

Predictive Neural Network Modeling for Diesel Engine Part Wear Assessment via Analysis of Wear Element Concentration in Used Oil

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Abstract

This paper introduces a nondestructive method for estimating wear in diesel engine parts. Ulaanbaatar Railway, Mongolia's major railway company, has utilized Russian-manufactured 2TE116Um series diesel locomotives since 2010, following maintenance schedules outlined by the manufacturer. However, observations during the initial maintenance period from 2010 to 2016 necessitated adjustments to align maintenance schedules with Mongolia's unique operating conditions. Assessing diesel engine wear and predicting part lifespans based on wear element concentrations in engine oil has global applicability. Nonetheless, the existing Russian-approved methodology, different chemical compositions in diesel engine parts compared to other locomotive manufacturers, poses challenges in implementing recent approaches like neural networks (NN) for accurate predictive maintenance scheduling. Addressing this challenge, our study conducted spectral analysis of engine oil under Mongolia's operational conditions, analyzing wear element concentrations and their fluctuations. Furthermore, during maintenance periods, engine parts were disassembled and measured. Subsequently, data were utilized to train a neural network model to predict remaining useful life of the parts. Our two-stage neural network model demonstrated a remarkable improvement in predictive accuracy compared to traditional mathematical models, with an $R=0.99$, $R=0.82$ MSE. This enhanced model accurately assesses component wear, optimizing locomotive repair schedules, thereby potentially reducing maintenance expenses, and enhancing locomotive performance significantly.

Keywords: wear elements, neural networks, used oil, wear of diesel engine parts, Machine Learning (ML), Lubrication Condition Monitoring (LCM)

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1. INTRODUCTION

Locomotive maintenance involves utilizing information gathered through the monitoring of physical assets to

recommend necessary actions. This monitoring process, known as condition monitoring, involves regular evaluations of real-time operational conditions to optimize equipment performance by using health data to identify deviations or faults in the equipment.

Various techniques, such as vibration analysis, thermography, acoustic emission, and ultrasound, are employed to diagnose signs of wear and tear. Concurrently, lubricant monitoring tracks the entire wear and tear process of components, starting from normal conditions. Lubrication condition monitoring (LCM) is a pivotal approach that supplements predictive and proactive maintenance strategies. It is primarily employed as an initial defense mechanism to detect early signs of equipment deterioration, thereby preventing potential catastrophic equipment failures [1]. It plays a multifaceted role, serving as an early warning, diagnostic, and prognostic tool for machinery. By employing analysis methods such as spectral, iron spectrum, electrochemical, etc., LCM guides maintenance timing of the machine and replacement of the lubrication oil, offering valuable insights into machinery conditions and lubricant health [1]– [5]. At the core of LCM lies the retrieval and examination of vital physical and chemical attributes from lubricants, facilitating informed maintenance decisions. Among the pivotal techniques for diagnosing faults in mechanical equipment within the LCM realm, oil spectrum analysis is highly important [5]– [8]. This approach adeptly detects abrasive elements in oil, assesses additive conditions, and gauges oil pollution levels; this approach is now recognized as one of the most efficacious methods for LCM.

One significant research contribution is the work of Passoni et al. [5], where Raman spectroscopy was utilized to accurately distinguish automotive lubricants with varying SAE specifications. Sejkorov et al. [6] applied Fourier transform infrared spectroscopy (FTIR), partial least squares (PLS), and principal component regression (PCR) to predict the kinematic viscosity of SAE 140 oil under 100°C wear conditions. Zzeyani et al. [7] investigated the degradation of synthetic lubricating oil in diesel vehicles using electronic paramagnetic resonance (EPR) and FTIR, emphasizing the efficacy of FTIR in assessing oil quality and degradation rate. Zhou et al. [8] developed a model for predicting acid values based on the infrared spectrum monitoring method. The American Society for Materials and Testing (ASTM) has adopted rotating disc electrode atomic emission spectrometry (RED-AES) as the standard test method for determining worn metals and contaminants in lubricants, as outlined in ASTM D6595-17 [9]. The essence of the LCM program lies in its fundamental concept: evaluating and analyzing information derived from lubricant analysis to produce practical and actionable outputs for maintenance decision support [1]. The application of the LCM program in maintenance decision-making can be classified into three complementary areas: detection, diagnosis, and prognosis [10]. Prognosis entails forecasting the future performance of a system by examining its degradation or deviation from the anticipated state during regular operations. This study aimed to confirm the occurrence of a fault and assess the wear of diesel engine parts to determine the best time for maintenance intervention. For instance, an increase in the count of wear elements could serve as a predictor of the remaining useful life of a diesel engine [11].

Accurately predicting the wear of locomotive diesel engine parts holds significant potential for streamlining maintenance strategies, optimizing resource allocation, and improving overall operational performance. Traditional approaches to estimating wear often hinge on subjective evaluations or empirical models, which may lack precision and resilience. Therefore, there is a pressing need for advanced techniques capable of offering more reliable predictions. The concentration of wear products presents in used engine oil for locomotives has emerged as a potential indicator of the health and wear status of diesel engine components. These wear products, encompassing metallic debris and contaminants

generated during engine operation, are identifiable through oil analysis. Nonetheless, constructing a model that effectively utilizes this information to precisely estimate the Remaining Useful Life (RUL) remains a complex undertaking.

