

Research Article

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A Comparative Analysis of Artificial Intelligence-Based Methods for Fault Diagnosis of Mechanical Systems

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Abstract: The present research studied fault diagnosis of composite sheets using vibration signal processing and artificial intelligence (AI)-based methods. To this end, vibration signals were collected from sound and faulty composite plates. Using different time-frequency signal analysis and processing methods, a number of features were extracted from these signals and the most effective features containing further information on these composite plates were provided as input to different classification systems. The output of these classification systems reveals the faults in composite plates. The different types of classification systems used in this research were the support vector machine (SVM), adaptive neuro-fuzzy inference system (ANFIS), k-nearest neighbor (k-NN), artificial neural networks (ANNs), Extended Classifier System (XCS) algorithm, and the proposed improved XCS algorithm. The research results were reflective of the superiority of ANFIS in terms of precision, while this method had the highest process duration with an equal number of iterations. The precision of the proposed improved XCS method was lower than that of ANFIS, but the duration of the process was shorter than the ANFIS method with an equal number of iterations.

Keywords: Composite plate, XCS, signal processing, artificial intelligence

1 Introduction

Demand for materials with high strength and stiffness and low weight has increased in various industries since about

half a century ago. Because no single-component material could manage to meet all these needs, the composite theory was introduced. The advantage of the composite is that it reveals the best features of its constituents and has features that can be viewed in none of its individual components. Fiber composites consist of two constituents, including fiber and matrix. The fibers can be placed at the matrix in different directions, and this enhances the strength of the composite in the given direction. Defects in a composite decrease its strength, especially during loading. Therefore, it is of necessity to identify the defects, and this requires a system of higher levels of reliability and security and lower costs [1, 2]. On the other hand, following the evolution of fault diagnostics, they have been used as preventive maintenance means in recent years. Before the emergence of the conditional fault diagnosis methods, which have been used so far, fault diagnosis was defined as maintenance before system damage. However, implicit faults require a method of maintenance in which diagnosis takes place based on the measurement data. As mentioned in References [3–6], many researchers still investigate into diagnostics. In an industrial production process, insignificant errors may result in product damage, increased production costs, line shutdown, and environmental damage. The need for meeting this increasing demand has led to considerable measures for monitoring and maintaining industrial systems and detecting faults [7].

Numerous studies have been carried out on fault diagnosis in composite plates using experimental analyses. Song *et al.* [8] introduced a complete methodology based on the Laplace transform for the analysis of free bending vibrations in laminated composite cantilevers with surface cracks. They used Hamilton's principle of variation and Timoshenko's beam theory to develop the damage identification technique. Just-Agosto *et al.* [9] used the neural network model in combination with the effects of thermal and vibratory damage identification to develop the damage identification method. They used the enhanced technique to sandwich composites for crack detection. Perera *et al.* [10] applied the genetic algorithm (GA) to the multi-

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criteria optimization of damage identification. They compared the GA optimization results, which was based on the union functions, to the Pareto optimization results. Friswell *et al.* [11] combined the genetic and eigen sensitivity algorithms to locate damage in structures. They used GA to optimize discrete damage location variables. Fang *et al.* [12] explored the performance of the structural damage detection technique, which was based on the frequency response and neural network model. They studied the most expensive heuristic adaptable mitigation algorithm to improve convergence speed. They concluded that the neural network technique could estimate the damage conditions with high precision.

Beena and Gnguli [13] proposed a new fuzzy-based fault detection method for structural systems. They used continuous mechanisms and the finite element method to measure vibration parameters that cause damage to structural systems. Their proposed technique functions properly with noise-related structure damage. They also used the neural network model based on Hebbian learning to develop a damage identification system using fuzzy cognitive maps. Kuo and Chang [14] proposed a fault diagnosis system that used data acquisition, feature extraction, and pattern recognition to diagnose faults in blades with the aid of double slip sensors. The feature extraction algorithm was based on the backward diffusion artificial neural network (ANN) model. The fuzzy logic technique was also used to accelerate the diffusion process. According to these researchers, the system results were extremely similar to the experimental analysis results.

Wang *et al.* [15] compared the performances of two fault diagnosis systems, namely, the recurrent neural networks and fuzzy neural systems, using two benchmark data sets. As stated, it was found that the prediction system (which depends on the future consequences and fault prediction) is more valid than the neural network fault diagnosis system in monitoring motor conditions. Pawar and Ganguli [16] designed a structural health monitoring methodology that used the genetic fuzzy system for in situ fault identification. They used the displacement and force-based measurement differences between damaged and non-damaged conditions to develop rules. They used data unions for the genetic and fuzzy systems. Extensive research has been carried out on the monitoring of the induction motor bearing in the past three decades [17]. Bearings normally demonstrate local faults in the inner rings, outer rings, or cages. The size and period of the impacts are determined by rotation speed, fault location, and bearing characteristic dimensions. Hence, Thomson and Tandon *et al.* used vibration signals to monitoring bearing health [18, 19].

