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Development of diagnostic parameters for assessing the operation of a diesel engine on site

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Abstract
The paper aims to develop the on-site diagnostic parameters for assessing the operation of engines through the content (g/ton) of wear elements and contaminants in used oil. Here, it refers to heavy-machinery vehicles used in various industries of Mongolia such as agriculture, railway, building and road construction, mining etc. This study analyzed the results of measurements in the used oil samples from 20 diesel engines over a maintenance period of 5-6 years using spectral analysis. It focuses on three key goals: determining the content of wear elements and contaminants in used oil (g/ton), studying the intensity of engine wear during one period of maintenance, and using non-parametric statistical methods to develop the on-site diagnostic parameters based on the concentration of wear elements and contaminants in the samples of used oil.
The diagnostic parameters determined as a result of this study can enable technicians to perform diesel engine maintenance based on the actual technical condition of the engine, rather than relying solely on the manufacturer's recommended maintenance schedule, reduce the repair cost by addressing the aspects before serious breakdowns or delays occur and improve overall the engine performance, resulting in significant benefits for the transportation and heavy-machinery industries.

Keywords: Spectral Analysis, Maintenance Schedule, Wear Elements, Wear Elements Concentration, Diagnostic Parameters, Used Engine Oil

Introduction
Diesel engines are commonly used in transportation and heavy machinery industries due to their high efficiency and durability. As such, it is crucial to have a robust understanding of the performance and technical condition of these engines to ensure safe and reliable operation. To achieve this goal, accurate and reliable diagnostic parameters are needed to assess key parameters of engine performance, including efficiency, power output, and overall technical condition. These parameters may include engine speed, oil pressure, coolant temperature, fuel consumption, exhaust emissions, and more. They are used to identify issues or anomalies in the engine, monitor its performance over time, and make necessary adjustments or repairs to maintain optimal performance and efficiency.
The schedule of routine maintenance in a planned preventive maintenance system is recommended by the manufacturer, based on standard parameters (values) for reliable operation of diesel engines and cost-effective maintenance practices [1]. While this system provides benefits such as improved technical inspection and enhanced reliability, it can also result in unnecessary costs, such as mandatory disassembly for component inspection and regular planned maintenance without considering the actual condition of the machinery. Thus, condition monitoring method in machine maintenance is necessary to analyze the performance of machines [2].

Machinery condition monitoring and diagnostics for locomotives is the process of continuously monitoring the health and performance of the diesel engine and its components. According to Gharib and Kovács, effective diagnostic strategies are crucial in enhancing competitiveness, boosting productivity and ensuring workplace safety [3]. Technical diagnostics provide solutions for various challenges, including assessment of actual technical conditions, detection of defects, pinpointing failed components without disassembling parts, and making informed maintenance decisions for sustained machine reliability.

The goal of this study is to identify potential issues before they become serious problems, allowing for proactive maintenance and repairs to be performed, reducing downtime and increasing the overall efficiency of the locomotive. This is achieved through the use of various technologies and techniques of machinery technical diagnosis, such as vibration analysis, thermography, ultrasonic testing, tribology-based monitoring and lubricant analysis, to monitor and diagnose the condition of different components of the engine. The International Organization for Standardization (ISO) provides guidelines for machinery condition monitoring and diagnostics.

Overview of diagnostic parameters

The manufacturers of diesel engines recommend adhering to the operating guidelines, which provide information on the physical-chemical and other properties of lubricating oils. This paper outlines the guidelines provided by diesel engine manufacturers for determining the technical condition of components through analysis of wear elements in used engine oil. The normal, abnormal, and critical limits of concentration of wear elements and contaminants in used oil during engine operation are defined according to the GOST20759 standard, which is followed in order to determine qualitative and quantitative variables of wear elements in used oil of the 16ChH26/26 diesel engine. Spectral analysis is used as the method of diagnosis, allowing for early detection of damage and failures, and estimation of wear degree and remaining useful life of components. The parameters are presented in Table 1.

Table 1.
Limits of wear elements concentration for diesel engine diagnosis

Element	**Symbol**	**Concentration**			**Components**
		Normal	Abnormal	Critical	
Iron	Fe	<65	65-100	>100	Cylinder, Rings, Crankshafts, Gears, Rust
Lead	Pb	<15	15-20	>20	Bearings, babbitt
Aluminum	Al	<20	20-30	>30	Bearings camshaft
Copper	Cu	<50	50-100	>100	Bronze bushing
Chrome	Cr	<10	10-15	>15	Rings
Tin	Sn	<5	5-10	>10	Piston skirt

Tribology examines the extent of wear, while lubricant analysis evaluates the technical condition of machinery by analyzing the lubricant state. Lubrication condition monitoring (LCM) has become a crucial aspect in making decisions on engine maintenance systems, as evidenced by the growing number of research papers published in the past five years [4]. This monitoring involves the analysis of physical-chemical parameters in used engine oil, oil additives, contaminants, and wear elements. In particular, significant information can be obtained from the buildup of wear particles in used oil, including the engine's technical condition and the normal functioning of subsystems [5]. D02 Committee proposed a test method that covers the rapid determination of 22 elements in used lubricating oils and in base oils, and provides rapid screening of used oils for indications of wear [6]. Fernández-Feal et al. aimed to determine the concentration of metals in a mineral-based lubricating oil before, during, and after its use in a truck engine, with the goal of understanding the variation for predictive purposes [7]. Zhao proposed a comprehensive reference guide of common in-service oil analysis techniques to help readers understand and choose the right technique and instrumentation for their needs [8].

