A Fault Detection Technique based on Deep Transfer Learning from Experimental Linear Actuator to Real-World Railway Door Systems.

Minoru Shimizu[1], Suresh Perinpanayagam[1], and Bernadin Namoano[2]

[1]*Integrated Vehicle Health Management Centre, Cranfield University, Bedfordshire, MK43 0AL, United Kingdom*
minoru.shimizu@cranfield.ac.uk
suresh.nayagam@cranfield.ac.uk

[2]*Digital Engineering and Manufacturing Centre, Cranfield University, Bedfordshire, MK43 0AL, United Kingdom*
Bernadin.Namoano@cranfield.ac.uk

ABSTRACT

Fault detection for railway door systems based on data-driven approaches has been investigated in recent years due to the massive amount of available monitoring data. Despite much attention to its application, the major challenge is the lack of available faulty datasets to build a reliable model since railway maintenance is usually conducted regularly to avoid significant defects from economic and safety points of view. We aim to tackle the issue by employing transfer learning. Firstly, a long-short term memory-based deep learning model is built using linear actuator experimental datasets. Then, a transfer learning technique is employed to adjust the deep learning model to be available to real-world railway door systems using a small amount of faulty data. As a result, high fault detection accuracy can be obtained at 0.979 as F1 score. The result reveals that an accurate fault detection model can be built even though a large number of labelled datasets is unavailable. In addition, the proposed method is applicable to other door systems or electro-mechanical actuators since the method is unspecific to physical mechanisms and fault modes, and the only motor current signal is used in this research. The signal is primarily available from the controller or motor drive without additional sensors.

1. INTRODUCTION

Fault detection serves an important role in maintenance activity in the railway industry from economic and safety points of view and has been investigated in recent years. The train door is one of the most critical subsystems that can cause service delay or breakdown, leading to the increased cost of operation and maintenance. As reported in (Cauffriez et al., 2012) and (Qin et al., 2013), door systems are responsible for 30% to 60% of the total failures in railway vehicles. In order to prevent these failures, predictive maintenance based on data-driven approaches is attracting more and more attention recently due to the massive amount of available monitoring data.

Despite much attention to its application, the major challenge is the lack of available faulty datasets to build a reliable model since railway maintenance is usually conducted regularly to avoid significant defects. As a consequence, previously proposed methods by (Yan & Lee, 2005), (Sun et al., 2018), and (Ham et al., 2019) for door systems could be impractical in the real-world industry because the methods are based on supervised learning models using a large amount of labelled dataset.

To tackle the issue, we employ a transfer learning (TF) technique, which enables building a fault detection model with a small amount of faulty data. The common TF approach for machine learning is to copy over the weights learned for task A to a network that will be trained for task B (Russell & Norvig, 2021). In this research, linear actuator test rig datasets are utilised, publicly available to download at (C. Ruiz-Carcel and A. Starr, 2018). Firstly, a long-short term memory (LSTM) based deep learning (DL) model is built using linear actuator experimental data. Then, the transfer learning technique is employed to adjust the deep learning model to be available to real-world railway door systems using a small amount of faulty data. Finally, the model fault detection accuracy is validated. The main contributions of the paper are summarised as follows:

1) An accurate fault detection model for railway door systems can be built with a small amount of faulty operational data by employing a transfer learning technique using the experimental linear actuator dataset.

2) The proposed method is applicable to other door systems or electro-mechanical actuators since the

method is unspecific to physical mechanisms and fault modes, and the only motor current signal is used in this research.

The remainder of this article is organised as follows. Section 2 provides a dataset explanation, followed by the methodology, the proposed methodology, and validation performance metrics in Sections 3, 4, and 5. The result and discussion are given in Section 6. Finally, Section 7 concludes this article.

2. DATASETS

2.1. Linear Actuator Experimental Dataset

As stated in (Ruiz-Carcel & Starr, 2018) and (López de Calle-Etxabe et al., 2020), the main element of the test rig consists of a ball screw mechanism with a threaded shaft containing a helical raceway for the displacement of the bearing balls housed inside the nut. Varying loads are generated by attaching a secondary actuator. The actuators are connected through a load cell so that the cell provides feedback to the controller, different operating conditions can be represented by changing the load setpoint. The load setpoints are 196.13 N, 392.3 N, and -392.3 N, respectively. As fault modes, three types of faults are seeded with increasing severity: lack of lubrication, spalling, and black lash. The experiments have been conducted in two motion profiles: trapezoidal (constant speed) and sinusoidal (smooth acceleration and deceleration). The 3D model of the test rig and lateral view of the rig is given in Figure 1 and Figure 2. Further details regarding the test rig and the seeded faults can be found in (Ruiz-Carcel & Starr, 2018), and the raw data is available to download at (C. Ruiz-Carcel and A. Starr, 2018).