Singh *et al.* published review articles on the health monitoring of the induction motors based on the current and noncurrent signals [20]. As bearing failure in the induction motors affects the stator current signal, Benbouzid used the frequency and time–frequency methods of the current signal analysis [21, 22]. Frequency methods have been widely used with the vibration and current signal analyses to diagnose faults in bearings. Lebold *et al.* used the frequency domain methods, which were mainly based on the Fourier transform, for fault diagnosis [23]. Yazici used more advanced methods than FFT such as the short-time Fourier transform to detect faults in bearings [24].

Li *et al.* [25] calculated the energy diffused around the harmonics and used the results as the input to the neural network model. Nikolaou *et al.* used the wavelet packet method to monitor faults in bearing [26]. Prabhakar *et al.* used the wavelet transform method to diagnose fault [27]. Eren *et al.* used the wavelet packet transform method (with the Coiflet4 wavelet) and the current signal analysis (with the effective value criterion) to diagnose faults in the outer ring and cage of a bearing [28]. The main part of the project is to improve the accuracy of the detection systems based on features or information added to the artificial intelligence (AI) model. Hence, the feature selection is of importance. This study was to investigate the possibility of improving the feature selection using the AI models such as ANN, neuro-fuzzy neural network, Extended Classifier System (XCS) algorithm, and Extended XCS Algorithm.

The proposed method is presented in Section 2. Section 3 deals with the laboratory experiments. In Section 4, the analysis and evaluation of laboratory findings and a method to improve the detection of defects in composite panels are discussed. Finally, Section 5 contains the findings from the study.

2 The Proposed Method (XCSN)

Machine learning refers to a wide range of supervised and unsupervised learning algorithms that aim to avoid exhaustive search in data mining and replace these time-consuming searches with intelligent methods that involve identification of patterns in data and data classification or behavioral modeling. Many data mining methods have been proposed in the past two decades. These methods use different supervised, unsupervised, or reinforcement learning algorithms to recognize and assign patterns. Classifier systems are a successful example of these methods.

In general, classifier systems include a set of “if-then” rules, each of which offers a potential solution to the prob-

lem. These rule sets are assessed gradually with the aid of a reinforced learning mechanism and are updated at certain intervals using an GA. In the course of this gradual evolution, the system learns behavior from the environment and presents proper solutions to user queries in the application phase.

The first classifier system was the learning classifier system (LCS), which was introduced in 1976 by Holland. In this system, each rule was evaluated with a criterion called “strength.” The strength of a rule would increase the proportion to its accurate responses to training problems within the framework of reinforcement learning criteria, and an evolutionary search algorithm (normally the GA) was responsible for the generation of new rules and omission of inefficient rules. At the end of the training phase, the data rules offered the relative potential for proposing acceptable solutions to new problems. However, the success of LCS depended on the selection of suitable values for system control parameters, which hinged on the experience of the system designer.

After the introduction of the LCS, other classifier systems such as the XCS were proposed. Before the introduction of XCS in 1995, these systems were poorly capable of finding proper solutions. However, since 1995, these systems have transformed into more intelligent and precise systems, and it is currently believed that XCS and its enhanced versions are capable of solving complicated problems without the need for adjusting parameters. With the emergence of the extended classifier system with continuous variables (XCSR), some of the weaknesses of binary classifier systems such as their inability to introduce certain ranges for variable values were overcome, and these systems are known as one of the most successful learning agents for solving data mining problems in partially observable environments.

In the common strategy, in training XCSR, only the fitness of rules accurately responding to training data is increased. In other words, the likelihood of participation of a rule in the new rules generation process directly depends on the response of that rule to training data, and a realistic calculation of this likelihood calls for a large amount of training data. As training data is usually limited with actual problems and it is difficult to increase the amount of data, XCSR is not effective in such applications with regards to calculation time and costs.

In the following, a new method for improving the performance and convergence rate of XCSR using limited training data is proposed.

In the proposed method, first, a limited training data set is used to modify rule properties (including “prediction,” “prediction error,” and “fitness”) using the follow-

ing relations.

$$\text{If } \exp i < 1/\beta \text{ then } P_i = P_i + (R - P_i) / \exp i, \quad (1)$$

$$\varepsilon i = \varepsilon i + (|R - P_i| - \varepsilon i) / \exp i$$

$$\text{If } \exp i \geq 1/\beta \text{ then } P_i = P_i + \beta (R - P_i), \quad (2)$$

$$\varepsilon i = \varepsilon i + \beta (|R - P_i| - \varepsilon i)$$

$$\text{If } \varepsilon i < \varepsilon 0 \text{ then } k_i = 1 \quad (3)$$

$$\text{If } \varepsilon i \geq \varepsilon 0 \text{ then } k_i = \beta (\varepsilon i / \varepsilon 0) - \gamma \quad (4)$$

