Automatic Fault Detection and Classification in Lift Door Systems Using Vibration Signal Features

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Abstract. The Internet of Things (IoT) is shaping the concept of the modern intelligent built environment. The latest developments in IoT have led to secure, energy efficient systems enabling low-cost real-time analytics**.** In the Vertical Transportation (VT) technologies developed by the lift industry real-time analytics are facilitating predictive maintenance which in turn decreases operational and downtime costs. Data driven predictive maintenance does not always reach an optimal performance because the quality and quantity of the data matters. Fault classification and the estimation of the remaining useful life (RUL) requires a deep understanding of failure modes and component degradation. In lift systems, most of the malfunctions are due to faults developed by the automatic power operated door systems. The most widespread Structural Health Monitoring (SHM) sensor technology used in monitoring the door mechanisms are acoustic and vibration sensors. In this paper, an automatic fault detection system using Artificial Neural Networks (ANN) is implemented using vibration signal features. Obtained results reveal that the fault classification performance is high (>70%) under low noise environmental conditions.

Keywords: Internet of Things, Iintelligent Built Environment, Predictive Maintenance, Remaining Useful Life, Vibration Signal Features, Artificial Neural Networks.

1. Introduction

Engineering systems are designed using relevant failure criteria so that they can operate under specific loads and conditions. However, the actual behaviour of a system is not fully known until it is in service [1]. Due to unpredicted loads, the system may fail and will no longer operate satisfactorily.

The more real-time information a manufacturer has about the status of customers' equipment, the better the equipment could be maintained. Ideally, real time analytics allow the maintenance service team the detection of potential problems early enough to prevent them from even happening. Real time predictive maintenance in lift systems utilises a wealth of sensor data and advanced analytical methods to predict failures well before immediate action is taken. This maintenance approach is usually taken when high costs are incurred due to downtimes or maintenance. Real time analytics enable the estimation of the RUL of assets with increasing accuracy. Most relevant lift manufacturers such as ThyssenKrupp AG are implementing Industry 4.0 solutions enabling predictive maintenance solutions such as MAX [2].

Most of the service calls of elevators are related to the door mechanism [3]. On average, the number of opening and closing cycles of a door elevator per year is estimated to be above 100000. All these operating cycles produce a lot of wear and tear on the equipment that opens and closes the doors, especially if it is not properly maintained. A detailed study of call-back data over a three-year period in four different cities in the US has also confirmed that the door operator is the most frequent fault in lift systems [4].

Fault classification applies a data mining technique [5] for the prediction of different fault classes. It is an example of supervised learning and it requires categorical labels. Fault classification involves two steps. The first step is the learning/training step in which a classifier is built to describe a predetermined set of faults using labelled data. The second step evaluates the model for classification of unknown data such as test data for estimating the classifier accuracy. There are many classification algorithms like decision trees, K nearest neighbour, naive Bayesian classifier, support vector machines (SVM) and artificial neural networks (ANN) [6]. In this study the fault classifier is based on ANN [7].

An artificial neural network (ANN) is a computational model based on the structure and functions of biological neural networks. An ANN consists of nodes in different layers; input layer, intermediate hidden layer(s) and the output layer. The connections between nodes of adjacent layers have "weights" associated with them. Learning of neural network is performed by adjusting the weight of connection. ANN can be classified in two types: feed-forward network and recurrent networks depending on the way they channel information. The feed-forward neural network is the network in which connections between units do not form cycle whereas in recurrent neural network connection form cycles [7]. The main advantages associated with neural network are the ability to identify highly complex non-linear relationships between input and output variables without the need to understand the nature of the physical process, inferring unseen relationships on unseen data and their tolerance to noisy data [8]. ANN parallelism increases the speed of the network. However, there are drawbacks: ANN training is costly, time consuming, it plays an important role in classification accuracy and it is difficult for humans to interpret the symbolic meaning behind the learned weights and of "hidden units" in the network. There are many algorithms used for training of neural network [9,10].

2. Door mechanism

The lift (elevator) door system comprises landing (hoistway) doors and car doors. Most elevators intended for passengers have fully automated power-operated doors. The standard arrangement for automatic power operation involves a 'master' operator, a self-contained electric motor driven unit mounted on the car top. There are several different types of door configurations depending on the number of panels, typically doors range from a single panel to four panels. A review of door classification and door components is discussed in [3]. The study involves automated power-operated doors, with an electronically controlled door operator as shown in Fig.1.

