



Application of Neural Network Models in Predicting TBM Performance and Managing Excavation Costs: A Case Study of the Mechanized Excavation of the Twin Tunnels of Tabriz Urban Railway Line 1

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Abstract

During mechanized tunnel excavation operations, support locomotives refer to a fleet assigned such tasks as transporting foam and grout—the injection slurry used to fill the annular void between the excavated tunnel surface and the rear face of the segmental lining—delivering precast reinforced-concrete segments into the tunnel and to the excavation face, and removing excavated spoil from the tunnel. Accordingly, this fleet plays a key role and has a direct impact on the tunnel excavation phase. This study investigated and predicted the performance of the support locomotive fleet used in the tunnel boring machine operations of Tabriz Urban Railway Line 1. In the first stage, each locomotive was divided into four principal systems: mechanical (engine), electrical, hydraulic, and pneumatic. In the subsequent stages, each of these four systems was further decomposed into smaller-scale subsystems and components. Field studies were then conducted, and failure data from five locomotives were collected using methods endorsed by internationally recognized project management standards, including expert judgment. Following data integration, more than 30,000 failure-related observations were obtained. Pareto analysis, linear regression, and artificial neural networks were examined as statistical and intelligent analytical methods. The findings indicated that the neural network method generated predictions that closely approximated the actual values, with low error and high accuracy.

Keywords: metro, mechanized tunnel excavation, failure, artificial neural network, locomotive, linear regression, Pareto analysis

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1. Introduction

Rapid urbanization, population growth, traffic congestion, environmental degradation, and increasing pressure on surface transportation networks have intensified the need for high-capacity urban rail systems. Metro systems are increasingly regarded as essential components of sustainable urban mobility because they can transport large numbers of passengers while reducing road congestion, travel time, fuel consumption, and transport-related emissions. Beyond their direct transportation function, metro networks influence the spatial organization of cities,

accessibility to employment and services, and the quality of public spaces surrounding stations. Consequently, metro development should be understood not merely as a civil engineering undertaking but as a multidimensional infrastructure program involving technical, operational, financial, environmental, organizational, and human considerations. Research on public spaces around subway stations has further demonstrated that metro infrastructure affects users' emotional responses, perceptions, and interactions with the urban environment, reinforcing the



strategic significance of well-designed and efficiently operated underground transportation systems [1].

The construction of metro tunnels is among the most complex, capital-intensive, and risk-sensitive activities in urban infrastructure development. Underground construction must be performed under conditions characterized by geological uncertainty, restricted access, limited working space, stringent safety requirements, and strong interdependence among equipment, personnel, materials, and logistical processes. Metro tunneling also involves extensive underground structures, including running tunnels, shafts, cross passages, stations, ventilation facilities, and supporting systems, each of which must be designed and executed in accordance with geological, structural, operational, and urban constraints [2]. Any disruption in one component of this integrated system can affect project duration, excavation continuity, equipment productivity, and overall cost performance. Therefore, the management of mechanized tunneling projects requires reliable information, continuous operational monitoring, systematic failure analysis, and predictive decision-support tools capable of addressing the nonlinear and uncertain behavior of construction systems.

Mechanized tunneling using tunnel boring machines (TBMs) has become a preferred excavation method for many long urban tunnels because it provides relatively high advance rates, improved working conditions, reduced surface disturbance, and greater control over excavation geometry compared with conventional methods. Nevertheless, the economic and operational advantages of TBM excavation depend heavily on the compatibility between machine characteristics, geological conditions, operational parameters, and project logistics. TBM performance is not determined by a single factor; rather, it emerges from complex interactions among rock or soil properties, cutterhead characteristics, thrust force, torque, penetration, cutter consumption, machine utilization, crew performance, maintenance practices, and material-handling operations. Accordingly, the estimation of TBM performance has long been recognized as a critical problem in tunneling engineering because errors in predicting excavation rates, downtime, or resource consumption can lead to major deviations in construction schedules and budgets [3].

The cost structure of mechanized tunneling is particularly sensitive to equipment productivity and downtime. TBMs require substantial initial investment, specialized supporting equipment, trained personnel, continuous maintenance, and

a coordinated supply chain for segments, grout, foam, grease, spare parts, and other consumables. In addition, excavated material must be removed from the tunnel face without interrupting the excavation cycle. Excavation costs therefore depend not only on the nominal capacity of the TBM but also on the efficiency of the entire production system. In railway and transportation projects, accurate computation of excavation and earthwork quantities is fundamental to budgeting, resource allocation, and cost control, particularly where project geometry and operational constraints create substantial uncertainty [4]. From a project-management perspective, predictive models that connect equipment condition, failure behavior, repair duration, and production continuity can support more realistic cost estimates and improve managerial control over excavation operations.

TBM performance has traditionally been evaluated using empirical, statistical, and mechanistic models. Empirical models are generally constructed from previous project data and attempt to establish relationships between observed machine performance and geological or operational variables. Although such models may be useful under conditions similar to those from which they were derived, their transferability is often limited. Statistical techniques such as linear and nonlinear regression can estimate the effects of explanatory variables on penetration rate, utilization, or downtime; however, conventional regression models usually require assumptions concerning functional form, variable independence, error distributions, and linearity. The relationships governing TBM performance are frequently nonlinear and may involve threshold effects and complex interactions that are not easily captured using traditional analytical methods. This limitation has motivated the growing application of computational intelligence, machine learning, and artificial neural networks in tunneling research.

Artificial neural networks are data-driven computational models inspired by the interconnected structure of biological neural systems. They consist of input, hidden, and output layers composed of processing units or neurons connected through adjustable weights. During training, the network modifies these weights to minimize the discrepancy between predicted and observed outputs. Neural networks are particularly suitable for problems in which the underlying relationships are nonlinear, multidimensional, uncertain, or insufficiently represented by explicit mathematical equations. Their ability to learn patterns directly from historical data has made them valuable for prediction,

classification, estimation, fault diagnosis, and decision support across engineering and management applications. Nevertheless, the quality of neural-network predictions depends on appropriate network design, data preprocessing, training procedures, validation, and the avoidance of overfitting.

The development of an effective neural-network model requires several methodological decisions, including the selection of input and output variables, the number of hidden layers, the number of neurons, transfer functions, training algorithms, stopping criteria, and performance measures. Kaastra and Boyd emphasized that neural-network forecasting should follow a systematic design process involving problem definition, variable selection, data collection, preprocessing, network construction, training, and evaluation [5]. Although their work focused on financial and economic time series, the underlying design principles are directly relevant to engineering forecasting because both domains involve noisy data, nonlinear relationships, uncertainty, and the risk of model overfitting. Similarly, best-practice research on neural-network classification has stressed the importance of training-set representativeness, architecture selection, generalization assessment, and independent validation [6]. These principles are essential when failure and maintenance data are used to predict equipment behavior in tunneling projects.

