Proceedings of the Seventh International Conference on Research in Intelligent and Computing in Engineering pp. 145–150 DOI: 10.15439/2022R30 ISSN 2300-5963 ACSIS, Vol. 33

Optimized Approach of Feature Selection Based on Binary Genetic Algorithm in Classification of Induction Motor Faults

Truong-An Le
Institute Of Engineering Technology
Thu Dau Mot University
Binh Duong, Vietnam
anlt@tdmu.edu.vn

***Abstract*—In this paper, an effective model for detection and classification of multiple faults in induction motors is presented. Signal analysis method S-transform is applied to analyze and extract features from the current signals of four test motor states including three fault states (bearing fault, broken rotor bar, stator winding short-circuit) and one normal state. The feature set is extracted based on signal spectrum. With strong exploration capabilities in the search space, binary genetic algorithm (BGA) is proposed to select the optimal feature subset. As the classifier, the backpropagation neural network and support vector machine are used. The simulation results showed that the average accuracy of 100 trails is 98.3% and the optimal feature subset equal to 36% of total original features. As such, 64% of irrelevant features have been removed. In conclusion, the proposed model combined with BGA reached highly effective in the classification of induction motor.**

***Index Terms*—S-transform, binary genetic algorithm, SVM, BPNN, feature selection, fault detection.**

I. Introduction

Induction motors are widely used in many fields, especially in industry. How to make the electric motor work stably, that can detect faults early to avoid serious damage is a worth considering. The priority tasks to ensure the longevity of electric motors are maintenance and fault diagnosis [1]. In fact, many incidents have occurred leading to serious losses in production [2]. Therefore, the main topics mentioned include condition monitoring and fault diagnosis of induction motors in healthy and faulty conditions; detect broken bars fault, bearing damage, and inter-turn short circuit fault in induction motors [3]. There have been many studies focusing on data analysis methods such as Fast Fourier transform (FFT) [4], Wavelet transform (WT) [5], short-time Fourier transform (STFT) [6], S-transform (ST), and Hilbert-Huang transform (HHT) [7] which are combined with the classification models use supervised learning algorithms such as k-nearest neighbor (k-NN), support vector machines (SVMs) and artificial neural networks (ANNs). However, signal analysis methods are used to extract characteristics of signals in the time-frequency domain. And then intelligent classification models were applied to solve the classification problem, which does not achieve high efficiency. Because the extracted features are originally based on the human experience. In which there are features that carry very little information, they are not effective for the classification process. Therefore, the feature selection techniques are used to select the most important features, increasing classification efficiency and reducing computation time [8-11].

In recent years, there has been a lot of research using optimization algorithms for the feature selection process to remove irrelevant and redundant features from datasets to improve the performance of the machine learning algorithms [12]. There are many optimization algorithms used such as ant colony optimization (ACO), particle swarm optimization (PSO), and their variants. One of them is the genetic algorithm (GA). The main idea of GA is to combine different solution generation after generation to extract the best genes (candidates) from each. By doing so, it creates new and more fitted individuals. Besides, one of GA's outstanding abilities is exploring the search space. However, its limitation is the high computational cost. Based on the advantages of GA, this paper proposed a method to optimize the feature set extracted from the S-transform method based on the binary genetic algorithm to detect induction motor faults. Signal analysis method S-transform is applied to analyze and extract features from the current signals of four test motor states including three fault states (bearing fault, broken rotor bar, stator winding short-circuit) and one normal state. The feature extraction process of the current signals based on spectrum analysis is also implemented. Binary genetic algorithm (BGA) is used to select the most important feature to improve classification efficiency. This is a variant of GA that works in the binary region. Two well-known classification methods, back propagation neural network (BPNN) and SVM, are applied separately to compare the performance of the two models and select the best classifier.