The traditional approach to estimating the Remaining Useful Life (RUL) of a locomotive diesel engine often depends on simple mathematical calculations [12]. Nevertheless, these conventional methods, which rely on fleet-wide engine wear rates, often demonstrate reduced reliability. Consequently, a model capable of precisely evaluating the RUL of a diesel engine by utilizing the concentration of wear products in used oil and the operating mileage is needed. Tackling this challenge entails harnessing neural networks, a subset of artificial intelligence, to create a more resilient and accurate predictive model. Numerous studies have explored the utilization of neural network models in evaluating engine performance and wear. Manieniyani et al. [13] investigated the influence of neural network models on predicting wear in a DI diesel engine using a B20 blend of Methyl Ester of Mahua (MEOM) and diesel. In a different approach, Zheng et al. [14] introduced an innovative method employing deep neural network techniques to model marine diesel engine performance by incorporating virtual sample generation technology. Mohanty et al. [15] concentrated on examining the morphological characteristics of wear particles and employed an artificial neural network (ANN) model based on intelligence. Rahimi et al. [16] investigated the in-operando effects of oil metal pollution on diesel engine conditions using extensive datasets and Support Vector Machine (SVM) and Radial Basis Function (RBF) models. They reported the highest accuracy in forecasting engine conditions when using the cubic polynomial (poly 3) and RBF kernel functions in SVM and RBF-NN classifiers employing two training methods, *trainbr* and *trainlm*. For engine condition predictions, the RBF and SVM classifiers achieved average accuracies of 99% and 97%, respectively. In their study, Kang et al. [17] introduced an innovative model for wear assessment based on support vector regression, which incorporates fuzzy uncertainty to account for random behavior in small sample sizes. Can et al. [18] employed artificial neural networks to predict the combustion characteristics of a single-cylinder diesel engine utilizing various models, such as multilayer perceptron (MLP), an adaptive neuro-fuzzy interference system (ANFIS), and a radial basis function network (RBFN). Another interesting work on neural networks is used on quadcopter stabilization [22]. They present a neural network control model for quadcopter stabilization. A single hidden layer network model was estimated to investigate the dynamics of the UAV. A control system with a classical PID controller was used to train the neural network model. Notably, Prabhu, Avinash, and Amin [19] utilized artificial neural networks for determining and optimizing the performance and emission parameters of compression ignition engines using alternative gaseous fuels. However, there currently exists a research gap in the specific context of addressing diesel engine part wear through neural network methods.

The literature background can be divided into two main sections: 1) RUL prediction based on sensor information. 2) Oil analysis is used to classify whether the engine is in a normal or critical condition. However, our objective in this research is to use oil analysis-based RUL prediction for engine parts, which is not covered. Therefore, we propose an innovative two-stage neural network model to predict the RUL of locomotive engine parts.

2. MATERIALS, METHODS AND MODELING

The experimental research methodology involved materials, data collection, data processing, and an overall modeling approach. The primary focus of the study was to model the wear of diesel engine parts based on the amount of wear elements in used oil utilizing two core databases. Initially, spectroscopic methods were employed to track the changes in wear element concentrations in used oil until the point of oil change. Subsequently, data

regarding the diesel engine parts measurements, which explain how much parts are under wear after routine maintenance, were collected and analyzed.

2.1. Experimental setup

This research involved the examination of the 16ChH26/26 diesel engine, a product of the JSC "Kolomensky Zavod," which features 16 cylinders with a power output of 2650 kW. The engine's operational manual recommends changing M14G2 motor oil every 50,000 to 100,000 kilometers based on the chemical and tribological characteristics of the oil. Test oil samples were collected during maintenance intervals on locomotive TU-3, which were carried out every 15,000 kilometers.

This research used an iCap 7000+ Inductively Coupled Plasma Optical Emission Spectroscopy (ICP OES) device for spectrographic oil analysis. This advanced instrument enabled precise and comprehensive examination of the oil samples, contributing to the accuracy and reliability of our analytical findings. This equipment functions as a combined inductively coupled argon gas plasma and optical emission spectrometer, predominantly employed to identify wear metal elements, contaminants in oil, and additive elements in lubricants. The instrument utilizes a technique that separates light and transforms it into electrical energy through a detector. Its optical design and CID detector were optimized for analyzing solid-state substances, enabling the measurement of various elements and concentrations across a wide array of sample types.

2.2. Test procedure

Diesel engines, recognized for their efficiency and durability, are nonetheless subject to wear and deterioration due to operational stresses and environmental conditions. The wearing process generates minuscule particles known as wear elements, which become integrated into the lubricating oil. Monitoring the concentration of these wear elements in used oil provides vital insights into engine wear patterns and degradation mechanisms, aiding in pinpointing critical components undergoing wear and estimating overall engine wear. The chemical compositions of the material components were analyzed to create a list of controlled elements that are necessary for the wear classification algorithm based on small parts. Monitoring the concentrations of nine elements, such as (Fe), (Cu), (Sn), (Pb), (Si), (Mg), (Ni), (Mo), and (Cr), is crucial for locomotive diesel engines [20].

In accordance with established procedures, oil samples were meticulously obtained to ensure an accurate representation of the engine's condition; the samples were labeled with the corresponding engine mileage, locomotive model, and operating conditions. This rich dataset facilitated a detailed analysis of the engine's performance and degradation over time. Chankin et al. [22] devised a dynamic model to ascertain wear product concentrations in locomotive diesel engine oil, facilitating the monitoring of wear rates during operation. Ovcharenko and Minakov [23] developed a mathematical model for wear product accumulation in engine oil utilizing an artificial neural network, allowing real-time assessment of the technical conditions of D49 diesel engine parts and thereby enhancing the repair process.

2.3. Data collection and Preprocessing

The extensive data collection process involved gathering pertinent data on diesel engine performance and maintenance from operational locomotives equipped with monitoring systems that captured various engine parameters. The MSU-TP system provides regular monitoring of the engine's technical condition for control, diagnosis, and adjustment.

Additionally, oil samples were systematically collected during routine maintenance and repair operations.

To achieve the primary research objective of developing a staged neural network model, real data were collected as follows: 1. The concentration of wear elements in diesel engine oil, 2. The wear and tear of diesel engine parts. The collected data is subsequently preprocessed to train the neural network.