MATLAB-based neural-network tools have been widely used to implement feedforward and backpropagation models because they provide standardized functions for network initialization, training, simulation, validation, and error analysis. The Neural Network Toolbox provides methods for constructing multilayer networks, applying transfer functions, preprocessing data, and evaluating network performance using indicators such as mean squared error and regression coefficients [7]. In practical applications, data are commonly divided into training, validation, and testing subsets. The training dataset is used to estimate network weights, the validation dataset is used to monitor generalization and prevent overfitting, and the testing dataset provides an independent assessment of predictive performance. This structure is especially important in equipment-failure prediction because an apparently accurate model may merely reproduce patterns in the training data without providing reliable predictions for new operational observations.

Artificial neural networks have been applied extensively to TBM performance prediction. Benardos and Kaliampakos developed an artificial neural-network model for estimating

TBM performance and demonstrated that neural methods can capture the complex relationships between geological conditions and machine behavior [3]. Their findings supported the use of data-driven nonlinear modeling as an alternative to conventional empirical relationships. Yagiz et al. subsequently evaluated nonlinear prediction tools for estimating TBM performance and showed that intelligent computational approaches could provide effective estimates under complex geological conditions [8]. Such studies established an important methodological foundation for applying neural networks to excavation performance, penetration rate, and machine productivity.

Further evidence has been provided by investigations specifically addressing TBM penetration rate and operational efficiency. Gholamnejad and Tayarani applied artificial neural networks to the prediction of TBM penetration rate and reported that neural models could represent the nonlinear influence of geological and machine-related variables more effectively than simpler predictive techniques [9]. Nejati and Ahmadi similarly used an artificial neural network to estimate TBM efficiency, demonstrating the potential of this approach for evaluating machine performance under varying operational conditions [10]. These studies indicate that neural-network models can support planning and operational decision-making by producing performance estimates from multiple interacting inputs. However, much of the previous literature has focused on the TBM itself, particularly penetration and advance rates, while comparatively less attention has been devoted to the support equipment whose failures may interrupt the entire excavation cycle.

The importance of geotechnical parameters in TBM performance has also been examined through combined statistical and neural approaches. Torabi et al. investigated the effects of geotechnical variables on TBM performance in the Tehran–Shomal Highway Project using artificial neural networks and SPSS-based analyses [11]. Their study illustrated the value of combining conventional statistical software with intelligent modeling techniques to identify influential variables and improve predictive accuracy. This combined approach is relevant to failure analysis because descriptive statistics and Pareto analysis can identify the most frequent or costly failure categories, whereas neural networks can model the nonlinear relationships among failure type, occurrence time, and repair duration. The integration of these techniques can consequently provide a more comprehensive basis for maintenance prioritization and excavation cost management.

TBM operating costs are also affected by the consumption and deterioration of excavation components. Cutter wear and replacement represent important sources of downtime and cost, particularly in abrasive or heterogeneous geological formations. Zahiri et al. developed an empirical model for predicting cutter consumption in full-face TBMs, highlighting the relationship between operational conditions, tool consumption, and project expenditure [12]. Although cutter consumption concerns the primary excavation machine, the broader managerial implication is that the cost of mechanized tunneling is shaped by the reliability and serviceability of multiple interdependent components. Predictive models should therefore extend beyond penetration rate and include failures, maintenance durations, and the performance of auxiliary systems that directly influence the continuity of excavation.

Among the most important auxiliary components in mechanized metro tunneling are the support locomotives responsible for transporting excavated spoil, precast concrete segments, grout, consumables, equipment, and personnel. These locomotives operate in constrained underground environments and are often required to travel over a single-track route between the tunnel face and the shaft. Their mechanical, electrical, hydraulic, and pneumatic systems must function reliably under heavy loads, repetitive cycles, dust, moisture, restricted ventilation, and continuously increasing haulage distances. Technical documentation concerning tunnel locomotives emphasizes the importance of correct operation, inspection, maintenance, and system coordination in ensuring reliable underground transport [13]. A locomotive failure inside a single-track tunnel can obstruct the movement of other trains, delay segment and grout delivery, prevent spoil removal, and force the TBM to stop. Thus, even when the TBM itself remains technically operational, excavation may be suspended because of a failure in the supporting logistics system.

This operational interdependence has direct implications for project cost management. TBM downtime generates costs through idle labor, underutilized capital equipment, disrupted shift schedules, delayed segment installation, and extended project duration. Repeated locomotive failures may also increase expenditure on spare parts, emergency repairs, workshop services, and replacement equipment. Therefore, failure data should not be treated solely as maintenance records; they represent valuable managerial information for identifying critical subsystems, estimating future repair durations, planning preventive maintenance,

and controlling excavation costs. Pareto analysis is particularly useful in this context because it enables managers to distinguish the relatively small number of failure causes responsible for a large proportion of downtime, repair effort, or expenditure. Once critical failures have been identified, predictive modeling can estimate their likely operational consequences and support risk-based maintenance decisions.

The human and organizational dimensions of urban railway operations must also be considered. Equipment performance depends not only on technical design but also on operator competence, maintenance discipline, communication, motivation, and coordination among engineering teams. Research conducted among employees of the Isfahan Urban Railway Organization showed that meaning in life can influence job performance through intrinsic and extrinsic motivation, indicating that organizational and psychological variables are relevant to the effectiveness of urban railway personnel [14]. In mechanized tunneling, motivated and well-coordinated employees are more likely to follow inspection procedures, report early warning signs, respond efficiently to failures, and support the reliable operation of locomotives and TBMs. Consequently, predictive maintenance should be embedded within a broader management system that integrates technical data with clear responsibilities, trained personnel, and performance-oriented organizational practices.

Recent railway research has increasingly adopted mathematical modeling and dynamic analysis to evaluate complex operational behavior. For example, the dynamic characteristics of railway stabilization operations under different track conditions have been investigated through mathematical modeling, illustrating how system behavior can change in response to operating status and infrastructure conditions [15]. Although such work addresses a different railway application, it reinforces the general importance of model-based analysis in understanding equipment–infrastructure interactions. Tunnel locomotives similarly operate under changing loads, track conditions, gradients, travel distances, and environmental constraints, all of which may affect system stress and failure probability. Data-driven models can complement mechanical analysis by extracting recurring patterns from actual operating histories.