In this study, the model of diagnosis and classification of motor faults works in three phases:

i. Feature extraction: S-transform method is adopted is adopted to analyze the current signals from the test motors. The information-carrying features of the signal are extracted in the time and frequency domain from the spectrum of the signal.

ii. Feature selection: BGA is applied to remove redundant and irrelevant features and find the optimal feature subset. The number of features in the optimal feature subset will be smaller than the original feature set, which means reducing the size of the dataset for the next classification process.

iii. Classification: Two common classifiers (BPNN and SVM) are applied. The efficiency of each classifier is evaluated and compared separately based on the input dataset which is the optimal feature subset of the BGA. Finally, the best fault detection model is found.

II. Feature Extraction

The S-transform is a generic form of the short-time Fourier transform (STFT) with a feature that can change the width of the window function. This can overcome other algorithms with fixed window functions in the frequency domain [13]. The S-transform spectrum contains important characteristics that are used to identify motor failures.

The STFT of signal is defined as (1)

$$STFT(\tau, f) = \int_{-\infty}^{\infty} h(t) g(\tau - t) e^{-j2\pi ft} dt \tag{1}$$

where τ is spectral localization time, f is Fourier frequency and $g(t)$ is window function.

The S-Transform is obtained by defining Gaussian window function, shown as

$$g(t) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-t^2}{2\sigma^2}} \tag{2}$$

The dilation (window width) σ is made proportional to the inverse of frequency, shown as

$$\sigma(f) = \frac{1}{a + b|f|} \tag{3}$$

If $a = 0$, $\sigma(f)$ means S-Transform and $\sigma(f)$ denotes STFT for $b = 0$ [14].

Substituting (2) and (3) in (1), the S-Transform of $h(t)$ is obtained as

$$S(\tau, f) = \int_{-\infty}^{\infty} h(t) g(\tau - t, f) e^{-j2\pi ft} dt \tag{4}$$

After the signal is analyzed by ST method, based on time-frequency matrix, feature extraction process is implemented as shown in Fig.1, including the following steps:

Step 1: The selection of features for the classification process is an important step to achieve high efficiency. In the time domain, five characteristics is selected including maximum (Max), minimum (Min), Mean, mean square error (Mse) and standard deviation (Std), to form five characteristic curves named Tmax, Tmin, Tmean, Tmse, and Tstd. Similarly, in the frequency domain, five same properties are selected and obtained the following five characteristic curves, named Fmax, Fmin, Fmean, Fmse, and Fstd.

Step 2: Each characteristic curve in the time and frequency domain will have five values extracted (Max, Min, Mean, Mse, and Std). Thus, 50 features are extracted from ten curves.

Step 3: The values of the characteristics are quite different. Therefore, we need to normalize the data before taking the next steps. A proposed simple normalized method is rescaled the feature values between 0 and 1.

Step 4: Perform feature selection method.

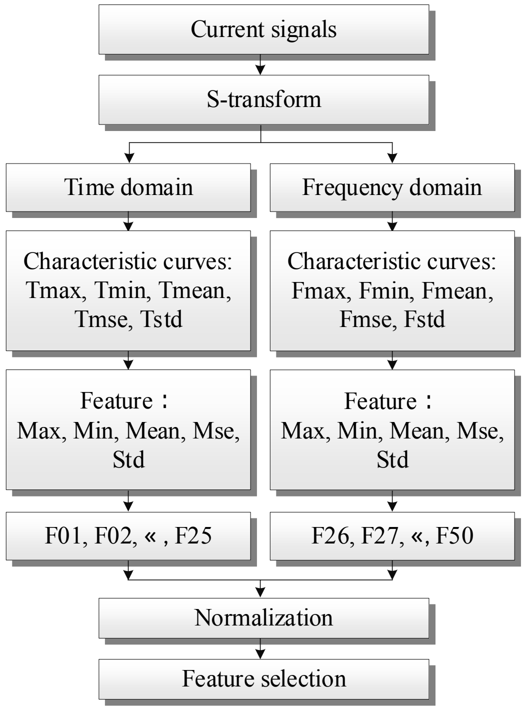

Fig. 1. Feature extraction process

III. Feature Selection

GA is one of the evolutionary algorithms. It is inspired by natural selection. Genetic algorithms use operators inspired by biological processes such as mutation, crossover, and selection to solve search and optimization problems [15]. In a genetic algorithm, there are five main stages: coding of chromosomes, initialization of the population, evaluation of each chromosome, generation of new chromosomes based on genetic operations such as selection, crossover, and mutation. The final condition is the end of the evaluation and genetics process.

