and its slope are used as functions for diagnosing a malfunction in a multiphase induction motor; and an identification system based on a neural network is now exposed. According to the parameters of the state of the engine, the procedure can recognize another malfunction. This proposed approach is smart, reliable and accurate.

The article demonstrates the problems of diagnosing asynchronous motors in case of a rotor, stator and shaft bearing malfunction [8-10]. For diagnostic purposes, methods of artificial intelligence based on ANN are used. A direct neural network (FFNN) is used [8]. The use of artificial neural network (ANN) stands out as a facilitating mechanism for solving problems in many areas [7]. From this point of view, a study was carried out by introducing and analyzing the neural network and the multilayer perceptron (MLP) of the radial basis function (RBF) in order to compare the results based on quantitative procedures with an emphasis on training and testing, helping to classify faults in an induction motor [8]. In this work, ANN is trained and tested with the motor voltage and its inclination. The effectiveness of the developed FFNN is evaluated for troubleshooting in a multiphase induction motor.

The article is organized as follows. Section 2 gives a preliminary Least Mean Squares (LMS) algorithm, and then shows how to extract the presented features using LMS. A brief introduction about FFNN is given in the third section. Section 4 displays the results of modeling and analysis and shows the results of the classification method. Finally, the conclusions are presented in section 5.

II. FEATURE EXTRACTION

A. LMS Algorithm

The LMS procedure for signal attribute extraction is represented in Fig. 1, at which y_t refers the true signal, $\hat{y}_t$ describes the signal esteem and $X_t = [x_{0t}, x_{1t}, \ldots, x_{N-1t}]^T$ is the input signal vector in the t[th] moment.

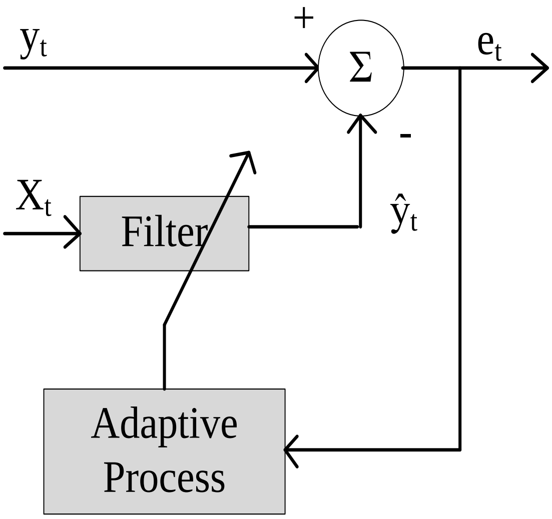

Fig. 1. LMS Filter

The filter can estimate accurately the signal having the right significance of its own W_t, and it is accessed through diminishing the squared of this error signal e_t [11]. So awareness is gained by the frame that will be symbolized like a trained filter in which the filter coefficients are accommodated in a fashion in their esteems. At each iteration, the weight vector W_t is figured as,

$$W_{k+1} = W_k + \mu(-\nabla_k) \tag{1}$$

At which $W_t = [w_{0t}, w_{1t}, \ldots, w_{N-1t}]^T$ is the filter coefficient, μ is the adaptation parameter and ∇_t can be actually the gradient of this error execution surface with regard to filter coefficient, this is figured as,

$$\hat{\nabla}_k = -2e_k X_k \tag{2}$$

Even the recursion (1) is popularly known as the LMS approach and also it is initialized by setting to zero. The procedure is started by calculating the error signal e_t, and it is required to compute the coefficient. Until the stability states have been accomplished, the following procedure is implemented. The stableness of the this loop system is handled with the parameter μ and also it needs to match the following standards,

$$0 < \mu < \frac{2}{Total\ input\ power} \tag{3}$$

At which μ the input power cites to the total amount of the mean square value of these input signals. The LMS strategy absorbs moment to learn regarding its own input with minimum mean square error when μ is little and vice versa. Hence, a time measure step sized ordering of μ is needed for convergence [11].