$$F_i = f_i + \beta \left[\left(k_i / \sum k_j \right) - f_i \right] \quad (5)$$

where β is the learning rate, εi denotes the rule strength, $\exp i$ shows the prediction error, P_i is the rule prediction, R is the environment reward, k_i is the rule precision, and f_i stands for the rule fitness. The index i shows the rule number in the rule set. In the next step, to increase the diversity of the data sets, the “remainder random selection” is used to select several pairs of parents from the strings showing the condition section of the existing data. The condition section of the new data is created using the crossover method applied to the parent strings. In this method, the value of each conditional variable is obtained using the following relation:

$$a_i = \alpha (a_i F) + (1 - \alpha) (a_i M) \quad (6)$$

where a_i is the i -th conditional variable in the new data set, $a_i F$ is the i -th conditional variable in the first parent (father), $a_i M$ is the i -th conditional variable in the second parent (mother), and α is the parent’s participation coefficient, which is determined with an adaptive method. The new data performance section is also generated using the nonlinear mapping of the conditional variable space to the performance space using the existing data. Diversification of the existing data continues to satisfy the learning cessation condition (e.g., until the percentage of accurate solutions to the test data reaches a predetermined threshold) using the completed data. The text is to be typeset in 10 pt Times Roman, single spaced with baselineskip of 13 pt. Text area (excluding running title) is 5 inches (30 picas) wide and 7.8 inches (47 picas) high. Final pagination and insertion of running titles will be done by the publisher. Number each page of the manuscript lightly at the bottom with a pencil.

3 Laboratory Experiment

The mechanical properties of composite materials can be greatly reduced in the presence of defects and flaws. Although delamination and fiber defects are the normal consequences of hitting, the composites can also experience degradation because of inclusions. Non-detection of such defects may be caused by the point that the defects are not sensitive enough to conventional features of time domain such as peak amplitude and signal amplitude. Furthermore, there would be some problems when the properties of the substrate and bonding material have similar acoustic impedance. In this section, to diagnose faults and classify the composite plates a healthy, a slightly defective, and a moderately defective composite plate were used along with a composite plate with a separate location fault as shown in the Figure 1.

In the slightly defective composite plate (Figure 1b), in addition to the composite layers, a thin layer is embedded in the marked section of the composite plate. Similarly, in the moderately defective composite plate (Figure 1d), the same process was completed using a larger layer. In the composite plate with the separate location fault (Figure 1c), the layer was embedded in another part of the composite plate.

To obtain the experimental data and vibration signals, vector data sets were used. The data sets contain the following items:

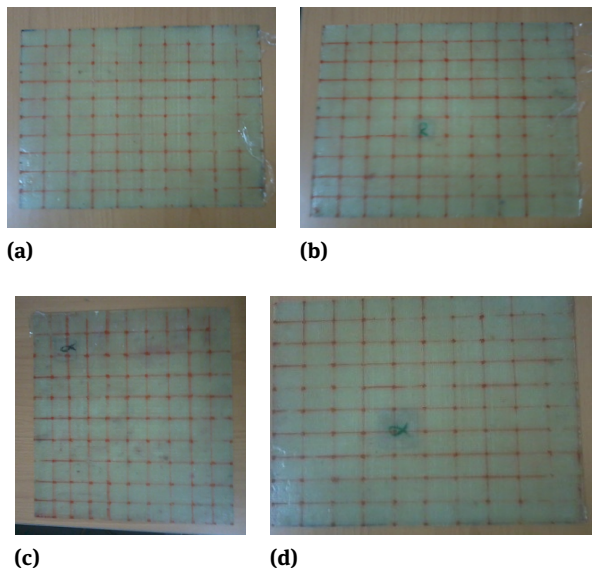


Figure 1: (a) Healthy composite plate, (b) slightly defective composite plate, (c) a composite plate with a separate location fault, and (d) a moderately defective composite plate

1. Defective and non-defective composite panels of the same length and width
2. Four-channel pulse data logger (Model c3560)
3. PULSE Lab Shop Software manufactured by B & K Company
4. ENDEVCO accelerometer (Model C2222)
5. Composite panel stools
6. Hammer RION (Model PH-5120463)

As specified in Figures 2 and 3, one of the four inputs connects the pulse data logger to a single-axis accelerometer, which simultaneously performs data logging with a specified frequency range, and connects another input to a hammer embedded for hitting. Vibration signals with a sampling frequency of 800 Hz have performed sampling for 8 s for all composite panels. In this study, the acceleration signal is used in the Z-direction that is perpendicular to the composite panels.



Figure 2: 2 B & K data logger

In this procedure, each composite plate is connected to a metal stool using an elastic string (Figure 4). An ENDEVCO 2222c accelerometer was installed for all of the 45 points marked on all of the composite plates. A special hammer was used to hit a part of the composite, and the recorded signal was displayed on the computer screen. This procedure was repeated three times for all of the points. Afterwards, the signals recorded from each composite plate were saved in a separate file.