Currently, there are many studies applying GA to solve optimization problems, find optimal results on real number search space [16]. That approach is also known as continuous GA [17]. Unlike continuous GA, binary GA operates on binary search space. Then the chromosome is a bit string, also known as a binary chromosome. Inside the binary chromosomes are genes that carry the value 0 or 1. In this study, the binary chromosomes are feature subsets. In which, gene 0 represents the unselected feature with the corresponding position in the binary chromosome and gene 1 represents the selected feature. The initial population is a randomly generated set of chromosomes. Chromosomes are evaluated by a fitness function. In this study, the k-NN approach was used as a fitness function for chromosome evaluation because k-NN is an efficient classifier and especially does not cost much to compute. Fitness value is the classification error rate by k-NN. The classification error rate is calculated based on the number of false predictions out of the total number of prediction samples. Next is the process of generating new chromosomes (new individuals) based on the genetic inspiration in nature that good parents will produce good children. First the evaluated chromosomes will be ranked, the dominant individuals will be kept and passed on to the next generation. The rest of the population is used to create new individuals through crossover and mutation. Based on these mechanisms, new individuals are generated that have the good traits of the previous generation and are potentially characterized through crossover and mutation operations. It can be said that BGA in particular or GA in general have the ability to find excellent individuals in the local area and probe potential individuals in the global area. The setting parameters for the BGA are shown in Table 1. A flowchart of the feature selection approach of the BGA is shown in Fig. 2 and the step-by-step process is described as follows [18]:

Step 1: Randomly generate a population of n chromosomes. Note that the number of chromosomes in the population greatly affects the computation time of the algorithm.

Step 2: The chromosomes in the population were evaluated by the fitness function. The value of the chromosomes is expressed through the fitness value.

Step 3: The next generation is created through the following three operations:

Selection: Based on the fitness value ranking, parental chromosome pairs are selected.

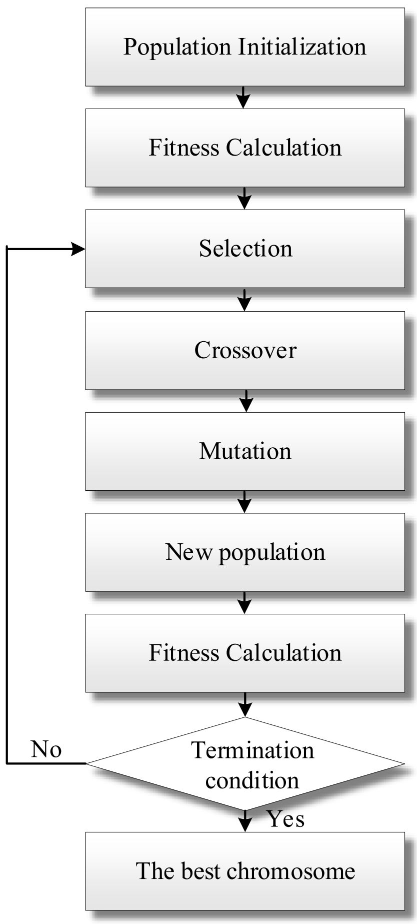

Fig. 2. Flowchart of BGA

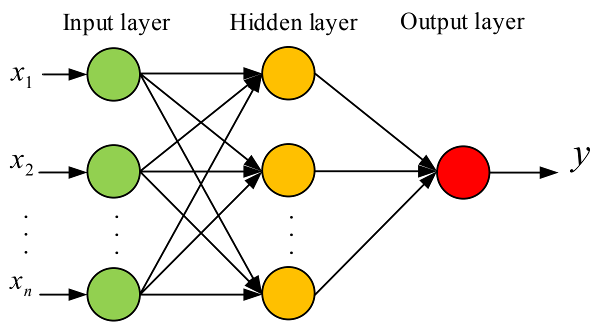

Fig. 3. Schematic diagram of BPNN

Crossover: Crossed between parents to produce a new individual with many good traits from the parents with a predetermined crossover probability.