B. Feature Extraction using LMS

The voltage signal of an induction motor could be shown in discrete manner as,

$$\begin{aligned} V_{a_k} &= V_m \cos(\omega k\Delta T + \varphi) + \epsilon_{a_k} \\ V_{b_k} &= V_m \cos\left(\omega k\Delta T + \varphi - \tfrac{2\pi}{3}\right) + \epsilon_{b_k} \\ V_{c_k} &= V_m \cos\left(\omega k\Delta T + \varphi + \tfrac{2\pi}{3}\right) + \epsilon_{c_k} \end{aligned} \tag{4}$$

where, V_m is the fundamental component's maximum magnitude, ϵ_t is the noise found in the voltage waveform, t is the sampling period, φ is the fundamental component's phase, and ω is the voltage's angular frequency. The complex form of signal arrived from the motor voltage is got by αβ transformation [11] as stated as follows,

$$\begin{bmatrix} V_{\alpha_k} \\ V_{\beta_k} \end{bmatrix} = \sqrt{\frac{2}{3}} \begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} [V_{a_k} \quad V_{b_k} \quad V_{c_k}]^T \tag{5}$$

The complex voltage can be gotten as,

$$V_k = V_{\alpha_k} + jV_{\beta_k} \tag{6}$$

The voltage V_t can be modelled as,

$$\begin{aligned} V_k &= Ae^{j(\omega k\Delta T + \varphi)} + \xi_k \\ V_k &= \hat{V}_k + \xi_k \end{aligned} \tag{7}$$

In which, A is the amplitude of this signal V_t, and ξ_t is voltage's noise component and $\hat{V}_t = Ae^{j(\omega t\Delta T+\varphi)}$.

The voltage could be modelled as,

$$\widehat{V_k} = \hat{V}_k - 1^{e^{j\omega\Delta T}} \tag{8}$$

This version is also used in the proposed attribute estimation and the scheme that describes the extraction method is depicted in Fig. 2. The error signal e_t in this particular circumstance is figured as,

$$e_k = V_k - \hat{V}_k \tag{9}$$

At which $\hat{V}_t$ is the voltage's estimated value at the t[th] moment. Afterward,

$$W_k = W_{k-1}\hat{V}_{k-1} \tag{10}$$

where the weight $W_t = e^{j\hat{\omega}_{t-1}\Delta T}$, $\hat{\omega}$ can be the angular frequency's estimated value. The model's importance is that the input consists of only one the weight vector and component vector. This complex LMS approach as formulated in [11] is employed to gauge that the condition. The system lessens the error square by recursively altering W_t at each time period as,

$$W_k = W_{k-1} + \mu_k e_k \hat{V}_k^* \quad (11)$$

where * represents the voltage complex and μ is the variable managing the convergence and also controlling the stability.

The step size μ_t is diverse as in [11] for convergence of the LMS approach, when the noise presents. For complicated conditions, the equations is upgraded as,

$$\mu_{k+1} = \lambda\mu_k + \gamma p_k p_k^* \quad (12)$$

At which p_t reflects the autocorrelation of e_t and e_{t-1} is currently calculated as

$$P_k = \rho p_{k-1} + (1-\rho) e_k e_{k-1} \quad (13)$$

At which ρ is an exponential weighting factor and $0 < \rho < 1$, $0 < \lambda < 1$ and $\gamma > 0$ controlling the speed of convergence. μ_{t+1} is set to μ_{max} or μ_{min} If it moves over or under the upper and lower constraints respectively. All these principles have been chosen dependent on indicate numbers clarified in [11].

The motor voltage magnitude A_t is computed at any period t from the evaluated esteem of voltage $\hat{V}_t$ as,

$$A_t = |\hat{V}_t| \quad (14)$$

The slope S_t is figured as follows,

$$S_t = \frac{(A_t - A_{t-1})}{\nabla T} \quad (15)$$

where A_t and A_{t-1} are the motor voltage magnitudes at the time interval t and t+1 correspondingly.

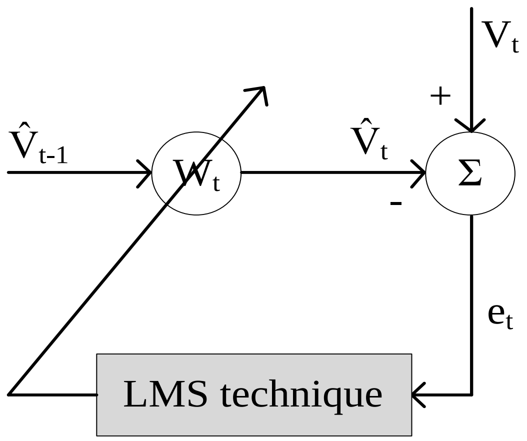

Fig. 2. Feature extraction using LMS

III. FEED FORWARD NEURAL NETWORKS

Feed-forward neural networks (FFNNs) are truly exceptional ANN types that can be managed. FFNNs contain a list of processing factors called "neurons". Neurons are distributed in several layers. The first level is known as the input level, and this level is also reflected by the input coefficients. The last level is known as the exit. All levels between inlet and outlet are known as hidden layers [8]. Multilayer Perceptron (MLP) can be a very common and popular form of all FFNNs. The neurons in the FFNN were combined in one-sided and one-sided modes. Bonds were represented by weights that can be real numbers for the period [-1, 1]. In Fig. 3 shows the proposed FFNN with one hidden layer for fault classification in multiphase induction motor. Each node from the network output level is calculated in two steps. First, the wording calculates the input total..