In our research, trapezoidal motion profiles are chosen to build a model since railway door systems have relatively constant speed profiles, as will be explained in Section 2.2. The position measurement and current signal include extension and retraction operations, as described in Figure 3 and Figure 4. The current signals of the extension operation are extracted and used to build a model since the extension operation corresponds to the closing operation of railway door systems, which is used in this research and will be explained in detail in Section 2.2. The noises are reduced by using a low pass filter on a window of 0.15 seconds. The current profiles of lack of lubrication are chosen as faulty current signals. Normal and faulty current profiles are described in Figure 5 and Figure 6. Some faulty characteristics are observable. For example, there is a certain amount of overshoot in normal profiles, whereas the overshoot becomes less in faulty profiles. The dataset has three different loading conditions. The three types of loading conditions are assumed as the same class label. For instance, normal profiles from three loading conditions, shown in Figure 5, are categorised as normal class and vice versa.

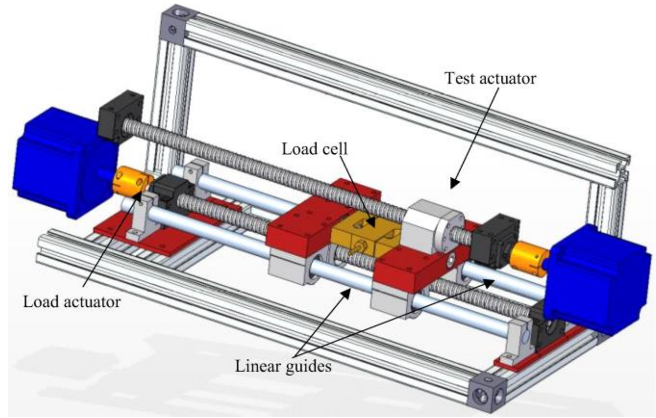

Figure 1. 3D model of the test rig (Ruiz-Carcel & Starr, 2018)

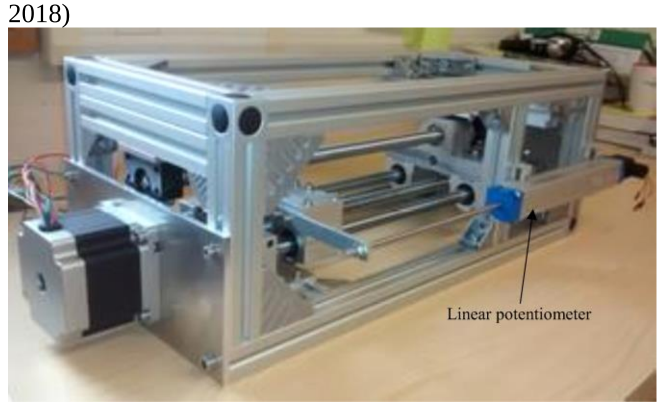

Figure 2. Lateral view of the rig (Ruiz-Carcel & Starr, 2018)

