Journal of Robotics and Control (JRC)
Volume 6, Issue 3, 2025
ISSN: 2715-5072, DOI: 10.18196/jrc.v6i3.25698

Advanced Predictive Control Systems for Elevators Utilizing Intelligent Wavelet Techniques for Fault Signal Analysis

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***Abstract*—Elevators play a critical role in modern infrastructure, requiring robust predictive control systems to ensure safe and efficient operation. This research work investigates an advanced predictive control system for elevators, integrating intelligent techniques with Wavelet analysis for fault signal analysis. The study aims to enhance the maintenance strategies to minimize downtime and improve reliability. In recent works, the Discrete wavelet transforms with different types like, Daubechies and Symlet, were used for the purpose of decomposition. In this work, the Coiflets Discrete Wavelet Analysis (CDWA), which is classified as one of the well utilized methods for analog signals is applied for the recorded data that obtained from a simulated elevator model for the purpose of enabling the identification of subtle anomalies indicative of potential faults in elevator systems. Concurrently, AI-based intelligent techniques, represented in the use of Backpropagation Multi-Layer Perceptron (BMLP) neural network, are utilized to analyze the decomposed signals, predict impending faults, and recommend proactive maintenance actions. By combining Wavelet analysis with AI-based fault signal analysis, the proposed predictive control system offers a comprehensive approach to elevator maintenance, leading to increased operational efficiency, reduced maintenance costs, and most importantly enhanced safety. The mean square error (MSE) is used to measure the performance of the system, while the convolution matrix is used to assess the accuracy. The findings of this research contribute to the development of smarter and more reliable elevator systems, aligning with the growing demand for intelligent infrastructure in modern urban environments.**

Keywords—CDWA; BMLP; Energy Distribution; Fault Elevator.

I. INTRODUCTION

Elevators are one of the basic systems used in high-rise buildings, the high consumption of elevators may expose them to unplanned malfunctions and may stop suddenly, making the building uncomfortable to use the elevator, thus, early detection of some faults usually occur in elevator systems can help to increase the reliability and general safety [1]-[5]. The most expected and predicted faults in elevator systems are cutting cables because of their wear and tear, poly and sheave wear, power supply issues, brake system failure, sensor failures, and motor failures, AI and the signal processing methods are mostly used for the purpose of detecting these mentioned faults. One or more of the mentioned faults can be happen suddenly. The issue of elevator cable failure can stem from various factors, including environmental conditions (humidity, temperature fluctuations, and corrosion), excessive loads, poor maintenance, mechanical wear, and manufacturing defects. Additionally, improper installation, frequent high-stress cycles, and material fatigue contribute to cable degradation over time [6]-[10]. In this article, the expected and predicted faults are supposed to be relating cables holding the elevators such as steel-cable cuts during operation, cuts during riding, and cuts during cuts off the supplied electricity. In this work, a fault detection technique is proposed and suggested to be applied to an elevator system, a special simulated elevator is considered and used as an example, this chosen system is designed to operate between seven floors, and faults were meant to be as faults in connected steel-cables inside the system. The subsequent sections describe the experimental procedures and detailed methodology used in this work, results are discussed, and a conclusion is presented for the proposed fault detection technique.

A. Related Work

The increasing interest of people in utilizing automated facilities instead of doing daily physical activities, including the use of elevators in high-rise buildings, has led to an increase in the service hours of elevators. The efficiency of elevator performance varies according to its components and the type of its main elements [11]. Continuous service of elevators may expose them to malfunctions, so engineers resort to constant and periodic maintenance. Technicians perform continuous inspections of the electromechanical system and elevator operation to in-site check the main components such as steel cables, bearings, gearbox components, and motors. In the two studies presented in [12], [13], the DWT is mounted with different intelligent methods and used for fault detection by decomposing the vibrating signals due to the unhealthy work of its bearings. However, with the advancement of technology, several methods have emerged to detect elevator malfunctions in an accurate and highly efficient ways.