$$S_j = \sum_{i=1}^{n} \omega_{ij} I_i + \beta_j \quad (16)$$

where, I_i is input feature i, along with w_{ij} is that the weight of connection between I_i and the hidden neuron j. Secondly, the activation function can be used to activate the output signal of the nerves depending on the significance of their summation function. Different kinds of activation functions can be used in MLP. Using the sigmoid function, that is most often used in the literature, so that the output signal of node j from the hidden layer can be calculated as,

$$f_j(x) = \frac{1}{1 + e^{-S_j}} \quad (17)$$

The output of the MLP is finally obtained as,

$$\hat{y}_k = \sum_{i=1}^{m} W_{kj} f_i + \beta_k \quad (18)$$

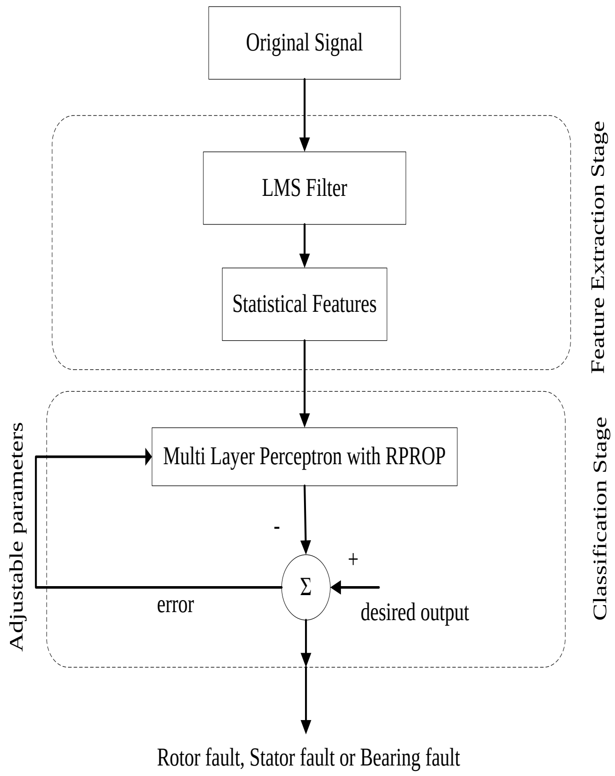

Fig. 3. Feed forward neural networks for fault classification in multiphase induction motor

To assess the purpose of this installed representative, we now use the MSE as a function of physical fitness, which depends on the calculation of the error between the true and predicted values from the set agents for the work samples.

The MSE was shown in (19), where y is the true value, ˆy is the predicted value, and n is the number of instances in the data set. The formula for MSE is given as,

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y-\hat{y})^2 \quad (19)$$

Table 1. FFNN parameters

Structure	
Total layers	3
Neuron on each layer	Input: 2, hidden: 5, output: 3
The initial agent	Random
Activation functions	Tangent sigmoid
Training parameters	
Training technique	RPROP
Learning rate	0.75
MSE	1E−05

IV. SIMULATION AND ANALYSIS

A. Data Generation

Diagnosis of multiphase induction motor malfunctions can be a classification of models. Input project space can be sorted by FFNN and implemented in project classification and recognition. This is a nonlinear dilemma for troubleshooting in a multiphase induction motor with amplitude and voltage slope. The proposed FFNN systems were used for multi-phase induction motor troubleshooting. Data generation using equation estimation has several edges. Potentially, it is possible to change the parameters of their testing and training signal with a choice and limited method.

The signals were very close to the real circumstances. On the other hand, different signals are created that belong to exactly the same categories, and it is possible to evaluate the capabilities of classifiers in accordance with FFNN [8]. The input to the FFNN-based fault classification system was obtained based on the model in [8]. Three types of various faults were considered. 200 examples of each class using parameters were prepared for training, and 200 other situations were prepared for analysis. The test and training voltage signals are sampled at 256 values / cycle, as well as at a frequency of 50 Hz. Thus, 16 power frequency cycles that operate with interference use a total of 4096 parts.

A. Simulation Results

Data collection for testing and training has been created. The dimensions at the bottom right explain the different attributes obtained by the LMS filter, in other words, the total number of estimated data will be 2 × 600, where two are the size of the object in each case, and 600 out of 200 cases for categories are multiplied by 3 classes. This can be classified using MLP-NN.

