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RESEARCH ARTICLE

A Dual Soft-Computing Based on Genetic Algorithm and Fuzzy Logic Defect Recognition for Gearbox and Motors: Attempts Toward Optimal Performance

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ABSTRACT Motor and gearbox are considered the main components in various machines related to its supplying power and transmitting motion role. Operating machines acquire vibration signal that are continuously monitoring by sensors placing close to vibration source. This for processing and identify the machine' components status. Breakdown of the rotating machine causes significant losses and costs, so the analysis of its vibration signals proved literately avoiding these drawbacks with effective faults diagnosis. This paper proposing two models for gearbox and motor faults identification as an attempt towards finding the optimal performance: The first developed model is a fuzzy logic (FL) based model and the other is genetic algorithm (GA) based model. The intended output of both models reduce time and cost of maintenance. It also indirectly increases the machine component's life. Additionally, the computational analysis proved that, concerning execution time and accuracy; and with the powerful straight forward representation for uncertainties offered by the Fuzzy Logic; it is indeed reliable, however it presented lower classification accuracy (96% for gear box faults and 93% for motor faults) and lower generalization schema. Yet, the proposed strategy which integrates GA and SVM recorded high performances in optimization and higher classification capabilities (97% for both gear box and motors faults). These factors illustrate the effectiveness and optimal performance of the genetic based model.

INDEX TERMS Genetic algorithm (GA), fuzzy logic (FL), gear box and motor, fault identification.

I. INTRODUCTION

Soft computing diagnostic systems for machinery components in general and the rotating machinery in specific are highly nominated for reducing costly breakdowns and avoiding catastrophic accidents. The Rotating Machinery is vital equipment in the modern industry. Based on that, the maintenance needed because of chronic run, breakdown, and/or heavy load; is mostly costly relative to time and productivity. In addition, if maintenance is totally ignored, the rotating machinery would inevitably generate variant faults that urgently need treatments. Off course, not all kinds and degrees of faults require replacement of the components but may lead to accidents, economic loss and casualties. Fortunately, early identification of such faults, these undesired costly events could be at least minimized to certain acceptance margins.

In the machinery environment, a variety of diagnosis approaches that is based on computational intelligence techniques, has been proposed in literature [1]–[3], [5], [6].

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These approaches have gone through tremendous reported progress with verified achievements. However, different datasets, machine configurations, and hyper-parameters are most need to be set in performance verification for many models. Therefore, we can describe the comparisons which limit the strong recommendation of one model over the rest in general as unrealistic if not relative to the data nature and the specific rotating machine architecture. This in turn opens and encourages the investigation while these parameters change.

Classification is considered a core objective and discovery issue in the field of soft computing, in which each input value is mapped to a certain class of a given set of classes [7]. In fact, the main diagnostic success depends on the identification or the right classification of defects in motor and gearbox. The soft computing diagnosis approaches in this domain mainly consist of (1) feature extraction using a selected signal processing method [ex: Fast Fourier transform (FFT) spectrum kurtosis (SK), and wavelet transform (WT)]; and fault classification using a selected computational intelligence technique such Fuzzy Systems [1], Evolutionary Computation [4] (ex: Genetic Algorithm), Neural Network, Swarm Intelligence, or Artificial Immune System [5], [6]. Then (2) building a classifier that is benefited from these important set of extracted feature. On the other hand, signals (in both time and frequency domains) have important information on machinery condition and considering the existence of a high number of feature directed for fault diagnosis, the feature selection process, still attracts research. Furthermore, in the case of motor and gearbox defects; the fuzzy logic [3], [4], [5], [8] has been nominated for control systems, while the genetic algorithms [4] have been reported as a success choice for optimization problem.

Generally, with existence of uncertainty or noise interference, the classification ac curacies impacted with classical crisp procedure [3]. In contrast, fuzzy sets and fuzzy logic attempt soft classification of data a more sensitive and flexible ways. Actually, the fuzzy rules approach for classification imitates the human knowledge expression, hence it leads to efficient, and easily interpretable fuzzy classifiers [8]. Fuzzy rule-based classification has been used for multivariate domains and data natures, however considering practical implementation, there are two main fuzzy rules formulation approaches [9]: (1) generate fuzzy inference rules based on the expert's knowledge in the domain, (2) formulate a list of FL "if then rules" from a set of given data [8], [9]. Using Wavelet samples with the fuzzy logic increase the advantage of being able to detecting the faulty and healthy conditions [10]–[13].

The authors of this paper have been motivated to develop a robust system for the multi/class faults identification for gears and motors, by obtaining the optimal performance on time, frequency domains based on the vibration signals generated from the mechanical parts of the rotating machine. Accordingly, we built dual systems. The first used the fuzzy logic theory and the other the genetic algorithms for optimization set of discriminative features and support vector machine for classification. Both approaches are evaluated on collected vibration signals of variant fault classes. For the fuzzy logic approach, the simulations were conducted under a range of scenarios as in the experimental results section. The failure data obtained by the simulation was fed into MATLAB's "Fuzzy logic toolbox" [14], [15]. The major contribution of this work is to have an efficient higher diagnostic performance for Gearbox and Motor Faults identification [16], [17]. In fact, the paper aimed supporting some industries offering the presented aided fault diagnostic system in this study for simple identification of machine breakdown or faults. This is, even with their absent knowledge of machine complexities. With a simple and efficient prototype that can be easily updated to their input data. In addition, for the academic field; the main contribution, is that we presented a detailed description of developing three main traditional artificial intelligence and soft computing techniques (genetic algorithms, SVM and Fuzzy logic) using the signal processing generated from rotating machinery. We also conducted various experiments attempting the optimal performance and validating the proposed models.

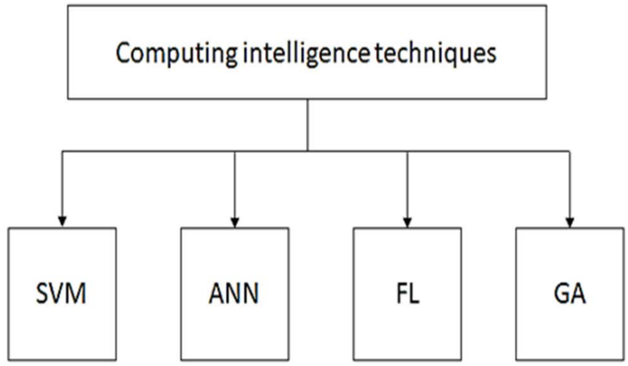

FIGURE 1. Taxonomy of computing intelligence diagnostic techniques.

The paper is organized as follows: Section II related work. Section III provides the preliminary concepts of defect types. The developed methods are in Section IV. The computational results and discussion are in Section V. The conclusion in Section VI summarizes the research finding and the intended future work.

II. RELATED WORK

Many authors were motivated developing fault diagnosis systems that handle signal processing input. Some related computing intelligence techniques for fault diagnosis are explored in this section and classified into four major categories, see Figure 1.

