1D-CNN-Based Fault Diagnosis for Traction Motors Using Vibration and Current Signals

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***Abstract*—Accurate defect detection of traction motors is essential for preserving the performance and safety of electric cars and industrial gear. This research presents a one-dimensional convolutional neural network (1D-CNN) architecture for the automated identification of faults using vibration and current information obtained from a 150 kW traction motor operating under varying load and speed circumstances. The proposed technique concurrently analyses time-series vibration and current data, allowing the model to detect both mechanical and electrical irregularities. The dataset includes several defect kinds and healthy operating settings, offering a realistic basis for training and assessment. Experimental findings indicate that the 1D-CNN model attains a classification accuracy of 98.7% with just vibration signals, 97.5% with only current inputs, and 99.4% when both modalities are integrated. The precision, recall and F1-score of the integrated signal model are above 99 percent in all types of faults, which shows good performance even in varying operations. The findings underscore the efficacy of multi-signal 1D-CNN architectures for the prompt and precise detection of traction motor faults, reducing dependence on human feature extraction and facilitating predictive maintenance tactics. The proposed method provides a scalable and generalizable solution for practical traction systems, enhancing operating dependability and decreasing maintenance expenses.**

Keywords*—Traction motor, Fault diagnosis, 1D-CNN, Vibration analysis, Current signals, Multi-sensor data, Predictive maintenance, Deep learning.

I. INTRODUCTION

Traction motors are vital elements in electric cars, high-speed trains, and industrial equipment, where their dependable functionality is crucial for safety, performance, and efficiency. Deficiencies in traction motors, resulting from mechanical degradation, electrical irregularities, or operating strains, may result in unanticipated downtime, expensive repairs, and safety risks. Timely and precise defect detection is essential for predictive maintenance and operational dependability. Conventional defect diagnostic methods often depend on human inspection, statistical signal analysis, or traditional machine learning using manually constructed characteristics.

Although successful for severe faults, these approaches encounter difficulties in identifying early-stage or complex fault patterns owing to the nonlinear and non-stationary characteristics of vibration and current data. Feature extraction requires considerable subject understanding, limiting flexibility. Recent advancements in deep learning, namely1D-CNNs, permit automated feature extraction straight from unprocessed time-series inputs. Through the analysis of both vibration and current data, 1D-CNNs may capture complementing mechanical and electrical defect features, hence enhancing diagnostic accuracy under varying load and speed situations.

This research presents a failure detection system for traction motors based on a one-dimensional 1D-CNN using multi-sensor data. Empirical evidence on an publicly available data reveals higher accuracy, precision and resilience, highlighting the potential of deep learning toward intelligent, data-driven, motor health monitoring and predictive maintenance systems.

II. LITERATURE REVIEW

An adaptive weighted distillation technique is used to weight samples based on fault uncertainty, a lightweight DSResNet-18 model is used for efficient feature extraction, and a dynamic alpha adjustment is employed to balance losses in the proposed fault diagnostic method, MDAWKD, for traction motors [1]. There was a decrease in model complexity and an improvement in diagnostic accuracy, according to the simulation data. By combining kernel principal component analysis with support vector machines, this research introduces a new adaptive fault diagnostic approach for traction motors that fail due to inter-turn short circuits [2]. It optimises by extracting signals from motor phase currents, compressing characteristics, and using a differential evolution technique. Motor samples under different operating circumstances are used to verify the approach.

Problems with interturn short circuits (ITSCs) in the stator windings are a common issue with high-speed train traction motors, which transfer mechanical and electrical energy [3]. Using impedance analysis and high-frequency voltage injection, this study presents an online diagnostic approach for ITSC defects. To accurately diagnose faults, it builds an ITSC model, examines impedance characteristics, and uses the Goertzel method. This work introduces a voltage-current hybrid model flux estimator–based fault diagnostic approach for traction motor ITSC fault detection [4]. The PI module of the flux estimator is used to get the signal for fault characterisation; this module is designed to make up for flux inaccuracies in low-speed stator resistance measurements and pure integration.

