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Reducing Train Delays with Machine Learning-Based Predictive Maintenance for Railways

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ABSTRACT

The railway network constitutes a vital component of public transportation in many countries, serving millions of passengers and transporting significant volumes of freight. Nevertheless, a persistent challenge within this system is the frequent occurrence of train delays, which arise from diverse causes and result in financial losses, passenger dissatisfaction, and diminished trust among users. Consequently, enhancing operational efficiency and minimising delays has become a central objective for transportation planners and policymakers. In addressing this issue, the present study applies machine learning algorithms (MLAs), specifically multilayer perceptron (MLP) neural networks and the adaptive neuro-fuzzy inference system (ANFIS), to predict potential defects in railway vehicles and improve maintenance and repair strategies within the Iranian railway network. The findings reveal that ANFIS achieves superior predictive accuracy. Building on this, a mathematical model in combination with the Particle Swarm Optimization (PSO) algorithm was developed to optimise train allocation across stations and generate schedules aimed at reducing delays. The employed algorithms proved to be highly effective for predictive maintenance and repair of railway vehicles, ultimately contributing to delay reduction within the railway system.

1. Introduction

Railway networks represent a fundamental pillar of national transportation, facilitating the movement of millions of passengers and substantial volumes of freight across the country each year. One of the primary challenges faced by this system is the frequent occurrence of train delays, which may arise from a variety of operational and technical factors. According to established schedules, a train delay occurs when a train fails to depart from its origin or arrive at its destination on time. Such delays can result from infrastructure failures, signalling and communication issues, mechanical faults in locomotives or rolling stock, accidents, and other related causes [33]. Delays in train operations are widespread and disruptive, often producing significant consequences. In addition to generating passenger dissatisfaction and reducing the confidence of freight customers, these delays have

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broader socioeconomic implications. Enhancing operational efficiency and minimising delays continues to be a core goal for railway planners and administrators [18; 23].

Historically, railway vehicle maintenance has relied on conventional procedures and predetermined schedules [3]. These traditional approaches, based on fixed intervals or reactive interventions, often prove suboptimal and can lead to service interruptions. The emergence of digital technologies has facilitated the application of machine learning (ML) techniques within the railway sector. Research has demonstrated that ML contributes effectively to predictive maintenance, helping to reduce mechanical failures and service disruptions [28]. By proactively addressing equipment faults, ML frameworks improve both reliability and cost efficiency. Algorithms commonly applied in this context include decision trees, artificial neural networks (ANNs), and support vector machines (SVMs). Among these, ANNs and SVMs have shown strong performance in forecasting maintenance requirements for railway applications [20]. These approaches are valued for their adaptability to dynamic conditions and their ability to maintain continuous train operations.

Analyzing operational data to identify patterns and extract actionable insights plays a vital role in managerial decision-making. Conventional software typically supports routine monitoring, reporting, and short-term planning; however, valuable patterns often remain hidden within large datasets. Data mining has been recognised as an effective method for discovering these patterns. Once identified, these insights enable railway managers to reduce passenger train delays and enhance service quality [9]. For instance, clustering delays caused by vehicle failures allows classification into distinct categories. Examining these clusters helps to uncover relationships between delay types and underlying causes, thereby facilitating targeted interventions. Such measures improve passenger confidence and strengthen trust among freight and cargo customers. To sum up, it can be stated that using MLAs in the maintenance and repair of railway vehicles to reduce train delays is both highly significant and essential.

The principal contributions are summarised as follows:

- Reducing delays and improving services: Train delays diminish passenger satisfaction and the quality of freight services. The application of MLAs in maintenance enables more effective reduction of delays and improvement of service delivery.
- Increasing productivity and lowering costs: MLAs support improved operational efficiency and cost reduction in locomotive maintenance. By identifying components requiring attention, MLAs increase the precision and effectiveness of repairs. Early detection of potential issues reduces reliance on manual inspection, shortens repair times, limits service interruptions, and enhances vehicle reliability.
- Enhancing resource distribution and optimal planning: MLAs assist in prioritising vehicles for repair and allocating resources efficiently, improving overall railway performance and reducing delays.
- Promoting prevention and prediction: Algorithms trained on operational and technical data can learn continuously, enhancing the ability to prevent and predict defects and avoid sudden disruptions.

Previous studies support these applications. MLAs have been successfully used to predict maintenance requirements Bukhsh et al. [6], reviewed as effective in diagnosing and forecasting rail defects [10], applied in models for identifying rail defects and joints using acceleration data [22], and implemented in Greek railways where data mining and preventive maintenance improved strategic decision-making and resource allocation [34]. Collectively, these studies illustrate the value of ML in enhancing maintenance processes and reducing train delays.

The present study objectives are as the following:

- Prediction and Prevention of Faults: MLAs enable improved forecasting of vehicle defects and facilitate timely maintenance interventions when progressive faults are detected.

- Optimizing the Maintenance Planning: ML supports the scheduling of repairs at appropriate times and locations to prevent delays.
- Enhancing Preventive Maintenance: By identifying recurrent failure patterns from operational data, MLAs facilitate preventive actions that reduce both the frequency and severity of faults.
- Improving Failure Detection System Performance: ML improves the accuracy and speed of fault detection, thereby shortening repair durations and minimizing downtime.
- Improving the Railway Network's Performance: The integration of ML methods in maintenance elevates overall system performance and increases passenger satisfaction and confidence among freight stakeholders.

The main study innovations are as follows:

- Application of MLAs and technical data analysis to more accurately detect faults and component failures.
- Optimized repair planning through analysis of vehicle performance data and environmental factors, such as weather, traffic, and travel schedules, ensuring timely interventions and minimizing unexpected disruptions.
- Development of intelligent maintenance systems by training MLAs on vehicle performance records, prior repair history, and operational conditions, supporting scheduled inspections and repairs.
- Prediction of component lifespans and replacement requirements using MLAs, enabling preventive maintenance and timely replacement of parts to reduce train delays.

This article is structured as follows: Section 2 provides theoretical foundations and literature review. In Section 3, the proposed methodology is described. Results and discussions are given in Section 4. Eventually, the paper concludes in Section 5.

2. Literature Review

2.1 Theoretical Foundations

2.1.1 Railway Vehicle Maintenance and Repairs

The maintenance and repair of railway vehicles constitute a critical function essential for ensuring the safe and efficient operation of railway systems. Rail vehicles, including freight wagons, passenger carriages, locomotives, and associated equipment, form the core infrastructure responsible for transporting passengers and cargo globally. The significance of maintenance and repair activities in rail vehicles can be summarized as follows [17; 30]:

- Keeping Safety and Building Trust: Ensuring the safety of passengers and freight is paramount in railway operations. Regular and timely maintenance prevents accidents caused by mechanical or technical failures, while simultaneously enhancing the confidence of passengers and cargo owners in the reliability of the railway system [11].
- Reducing Delays and Enhancing Performance: Technical faults and component failures can lead to unforeseen train delays. Implementing predictive and routine maintenance allows for smoother operations, improved system performance, and the minimization of service interruptions.
- Increasing Useful Life and Productivity: Proper and timely maintenance extends the operational lifespan of railway vehicles, reducing the need for early replacement of damaged parts and components. This contributes to higher productivity and profitability within the railway network.
- Energy Efficiency and Pollutant Reduction: Well-maintained rail vehicles operate more efficiently,

optimizing fuel consumption. This not only lowers operational costs but also mitigates environmental pollution and improves air quality in areas surrounding railway tracks and stations.

- Raising Customer Satisfaction: Systematic maintenance enhances reliability, leading to increased satisfaction among passengers and cargo owners. Sudden failures or unexpected delays can diminish customer trust and reduce confidence in the railway transport system.