Supported Vector Machine (SVM) is a computing intelligence technique built upon a statistical concept. SVM overcomes dimensionality disaster and can use a small sample set. It uses the structural risk minimization idea to solve the local minimum problem. It is a suitable classifier for fault diagnosis, [18]. To report the induction motors faults, Konar *et al.* [19] employed the SVM and wavelet transform, and Li *et al.* [20], combined the wavelet transform with SVM and neighborhood rough. To reach the rotating machinery fault diagnosis success, Cheng *et al.* [21] employed SVM and the singular value decomposition (SVD) technique based on EMD (Empirical Mode Decomposition). The same idea is adapted by Zhang *et al.* [22], but they use an optimal model of SVM (ESVM), to resolve the problem of classification multiclass, based on the use of EEMD (Ensemble Empirical Mode Decomposition) and an integrated permutation entropy. The classification on multiclass can be improved not only by the use ESVM, but also using a multiscale FuzzyEn SVM (FSVM) [24]. A hybrid model based on ESVM and FSVM is also proposed by Zheng *et al.* [23] for rolling bearing fault-diagnosis. In addition, Hang *et al.* [25], pro- posed the EEMD method for fault features extraction, and then, they used the FSVM was adopted for fault diagnosis classification.

Artificial Neural Network (ANN) is a high-dimensional model nominated on mathematical calculation to achieve a parallel distribution of information. ANN uses a set of interconnected nodes in order to transfer information between various layers to achieve certain connection function of fault symptoms and fault reasons that is always a non-linear relation. Regarding its efficiency for mapping various relations, ANN has been generally employed in fault detection. The phases of ANN includes extracting the features using the time frequency analysis then the network is formed by a set of variables that will be then optimized to obtain the fault diagnosis classification. Authors is [26], used the Wavelet Packet Transform (WPT) to extract the features and the recurrent neural network (RNN) for classification of the faults. In addition, to extract the features, Lei *et al.* [27] combined the wavelet with EEMD, then added EMD to preprocess the extracted characteristics. Also, in [28], the authors used ANN for fault diagnosis in rotating machinery. Cui *et al.* [29] employed a novel concept using the Back propagation Neural Network (BPNN) and coefficient entropy of wavelet packet decomposition to classify several faults diagnosis of rolling bearings. Zhao *et al.* [30], utilized BPNN, but they improved the feature extraction by using the shuffled frog leaping (SFL) algorithm. Saravanan and Ramachandran [31], combined the Discrete Wavelet Transform (DWT) and the ANN for identifying the spur bevel gearbox faults,.

Fuzzy Logic (FL) is the process where people can think logically about the information. This model is appropriate for complex data that need a qualitative analysis using mathematical model. According the sophisticated issues generated by mechanical engineering practice, the fuzzy logic achieved recently good performance in fault diagnostics because it appears compatible with the way of human thinking and its processing. While ANN imitates human brain neuron function, the FL imitates the human thinking in both self learning and direct analysis of data. Several systems were proposed in literature based on FL for fault diagnosis in machinery environment. Zheng *et al.* [32], combined the local characteristic scale decomposition (LCD) method with the fuzzy entropy (FE) model for fault detection. LCD extracts the features and (FE) is employed to detect the failed component. Zhang *et al.* [33], presented an early fault diagnosis approach using the Adaptive neuro fuzzy inference system and a multi-scale entropy. Tran *et al.* [34] proposed an Adaptive neuro fuzzy inference system and combined with the decision tree for identical objective. Their method was performed to diagnose the induction motors faults. Wu *et al.* [35], integrates the Adaptive neuro fuzzy inference system and DWT to identify the gear faults. The DWT extracted the features (energy spectrum characteristics) and then injected these features to the ANFIS model.

Genetic Algorithm (GA) is highly nominated for feature optimization in fault diagnosis systems. Many systems are proposed using the GA, such as the work presented by Li *et al.* [36], which presented an adaptive stochastic resonance system for weak impulsive features detecting the sub-merged in noise. After extracting the features, the authors were then optimized by the GA to exclude the weak impact features of a gearbox. Lu *et al.* [37], adapted the GA algorithm to retrieve the optimal multi wavelets from an adaptive multi wavelet library. Then, they applied the autocorrelation analysis for early rolling bearings fault diagnosis. Authors in [38] applied the GA to optimize the parameters of the Morlet wavelet. Yan *et al.* [39] combined the optimal Variational mode decomposition and the envelope spectrum analysis to eliminate the faults. They applied the GA to optimize the parameters of the Variational mode decomposition algorithm. Ciancio *et al.* [40], applied the GAN to optimize the ANN architecture like (hidden layers number and neurons number of each layer, the activation function type, and the training other parameters). In addition, authors in [41], proposed GA to optimize their ANN network to detect the fault diagnosis for rolling bearings.

Although research on fault identification of mechanical system has made good achievements, some limitations need to be further enhanced. No exact one model can reach the optimal. For example, SVM achievement depends on the kernel function to determinate the hyper-plan for a single classifier. However, the choice of the appropriate classifier can influence on the obtained results for multi-classification. ANN technique is a nonlinear structure that needs a complex learning environment and many entrained parameters to achieve a good accuracy. GA can be used then to optimize the extracted features in order to refine the obtained results. However, difficult to directly identify faults. Therefore, a multi model is preferred.

III. PRELIMINARY CONCEPTS OF DEFECT TYPES

A. MECHANICAL MACHINE COMPONENTS

Electrical motor and gearbox are considered the main source of operation and transmission in mechanical machine.

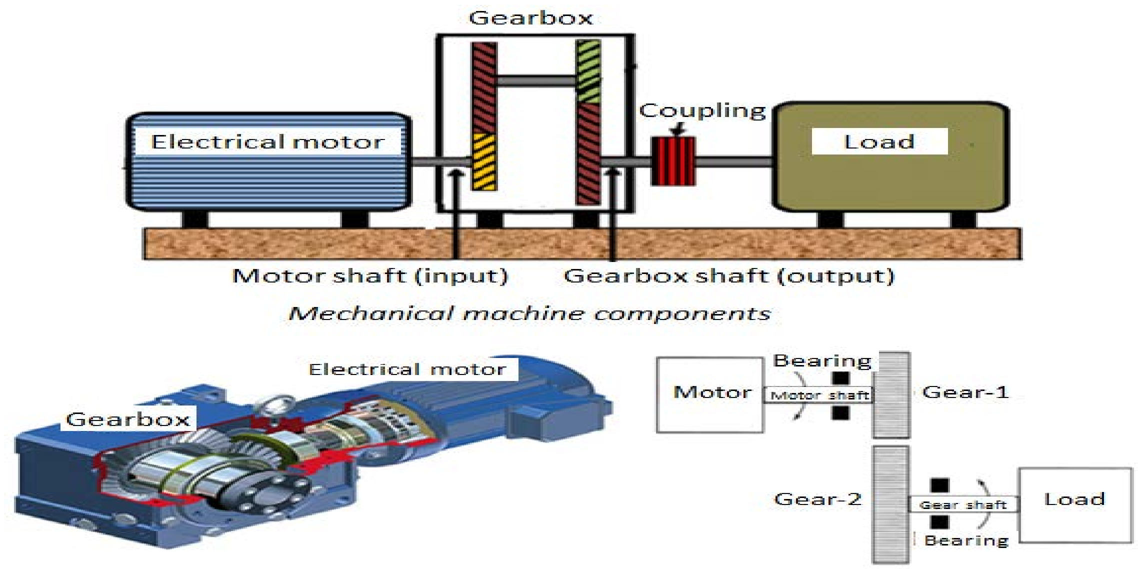

FIGURE 2. Schematic of gearbox connected to motor [42], [43].