Addressing the issues of defect diagnostic accuracy under varied working circumstances, the improved dual-label random forest (IDLRF) technique is presented in [5]. It presents a new approach to multi-classification decision trees by separating nodes using a Gini index with two labels. To further improve the IDLRF algorithm's fault diagnostic performance, a dual-label ensemble technique is also created. This paper proposes a Hi/Hc optimisation method to detect faults in high-speed train traction motors by utilising nonlinearity of a system with a Takagi-Sugeno fuzzy model [6]. The aim of a fuzzy observer-based fault detection filter (FDF) is to strike a compromise between fault sensitivity and disturbance resilience. A study of CRH5 EMUs is a demonstration of concept of the approach.

An open-circuit diagnosis method of open-switch issues in three-level inverters in electric traction systems in railways is described [7]. It represents errors as additive inputs with an MLD nonlinear model with intermediate variable observers. The method has been validated through simulation experiments, and it involves circuit analysis to approximate these defects. Electrical traction systems are vulnerable to main circuit ground faults (MCGFs), which may happen in clusters of problems [8]. Single point ground faults (SPGF) are of six different types and current techniques do not differentiate between them, leading to poor isolation of problem bogies. To improve SPGF's operating efficiency and safety, this paper suggests a distinct operational approach, which is supported by hardware trials.

The loss of performance in high-speed train traction systems makes fault detection (FD) more difficult [9]. Using a federated neural network architecture that combines a variational autoencoder with an autoencoder, this study presents a new dynamic FD technique that makes use of transfer learning. Proven in case studies, the technique streamlines model training, increases FD accuracy, and doesn't need exact physical models or specialised skills to operate. A synchronous reluctance motor developed for electromobility's electric traction is presented in the article [10]. It has a dual three-plus-two phase winding and a four-pole rotor with flux barriers, so it may run independently for efficiency and fault tolerance or with increased torque. Internal combustion engines serve as design inspiration.

It is critical for health management that traction motor bearing problems in high-speed trains be accurately diagnosed. Difficulties such as weak fault characteristics and multidomain variability are obstacles to vibration signal analysis [11]. An innovative approach based on spectrum transition entropy (SpTE) is put here, which optimises parameters for enhanced sensitivity and incorporates symbolisation and transition probability matrices. This paper proposes a framework grounded on zero-shot learning (ZSL) to detect inverter open-circuit issues in traction systems to overcome the limitations of the traditional methods [12]. To enable diagnosis without problem data, it builds a fault attribute description matrix, learns using a naive Bayes classifier, and tests its efficacy.

To address the challenges posed by noise, the current study describes an objective-based approach to detect defects in industrial motors [13]. Minimising dependency on noise covariance is achieved with an iterative optimisation Kalman filter, a stable kernel representation and subspace identification are employed to design a robust reduced-order observer, and a permanent magnet synchronous motor is used to test it. For MVDC rail systems, this paper introduces an IMMC, or isolated modular multilevel converter, which converts direct current to direct current [14]. By using a medium frequency transformer, it effectively transforms MVDC power for traction motors while simultaneously decreasing the number of switches and offering the capacity to stop fault current. A prototype and simulations are used to assess performance.

It looks at a method for identifying contactor problems in ETDSs [15]. The method's efficacy is confirmed by experimental findings after it presents a model for operational condition estimate, analyses failure modes, and creates mechanisms for diagnostic enablement and feature extraction. In reference to detection of defects in the traction drive system, the research considers noise with an unknown probability distribution [16]. It handles these uncertainties by means of distributionally robust optimisation with the help of the Wasserstein measure. To guarantee dependable performance regardless of uncertainties in the distribution of noise, an experimentally verified fault detection system was built.