In summary, the maintenance and repair of railway vehicles are essential for ensuring operational safety, reliability, and customer trust, while also improving performance, reducing delays, prolonging vehicle lifespan, optimizing energy usage, and enhancing overall customer satisfaction. The adoption of machine learning approaches is particularly valuable in this context, as it supports the prediction of vehicle failures and optimizes maintenance and repair strategies to improve the performance of railway systems [31].

2.1.2 Types of Common Failures in Rail Vehicles

Over time and with continuous operation, railway vehicles are prone to developing faults and technical defects due to harsh operational conditions and diverse environmental factors. The impact of these failures on train performance varies according to the type of fault and its severity. Some of the common malfunctions in rail vehicles and their corresponding effects are outlined as follows [24; 25]:

- Failure of Passenger Train Wagon Equipment: Components such as doors, windows, coupling systems, wheel and axle assemblies, and control levers may experience wear and deterioration, leading to operational delays.
- Failure of the Brake System: Malfunctions in the braking system present significant safety risks. Ineffective or broken brakes compromise the control of train speed, potentially causing delays and accidents.
- Failure of the Electrical System and Joints: Defects in the electrical system or its connections can result in power outages, disrupting the operation of onboard electronic and electrical systems, and causing stoppages and travel delays.
- Failure of the Air Conditioning System: During periods of high temperatures, malfunctions in cooling or ventilation systems can create substantial discomfort for passengers, affecting the quality of travel.

Failure of the Engine and Power Transmission System: Failures in the engine or transmission system represent major causes of delays. Such defects may prevent the train from moving entirely or significantly slow its operation.

Overall, these malfunctions contribute to train delays, reduced operating speed, interruptions in scheduled movement, increased operational costs, and diminished customer satisfaction. To mitigate these challenges, the implementation of ML techniques for fault detection and prediction offers a promising approach to enhancing operational performance and minimising train delays within the railway network.

2.1.3 Predictive Maintenance and Repairs

Maintenance and repair involve activities aimed at ensuring that equipment and system components operate correctly under all conditions. The primary objective of these activities is to preserve and improve the performance and reliability of rail vehicles. Several approaches are employed for maintaining and repairing railway vehicles, with the three principal methods summarised as follows [13; 15]:

- Corrective Maintenance and Repairs: This approach entails performing maintenance only after a failure has occurred. While it represents the most straightforward and traditional method, it often results in unexpected breakdowns, critical operational disruptions, and increased maintenance costs.

- Preventive Maintenance (PvM) and Repairs: Preventive maintenance involves scheduling regular replacement or servicing of parts based on historical failure data and manufacturer recommendations. By calculating the Mean Time Between Failures (MTBF), maintenance teams can design proactive maintenance programmes to avert unexpected failures. Although this approach can reduce unplanned disruptions, it may incur additional costs and require consideration of the remaining useful life (RUL) of components.
- Predictive Maintenance (PdM) and Repairs: Predictive maintenance relies on continuous monitoring of mechanical conditions and other operational parameters over time. By leveraging modern technologies, including sensors and data acquisition tools, real-time information from various equipment components can be analysed using MLAs and statistical models to anticipate potential failures. This approach significantly contributes to reducing train delays and minimising costs associated with unforeseen breakdowns.

2.2 Deep Learning

Deep learning is recognized as a specialized subfield within machine learning. Its primary objective is to develop intelligent computational systems capable of learning new concepts and providing solutions to specific problems in a manner analogous to human reasoning. This area represents a crucial component of data science, as it integrates statistical analysis and predictive modelling to address a variety of challenges. Through the application of deep learning techniques, data scientists can efficiently gather, process, and interpret large-scale datasets with increased speed and accuracy. Deep learning algorithms analyses diverse forms of input from the external environment, such as images, audio, and text, to identify underlying patterns that can be utilized for predictive purposes. To understand deep learning comprehensively, it is necessary to examine the architecture of its models. These models are composed of multiple layers, forming structures known as neural networks, which are inspired by the organization of the human brain. Biological neurons comprise elements such as dendrites, the nucleus, the cell body, the axon, and axon terminals. Neurons receive input signals from sensory organs—including sight, hearing, smell, and touch—through the dendrites. This information is then transmitted along the axon and communicated to the dendrites of subsequent neurons via synaptic terminals. Similarly, in neural networks, each layer receives input in the form of numerical vectors through numerous nodes, processes this information, and transmits the output to the next layer. The weights within the network function analogously to synapse in the human brain, representing the parameters that the network must learn. By adjusting these weights, the neural network determines the relative importance of each input in producing the final output [19].

2.3 MLP Neural Network

The MLP neural network represents a type of machine learning model that utilises artificial neurons for information processing. It consists of multiple layers of neurons; each fully connected to the preceding and subsequent layers. Within the network, every neuron layer employs an activation function to transform the outputs received from the previous layer. MLP neural networks are versatile and can be applied to a wide array of tasks, including classification, regression, and data compression. Their widespread adoption is attributed to their substantial learning capability and their proficiency in modelling intricate patterns [29]. Figure 1 illustrates the structural configuration of a neural network.

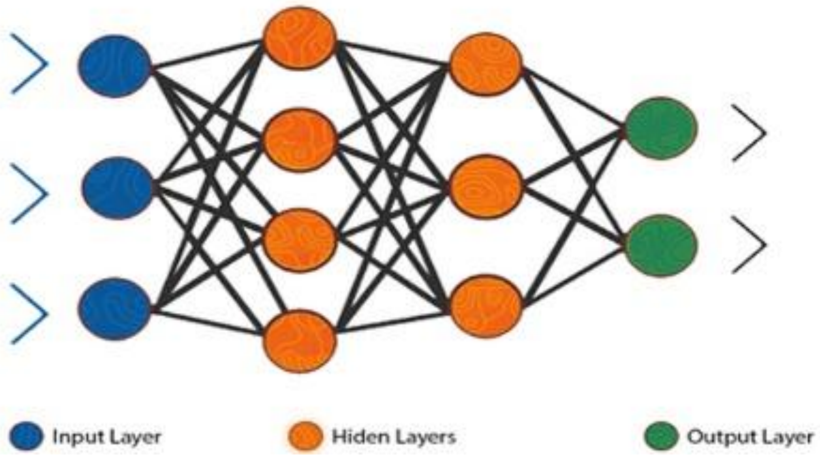

Fig.1: MLP Neural Network Structure Consilvio et al. [13]

An MLP network is typically composed of three principal layers:

- Input Layer: This layer is responsible for receiving the input data attributes. The number of neurons within the input layer corresponds directly to the number of input features.
- Hidden or Intermediate Layers: These layers commonly referred to as hidden layers, contain neurons that enable the network to learn complex patterns and relationships among features. The architecture allows flexibility in both the quantity and size of hidden layers, as they perform the primary computational functions of the network.
- Output Layer: The output layer produces the network's final predictions or classifications. The configuration of a neural network varies according to the specific problem it is designed to address.

2.4 ANFIS

ANFIS is a highly efficient machine learning approach that integrates the strengths of Artificial Neural Networks (ANN) and Fuzzy Logic (FL). This hybrid model is widely employed by researchers and engineers for tasks such as classification, regression, and control system design due to its robust performance [16]. A principal advantage of ANFIS lies in its capacity to address nonlinear and highly complex problems. Its adaptive learning mechanism allows the system to refine parameters in response to input data while detecting and predicting subtle patterns. The architecture of ANFIS comprises five essential layers:

- Input Layer: This layer receives raw data entering the system.
- Fuzzy Layer: Fuzzy logic principles are applied, defining membership functions and establishing fuzzy rules.
- Normalization Layer: Outputs from the fuzzy layer are weighted and normalized based on the input data.
- Inference Layer: Fuzzy logic operators are applied to the normalized outputs to derive final inferences.
- Output Layer: This layer generates the system's final output.