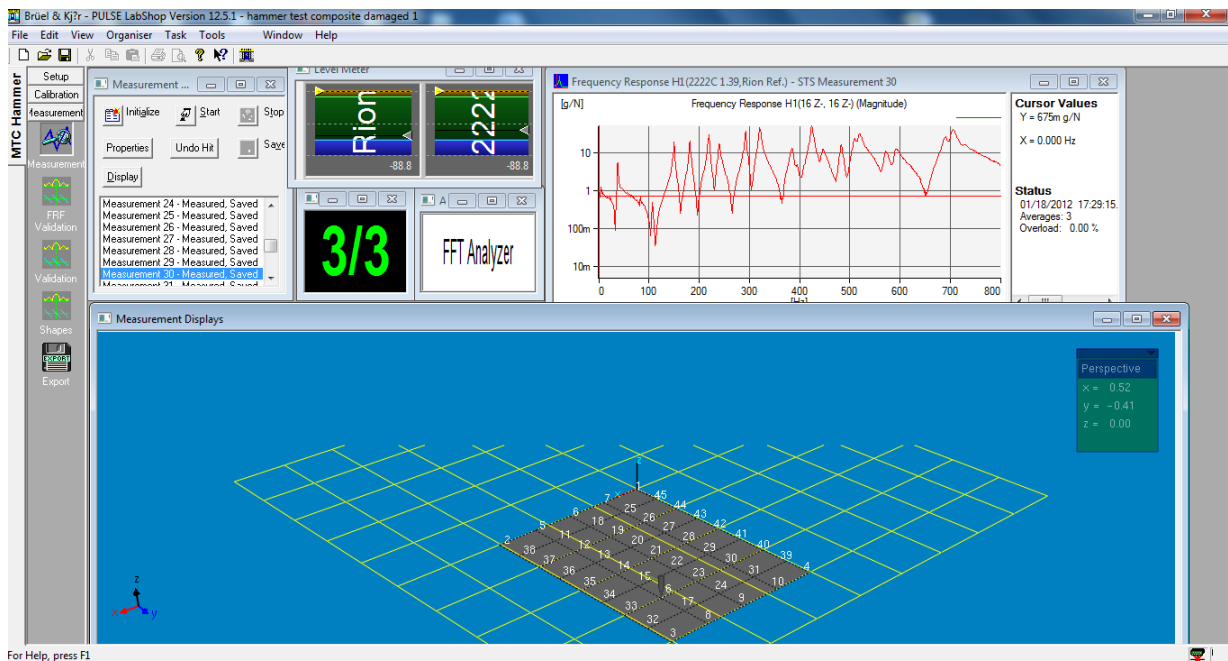


Figure 3: Schematic of PULSE Lab Shop Software



Figure 4: A view of a vibration testing on the slightly defective composite plate

4 Analysis and evaluation of experimental results

The analysis and evaluation of the experimental results obtained in the Vibration and Acoustics Laboratory of Tehran University are described in this section.

First, the result data were preprocessed and prepared, and then the feature extraction procedure (including extraction of time, frequency, and time–frequency features) was applied to the data. The IDE algorithm and sensitivity analysis method were used to select the most effective extracted features from the data. Afterwards, the faults of composite plates were classified using XCS, adaptive neuro-fuzzy inference system (ANFIS), MLP, radial basis function (RBF), support vector machine (SVM), and KNN, and the proposed method and the results of these different classifier methods were compared at the end.

4.1 Preprocessing vibration signals

A sample of vibration signals obtained from testing the composite panels for 8 s at a sampling frequency of 800 Hz is shown in Figure 5.

As we observe, no specific information indicating their features can be achieved from the appearance of this signal and other similar signals. Therefore, there is a need to analyze them in various domains.

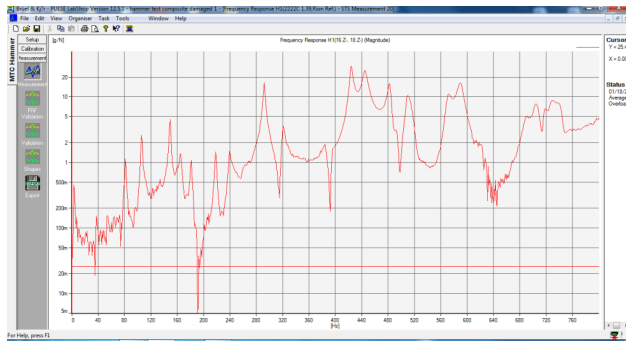


Figure 5: A sample of vibration signals

In order for the required number of data to be generated to train classification methods, averaging was carried out on all three cycles. After applying this procedure, 60 cycles of data were obtained for each of the composite panels; thus, a total of 240 data sets were created for different defects of the composite panels.

4.2 Feature extraction of vibration signals

Raw data often face problems such as noise, bias, and extreme changes in dynamic sampling range, and their use would weaken further designs. Preprocessing also consists of more complex conversions to reduce the data dimensions. To sum, it can be noted that the data preprocessing includes all conversions performed with the raw data to make them simpler and more effective for further processing operations such as classification. There are various preprocessing tools and methods such as normalization (*i.e.*, conversion of data into new data with appropriate change or distribution range), whitening (to uncorrelated the data), and reduced dimensions (to remove repetitive, irrelevant, or extra data for the classification).