In this paper we are going to introduce a method to diagnose open-circuit (OC) faults in traction systems based on finite control set-model predictive control (FCS-MPC) [17]. The method does not require a threshold. Through the removal of threshold dependency, validation of faults based on residual analysis optimization and resilience based on experimental validation all help to enhance the dependability of this method. Addressed in the paper [18] are fault detection in traction drive systems that have been affected by deterministic disturbances and stochastic sounds. It introduces a dynamic model, forms a residual generator that becomes decoupled with the disturbances, and an optimisation problem that is distributionally resilient. The resilience and good detection conditions of the method are supported by experiments and simulations. This work presents a defect-detection solution to the Electric Multiple Units (EMU) with the use of machine learning by using high-density on-board data [19].

III. Proposed Method

The system of fault detection in traction motors that is proposed is an autonomous system that analyzes the data on vibration and currents to identify mechanical and electrical problems. This system adds multi-sensor data collection, signal-preprocessing, and a 1D-CNN architecture with providing more specific and robust fault classification under different operating conditions. The proposed system operation can be divided into four main steps, namely, data collecting, signal preprocessing, model creation, and classification workflow.

Data Acquisition: The system is built upon high quality dataset which consists of vibration and current signals of a 150-kW traction motor working under different load and velocity conditions. The motor is equipped with many sensors, such as vibration assessment acceleration sensors, electrical parameters measuring transducers. It includes multiple failure scenarios, such as rotor unbalance, bearing defects, and stator winding issues, in realistic operation scenarios, in addition to healthy motor settings. Simultaneously recording vibration and current data, the system ensures that mechanical and electrical anomalies are documented, hence offering additional data in identifying the defect.

Signal Preprocessing: Raw sensor signals can be corrupted with noise and can contain additional products of vibration of their environment, electrical coupling or operational variations. In order to solve this, a series of preprocessing operations are first employed in the system. Reduction of noise such as low-pass and band-pass filtering is performed to avoid the loss of frequency ranges that are most important in detecting defects.

The vibration and current signals are then separated into constant period time scans to give homogeneous samples that can be analysed using time-series analysis. To avoid skewing of the model, normalisation is employed to ensure that variations in operating conditions of amplitude of the signal do not affect the model. Moreover, techniques of data augmentation, including time shifting and scaling, can be employed to enhance the robustness of the training data so that the model could successfully generalise to work well with different motor speeds and loads.

Model Architecture: The suggested system relies on a 1D-CNN which has been specifically designed to run sequential time-series data. The 1D-CNN consists of numerous convolutional layers in which a set of learnable filters that slide over the input signal captures the temporal signal. The reason is that convolution technique allows the model to detect local phenomena, including transient spikes, oscillation, or periodic variations, which indicate motor defects.

Following every convolutional layer, there is activation, which mostly consists of ReLU (Rectified Linear Unit), and makes the network nonlinear, enabling it to identify intricate correlations in the input. To reduce dimensionality of features, reduce overfitting, and focus on the most salient characteristics of the input signals, pooling layers such as max pooling are employed. After numerous convolutional and pooling layers, the obtained feature maps are flattened and then sent to fully connected layers where complex reasoning and data incorporation between vibration and current signals are carried out.

The proposed 1D-CNN, as shown in figure 1, takes vibration and current measurements as inputs and processes them through three convolutional blocks each with 1D convolution, ReLU activation, and max pooling to extract time-related information. The flattened features pass through two fully linked layers with Relu and dropout to further incorporate features. The softmax output layer classifies motor states based on healthiness or the different types of defects.

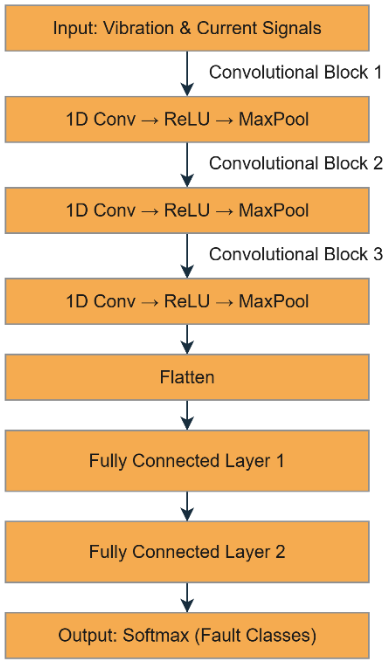

Fig. 1. 1D-CNN Architecture for Traction Motor Fault Diagnosis Using Vibration and Current Signals

Table 1 provides the 1D-CNN layers, such as convolutional, pooling, fully connected, and output layer, necessary parameters in the analysis of vibration and current data during the defect diagnostics.