The increasing use of digital technologies in railway infrastructure further supports the transition from reactive to predictive management. Emerging frameworks integrate geographic information systems, distributed data processing, and machine learning to assess infrastructure performance

and resource efficiency. A recent federated-learning-enhanced GIS framework for circular water infrastructure assessment in railway stations illustrates the broader movement toward digitally integrated, data-driven railway asset management [16]. Such approaches demonstrate that railway infrastructure management is increasingly based on the continuous collection, integration, and analysis of operational data. Within mechanized tunneling, historical failure records can provide a comparable foundation for intelligent maintenance planning, provided that the data are systematically coded, cleaned, and analyzed.

Despite the development of predictive models for TBM penetration, efficiency, and component consumption, a significant research gap remains regarding the performance of support locomotives and their effect on excavation continuity and cost management. Existing studies have primarily considered geological parameters and the primary excavation machine, whereas the logistics fleet has often been treated as a secondary operational element. In practice, however, the TBM and the locomotive fleet operate as an integrated production system. The TBM cannot maintain continuous excavation unless spoil is removed and segments, grout, and consumables are delivered at the required rate. Therefore, evaluating only the performance of the TBM may produce an incomplete representation of mechanized tunneling productivity.

The Tabriz Urban Railway Line 1 project provides an appropriate case for addressing this gap because its twin

deep tunnels were excavated using TBMs supported by a fleet of tunnel locomotives operating under constrained single-track conditions. The availability of extensive operational and failure records from multiple locomotives makes it possible to examine failure frequencies, repair costs, and maintenance durations using Pareto analysis, linear regression, and artificial neural networks. The comparison of conventional statistical prediction with neural-network modeling can also clarify whether nonlinear intelligent methods provide greater accuracy in estimating total repair duration. Such evidence can contribute to maintenance prioritization, equipment availability, operational scheduling, cost forecasting, and the broader management of mechanized tunneling projects.

Accordingly, the aim of this study is to develop and evaluate artificial neural-network and statistical models for predicting support-locomotive failure and repair performance in the mechanized excavation of the twin tunnels of Tabriz Urban Railway Line 1 and to assess their application to TBM operational continuity and excavation cost management.

2. Methodology

In the neural network approach, one or more neurons together constitute a network layer. A network may consist of one or more such layers. Figure 1 shows a single-layer network with R inputs and S neurons.

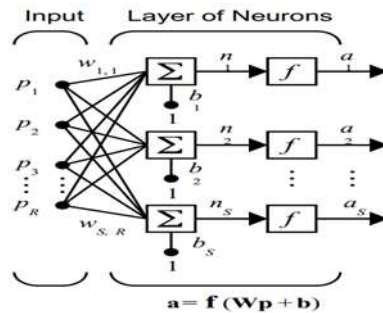


Figure 1. A Single-Layer Network

In this network, the elements of the input vector p are applied to all neurons. After being multiplied by the weights and combined with the bias terms, they are passed through the transfer function to generate the output. The output of the above network is a vector. It should be noted that the number of inputs (R) does not necessarily have to equal the number of neurons (S).

According to Equation 1, different transfer functions can be used within a single-layer network to construct a

composite single-layer network. In the single-layer network shown above, the weight matrix (W) is an $S \times R$ matrix.

In this matrix, $w_{n,m}$ represents the weight associated with input applied to neuron m .

$$W = \begin{bmatrix} w_{1,1} & w_{1,2} & \cdots & w_{1,R} \\ w_{2,1} & w_{2,2} & \cdots & w_{2,R} \\ \vdots & \vdots & \ddots & \vdots \\ w_{S,1} & w_{S,2} & \cdots & w_{S,R} \end{bmatrix} \quad (1)$$

A single-layer network with S neurons and R inputs can be represented schematically, as shown in Figure 2.

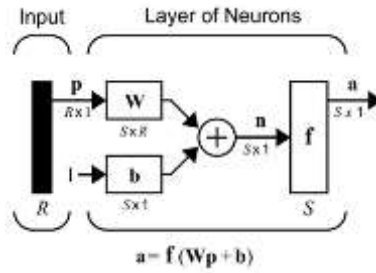


Figure 2. Schematic Representation of a Single-Layer Network

When the results obtained from the training procedure are not satisfactory, several approaches may be used to improve them. When the network does not provide adequate accuracy, its initialization and training procedures may be repeated. Each time the network is initialized, its adjustable parameters are assigned different values; therefore, the training process produces a different solution.

Another approach to improving network performance is to increase the number of neurons in the hidden layer. Increasing the number of hidden-layer neurons enhances network flexibility because it provides a larger number of adjustable parameters for optimization.

The number of neurons should always be increased gradually until the optimum value is reached. If the hidden layer is selected to be excessively large, the training procedure may encounter difficulties, consume unnecessary time and computational resources, and fail to produce satisfactory results.

Another method of improving the results is to use a larger volume of training data. This approach improves the generalizability of the network and enhances its performance when applied to new data.

In batch training, the weights and biases are updated after all members of the training dataset have been presented to the network. The gradients calculated for each input are summed, and the resulting aggregate values are then used to update the weights and biases. Different batch-training methods based on the backpropagation algorithm are discussed below.

As shown in Figure 3, the Tabriz metropolitan and suburban metro network consists of five lines, including four urban lines and one suburban line, with a total length of 100 km. After Tehran and Karaj, it has the largest number of metro lines among the metropolitan areas of Iran.

Tabriz Metro Line 1 is 17 km long and comprises 18 stations. It begins at El Goli Square, proceeds along Shahid Engineer Bakeri Boulevard, Imam Street, Amin Intersection (Mohagheghi), Fajr Garden (Golestan), and Khayyam Street, and terminates in Laleh District. Approximately 8 km of the route was designed as a deep tunnel and excavated by two tunnel boring machines (TBMs) at depths of approximately 16–25 m.



Figure 3. Layout of the Tabriz Metropolitan and Suburban Metro Network

Tunnel excavation was performed using TBMs manufactured by NFM Technologies of France. The

excavated diameter of the tunnels is approximately 6.88 m, whereas the finished internal diameter after installation of

the precast concrete lining segments is 6 m. The transportation of segments and other materials required for excavation, as well as the removal of excavated material from the tunnel, is performed by locomotives. Therefore,

coordination between the TBM and the locomotives is critically important to tunnel excavation operations.

The technical specifications of the TBMs used on Tabriz Metro Line 1 are presented in detail in Table 1.

Table 1. Technical Specifications of the TBMs Used on Tabriz Metro Line 1

Specification	Value
Excavation diameter	6.88 m
External tunnel diameter	6.25 m
Internal tunnel diameter	6 m
Machine length	102 m
Machine weight	620 metric tons
Maximum advance rate	80 mm/min
Number of segments	6 (5 + 1)
Total ring weight	22 metric tons
Number of cutting tools on the cutterhead	185
Machine thrust force	44,000 kN

The support locomotives used on Tabriz Metro Line 1 are small-scale locomotives manufactured by SCHÖMA, Germany. This model is one of the company's most widely used and best-selling locomotives and is also referred to as a tunnel locomotive.