Mutation: With a predetermined mutation probability, this operation causes mutations at several positions in the chromosome.

Step 4: The new generation is evaluated by fitness function. The value of the best individuals through each generation is recorded.

Step 5: If the end condition is satisfied, stop, and return the best solution in current population.

Step 6: Go to step 3 if the stop condition is not met.

IV. CLASSIFICATION

A. Backpropagation Neural Network (BPNN)

In the field of motor fault detection, artificial neural networks are showing superiority. The backpropagation algorithm belongs to a supervised learning group, which is the most common group of machine learning algorithms. In a BPNN the input layer is connected to the hidden layer and output layer by means of interconnection weights. This algorithm helps calculate these interconnection weights from the output layer to the input layer. The output layer is calculated first because it is closer to the expected output and loss function [19]. The BPNN using in this study includes three layers, The number of input neurons is determined by the optimal number of feature sets after being selected by BGA, 20 hidden units in the hidden layer, 1 output units in the output layer. The schematic of BPNN structure is shown in Fig.3

TABLE I. PARAMETERS USED IN BGA

BGA Parameters	Value
Population size	100
Sample lenght	50
Chromosome type	bitstrings
Fitness function	k-NN
Number of generations	100
Crossover	Two points crossovers
Mutation	Uniform
Mutation probability	0.1
Selection tournament	2
Elite count	2
Number of stall generations	50

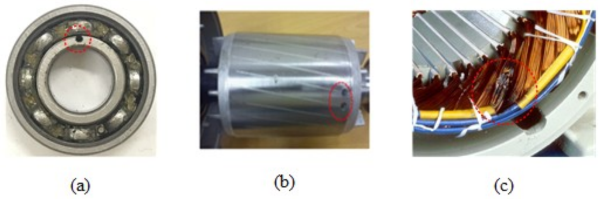

Fig. 4. Types of faults a) Bearing damage; (b) Broken rotor bar; (c) Stator winding short-circuit

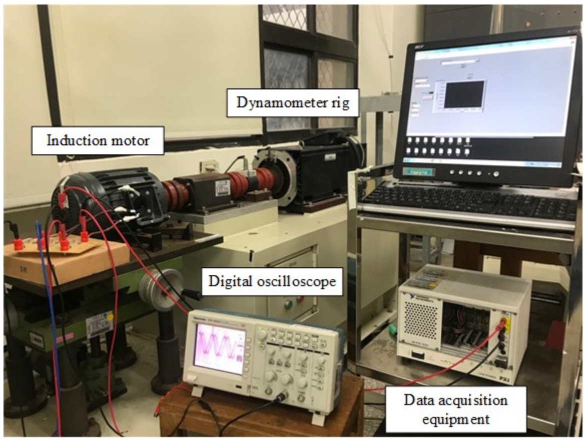

Fig. 5. Experimental setup

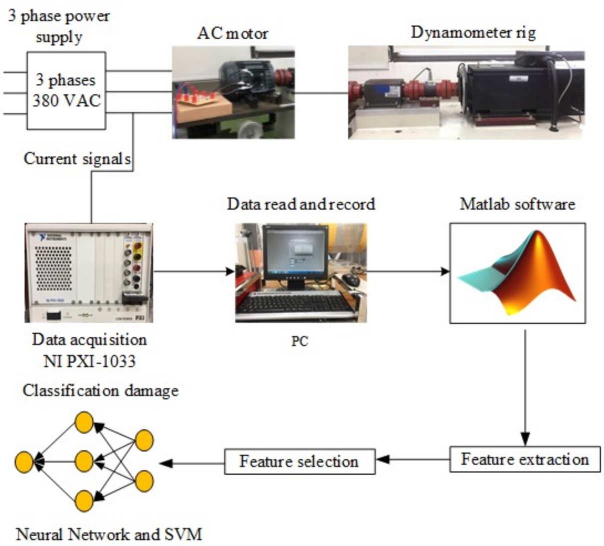

Fig. 6. Experiment process

where are $x_1, x_2, \ldots, x_n$ input units, and y are output units.