TABLE I. 1D-CNN LAYER PARAMETERS FOR TRACTION MOTOR FAULT DIAGNOSIS

Layer	Type	Parameters
Input	Signals	2 channels (Vibration, Current)
Conv 1	1D Conv + ReLU	64 filters, kernel=3, stride=1
Pool 1	Max Pooling	pool=2
Conv 2	1D Conv + ReLU	128 filters, kernel=3, stride=1
Pool 2	Max Pooling	pool=2
Conv 3	1D Conv + ReLU	256 filters, kernel=3, stride=1
Pool 3	Max Pooling	pool=2
Flatten	-	-
Dense 1	Fully Connected	512 neurons, ReLU, dropout=0.5
Dense 2	Fully Connected	256 neurons, ReLU, dropout=0.5
Output	Softmax	Num. of fault classes

Multi-Sensor Fusion: The amalgamation of both the vibration and current information is a major aspect of the suggested system. This multi-modal approach allows the network to obtain complementary fault behaviour such as vibration sensors sensitive to mechanical anomalies such as bearing defects or rotor lopses, and current sensors sensitive to electrical faults such as stator winding or rotor bar issues.

Each signal modality can be processed by the system by parallel 1D-CNN branches and feature fusion, or features can be fused together on the input level as a multichannel time series. By maximising mechanical and electrical behaviour correlations, feature fusion maximises the ability to differentiate between similar defect types and minimises the risk of the model making a misclassification.

Training Workflow: The 1D-CNN is trained within a supervised learning system using labelled data points of the dataset. The model is trained by minimizing the loss, typically a categorical cross-entropy loss, to minimise the gap between the predicted fault classes and the true labels. The backpropagation and gradient descent methods are used to repeatedly perform adjustments on the weights of convolutional and fully connected layers so as to detect the relevant fault patterns. Strategies such as as dropout, batch normalisation and early stopping have been employed to reduce overfitting, and ensure consistent convergence. The network is optimised using mini-batch stochastic gradient descent, which is more compute-efficient and learning is more stabilised, particularly when dealing with large time-series.

Inference and Fault Classification: The 1D-CNN can learn new vibrations and current signals of a traction motor in real-time or offline after the training. The signals are initially pre-processed and divided as during the training period. Convolutional filters and fully connected layers are then used to obtain the feature representations by the model and give a fault probability of all the classes.

The technology can also label the motor states as either healthy or denote them to a specific problem classification and allows predictive maintenance decisions to be made. Output probabilities can have confidence thresholds to deal with unclear or ambiguous cases, therefore ensuring reliable diagnostic recommendations.

Scalability and Adaptability of the System: The proposed work is inherently scalable and capable of adapting to different types of motors and working conditions. By re-training the model using additional data sets or changing the size of convolutional filters and network depths, the system can fit larger-power motors or a variety of sensor configurations or different types of faults.

Additionally, the modular architecture also makes it easy to add additional sensor modalities, including temperature or audio input, without large architectural changes. This flexibility makes the system suitable to use in the industrial setting, electric vehicles, or railroad traction, where operating conditions vary greatly and reliability is key.

IV. RESULTS AND DISCUSSIONS

The vibration and current signals that were captured from traction motor while it was running under a variety of load and speed circumstances are included in this collection [20]. It is intended for the purpose of analysing motor behaviour and generating defect diagnostic models under a variety of different operating conditions.

- A traction motor with a power output of 150 kW
- Two types of signals are vibration and current.
- The conditions of operation include varying loads and speeds.
- Several different types of failures, including mechanical and electrical ones
- High-frequency time-series data that are ideal for 1D-CNN analysis
- The goal is to provide assistance in the construction of machine learning and deep learning models for the purpose of problem detection and predictive maintenance.