These locomotives are used for applications such as transportation in mines, transportation in tunneling projects, and support operations in mechanized excavation.

CHL-200G locomotives are used on Tabriz Metro Line 1. The general specifications of this type of locomotive are presented in Table 2.

Table 2. General Specifications of the Locomotives

Item	Quantity
Height	2,150 mm
Length	1,500 mm
Width	36 metric tons
Unloaded speed	30 km/h
Loaded speed	6 km/h
Tractive force	255 kN
Engine type	DEUTZ 1015
Engine power	286 kW
Axle spacing	900 mm

Figure 4 shows an example of these locomotives.



Figure 4. SCHÖMA CHL-200G Locomotive

Considering the excavation process and the structural characteristics of the deep tunnels of Tabriz Metro Line 1, the tasks assigned to the locomotives are as follows:

- Transporting excavated material from the tunnel face to outside the tunnel
- Transporting segments, namely precast concrete components, to the TBM
- Transporting grout, or ready-mixed concrete, to the TBM
- Transporting personnel and other materials required for tunnel excavation, such as foam and grease

The locomotives pull three types of equipment: muck-car flatbeds, segment carriers, and grout cars. The muck-car flatbeds are empty wagons that are filled with excavated material at the tunnel face as excavation progresses. The second type of equipment consists of segment carriers on which the segments are placed. Finally, the grout car contains an agitator and transports grout into the tunnel.

These considerations demonstrate that locomotives play a role in tunnel excavation equivalent to that of the TBM and that their stoppage results in the suspension of excavation operations. However, the principal question is how the failure of one locomotive can create a serious problem when five locomotives are available for two tunnel sections. The explanation is that the locomotives travel in both directions on a single-track system. In addition, the space available in urban shafts is limited—approximately 200 m on Line 1—and the haulage distance progressively increases as tunnel excavation advances. Consequently, locomotive failures are

particularly likely to occur inside the single-track tunnels, where a failed locomotive may obstruct the entire transport route.

In general, the operating cycle of the locomotives in one of the tunnels is as follows:

- A locomotive leaves the tunnel pulling six loaded muck-car flatbeds, each with a capacity of 25 metric tons.
- The locomotive then enters the tunnel with six empty muck-car flatbeds, two segment carriers containing the segments required for one excavation ring, and one loaded grout car.
- The loaded muck-car flatbeds of the locomotive that has recently exited the tunnel are unloaded by cranes at the material stockpile. The empty segment carriers and grout car, which were used by the TBM during the previous cycle, are then reloaded.
- When the locomotive that previously entered the tunnel exits, the locomotive that has most recently been reloaded re-enters the tunnel and rejoins the excavation circuit. This cyclical process continues throughout tunnel excavation.

These locomotives consist of four main systems: the pneumatic system, engine system, electrical system, and hydraulic power-transmission system.

In practice, the coordinated functioning of these four systems determines locomotive performance. Tables 3–6 present the locomotive systems, their respective subsystems, and the functions of each subsystem.

Table 3. Pneumatic Subsystems

System	Subsystem	Function
Pneumatic	Air compressor	Generates compressed air within the system
Pneumatic	Air cooler	Cools the compressed air generated by the compressor
Pneumatic	Moisture trap	Removes moisture from the compressed air
Pneumatic	Main air reservoir	Stores the compressed air generated by the compressor
Pneumatic	Solenoid-valve block	Distributes compressed air throughout the system
Pneumatic	Pneumatic solenoid valve	Acts as a system actuator
Pneumatic	Regulator	Regulates air to the required pressure
Pneumatic	EVOL rail	Regulates compressed air throughout the system
Pneumatic	Accumulator	Stores compressed air for use when required
Pneumatic	Pneumatic sensor	Indicates the compressed-air pressure level
Pneumatic	Check valve	Directs compressed air in one direction along its flow path
Pneumatic	Four-position valve	Controls brake activation and subsequent brake release
Pneumatic	Air hose	Conveys compressed air throughout the pneumatic circuit

Table 4. Engine Subsystems

System	Subsystem	Function
Engine	Engine cylinders	Perform combustion and generate energy

Engine	Fuel-supply system	Delivers fuel to the cylinders
Engine	Cooling system	Cools the engine coolant and circulates it through the system
Engine	Air-intake and exhaust system	Directs exhaust gases toward the exhaust system and supplies air to the engine for combustion

Table 5. Electrical Subsystems

System	Subsystem	Function
Electrical	Solenoid valve	Actuates the pumps
Electrical	Electrical sensor	Indicates the oil-pressure level in the hydraulic motor
Electrical	Electrical power-supply system	Transfers engine motion to the alternator and subsequently charges the battery to provide electrical power
Electrical	Body-mounted lamps	Provide illumination and visibility within the tunnel
Electrical	Dead-man device	Issues a warning to prevent loss of operator alertness
Electrical	Starter motor	Starts the diesel engine

Table 6. Hydraulic Power-Transmission Subsystems

System	Subsystem	Function
Hydraulic power transmission	Hydraulic filter	Filters hydraulic oil
Hydraulic power transmission	Hydraulic hose	Conveys hydraulic oil
Hydraulic power transmission	Driveshaft	Transfers power from the engine to the distributor
Hydraulic power transmission	Distributor	Transfers power from the engine to the hydraulic pumps
Hydraulic power transmission	Hydraulic pump	Transfers power to the hydraulic motor
Hydraulic power transmission	Hydraulic motor	Transfers power to the axle
Hydraulic power transmission	Axle	Transfers power to the wheels
Hydraulic power transmission	Bearings and wheels	Propel the locomotive

3. Findings and Results

Two different software packages were used for the relevant components of this study. SPSS was used for the qualitative statistical analyses, particularly Pareto analyses, because it provides powerful tools for graphical and descriptive analyses, including bar charts. Artificial neural networks were used to identify the most appropriate statistical distributions for failures and to determine the corresponding distribution parameters.