Faults appear as variables that express a malfunction in many cases. These faults can be identified using a mathematical model and pattern classification. Artificial intelligence has played an important role in our lives. One of the applications used with artificial intelligence technologies is troubleshooting elevators and elevator doors. Lee et al [14] used a Back Propagation (BP) neural network to fault diagnosis of the elevator door system. Many researchers proposed a Neural Network (NN) for fault detection by training and testing data samples and recall properties. The input parameters of the NN are a set of features extracted from raw sensor information. The output of the NN is then provided for a competitive network to generate a fault vector, which can indicate the normal or faulty running status messages. In [15], Zhang, H., et al. presented a combination between extension theory and the fuzzy logic to enhance and improve the accuracy and efficiency of the elevator system, the findings of the proposed methods make the presented model more accurate in analyzing the elevator performance metrics (such as speed, safety, and comfort) compared to traditional evaluation methods. Li and Ai [16] combined BP neural networks with Bayesian algorithm and used noisy input data for predictive fault elevator. Kamal Hadad et al. [17], suggested a novel method for the classification and detection of faults in a nuclear power plant by using wavelet transform and Artificial Neural Network (ANN). They used multilayer neural network BMLP with Re-current Back-Propagation (RBP) algorithm. Tian et al [18] presented methods to improve ant colony optimization to detect elevator faults quickly through the shortest path to achieve a timely diagnosis of faults. Lian Chen et al [19] suggested methods with AI to classify the faults in elevators and designed a model based on the integration of BP, Radial Basis Function (RBF), K-Means and Support Vector Machine (SVM) algorithms. Leii [20] designed a system to diagnose distributed elevator faults from mechanical wear and electrical problems by using long-term memory (PCA-LSTM). It has achieved an accuracy rate of 90%, which facilitates the process of diagnosing problems that occur in elevators. Pan W. et al [21], proposed the fuzzy methods with machine learning to assess elevator risk. The SVM model is designed for elevator risk assessment and high accuracy is achieved after adding the maximum information coefficient method, enhanced by Correlation-Based Feature Selection (MIC-CFS) method. Chahinez et al. [22] improved a method for fault diagnosis and vibration monitoring based on CDWT theory. The fault features can be efficiently extracted from the power distribution and thus the fault location can be easily found using the fast Fourier transform method [22]. Chen et al. [23], presented CDWT-based method with Convolution Neural Network (CNN) for the detection of failure situations in planetary gearboxes. A literature summary for the most related mentioned works is presented in Table I.

II. METHODOLOGY

This section, presents the Elevator System Modeling Setup, the proposed method, and the work architecture.

A. Elevator System Modeling Setup

Most of the electromechanical systems are critical for modern buildings, these systems face challenges such as mechanical failures, electrical faults, and safety risks. Traditional testing methods are costly, time-consuming, and potentially hazardous. Simulation offers a safer, cost-effective alternative for analyzing performance, optimizing control strategies, and predicting failures [24]-[29].

TABLE I. SUMMARY OF THE LITERATURE

Source, Year	Propose Method (Diagnosis Used Techniques)	Classified fault/Error
[14] 2000	Back Propagation Neural Network	Fault in Door system (Electrical Vibrated Signal)
[16] 2010	Back Propagation + Bayesian algorithm	Distorted and unhealthy data
[17] 2011	ANN+BMLP+ Wavelet + RBP	Muclear noisy power
[18] 2018	Anti Colony Optimization	Faults quickly through the shortest path
[19] 2019	SVM+ AI+KNN	Noisy and healthy Signal
[20] 2024	PCA-LSTM	Mechanical wear and electrical problems
[21] 2024	Fuzzy +SVM	Elevator risk assessment

Since collecting real data on the elevator system during different classes of faults is not always available and generating fault tests could be dangerous or destructive to the system, modeling and simulation of the system for the test setup is selected. The modeling example presented by MathWorks is utilized to build an elevator control system to test the proposed fault detection system. In this case study, the elevator system was modeled using Simscape™ Multibody™ by using blocks to represent and connect the physical components of the elevator. Various types of elevator systems with different physical components can be presented. For simplicity, the traction elevator system shown in Fig. 1. is modeled including its main elements that dominate the performance and safety of the elevator system and cause the expected possible faults [30].