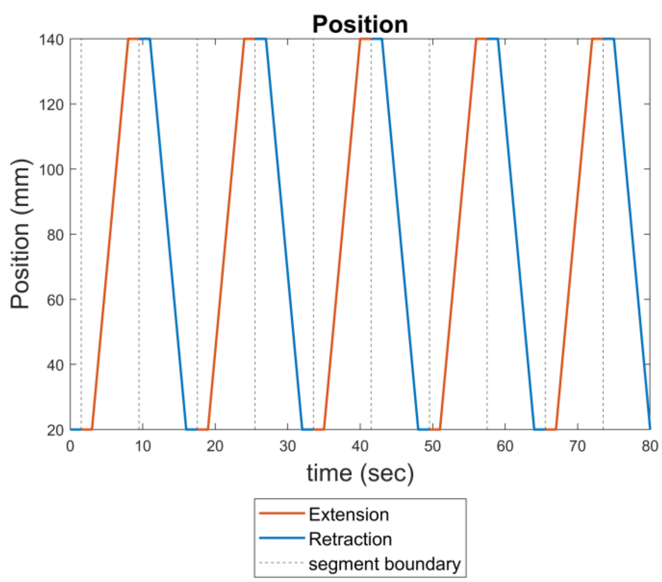

Figure 3. Position measurement of the linear actuator test rig

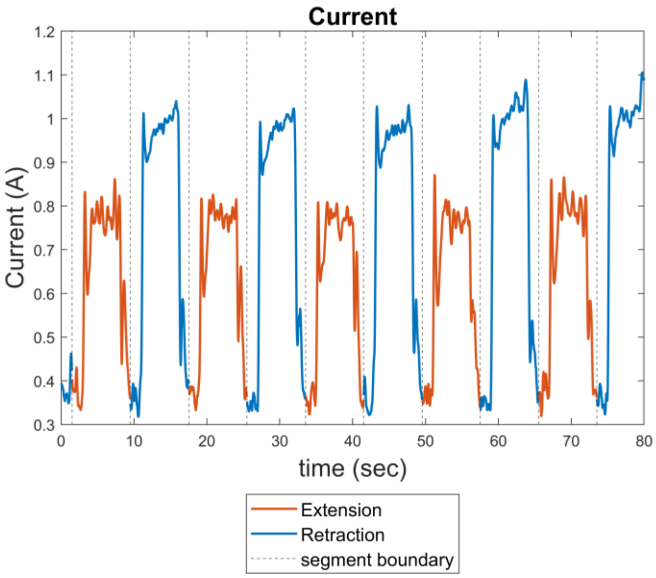

Figure 4. Current signal example of the linear actuator test rig

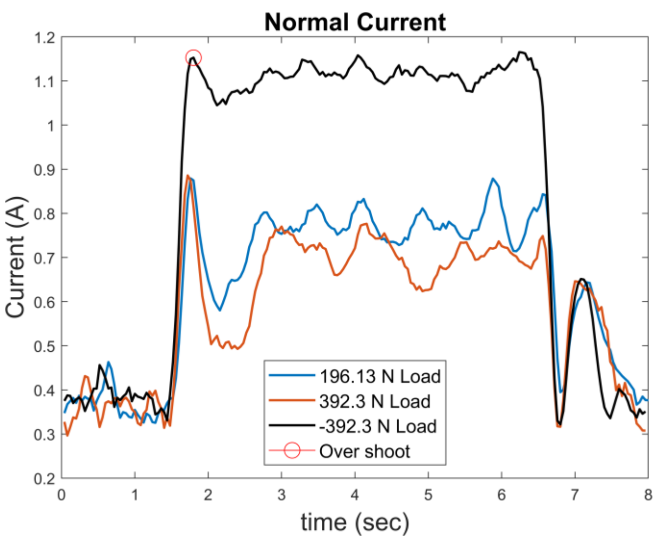

Figure 5. Normal current signals of the linear actuator test rig

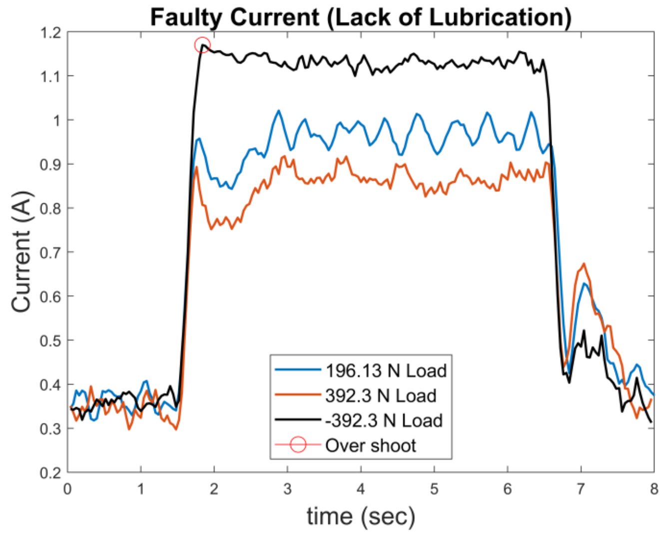

Figure 6. Faulty current signals of the linear actuator test rig

2.2. Railway door systems operational dataset

In this study, large real-world datasets acquired from railway door systems are employed. An electric door is considered, which is composed of a voltage power source, a DC motor, a door control unit (DCU), a transmission and door leaves. In short, a DC motor, powered by a voltage source and controlled by DCU, can output the specified shaft angular velocity and torque, which are transmitted to transmission so that the door leaves can move in a pre-designed manner (Shimizu et al., 2022a). The door current signal is collected through the communication port from the DCU at a frequency of 50 Hz. The low pass filter is applied on a window of 0.25 seconds, representing five consecutive measurement time intervals to reduce noise carried by current signals.

An example of the signal profiles of the opening and closing operations is shown in Figure 7. In the opening profile, the speed and current increase steadily up to a maximum, followed by a slight curve, and then decrease to zero. The closing profile follows a similar pattern with two main differences in the current. One is that the peak in the closing profile is lower than the opening. The second is an abrupt change at the end of the closing profile, followed by a slight bump of the speed, which promotes pushing the door to its maximal reachable position where a locking process can be triggered (Bernadin Namoano, 2017). It should be noted that concrete fault types are unidentifiable in the railway operational dataset (Shimizu et al., 2022b). The linear actuator experimental current signals of the three fault modes, which are lack of lubrication, spalling, and black lash have been compared to the faulty signals in the railway door operation. However, none of the fault modes resembles the faulty signals in the railway door operation. It is possible, therefore, that the observed faulty behaviour could be accompanied by several fault modes because the train door system contains many components. The identification and diagnosis of fault modes are out of the scope of this paper.