We acknowledge that there is an existing dataset, but it is crucial to emphasize that our dataset has time series features and may differ significantly from open datasets due to factors such as data collection methods, sensors used, and the specific locomotive model under consideration. We will explicitly mention that the existing dataset is not directly comparable to our work because of these differences and most importantly, the lack of time series features. We agree that the working conditions of locomotives, including weather conditions, play a significant role in the performance and health of the system. In our revised manuscript, we provide additional details on how specific working conditions, such as temperature, humidity, and environmental factors, impact locomotive performance and consequently, the characteristics of our dataset.

2.3.1. The concentration of wear elements in diesel engine oil

The experiment included the analysis of 20 engines' oil use through 312 tests conducted during various phases, including technical maintenance (TM), routine maintenance (RM), oil changes, and when needed. During the routine maintenance of the diesel engine at every 300,000 kilometers, the oil was changed 3-5 times or at intervals of every 75,000 kilometers in accordance with the physical and chemical specifications. For instance, specific test outcomes for locomotive diesel engine number 1, comprising mileage and the concentration (measured in g/ton) of wear elements as determined through spectral analysis in used oil, can be found in Table I. diesel engine oil.

The total mileage for complete oil change was divided into periods I-IV, and the concentration of wear elements (g/ton) and corresponding statistical parameters were determined via spectral analysis of the used oil (Figure 1; Table II).

TABLE I

Mileage and changes in wear element concentration in used oil samples, g/ton

Mileage, 1000 km	Date	Fe	Pb	Al	Cu	Cr	Oil changed	Measured by unfolding
0								-
15	2016.01.14	8	0	5	2	1	-	-
30	2016.02.10	9	0	3	1	1	-	-
45	2016.03.16	24	2	5	2	1	-	-
60	2016.04.10	30	1	2	1	1	-	-
75	2016.05.18	34	2	6	3	2	-	-
90	2016.06.20	37	4	6	4	2	+	-
15	2016.07.25	16	1	3	2	1	-	-
30	2016.09.02	10	0	3	1	1	-	-
45	2016.10.04	20	1	4	3	1	-	-
60	2016.11.10	16	1	3	2	1	-	-
75	2016.12.20	24	1	3	1	1	-	-
90	2017.01.24	30	1	4	2	2	-	-
105	2017.03.04	37	3	6	6	2	+	-
15	2017.04.14	21	1	4	1	1	-	-
30	2017.05.20	27	2	4	2	1	-	-
45	2017.06.02	34	2	3	2	1	-	-
60	2017.06.28	60	4	10	4	1	-	-
75	2017.08.01	67	4	13	4	8	+	-
0								-
15	2017.08.30	9	0	3	1	1	-	-
30	2017.09.24	18	2	4	3	2	-	-

45	2017.10.20	24	2	4	5	2	-	-
60	2017.11.30	29	2	4	3	2	-	-
75	2017.12.24	36	4	6	7	3	-	-
90	2018.01.29	39	4	8	8	5	+	+

Note: (+) indicates no change in oil content and was not measured by unfolding (-)

TABLE II

Statistical analysis of wear element concentration in used engine oil: Periods I-IV of total mileage

parametrs	I					II				
	Fe	Pb	Al	Cu	Cr	Fe	Pb	Al	Cu	Cr
Mean	20.12	1.12	3.85	2.03	0.99	30.47	1.84	4.94	3.72	1.67
Standard Error	1.98	0.22	0.31	0.22	0.14	2.95	0.37	0.41	0.38	0.16
Median	17.00	1.00	3.00	2.00	1.00	25.50	1.00	4.00	3.00	1.00
Mode	17.00	1.00	3.00	1.00	1.00	30.00	1.00	3.00	2.00	1.00
Standard Deviation	11.38	1.24	1.79	1.29	0.82	17.70	2.23	2.48	2.29	0.99
Sample Variance	129.61	1.55	3.20	1.66	0.68	313.34	4.96	6.17	5.23	0.97
Kurtosis	0.29	2.74	0.08	2.05	5.37	3.83	11.99	7.45	2.05	2.84
Skewness	1.04	1.62	0.80	1.53	1.84	1.93	2.99	2.44	1.50	1.69
Range	42.00	5.00	7.00	5.00	4.00	78.00	12.00	12.00	9.00	4.00
Minimum	6.00	0.00	1.00	1.00	0.00	10.00	0.00	3.00	1.00	1.00
Maximum	48.00	5.00	8.00	6.00	4.00	88.00	12.00	15.00	10.00	5.00
Sum	664	37	127	67	33	1097	66	178	134	60
Count	33.00	33.00	33.00	33.00	33.00	36.00	36.00	36.00	36.00	36.00
Largest (1)	48.00	5.00	8.00	6.00	4.00	88.00	12.00	15.00	10.00	5.00
Smallest (1)	6.00	0.00	1.00	1.00	0.00	10.00	0.00	3.00	1.00	1.00
Confidence Level (95.0%)	4.04	0.44	0.63	0.46	0.29	5.99	0.75	0.84	0.77	0.33

Figure 1 and Table 2 visually depict a notable increase in the iron concentration found in the used oil samples. The initial period (I) revealed a mean iron concentration of 20.1 g/ton, accompanied by a variance of 11.8. Subsequently, by the fourth period (IV), the iron concentration had risen to 32.3 g/ton, demonstrating a variance of 13.37 g/ton.