In this section, the feature extraction procedures of the time, frequency, and time–frequency methods are discussed for the signals obtained in the previous section.

Of time features including the signal features in the time domain, eight features were extracted for each data cycle. Moreover, 10 features were extracted for any given data cycle from the frequency features, which include frequency characteristics of vibration signals in the frequency domain. In continuance, the existing data were analyzed up to level 3 to extract time–frequency features using wavelet packet analysis. Then, all 12 features obtained at different levels were used for feature extraction. Two features including standard deviation and signal energy were extracted from each signal. In other words, a total of 24 time–frequency features were extracted from each exist-

ing data cycle. Table 1, for example, represents the standard deviation of the signal at the third level of wavelet packet for the data cycle and different states of the composites. Evidently, this feature cannot distinguish different defects at a glance and this indicates the need for a stronger process to distinguish different states.

Table 1: Standard deviation of the signal at the third level of wavelet packet

Signal/ status	Non- defective	Defects of small size	Defects of medium size	Separate location defect
AAA3	7.534	7.160	8.91	8.91
DAA3	18.87	12.35	12.76	41.73
ADA3	23.15	20.83	18.14	14.73
DDA3	44.35	38.43	39.94	42.82
AAD3	6.754	1.32	2.64	17.24
DAD3	8.67	7.51	6.64	9.89
ADD3	32.49	29.58	25.70	22.89
DDD3	46.49	35.72	33.48	38.59

4.3 Selecting features from vibration signals

As all extracted features do not contain important and necessary information and given that the volume of data provided by the discrete wavelet coefficients is extremely high and that processing these data is difficult, in general, and impossible to be applied to intelligent systems in particular, effective features then should be selected so that they provide more information about the composite state. In this respect, statistical data obtained from discrete coefficients are usually calculated and are used as the basis of comparison.

Because all extracted features do not contain important and necessary information, therefore, effective features representing greater and more significant information about various defects of the composite panels should be selected. For this purpose, one of the feature selection algorithms called IDE was used. The threshold limit of the IDE algorithm was set at 0.5 for feature selection in the time-domain method. Of eight time-domain features, only three features (namely, Kurtosis, Crest Factor, and number of peak amplitudes) had a value greater than the threshold value. The threshold limit of the IDE algorithm was also set at 0.5 for feature selection in the frequency domain method. Of 10 features, 4 frequency features, namely,

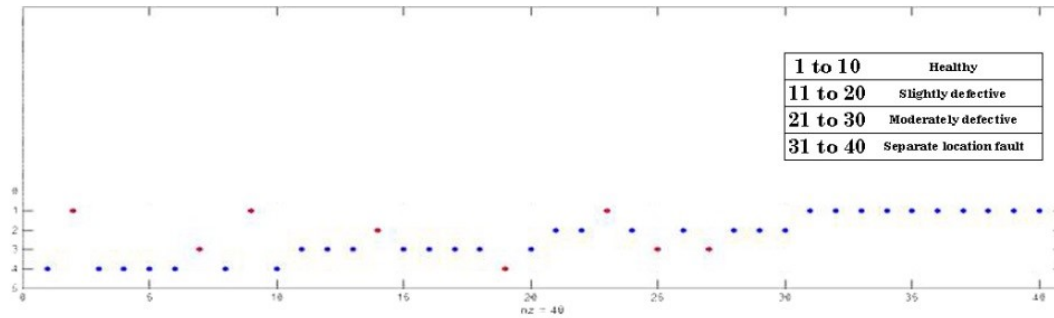


Figure 6: Classifying test data using IDE parameters and the k-NN algorithm

F3, F5, F8, and F9, had a value greater than the threshold value. Finally, the following eight features in time-frequency domain method, respectively, had the greatest threshold values above 0.5.

1. Signal SD (AAD3)
2. Signal Energy (ADD3)
3. Signal SD (DAA3)
4. Signal SD (ADA3)
5. Signal SD (DDA3)
6. Signal Energy (AAA3)
7. Signal SD (DAD3)
8. Signal Energy (DAA3)

The features of the vibration signals show that less-concerned features contained more useful information. As this number of features is large to be used for the input of a classification system and greatly reduces the speed in these systems, therefore, the IDE algorithm with the threshold limit of 0.7 was again run for 15 features selected from the previous stage. At this phase, five following features had values greater than or equal to the threshold value: Kurtosis, F8, F9, Signal SD (AAD3), and Signal SD (DAA3).

4.4 Composite State Classification

After obtaining the most effective features, the different states of composite plates were classified. As observed in the previous section, the problem of classifying composite faults is not simple, and it is not possible to classify the composites with a glance at the data. To solve this problem, different classification methods were used. The methods used in this research were ANFIS, SVM, KNN, neural network model, XCS classifier system, and improved XCS. Groupings are given in the following sections and in Table 2.

