A New Fault Detection and Classification Approach for Platform Screen Door Systems Using Artificial Neural Networks

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***Abstract*— Platform Screen Door (PSD) system, which is called a safety-critical system, is a sliding barrier door installed on the sides of a platform in many modern metros and RBT (Rapid Bus Transit) stations. Failures that may occur in the PSD system will seriously affect the availability of train transportation as well as the passenger's safety. In this study, data-driven fault detection and classification method have been studied on the PSD system to ensure the safe and reliable operation. An artificial neural network (ANN) is preferred because of its powerful capabilities. Different operating conditions (normal and faulty) were created artificially on the PSD and the motor current, motor voltage, and door speed signals were used as input dataset. Datasets were collected over 1000 on/off cycles and related 18 features were calculated for each operating condition. Different parameters (features, neuron numbers, and input signals) were investigated and performance metrics such as accuracy, sensitivity, and precision were calculated comparatively. According to the results, ANN with three layers (input-hidden-output) and the number of neurons 12-9-7, respectively, show the best performance. In addition, the highest accuracy value (%97.1) is obtained when the motor current and motor voltage are taken together as the input signal. Consequently, it is observed that the ANN structure is a useful AI tool in fault detection on the PSD system.**

Keywords— Platform Screen Door (PSD) system, fault detection, fault classification, artificial neural network, data-driven approach, motor current,

I. INTRODUCTION

Due to rapid urbanization, big cities around the world are constantly struggling with air pollution and traffic congestion. Therefore, easy and reliable transportation, especially the metro, plays a very important role in reducing traffic congestion and air pollution. Due to the higher speed of the next-generation trains and their autonomous transportation systems, using the Platform Screen Door (PSD) system has become a basic requirement in the last two decades [1]. PAKS structures are defined as sliding door system that acts as a barrier between the passenger and the vehicle at many modern metro stations [1] and many RBT (Rapid Bus Transit) stations [2]. PSD systems are called safety-critical systems in terms of their functionality, and they serve many functions in railways such as optimization of station energy consumption, air quality control, suicide prevention, and safety by protecting passengers from access to train tracks [3].

The PSD system not only creates a barrier between the platform and rail but also ensures the safe boarding/departure of the train trucks. For this reason, the PSD system for metro stations is rapidly spreading and being used today. Therefore, especially in the last ten years, different studies have been carried out on the PSD system. These studies mostly focus on the impact of the PSD system on the environmental conditions of the station [4-6], the air leakage of the station [7], the energy consumption of the station [8], the passenger waiting time [9], the emergency evacuation of the passenger [10], functional safety and security [11]. In addition, Simulink modelling of PSD [12] and controlling/monitoring approach of PSD system [13] have also been studied in the literature more recently. However, none of these studies are on the detection and classification of faults that may occur in PSD systems.

From an engineering point of view, condition monitoring and diagnostic tools need to be developed to comply with the requirements of safety-related standards and achieve the desired safety level (referred to as the Safety Integrity Level or SIL) [14-15]. The main purpose of condition monitoring and fault diagnosis is to detect, locate and isolate the faults as early as necessary. Especially in railway applications, being able to effectively detect and classify the faults that may occur in the systems can minimize and even prevent the downtime of transportation resulting in high availability.

Fault diagnosis methods in railway systems were categorized into two groups data-driven and model-driven [16]. In general, model-driven diagnostics uses logical and mathematical models of the monitored system, while data-driven diagnostics uses artificial intelligence models learned from available data for healthy and faulty conditions [17]. Summaries of previous studies in the literature for both approaches are given below.

The model-based approach is generally based on mathematical modeling and application studies have been carried out, especially on train door systems [18-21]. In addition, a knowledge-based ontological approach has been developed for fault diagnosis of train door systems [20]. In this approach, better semantic knowledge about the train door improved the fault detection process. Recently, Cauffriez et al. [21] have studied the bond graph methodology to construct a reference model of the train door system and then investigated the general model-based diagnosis system including fault indicators and residual thresholds in presence of train door failures. In addition, in [22], a fault diagnosis method is presented by performing principal component analysis in general process monitoring. The most important constraint in model-based diagnostics is the need for good expertise on the system being studied. Another limitation is that it is very difficult to describe systems (train door system, platform screen door system, elevator door system, etc.) containing many mechanical and electrical components with accurate and precise mathematical modeling.