The ANFIS architecture effectively combines the benefits of neural networks and fuzzy systems. The trainability of neural networks is exploited through weighted connections, allowing the model to be trained using the error backpropagation algorithm. Simultaneously, the imprecise modelling capabilities of fuzzy systems are utilized, enhancing decision-making under uncertainty and improving predictive accuracy [5].

2.5 Review of Similar Studies

Delay prediction in public transportation using neural networks has been investigated [32]. A rule-based neural network system was developed to forecast delays in the public transportation system. By analyzing existing data and variables related to public transport, the neural networks were trained to predict future delays. A methodology for modelling train delays and their propagation across station networks using stochastic techniques was introduced [26]. This approach combined mathematical formulations with detailed simulations, capturing a wide range of delay scenarios in transit systems. Fuzzy Petri net (FPN) models have also been applied for estimating train delays [2]. These models are suitable for addressing the complexity and uncertainty inherent in transportation systems. Predictive maintenance for railway braking systems using data analytics has been applied [12]. Comprehensive datasets from train operations were analyzed with advanced analytical methods to identify patterns related to equipment failures and performance anomalies. This approach enabled early detection of critical failure indicators, allowing for more precise fault prediction. A risk-informed maintenance scheduling model tailored for railway systems was proposed using a rolling-horizon optimization technique [13]. The model dynamically updated maintenance plans through real-time sensor inputs and continuous monitoring of equipment conditions, enabling anticipation and mitigation of potential failures. Hybrid ANFIS models integrated with metaheuristic optimization algorithms have been developed to overcome performance limitations of standard ANFIS models [8].

Passenger train delays in railway zones of the Islamic Republic of Iran were predicted using passenger train movement and weather data via machine learning algorithms [28]. Considering the effects of winter weather on train delays, incorporating weather data improves decision-making and preventive measures. Passenger train delay data from 2017 to 2021 and corresponding weather data from synoptic stations were analyzed, comprising 46,596 records. Independent variables included year, month, day of the month, day of the week, axis of movement, type of train, railway zone, maximum wind speed, minimum horizontal visibility, minimum temperature, maximum temperature, number of ground surface freezing reports, and 24-hour rain and snow precipitation. The CRISP-DM methodology was employed for implementing machine learning and data mining techniques. Prediction modelling was performed as a categorization task, with the dependent variable, delay, divided into timely and delayed categories. Supervised learning methods were used to predict the impact of weather factors on train delays. Cross-validation was applied to evaluate model accuracy. The results showed that winter weather factors over the five-year period had positive, negative, or neutral effects on train delays. Preventive measures were proposed to enhance adaptation to climatic challenges [27].

3. Methodology

The methodology of the present study focuses on assessing the potential to predict train delays arising from railway vehicle failures using a machine learning algorithm. The primary objective of this research is to examine and optimize the impact of predicting maintenance requirements of railway vehicles on operational performance and the prevention of train delays within the Iranian railway network. Previous literature has demonstrated that the application of machine learning algorithms in predictive maintenance can significantly enhance the efficiency and accuracy of forecasting operational disruptions [1; 21]. Consequently, this study aims to employ such techniques to evaluate the capability of predicting train delays caused by railway vehicle malfunctions and to optimize maintenance interventions to mitigate these delays within Iran's rail infrastructure. The machine learning algorithm functions by predicting faults in railway vehicles during their operation and determining the necessary maintenance actions to prevent failures. This process utilizes observational data, historical records of prior failures, operational experience, and preventive maintenance guidelines relevant to the Iranian railway fleet. By analyzing this information, the algorithm identifies patterns that can be used to infer the probability of vehicle failure and to assess operational status.

In the first stage, failure reports from railway vehicles collected during train operations across the Iranian railway network are processed using two approaches: the MLP neural network and the adaptive neuro-fuzzy inference system (ANFIS). These models are employed to detect initial failures and assess the likelihood of imminent service disruption. For instance, a classification output of 0 indicates that no failure is expected in the next n days, whereas a classification output of 1 corresponds to a predicted type-1 failure within the same period. By evaluating failure probabilities from both models and comparing their outcomes, the model yielding the highest predictive accuracy is selected. In the second stage, a mathematical model is formulated using the calculated failure probabilities. This model enables optimization of the expected delay by adjusting operational schedules accordingly. The sequence of these steps and the associated workflow are outlined in the subsequent sections.

4. Data Sets

In this section, the dataset derived from reports on passenger train wagon failures within the Iranian railway network during 2022 was utilized. The variables included in the analysis were treated as indicators of failure.

4.1 Data Pre-Processing

Data pre-processing represents a fundamental stage in machine learning–based modelling for predicting railway vehicle failures, as the integrity and quality of the input data directly influence the predictive performance of the model. This stage encompasses processes such as data cleaning, dimensionality reduction, and transformation to enhance the effectiveness and efficiency of the machine learning algorithm. To ensure robust analytical outcomes, datasets are conventionally divided into three distinct subsets: a 70% training set to enable the model to learn and identify patterns, a 15% testing set to evaluate model performance on previously unseen data, and a 15% validation set to assess generalizability and reduce the likelihood of overfitting. Adopting this structured data partitioning approach substantially enhances the accuracy, reliability, and robustness of predictive models [4].

4.2 Selecting the Right Model for Railway Failure Prediction

When predicting rail vehicle failures, the choice of an appropriate machine learning model is determined by several factors, including the nature of the problem, the quality and volume of available data, and computational requirements. Two particularly effective approaches are the MLP neural network for detailed classification of failures and the ANFIS for managing uncertain and complex datasets. ANFIS integrates fuzzy logic with artificial intelligence to handle real-world railway data that often involves multiple interacting factors such as operating conditions, maintenance quality, and the age of the vehicle [7; 14; 16; 35]. A key advantage of ANFIS is its ability to model these intricate relationships accurately while continuously adapting to new data, which is essential in dynamic railway environments. This adaptability is achieved through the application of the error backpropagation (BP) learning algorithm. Given that data on rail vehicle failures and maintenance activities are constantly evolving, ANFIS can adjust to these changes, maintaining the accuracy of predictions. Furthermore, the interpretability of ANFIS is enhanced by its fuzzy system component, which allows clear articulation of decision rules. In the context of rail transportation, this capability is vital for understanding the underlying causes of vehicle failures, thereby supporting improvements in maintenance and repair strategies.

4.3 Mathematical Model

Mathematical models are employed to allocate trains to stations with the aim of generating more precise and realistic passenger train schedules, while considering the probability of component and equipment failures. These models, supported by advanced mathematical and computational algorithms, are widely used in operational optimization and transport planning to simulate various scenarios, including potential breakdowns and consequent delays. This study proposes a mathematical framework designed to optimize train scheduling, with a particular focus on station arrival times. The model seeks to reduce operational delays by accurately calculating passenger train timings while incorporating the likelihood of mechanical faults. The ANFIS model is utilised to enhance scheduling precision across diverse operational conditions. This methodology allows for more reliable fault prediction, facilitating improved operational management and more accurate coordination of departure times. The ANFIS model incorporates the following input parameters:

4.4 The Objective Function

$$\min \sum_{i=1}^{N} w_i(c_i - a_i) \tag{1}$$

The stated objective function aims to minimize the cumulative delay across the entire railway network, thereby optimizing both service performance and the scheduling of repair operations for trains operating between stations.