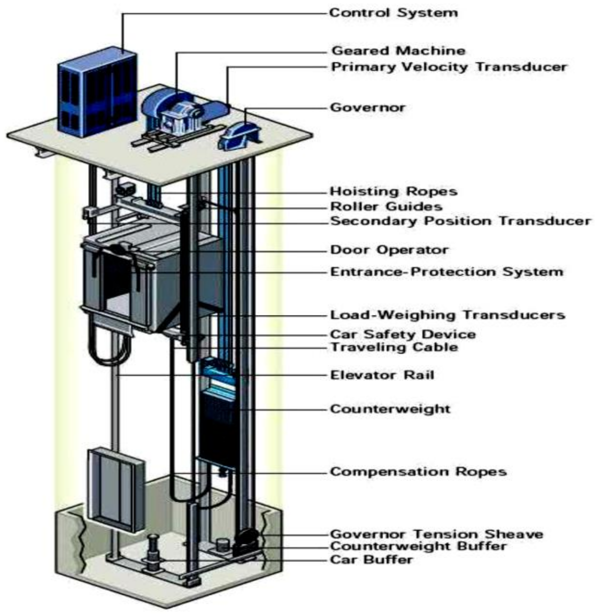


Fig. 1. Diagram of traction elevator components [30]

The main components are: the elevator cabin (car), counterweights, motor shaft and driving pulleys, steel cables, and passengers. The physical properties of the elevator system and motion information used during the simulation are presented in Table II. The values of parameters were given by the example in Mathworks and the behavior of the elevator was studied thoroughly in [31].

TABLE II. PHYSICAL PROPERTIES OF THE ELEVATOR SYSTEM FOR MODELING AND SIMULATION

Elevator cabin mass	1200 kg	Elevator constant velocity	1.5 m/s
Elevator counterweight mass	2250 kg	Elevator acceleration/deceleration	±1 m/s2
Total passengers weight	450 kg	Distance between floors	3.6 m
Steel cable stiffness value (N/m)	$K = 100\,((25.25 - L)^3 + (25.25 - L)^2 + 250)$		Damping ratio = 3000 (N.s/m)

To build or to simulate the model of the proposed elevator, the physical illustration of the system can be represented concerning impedances Zi for each element to construct the impedance diagram as shown in Fig. 2. The symbol $F.V_i$ represents the flow variable which can be torque or force while $P.V_i$ represents the potential variable which can be angular or linear velocities. All related impedances, potential variables, and flow variables are presented in Table III. This impedance diagram was presented in modeling using Multibody in Simscape library components to represent each impedance. For additional details on the example that serves as the foundation for the system modeled in this work, please refer to the elevator example available at the website link in [32]. The modeling of any traction elevator can be performed using the simplified impedance diagram presented in Fig. 2. After assigning all approximate physical properties and performing necessary validation, a set of simulations can be performed to collect recorded data for signal analysis. In the current work, validation is not performed since no specific real elevator system is modeled. However, for verification purposes, the raw acceleration data in Fig. 3 have been collected from a real-world healthy elevator system to improve the generalization of the proposed system model. This acceleration signal shows a verification of the modeled acceleration signal and system behavior.

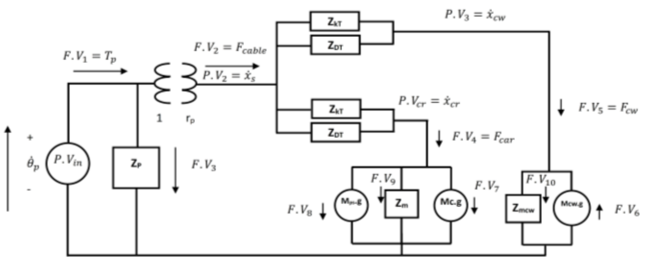


Fig. 2. The Impedance diagram of the simplified elevator system

The motion planning of the presented elevator is calculated using the kinematic equations considering the inputs: traveling distance (for a maximum of 6 levels), maximum acceleration/deceleration, and maximum linear speed of the elevator's car. In this way, the input angular speed is used to define the car velocity profile. The angular speed of the sheave can be considered fully controlled by the electrical motor. This input is the potential value of the elevator system $P.V_{in}$ to have controlled motion input while the driving torque, $F.V_1$, is computed depending on the total impedance of the system. The output of the elevator system is the car motion represented as $P.V_{cr}$ which is the linear motion needed for fault signal analysis.