On the other hand, a data-driven approach for fault diagnosis both on the train door system and on different systems was employed in the literature, unlike the model-based fault diagnosis approaches. In these studies, with the recent emergence of Industry 4.0 and the use of new digital technologies, the use of Artificial Intelligence (AI) based systems has become widespread [23]. The main limitation of using AI systems for data-based diagnostics in the industry was the inability to obtain industrial-scale data. The use of AI models in data-based diagnostics has increased significantly over time, with the increase in the quality of this data (noiseless, complete, appropriate value ranges, appropriate sampling, time/frequency domain transformations) and the acquisition of data that can express faulty situations [23]. Sun et al. [24] proposed an error detection system using machine learning models that can detect air leaks in the train door system. Pressure signal and support vector machine algorithm were used for classification. In another study, they performed fault diagnosis studies on motor current data using Bayesian network probabilistic machine learning classification models for bearing and roller faults in the train door system based on three different door movement conditions [25]. In another study, diagnosing faults in a different train door system was done with a similar model [26]. Motor vibration signals for normal operation and four different faulty operations were collected and fault diagnoses were carried out based on the Bayesian network model. In addition, more studies for fault diagnosis of train door systems based on different machine learning algorithms [27-30] and deep learning models [31-32] have been increasingly continuing recently.

Among these studies, especially Artificial Neural Networks (ANNs) structures have been shown to be very effective in fault diagnosis for real systems. There are various studies in the literature to diagnose different faults with high accuracy on real applications such as elevator doors [33], electric motors [34-35], and train door systems [31-36] using different ANN structures. However, as far as we know, no fault diagnosis method has been made for the PSD system in the literature. Considering the rapid increase in the usage of PSD systems in both metro and Metrobus stations in recent years, it is of great importance to detect possible faults in PSD.

In this study, fault detection and classification in full-length PSD systems used in the metro station are investigated by using the ANN model. For this, motor current, door speed, and motor voltage data have been collected and 18 features in total have been extracted via statistical methods for training and testing of ANN models. In addition, normal and faulty operating conditions of the PSD system have been identified and classified by using these ANN models. Figure 1 summarizes the steps applied in this study. To the best of our knowledge, this is the first report on fault detection for the PSD system.

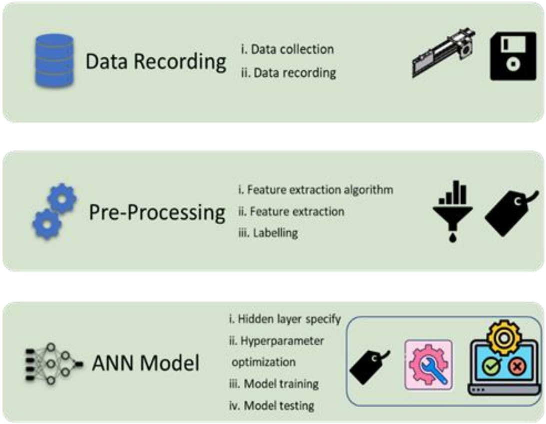

Fig. 1. The Sequential steps applied in this study.

This paper is organized as follows; Section II will present the PSD structure. Moreover, the PSD drawing, architecture, and technical properties will be discussed in detail. In section III, the Proposed ANN model with subsections will be studied. Fault detection and classification results will be presented in section V followed by the conclusion in Section IV.

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II. THE STRUCTURE OF PSD SYSTEM

A. The mechanical and electrical structures of PSD System

PSD is an integrated system consisting of many door types that perform different tasks. There are four different door types in the PSD system shown in Figure 2. These are Automatic Sliding Doors (ASD), Emergency Exit Doors (EED), Platform Ending Doors (PED), and Fixed Panels (FP). Among them, only the Fixed Panel does not have a movable door leaf and therefore does not give passenger access. While EED systems can be used for the evacuation of passengers from the train to the platform, PED systems can be used for the evacuation of passengers from the tunnel to the station. Both door systems are suitable for manual usage.