B. Support vector machine (SVM)

(SVM) is a supervised learning algorithm that can be used for binary classification or regression. In recent years, this method is commonly used in the diagnosis and detection of motor faults. SVM used the margin of separation between the two classes in the data is maximized. In this paper, SVM is used to classify motor failures. Each motor failure case is treated as a separate class corresponding to a separate label.

Given the multi-class training ability of SVM as well as its popularity in the field of pattern recognition, the selection of SVM in this study is appropriate. Besides, One vs All (OVA) technique is one of the important techniques established in SVM. OVA allows splitting multiple classes into two classes. This means that each classified object will be treated as a positive class and the rest of them as a negative class. The radial basis function is considered a kernel function.

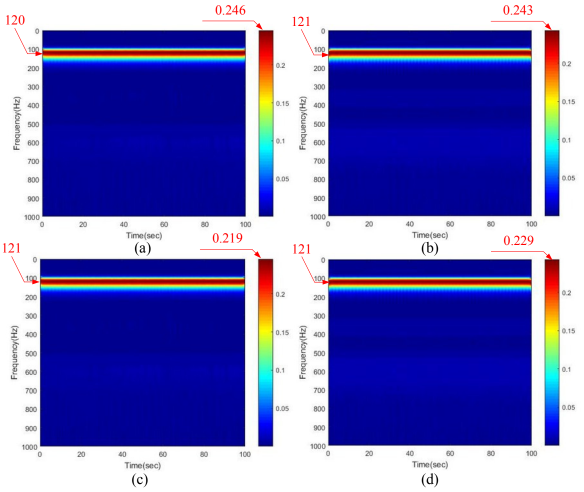

Fig. 7. S-transform spectrum

(a) S-Transform spectrum of healthy motor with a maximum amplitude of 0.246 occurs at 120Hz;
(b) S-Transform spectrum of bearing damage motor with a maximum amplitude of 0.243 occurs at 121Hz;
c) S-Transform spectrum of broken rotor bar motor with a maximum amplitude of 0.219 occurs at 121Hz;
(d) S-Transform spectrum of stator winding short-circuit motor with a maximum amplitude of 0.229 occurs at 121Hz.

V. Experiment and Results

A. Experimental setup

In this study, four different fault cases of induction motors were analyzed. These include three fault states (bearing fault, broken rotor bar, stator winding short-circuit) and one normal state as shown in Fig. 4. Bearing damage is created by drilling a hole through the inner race. Two small 2.0 mm diameter holes were created on the cage bars to simulate broken rotor bar fault. The stator winding short-circuit fault is created by damaging the insulation of the windings on the stator. And Fig. 5 describes the hardware connection of the experiment. We used a dynamometer rig (69Hz/11kW/2000rpm) and torque sensor which are considered as a dummy load of the induction motor to perform the experiment. The induction motor used in this experiment is the three phases squirrel-cage motor, 4 poles, 2 HP, 380VAC and 60Hz.

The voltage signal is measured on a phase of the test motors by the data acquisition device, NI PXI-1033, and record data on personal computer (PC). The sampling rate is 1000Hz, the measurement time is 100 seconds, measuring 50 signals for each type of motor faults. This study uses the MATLAB program to compile and analyze signals. The analysis method is S-transform. The experiment process is shown in Fig.6.