4.5 Constraints

The stop time of the train (at each station) γ_i cannot exceed the scheduled time τi.

$$\gamma_i + y_i \le \tau_i \quad \forall i \tag{2}$$

The constraint for train speed:

$$\sigma_i \le speed\ limit \quad \forall i \tag{3}$$

The constraint concerning time allocation for trains at a station: This condition ensures that each train is assigned an appropriate time slot at the station, preventing scheduling conflicts and maintaining a smooth flow of train operations within the time-space diagram.

$$u_{j-}u_i - p_i - (\sigma_{ij} - 1).T \ge 0$$
$$\forall\ 1 \le i\ .j \le N\ .i \ne j \tag{4}$$

The constraint concerning space allocation for trains at a station: This condition ensures that each train is assigned a specific track or platform at the station, preventing spatial conflicts and allowing for safe and efficient train movements within the railway network.

$$v_{j-}v_i - s_i - (\delta_{ij} - 1).S \ge 0\ .$$
$$\forall\ 1 \le i\ .j \le N\ .i \ne j \tag{5}$$

This constraint ensures that train allocations at each station are managed to avoid conflicts or overlaps in the time-space diagram, thereby maintaining safe and orderly train operations.

$$\sigma_{ij-}\sigma_{ji} + \delta_{ij} + \delta_{ji} \ge 1\ .$$
$$\forall\ 1 \le i\ .j \le N\ .i \ne j \tag{6}$$

This constraint ensures that each train is assigned to a station in a manner that prevents any overlap in the time-space diagram, thereby maintaining safe and conflict-free train movements.

$$\sigma_{ij-}\sigma_{ji} \le 1\ .$$
$$\forall\ 1 \le i\ .j \le N\ .i \ne j \tag{7}$$

This constraint ensures that trains are allocated to stations in a way that prevents any overlap on the time-space diagram, maintaining safe and orderly train operations.

$$\delta_{ij-}\delta_{ji} \le 1\ .$$
$$\forall\ 1 \le i\ .j \le N\ .i \ne j \tag{8}$$

The computational constraint for train post-repair departure from the station: This condition ensures that trains can only depart after completing the necessary maintenance or repair activities, taking into account the time required for inspections and servicing, thereby preventing premature departures and potential operational conflicts.

$$p_{i-}u_i = c_i \,. \quad \forall\, 1 \le i \le N \,. \tag{9}$$

The constraint for the time horizon of train planning: This condition defines the total planning period for train operations, ensuring that all scheduling, maintenance, and repair activities are confined within a specified timeframe to allow realistic and implementable train movement and delay optimization.

$$a_i \le u_i \le T \,. \quad \forall\, 1 \le i \le N \tag{10}$$

The constraint for station capacity or available space: This condition ensures that the number of trains present at a station at any given time does not exceed the station's physical capacity, preventing overcrowding and allowing safe and efficient train operations.

$$0 \le v_i \le (S - s_i) \quad \forall\, 1 \le i \le N \tag{11}$$

The constraint for parameter range: This condition ensures that all model parameters, such as train speeds, repair times, or delay values, remain within predefined minimum and maximum limits, maintaining realistic and feasible outcomes for the optimization process.

$$u_i . v_i \,\epsilon\, R^+ \quad \forall\, 1 \le i \le N \tag{12}$$

The constraint for binary variables regarding the train time-space diagram: This condition ensures that binary decision variables, which indicate the presence or absence of trains at specific times and locations, take only values of 0 or 1. This guarantees a clear and unambiguous representation of train positions and movements within the time-space framework.

$$\sigma_{ij} \epsilon \{0.1\} \,.\, \delta_{ij} \epsilon \{0.1\} \quad \forall\, 1 \le i \,.\, j \le N \,.\, i \ne j \tag{13}$$

Where:

S: Longitudinal Distance between Two Train Stations
i: Number of Train
T: Length of the Scheduling Horizon
N: Total Number of Incoming Trains
p_i: Failure Repair Time of Train i
s_i: Size of Train i
a_i: Arrival Time of Train i
$\mathrm{w_i}$: Weight Assigned to Train i
u_i: Repair Start Time for the Failure of Train i
v_i: Stop Position of Train i
$\mathrm{c_i}$: Departure Time of Train i
σ_{ij}: If in Time-Space Diagram, Train i is Completely on the Left of Train j ,1, Otherwise 0
δ_{ij}: If in Time-Space Diagram, Train i is Completely Above Train j, 1, Otherwise 0

In summary, this section outlines the methodology for optimizing train delays. The proposed approach integrates machine learning techniques for predictive maintenance of rail vehicles, employing a hybrid model that combines MLP neural networks and ANFIS methods. This architecture facilitates precise failure prediction using MATLAB 2021 software. Ultimately, the developed mathematical model aims to minimize train delays, serving as an instrument to optimize maintenance and repair operations and enhance overall railway network efficiency.

5. Results and Discussion

5.1 Model Evaluation

Considering the study goal to analyses the data regarding breakdowns of railway vehicles in train architecture within the Iran railway network, two algorithmic methods, i.e., MLP and ANFIS, were implemented. Initially, the probability of future breakdowns was predicted, and subsequently, using a mathematical model, the extent of breakdown-induced delays was optimized through an appropriate schedule. The major issues depicted in the train travel and movement data of the Iran railway network in 2022 indicate the types of railway vehicle failures in trains as: tampon defects, wheel and axle breaks, binding breakdown, bearing box heating, loosened wheel rim, power and ventilation system failure, brake system failure, and other factors representing certain unfavorable wagon operations.

5.2 Multilayer Perceptron (MLP) Neural Network Architecture for Failure Prediction

The model's inputs consist of eight types of breakdowns for each train within a given time. These data are fed into the input layer of the network, where the number of neurons corresponds to the number of input attributes (eight failure variables). One or more hidden layers are included, with their number and the neurons within each layer determined through optimization of the network architecture. The output layer contains a single neuron, which predicts the probability of a future breakdown. Figure 2 illustrates the architecture of the MLP neural network. In this configuration, the model incorporates 8 input parameters, 5 neurons in the first hidden layer, 2 neurons in the second hidden layer, and a single output neuron representing the predicted train breakdown. The dataset was randomly divided into 70% for training and 30% for testing. The network was trained using the Levenberg-Marquardt (LM) algorithm, implemented as trainlm in MATLAB. Following 30 training iterations and subsequent testing, the estimation results were obtained.

Figure 3 presents the correlation values of the data within the MLP neural network model for failure prediction.

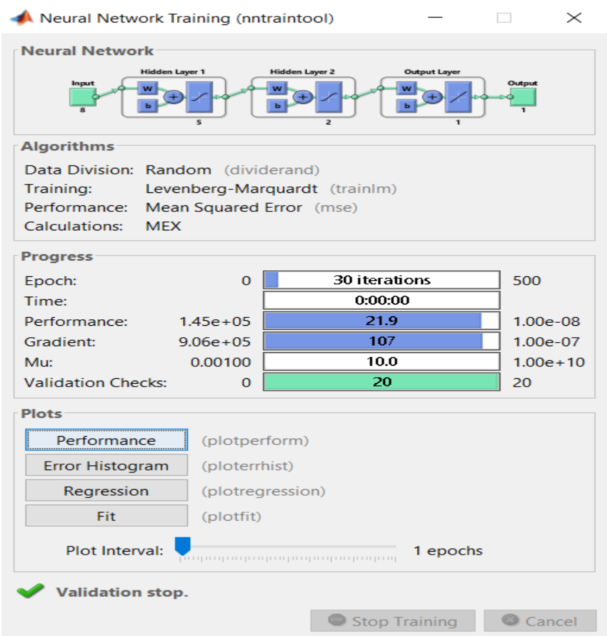

Fig.2: Architecture of MLP Network for Breakdown Prediction

These correlation values reflect the degree of dependency between the variables. In this context, the figure shows the correlations between the MLP model's input and output variables, highlighting both the strength and direction of their relationships. Such information is useful for assessing the model's predictive capability and provides insights into the relevance of different variables in predicting failures.