In this research, current signals in closing operations are used for fault detection purposes. The example of the normal and faulty signals of closing operation is shown in Figure 8. The normal current signal has flat curves from 3.2 sec to 4.0 sec, while there are negative peaks and fluctuations in that of faulty data. It is noteworthy that the faulty characteristics of door systems differ from those of a linear actuator test rig, as explained in Section 2.1.

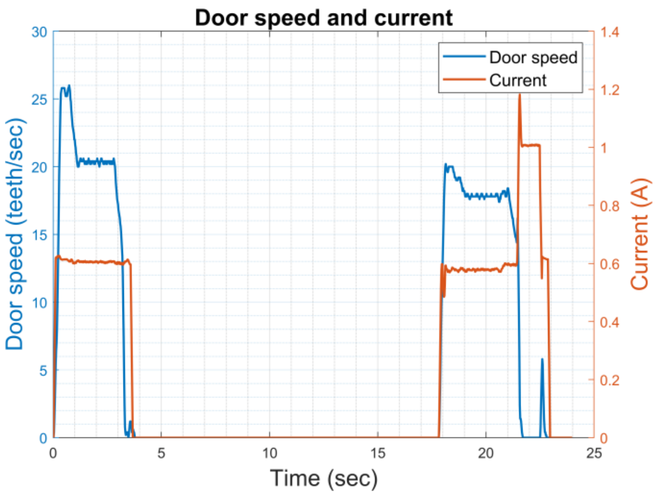

Figure 7. Current signal of door systems

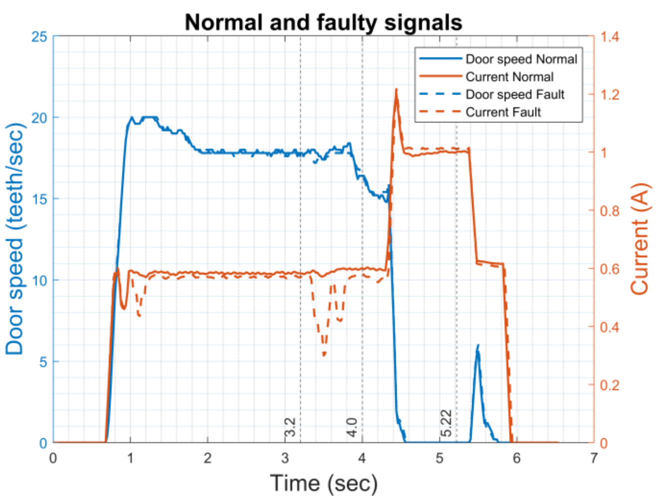

Figure 8. Normal and faulty signals of the closing operation

2.3. Train and test dataset

The train and test dataset for the linear actuator test rig is given in Table 1. A test rig's train and test datasets are used to build a fault detection model. Then, the model is transferred to a fault detection model for door systems with a small amount of door system dataset, including only ten normal and five faulty data, given in Table 2.

Table 1. Train and test dataset for a test rig model

	Normal	Faulty	Total
Train	120	240	360
Test	30	60	90

Table 2. Train and test dataset for a TF model

	Normal	Faulty	Total
Train	10	5	15
Test	50	50	100

3. METHODOLOGY

3.1. Long Short-Term Memory

The LSTM is one of the most popular types of recurrent neural networks (RNNs), enabling information to be preserved over many time steps, which was initially proposed by (Hochreiter & Schmidhuber, 1997). Several variants of the RNN architecture have been proposed since its inception, including gated recurrent units (GRUs). However, (Greff et al., 2017) presented a large-scale comparative analysis of RNN variants and reported that none of the RNN variants can improve upon the standard LSTM architecture significantly. This result can be attributed to the LSTM architecture, including three gating units, which control the flow of information in the LSTM (Russell & Norvig, 2021). The forward propagation process can be expressed as the following equations:

$$\tilde{\boldsymbol{s}}_{\boldsymbol{t}} = tanh(\boldsymbol{W_c h_{t-1}} + \boldsymbol{U_c x_t} + \boldsymbol{b_c}) \tag{1}$$

$$\boldsymbol{f_t} = \sigma\left(\boldsymbol{W_f h_{t-1}} + \boldsymbol{U_f x_t} + \boldsymbol{b_f}\right) \tag{2}$$

$$\boldsymbol{i_t} = \sigma(\boldsymbol{W_i h_{t-1}} + \boldsymbol{U_i x_t} + \boldsymbol{b_i}) \tag{3}$$

$$\boldsymbol{o_t} = \sigma(\boldsymbol{W_o h_{t-1}} + \boldsymbol{U_o x_t} + \boldsymbol{b_o}) \tag{4}$$

$$\boldsymbol{s_t} = \boldsymbol{s_{t-1}} \odot \boldsymbol{f_t} + \boldsymbol{i_t} \odot \tilde{\boldsymbol{s}}_{\boldsymbol{t}} \tag{5}$$