B. Simulation Results

Similar to the introduction section, the results are presented in three phases:

TABLE II. The classification accuracy under noise condition

SNR (dB)	Accuracy (%)					
Methods	Normal	30dB	25dB	20dB	15dB	10dB
SVM	**98.3**	**97.6**	**85.4**	**64.1**	43.9	30.9
BPNN	96.7	88.0	80.5	67.3	**59.3**	**49.6**

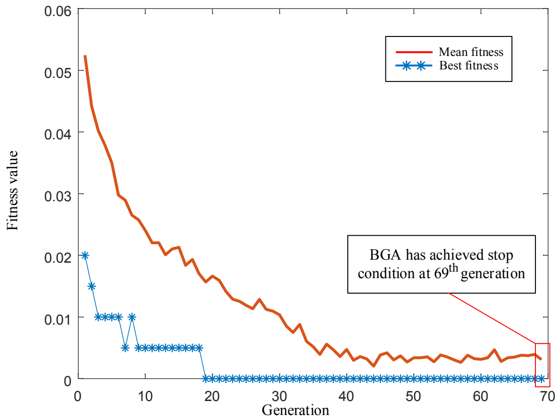

Fig. 8. BGA simulation

a) Feature extraction

After analyzing the current signal by S-transform, we obtained the spectrum diagram with the horizontal axis denotes the time domain and the vertical axis denotes the frequency domain. The S-transform spectrum of each type of motor faults in the no-load condition are shown in Fig. 7. Then 50 features are extracted from the 10 characteristic curves. The important features in the feature dataset are selected by BGA to increase the accuracy and decrease the running time of the classifier.

b) Feature selection using BGA

Based on the BGA configuration in Table 1, the following results were obtained. The purpose of the BGA is to minimize classification error based on the fitness function. The mean fitness value of each population converges to a minimum value. The stall generation is the number of generations counted by the program since the last upgrade of the fitness value, that is, the mean relative change in the value of the best fitness function over generations is less than the setting value 10^{-6}. The BGA terminates at generation 69^{th}. The optimal feature subset obtained 18 features in the original feature set. The particular feature indexes are 5, 6, 8, 10, 11, 15, 16, 20, 26, 27, 28, 29, 38, 39, 42, 43, 48, 49. Thus, the optimal feature subset is 36%. That means the number of redundant features removed is 64%. The simulation results are shown in Figure 8, where Mean fitness curve is the mean fitness value of a population and Best fitness curve is the best fitness value of an individual.

c) Classification

The results of classifying motor faults based on BPNN and SVM are shown in Table 2. One of the limitations of this study is the selection of two classifiers (BPNN and SVM) based on personal experience. To ensure the stability of the training model, the training dataset uses 80% of the input dataset. In normal conditions, the classification accuracy of both models (SVM, BPNN) used in this study achieves the average of 100 tests, 98.3% and 96.7% respectively. In order to increase the reliability of the identification model, we simulated interference from the environment into the feature dataset by adding SNR=30dB, SNR=25dB, SNR=20dB, SNR=15dB, SNR=10dB of white noise to the original signal with increasing levels. That is, the smaller the SNR, the greater the noise level. In table 2, the results showed that SVM model is better than BPNN model in noise conditions. However, at high noise level (SNR = 15dB, 10dB), SVM proved less effective.

VI. Conclusion

In this study, BGA is proposed for feature selection and the results achieved are very positive and reliable. The proposed model has the ability to identify types of common faults of induction motors with the accuracy is 98.3% in normal condition. However, the feature selection technique using basic BGA, the convergence speed of BGA has not been evaluated in this study. In the future, we will investigate the hybrid method between BGA and another optimization method to improve the model's performance.

References

[1] A. Choudhary, D. Goyal, S.L. Shimi, *et al.*, "Condition Monitoring and Fault Diagnosis of Induction Motors: A Review," *Arch. Computat. Methods. Eng.*, vol. 26, no. 4, pp. 1221–1238, Sep. 2019.

[2] H. Henao, G. Capolino, M. Fernandez-Cabanas, F. Filippetti, C. Bruzzese, E. Strangas, S. Hedayati-Kia, "Trends in Fault Diagnosis for Electrical Machines: A Review of Diagnostic Techniques," *IEEE Ind. Electron. Mag.*, vol. 8, no. 2, pp. 31-42, Jun. 2014.

[3] T. Yang, H. Pen, Z. Wang, "Feature Knowledge Based Fault Detection of Induction Motors Through the Analysis of Stator Current Data," *IEEE Trans. Instrum. Meas*., vol. 65, no. 3, pp. 549-558, Jan. 2016.