TABLE III. IMPEDANCE DIAGRAM PARAMETERS

$P.V_i$	$P.V_{in}$	The input angular velocity at the motor system $\dot{\theta}_p$
	$P.V_2$	The transformed linear velocity of wrapped steel cable at the drive sheave $\dot{x}_s$
	$P.V_3$	The linear velocity of the counterweight $\dot{x}_{cw}$
	$P.V_{cr}$	The linear velocity of the car $\dot{x}_{cr}$
$F.V_i$	$F.V_1$	The applied torque at the motor system T_p
	$F.V_2$	The transformed forces into the steel cables F_{cable}
	$F.V_3$	The torque needed to overcome the inertia of the sheave
	$F.V_4$	The force transmitted into the steel cable at the connection ports of the car F_{car}
	$F.V_5$	The force transmitted into the steel cable at the connection ports of the counterweight F_{cw}
	$F.V_6$	The force related to the gravity of counterweight
	$F.V_7$	The force related to the gravity of the car
	$F.V_8$	The force related to the gravity of the passengers
	$F.V_9$	The force needed to overcome the inertia of the car
	$F.V_{10}$	The force needed to overcome the inertia of the counterweight
Zi	ZP	Related to the inertia of the motor system
	ZkT	Related to the total stiffness of six steel cables (steel cable's change in length dependent)
	ZDT	Related to the total damping ratio of six steel cables
	Zm	Related to the inertia of the car
	$Zmcw$	Related to the inertia of counterweight

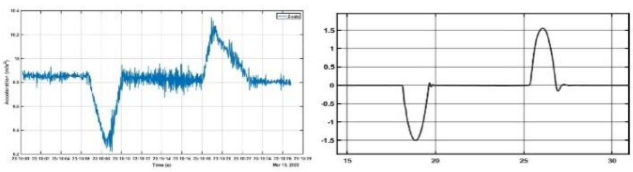


Fig. 3. The vertical acceleration data for: Left, Real-world recorded raw acceleration data from level 3 to level zero. Right, simulation acceleration data from level 4 to level 1

B. Elevator System Fault Scenarios Modeling

The proposed elevator system is modeled, simulated, and verified firstly considering a healthy work signal, other cases were presented then with varieties of supposed faulty signals; to obtain these cases, the following three scenarios have been considered and applied: First, the stiffness and damping effect of one steel cable is changed to zero for the purpose modeling a cut in one steel cable while the elevator starts moving up. Second, modeling one steel cable cut while passengers are riding the car. Third, modeling another steel cable cut while the elevator system is moving down and experiencing power cuts. The motion data are collected for the car during these three scenarios alongside the healthy case on many different floors signal analysis and classification, the signals are recorded for acceleration and velocity in vertical direction (AX, VX) and then evaluated using special feature extraction method, and finally classified using AI techniques. The modeled elevator, integrating both mechanical and electrical components, provides a comprehensive framework for fault diagnosis. By simulating potential system failures and leveraging AI-based feature extraction, it is enabled efficient identification prediction and classification of faults in real-time [33]-[36]. The proposed model not only enhances predictive maintenance but also contributes to improving overall system reliability and safety. Through this approach, we aim to advance the functionality and longevity of modern elevator systems, paving the way for smarter, more resilient infrastructure.

