Enhancing AI Model for Fault Detection in Rail Through the Evaluation of AE Parameters with Proper Weighting Approach: A Comprehensive Study

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Abstract. The reliable detection of faults in rail systems plays a crucial role in ensuring safe and efficient transportation. In recent years, artificial intelligence (AI) techniques, particularly neural networks, have shown promising results in fault detection applications. However, the selection of input parameters with proper weight function is not considered scientifically in the prevailing studies. The study focuses on the evaluation of Acoustic Emission (AE) parameters using an appropriate weight function to enhance the accuracy and effectiveness of fault detection. The research explores the significance of various AE parameters, including amplitude, count, energy, frequency, RMS, etc., containing the fault information through the signal. Additionally, a new methodology is introduced to assign different weights to individual AE parameters based on their importance, ensuring the AI model concentrates on the most relevant features. Extensive experiments are conducted in the laboratory to generate the AE data using pencil lead break (PLB) on the top flange of the rail, as it is considered more prone to damage. The performance of the AI model is compared in terms of accurate fault localization using the developed artificial neural network (ANN) model, demonstrating its superiority in terms of accuracy, robustness, and efficiency. The results highlight the considerable enhancement achieved through the evaluation of AE parameters with a proper weight function, contributing to safer and more reliable transportation infrastructure.

Keywords: Structural Health Monitoring (SHM), Artificial Neural Network (ANN), Non-destructive Testing (NDT), Artificial Intelligence (AI), Rail Section

1 Introduction

The reliable detection of faults in rail systems is of utmost importance to ensure the safety, efficiency, and reliability of railway transportation networks [1,2]. A timely and accurate identification of faults is crucial for proactive maintenance, preventing

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potential accidents, and minimizing disruptions to railway operations [3,4]. Therefore, for the railway to run smoothly, real-time fault detection of these rail sections is the need of the hour. In Non-Destructive Testing (NDT), the Acoustic Emission (AE) methodology is a cutting-edge approach to damage detection in real-time [5,6]. Acoustic emission (AE) signals emerge from confined origins and travel as elastic waves, a phenomenon commonly referred to as fault localization (Shiotani & Ohtsu, 1999; Behnia et al., 2014) [7,8]. In the quest to replicate these particular kinds of structural impairments or fractures, a substantial number of researchers have embraced the Hsu-Neilson source, commonly known as Pencil Lead Break (PLB), as a means to emulate this specific type of fault or AE source. These signals can be effectively captured using appropriate AE sensors strategically positioned along the rail. The AE technique proves to be particularly invaluable in the precise localization of faults, a challenging task in rail sections owing to their intricate geometrical configurations and the complex nature of AE wave propagation. The fundamental characteristics viz., Amplitude, counts, duration, RMS, Rise time etc., of the AE signal can be used to locate the fault position in the rail section. The literature strongly suggests a promising and bright future for fault detection in rail sections through the application of this methodology. More importantly, in recent times the application of this technique has been found to be effective in fault detection in rail in real-time. Authors in their study either adopted the signal processing approach, analytical approach, geometric approach etc. to find the location of the fault. In the aforementioned approaches, the determination of wave velocity and time of arrival is very critical and it becomes more challenging in the case of railway track. Artificial intelligence (AI) techniques, particularly neural networks, have shown great potential in fault detection applications in recent years. Ebrahimkhalou and Salamone (2018) introduced an innovative localization technique that harnesses the power of deep learning algorithms to analyze the edge reflections of Acoustic Emission (AE) waves [9]. Kundu et. al. (2023) introduced an innovative approach i.e., artificial neural network (ANN) for the localization of damage in rail and compared the methodology with the conventional signal processing approach i.e., Wavelet Transformation (WT) and showed great potential in terms of application in railway [10]. Recently, Pal et al. (2023) demonstrated the performance of the AI model in fault detection in railways using a single AE sensor data. Developing AI models requires the selection of suitable AE parameters with proper weights [11-13]. Many authors in past have considered the relative weightage to the AE parameters randomly and the process is time-consuming, and not scientific [14,15]. However, the scientific selection of input parameters and the appropriate weights for the selective AE parameters to optimize the performance of these models can be more effective.

This research paper aims to bridge this critical gap by focusing on the comprehensive evaluation of Acoustic Emission (AE) parameters using a scientifically designed weighting approach to the AE parameters. The primary objective is to enhance the accuracy and effectiveness of fault detection in rail systems. By employing a diverse range of statistical methods and analyzing the distribution of various features, weights are calculated for each influencing parameter, to improve the performance of AI models and enable more accurate fault detection in the rail section.

2 Methodology

2.1 Generation of AE/fault signal in laboratory

To conduct this research, we simulate the AE signal using PLB over the rail section. The interaction between the wheel and track can result in wear and tear on the rail section. As the Top Flange (TF) of the rail section is more prone to damage, we perform the PLB on the TF of the rail section to simulate the damage source [4]. Previous research has consistently indicated that the most optimal placement for the AE sensor is on the web of the rail section. This strategic positioning facilitates precise distance measurements between the source and the sensor and enables the capture of high-quality AE signals emitted from every segment of the rail section.