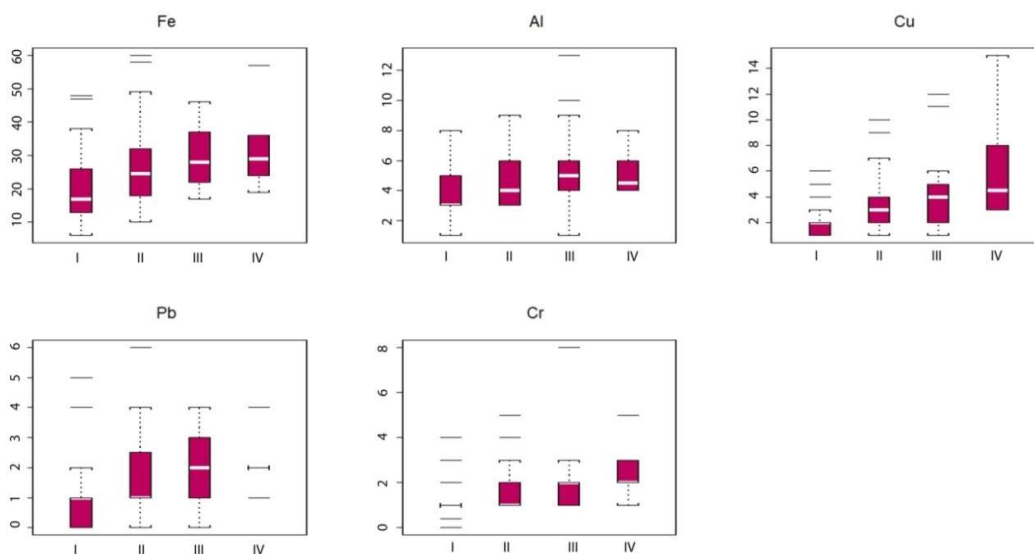


Figure 1. The variation coefficient/changes/in the concentration of wear elements in used oil in periods I-IV of mileage for complete oil change; g/ton

continuation of the TABLE II

III					IV				
Fe	Pb	Al	Cu	Cr	Fe	Pb	Al	Cu	Cr
34.36	2.08	5.40	4.32	1.92	32.33	2.17	5.17	6.33	2.50
3.19	0.22	0.50	0.63	0.29	3.68	0.27	0.44	1.28	0.38
29.00	2.00	5.00	4.00	2.00	29.00	2.00	4.50	4.50	2.00
21.00	2.00	4.00	4.00	1.00	28.00	2.00	4.00	3.00	2.00
15.94	1.08	2.48	3.17	1.44	12.74	0.94	1.53	4.42	1.31
254.24	1.16	6.17	10.06	2.08	162.42	0.88	2.33	19.52	1.73

1.49	-0.53	2.87	7.66	13.69	0.83	1.33	0.05	0.87	0.65
1.44	0.26	1.33	2.53	3.33	1.27	1.21	1.14	1.43	1.15
60.00	4.00	12.00	15.00	7.00	38.00	3.00	4.00	12.00	4.00
17.00	0.00	1.00	1.00	1.00	19.00	1.00	4.00	3.00	1.00
77.00	4.00	13.00	16.00	8.00	57.00	4.00	8.00	15.00	5.00
859	52	135	108	48	388	26	62	76	30
25.00	25.00	25.00	25.00	25.00	16.00	16.00	16.00	16.00	16.00
77.00	4.00	13.00	16.00	8.00	57.00	4.00	8.00	15.00	5.00
17.00	0.00	1.00	1.00	1.00	19.00	1.00	4.00	3.00	1.00
6.58	0.44	1.03	1.31	0.59	8.10	0.60	0.97	2.81	0.84

Univariate regression analysis was carried out to assess the relationship between the changes in wear elements (y) within the oil used throughout periods I-IV (x) until the engine oil change occurred. This analysis highlighted a potential logarithmic correlation, indicated by the equation

$$y = 19.33\ln(x) + 23.72 \quad (1)$$

achieving an R=0.9.

2.3.2. The wear and tear of diesel engine parts

The manufacturers of the 16XH26/26 diesel engine follow the mileage-based repair recommendations stipulated by the open carriage manufacturer. These guidelines specify the RM 1 repair at 150,000 km, the RM 2 repair at 300,000 km, and the RM 3 repair at 600,000 km. In this study, we analyzed the wear statistics and residual reserves of specific parts during the RM 2 and RM 3 repairs. The wear intensity of diesel was assessed by disassembling the engine during the operational periods detailed in Table III.

TABLE III

The parameters of wear in diesel engine parts

Mileage measured by disassembling, km	Cylinder liner	Piston Pins	Pin connecting rod	Crank Main journals	Crank pin journals	Connecting rod bronze bushing	Crank pin journals	Bronze bushing
389	0.032	0.022	0.020	0.059	0.030	0.121	0.200	0.147
358	0.033	0.040	0.023	0.060	0.045	0.111	0.173	0.120
330	0.025	0.012	0.039	0.031	0.030	0.121	0.176	0.100
391	0.033	0.024	0.039	0.061	0.048	0.117	0.189	0.155
333	0.033	0.017	0.021	0.062	0.054	0.108	0.203	0.147
456	0.056	0.038	0.042	0.016	0.012	0.117	0.185	0.103
410	0.040	0.032	0.032	0.060	0.049	0.182	0.185	0.188
350	0.033	0.031	0.028	0.064	0.032	0.168	0.214	0.123
333	0.032	0.032	0.037	0.049	0.025	0.117	0.191	0.100
551	0.060	0.026	0.026	0.033	0.029	0.103	0.196	0.133
551	0.060	0.040	0.042	0.064	0.054	0.182	0.214	0.188

The findings regarding the wear rate of diesel engine parts revealed that 95% of the parts experienced wear ranging from 0.05 mm to 0.06 mm during each maintenance session. Additionally, 95% of all the bearing types exhibited wear within the range of 0.17 mm to 0.21 mm. The residual useful life of these parts was estimated to be between 0.7% and 0.85%, as determined by comparing the wear rate against the replacement criteria outlined in the routine maintenance guidelines. To prepare the collected data for analysis, several pre-processing steps were executed. These steps were aimed at improving the data quality, addressing missing values, and standardizing the dataset. Normalization methods, such as scaling or standardization, were applied to ensure that all features were on a comparable scale. This process was essential for preventing any specific feature from exerting undue influence on the analysis due to its greater magnitude.