Fig. 2. Schematic drawing of PSD sliding door system

PSD sliding door system has similar mechanical and electrical structures as the train passenger access system [21], [37]. It usually consisted of several sub-systems such as the driving unit, carrying unit, control unit, and door leaf. A schematic drawing of the full-height PSD sliding door system which is fabricated by Albayrak is depicted in Figure 3.

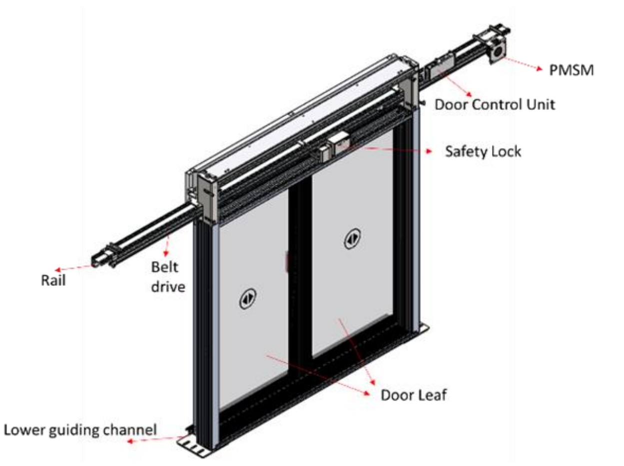


Fig. 3. Schematic drawing of PSD sliding door system

Each unit has special components in order to fulfill the related tasks. Detail architecture structure of the PSD sliding door system is also given in Figure 4. The Belt-drive assembly, which is connected to the motor and motor pulley, moves linearly along the rail. The hanging part of the door moves along the carrying rail by the carrying roller. The hanging part and carrying roller are fastened together to move linearly as a single unit along the rail. It is important to note that carrying roller is an eccentric roller to prevent door vibration during the operation. The PSD test bench is provided by Albayrak from the ALPSD-1000 series.

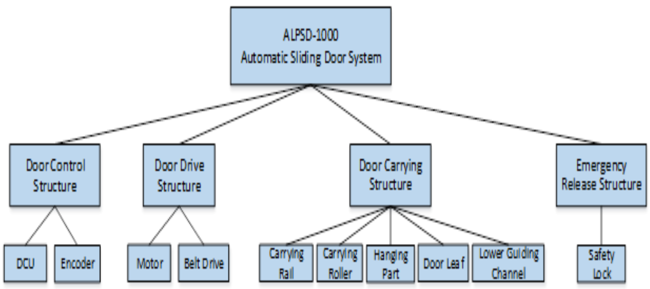


Fig. 4. The architecture of PSD sliding door system

B. PSD Sliding Door Faults and Data Acquisition

In this study, a total of seven different scenarios (including normal operating conditions) were applied to PSD sliding door system to employ ANN-based fault diagnosis. Table 1 shows these conditions, corresponding labels, and the number of data used in the study. In order to show the applicability of the fault diagnosis with ANN models on the PSD sliding door system, faulty conditions that can be artificially created easily were selected. Moreover, the likelihood ratings for this faulty status are not taken into account. In addition, each faulty condition defined in Table 1 was applied separately (individually) to the PSD system. For each case, the sliding door system was operated repeatedly with 1000 opening/closing cycles.

Table I. Operating Conditions of PSD system (normal and faulty)

ID	Operating Conditions	Number of on/off cycle	Labelling
N	Normal/Healthy	1000	0
F-1	Belt fatigue	1000	1
F-2	Belt loose	1000	2
F-3	Belt teeth wear	1000	3
F-4	Belt drive pulley teeth wear	1000	4
F-5	Belt drive pulley misalignment	1000	5
F-6	Motor pulley teeth wear	1000	6

In the literature, the electrical motor current signal has been widely used in data-driven fault diagnosis. In real systems such as electric motors [34], elevator doors [33], and train door systems [31-32], the motor current signal is acquired as a time series with a certain sampling frequency. In this study, motor current and voltage, which is typical electrical signature signals, were taken from DCU for 3 hours using MODBUS-TCP communication protocol with 20Hz sampling frequency. In addition, the speed data of the PSD sliding door during opening/closing were also collected as a function of time using DCU in the same manner.