The dataset enables multi-sensor analysis, allowing the model to detect both mechanical and electrical problems. The fluctuating operating circumstances provide a credible basis for assessing model robustness and generalisation across various motor states. Table 2 displays time-series data from a traction motor, encompassing speed, frequency, load, current, vibration, and temperature, accompanied by numerical and categorical fault labels, facilitating multi-sensor analysis for the identification of mechanical and electrical faults.

TABLE II. TRACTION MOTOR DATASET

Time s	Speed rpm	Freq Hz	Load torque Nm	Stator current A	Vibration m s2	Temperature C	Fault label	Fault type
0	1800	180	131.0112	240.3561	-6.64E-06	42.36752	0	Normal
0.010002	1800.05	180.005	119.8225	162.1644	-0.01312	78.92838	0	Normal
2.870574	1812.806	181.2806	115.8341	149.5596	0.022546	57.989	1	BearingFault
2.880576	1811.978	181.1978	121.6158	192.3629	-0.01729	65.44721	1	BearingFault
12.87257	1893.587	189.3587	100.9002	147.0605	-0.04671	55.13875	2	RotorImbalance
12.88258	1893.534	189.3534	104.3566	160.0276	-0.02798	71.78267	2	RotorImbalance
49.83997	1784.219	178.4219	115.6149	165.0091	-0.00522	75.39178	3	StatorShort

Table 3 is the distribution of 20,000 samples in four groups of fault with 70:15:15 ratio to train and validate and test the models to give fair and strict evaluation of the model.

TABLE III. DATASET DISTRIBUTION AND SPLIT FOR TRACTION MOTOR FAULT CLASSES

Fault Class	Total Samples	Training (70%)	Validation (15%)	Testing (15%)
Normal	5000	3500	750	750
BearingFault	5000	3500	750	750
RotorImbalance	5000	3500	750	750
StatorShort	5000	3500	750	750
Total	20000	14000	3000	3000

Figure 2 shows a confusion matrix that outlines the classification effectiveness of the 1D- CNN model on all the categories of fault. The rows correspond to actual conditions of the motors, and the columns to the projected classes. High values on the diagonal indicate accurate identification of both defective and normal states, and low off-diagonal values would indicate a few misclassifications indicating the robustness and reliability of the model in fault diagnosis.

Table 4 shows the results of the 1D-CNN model to predict each kind of traction motor faults. Those high and constant values in all classes would mean that the model works well in separating between normal and problematic conditions, demonstrating significant multi-sensor features capture, and reliable fault detection in diverse operation rates and load conditions.

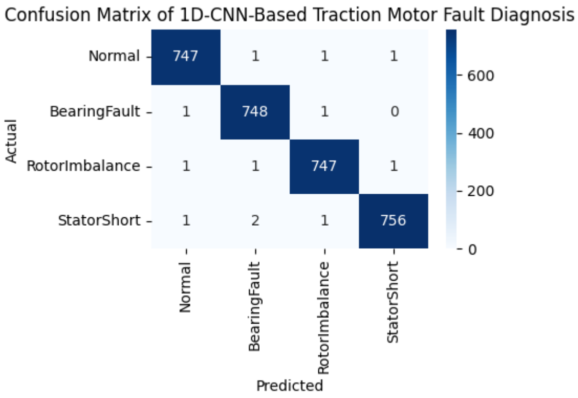

Fig. 2. 1D-CNN Fault Classification Confusion Matrix

TABLE IV. PERFORMANCE METRICS OF 1D-CNN ON VIBRATION AND CURRENT SIGNALS

Fault Class	Precision (%)	Recall (%)	F1 Score (%)
Normal	99.60	99.60	99.60
BearingFault	99.47	99.73	99.60
RotorImbalance	99.60	99.60	99.60
StatorShort	99.74	99.47	99.60
Overall	99.60	99.60	99.60

The accuracy of training and validation of the 1D-CNN model during 15 epochs is shown in figure 3. Both curves are steadily increasing, and the last epoch is the validation of 99.80. The high correlation of training and validation curves represents a minimal overfitting effect, which shows that the model efficiently is taught using vibration and current data and can successfully generalise to new motor failure data.