2.4. Results of the traditional approach

The traditional approach to calculating the remaining useful life of a locomotive's diesel engine employs the following mathematical model. The value of the remaining useful life

(L_{RUL}) is calculated from the discrepancy between the full reserve and the current mileage, which indicates the wear of diesel engine parts, using the following formula:

$$L_{RUL} = \frac{G}{\alpha \cdot K_N} - L \quad (2)$$

Here,

G – permissible wear, g;

α – oil exchange coefficient (characterizing the operating conditions of the diesel engine and calculated as the arithmetic average of the predicted wear elements for a park of diesel locomotives of the same series; t/thousand km),

K_N – average concentration at the time of forecasting, g/t;

L – mileage at the time of forecasting, thousand km.

The average concentration (K_N) at the time of forecasting was calculated using the following formula:

$$K_N = \frac{\sum_{r=1}^N K_r}{N} \quad (3)$$

Here,

K_r – the concentration of wear elements in the oil of sample r ;

N – number of samples taken since diesel repair

3. NEURAL NETWORK ARCHITECTURE DESIGN

The innovative neural network model, designed to predict the wear of diesel engine parts by analyzing the fluctuation in wear product concentration within the operational oil, is structured as a two-stage architecture model (refer to Figure 2). The initial stage features a model that evaluates the variation in wear product concentration within the engine's operational oil based on the locomotive's operational mileage. This first stage is intended for diagnosing abrupt changes in the wear rate of engine parts and serves as input for the subsequent stage. As the object of our study was manufactured in Russia, wear elements were selected in accordance with the Russian GOST 20759 standard. The analysis involved the use of diagnostic indicators outlined in the standard.

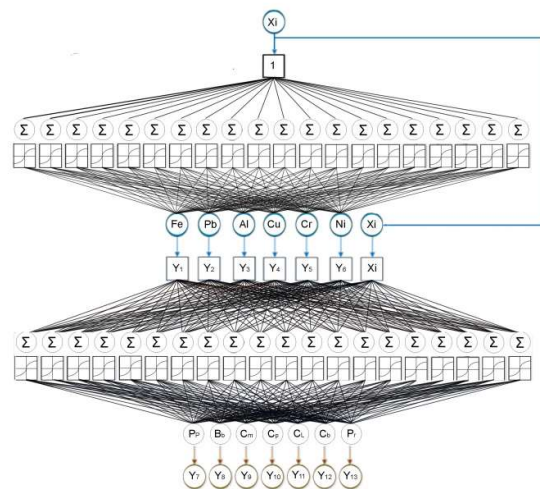


Figure 2. Proposed neural Network Architecture

The subsequent stage comprises a model that estimates the wear of engine parts, relying on the concentration of wear products in the engine's operational oil and the locomotive's mileage. The aim of this subsequent stage is to predict the wear of diesel engine parts. While the interval for oil changes might vary depending on the locomotive's average daily mileage, data collection for the first stage typically spans approximately one month. During the RM 2 repair period, the wear product concentration analysis of the oil involved 3-5 oil changes.

However, data for the second stage, concerning part wear, are solely acquired during the RM 2 and RM 3 repairs, resulting in a longer interval between assessments, occurring approximately once every three years.

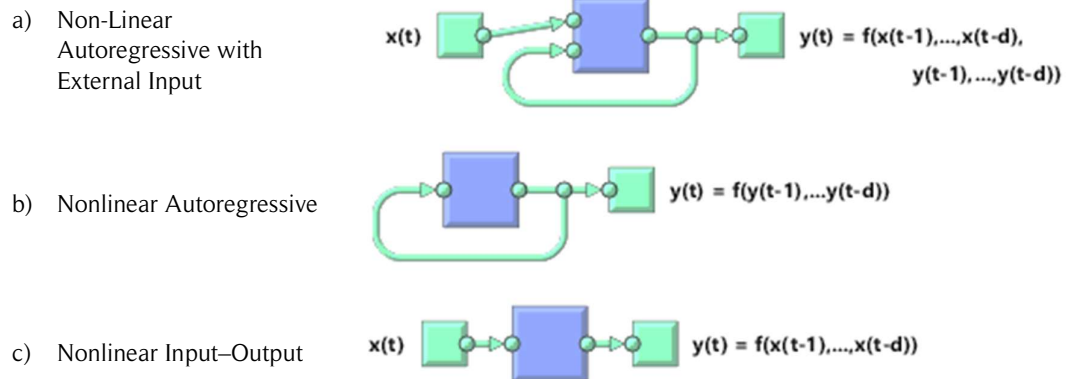


Figure 3. Neural Network Architectures for comparison

The study's reported wear of diesel engine parts encompasses Piston Pins (Pp), Bronze Bushing (Bb), Crank Main Journals (Cm), Crank Pin Journals (Cp), Cylinder Liner (CL), Connecting Rod Bronze Bushing (Cb), and Pin Connecting Rod (Pr). To compare the performance of the neural network models, we utilized three different architectures in the time series problem domain. a) Nonlinear autoregressive model with external input (NARX) [23], b) nonlinear autoregressive (NAR) [24], and c) nonlinear input–output model [25]. The architecture of these models are illustrated in Figure 3.

3.1. Development and training of the neural network model

The neural network model was designed and trained using MATLAB 2022 software. The neural network toolbox within MATLAB facilitated the creation and execution of the artificial neural network simulation (Figure 4). The architecture of the model was meticulously structured, taking into account the particular problem of predicting diesel engine performance. The specifics regarding the number of layers, neurons per layer, and activation functions were determined through a process of experimentation and optimization (TABLE). The dataset was divided into 216 samples for training, 47 for validation, and another 47 for testing, in accordance with established practices in machine learning. Table IV shows the hyperparameters of the neural network.