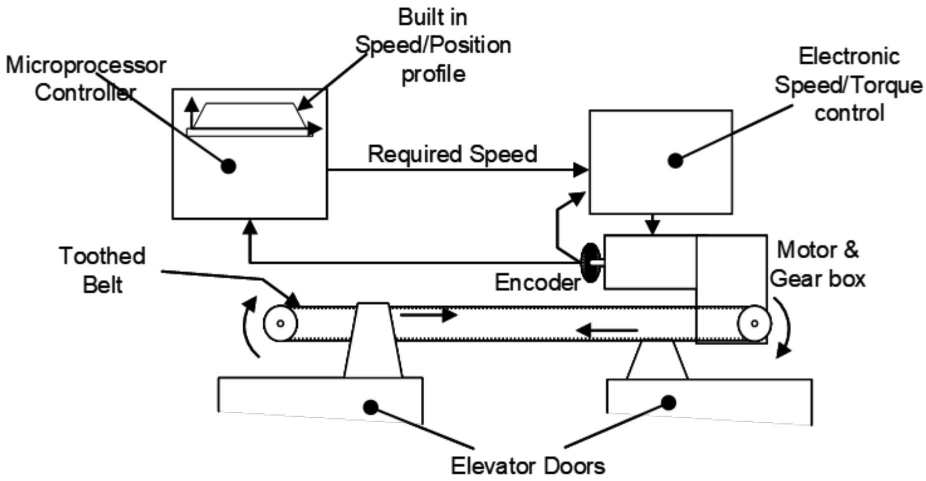

Fig. 1. Automated power-operated elevator door with an electronically controlled door operator

Most relevant faults in these mechanisms are:

- Motors with defective bearings (shaft bearings defective).
- Incorrect belt tensions.
- Worn-out door sill.
- Worn-out door rollers (door rollers defective).
- Sluggishness of door guide (door panel guide dirty).
- Door lock out of alignment (door interlock error).
- Worn-out door cam.
- Worn-out door ropes (door rope frayed).

3. Defects classification using vibration measurements

The complexity and cost of the automatic fault classifier was the main constraint in this research. In terms of cost, only one high specification vibration sensor could be placed in the door mechanism.

The best location to place the vibration sensor was the top centre of the door operator case. This location was identified after conducting modal analysis tests with impact hammer excitation. The structure was excited with the hammer near the locations were the defective components are fitted in. The vibration signals were recorded with an acquisition platform of 24bits and a sampling rate of 96ksamples/s. The piezoelectric accelerometer was a B&K 4382 connected to a (0-40dB) gain charge amplifier.

After placing the vibration sensor in the door mechanism, several tests were systematically conducted using door operational cycles. A door operational cycle consists of the following phases: silence (doors closed), doors transient open (variable speed), doors opening (constant speed), reverse motor direction, doors closing (constant speed), doors transient close (variable speed), silence (doors closed). The different phases after pre-processing the raw vibration signal are shown in Fig. 2. The timing of these phases could be estimated, or obtained directly from the lift controller records.

Various door operation cycles were conducted with and without different types of defects. After these tests, it was concluded from the vibration spectrogram that not all defective parts could be easily detected with a monitoring system mounted on the carrier of the cabin door. Table 1 summarises the defects that could be detected with this vibration sensor.