$$\boldsymbol{h_t} = tanh(\boldsymbol{s_t}) \odot \boldsymbol{o_t} \tag{6}$$

where $\boldsymbol{x_t}$ and $\boldsymbol{h_t}$ are input and hidden state, $\boldsymbol{f_t}$, $\boldsymbol{i_t}$, and $\boldsymbol{o_t}$ are forget gate, input gate and output gate, $\boldsymbol{s_t}$ is state unit at time step t, correspondingly. The $\boldsymbol{b_c}$, $\boldsymbol{b_f}$, $\boldsymbol{b_i}$, and $\boldsymbol{b_o}$ are bias vectors, σ is an activation function, and $\boldsymbol{W_c}$, $\boldsymbol{W_f}$, $\boldsymbol{W_i}$, $\boldsymbol{W_o}$, $\boldsymbol{U_c}$, $\boldsymbol{U_f}$, $\boldsymbol{U_i}$, and $\boldsymbol{U_o}$ are weight matrices, respectively. The $\odot$ symbol denotes element-wise multiplication. The forget gate $\boldsymbol{f_t}$ determines if each element of $\boldsymbol{s_{t-1}}$ is remembered or forgotten. The input gate $\boldsymbol{i_t}$ determines if each element of the state unit $\boldsymbol{s_t}$ is updated by the latest information at the current time step. The output gate $\boldsymbol{o_t}$ determines if each element of the state unit is transferred to the hidden state (Russell & Norvig, 2021). The calculation flow can be described as an LSTM block diagram and an LSTM network, as shown in Figure 9 and Figure 10.

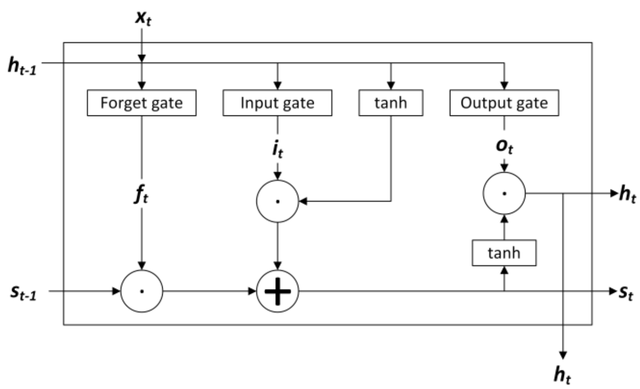

Figure 9. LSTM block diagram

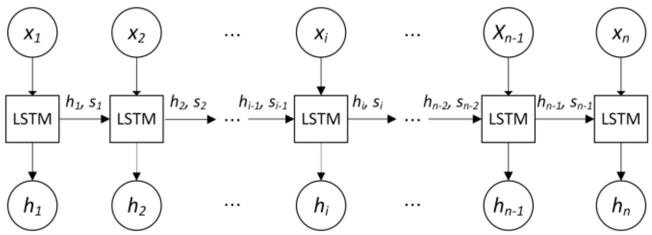

Figure 10. LSTM network

3.2. Transfer Learning

In general, the TL means that experience with one learning task helps an agent learn better on another task (Russell & Norvig, 2021). In TL for machine learning, two domains are usually considered: source domain and target domain. The objective of TL is to improve the model of the target domain using information from the source domain, where the source and target domain are not the same.

For neural network-based models, learning consists of adjusting weights, so the most plausible TF approaches for machine learning is to copy over the weights learned for task A to a network that will be trained for task B (Russell & Norvig, 2021). In this research, the parameter-based TL is chosen, which means transferring knowledge through shared parameters between source and target domain models. The source domain is the linear actuator test rig, while the target domain is railway door systems in this research.

4. PROPOSED METHODOLOGY

4.1. Fault detection workflow

The proposed fault detection workflow is shown in Figure 11. The workflow is divided into two procedures, offline and online.

In the offline, current signals of the linear actuator test rig are used as training datasets to train a fault detection model. For the sake of convenience, the term 'the test rig DL model' is used to refer to this model. In this procedure, the current signals are segmented and pre-processed to reduce noises by a low pass filter, followed by training a test rig DL model. Then, a fault detection model available to real-world railway door systems is built with TL using a small amount of faulty data, as will be explained in detail in Section 4.2. The fault detection model for door systems is defined as 'the door system DL model'.

The door system DL model with TL created offline are implemented on the online procedure to detect faults. The current signals of railway door systems are pre-processed and segmented. Then, faults can be detected by using the door system DL model with TL generated offline. The fault detection workflow can be executed once one door operation is terminated so that a fault can be detected as early as possible.

The proposed method offers remarkable advantages in terms of practical fault detection applications available in the industry. Firstly, an accurate fault detection model for railway door systems can be built with a small amount of faulty operational data by employing a TL technique using the experimental linear actuator dataset. Besides, the proposed method is applicable to other door systems or electro-mechanical actuators since the method is unspecific to physical mechanisms and fault modes, and the only motor current signal is used in this research.