TABLE IV

Hyperparameters of the neural network

Parameters	input α_k , weight θ_k , Bias b
Number of layers	2
Number of unit for layer	20
Learning rate	0.031
Epoch	14
Activation function	sigmoid

We experimented with multiple hyperparameter variations to determine the most effective values for the neural network. Specifically, we focused on exploring the number of neurons in the hidden layers (5, 10, 15, 20, 25, and 30) to identify better-performing hyperparameters. The training results revealed that the range between 20 and 30 neurons yielded the highest mean squared error (MSE) of 0.99. Table 5 shows the effect of the number of neurons in the network on the MSE. When too few neurons cannot converge well, after 20 or more neurons, the model converges well, but adding more neurons does not affect the

model. Despite the consistent MSE, we observed differences in learning time across this range. Consequently, we determined that 20 neurons were the optimal count.

TABLE V

Hyperparameters of the neural network	
Number of neurons	MSE
1	0.324
5	0.831
10	0.971
15	0.994
20	0.997
25	0.997
30	0.997

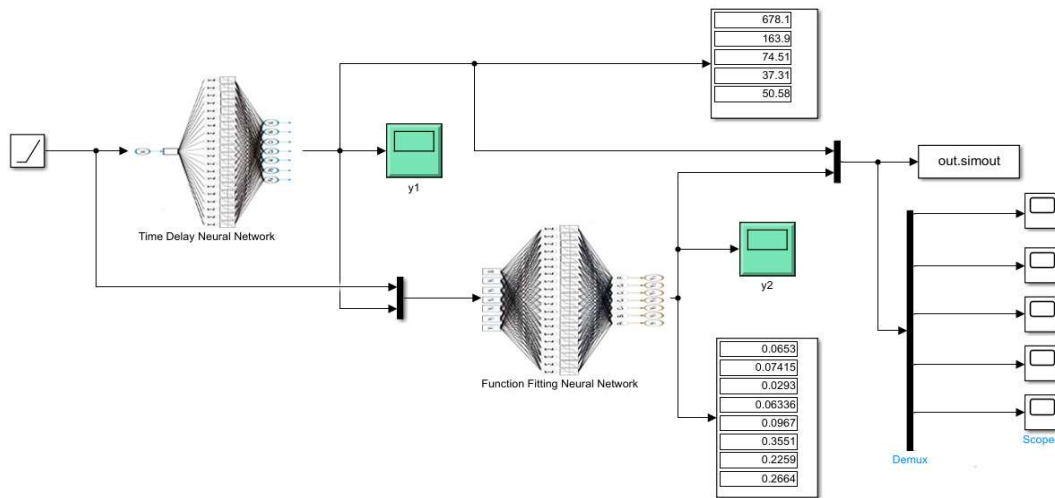


Figure 4. Simulink model of proposed neural network

The Levenberg–Marquardt algorithm was used for training. This algorithm is memory intensive but takes less time. The learning process automatically stops when there is no further improvement in generalization, as evident from an increase in the mean squared error of the validation sample.

The training process involved iterative adjustments of the network's weights and biases using backpropagation and gradient descent algorithms. The objective was to minimize the prediction error and improve the model's accuracy in estimating engine wear.

3.2. Model Evaluation and Performance Analysis

After training the neural network model, it was evaluated using the test dataset that was not used during the training process. Performance metrics, such as the mean squared error (MSE), root mean squared error (RMSE), and coefficient of determination (R-squared), were computed to assess the model's accuracy and generalizability. The mean square errors of the training, validation, and test sets stabilized after 8 epochs (Figure 5.a).

The graph shows the MSEs on the training data, the validation data, and the test data. The training data is the data that the model is trained on. The validation data is a separate set of data that is used to monitor the model's performance during training. The test data is a separate set of data that is used to evaluate the model's performance after training is complete. The best validation performance is achieved in epoch 8. This means that the model's predictions on the validation data were the most accurate at epoch 8. The top left

corner of the right image (Figure 5.b) shows the training, validation, test, and all R-squared values.

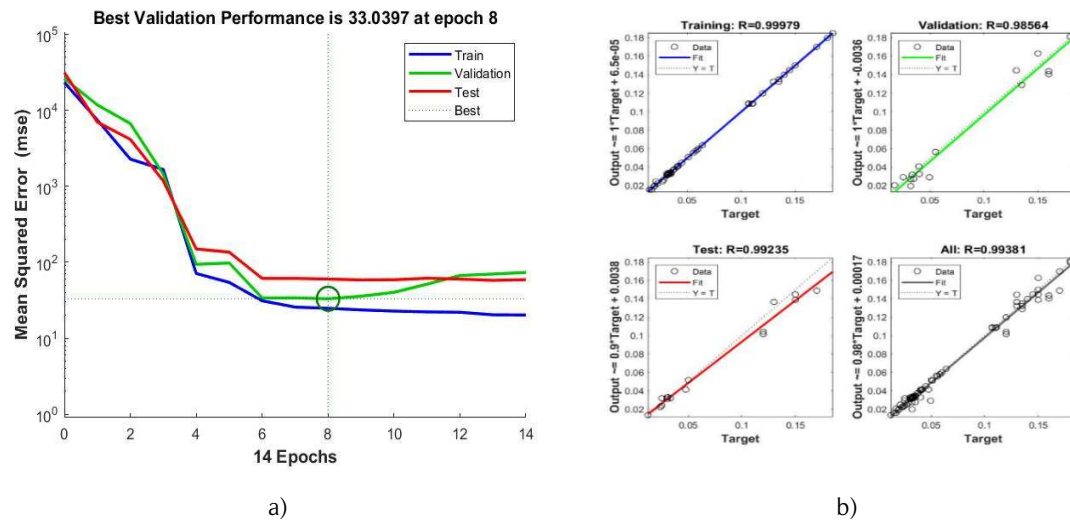


Figure 5. Parameters of the trained neural network, a) Training performance, b) Training output vs target

The R-squared value is a statistical measure that represents the proportion of variance (i.e., how spread out the data is) in the dependent variable that is explained by the independent variable(s) in a regression model. In this case, the R-squared values appear to be high, which suggests that the ANN model is able to explain a large proportion of the variance in the target variable. Additionally, various visualizations and plots were generated to analyze the model's performance in detail. These included scatter plots of the predicted versus actual remaining service life, error distributions, and trend analysis of the model's predictions over time.