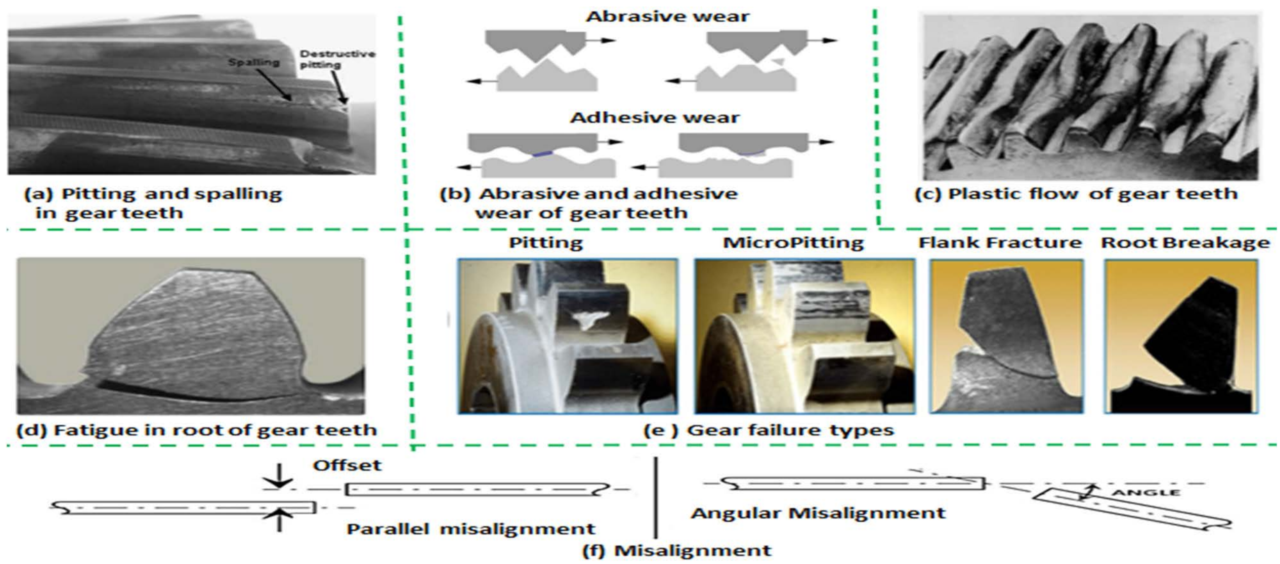

FIGURE 3. Types of gear failures [45], [46].

Connection between motor and gearbox by using coupling to produce source system can be used for operating any load shown in figure 2 [42]. Shafts, bearings, and gears are the core components of any gearbox. Rotor, bearing, stator, end plate, and wire are the motor components [43].

1) GEARBOX FAULTS

A gear drive is a component of a power system that has load characteristics unique to the application. The gear drive package is a subsystem within the overall system, and it is subject to additional load changes generated or contained within it, in addition to conveying the overall system's load demands [44].

Surface fatigue (pitting, and spalling), wear (abrasive, and adhesive wear), plastic flow (cold flow, wire edging, and peening), and breakage (fatigue in tooth root) are the most faults appeared in gearbox. Alignment between gearbox shaft and motor means that the shafts are collinear; they are aligned in a straight line. Shaft misalignment are classified parallel or angular as shown in figure 3 [45], [46].

2) MOTOR FAULTS

Rotor imbalance, motor shaft misalignment defect, twisted support, bearing defects, and soft foot of motor supporting are some of mechanical faults that can be appeared in the motor. Some of electrical defects of motor can be air gap, overloading, single phasing, and stator looseness as shown in figure 4 [47], [48].

B. FUZZY CONTROL SYSTEM

The classical logic theory can treat well with the discrete values (ex 1 or 0, T or F), however fails with partial truth and

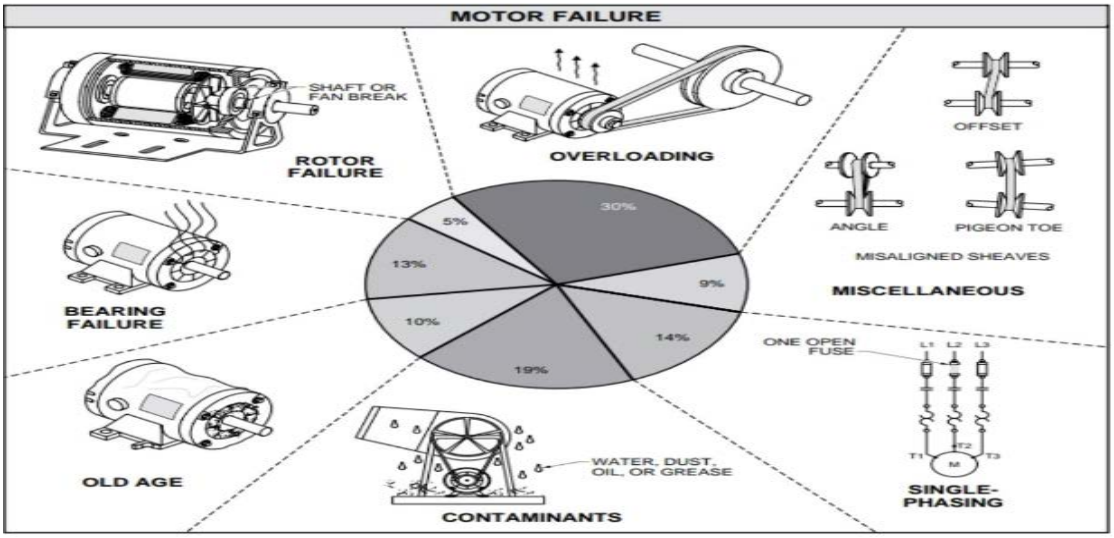

FIGURE 4. Types of motor failures [47], [48].

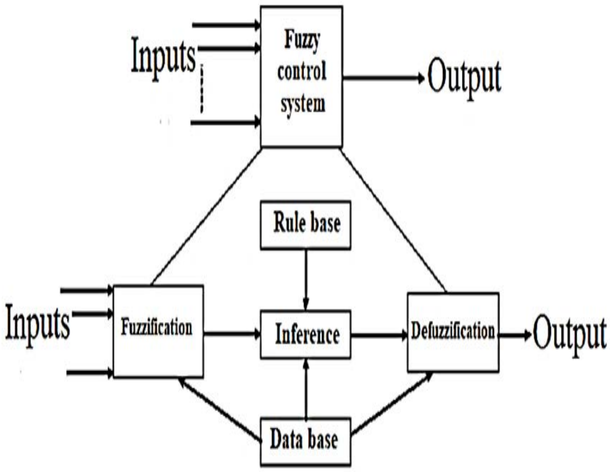

FIGURE 5. Structure of fuzzy logic controller [51], [52].

uncertainties. In contrast, fuzzy logic is a mathematical model that evaluates analog input values in terms of logical variables that take on continuous values [0,1] and deal very well with partial truth. The systems based on fuzzy logic concept are less expensive to create and cover a wider range of operating situations, making them ideal for identifying gearbox and motor issues in our objectives. The conditional statements that make up fuzzy control system are typically described using fuzzy If-Then rules [49], [50]. A comprehensive fuzzy control system is made up of four components. Defuzzification, Fuzzification Knowledge Base, Inference Engine as shown in figure 5 [51], [52].