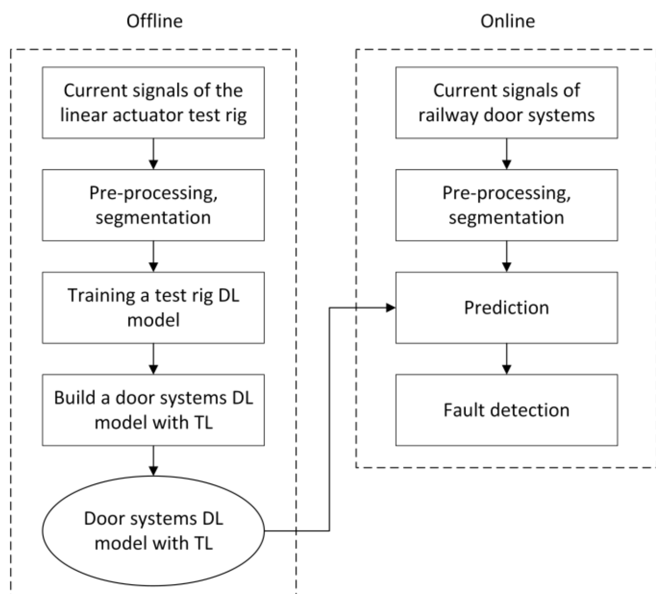

Figure 11. The proposed fault detection workflow

4.2. Transfer Learning workflow

The test rig DL model built with the linear actuator dataset is described in Figure 12 and Table 3. The model consists of a batch normalisation, an LSTM, a fully connected (FC) layer, a softmax layer, and output layer. The batch normalisation layer normalises a mini-batch of data.

Once the test rig DL model is built, the transfer learning technique is employed to adjust the test rig DL model to be available to real-world railway door systems using a small amount of faulty data, as described in Figure 13. The parameters of the LSTM layer from the test rig DL model are copied to the door system DL model, while the parameters of the FC and softmax layers from the test rig DL are replaced with initialised new layers in the door system DL model. Then, the hyperparameters are tuned with a small amount of door data, as given in Table 2. It is noteworthy that the learning rates for the FC and softmax layers are modified to be larger than the LSTM layer so that learning is faster in the new layers than in the transferred layer, as given in Table 4. The optimiser, max epoch and mini-batch size for the hyperparameter tuning are Adam, 15, and 2000, respectively.

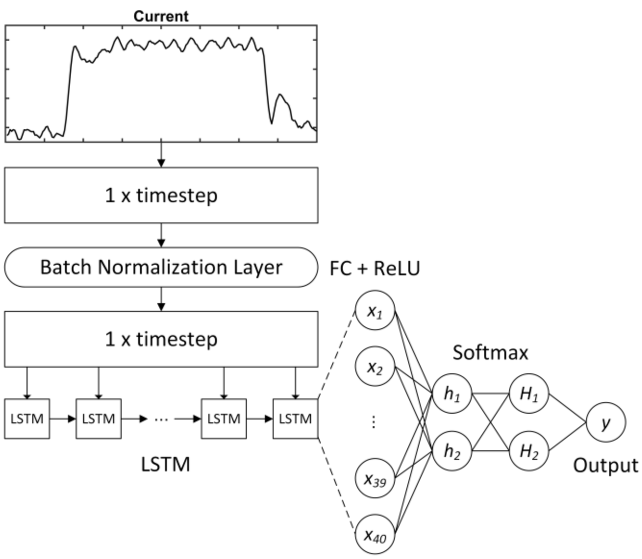

Figure 12. Fault detection model with experimental data

Table 3. Hyperparameters of a fault detection model for a linear actuator test rig.

Layer	Hyperparameter name	Hyperparameter
Whole layers	Optimiser	Adam
	Max epoch	3000
	Mini-batch size	120
	Learning rate	0.0001
LSTM	Activation function for the hidden state	Tanh
	Activation function for the gates	sigmoid
	Number of activation units	40
FC	Number of hidden units	2

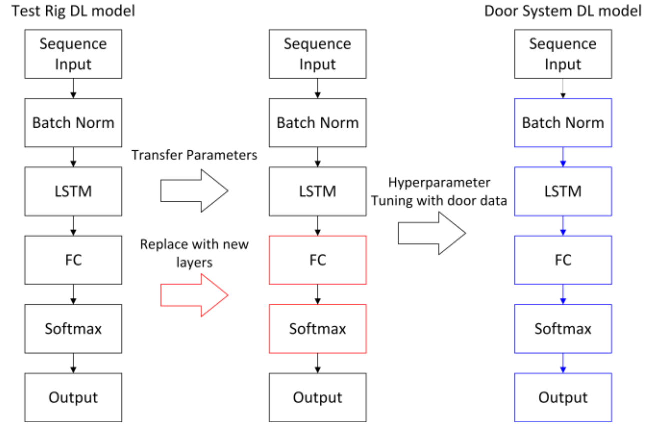

Figure 13. The proposed TL workflow

Table 4. Learning rate for TL

Layer	Hyperparameter name	Learning rate
LSTM	Weight parameters	0.0001
	Bias parameters	0.0001
FC	Weight parameters	0.0005
	Bias parameters	0.001