The first stage of the analysis involved data collection. For this purpose, locomotive behavior over time was examined by integrating failure data from five locomotives with an aggregate operating duration of approximately 30,000 hours. The next stage involved Pareto analysis. The Pareto principle was introduced in 1906 by the Italian

economist Vilfredo Pareto to describe the unequal distribution of wealth among countries. According to this principle, approximately 80% of the effects and problems occurring in organizations—and even in technical systems—are attributable to 20% of the underlying factors and causes. If this critical 20% can be identified and controlled, a substantial proportion of errors and failures can be prevented. A Pareto chart can be used to examine the different causes of defects, identify those with the highest frequencies, and prioritize them for corrective action. Figures 5–10 present Pareto analyses in the form of bar charts for failure percentages, costs, and repair durations. It should be noted that the analysis was limited to failure modes with documented occurrence histories; therefore, it does not guarantee that other subsystems will not fail in the future. The observed failures are presented in Table 7.

Table 7. Observed Failures

System	Subsystem with a Recorded Failure
Pneumatic	Air hose
Pneumatic	Check valve
Pneumatic	Regulator
Pneumatic	Pneumatic solenoid valve
Pneumatic	EVOL rail
Electrical	Electrical power-supply system
Electrical	Electrical sensor
Electrical	Solenoid valve
Hydraulic	Hydraulic pump

Engine	Engine cylinders
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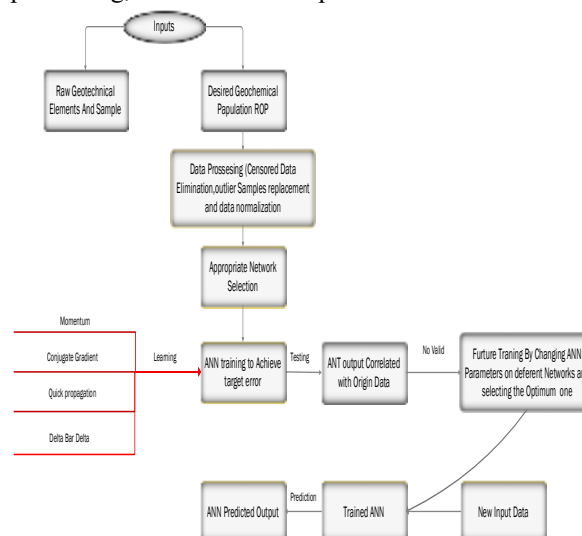
Table 8. Consolidated Results Extracted from the Supplied Figures

Analysis Level	System/Subsystem	Failure Percentage (%)	Cost Percentage (%)	Repair-Time Percentage (%)
System	Pneumatic system	61	9	5
System	Electrical system	20	8	2
System	Hydraulic system	11	79	54
System	Engine system	8	4	39
Subsystem	Check valve	20	—	1
Subsystem	EVOL rail	14	—	2
Subsystem	Hydraulic pump	11	—	54
Subsystem	Regulator	10	—	1
Subsystem	Air hose	9	—	1
Subsystem	Pneumatic solenoid valve	9	—	0.4
Subsystem	Engine cylinders	8	—	39
Subsystem	Electrical sensor	8	—	0.8
Subsystem	Electrical power-supply system	6	—	0.3
Subsystem	Electrical solenoid valve	5	—	0.5

Neural networks in MATLAB are used for clustering, estimation, and prediction. Neural-network modeling is classified as a nonlinear analytical approach. In the present analysis, a feedforward algorithm, which is trained through backpropagation, was employed. The model was implemented using the MATLAB command-line function `newff`. A neural network with one hidden layer comprising multiple neurons can solve the nonlinear problem associated with the penetration rate. The `tansig` transfer function was used for the single hidden layer, whereas the `purelin` function was used for the output layer.

The neural network had eight inputs and one output. Manual normalization of the numerical values was not required because this process was performed using the `mapminmax` function. After data preprocessing, the dataset

was used to train the network. In this modeling procedure, 70% of the data were allocated to training, 15% to validation, and the remaining 15% to network testing. After training and prediction were completed for each of these three subsets, the error function and the regression coefficient, or correlation coefficient, were calculated separately for each subset. The optimal architecture was selected based on the lowest mean squared error. Other error functions may also be used in neural networks, including the sum of squared errors (SSE) and root mean squared error (RMSE). After each run, the existing network was closed. Otherwise, rerunning the same network could cause it to become adapted to the previous execution, thereby producing unreliable results. Figure below presents the computational procedure used in the neural network.

**Figure 5.** Neural Network Implementation Flowchart

Before running the program, the number of neurons in the hidden layers must first be calculated. For this purpose, the number of hidden-layer neurons was estimated using

different empirical formulas, and the results were entered into Table 8.

Table 9. Number of Neurons in Each Hidden Layer

Estimated Number of Neurons	Formula
≤ 17	$\leq 2N_i + 1$
4.5	$(N_i + N_o)/2$
1.2	$[2 + N_o N_i + 0.5 N_o (N_o^2 + N_i) - 3]/(N_i + N_o)$
5.33	$2N_i/3$
2.82	$\sqrt{N_i N_o}$
16	$2N_i$

For statistical or intelligent prediction of the total failure duration, eight failure types were selected from among the

failures examined. These failure types were assigned codes 1–8, as shown in Table 9.

Table 10. Failure Codes Used in the Statistical Analysis

Failure Type	Failure Code
Regulator	1
Check valve	2
Pneumatic solenoid valve	3
EVOL rail	4
Electrical power-supply system	5
Electrical sensors	6
Solenoid valve	7
Hydraulic pumps	8

Linear regression was one of the methods employed in this analysis. In linear regression, the dependent variable, y_i , is expressed as a linear combination of the coefficients, or model parameters. Regression analysis measures the effects of two or more variables on a dependent variable.

Following the linear regression analysis of the eight failure codes and as illustrated in Figure 6, the estimated

model was formulated as Equation 2, which represents the principal equation for calculating total repair duration:

$$\text{Total Repair Duration} = -297.5 - 0.0453X + 115.34Y \quad (2)$$

In the above equation, X represents the failure time and Y represents the corresponding failure code.

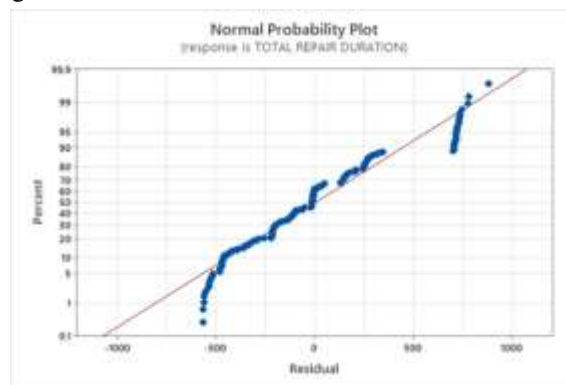


Figure 6. Normal Probability Plot for the Eight Failure Types

Figures below presents the predicted and actual values obtained from the equipment, together with the correlations between them. Figures 8 and 9 present the error histogram

and the mean squared error plot generated using the neural network, respectively.