III. Feature Extraction

The research work is structured into two parts, the theoretical part and the practical part. Each one of these two parts is included a combination between feature extraction techniques and use of the machine learning techniques (AI based techniques) represented in the Backpropagation Multi-Layer Perceptron neural network (BMLP-NN). All the work steps are applied for a special designed and simulated elevator system. The feature extraction process is usually done for a set of data gathered and recorded from the presented simulated system. For analog representation of any signals, the data are mostly represented in position, velocity, and acceleration. In this work, two types of data signals are considered and examined: acceleration signals and velocity signals. Each of these two types of signals are represented and recorded under four cases. The discrete wavelet transform has multi types, many of them are used for continues analog signals, in this work, both the velocity and the acceleration signals are recorded for each of the four mentioned cases. The first case represented in a cut in steel cable during an electrical fault, while the elevator system moving up, the second case is represented cutting cable while riding, the third case represented by Cutting in Electricity Signal, and finally the fourth case represented in a healthy elevator work (no cutting in steel cables or electricity supplier). For each case, 3973 samples were recorded for both the acceleration and the velocity [30], [37]-[39]. As mentioned before, Different types of feature extraction methods can be used to extract the high frequencies parts of signals beside the times [40]-[42], the wavelet transform is one of these affected techniques dependent on both time and frequency to find the features. Two general types are there in wavelet transform, the continuous and the discrete types. The Discrete Wavelet Transform (DWT) is mostly used, especially when a large amount of data is used. Different filters can be used under the DWT, the most used filters are the Daubechies, Symlet, Haar, and Coiflets [43]-[47]. Each one of these filters has different types, While the mostly filters used are the Daubechies with its types and also the Symlet, and according to its adjacent properties to the Daubechies and Symlet with some differences, the proposed method include tesing the Coifelts filter and compare it with the others, as a result, the Coiflet type (CDWA) is adopted. Coiflets filter is a type of wavelet used in signal processing [48], particularly valued for their high degree of vanishing moments, which allows them to effectively capture both smooth polynomial behavior and oscillations in signals [49]. Unlike Daubechies wavelets, Coiflets are symmetric and orthogonal [50], which makes them highly suitable for tasks requiring minimal phase distortion, such as image compression and noise reduction. Coiflets are characterized by having both the scaling and wavelet functions with a minimum number of vanishing moments [51], which ensures efficient representation of polynomial signals. The wavelets in this family (e.g., Coiflet 6, Coiflet 12) exhibit more precise localization in both time and frequency domains [52], [53], making them specifically useful for tasks, like compression, and denoising in medical, industrial, and engineering applications. The CDWA can be applied using one or more than one level [54]-[56]. These levels are mostly focused on the highest frequency sections, each time (for each level), when the feature extraction process is applied, new signals are produced. The next level then has to be processed over the resulting signal from the level before. In this work, five levels were applied under the Coiflet 6 DWT, that because the 5 level is the best step gives features in compare with the 1, 2, 3, and 4 levels, and according to the complexity happened in each time of adding a level, the 5-level is selected. According to that, five signals (coming from the five level) are obtained for each one of the velocity and the acceleration, thus 10 inputs signals (2×5), are represented for four signals In other word, the ten resulted features were repeated four times (one ten for each class), whenever the output of each feature extraction level is equal to 1990 feature (output), these output will constructed from the four cases to be 4×1990 which will be equal to 7960 sample for each input to the NN, thus for each feature (1, 2, 3, to 10) four parts coming from the four classes were combined. Then finally, ten signals are constructed and used as inputs to the NN as presented in Fig. 4.

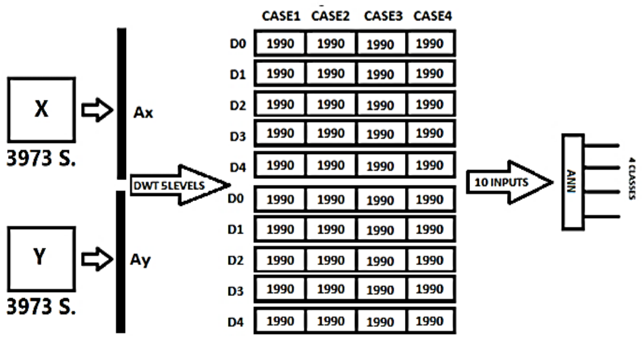


Fig. 4. Feature detection and NN input data creation

While S. is Sample, D0-4 represents the obtained data from the five levels.

IV. Result and Discussion

In this section, the experimental work and the work results will be analyzed and discussed.

A. Classification Using the BMLP-NN

As mentioned before, two parts of work are included, the first one is represented in feature extraction, while the second one is represented in classification [57]-[60]. In the classification part, the BMLP-NN [61] is applied. This technique is used for the purpose of classification [62], [63]. Ten produced data are used as inputs to the BMLP-NN, the used NN is designed here using one hidden layer with 18 neurons [64]-[68]. The selection of number of hidden layer and neurons inside it is done by check the number of neurons from one to twenty (1-20), as happened in [64]-[66]. By selecting one hidden layer and eighteen neurons, the accuracy is reached 100%. As mentioned, the input signals are generally recorded for four cases from a simulated elevator system, thus, the outputs (Targets) are designed to be four as the number of classes (outputs), Fig. 5.