III. Proposed ANN Based Fault Detection Approach

The proposed ANN based fault detection composed of two parts; the first part is data processing. In this part, the obtained data from the DCU of the PSD system is labelled first then the data is converted to features by applied statistical methods to obtain training and test dataset. The second part is the ANN model and fault classifier. The proposed system is shown in Figure 5 as block diagram.

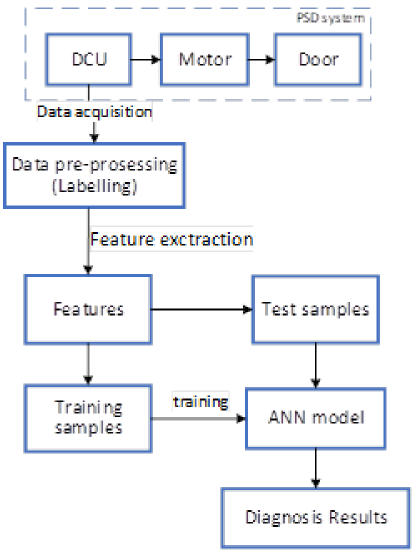


Fig. 5. The flowchart of ANN fault detection approach

In order to better understand the properties of input signals (motor current, motor voltage, and door speed) and the difference between normal and faulty operating conditions of the PSD sliding door system, the fundamental and commonly used statistical features, mean, standard deviation, skewness, kurtosis, range and RMS (Root Mean Square), are extracted from each signal as shown in Table 2, resulting in the total 18 features. The names and formulas of these time domain features are also given in Table 2.

Table 2. Feature extraction for operating conditions

Data	**Mean** $\frac{\sum x_i}{N}$	**Skewness** $\frac{\sum (x_i-\bar{x})^3/N}{SD^3}$	**Standart Deviation (SD)** $\sqrt{\frac{\sum (x_i-\bar{x})^2}{N-1}}$	**Kurtosis** $\frac{\sum (x_i-\bar{x})^4/N}{SD^4}$	**RMS** $\frac{\sqrt{\sum {x_i}^2}}{N}$	**Range** $\max(x)-\min(x)$
Current	Mean_1	Skewness_1	$\text{Standart Deviation}_1$	Kurtosis_1	RMS_1	Range_1
Speed	Mean_2	Skewness_2	$\text{Standart Deviation}_2$	Kurtosis_2	RMS_2	Range_2
Voltage	Mean_3	Skewness_3	$\text{Standart Deviation}_3$	Kurtosis_3	RMS_3	Range_3

Windowing was performed on the time series input data signals (motor current, motor voltage, and door speed) based on an open/close cycle of the door. These features given above are calculated separately for each operating state, and for 1000 open/close cycles.

Artificial neural network (ANN), similar to neuron cells, is a mathematical model that reflects human learning ability [38-39]. ANN which has a strong connection between input and output variables is a structure consisting of processing elements, inputs, and outputs. In the last two decades, ANN has been used to perform various tasks such as classification, clustering, pattern recognition, image processing, control, optimization, and modeling [39]. The basic structure of the ANN is shown in Figure 6. There are basically three layers in ANNs: input, hidden, and output layers. Depending on the complexity and nonlinearity of the problems, the hidden layer may contain a different number of layers. In theory, although ANNs can contain an arbitrary number of input and output variables, this is directly affecting the computational cost [40]. Since the number of neurons in the layers, training algorithms, number of iterations, and performance metrics can be adjusted before the training process, it can be noted that ANN is a very flexible and versatile tool [39].