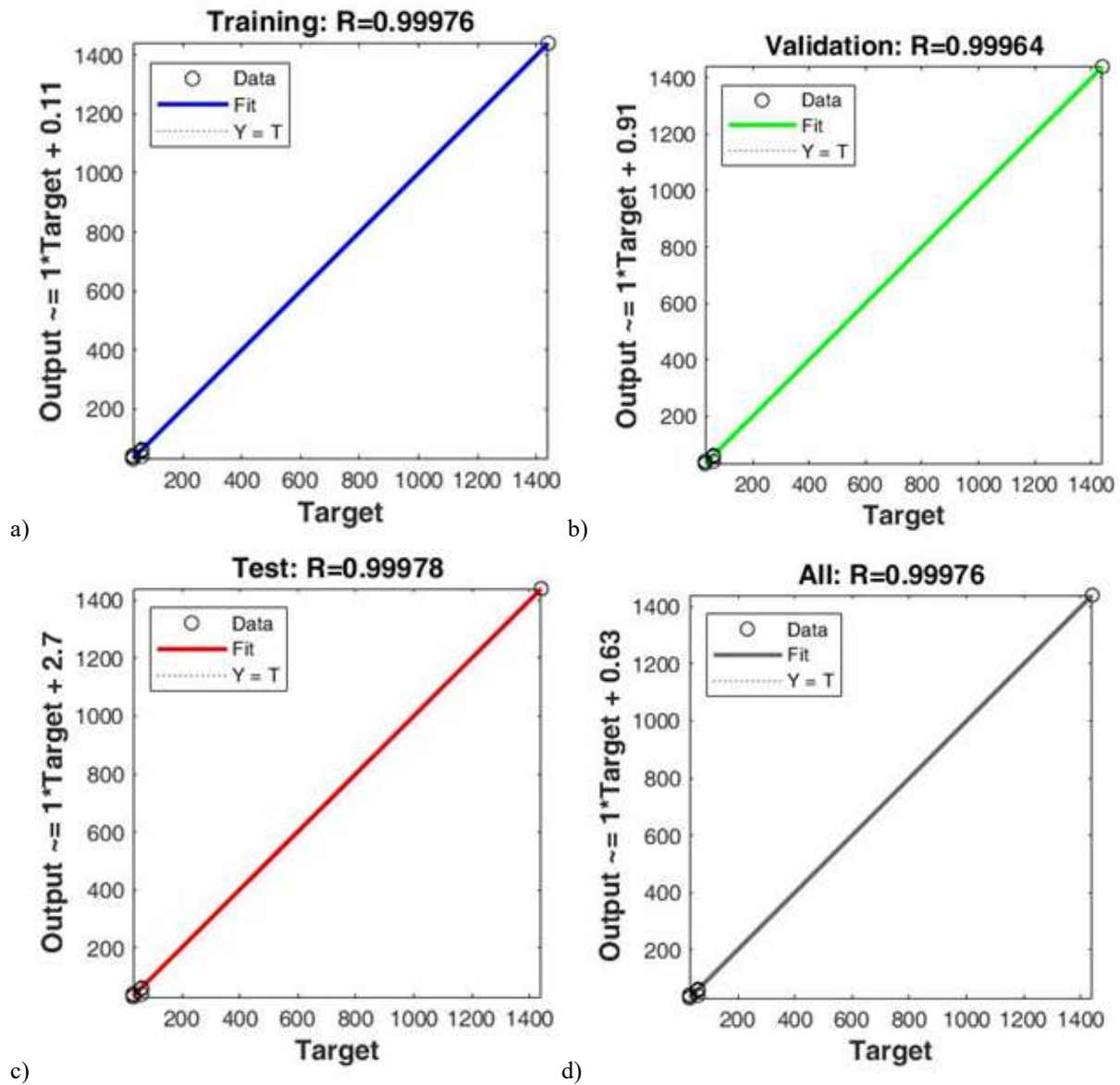


Figure 7. a). Training Phase; b). Validation Phase; c). Testing Phase; d). Entire Dataset

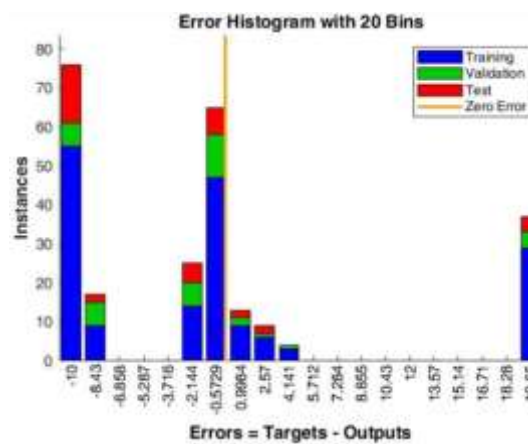


Figure 8. Error Histogram

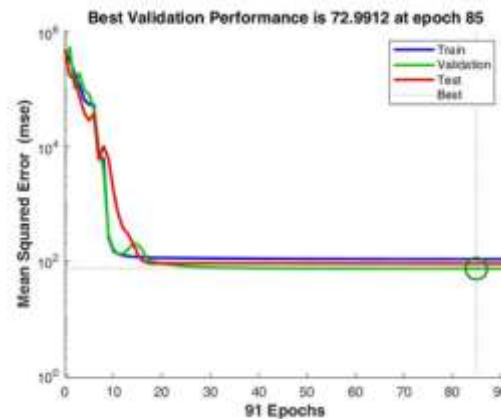


Figure 9. Mean Squared Error Plot

The performance of each architecture was evaluated using two parameters: mean squared error and the correlation coefficient. The best architecture was selected based on the lowest mean squared error. Other neural-network error functions may also be used, including root mean squared error and the sum of squared differences. Fourteen models with different numbers of hidden-layer neurons were selected for evaluation. Following model implementation, the 2–5–1 architecture exhibited the lowest error among all the evaluated models. The mean squared error of this model was 126, and its coefficient of determination was 0.999. Mean squared error was the principal criterion used to select the optimal network topology.

4. Discussion and Conclusion

The findings of the present study demonstrate that artificial neural networks can provide a highly accurate framework for predicting the total repair duration associated with support-locomotive failures in mechanized tunnel excavation. The analysis was based on failure records collected from five locomotives with an aggregate operating history of approximately 30,000 hours. The locomotive structure was decomposed into four principal systems—pneumatic, electrical, hydraulic power transmission, and engine—and subsequently into their constituent subsystems. Pareto analysis was used to identify the distribution of failure frequency, repair cost, and repair duration, while linear regression and artificial neural-network modeling were applied to predict total repair duration. Among the 14 evaluated neural-network configurations, the 2–5–1 architecture produced the best predictive performance, with a mean squared error of 126 and a coefficient of determination of 0.999. These results indicate that the

neural-network predictions closely approximated the observed values and that the model explained nearly all the variation in the target variable within the analyzed dataset.