Based on the analyses conducted, the results obtained from failure modelling and prediction using the MLP neural network are illustrated in the subsequent graphs. These include visual comparisons between the actual observed data and the model's predicted values, thereby evaluating the accuracy and efficiency of the network. By illustrating the alignment between predicted and actual failure data, these graphs serve as a measure of the model's overall predictive effectiveness.

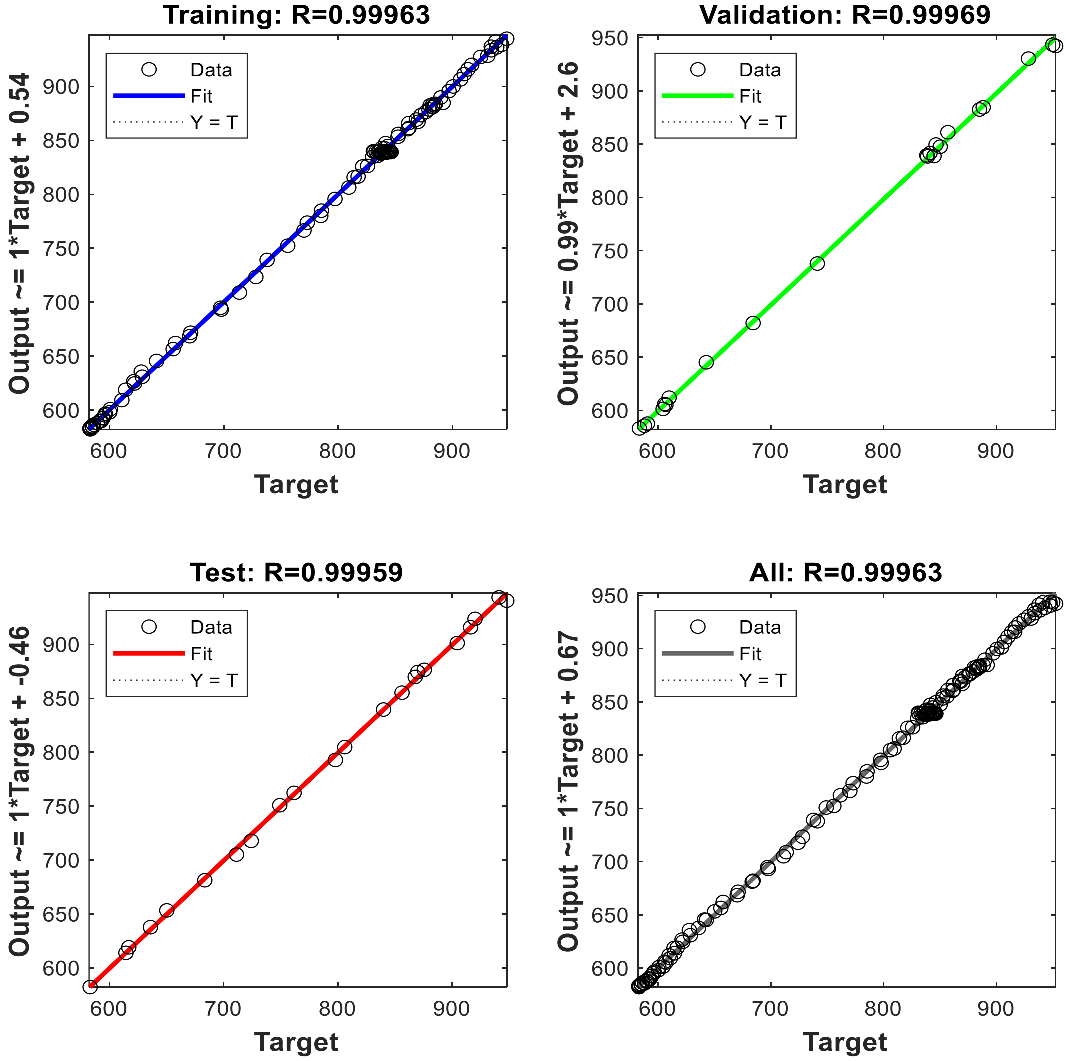

Fig.3: Data Correlation Values in MLP Neural Network Model for Failure Prediction

Figure 4 illustrates the outcomes of the training phase of the MLP neural network for failure prediction. In this stage, the model learns and adapts to the patterns present in the training dataset. The figure provides visual outputs, such as charts or tables, that demonstrate the network's dynamics and predictive accuracy. To evaluate the model's performance during training, key metrics including Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and regression analysis are employed. These measures enable the assessment of how effectively the model captures failure trends and its reliability in predicting potential failures.

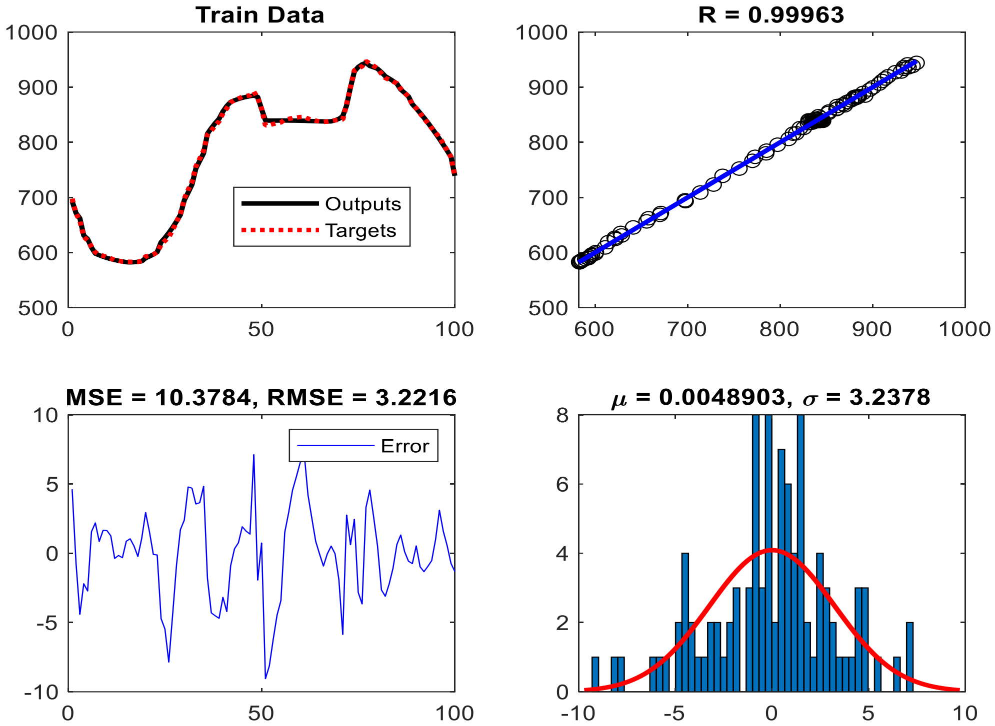

Fig.4: Assessing the Effectiveness of the MLP Neural Network Model During the Training Phase for Predicting Failures

Figure 5 presents the evaluation of the MLP neural network during the testing phase for failure prediction. In this stage, the model is validated using previously unseen test data to determine its generalization capability. Performance is measured through indicators such as MSE, MAPE, and regression analysis, which serve to evaluate the accuracy and efficiency of the predictions. The findings provide valuable insights into the reliability of the model and its effectiveness in predicting failures under practical conditions.