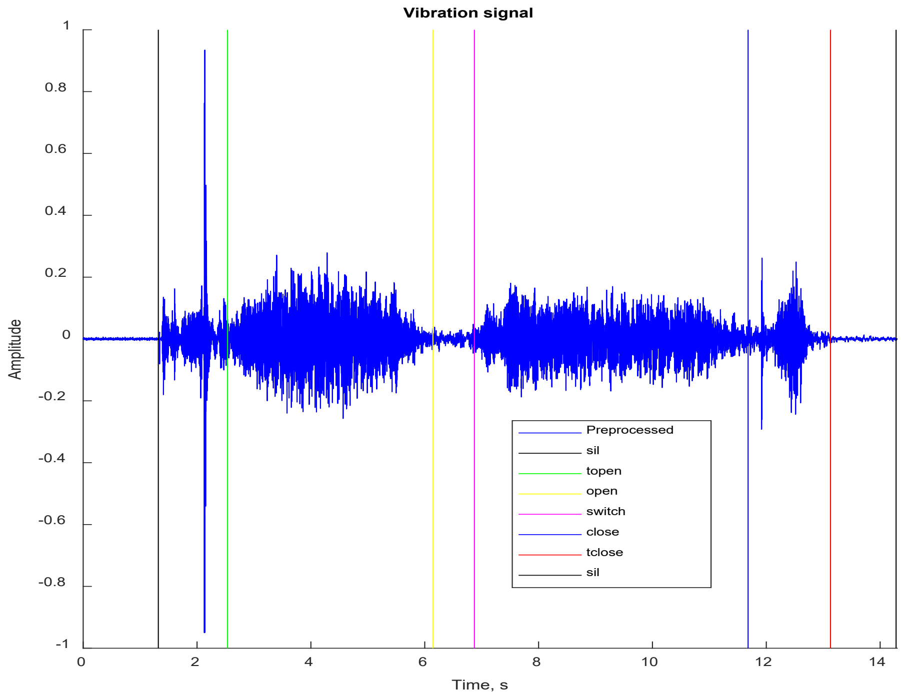

Fig. 2. Phase separation of the door vibration signal. Motor fault.

Table 1. Fault detection using the spectrogram

Defect (Fault)	Detection	Frequency band in the spectrum
Motors with defective bear-ings	good	1-2kHz
Incorrect belt tensions	poor	1-1.2kHz
Worn-out door cam	good	1-6kHz
Worn-out door rollers	good	630Hz-10kHz
Rough-running door guide	satisfactory	2-10kHz
Door interlock bent	poor	--
Defective shaft door spring	good	1-10kHz
Worn-out door parts	good	1-1.2 kHz

4. ANN training process

The vibration sensor recording of each door operational cycle was stored in order to build an ANN training dataset. The number of vibration recordings for each class of defect are shown in Table 2. It should be noted that there are defect classes that have not taken into consideration in this research.

Table 2. Vibration recordings (Dataset)

CLASS	Defect (Fault)	Door Operation cycles	ID
1	No defect	40	NOE
2	Worn-out door cam	0	CAM
3	Door interlock bent	10	LCK
4	Worn-out door rollers	56	ROL
5	Motors with defective bearings	10	MOT
6	Different belt tensions Door rope torn	15	RPE
7	Rough-running door guide Door panel guide dirty	0	GDE
8	Loosened motor chain	0	MOC

Each vibration record was divided according to the door operational phases and it was labelled with a type of defect or target class. The raw vibration signals that were obtained with 24bit resolution and a sampling frequency of 44.1KHz were pre-processed by removing the average value and then they were normalised by dividing by the standard deviation. The spectra of the 'silence' frames of the signals were also subtracted from the whole signal in order to remove the stationary noise. After pre-processing, spectrograms and cepstrograms of the input signal were chosen as the extracted signal features, respectively. The spectrogram was obtained using a Hanning window of 256 samples and applying an overlap of 25%. The cepstrogram was later obtained from the spectrogram and both signal features were stored in files forming a training dataset. Only the first 64 coefficients were used in the cepstrogram. A block diagram of the feature extraction process is shown in Fig. 3.