The fuzzyfication phase turns the control inputs crisp values to fuzzy terms. This terms are defined by linguistic variables or fuzzy sets (ex: low, medium, high, short, tall, big, slow, ect..). Each term is proceeded to be assigned a value range using a membership function. The universe of discourse refers to all the various values that a variable can take. Fuzzy membership function can be triangular, trapezoidal, or other shapes according to the nature of data. The module reported in this study is implemented using fuzzy logic toolbox of MATLAB [53], [54].

C. GENETIC ALGORITHMS (GAs)

Genetic Algorithms (GAs) [55], [56], is a successful evolutionary based algorithm that is often used in a wide optimization problem. If convergence is not reached, then the algorithm keeps evolving through generations. It is a random search that is initiated by a set of stochastic generated finite string (individual). These formulate population according to population number parameter predefined. Every generation forms its population by a rate $GAP_{rs} \in [0; 1]$ of survivors from the previous generation and a rate of GAP_{rc} of individuals created by the crossover operator on the constructed individuals in the population. The fitness function drives the chromosomes selection for mating and survival on the basis of an objective criteria that assesses the quality of each candidate solution, where the higher the fitness, the more to be selected. Then, some randomly selected individuals are mutated with uniform probability $GAP_{rum} \in [0; 1]$. GAs target the exploration of the most promising presenters for the objective function as the result of the hybridization of two divergent research lines. First, it explores of the search space itself. Second, it explores of the knowledge gained during the exploration. This concludes the most promising results of the defined problem. On the other hand, the mutation operator guides the search to the unexplored parameters or areas of the search space. One drawback of GAs evolving algorithms is their tendency to fall in local minima within a complex objective function [8], [9], [54], [55]. In this paper, this problem is treated by a suitable tuning of the recombination rates GAP_{rc} and GAP_{rum}. In the following the influence and control of Gas operators:

Algorithm 1 Basic Genetic Algorithm

1. Set N = 0
2. While N < 50
3. {Generate stochastic pool population of 256 chromosomes (solution that suits solving problem)
4. Evaluate each chromosome with regarded fitness function
5. Select from the pool, based on function of fitness to construct initial population of 35 chromosomes
6. Select two chromosomes, for mating Crossover operator.
7. Apply Crossover to the pair at a randomly chosen individuals (GAP_{rc} =0.8)
8. Mutate the two offspring (GAP_{rum} =0.001)
9. Form the new population from results consequently with population size and fitness function constrains.
10. swtich (current, new) population.
11. N = N+ 1}
12. Select optimal chromosome

The population size has a direct impact on the performance of genetic algorithms. Generally, with population size greater than 30 and less than 200 individuals, an appropriate diversity and complexity of the analysis of the algorithm is reached.

The fitness function is the objective formula used to judge the suitability of every individual to represent and optimal solution for the problem. It guides the search process to obtain the most perfect solution exist. Its quality is the core value that affects the parameters of the algorithm. It copies mostly the individuals of high fitness to the next generation. However, with rarely random choice, it copies bad fitness for overbeaten falling in the local optima. Assume a population size of S, the probability defined as Ps, for individual inherit the next generation is:

$$P_s = \mathrm{P_s} = \frac{\mathrm{fit(i)}}{\mathrm{S}} \tag{1}$$

The crossover operation generates a pair of new individuals holding partial information from each parent with aim of the enhancement in the fitness function. Therefore, the probability often is set to a value between (0.5 to1.0) [9], [16], to sure that the new offspring are not identical copies from parent and hence enrich the diversity of the search space for optimality.

The mutation operation is implemented to increase diversity and prevent search stagnation by flipping a random bit of the chromosome from 1 to 0 or 0 to 1. This rarely happen in natural production; Therefore, the probability often is set to a very small value between (0.01 and 0.05) [9], [16].

D. SUPPORT VECTOR MACHINE (SVM)

Various fields of research recommended the supervised learning algorithm SVM [21] as a classifier in high dimensional spaces and availability of small samples. Basically, SVM handle binary classification problems; however, it can be modified to handle multiclass problem with different approaches. The following presents its mathematical illustration model for two-class classification. It start by detecting a hyper-plane in the space of all available inputs to split the positive samples from the negative samples. With a given data set $\{(x_i, y_i), i = 1, 2 \ldots n\}$ where $x_i \in R^n$ and y_i is either 1 or −1, the dividing hyper-plane can be expressed as:

$$\mathrm{w.x} + \mathrm{b} = 0 \tag{2}$$

where the weight vector w is perpendicular on the splitting hyper plane. The bias b controls the separation parameter increment. In the case of linearly clustered vectors, the data points will be classified by

$$\mathrm{w.x} + \mathrm{b} >= 1 \quad \forall\, y_i = 1 \tag{3}$$

$$\mathrm{w.x} + \mathrm{b} <= 1 \quad \forall\, y_i = -1 \tag{4}$$

In addition, an optimization by the quadratic programming must be used to maximize the separation 2/|w| between two classes relative to y_i(w. x + b) >=1, 1< i < n (Eq.4). The solution will reach w∗ and b∗ and hence the discrimination function is in Eq.5

$$\mathrm{Minimize}(1/2)||w||^2 \tag{5}$$

$$\mathrm{f(x)} = \mathrm{sgn}(\mathrm{w}^*.\mathrm{x} + \mathrm{b}^*) \tag{6}$$

The linear boundary in many cases of binary class is non-efficient, therefore non-linear boundary is recommended for accurate splitting by using Kernel functions (Polynomial Radial basis, Gaussian radial, etc.), see Eq.7.

$$f\,(x) = sgn\left(\sum\nolimits_{i=1}^{n} \mathrm{y_i} \propto_\mathrm{i} \mathrm{k}\left(\mathrm{x_i}, \mathrm{x_j}\right) + \mathrm{b}\right) \tag{7}$$

When applying SVM to 3 or more multiple classifications, the procedure of the decision tree levels is employed. It starts as root node, separates the categories into two subclasses, and then repeats until reach one class according to the number of classes. This procedure formulates a binary tree in each level and the SVM classifier is trained on each decision node.

IV. DEVELOPED METHODS

The Proposed dual model in this study contains fuzzy logic-based model and genetic algorithm-based model for faults identification in gear and motors based on vibration signals data. A flowchart of both models for optimal performance is in figure 6.