Table 2: Number of classification of composite plates

Group	Healthy	Slightly defective	Moderately defective	Separate location fault
Number	1	2	3	4

4.4.1 Classification with k-NN

The average precision resulted from 10 applications of the k-nearest neighbors (k-NNs) algorithm to the test data set for a certain number of neighbors is given in Table 3. For $k = 23$, the average precision was more satisfactory than other values.

After setting k to 23 ($k = 23$), the k-NN algorithm was applied to the test data.

As seen in Figure 6, the k-NN method failed to accurately classify all of the test data. In other words, of the 40 test data items, 32 data items are classified accurately and 8 data items are classified inaccurately.

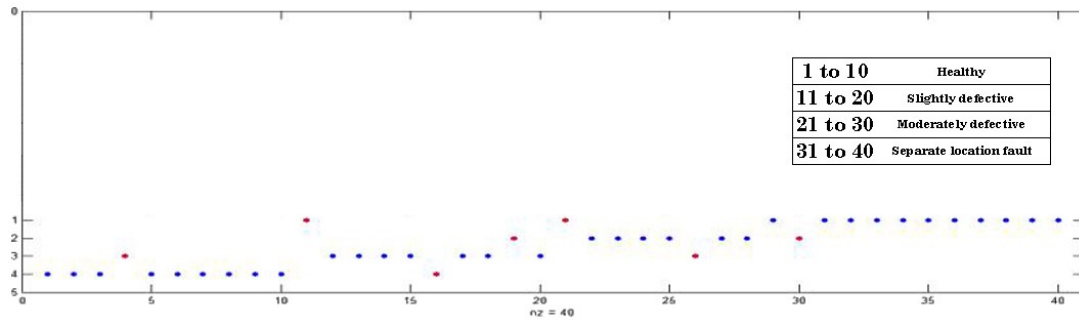
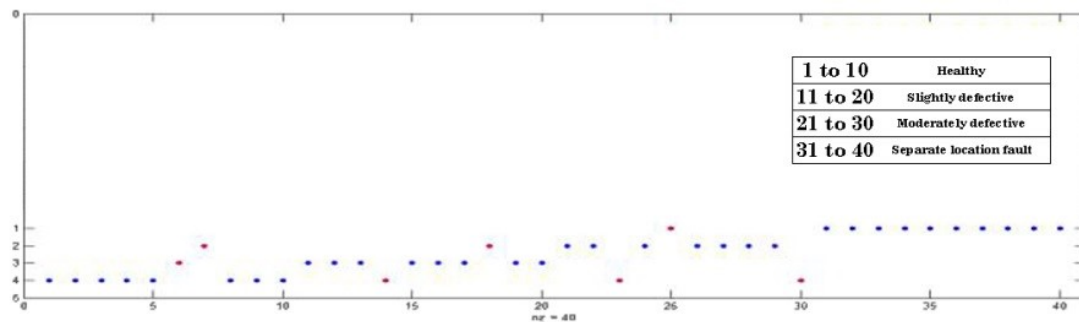
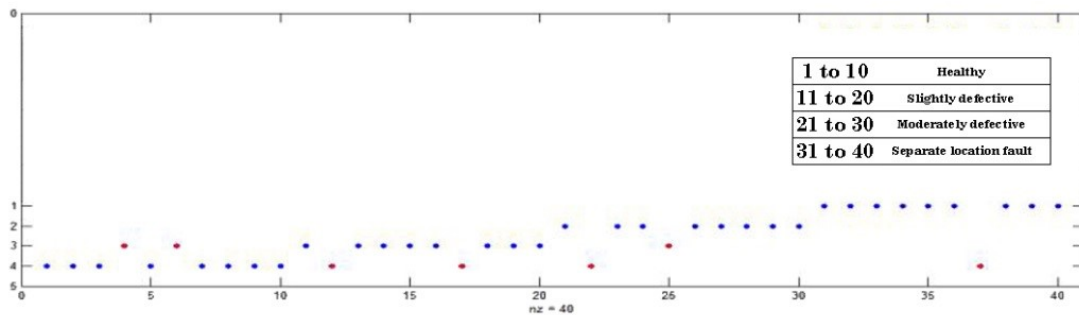
4.4.2 Classification with SVM

The data was divided into the training and testing categories. Of the 240 data items, 200 items were selected as training data and 40 as test data. The output diagram resulted from the application of this method to each test data item was prepared.

As seen in Figure 7, SVM yielded better results than k-NN, because of the 40 test data items, 33 were recognized accurately and 7 were identified inaccurately.

Table 3: k-Value average precision

K value	15	17	19	21	23	25	27
Average precision	70.2	71.4	74.8	78.95	80	79.19	78.63

**Figure 7:** Classifying test data using IDE parameters and the SVM method**Figure 8:** Test data classification using IDE parameters and the MLP method**Figure 9:** Test data classification using IDE parameters and the RBF method

4.4.3 Classification with Neural Networks

Following a trial-and-error process, the best MLP neural network was obtained with the specifications given in Table 4.