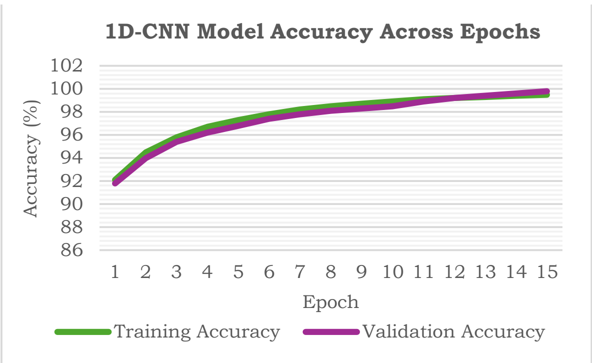

Fig. 3. 1D-CNN Accuracy Curve

The training and validation loss of the 1D-CNN model during the 15 epochs are shown in Figure 4. Both the losses water down gradually which is an indication of efficient learning of vibration and current inputs. The small error in the intersection between training and validation loss reflects that there is minimal overfitting and the gradual decrease towards small values depicts convergence of the model and the capability of detecting faults in traction motors, as indicated by the model reliability.

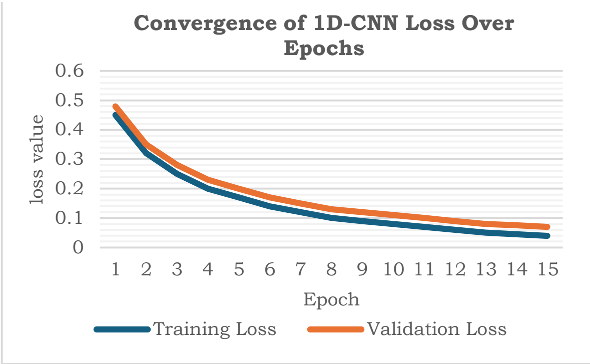

Fig. 4. Loss Trends of 1D-CNN During Training

The suggested 1D-CNN model (despite being highly accurate) possessed many limitations. It requires a lot of labeled data to train, which makes it less suitable with less frequent or new types of defects. Hardware costs can be increased by high-frequency sensors of vibration and current. The effectiveness of the model can reduce due to adverse environmental conditions or unknown circumstances under which it can be used. Besides, deep networks are expensive to train, requiring the use of GPUs to learn and implement deep networks successfully.

The work of the future can focus on enhancing the sturdiness and viability of the model. Additional sensor modalities (such as temperature and audio sensors) could be included to improve early detection of defects. Lightweight or even compressed 1D-CNN could be used to run on edge devices. Transfer learning and semi-supervised techniques can reduce the need to use a large set of labelled data, whereas real-time monitoring systems could help improve predictive maintenance of traction motors in diverse operating environments.

V. CONCLUSIONS

This study suggested a model that employs 1D-CNN in the offline detection of faults in traction motors with vibration and current signals. It involves the use of multi-sensor of time-series data to detect the mechanical and electrical anomalies with an appropriate degree of accuracy in the normal functioning and varying kinds of faults including defects in bearings, rotor imbalance and short-circuit in stators. The combination of both vibration and current data within one deep learning system allows the system to automatically identify the relevant features, thus skipping human feature engineering. The model is largely resilient and generalised as its performance is the same on both training and validation datasets. The ability to maintain better performance in changing load and speed conditions highlights the suitability of 1D-CNNs to typical traction monitoring of motors. This suggested system will provide a scalable, reliable and data-driven predictive maintenance solution enabling early defect detection and increased operational reliability. The areas of development in the future can focus on a real-time implementation, the multi-sensor fusion, and adaptation to any other type of motor or industrial use.

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