5. VALIDATION PERFORMANCE METRICS

A confusion matrix is used to analyse the performance of a fault detection system. A confusion matrix is a two-dimensional table of counts of how often each category is classified or misclassified as each other category. In the case of binary classification for fault detection, the confusion matrix has the following four elements: positive (faulty) sets are either detected or not; similarly, negative (normal) sets are either detected or not. These elements are true positive (TP), false negative (FN), true negative (TN) and false positive (FP), respectively, as given in Table 5. Once populated, this matrix is then used to derive performance metrics commonly used in the industry (Ian K. Jennions, 2013), as given in the following equations:

$$Precision\ (P) = \frac{TP}{TP + FP} \tag{7}$$

$$Recall\ (R) = \frac{TP}{TP + FN} \tag{8}$$

$$F1\ score = \frac{2PR}{P + R} \tag{9}$$

In general, precision measures how many of the samples predicted as positive are actual positive. Recall, on the other hand, measures how many of the positive samples are captured by the positive predictions. There is a trade-off between optimising precision and optimising recall (Andreas C. Müller, 2016). A perfect recall can be obtained given that all samples are predicted as positive class, and therefore the precision can be very low, which means there are too many false alarm occurrences. On the contrary, precision can be perfect if a model predicts only a single sample which is the most likely to be positive as positive and the rest as negative. In that case, however, recall can be very low. One way to take precision and recall into account and summarise them is the calculation of the harmonic mean of P and R, which is the F1 score given in equation (9). In this research, the F1 score is applied to evaluate fault detection accuracy, which is ranging from 0 to 1. A high F1 score means high fault detection accuracy and vice versa.

Table 5. Confusion matrix

		Predicted Class	
		Normal	**Faulty**
Actual Class	**Normal**	True Negative (TN)	False Positive (FP)
	Faulty	False Negative (FN)	True Positive (TP)

6. RESULTS AND DISCUSSION

The fault detection accuracy is given in Table 6, Figure 14 and Figure 15, where negative (normal) and positive (faulty) correspond to 0 and 1. As a result, high fault detection accuracy can be obtained at 0.979 as F1 score for door systems DL with TL. For comparison purposes, the door systems DL model is built from scratch, which means the model has the same network architecture and hyperparameter setting as given in Table 3, and is trained by using the door system dataset given in Table 2 without employing the TL technique. However, the F1 score for the door systems DL built from scratch is considerably lower than the TL-based model at 0.734.

The result reveals that an accurate fault detection model for railway door systems can be built by employing the TL technique with the linear actuator experimental data even though a large amount of labelled door datasets is unavailable. In addition, the proposed method is applicable to other door systems or electro-mechanical actuators since the method is unspecific to physical mechanisms and fault modes, and the only motor current signal is used in this research. The signal is primarily available from the controller or motor drive without additional sensors.

Table 6. Fault detection accuracy

Model	Precision	Recall	F1 score
Test rig DL	0.967	1.00	0.983
Door systems DL with TL	1	0.960	0.979
Door systems DL built from scratch	0.750	0.720	0.734