[4] K. Li, P. Chen, H. Wang, "Intelligent Diagnosis Method for Rotating Machinery Using Wavelet Transform and Ant Colony Optimization," *IEEE Sens. J.*, vol. 12, no. 7, pp. 2474-2484, Apr. 2012.

[5] C.Y. Lee and T.A. Le, "Intelligence bearing fault diagnosis model using multiple feature extraction and binary particle swarm optimization with extended memory," *IEEE Access*, vol. 8, pp. 198343-198356, Nov. 2020.

[6] LH. Wang, XP. Zhao, JX. Wu, *et al.*, "Motor Fault Diagnosis Based on Short-time Fourier Transform and Convolutional Neural Network," *Chin. J. Mech. Eng.*, vol. 30, no. 6, pp. 1357–1368, Nov. 2017.

[7] R. Mythily and W. Aisha Banu, "Feature Selection for Optimization Algorithms: Literature Survey," *J. Eng. Appl. Sci.*, vol. 12, no.1, pp. 5735-5739, 2017.

[8] B. Ji, X. Lu, G. Sun, W. Zhang, J. Li, Y. Xiao, "Bio-inspired feature selection: An improved binary particle swarm optimization approach," *IEEE Access*, vol. 8, pp. 85989-86002, May 2020.

[9] J. Li, H. Kang, G. Sun, T. Feng, W. Li, W. Zhang, B. Ji, "IBDA: improved binary dragonfly algorithm with evolutionary population dynamics and adaptive crossover for feature selection," *IEEE Access*, vol. 8, pp. 108032-108051, Jun. 2020.

[10] C. Y. Lee, T. A. Le, Y. T. Lin, "A Feature Selection Approach Hybrid Grey Wolf and Heap-Based Optimizer Applied in Bearing Fault Diagnosis," *IEEE Access*, vol. 10, pp. 56691-56705, May 2022.

[11] C. Y. Lee and T. A. Le, "An enhanced binary particle swarm optimization for optimal feature selection in bearing fault diagnosis of electrical machines," *IEEE Access*, vol. 9, pp. 102671-102686, Jul. 2021.

[12] Z. Huang, C. Yang, X. Zhou, T. Huang, "A hybrid feature selection method based on binary state transition algorithm and ReliefF," *IEEE J. Biomed. Health Inform.*, vol. 23, no.5, pp. 1888-1898, Sep. 2018.

[13] T. Zhong, S. Zhang, G. Cai, Y. Li, B. Yang and Y. Chen, "Power Quality Disturbance Recognition Based on Multiresolution S-Transform and Decision Tree," *IEEE Access*, vol. 7, pp. 88380-88392, Jun. 2018.

[14] M. V. Chilukuri and P. K. Dash, "Multiresolution S-transform-based fuzzy recognition system for power quality events," *IEEE Trans. Power Deliv.*, vol. 19, pp. 323-330, Jan. 2005.

[15] Mitchell, M., "Genetic algorithms" In *Encyclopedia of Computer Science*, pp. 747-748, Jan. 2003.

[16] Y. J. Gong, J. J. Li, Y. Zhou, Y. Li, H. S. H. Chung, Y. H. Shi, J. Zhang, "Genetic learning particle swarm optimization," *IEEE Trans. Cybern.*," vol. 46, no. 10, pp. 2277-2290, Sep. 2016.

[17] P. Ignaciuk and Ł. Wieczorek, "Continuous genetic algorithms in the optimization of logistic networks: Applicability assessment and tuning," *Applied Sciences*, vol. 10, no. 21, p. 7851, Nov. 2021.

[18] L. Haldurai, T. Madhubala, R. Rajalakshmi, "A Study on Genetic Algorithm and its Applications," *IOSR J. Comput. Eng.*, vol. 4, no. 10, pp. 139-143, Oct. 2016.

[19] V. Singh, P. Gangsar, R. Porwal, A. Atulkar, "Artificial intelligence application in fault diagnostics of rotating industrial mac