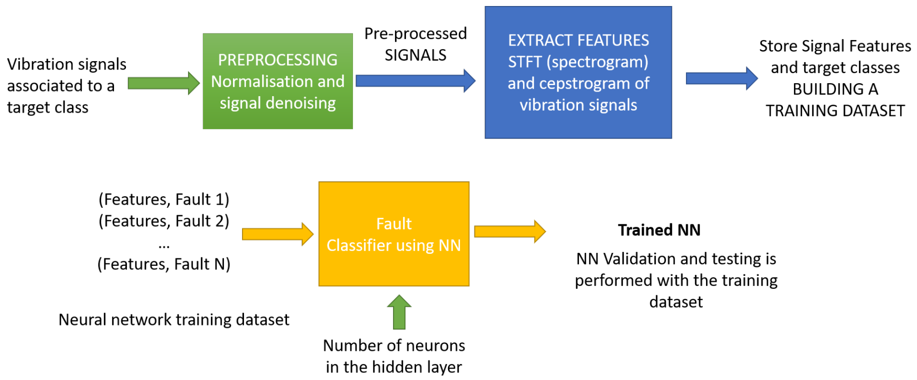

Fig. 3. Training dataset and ANN training process

A pattern recognition network was trained using the following operational phases of the door mechanism: doors transient open (variable speed, TOPEN), doors opening (constant speed, OPEN), doors closing (constant speed, CLOSE), doors transient close (variable speed, TCLOSE). The network used was is a feedforward ANN that has been trained to classify inputs according to the target classes. The input size dimension of the network has been fixed. This network was trained by framing the cepstrogram of the signals. The chosen input size dimension corresponds to approximately 1.6 s of the audio or vibration signals which was assumed long enough to detect the fault. The input size dimension of each ANN training sample corresponds to 200 time samples by 64 cepstrum coefficients (200x64 = 12800 points). The signal shown in Fig. 4 graphically demonstrates this concept. The records contained in red or green rectangles in Fig. 4 are approximately 1.6 s long each and they have a matrix dimension of 200x64 points in the cepstrograms, respectively. The overlap between these rectangular frames is 10% or 160ms. The spectrogram and the cepstrogram of each vibration file were framed and then stored depending on each operational phase leading to the total number of frames shown in Table 3.

The ANN was chosen according to the diagram presented in Fig. 5. The input size dimension is 12800 points and the output size dimension is 8 (the number of fault classes). The total number of neurons in the hidden layer was selected following a rule of thumb which is by selecting this number as about half of the input size dimension (or 6500 neurons). The larger this number is, the longer the training process will last.

The ANN was trained, tested and validated using the MATLAB Neural Pattern Recognition tool (or **nprtool**).

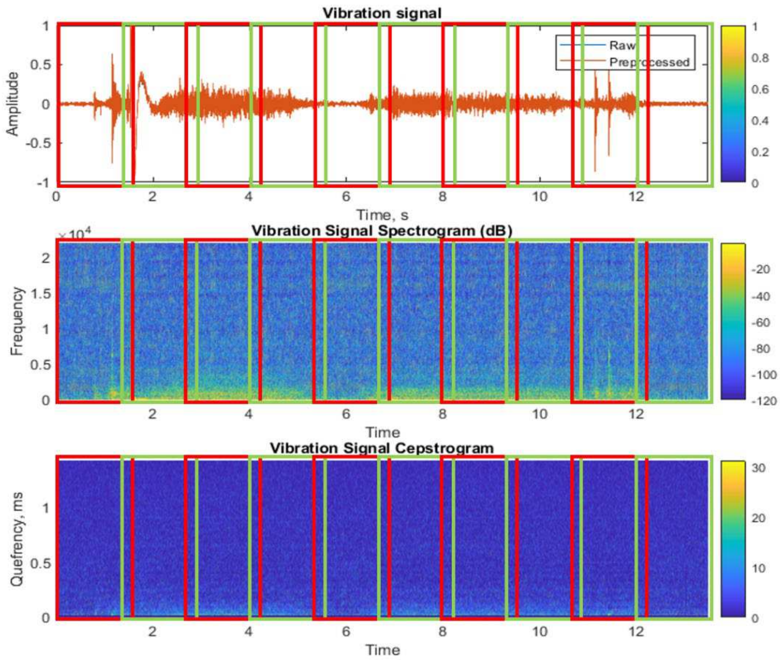

Fig. 4. Framing the spectrogram and the cepstrogram of the door vibration signal for training the ANN. Class 1 - No fault.

Table 3. Spectrogram and Cepstrogram frames on each phase in the Training Dataset

		Number of Frames per operation phase Spectrogram (size 200x129) and cepstrogram (size 200x64)			
CLASS	**Defect (Fault)**	**TOPEN**	**OPEN**	**CLOSE**	**TCLOSE**
1	No defect	99	261	306	186
2	Worn-out door cam	0	0	0	0
3	Door interlock bent	19	59	78	66
4	Worn-out door rollers	171	392	472	276
5	Motors with defective bearings	27	70	82	42
6	Different belt tensions Door rope torn	37	118	77	79
7	Rough-running door guide Door panel guide dirty	0	0	0	0
8	Loosened motor chain	0	0	0	0

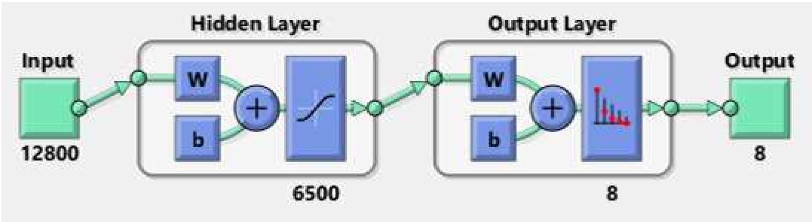

Fig. 5. ANN architecture.