As shown in Figure 8, from a population of 40 data items, the MLP neural network recognized 33 data accurately and 7 data inaccurately, but it yielded wrong results for two classes of classification data, which is a ma-

jor weakness. For data classification in an RBF neural network, the diffusion of the RBF must be determined. This value was calculated to be 0.4 following several trial-and-error operations.

As seen in Figure 9, the classification by the RBF neural network was wrong for four data classes, and it caused a larger output error than the MLP neural network. Therefore, the MLP neural network demonstrated a better performance than the RBF neural network.

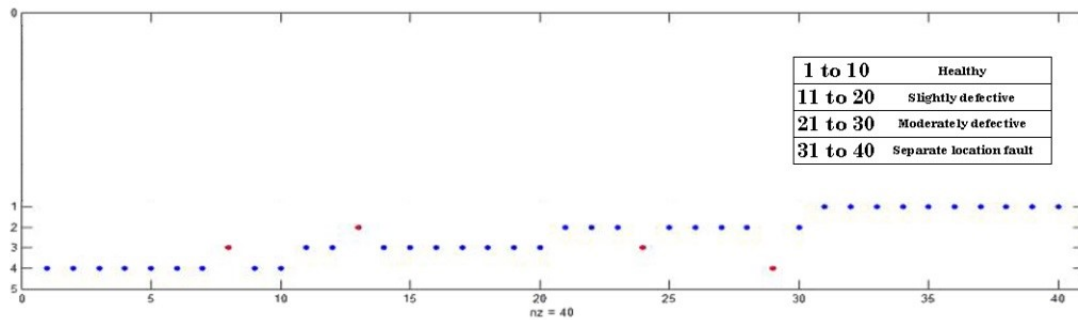


Figure 10: Test data classification with IDE parameters and the neuro-fuzzy network method

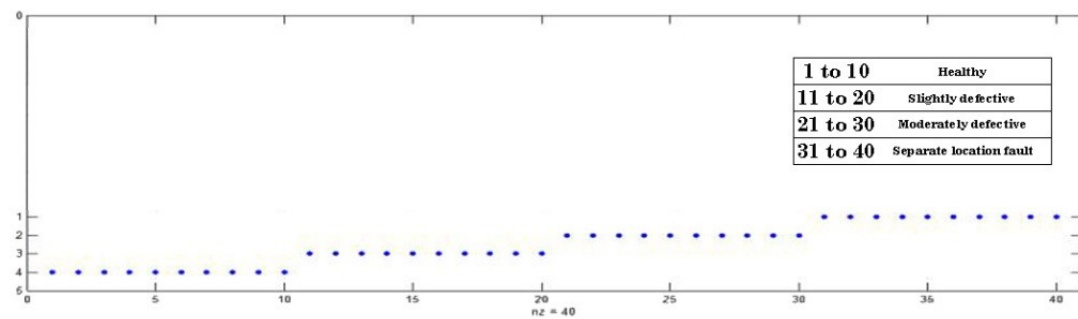


Figure 11: Test data classification using IDE parameters and the weighted neuro-fuzzy network method

Table 4: Specifications of the best neural network

Number of hidden layers	Number of neurons in the first hidden layer	Number of neurons in the second hidden layer	Number of neurons in the third hidden layer	Number of neurons in the fourth hidden layer	Prevention method	Neuron transfer function
4	8	7	10	7	Following error propagation	Hyperbolic tangent

Table 5: Weights of the input to the ANFIS network

Input no.	1	2	3	4
Weight	0.893	1	0.716	0.638

4.4.4 Classification with Neuro-Fuzzy Neural Network Method

Before training the system, first, the data was clustered using the subtractive method, which assumes 6 Gaussian functions for each input and then trains the system using a mixed training method.

After assigning weights to the network inputs, data were classified for the ANFIS network (Figure 10 and Ta-

ble 4). Figure 11 depicts the output of the new system for the test data.

As seen in Figure 11, the new neuro-fuzzy neural network recognized all of the 40 test data accurately.

4.4.5 Classification with the XCS

A total of 500 rule sets used in the XCS for recognizing the features extracted with IDE were created randomly. These rule sets included five condition sections and one result section. Of the 240 existing data items, 200 were used as training data and 40 were considered test data. After the application of this method, the output diagram was prepared for each test data item.