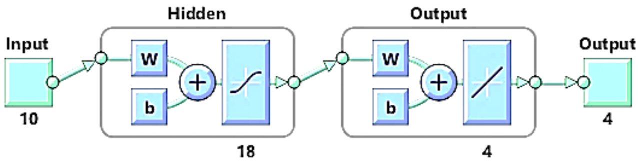


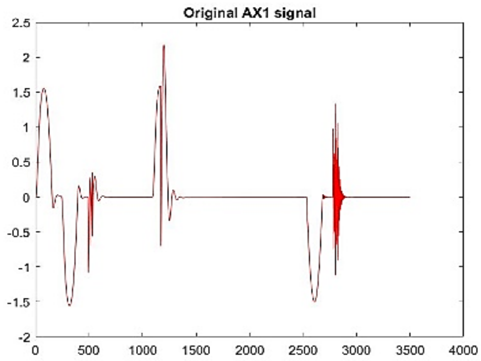
Fig. 5. The designed BMLP-NN in this work project

The recorded data set were separated into two parts, 70% for the training process, and 30% for the testing process [65], [66], all the experimental steps are done under Matlab 2020. After applying the mentioned neural network for the extracted features' signals under four supposed cases, the process is completed with 79 number of iterations, 79 number of epochs, while the performance which is calculated depended on mean square error was equal to 8.7198 X 10-15. It can be seen in Fig. 6), the recorded acceleration signals (AX), the original signal, the analyzed and CDWA signal, and the extracted five features from the five CDWA levels and the approximate signals (a, b, and c).

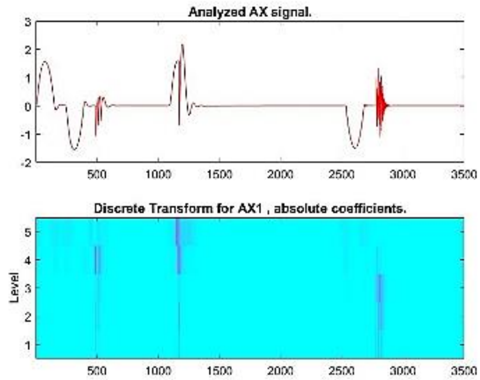
The Error histogram in neural networks visualizes the distribution of prediction errors, helping assess model accuracy and detect biases. A narrow, centered distribution around zero indicates high precision, while a wide or skewed distribution suggests poor generalization or training issues. In Fig. 7, the error histogram is calculated depending on the targets and the outputs of the used NN. The diagram of the NN performance is shown with details in Fig. 8.

The Elapsed time of the feature extraction process was 5.478 seconds, while the time of completing the process of building BMLP-NN and preparation elapsed time to complete the training process was equal to 33.047 seconds, the time that needed to complete the classification in the test part was equal to 1.335 seconds, thus the total time needed for the work including the feature extraction and the classification part was 6.814 seconds.

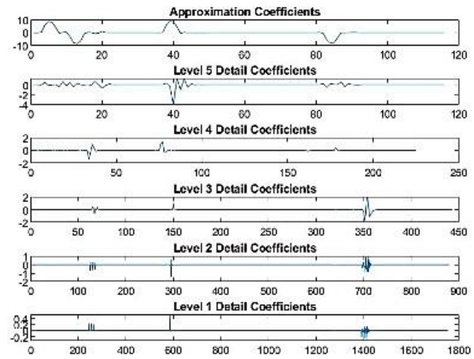
The Bayesian Regularization "trainbr", is used as an activation function in the used BMLP-NN. Regularization, Table IV, includes the details of the used BMLP-NN, includes the classified cases of the work, when using trainbr (Bayesian Regularization), functions like ReLU, Sigmoid, or Tanh help stabilize training, prevent overfitting, and improve generalization. Table V, includes the classified classes, Table VI, includes the needed times for the features extraction process, training process, testing process, and the overall needed time to complete the task process included the test and the feature extraction. The overall task time (6.814s) and testing time (1.335s) indicate a well-optimized process, ensuring quick classification. Despite the relatively longer training time (33.047s), it remains within an acceptable range for achieving high accuracy. The feature extraction time (5.478s) is also reasonable, contributing to an effective balance between computational cost and classification performance.