5. Results

For training, testing and validation of the ANN, the original training dataset was split into 70% of the samples for training the ANN, 15% of the samples for validation and the remaining 15% for testing. The training results are shown in the training confusion matrix. These results reflect the classification percentage of the ANN when all the inputs belong to the training dataset. A good classifier should show a very high overall accuracy in the training confusion matrix. The test and validation datasets contain samples that do not belong to the training dataset. These two datasets are useful for giving an estimate of the real fault classification performance.

The classification results for each door operational phase are presented in the test confusion matrices shown in Fig. 6.

In the confusion matrix plot, the rows correspond to the predicted class (Output Class) and the columns correspond to the true class (Target Class).

The diagonal cells correspond to observations that are correctly classified. The off-diagonal cells correspond to incorrectly classified observations. Both the number of observations and the percentage of the total number of observations are shown in each cell.

The column on the far right of the plot shows the percentages of all the examples predicted to belong to each class that are correctly and incorrectly classified. These metrics are often referred to as the precision (or positive predictive value) and false discovery rate, respectively. The row at the bottom of the plot shows the percentages of all the examples belonging to each class that are correctly and incorrectly classified. These metrics are often called the recall (or true positive rate) and false negative rate, respectively. The cell in the bottom right of the plot shows the overall accuracy.

The test confusion matrix is a real indicator of the ANN real classification performance. For example, in the TOPEN test confusion matrix in Fig. 6, the bottom row shows the percentages of all the samples that are correctly classified. For target class 1 (no error) the correctly classified percentage is 58.3% and incorrectly is 41.7%. This percentages are easily calculated considering that for target class 1, the output classes of the test confusion matrix where 7 for class 1, 2 for class 2 and 3 for class 5. The correctly classified percentage is 7/(7+2+3)= 58.3%.

Test Confusion Matrix -- Phase: *TOPEN*

Output Class	1	7 / 13.2%	0 / 0%	0 / 0%	6 / 11.3%	3 / 5.7%	3 / 5.7%	0 / 0%	0 / 0%	36.8% 63.2%
	2	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	NaN%
	3	0 / 0%	0 / 0%	0 / 0%	2/ 3.8%	0 / 0%	1 / 1.9%	0 / 0%	0 / 0%	0% 100%
	4	2 / 3.8%	0 / 0%	1 / 1.9%	18 / 34%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	85.7% 14.3%
	5	3 / 5.7%	0 / 0%	0 / 0%	2 / 3.8%	2 / 3.8%	2 / 3.8%	0 / 0%	0 / 0%	22.2% 77.8%
	6	0 / 0%	0 / 0%	1 / 1.9%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0% 100%
	7	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	NaN%
	8	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	NaN%
		58.3% 41.7%	NaN%	0% 100%	64.3% 35.7%	40.0% 60.0%	0% 100%	NaN%	NaN%	**50.9% 49.1%**
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	
		Target Class								

Test Confusion Matrix -- Phase: *OPEN*

Output Class	1	27 / 20%	0 / 0%	5 / 3.7%	6 / 4.4%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	71.1% 28.9%
	2	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	NaN%
	3	1 / 0.7 %	0 / 0%	7 / 5.2%	4/ 3.0%	1 / 0.7%	0 / 0%	0 / 0%	0 / 0%	53.8% 46.2%
	4	11 / 8.1 %	0 / 0%	0 / 0%	48 / 35.6%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	81.4% 18.6%
	5	2 / 1.5%	0 / 0%	0 / 0%	0 / 0%	9 / 6.7%	0 / 0%	0 / 0%	0 / 0%	81.8% 18.2%
	6	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	14 / 10.4%	0 / 0%	0 / 0%	100% 0%
	7	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	NaN%
	8	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	NaN%
		65.9% 34.1%	NaN%	58.3% 41.7%	82.8% 17.2%	90.0% 10.0%	100% 0%	NaN%	NaN%	**77.8% 22.2%**
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	
		Target Class								

Test Confusion Matrix -- Phase: *CLOSE*

Output Class	1	27 / 17.8%	0 / 0%	5 / 3.3%	11 / 7.2%	1 / 0.7%	0 / 0%	0 / 0%	0 / 0%	61.4% 38.6%
	2	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	NaN%
	3	1 / 0.7 %	0 / 0%	6 / 3.9%	1/ 0.7%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	75% 25%
	4	15 / 9.9 %	0 / 0%	1 / 0.7%	52 / 34.2%	1 / 0.7%	3 / 2.0%	0 / 0%	0 / 0%	72.2% 27.8%
	5	1 / 0.7%	0 / 0%	3 / 2%	0 / 0%	9 / 5.9%	2 / 1.3%	0 / 0%	0 / 0%	60% 40%
	6	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	13 / 8.6%	0 / 0%	0 / 0%	100% 0%
	7	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	NaN%
	8	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	NaN%
		61.4% 38.6%	NaN%	40% 60%	81.3% 18.7%	81.8% 18.2%	72.2% 27.8%	NaN%	NaN%	**70.4% 29.6%**
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	
		Target Class								