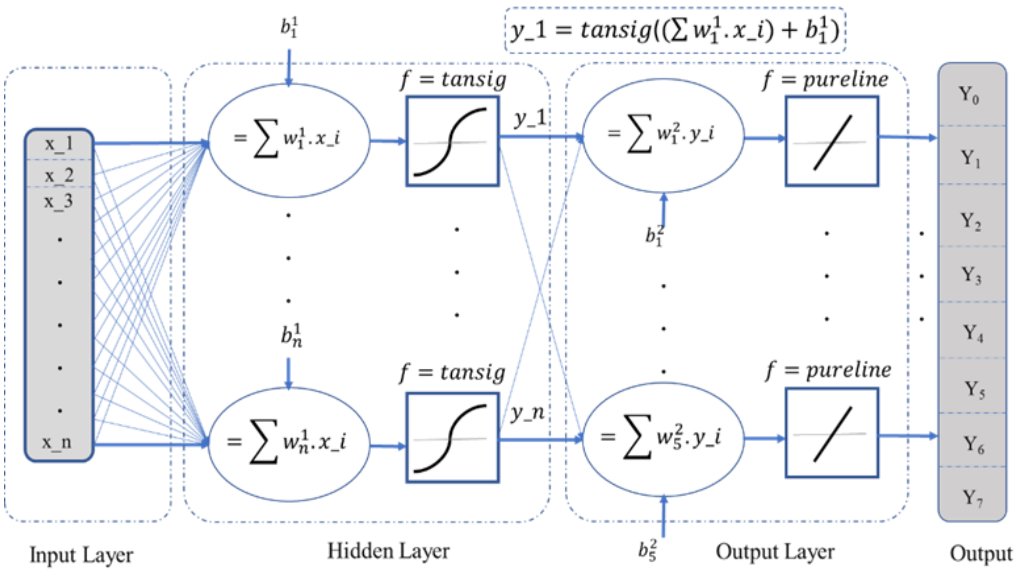


Fig. 6. Proposed Artificial Neural Network structure

Selecting the suitable ANN structure is a very important step to solving the worked problem. A single hidden layer was selected in the ANN structure used in this study. The number of neurons in the input layer is variable depending on the input signal combination (motor current, voltage, and speed). Likewise, since there are 7 different operating conditions (normal and six faulty states) in our output, 7 neurons are determined in the output layer. The number of neurons in the hidden layer was also taken as 5, 7, 9, and 12, and how the number of different neurons affected the ANN performance was investigated. Transfer functions of the hidden layer and output layer were chosen as tangent sigmoid and softmax, respectively. In addition, the learning rate of the ANN structure was 0.001 and the momentum coefficient was 0.85. For each input signal, 7000 features were calculated corresponding to 1000 open/close cycles. Then they were divided as 80:20 training and test data and used in the training and testing processes of ANN models.

There are two different approaches in ANN structures incremental and batch training [41]. Incremental training is also known as the sample-by-sample model and is mostly applied in dynamic neural networks. In this approach, which can also be applied to static networks, the weights are updated at each iteration. Although this approach involves little storage area as samples are taken one by one, the first bad sample can force training in the wrong direction. On the other hand, in batch training, the weights are updated after all the inputs have entered the neural network. This approach is also a more efficient working method for the MATLAB environment [42]. A batch training approach was used in this study.

A training algorithm reveals the decision function involved in updating the weights of the neural network. In the literature, many training algorithms have been studied for different applications. Training algorithms update the weights and biases according to different methods, making the match between input and output more accurate. It is not so easy to predict which of these training algorithms will perform the best [43]. In this work, Levenberg-Marquardt (LM) algorithm was used for training. studied. The LM algorithm is in the group of gradient algorithms and is used to solve nonlinear problems. A gradient is presented as backpropagation, which repeatedly adjusts the weights in ANN to minimize a measure of the difference between the actual output of ANN and the desired output [44]. As a result of the weight adjustments, the hidden layer performs its task better and enables the ANN to learn properly how to predict the relationship between input/output. The ANN topology used in this study is also fed forward because of no feedback in the structure.

The training process of ANN models was carried out using the input-output data sets created for training. The number of iterations (epochs) is 100 and the training error is 0.001. The optimized ANN model was then validated with the test data and the performance metrics of the model were calculated. The flow chart of these training and test steps is also given in Figure 5. In this study, a computer with MATLAB® (2018a) software and Intel Core™ i5-7200U CPU 2.50 GHz and 16 GB RAM memory was used as the computational environment.