2.2 Data Processing for the Development of the AI Model

Scaling of features: Machine learning algorithms operate on numerical data without understanding contextual meaning, leading to a bias towards higher numerical values during training. To mitigate this, we employed feature scaling techniques like the Standard Scaler for normally distributed features and the Min Max Scaler for non-Gaussian distributions with small standard deviations. However, the Min Max Scaler is sensitive to outliers. We applied it to features like Rise Time, Counts, and Duration for standardization and analysis.

Removal of Outliers: Outliers are data points that deviate significantly from the rest of the observations and can arise from measurement variability, novel data, or experimental errors.

We have employed Tukey's Interquartile Range (IQR) technique for outlier detection. Tukey's method is suitable for skewed or non-bell-shaped data as it does not make any distributional assumptions. According to the general rule, any data point outside the range of (Q1 - 1.5 IQR) and (Q3 + 1.5 IQR) is considered an outlier and can be removed. The IQR is a widely used procedure for outlier detection and removal in data analysis.

Fig. 1. Correlation matrix of the Dataset

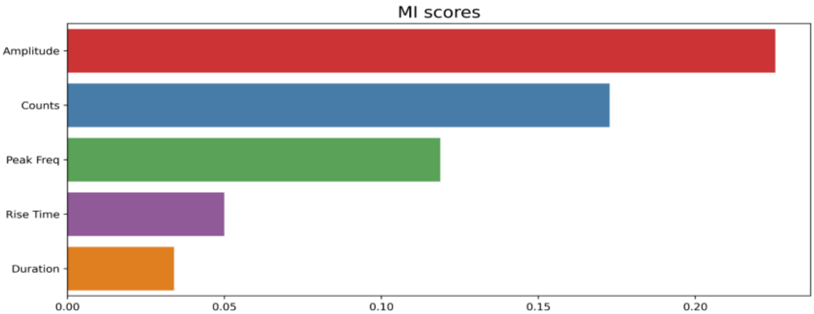


Fig. 2. Mutual Information Scores Bar Chart

Based on the information provided by the bar chart, it is evident that Distance and Amplitude are highly correlated. Utilizing both the correlation matrix scores (Figure 1) and the mutual information scores (Figure 2), we can initialize the weights of the Artificial Neural Network (ANN) model. MI score and the corresponding weights are shown in Table 1.

Table 1. MI score and corresponding weights of the AE parameters

Features	Score	Weights
Amplitude	0.22	0.37
Peak Frequency	0.11	0.20
Rise Time	0.05	0.08
Counts	0.17	0.28

Duration	0.03	0.07

Development of AI model

This study introduces a novel approach for localizing Acoustic Emission (AE) sources by leveraging fundamental features present in the AE signal. The key features, such as Amplitude, Duration, Peak Frequency, Count, and rise time (Figure 3), are utilized to train an Artificial Neural Network (ANN) model. The ANN employs a feed-forward backpropagation solver and consists of three hidden layers, each containing 20 neurons.

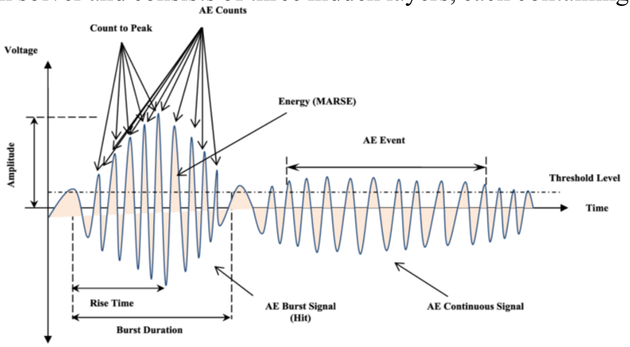


Fig. 3. AE parameters obtained from AE signal

3 Results and Discussions

This investigation develops and evaluates an advanced Artificial Neural Network (ANN) model, capable of handling multi-functional parameters through generalization. Figure 4 shows accurate predictions with an R-value of 1, indicating a perfect relationship between output and target values by regression curve. The ANN model has five input layers and three hidden layers, each with twenty neurons. To ensure the output closely approximates the target value, the Mean Square Error (MSE) is employed as a guiding metric in the ANN model. Using Feed-Forward Backpropagation, the model is refined in 150 iterations and completes localization in just 10 minutes, showcasing its real-world efficiency.