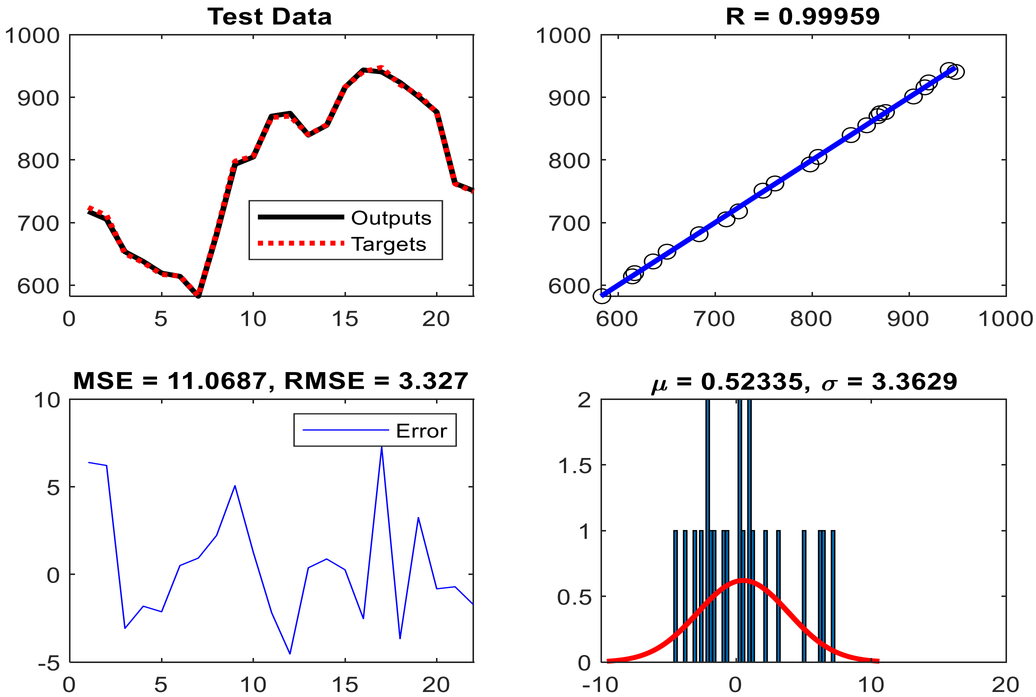

Fig.5: Assessing the Effectiveness of the MLP Neural Network Model during the Data Testing Phase for Predicting Failures

Figure 6 illustrates a comprehensive evaluation of the neural network's capability to forecast failures when applied to the complete dataset. The analysis contrasts predicted outcomes with actual failure instances through both graphical and tabular presentations, thereby emphasizing the model's accuracy and practical utility. This assessment aims to present a consolidated view of the model's predictive behavior in identifying potential system breakdowns. To reinforce the findings, performance metrics were compiled in a table, focusing on MAPE and MSE. MAPE captures the average proportional deviation between predictions and observed values, providing a scale-independent measure that facilitates performance comparison across different contexts. Conversely, MSE quantifies the mean squared deviation between estimated and actual results, serving as a widely recognized standard for numerical prediction accuracy. A lower MSE value signifies a stronger alignment between predictions and real outcomes, indicating superior model precision. Table 1 presents the performance indicators of the MLP model in predicting failures during both the training and testing phases. The findings highlight the model's predictive accuracy and reliability in identifying system breakdowns. Assessing its performance across distinct datasets further validates the model's precision and its capacity to generalize effectively to previously unseen data.

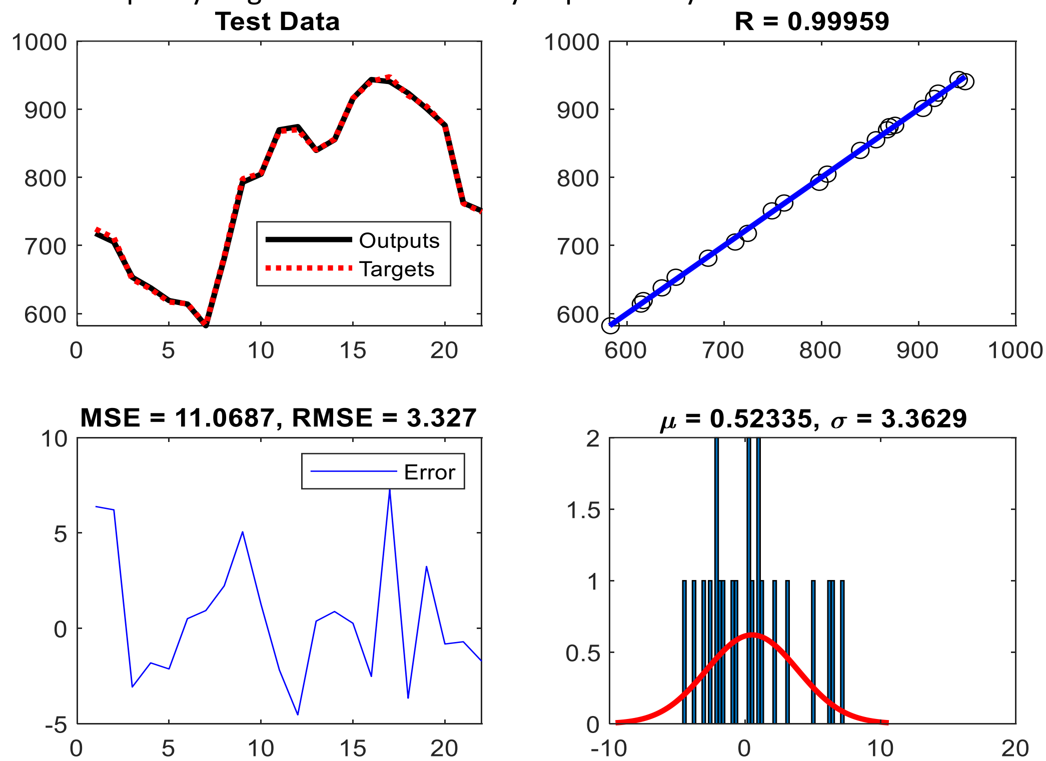

Fig. 6: Evaluating How the MLP Neural Network Performs in Predicting Failures When Trained and Tested on the Full Dataset

Table 1
Evaluation of MLP Neural Network Model for Failure Prediction

Index /Value	Training Stage	Testing Stage
MSE	10.3784	11.0678
MAPE	0.3169	0.3352
Regression	0.99963	0.99959

5.3 Adaptive Neuro-Fuzzy Inference System (ANFIS) Model

Figures 5–7 depict the performance progression of the ANFIS-based failure prediction model, highlighting the gradual enhancement in predictive accuracy across successive training iterations. The visual alignment of predicted outputs with actual failure occurrences underscores the model's increasing effectiveness in capturing real-world failure dynamics. Figure 7 illustrates the ANFIS model's performance in forecasting system failures during the training phase. The depicted learning curves indicate the progressive refinement of prediction accuracy over successive training epochs, showing consistent convergence of the model's outputs toward the observed failure data. This evaluation achieves two primary objectives: it quantifies the model's practical predictive capability and assesses its operational efficiency in handling intricate failure patterns.