(a) AX Signal



(b) Analyzed and CDWA for AX



(c) Features

Fig. 6. AX signal with its features

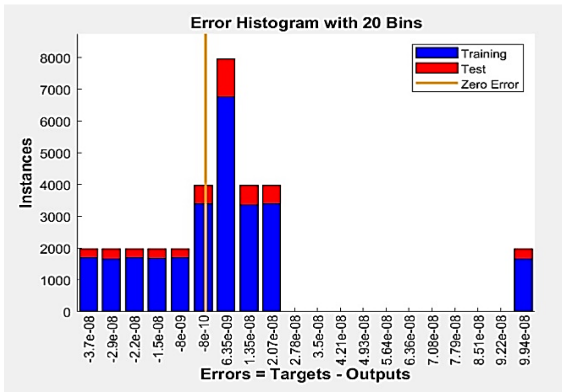


Fig. 7. Error histogram

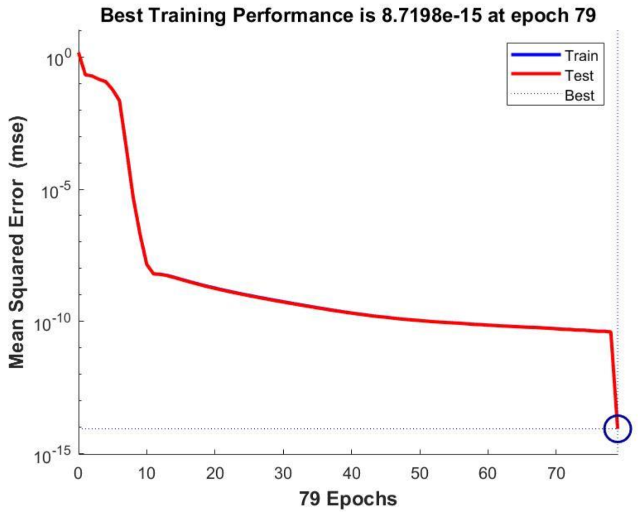


Fig. 8. BMLP-NN Performance

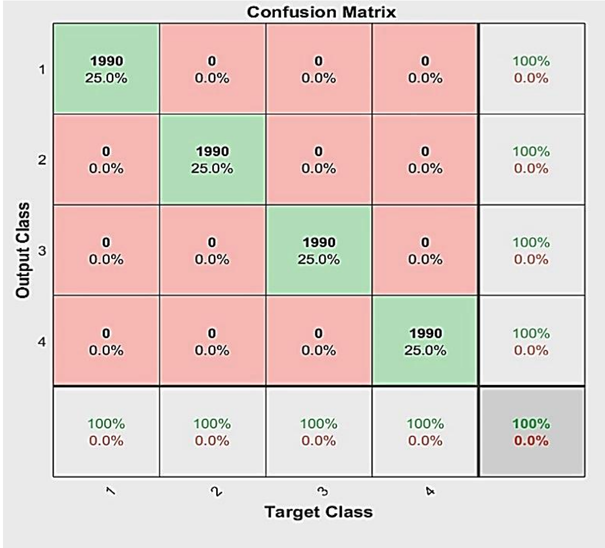


Fig. 9. Confusion Matrix

TABLE IV. BMLP-NN CHARACTERISTICS

	Characteristics	Values
1	Number of input layer neurons	10
2	Number of hidden layer neurons	18
3	Number of output layer neurons	4
4	Number of hidden layers	1
5	Hidden layer activation function	Bayesian Regularization
6	Learning rate	0.05
7	Maximum number of epochs	10000
8	Performance (MSE)	8.1798×10-15

TABLE V. THE PROJECT WORK CLASSIFIED CASES

Cases	Targets	Signal Type
1	[1 0 0 0]	Cutting in Moving Up Signal (CIMS)
2	[0 1 0 0]	Cutting in Riding Signal (CIRS)
3	[0 0 1 0]	Cutting in Electricity Signal (CIES)
4	[0 0 0 1]	Healthy Signal (HS)