IV. Results and Discussions

A. Performance Evaluation Metrics

The fault detection and classification performance of the ANN models are analyzed by the four-evaluation metrics such as (i) Precision (P), (ii) Sensitivity/Recall (R), (iii) F1-score (Fs) (iv) Accuracy (ACC). Precision is the fraction of the correctly classified operating conditions from the total classified operating conditions. On the other hand, Sensitivity (Recall) means how many of the actual positive operating conditions we were able to predict correctly with our model. F1-score which is a very effective evaluation metric is the harmonic mean of precision and sensitivity. The evaluation metrics explained above are determined by using the following equations:

$$Precision = \frac{\sum_i^M \frac{TP_i}{TP_i + FP_i}}{M}$$

$$Sensitivity = \frac{\sum_i^M \frac{TP_i}{TP_i + FN_i}}{M}$$

$$F1 - score = \frac{2 \times Precision \times Sensitivity}{Precision + Sensitivity}$$

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

Where TP and TN represent the number of operating conditions estimated correctly, on the other hand, FN and FP represent the number of operating conditions estimated incorrectly. M also indicates the number of classes in these formulas.

B. Experimental Results

The data sets used in this study consist of data obtained for 1000 open/close cycles and 7 different operating states (healthy/faulty) of 18 features in total calculated from motor current, motor voltage, and door speed signals. In order to reduce the effect of memorization during the training phase, the input and output data sets were mixed in the same way and the training and test datasets were created by dividing them in a completely random 80:20 ratio. The first three principal components are applied to determine the distribution of the input data set. As a result of this analysis, it is unlikely that the data set can be linearly separated.

In this study, input data signals were taken three different combinations as motor current only, motor current and door speed, and motor current and voltage. A similar ANN topology (shown in Figure 6) for these combinations was used.

In the first experiment, the motor current signal and the corresponding 6 input features were used as an input data set. As mentioned above, the number of neurons in the hidden layer is an important parameter to affect the ANN performance. Based on this parameter, performance metrics were calculated, and it is seen that 9 neurons in HL showed the best performance. It was observed that the increase in the number of neurons in the hidden layer costs a decrease in performance. In the second experiment, the input data set was selected from motor current and door speed signals resulting in 12 features. ANN structure was not changed except for the number of neurons in the input layer. Finally, in the third experiment, motor current and motor voltage signals were applied to the same network having the same parameters. Table 3 indicates all these input data combinations and related ANN layer properties.

Table 3. Optimized scenarios for performance evaluation

Experiment (input signal combination)	**Input Features**	**Input Data Set**	**ANN Topology**		
			Input layer	Hidden Layer	Output Layer
Motor current	6	7000x6	6	9	7
Motor current + door speed	12	7000x12	12	9	7
Motor current + motor voltage	12	7000x12	12	9	7

The training and test performance (confusion matrix) of all three cases are shown in Figure 7 indicating the left column for training and the right column for the test. Using motor current as input data gives reasonably good results. Adding door speed to the motor current signal for training the ANN model increases the test performance by a small amount. However, using motor current and voltage together for training was shown superior results compared to the other combinations.