A. COLLECTING DATA

The data in this study is real data provided by a special monitoring and maintenance company to investigate various machinery components. Table 1 shows several types of defects in the rotating machines. This data gathered by special monitoring devices that measure the mechanical vibrations during their work. Then analyze to determine the defects and suggest treatment and repair. We collected five types of faults connected to the machine type mentioned in section of preliminary concepts of defect types, as stated in Table 1, for this analysis

B. FUZZY LOGIC-BASED MODEL

This section explains the fuzzy model structure and its implementing. Based on the nature of the collected data and

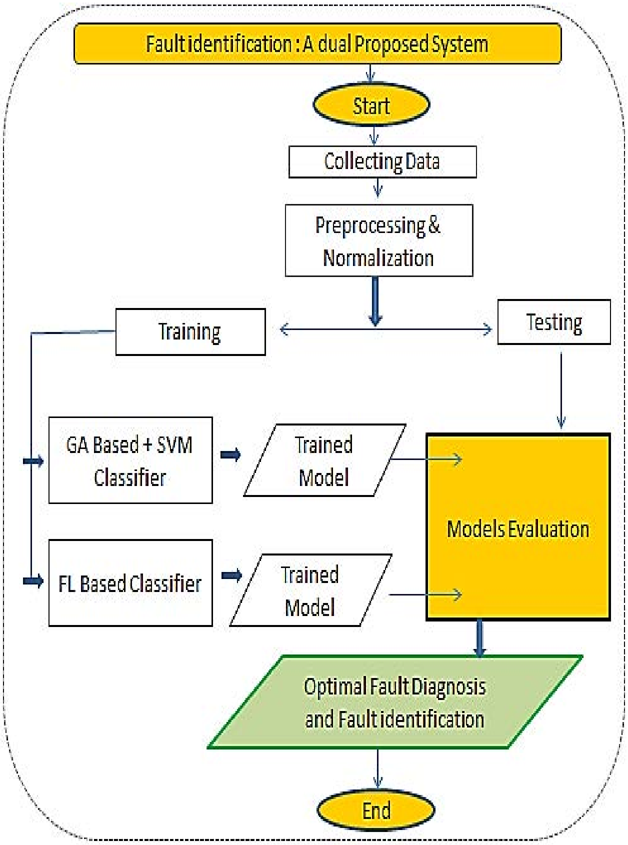

FIGURE 6. **The proposed dual models flowchart.**

TABLE 1. **Data types and defects.**

Defect Types				
Misalignment	Motor	Looseness	Bearing	Gear
PMISHV, PMISVV, P2MVV, …………	M2DEAV, M2DEHV, M2DEVV, …………	PLAV, PLHA, PLHV, ………..	BGBAVDE, BGBHVDE, BGBVVDE, ……………..	GBDEAV, GBDEHV, GBDEVV, ………..

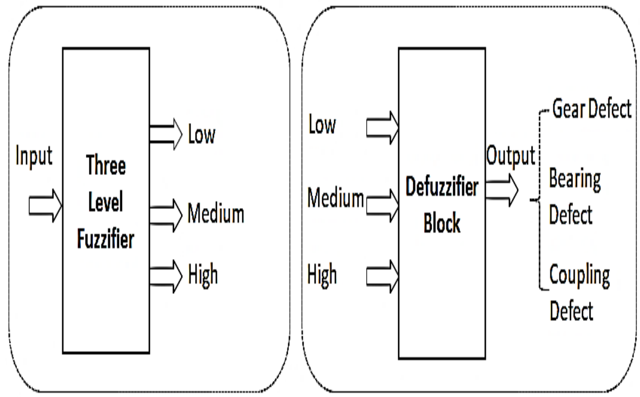

FIGURE 7. **The proposed fuzzy model two main phases, Inputs (fuzzication) & output (deffuzzication process).**

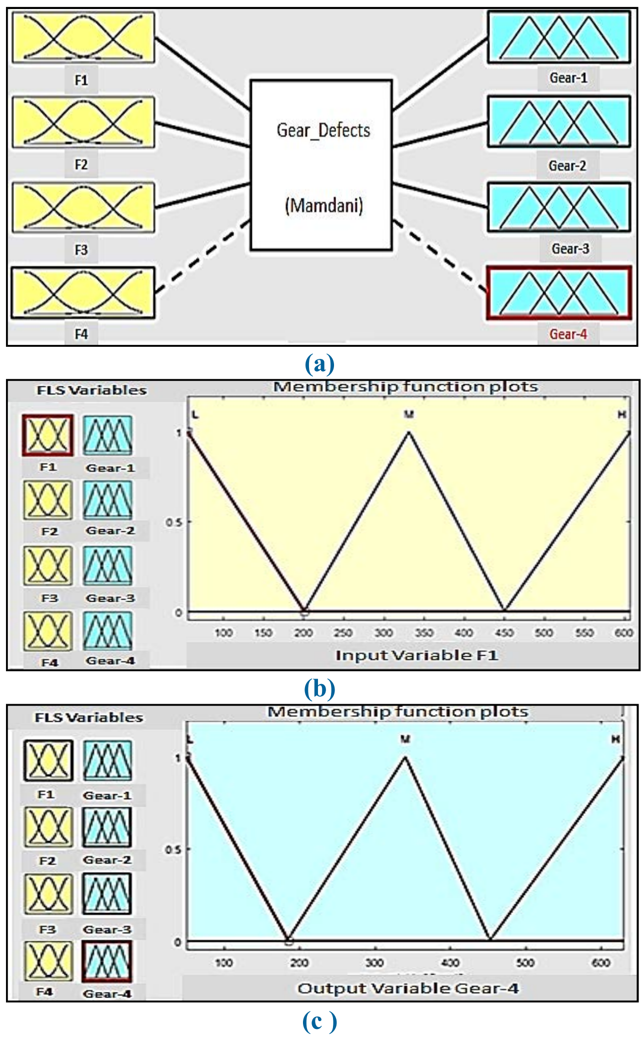

FIGURE 8. **(a) Gear fuzzy system, (b) Inputs of gear fuzzy system, (c) Outputs of gear fuzzy system.**

the two main faults categories (motor and gear); we developed two separate subsystems based on fuzzy logic. For linguistic variables in this case, we chose three fuzzy terms as low, medium, and high frequency ranges, as depicted in figure 7.

The designed gear fuzzy system for determining the faults occurrence, has three inputs and three outputs as in figure 8. Figure 8(a), shows the inputs. Figure 8(b) shows the different frequencies of all gears of gear box (Frequency range 1, Frequency range 2, and Frequency range 3). The figure also shows that the outputs are the type of fault that can appears in the gears (Bearing defect, Misalignment defect, and Gear defect) as shown in figure 7(c). Low (L), medium (M), and high (H) frequencies range of gear fuzzy system. Table 2 shows some of the fuzzy rules that implemented at frequency range to predict the type of defect of gearbox components.

The expected faults of electrical motor predicted and identified by motor fuzzy system through two inputs (frequency range1 and frequency range2) and two outputs (motor defect and looseness defect) as shown in figure9. Frequency ranges(Fr) of inputs divided to low(L), medium(M), and high values(H) as in figure 9b, 9c, and table 3.

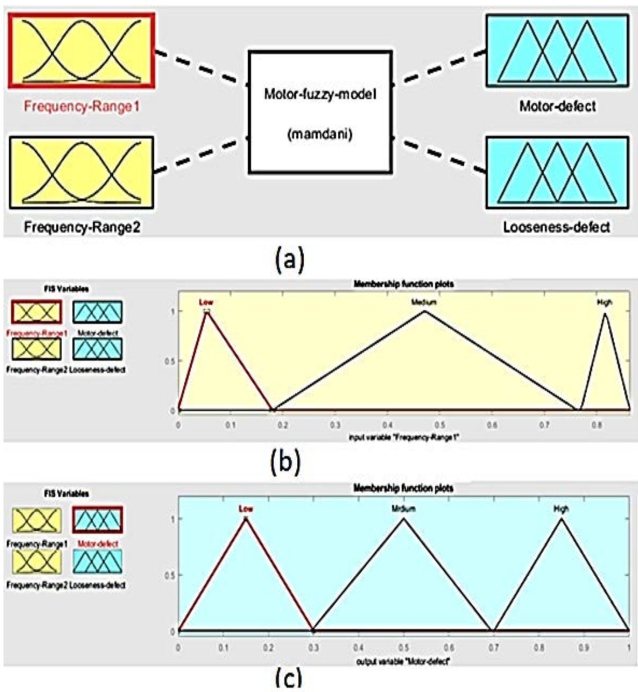

FIGURE 9. **(a) A fuzzy system for motor, (b), (c) Inputs, outputs parameters, respectively.**