TABLE VI. PROCESSING TIMES

Times	Second
Consuming task time	6.814
Testing Process	1.335
Feature Extractions	5.478
Training Processing	33.047

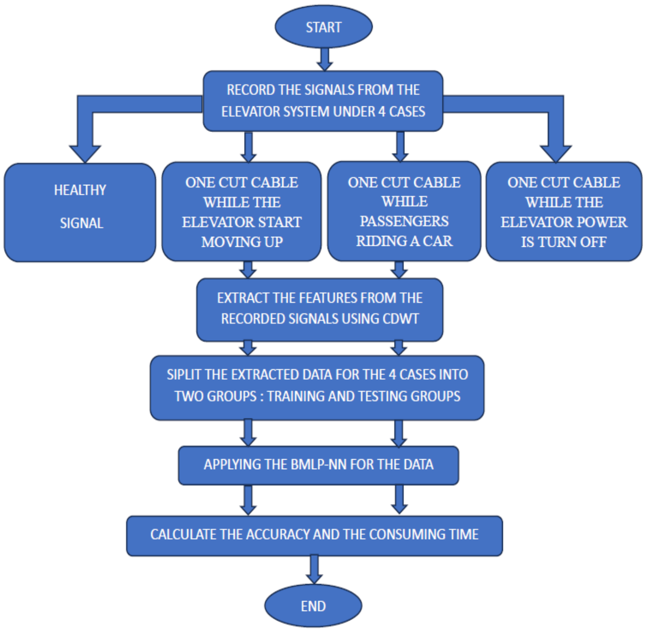


Fig. 10. Paper task steps

The obtained accuracy by applied the BMLP-NN that is proposed and applied for the features detected, was equal to 100%, the performance of the system which is assessed using the MSE is equal to the confusion matrix was used for the purpose of calculating the accuracy for the system, Fig. 9. 8,7198×10-15 using during the 79 epochs, the resulted accuracy is measured using the confusion matrix, this matrix is used for the purpose of Evaluate Filtering Accuracy – Ensures that the applied filter correctly modifies the signal. In Fig. 10, a flowchart involved the steps of the paper task.

The same procedure is applied for many sets of data, which is collected and recorded from a real and simulated robot system, the collected data are selected to have the same number of samples, four cases, and applied the same steps of features extraction and the classification methods.

V. CONCLUSION AND FUTURE WORK

The faults detection and diagnosis is applied in this work for the elevator simulated system, by considering four cases of work, three of them are included faults and errors in work, and one healthy case. According to the experimental steps applied to this simulated elevator system under the supposed cases and the provided results, the classification process that is applied using the BMLP-NN is applied for the extracted and concatenated data using CDWA, this classified data had accuracy equal to 100%. The use of CDWA with the Bayesian Regularization "trainbr activation function save the classification system from the overfitting problems. The consuming time for accomplishing the task encompassing both the feature extraction and classification processes was equal to 6.814 seconds, this time is consequently well enough when compared with those of other studies, this because the feature extraction processes are mostly complex and includes many steps can't be abbreviated. The proposed method is very robust under noisy conditions, it can be applied for elevator systems for the sake of errors or faults detection, alternatively, and based on the consuming time, the proposed method is convenient to be utilized in real-time. These findings will lead to predict the expected errors that may arise in the operation of the elevator system, in turn, this will enable the issuance of control signals to manage and address these errors, such as the immediate stopping of the elevator, increasing or decreasing the driving force as per with the outcome data.

The obtained results shown that the classification process of multi (four cases) open a new domain of work in the electromechanical systems, the error and fault detection can be discovered diagnosed, controlled and resolved using different type of features extraction methods, different types of classification intelligent methods and also the fuzzy control system is suggested to be used and compared with these methods. A deep learning system can be designed to extract and classify the signals instead of using two steps (feature extraction and classification with NN). These suggestions can be applied for many different errors or faulty signals, and also for multiple faults at instance, and it may be reducing the consuming time, the complexity, and enhance the performance of the system.

ACKNOWLEDGMENT

The authors have to thank the staff of college of engineering-University of Mosul, for their support.

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