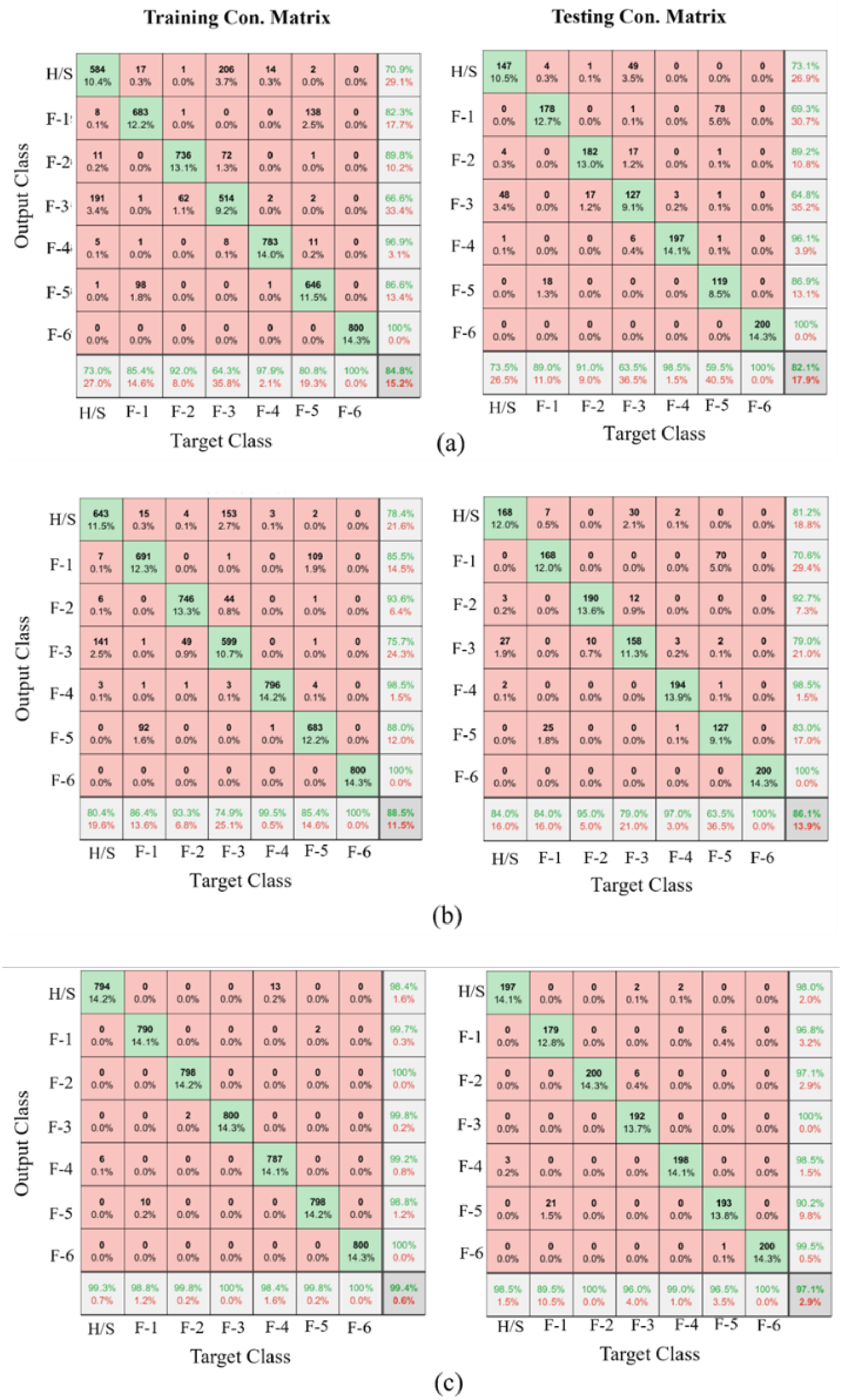
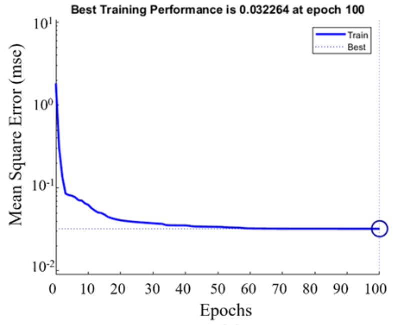
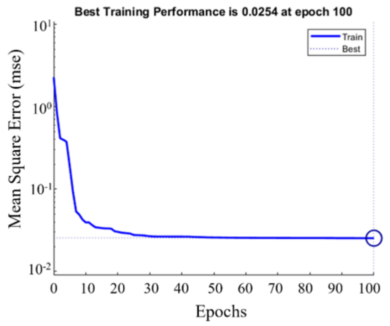


Fig. 7. Performans results (Confusion matrix) for the traning and test level of three cases

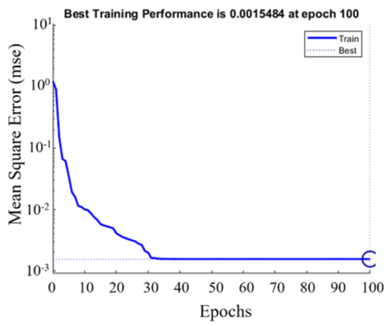
In order to understand the training performance, the change of mean square error (MSE) concerning epoch number was observed and shown in Figure 8. Adding door speed to the input features decreases the error by a small amount during the training stage. When the motor current and motor voltage are used as input signal, MSE of training for ANN model decreases more resulting better test performance.