The Pareto analyses showed that locomotive failures, maintenance costs, and repair durations were concentrated within a restricted set of systems and subsystems rather than being uniformly distributed across all locomotive components. The recorded failures were primarily associated with pneumatic components, including air hoses, check valves, regulators, pneumatic solenoid valves, and the EVOL rail, as well as electrical power-supply components, electrical sensors, solenoid valves, hydraulic pumps, and engine cylinders. This concentration is operationally important because it suggests that a limited number of recurring failure modes account for a substantial proportion of the interruptions experienced by the locomotive fleet. From a maintenance-management perspective, identifying these components enables technical managers to allocate inspection resources, spare parts, and preventive-maintenance activities more selectively instead of distributing resources equally across all subsystems.

This result is consistent with the managerial logic of condition-based and risk-based maintenance, in which equipment components are prioritized according to their observed contribution to downtime, cost, and operational disruption. The technical operation of tunnel locomotives depends on the coordinated performance of mechanical, pneumatic, electrical, and hydraulic systems, and failure in any one of these systems can compromise locomotive availability [13]. In the context of a single-track tunneling operation, the consequences of a locomotive failure extend beyond the failed unit itself. A disabled locomotive may obstruct the transport route, prevent the removal of excavated spoil, interrupt the delivery of segments and grout,

and ultimately force the TBM to stop. Therefore, the Pareto results should be interpreted not merely as a classification of maintenance problems but as an indication of the subsystems with the greatest potential influence on excavation continuity and project cost.

The strong predictive performance of the neural-network model supports the proposition that equipment failures and repair durations are governed by nonlinear relationships that cannot always be adequately represented through conventional linear methods. The linear regression model developed in this study related total repair duration to failure time and failure code. Although this model provided an interpretable mathematical relationship, its fixed linear structure could not fully represent complex interactions among failure categories, operating conditions, component deterioration, and maintenance outcomes. In contrast, the artificial neural network learned patterns directly from the observed data and generated predictions that exhibited an exceptionally high correspondence with actual repair-duration values. This result is consistent with the established capacity of neural networks to model multidimensional and nonlinear engineering processes without requiring the analyst to specify the exact mathematical form of the underlying relationship [7].

The results also align with earlier applications of artificial neural networks to TBM performance prediction. Benardos and Kaliampakos demonstrated that neural-network models could successfully capture complex relationships between geological and operational variables and TBM performance [3]. Similarly, Yagiz et al. found that nonlinear predictive tools were effective in estimating TBM performance under conditions characterized by complex interactions among machine and ground parameters [8]. Although the present study focused on locomotive failures rather than directly predicting TBM penetration, the underlying analytical problem is comparable. In both cases, performance is affected by multiple interdependent factors, the relationships among the variables are not necessarily linear, and accurate prediction is necessary for operational planning. The present findings therefore extend the application of neural networks from the primary excavation machine to the supporting logistics fleet on which uninterrupted TBM operation depends.

The high coefficient of determination obtained for the selected architecture is also compatible with previous research on the prediction of TBM penetration rate and efficiency. Gholamnejad and Tayarani reported that artificial neural networks were capable of predicting penetration rates

by learning nonlinear relationships among geological and operational variables [9]. Nejati and Ahmadi likewise demonstrated the usefulness of artificial neural networks for estimating TBM efficiency, emphasizing their capacity to integrate several influential factors within a unified predictive structure [10]. The present study reinforces these findings by showing that neural networks can also predict maintenance-related outcomes such as total repair duration. This is significant because repair duration directly influences equipment availability, cycle time, and the continuity of tunnel excavation.

The selection of the 2–5–1 network architecture also illustrates the importance of architecture optimization. Increasing the number of hidden neurons does not necessarily lead to improved performance. An excessively simple network may be unable to capture the underlying structure of the data, whereas an excessively complex network may overfit the training observations and perform poorly when exposed to new cases. The present study evaluated 14 architectures and selected the model with the lowest mean squared error, thereby applying a performance-based architecture-selection procedure. This approach corresponds with the systematic neural-network design principles proposed by Kaastra and Boyd, who emphasized that reliable forecasting requires appropriate variable selection, architecture specification, training, validation, and testing [5]. It is also consistent with recommendations that neural-network performance should be assessed through independent validation and generalization rather than training accuracy alone [6].

The division of the dataset into training, validation, and testing subsets further strengthened the analytical procedure. Seventy percent of the data were allocated to training, while 15% were used for validation and 15% for testing. This structure allowed the model to be trained on most observations while preserving independent subsets for monitoring overfitting and evaluating predictive performance. The close correlations obtained during the training, validation, testing, and overall-sample phases suggest that the selected network was not merely reproducing the training observations. Instead, it maintained a high level of predictive consistency across different portions of the dataset. This result supports the use of neural-network models as practical decision-support tools, although the exceptionally high coefficient of determination should still be interpreted cautiously until the model is externally validated using data from other locomotives or tunneling projects.

The effectiveness of combining Pareto analysis, regression, and artificial neural networks is another important finding. These techniques served complementary purposes. Pareto analysis provided a descriptive and managerial view of failure concentration, linear regression offered a transparent benchmark relationship, and the neural network supplied a flexible nonlinear predictive model. Torabi et al. similarly combined artificial neural networks with SPSS-based statistical analyses to investigate the influence of geotechnical parameters on TBM performance [11]. Their study showed that conventional statistical tools and intelligent methods should not necessarily be treated as competing alternatives. Rather, statistical methods can support data exploration and interpretation, while neural networks can improve prediction where relationships are complex. The present results confirm the value of this integrated methodology for maintenance and reliability analysis in mechanized tunneling.

The findings have direct implications for the management of excavation costs. Locomotive failures produce both direct and indirect costs. Direct costs include labor, replacement parts, repair materials, workshop operations, and emergency maintenance. Indirect costs arise when locomotive downtime delays spoil removal, segment delivery, grout supply, and other activities necessary for continuous TBM operation. Because the TBM is a capital-intensive machine, even relatively short interruptions may result in substantial idle-equipment and labor costs. Accurate prediction of repair duration can therefore improve short-term scheduling, contingency planning, resource allocation, and the estimation of probable excavation delays. More broadly, accurate quantity and cost calculations are essential in road and railway earthworks, where deviations in excavation operations can substantially affect project budgets [4]. The predictive framework developed in this study contributes to this objective by connecting failure information with anticipated maintenance time.