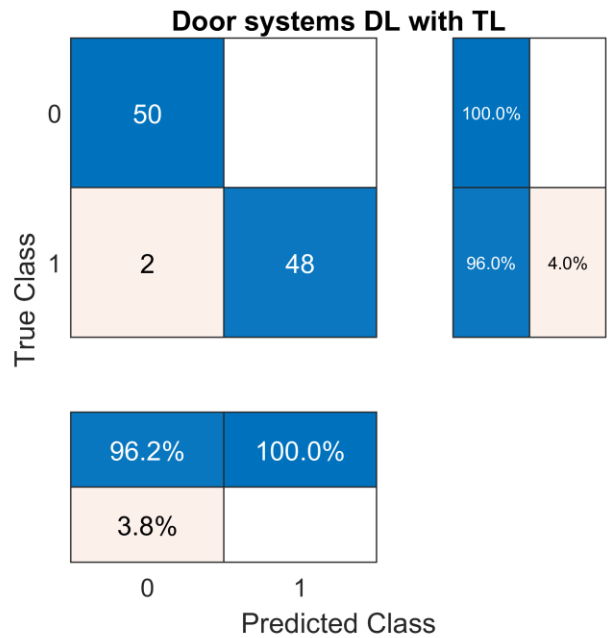

Figure 14. A confusion matrix for door systems DL with TL

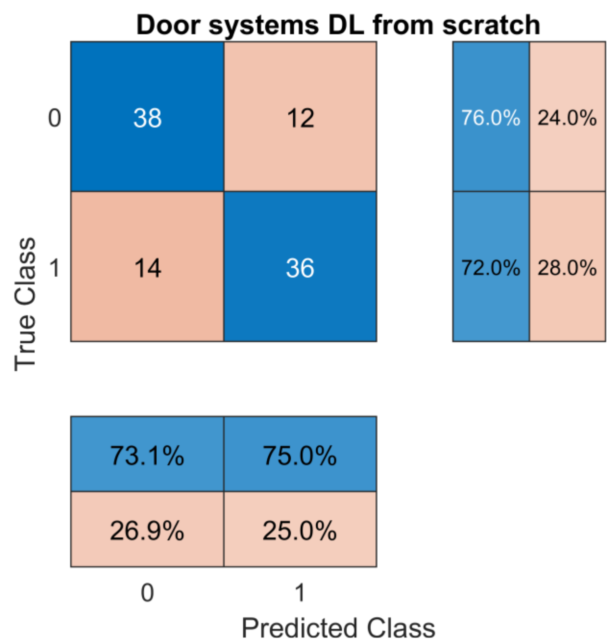

Figure 15. A confusion matrix for door systems DL from scratch

7. CONCLUSION

We aim to tackle the issue relating to the lack of labelled faulty data in the industry by employing a transfer learning technique. Firstly, an LSTM-based deep learning model is built using linear actuator experimental datasets. Then, the TL technique is employed to adjust the deep learning model to be available to real-world railway door systems using a small amount of faulty data. As a result, high fault detection accuracy can be obtained at 0.979 as F1 score. The door systems DL model is built from scratch for comparison purposes without using the TL technique. However, the F1 score for the door systems DL built from scratch is considerably lower than the TL-based model at 0.734.

The result reveals that the accurate fault detection model for railway door systems can be built by employing the TL technique with the linear actuator experimental dataset even though a large amount of labelled door system datasets is unavailable.

In addition, the proposed method is applicable to other door systems or electro-mechanical actuators since the method is unspecific to physical mechanisms and fault modes, and the only motor current signal is used in this research. The signal is primarily available from the controller or motor drive without additional sensors.

In future research, we insist that the fault diagnosis for railway door systems could take advantage of our proposed method. In the context of machine learning approaches, fault detection and diagnosis correspond to binary and multiclass classification tasks, respectively. Since the TL technique is generally available for the multiclass classification task, the diagnosis could be achieved once operational data of multiple fault modes is acquired. Thus, the test rig data would take more essential parts of fault detection and diagnosis study from a practical application perspective in the real-world industry due to TL techniques with DL, which are being advanced rapidly.

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BIOGRAPHIES

Minoru Shimizu received his Bachelor in Physics and Master in Chemistry and Material Science from Tokyo Institute of Technology, Japan. He is currently pursuing his MSc by research in Transport Systems at the Integrated Vehicle Health Management (IVHM) Centre, Cranfield University. Before he joined Cranfield, he has worked for several years as a research engineer in a construction and mining machinery manufacturer. He was responsible for overseeing the research and development of IoT monitoring systems for construction and mining machinery to improve customer productivity. His research interests include fault detection, diagnosis, and prognosis by machine learning and deep learning for railway asset systems.

Suresh Perinpanayagam has a Bachelor and Master in Aeronautical Engineering from Imperial College London. He pursued his PhD in Mechanical Engineering at the Rolls-Royce University Technology Centre at Imperial College, under the auspices of the European FP7 programme. He has worked on over 25 industry-led projects funded by industry partners, Aerospace Technology Institute (ATI), Engineering and Physical Sciences Research Council (EPSRC), UK Research and Innovation, and the European Commission. He has worked at the Ford Motor Company Development Centres in Dunton, UK and Merknick, Germany, and implemented an integrated data-centric engineering platform for new vehicle design and development. He is a Senior Lecturer in Intelligent Systems and a Chartered Engineer at Integrated Vehicle Health Management (IVHM) Centre / DARTeC. Suresh's expertise is in Data-Centric Engineering, Digital Twins & High-Fidelity Simulation, and Artificial Intelligence (AI) for Intelligent Systems.

Bernadin Namoano received his MSc degree in computer science in 2013 from Polytechnique University (France). Before joining Cranfield University in 2017, he worked as a software engineer in Paris, focusing on architectural design for big data, big time series data analysis, and software lifecycle implementation and maintenance. He completed his PhD funded by EPSRC and Unipart-rail/Instrumentel at Cranfield University in the field of condition monitoring applied to railway assets and was awarded the EPSRC Doctoral Fellowship Prize. He is currently working on the development of novel techniques for detecting, diagnosing and predicting faults using big temporal data.