TABLE 2. **Levels of gear fuzzy systems inputs values.**

Input Variables	Low	Medium	High
F1	1 - 200.8	200 - 450.2	449.7 – 828
F2	8 - 26.94	27.11 - 61.79	61 - 112.5
F3	35 - 119.6	119 - 280.5	280 - 502.7
F4	1 – 142	146 – 416	410 - 650

TABLE 3. **Exampleof gearbox fuzzy systems rules.**

If-Then rules joining inputs and output
If (Fr1=M) or (Fr2= L) or (Fr3=L) then (Bd=M) (Md=L) (Gd= L) (1)
If (Fr1= L) or (Fr2= L) or (Fr3=M) then (Bd=L) (Md= L) (Gd= M) (1)
If (Fr1=L) or (Fr2= H) or (Fr3= L) then (Bd=L) (Md= H) (Gd=L) (1)
If (Fr1=H) or (Fr2=H) or (Fr3=H) then (Bd=H) (Md= H) (Gd=High) (1)
If (Fr1=M) or (Fr2=H) or (Fr3=M) then (Bd=M) (Md=H) (Gd= M) (1)
If (Fr1=L) or (Fr2=M) or (Fr3=H) then (Bd=L) (Md=M) (Gd= H) (1)
If (Fr1=M) or (Fr2=L) or (Fr3=H) then (Bd=Medium) (Md=L) (Gd=H) (1)
If (Fr1=L) or (Fr2=M) or (Fr3= H) then (Bd=L) (Md=M) (Gd= H) (1)
If (Fr1=H) or (Fr2= L) or (Fr3=M) then (Bd= H) (Md=L) (Gd=M) (1)

TABLE 4. **Levels of gearbox fuzzy systems inputs values.**

Input Variables	Low	Medium	High
F- range 1	0.00612 – 0.187	0.14716 – 0.7634	0.77 – 0.8635
F- range 2	0 – 1.107	1.17 – 2.494	2.53 – 9.689

TABLE 5. **Examples of motor fuzzy systems rules.**

If-Then rules joining inputs & output
If (Fr1=L) or (Fr2= L) then (MOd= L) (Ld= L) (1)
If (Fr1=M) or (Fr2=L) then (MOd=M) (Ld= L) (1)
If (Fr1=M) or (Fr2=M) then (MO=M) (Ld=M) (1)
If (Fr1= L) or (Fr2=M) then (MOd= L) (Ld=M) (1)
If (Fr1=H) or (Fr2=L) then (MOd=H) (Ld= L) (1)
If (Fr1=L) or (Fr2=H) then (MOd=L) (Ld= H) (1)
If (Fr1=H) or (Fr2=M) then (MOd=H) (Ld= M) (1)
If (Fr1=M) or (Fr2=H) then (MOd=M) (Ld=H) (1)

Table 4 shows some of the fuzzy rules to predict the type of defect of electrical motor. For a simplified look for rules generated from system, Please note we will refere to Gear-defect (Gd), Bearing-defect(Bd) and Misalignment-defect(Md). Also, we will refere to Looseness-Defect(Ld), Motor-defcts(MOd). Figure 10 shows the vibration data for Multi-fault in its time domain and its corresponding FFT.

C. GENETIC ALGORITHM BASED MODEL

Genetic Algorithm (GA) is mainly recommended for obtaining the optimal feature set and removing the non-impacting features. The privilege of using GA over other methods is that it consumes less computational power. It is more robust algorithm and has efficient global searching capability. Figure 11 shows the proposed genetic algorithm-based model. In the following, the feature extraction details and the GA parameters have been stated carefully (initial population, individual evaluation, crossover, mutation), and algorithm was run for with in the acceptable range number of generations to achieve convergence.

Based on the fact that, the raw vibrational data is one dimensional time domain series data; extracting the set of differentiate the health indicator is a must. Therefore for diagnosing the motor or gear box faults, the common discriminative features include six important parameters (the root mean square (rms) (indicate the level of the defects); variance (measures of the dispersion of a waveform about its mean), Skewness (symmetry in a signal), kurtosis (check existence of peaks or flatness in sample), crest factor (check indicate rolling element or impacting in waveform) and maximum value(a second indicator for the severity of the defects)). These features represent the energy, vibration amplitude, and the time series distribution of the signal in the time domain and can be calculated from Eq.8-12. These were calculated relative to axial, horizontal and vertical directions that constitute 18 features set for each sample. All features are normalized by the corresponding absolute maximum value (of 0.0 to 1.0, except for the skewness with a range of −1.0 to 1.0) before injecting to the model. Example of the initial population individual "101001010110100100" means that features {1,3,6,8,10,11,13, 16} are activated in

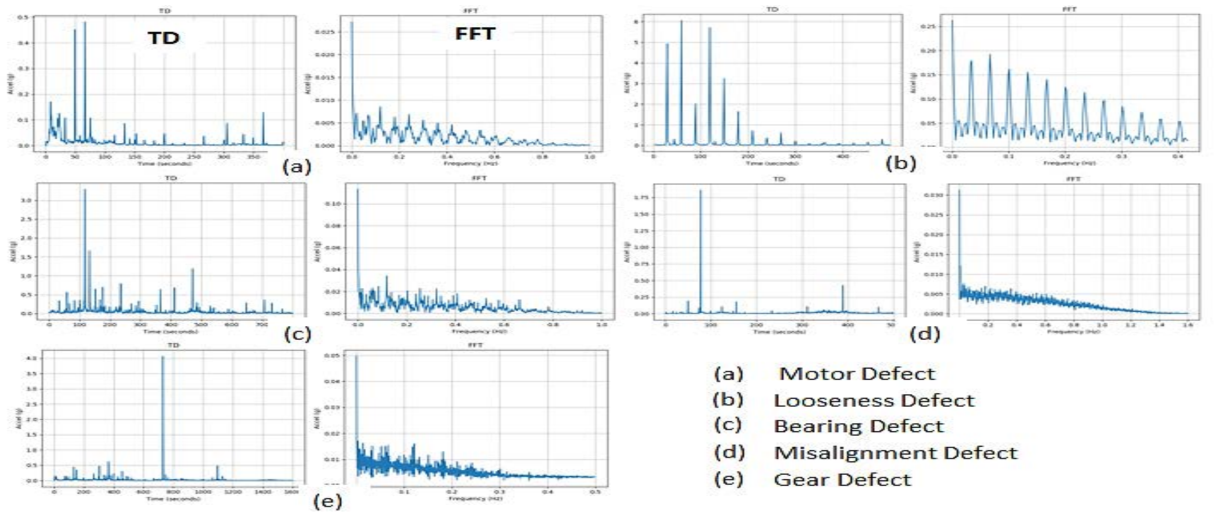

FIGURE 10. **Vibration data for multi-fault.**

this presentation and the rest are not selected.