4. RESULTS AND DISCUSSION

This paper presents a comparative analysis between the results derived from the developed MATLAB model and those computed through traditional statistical methods. Additionally, the study provides an overview of the relationship between the concentration of wear elements in the engine's used oil and the locomotive's operation, assessed using conventional methodologies.

4.1. Results of the MATLAB model

The Experimental Results section presents the outcomes derived from the application of the trained neural network model to the gathered dataset. This section specifically highlights instances where the model exhibited accurate predictions regarding the wear of diesel engine parts, thereby offering valuable insights for maintenance planning and decision-making. To demonstrate the effectiveness of the similar time series architectures, we compare Non-Linear Autoregressive with External Input (NARX), Nonlinear Autoregressive (NAR), Nonlinear Input-Output models with the same hyperparameter. Performance is measured by regression R values, which indicate the correlation between outputs and targets. Lower values are better, therefore zero means no error.

Table 6 shows the results of training on three different architectures. Due to the randomness of training initialization, every instance of training yields a different result. Therefore, we ran the training 10 times and averaged the regression R values. The results reveal little difference between the three different architectures; due to simplicity, we choose a simple nonlinear input–output architecture.

TABLE VI

Comparison of performance for different time series neural network architectures

Model name	Training R	Validation R	Testing R	Training time
Non-Linear Autoregressive with External Input (NARX)	0.987	0.996	0.997	7 s
Nonlinear Autoregressive (NAR)	0.996	0.998	0.994	4 s
Nonlinear Input–Output	0.997	0.997	0.998	2 s

The horizontal axes in Figures 6 and 7 indicate locomotive mileage (10 units = 100000 km scale). The vertical axis of Figure 6 indicates the concentration of wear elements in the used oil (g/ton), while the vertical axis of Figure 7 indicates the amount of wear in the parts (mm).

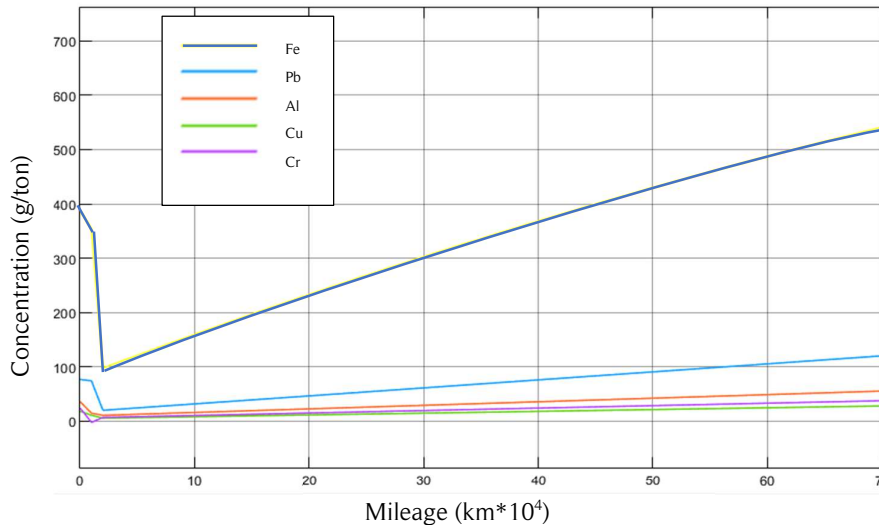


Figure 6. Relationship between the concentration of wear elements in the engine's used oil and the locomotive's mileage

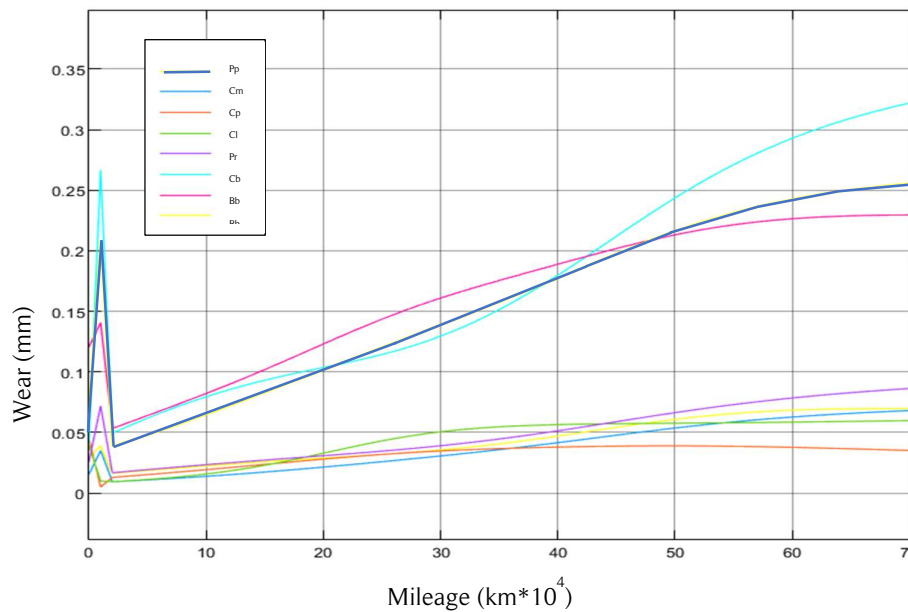


Figure 7. Relationship between wear of diesel engine parts and locomotive mileage

Figure 6 shows the model predictions for the concentration of each wear element based on mileage as the input. The model outcomes enable us to forecast future concentrations of

each element and facilitate the examination of wear characteristics. Figure 6 shows that the wear of the bronze bushing in the diesel engine connecting to the rod outpaces the wear observed in other parts of the device. The manufacturer's guidelines specify a wear reserve (expressed as a linear amount of wear) of 0.32 mm for this particular component. Consequently, the locomotive is expected to reach this wear limit after covering a mileage of 600,000 km.