The results should also be considered in relation to the broader determinants of TBM productivity. Previous studies have shown that penetration rate and machine performance are influenced by geological, geotechnical, and operational conditions [3, 8, 11]. Cutter consumption is another major determinant of cost and downtime because worn cutting tools require replacement and may reduce excavation efficiency [12]. The present study shows that support-equipment reliability represents an additional layer of performance that must be incorporated into evaluations of mechanized tunneling. Even when geological conditions are

favorable and the TBM cutterhead is functioning efficiently, excavation cannot continue if the logistics fleet is unable to transport spoil, segments, grout, and essential consumables. Thus, a comprehensive assessment of TBM performance should consider the entire production system rather than focusing exclusively on the excavation machine.

The operational setting of the Tabriz Metro Line 1 project further explains why locomotive reliability was critical. The locomotives operated on single-track routes within deep tunnels, and the available shaft space was limited. As tunneling progressed, the travel distance between the shaft and excavation face increased, lengthening the transport cycle and exposing locomotive systems to longer periods of continuous operation. These conditions likely increased the operational consequences of failures because a disabled locomotive could not easily be bypassed. Underground metro construction is characterized by restricted space, interconnected processes, and high dependence on coordinated equipment operation [2]. The current findings provide empirical support for this systems perspective by showing that the performance of a supporting vehicle can become as consequential as the technical availability of the TBM itself.

The observed importance of locomotive reliability may also be interpreted through recent research on railway-system dynamics. Railway equipment performance varies according to operating status, loading, track condition, and infrastructure interaction, and mathematical modeling can clarify these dynamic relationships [15]. Although the present model did not explicitly include track condition, load, gradient, environmental exposure, or travel distance, its strong performance indicates that historical failure patterns contained sufficient information to predict repair duration with high accuracy. Adding dynamic operating variables in future models may further improve explanatory power and provide greater insight into why particular failures occur.

The study also supports the broader movement toward data-driven railway asset management. Contemporary railway research increasingly uses machine learning, integrated information systems, and infrastructure data to improve resource efficiency and operational decision-making. The application of federated learning and geographic information systems to railway-station infrastructure illustrates the expanding role of intelligent analytical frameworks in railway management [16]. The current study contributes to this movement at the tunneling-construction level by demonstrating how historical

maintenance records can be transformed into predictive information. Instead of using failure records only for retrospective reporting, project managers can use them to anticipate maintenance requirements, estimate downtime, and reduce uncertainty in excavation planning.

Although the present study concentrated on technical variables, its findings also have organizational implications. The effectiveness of predictive maintenance depends on accurate data recording, timely fault reporting, adherence to inspection routines, and cooperation among operators, mechanics, engineers, and project managers. Employee motivation and job performance are relevant to the quality of these activities. Evidence from an urban railway organization indicates that both intrinsic and extrinsic motivation can contribute to employee performance [14]. Therefore, implementing a neural-network-based maintenance system requires more than software and historical data; it also requires an organizational environment in which personnel consistently document failures, follow maintenance protocols, and use predictive information in operational decisions.

The management implications extend to the design of metro and public transportation systems more generally. Efficient tunneling supports timely completion of metro infrastructure, while reliable metro systems contribute to accessibility and the quality of urban public environments. The design and operation of spaces associated with subway stations can influence human emotional responses and the perceived quality of urban settings [1]. Although this study addressed construction-phase equipment, delays and cost overruns during tunneling can affect the timely delivery and quality of the wider metro system. Improving the reliability of excavation logistics therefore has indirect relevance to broader urban mobility and public-space objectives.

Overall, the findings demonstrate that artificial neural networks provide a more flexible and accurate approach than a simple linear model for estimating locomotive repair duration in the studied mechanized tunneling operation. The integration of failure classification, Pareto prioritization, statistical modeling, and neural-network prediction created a framework capable of supporting both technical maintenance and managerial decision-making. The results extend prior research on neural prediction of TBM penetration and efficiency by showing that the same analytical logic can be applied to auxiliary equipment whose availability directly determines excavation continuity.

This study was subject to several limitations. The data were obtained from five CHL-200G locomotives used in a

single metro-tunneling project; therefore, the results may reflect project-specific characteristics such as the tunnel geometry, track arrangement, maintenance practices, operator behavior, environmental conditions, and locomotive model. The analysis was restricted to failure modes that had previously occurred, and it cannot exclude the possibility of failures in other subsystems. Moreover, the predictive model primarily used failure-related variables and did not explicitly incorporate potentially influential factors such as locomotive load, travel distance, track gradient, ambient temperature, moisture, maintenance quality, component age, operator identity, or spare-part availability. The very high coefficient of determination may also indicate that the model fitted the available dataset exceptionally closely, and its generalizability cannot be fully established without external validation. Finally, repair duration was emphasized as the principal output, whereas the wider financial consequences of downtime, including idle TBM costs and schedule-delay costs, were not directly quantified.

Future studies should validate the proposed model using data from other metro lines, tunneling projects, locomotive models, and geological environments. Larger longitudinal datasets should be developed by integrating sensor measurements, maintenance records, operating hours, locomotive loads, haulage distances, environmental conditions, and component-replacement histories. Comparative evaluations of neural networks, support-vector machines, random forests, gradient-boosting algorithms, recurrent neural networks, and hybrid reliability models could determine which method performs best under different data conditions. Future models should also predict failure probability, remaining useful life, repair cost, and the likelihood of TBM stoppage, rather than focusing only on repair duration. Integrating the predictive model with discrete-event simulation could reveal how locomotive failures affect the entire excavation cycle. External validation, sensitivity analysis, uncertainty quantification, and explainable artificial-intelligence techniques should also be used to increase model transparency and managerial confidence.

Project managers should establish a standardized digital system for recording every locomotive failure, including the failed component, occurrence time, operating conditions, repair activities, labor hours, spare parts, cost, and resulting excavation delay. Preventive-maintenance resources and inventories should be prioritized according to the failure modes responsible for the highest frequency, cost, and repair duration. The predictive model should be integrated into

daily planning so that supervisors can anticipate locomotive availability and adjust excavation, segment delivery, grout supply, and spoil-removal schedules accordingly. Critical spare parts for pneumatic, electrical, hydraulic, and engine subsystems should be stored near the project site, and maintenance personnel should receive targeted training in recurrent failure modes. The model should be periodically retrained with new data, and its predictions should be reviewed alongside engineering judgment rather than used as an entirely autonomous decision mechanism.

Authors' Contributions

Authors equally contributed to this article.

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Declaration of Interest

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Ethical Considerations

All procedures performed in this study were under the ethical standards.

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