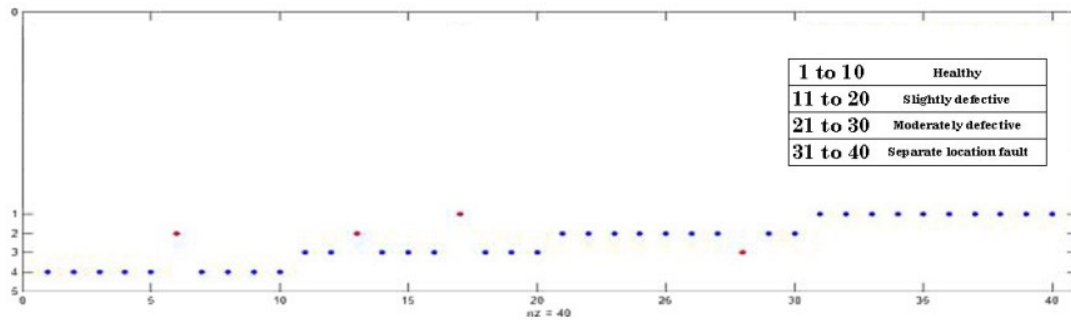


Figure 12: Test data classification using IDE parameters and the classic XCS method

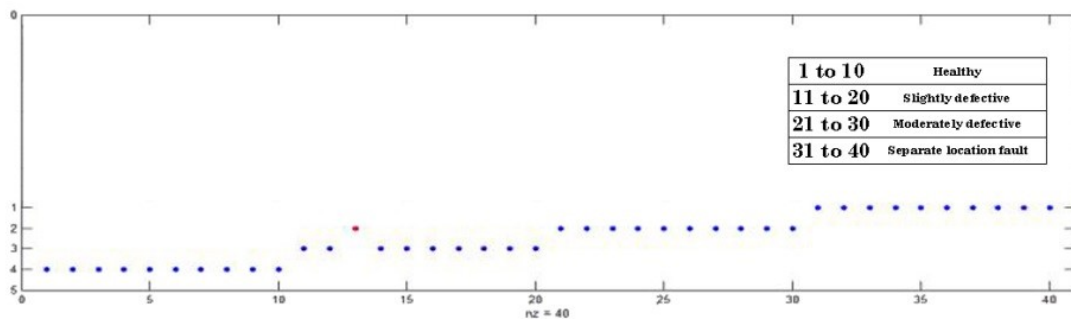


Figure 13: Test data classification using IDE parameters and the proposed XCS method

As seen in Figure 12, the classic XCS method classified all of the test data accurately. Moreover, of the 40 test data, it provided accurate solutions to 36 items and classified 4 data items inaccurately.

4.4.6 Classification with XCSN

A total of 500 rule sets used in the XCS for recognizing the features extracted with IDE were created randomly. These rule sets included five condition sections and one result section. Of the 240 existing data items, 200 were used as training data and 40 were considered test data. After the application of this method, the output diagram was prepared for each test data item.

As seen in Figure 13, the proposed XCS method classified most of the test data properly. Of the 40 test data items, it classified 39 data items accurately and 1 data item inaccurately. Moreover, as compared to the classic XCS and the neuro-fuzzy neural network, it required a shorter training and testing time.

5 Comparing Results of Fault Diagnosis System

In this section, a comparison was made between the results of different fault classification methods in terms of the computation cost and the percentage of accurate responses to test data using the two feature sets. To use experiment results of computations under equal conditions, all of the tests were carried out in laptops with a 2.4-Hz CPU and a 4-GB RAM.

As specified in Table 5, the computational cost of the KNN method compared to all the above measures is better in terms of both feature selection modes; however, the ANFIS method is the best method in terms of the correct response percentage in both feature selection modes, and with the help of the IDE algorithm, it correctly detects all classifications of feature selection. Considering both computational cost and correct response percentage, our proposed method received an acceptable percentage of correct response as well as about half of the computational cost of the ANFIS method. It is essential to note that selecting a method for classification entirely depends on the problem because the smallest percentage of error in some medical issues that are directly associated with human life cause a lot of damage. In these cases, the percentage of ac-

Table 6: Comparison of the results of classification systems in detecting defects

Method	Computational cost of the initial (selection in minutes)	Computational cost of the IDE (selection in minutes)	Correct response of initial selection (%)	Correct response of IDE selection (%)
SVM	4	5	80	82.5
ANFIS	8	10	92.5	100
MLP	4	4	85	82.5
RBF	5	5	82.5	82.5
KNN	2	2	77.5	80
XCS	5	6	85	90
IMPROVED XCS	4	6	90	97.5

curacy of a method is considered as the most important parameter. On the other hand, the computational cost may be the most important parameter in selecting a detection system. Hence, a method with the lowest required time would be used for this purpose.

As the time required for computational operations and the percentage of accuracy in engineering problems such as defect detection in composites must be acceptable, it is recommended that the proposed method is used to solve this problem.

6 Conclusions

In this research, fault detection of composite sheets using vibratory signal processing and methods based on the AI has been performed in such a way that vibratory signals have been taken from healthy and faulty composite sheets. Afterwards, using different methods of signal processing in time–frequency domain, some properties have been extracted from these signals and the most effective properties that contain more information about these composite sheets have been fed into different systems of classification, and their outputs show the fault type of composite sheet. The various systems of classification used in this research are SVM, comparative neural fuzzy deduction system, KNN, ANN, and the suggested optimized XCS algorithm. The results indicate that ANFIS method is superior concerning the accuracy, while it takes the longest runtime in the equal running numbers. It is suggested that optimized XCS method has a less accuracy than ANFIS but its runtime in the equal running numbers is shorter than the above method.

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