Test Confusion Matrix -- Phase: *TCLOSE*

Output Class	1	5 / 5.2%	0 / 0%	0 / 0.0%	1 / 1%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	83.3% 16.7%
	2	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	NaN%
	3	2 / 2.1%	0 / 0%	9 / 9.3%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	81.8% 18.2%
	4	21 / 21.6%	0 / 0%	0 / 0%	30 / 30.9%	2 / 2.1%	0 / 0%	0 / 0%	0 / 0%	56.6% 43.4%
	5	5 / 5.2%	0 / 0%	2 / 2.1%	4 / 4.1%	4 / 4.1%	0 / 0%	0 / 0%	0 / 0%	26.7% 73.3%
	6	2 / 2.1%	0 / 0%	2 / 2.1%	0 / 0%	1 / 1%	7 / 7.2%	0 / 0%	0 / 0%	58.3% 41.7%
	7	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	NaN%
	8	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	0 / 0%	NaN%
		14.3% 85.7%	NaN%	69.2% 30.8%	85.7% 14.3%	57.1% 42.9%	100% 0%	NaN%	NaN%	**56.7% 43.3%**
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	
		Target Class								

Fig. 6. Fault classification results using the vibration signal over the phases

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6. Conclusions

From the test confusion matrix results shown in Fig. 6, it could be concluded that training an ANN with the information in the OPEN and CLOSE phases has led to an overall classification accuracy in the test confusion matrix above 70% (77.8% and 70.4% respectively). The classification accuracy of the ANN using the information in the phases TOPEN and TCLOSE was poor (<60%). However, the results in these phases should be carefully examined because some faults could be well classified in TOPEN and TCLOSE phases. For example, it can be seen in the transient close phase (TCLOSE) that CLASS 6 is perfectly (100%) detected. After analyzing these results, it can be concluded that a voting scheme of two ANN trained with the OPEN and CLOSE phases is the best strategy to achieve better fault classification performance. With this voting scheme an overall classification accuracy higher than 70% could be achieved for all faults.

Data Availability

The vibration signal datasets used in this research were provided by the project sponsor (Thyssenkrupp Elevator AG). Restrictions apply to the availability of these datasets, which were used under license, hence are not publicly available. The datasets can be made available from the authors upon reasonable request and with permission of Thyssenkrupp Elevator AG.

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References

1. Worden, F.,. Dulieu-Barton, J.M.: An Overview of Intelligent Fault Detection in Systems and Structures. *SHM,* 3(1), 85–98 (2004).
2. Thyssenkrup MAX platform, URL: https://max.thyssenkrupp-elevator.com/en/, last accessed 2020/10/24.
3. Andrew, J.P., Kaczmarczyk, S.: Systems Engineering of Elevators. Elevator World, Inc., Mobile, Alabama, (2011).
4. Evert, A.: Applications for sensor fusion in vertical transportation. Georgia Tech Theses and Dissertations (2018). URL: https://smartech.gatech.edu/handle/1853/60264, https://max.thyssenkrupp-elevator.com/en/, last accessed 2020/10/24.
5. Gera, M., Goel, S.: Data Mining Techniques. Methods and Algorithms: A Review on Tools and their Validity. International Journal of Computer Applications (0975 8887) 113(18), (2015)
6. Nikam, S. S.: A comparative study of classification techniques in data mining algorithms. Orient J Comput Sci Technol, 8(1), 13–19 (2015).

7. Jain, A.K., Mao, J., Mohiuddin, K.M.: Artificial neural networks: A tutorial. Computer, 29(3), 31–44 (1996).
8. Introduction to Neural Networks, Advantages and Applications, https://towardsdatascience.com/introduction-to-neural-networks-advantages-and-applications-96851bd1a207, last accessed 2020/10/23.
9. Van Der Smagt, P.: Minimisation methods for training feedforward neural networks. Neural Networks, 7(1), 1–11 (1994).
10. Basheer, I. A., Hajmeer, M.: Artificial neural networks: fundamentals, computing, design, and application. J. Microbiol. Methods, 43(1), 3–31 (2000).