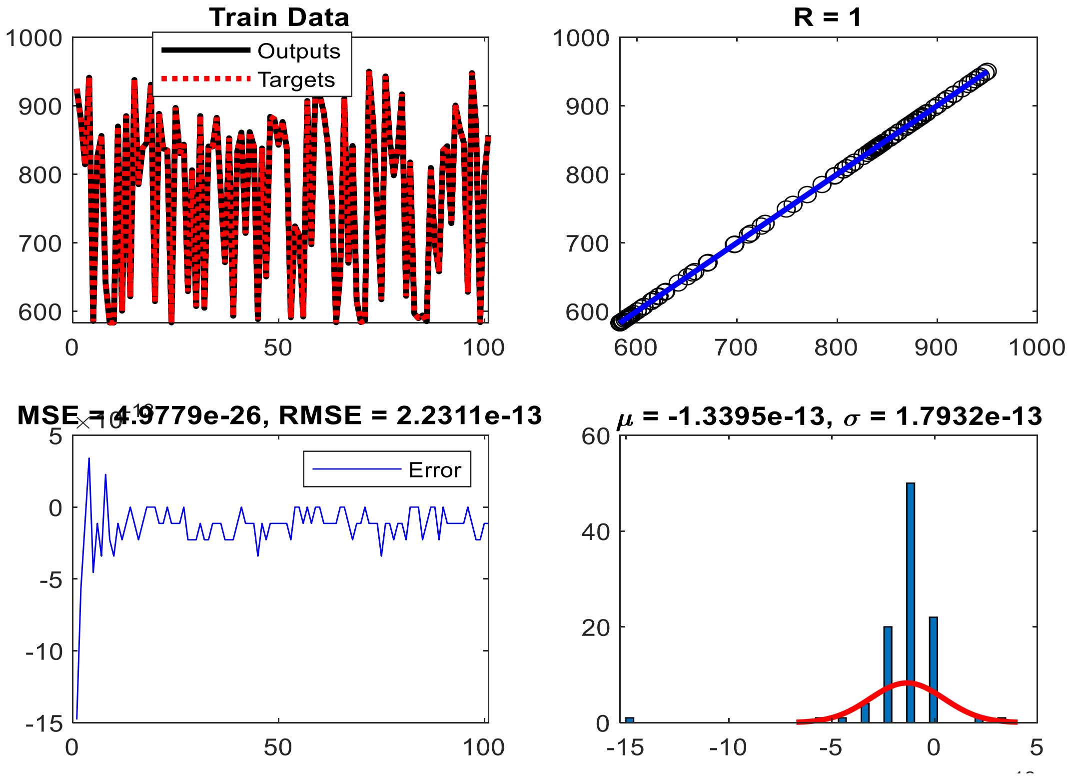

Fig.7: Assessing the Effectiveness of the MLP Neural Network Model during the Training Phase for Predicting Failures

Figure 8 presents the results of the ANFIS model during the testing phase for failure prediction. The side-by-side comparison between predicted values and observed data highlights the model's capacity to manage previously unseen operational information. Additionally, these results facilitate the assessment of two critical performance aspects: first, the predictive reliability of the model in forecasting failures, and second, its efficiency in utilizing computational resources while processing real-time diagnostic scenarios. Figure 9 illustrates the overall performance evaluation of the ANFIS model in predicting system breakdowns using the entire dataset. A detailed summary of the results is provided in Table 2. Moreover, Table 2 presents the performance metrics of the ANFIS model, including MSE, MAPE, and regression values for both the training and testing datasets. The results indicate high predictive accuracy and effective computational performance in forecasting system breakdowns, demonstrating the model's practical applicability for predictive maintenance operations.

Table 2
Evaluation of ANFIS Model for Failure Prediction

Index /Value	Training Stage	Testing Stage
MSE	4.9779×10^{-26}	505.7351
MAPE	1.9518×10^{-14}	1.6597
Regression	1	0.9843

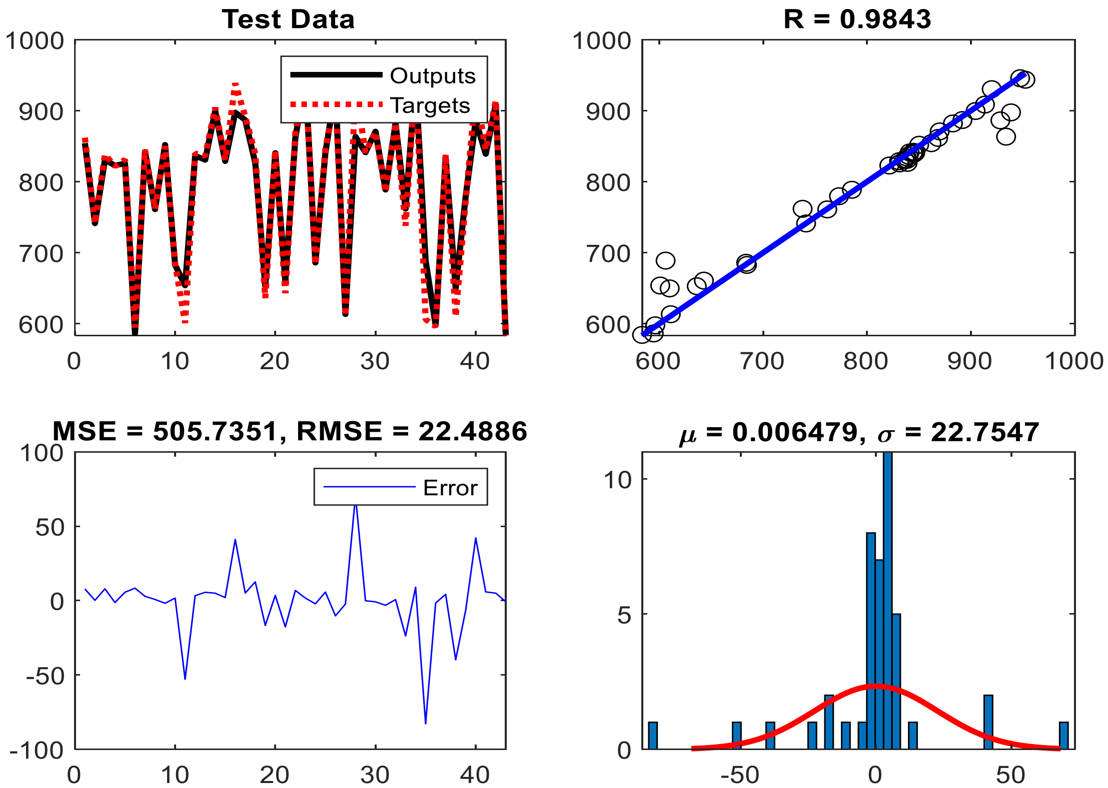

Fig.8: Assessing the Effectiveness of the MLP Neural Network Model during the Data Testing Phase for Predicting Failures