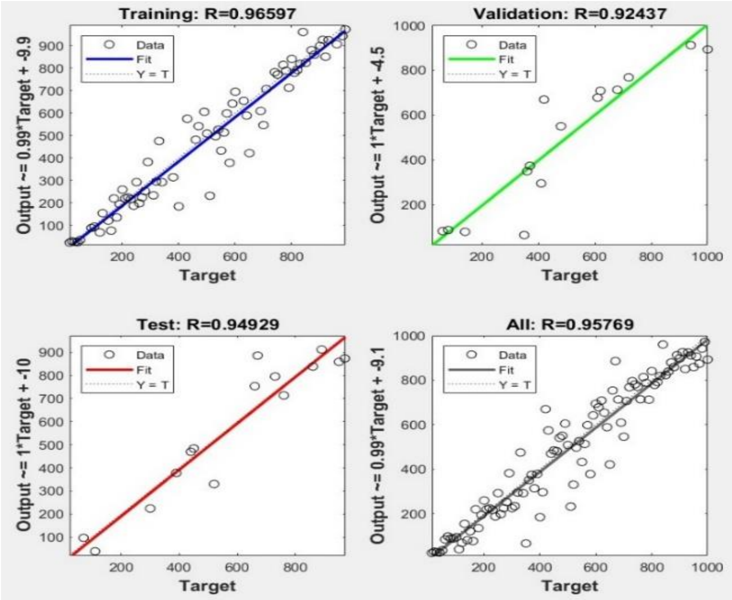


Fig. 4. Regression Curve

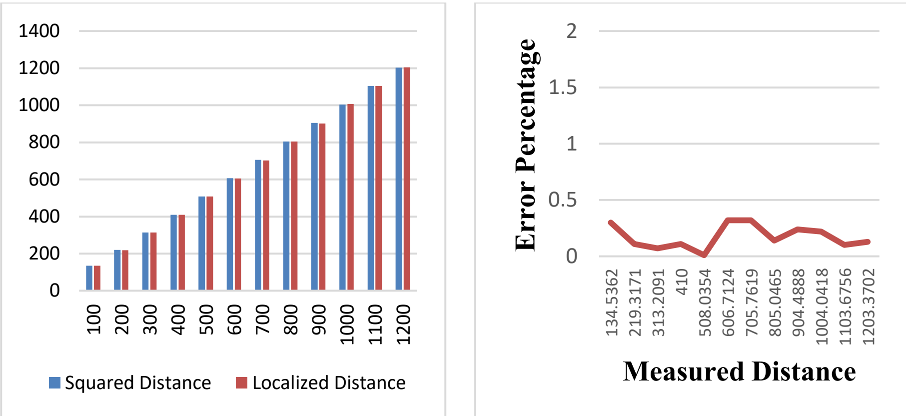
The main focus of our investigation is to localize Acoustic Emission (AE) sources for monitoring rail section health. Through a smart localization technique, we achieved excellent results, as shown in Fig. 4. Table 2 displays the localization outcomes, along with the percentage of error in localized distances compared to actual and predicted values. This approach enhances rail infrastructure safety and maintenance, ensuring the timely detection of simulated damages.

Table 2. Localized Distance and Error Percentage

Measured Distance (mm)	Localized Distance (mm)	Error Percentage
134.5362	134.952	0.30
219.3171	219.060	0.11
313.2091	312.982	0.07
410	409.560	0.11
508.0354	507.987	0.01
606.7124	604.754	0.32
705.7619	702.450	0.32
805.0465	803.902	0.14

904.4888	902.274	0.24
1004.0418	1006.351	0.22
1103.6756	1104.752	0.10
1203.3702	1205.045	0.13

In Figure 5 (a), a comprehensive evaluation of the actual squared distance versus the localized distance is presented. Notably, the comparison vividly illustrates the remarkable proximity between the localized distance and the actual squared distance. This alignment is visually evident and underscores the model's efficacy. Figure 5 (b) further reinforces this assessment through the depiction of an error percentage graph. This graph distinctly illustrates the minimal divergence in relation to distance measurements. Particularly noteworthy is the revelation that the maximum error percentage is a mere 0.32%. This figure stands as a testament to the exceptional accuracy achieved by the developed model.



(a) (b)

Fig. 5. (a) Comparison graph of the squared distance and localized distance, (b) Error percentage graph with respect to the distance

4 Conclusions

This study is the development of the AI model for fault detection in railways in real time using AE sensor data. While developing the model for fault location along the rail single AE sensor data is utilized when the sensor is placed on the web of the rail section. For a better model, suitable weights for the important AE parameters are found with the help of a methodology. The results of the investigation are highlighted below.

(i) AE parameters viz, Amplitude, Rise Time, count etc. with corresponding weights in ANN model as input predicts the damage location with an error less than 1%.

(ii) Choosing proper weight parameters via trial-and-error approach is time-consuming and unscientific, this method for selection of proper weight parameters can be effective and less time-consuming.
(iii) Same method can be utilized for other data sets for the development of an AI model for fault detection in the railway.
(iv) Proposed methodology will be useful in future research for making fault detection in railways fast and accurate.

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