Considering the classification efficiency with this system, these input characteristics can be used as input to the FFNN structure. The classification results are explained with respect to the 3 × 3 confusion matrix, as shown in Table 2. Errors are correctly classified by diagonal elements. The outside diagonals are misclassified.

The proposed FFNN classified 577 signals out of 600 failures, as shown in Table 2. It follows that the success rate is 96.17%, when there is no noise inserted in voltage forms.

Table 2. Performance Analysis

True class	Rotor fault	Stator fault	Bearing fault	Accuracy (%)
Rotor fault	200	0	0	100
Stator fault	20	180	0	90
Bearing fault	3	0	197	98.5

V. CONCLUSION

This paper proposes a method of extracting successful functions based on the least-squares method for classifying faults in multiphase induction machines. The proposed classification method is implemented using a multilayer perceptron neural system together with a computational algorithm for the evolution of consciousness. It functions as a classification algorithm based on a multilayered perceptron, as well as extracting elements consisting of an LMS filter. For scientific research, a comparison of efficiency in the accuracy of fault diagnosis is proposed. The average correct classification is approximately 96.17% for different fault signals, respectively.

REFERENCES

1. Tang G, Kong W, Zhang T. The Investigation of Multiphase Motor Fault Control Strategies for Electric Vehicle Application. Journal of Electrical Engineering & Technology. 2020 Jan 1;15(1):163-77.
2. Albsmeier ED, Bornemann KR, Chiu HC, Eaton Z, Hackbarth AJ, Mauk RA, Neis JJ, Brey ED, inventors; Kohler Co, assignee. Diagnostic method for an engine-generator set. United States patent US 10,509,075. 2019 Dec 17.
3. Luo G, Hurwitz JE, Habetler TG. A Survey of Multi-Sensor Systems for Online Fault Detection of Electric Machines. In2019 IEEE 12th International Symposium on Diagnostics for Electrical Machines, Power Electronics and Drives (SDEMPED) 2019 Aug 27 (pp. 338-343). IEEE.
4. Barrero F, Bermudez M, Duran MJ, Salas P, Gonzalez-Prieto I. Assessment of a Universal Reconfiguration-less Control Approach in Open-Phase Fault Operation for Multiphase Drives. Energies. 2019 Jan;12(24):4698.
5. Ayala M, Doval-Gandoy J, Rodas J, Gonzalez O, Gregor R. Current control designed with model based predictive control for six-phase motor drives. ISA transactions. 2019 Sep 6.
6. Candelo-Zuluaga C, Riba JR, López-Torres C, Garcia A. Detection of Inter-Turn Faults in Multi-Phase Ferrite-PM Assisted Synchronous Reluctance Machines. Energies. 2019 Jan;12(14):2733.
7. Santhosh K, Neela R. optimal placement of distribution generation in micro-grid using eagle strategy with particle swarm optimizer. International Journal of Pure and Applied Mathematics. 2018;118(18):3819-25.
8. Dutta S, Chen X, Jha S, Sankaranarayanan S, Tiwari A. Sherlock-A tool for verification of neural network feedback systems: demo abstract. InProceedings of the 22nd ACM International Conference on Hybrid Systems: Computation and Control 2019 Apr 16 (pp. 262-263).
9. Annamalai B, Swaminathan ST. Diagnostics of faults in induction motor via wavelet packet transform. IOSR Journal of VLSI and Signal Processing (IOSR-JVSP). 2016:01-6.

10. Annamalai, Balamurugan and Sivakumaran Thangavel Swaminathan. "Diagnostics of Faults In Multi-Phase Induction Motor Using Wavelet Transforms." (2014).
11. Ramos, C. J., Martins, A. P., & da Silva Carvalho, A. (2017). Power system frequency estimation using a least mean squares differentiator. International Journal of Electrical Power & Energy Systems, 87, 166-175.

AUTHORS PROFILE

A. Balamurugan, received B.E degree in Electrical and Electronics Engineering from Mookambigai College of Engineering, Trichy and M.E degree in Power electronics and drives from Periyar Maniammai University, Thanjavur in 2007 and 2012 respectively. He is a research scholar of Sathyabama institute of Science and Technology, Chennai. Currently, he is an Assistant Professor at Ariyalur Engineering College, Ariyalur. His research area is Power Electronics and drives. He is the life member of Indian Society for Technical Education.

Dr. T. S. Sivakuaran, received B.E degree in EEE from Annamalai University, Chidambaram, Tamilnadu in 1998 and M.Tech Degree in EEE from VIT University, Vellore, Tamilnadu in 2002. He received the Ph.D. degree in Power Electronics from Annamalai University, Chidambaram, Tamilnadu in 2009. Currently, he is a principal in Sasurie college of Engineering, Tirupur, Department of Electrical and Electronics Engineering.