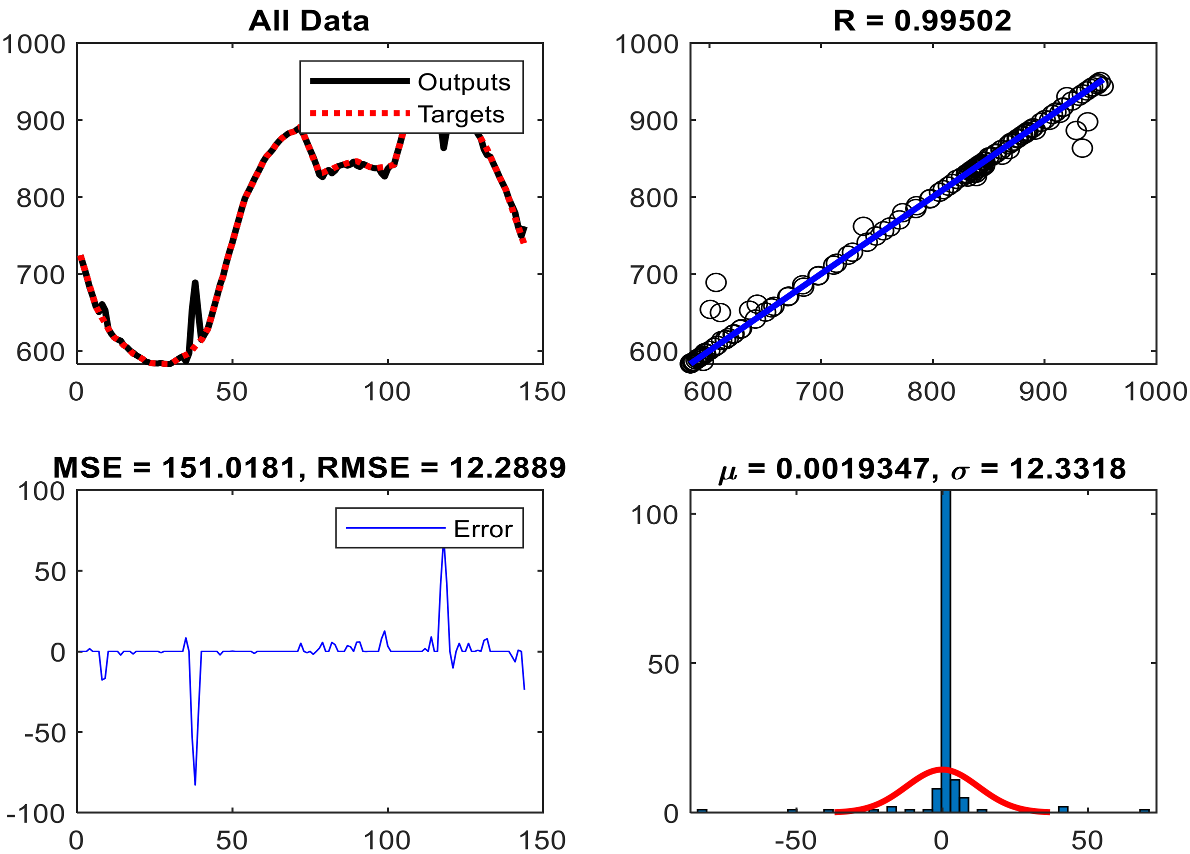

Fig. 9. Evaluating How the MLP Neural Network Performs in Predicting Failures When trained and Tested on the Full Dataset

5.4 Comparing Two Models

Table 3 provides a comparative overview of the MAPE values for the different models applied to failure prediction, highlighting their relative predictive accuracies. The analysis of the results clearly indicates that the application of the ANFIS model produced a considerable reduction in the MAPE for predicting rail vehicle failures. Consequently, the MAPE values derived from this model will be employed in the subsequent mathematical modelling to estimate the delay times associated with such failures.

Table 3
Comparing MAPE Values of the Models for Failure Prediction

Model	Testing Stage Related to MAPE
MLP	0.3169
ANFIS	1.9518×10^{-14}

5.5 Solving Mathematical Model for Predicting Delay Time

This section presents an analysis of train delays caused by rail vehicle breakdowns within the Iranian railway network, with the findings illustrated as case-specific data. In conducting this review, certain standards were consistently applied, such as adopting a uniform wagon length of 20 meters. For temporal planning, a comprehensive time horizon of 24 hours per day over all twelve months of the year was considered. Additionally, Figure 10 illustrates the convergence pattern of the PSO algorithm for the period from 21 March to 19 April within this network. As illustrated in Figure 10, the PSO algorithm achieved convergence after approximately 40 iterations, yielding the final value of the fitness function, which corresponds to the average train delay under the specified problem conditions. In this context, the fitness function is formulated to quantitatively evaluate train delays, assigning a numerical score to each potential solution. This score represents the average delay incurred relative to an idealized train movement schedule. A lower fitness value signifies greater efficiency and effectiveness in mitigating train delays. Consequently, the PSO algorithm seeks to minimize this value by optimizing the candidate solutions. During the optimization process, PSO explores the search space, progressively selecting and applying solutions that achieve improved fitness values (i.e., lower delays). The algorithm updates solutions iteratively until the changes in fitness function values become negligible, indicating that additional improvements are minimal. This stage, referred to as convergence, marks the attainment of a near-optimal solution. The results of this study confirm that this methodology successfully reduces failure-induced delays, demonstrating strong predictive and optimization performance.

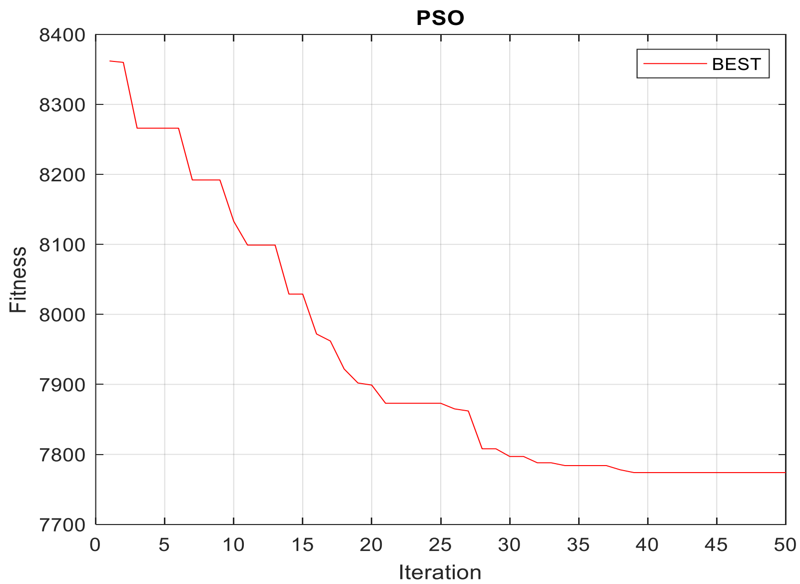

Fig.10: Convergence Diagram of PSO Algorithm

6. Conclusion

This study demonstrates that machine learning can fundamentally enhance railway maintenance by enabling predictive, data-driven strategies in place of traditional reactive repairs. Comparative analysis of MLP and ANFIS models revealed that ANFIS provides superior failure prediction, and its integration with Particle Swarm Optimization significantly improves scheduling efficiency, reducing unexpected delays and enhancing operational reliability. Implementing such ML-based approaches can deliver tangible benefits, including improved service consistency, lower maintenance costs, early fault detection, and more efficient resource utilization. The effectiveness of these systems relies on comprehensive historical datasets and adequate computational resources. Future research should explore real-time sensor integration, consider external influences such as weather and track conditions, and validate the approach across diverse railway networks. Overall, the findings highlight the potential of intelligent, predictive maintenance systems to create more resilient, efficient, and sustainable rail transport operations.

Author Contributions

Conceptualization, M.K., D.P., and A.H.; methodology, M.K. and A.H.; software, M.K. and A.H.; validation, M.K.; formal analysis, M.K., D.P., and A.H.; investigation, M.K.; resources, M.K.; data curation, M.K.; writing—original draft preparation, M.K.; writing—review and editing, M.K. and D.P.; visualization, M.K.; supervision, M.K. and D.P.; project administration, M.K.; funding acquisition, D.P. All authors have read and agreed to the published version of the manuscript."

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Data Availability Statement

All data generated or analyzed during this study are included in this published article.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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