$$\text{skewness} = \frac{\sum_{n=1}^{N} (x(n) - \text{mean}(x))^3}{(N-1)\sigma^3} \tag{8}$$

$$\sigma = \sqrt{\frac{\sum_{n=1}^{N} (x(n) - \text{mean}(x))^2}{(N-1)}} \tag{9}$$

$$\text{kurtosis} = \frac{\sum_{n=1}^{N} (x(n) - \text{mean}(x)^4}{(N-1)\sigma^4} \tag{10}$$

$$\text{crest} = \frac{\max |x(n)|}{\text{rms}} \tag{11}$$

$$\text{rms} = \sqrt{\frac{\sum_{n=1}^{N} (x(n))^2}{N}} \tag{12}$$

The genetic algorithm's chromosome representation is initialized with string of eighteen bits of 0's and 1's. These reflect the absence or existence features, respectively. The fitness function maps the outputs of the evaluation for the whole population to the fitness value of one single individual. That means the fitness is defined with respect to other members of the population. The fitness is defined as $\phi i/\phi_{av}$, where ϕ_i is the evaluation associated with individual i and ϕ_{av} is the average evaluation of all. The fitness of individual is better chosen when minimum within-class distance, therefore optimal features can be selected. The fitness value is computed relative to the sum of square error (SmSqE) of the testing data, as shown in Eq.13, where f(X) is the fitness value, $Ti\sim = \{t_1, t_2,, t_n\}$ is the value of predicted test set, and $T_i = \{t_1, t_2, \ldots, t_n\}$ is the test set. n represent the number in the test set samples. Individual with higher fitness value are being selected.

$$f(x) = \frac{1}{\text{SmSq}_e} = \frac{1}{\text{SmSq}_e(T^{\sim} - T)} = \frac{1}{\sum_{i=1}^{n} (t_i^{\sim} - t_i)^2} \tag{13}$$

Again, the fitness value obtained, control the acceptance of the new chromosomes replacement in the pool. It also ordered them where the higher stays on top for next generation. Roulette wheel algorithm is applied for this issue of best parent's selection. The new offspring are generated by single point crossover, and single point mutation.

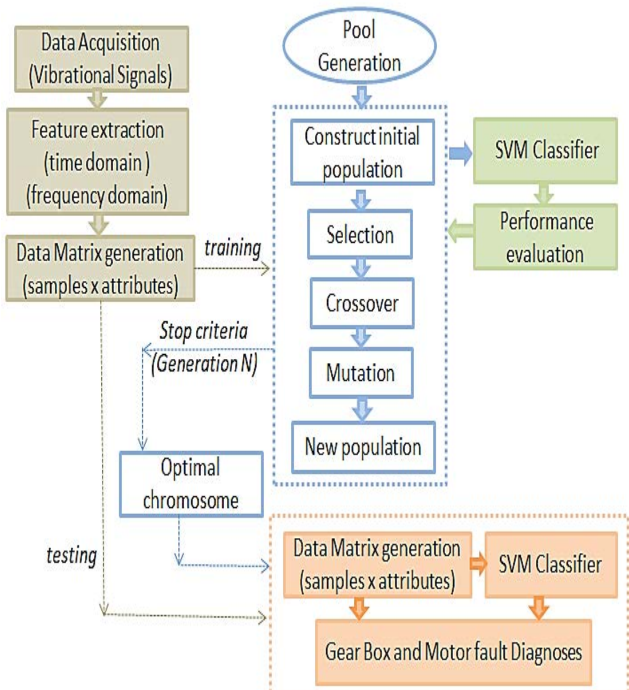

FIGURE 11. **Optimization approach for feature selection in gear box and motor fault diagnosis.**

Feature selection using GA in order to obtain most valuable features for fault diagnostics was very useful. The generation size is set to 100 (stopping criteria) and population size is set to 50. Crossover and mutation operator is being carried out at a rate of 0.8 and 0.001, respectively. For SVM parameters (C and γ) [6], [7], we set $C = 1.16$ and $\gamma = 1.817$.

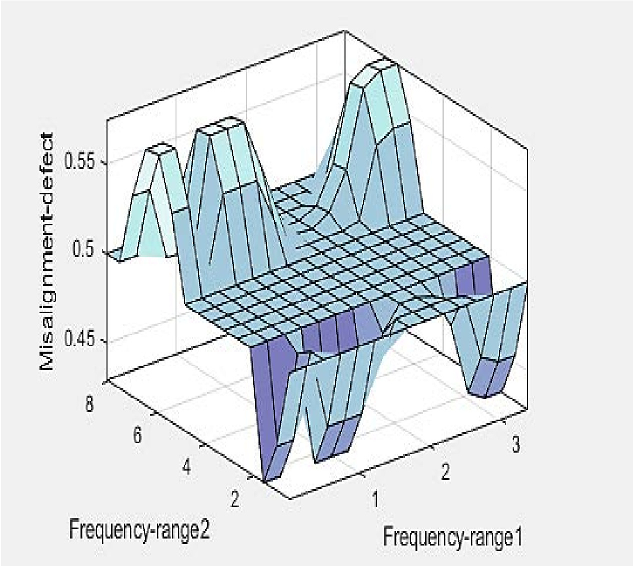

FIGURE 12. Output results of gearbox fuzzy system.

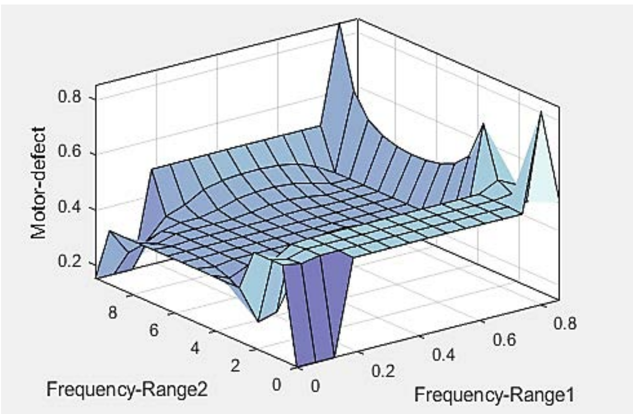

FIGURE 13. Output results of motor fuzzy system.

V. RESULTS AND DISCUSSION

In this section, the proposed models for multi class diagnosis to predict the machine gearbox and motor faults are evaluated and tested on vibration signals with five defects (motor, gear, looseness, bearing, and misalignment).

A. FUZZY MODELS RESULTS

Gearbox fuzzy system output is the gearbox fault type which change with changing frequency range of inputs. Gearbox fault types related to designed fuzzy system appeared in table 7 and figure 12 respectively. The comparison between experimentally and gearbox fuzzy model results appeared 96% accurate between them as shown in table 7. As appeared in table 9, the comparison between experimentally and motor fuzzy model results appeared 93%. Motor defect or looseness defect are the faults that identification by motor fuzzy system output. The values of frequency for each defect appeared in table 8 and figure 13 respectively.

TABLE 6. Gearbox fuzzy system inputs and outputs.

Variables	Inputs Frequency			Output Defect		
	range1 (Hz)	range2 (Hz)	range3 (Hz)	Bearing	Misalignment	Gear
	2.42	4.13	9.54	Bearing	---------	---------
	0.86	6.06	8.79	---------	Misalignment	---------
	3.29	4.41	28.3	---------	---------	Gear

TABLE 7. The values of Bearing, Misalignment, and Gearbox Defects from fuzzy system and experimental data. (Experimental data(ED), Fuzzy Result(Fr), Bearing(B), Misalignment(M), GearBox(G).)