(a)



(b)



(c)

Fig. 8. Mean square error results for the traning level of three cases

The obtained results related to the performance metrics for three cases (scenarios) was summarized in Table 4.

Table 4. Classification (performance) results of ANN model for three cases

Scenario	**Precision (%)**	**Sensitivity (%)**	**F1-Score (%)**	**Accuracy (%)**
Motor current	88,05	92,44	90,19	82,1
Motor current + door speed	90,46	94,66	92,51	86,1
Motor current + motor voltage	98,83	98,19	98,51	97,1

C. Discussions

In the literature, it has been focused on motor fault detection/diagnosis applications by using a data-driven approach. This approach is based on machine learning/deep learning models and data which is related to motor current mostly. This approach is also called motor current signature analysis (MCSA) and provides un-intrusive online monitoring for the motor. On the other hand, fault detection/diagnosis applications have been studied on various train door systems by using AI models including classical machine learning, deep learning, and artificial neural network topologies. A comparison that takes into account simulation methods, input data/signals, the number of features used to train the model, the number of classes, and system accuracy was realized between our study and previously reported works. This comparison is summarized and presented in Table 5. It can be seen that comparing the performance of the ANN model and the related works is very difficult because of the variable parameters, such as input data/signals, the number of classes, the number of input features, and simulation methods.

Table 5. Comparision of studied ANN models and previously reported works

Ref.	Methods	Application	Input signals	# of features	# of classes	Accuracy(%)
[24]	Multi-class Support Vector Machine	Air leakage fault detection on train door	Pressure signal	15	4	94.88
[27]	Multi-class support vector machine (multi-class SVM)	train plug door	non-stationary sound signals	wavelet energy entropy	8	95.52
[31]	Fisher’s discrimination, K-nearest neighbor, and convolutional neural network (CNN)	Train door system fault diagnosis	Motor current signal	13	8	99.5
[25]	Bayesian network (BN) and the information value (IV)	Fault diagnosis of a train door	Motor current	12	3	98.1
This study	ANN-with LM algorithm	fault detection of PSD system	Motor current	6	3	98.9
This study	ANN-with LM algorithm	fault detection of PSD system	Motor current + voltage + door speed	18	7	97.1

Ref [24] addressed fault classification on train door air leakage by using SVM algorithm and pressure signal. In addition, Ref [27] focused on more classes by using the same algorithm (SVM) and different features on sound signal and obtained more accuracy value than [24]. Furthermore,0 Ref [31] pointed out eight fault classes indicating similar type of faults by using different methods (classical algorithms and CNN) and different number of features on motor current signal. They reported satisfactory accuracy value over 99%. On the other hand, [25] employed Bayesion network algorithm with motor current signal for three fault classification and lower accuracy value was obtained compared to our ANN-based classification study on PSD with similar number of classes and input feature.

V. Conclusions

Data-driven fault detection and classification approaches allow continuous monitoring of systems and diagnosis of faults at an earlier stage. In this study, the sliding door system, which is the main component of the Platform Screen Door (PSD) system, has been analyzed and possible mechanical failure types have been examined using ANN models based on multiple data. ANN models, which are a more robust and efficient classifier, focused on and optimized over a different number of neurons. Experiments were carried out for 7 different operating conditions using four different ANN models. More specifically, 18 features were calculated by measuring motor current, door speed, and motor voltage signals over 1000 open/close cycles for each operating state, and the training/test behaviors and performances of ANN models were investigated. Each model was studied comparatively, considering performance metrics (accuracy, precision, precision, etc.). In this study, it was seen that the ANN structure with 12-9-5 neurons in the input-hidden layer-output layers, respectively, showed the best performance with 97.1% accuracy value. Precision, sensitivity, F1-score and mean square error values for optimized ANN model were obtained as 98.83%, 98.19%, 98.51% and 0.0015, respectively. A comparison between the results of this study and previous studies was also carried out in the discussion section.

In future studies, it will be possible to expand this work by performing using different input signals (number of features), comparing different ANN algorithms, and also by placing these ANN models on the edge device, and continuously monitoring the PSD sliding door system for fault detection.

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