Certain components, such as connecting rod bronze bushings (indicated by the blue and yellow curves in Figure 7) and piston sealing rings (represented by the red curve in Figure 7), exhibit a notably greater wear intensity than other parts. This heightened wear rate can be attributed to the relatively low metal density of these materials, which renders them more susceptible to accelerated wear (as depicted in Figure 7).

4.2. Results of the traditional approach

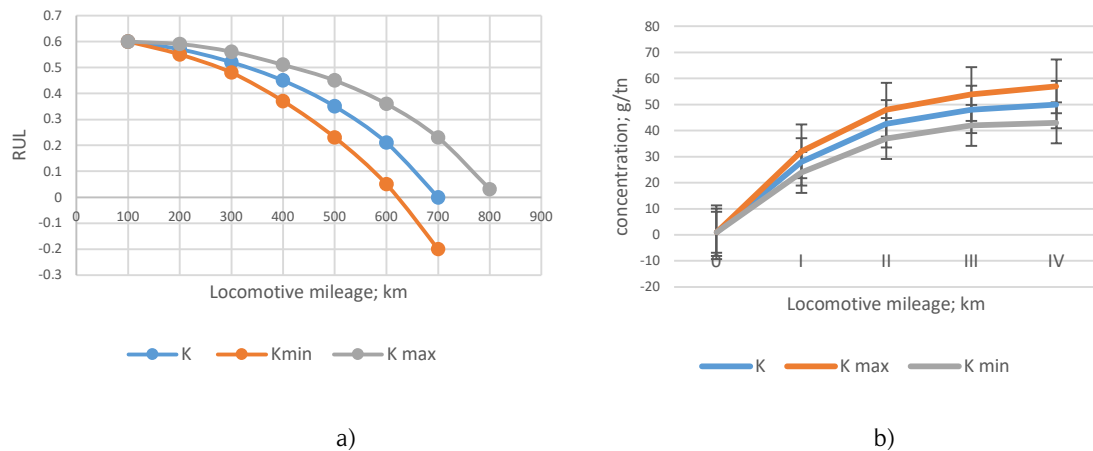


Figure 8. Relationship between wear of diesel engine parts and locomotive mileage. a) RUL vs mileage, b) Concentration vs mileage

Based on these estimations (using Equation 2), the (RUL; Figure 8.a) of the Connecting Rod Bronze Bushing is estimated to be at least 630,000 km and at most 810,000 km. It is evident from these results that the traditional estimation of the concentration (Figure 8.b) of Cb exhibits a greater deviation.

4.3. Discussion

The interpretation of the experimental results obtained from evaluating the proposed model for predicting the wear of diesel engine parts is now detailed. This analysis, derived from the wear product concentration data and corresponding engine part wear, provides significant insights into the effectiveness of the model. The collected data showed that the proposed two-stage architecture model successfully captured the variations in wear product concentration in the engine's working oil. The authors accurately estimated the wear in engine parts based on this concentration and the locomotive's mileage, aligning closely with observed service life during subsequent repairs. This interpretation affirms that the developed model shows great potential for accurately forecasting future trends in wear for diesel engines. By continuously monitoring the wear product concentration in the working oil and considering the operational mileage, proactive maintenance decisions can be made, thereby preventing failures and optimizing the overall maintenance strategy.

In this section, the model's performance is compared with that of existing techniques for wear trend analysis in diesel engines, including statistical approaches, physics-based models, and data-driven techniques discussed in prior literature. The results obtained from traditional

statistical methods, those calculated by the neural network (NN) model, and the actual test results were compared. In contrast to physics-based models that rely heavily on intricate knowledge of internal engine mechanisms and properties, the proposed model demonstrated competitive performance. Physics-based models often necessitate extensive parameter estimation and may not effectively capture the system's dynamic behavior as data-driven approaches can. This comparison highlights the strengths of the proposed model, which leverages machine learning techniques to adequately model the complex relationships between wear product concentration, mileage, and component wear, offering a practical and accurate approach for analyzing future trends in wear for diesel engines. This approach surpasses the limitations of traditional wear trend estimation techniques. A comparison of the training overall performance results of the models yields $R=0.99$ (shown in Figure 4) and 0.9 for the classical model results, as shown in equation (1), which indicates that the NN model is preferable for predicting maintenance. The UBTZ company does not manufacture diesel engine parts. Consequently, during unplanned maintenance of the locomotive, parts with varying reserves are replaced and installed in the engine. This limits the accuracy of this model in calculating the remaining useful life of the engine.

5. CONCLUSION

Comparative analysis demonstrated that the developed model outperforms traditional statistical methods, providing more accurate and reliable predictions. The integration of machine learning algorithms, especially artificial neural networks, enables the modeling of intricate relationships between wear product concentrations, mileage, and component wear.

This research further revealed that during "Flow Repair-2" maintenance, 95% of the parts exhibited wear ranging from 0.05 mm to 0.06 mm, and for all types of bearings, this wear ranged from 0.17 mm to 0.21 mm. Compared to the replacement thresholds suggested in routine maintenance guidelines, the remaining service life of the parts ranged from 0.7% to 0.85%. This highlights the remarkable durability of the 16XH26/26 diesel engine.

Moreover, this study underscores the importance of data-driven approaches in engineering and maintenance practices. The continuous monitoring and assessment of engine wear provided by our neural network model can lead to cost reductions, enhanced operational efficiency, reduced downtime, and improved environmental sustainability. The ability of the model to identify abnormal wear patterns and impending maintenance requirements plays a crucial role in ensuring the sustained reliability and longevity of diesel engines.

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