	ED	Fr	ED	Fr	ED	Fr
B	0.0011 – 2.041	2.42	2.66 – 4.237	4.13	4.66 – 7.019	9.54
M	0 – 2.326	0.86	2.74 – 4.001	6.06	4.211 – 8.038	8.79
G	0 – 9.016	3.29	10.211 – 19.97	4.41	20.003 – 35.917	28.3

TABLE 8. Motor fuzzy system inputs and outputs.

Variables	Inputs		Outputs	
	Frequency range1 (Hz)	Frequency range1 (Hz)	Motor defect	Looseness defect
	0.18	5	--------	Looseness defect
	0.792	9.74	Motor defect	--------

TABLE 9. The values of motor and looseness defects from fuzzy system and experimental data.

Parameters	Experimental data	Fuzzy result	Experimental data	Fuzzy result
Motor Defect	0 – 0.599	0.18	1.071 – 3.0115	5
Looseness defect	0.0205 – 0.745	0.792	1.02 – 6.07	9.74

B. GENETIC ALGORITHM RESULTS

Using the vibration signal generated from the devices which represent important information to obtain the most valuable features; it is separated into samples having identical number of points (dimension). Assume the number of points in one sample as window size (W); the most popular selection of the window size is mapped to one rotation (W_r), is described as:

$$\mathrm{Wr} = 60\ \mathrm{Fs}/\mathrm{R} \tag{14}$$

where; W_s is the sampling frequency of acceleration sensor in Hz and R is the revolution per minute of the rotating machine.

Table 11 shows the training data and testing data samples based SVM performance. This procedure generated a total of 889 for the proposed model (623 for training and 266 for

TABLE 10. Summarizes the training and testing samples.

No	Class	Samples		
		Training	Testing	Total
1	Motor	133	57	190
2	Looseness	89	38	127
3	Bearing	67	28	95
4	Misalignment	178	76	254
5	Gear	156	67	223
Total		623	266	
		889		

TABLE 11. Genetic algorithm based SVM performance.

Average evaluation	MGGASVM	SVM
on training samples	98.3	95.7
on testing samples	97.73	94.1

TABLE 12. Genetic algorithm based SVM performance.

Selected features	MGGASVM	Generation no
F{1,13}	95.13	20
F{6,13,16,18}	96.6	30
F{6,10,13,16}	97.2	40
F{1,6,10,13,18}	97.88	50

testing as percentage of 70% and 30% for training and testing, respectively). All samples for training and testing are randomly selected. Meanwhile, the SVM classifier reports 95.7 and 94.1% accuracy on training and testing samples, respectively; this when built without feature selection. The accuracy increases to 98.3% and 97.73% with feature selections support of the genetic algorithm on training and testing samples respectively. Accordingly, genetic algorithm selection of the most important features reduced the dimensionally of data matrix for the classifier and enhances the classification accuracy as well. Table 11 compares the classification accuracies of SVM for different set of features reported after different generation of genetic algorithm.

The sensitivity (Se), specificity (Sp), positive predictive value (PPV) and classification accuracy (ACC) were calculated for analysis and comparison to evaluate the performance of the classifier better. These statistical indices were defined in following equations: where TP, TN, FP and FN denote true positive, true negative, false positive and false negative, respectively.

$$s_e = \frac{T_p}{T_p + T_n} \times 100 \tag{15}$$

$$s_p = \frac{T_n}{T_n + F_p} \times 100 \tag{16}$$

$$PP_v = \frac{T_p}{T_p + F_p} \times 100 \tag{17}$$

$$ACC = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \times 100 \tag{18}$$

Table 13 shows the analysis of the performance of the genetic based classifier. Based in results in Tables 11 and 12, the proposed method using the MGGASVM reported higher identification rate, with an accuracy of 97.73%, an average sensitivity of 97.73%, an average specificity of 98.62% and an average positive predictive value of 97.635%.

TABLE 13. Analysis of the performance of the genetic based classifier.

Defect Types	S_e	S_p	PP_v
Motor	97.12	99.1	97.8
Looseness	97.77	98.5	98,7
Bearing	97.7	97.8	97.0
Misalignment	98.33	98.1	98.44
Gear	97.73	99.6	97.3
Average	97.73	98.62	97.635
Acc	97.73		

TABLE 14. Comparison of the proposed models.

Default type	Fuzzy Logic (Acc)	MGGASVM (Acc)
Gear	96%,	97%
Motor	93%	97%

Table 14 represents the accuracy achieved by the proposed models for predicting the machine gearbox and motor faults. Using Fuzzy Logic, accuracy achieves 96% and 93% respectively for gear and motor faults detecting. The MGGASVM model achieves 97%. This result proves that genetic algorithm model combined with support vector machine is more efficient then fuzzy model for faults classification. So, MGGASVM appears as a best solution for optimization set of discriminative features than fuzzy model that is built as a control system to detect the faults as an automatic diagnosis technique. The proposed MGGASVM shows its higher efficiency for diagnostic performance, regarding the use of the whole set of features for Gearbox and Motor Faults identification.

VI. SUMMARY AND CONCLUSION

Two proposed models for identification of motor and gear box faults have been the subject for this work. Firstly, fuzzy logic system designed and implemented on mechanical vibration signals collected from operating gearbox and motors. In fact we built two fuzzy models for classifying gearbox and electrical motor defects. Gear fault system has four frequency ranges as inputs (F1, F2, F3, F4) with three ranges (low, medium, and high) to get bearing, misalignment, and gear defects as fuzzy model outputs. Motor fuzzy system is the second model that designed with two frequency ranges as inputs to get looseness and motor defects as outputs.

On the second hand, some necessary preprocessing for the data samples like suitable segmentation of time domain raw vibrational signal for dimensionality reduction. Also, it increased the samples number for the second proposed genetic based model. This achieved by selecting appropriate window size to increase the training data, and the features quality and hence affects the classification accuracy. Then genetic algorithm was used to construct the initial features domain based on the vibration signal sample. The main objective was to reduce the number of feature variables, and maximize the classification accuracy by the support vector machine. Accordingly, the reduced feature matrix, improved the classifier performance in terms of computational time, thus marked the presented approach as suitable for rapid monitoring and identification of motor and gear faults. In addition, in this study, the genetic based model performance was investigated extensively, whereas different conditions for motor and gears were considered and observed that feature extraction has significant effect on diagnosis results and hence, the experiments show that this method has an excellent performance for fault identification.

The simulation results concluded that, in terms of execution time (if Elapsed time results of the genetic algorithms is cx then the execution time of the fuzzy logic consumed round 0.63cx) and accuracy effectiveness; and with Fuzzy logic meaningful and powerful representation for measurement of uncertainties; the fuzzy logic is reliable, however it presented lower classification accuracy and lower generalization schema. However, the proposed strategy which combines genetic algorithm and SVM method has presented high performances in optimization and higher classification capabilities. These illustrate the effectiveness of genetic based model and show that it is recommended for identification of gear box and motor faults.

Our future research aims to adjust the proposed models to suitable different configuration of mechanical devices. The proposed models were tested using this data specifically, however to authenticate the accuracy of both models in future work and with the adjustment intended, the authors will test of different data and built different models.

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