The diagnostic parameters of elements concentration given in the standard takes into account many factors, such as natural and climatic conditions, adjusted power of the engine, quality of technical servicing, scheduling of oil changes, and the addition of new oil [9]. Zaharia et al. determined viscosity, density, water content, fuel dilution and solid compounds of used oil in order to perform diagnostic analysis of locomotive diesel engine operation [10]. Macián et al. developed an approach to enable a more accurate wear determination from engine oil samples of internal combustion engines [11]. They concluded that relying solely on absolute concentration measurements to evaluate wear is inaccurate and can give false results. Raposo et al. shed light on diesel engine condition monitoring techniques, showing how variables such as soot and iron content indicate the engine's condition [12]. Bekana et al. analyzed used motor oil in agricultural machines to enable identification of a potential problem before a major repair is necessary [13].

The latest trend in diesel engine maintenance is towards non-invasive diagnostic methods and condition-based maintenance systems, which aim to reduce wasteful costs. One of the main forms of condition-based maintenance is predictive maintenance technology [13],[14]. This involves the use of sensors and data analysis tools to monitor engine performance in real-time, and predict potential issues before they occur. This allows maintenance to be scheduled proactively, reducing downtime and costs associated with unscheduled repairs. Unfortunately, this method could be expensive to implement, especially for older locomotives that may require retrofitting with new sensors and monitoring equipment; it also requires complexity and integration with an existing system. Predictive maintenance for lubricant oil analysis involves using data and analytics to anticipate when a machine component will fail, and to take proactive measures to avoid that failure. This is achieved by monitoring the condition of the lubricating oil and identifying changes in its properties, such as increased levels of wear metals, contaminants, or degradation products, which can indicate that a component is wearing down and may soon fail. By analyzing the oil data as done in this study, maintenance teams can schedule maintenance activities before a failure occurs, reducing the risk of unplanned downtime and increasing the lifespan of equipment.

Method

This section outlines the fundamental principles to determine diagnostic parameters in order to assess the technical condition of engine components via analyzing of wear elements (K) in used engine oil. This will require determining the critical concentration value (K_0) for each wear element [15]. The decision to repair or continue using the diesel engine is based on the comparison of K with K_0. If K is greater than or equal to K_0, the use of diesel is stopped and repaired. If K is less than K_0, it can continue to be used.

The normal state of the engine is represented by D_1 and the faulty state is represented by D_2. If $K < K_0$, the engine is accepted as being in state D_1 and if $K \geq K_0$, it is accepted as being in state D_2. The concentration density functions for the normal state D_1 and the faulty state D_2 are shown in Figure 1.

An error in diagnosis occurs when the diagnosis does not match the actual state of the engine. If the engine is diagnosed as being in a faulty state (D_2) but the actual state of the engine is 'normal', the false alarm probability is a first-type error. On the other hand, if the engine is diagnosed as being in a "normal" state but is actually in a "faulty" state, the second-type error probability is identified [5].

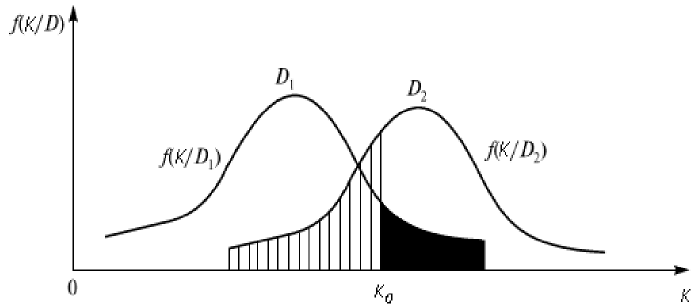

Figure 1. The distribution of diagnostic parameters in normal and faulty states

The cost of errors during technical diagnostics can be divided into two categories: C_1 and C_2 costs caused by false alarms and failure of fault detection, respectively. Although it can be difficult to accurately determine the cost of these errors, it is important to minimize both types of errors as much as possible.

The Neyman-Pearson method seeks to minimize the probability of undetected defects while maintaining a given acceptable level of false alarm probability [16].

$$P_1 \int_{K_0}^{\infty} f(K/D_1)dK \leq A \qquad (1)$$

where,

A : a given and acceptable level of the probability of false alarm,

P_1 : the probability in a state of without faults.

$$P_1 \int_{K_0}^{\infty} f(K/D_1)dK = A \qquad (2)$$

The equation (1) is based on the conditional probability of a high probability false alarm (without the P_1 multiplier). As seen in Figure 1, as the false alarm error increases (the K_o section moves to the left), the error rate for missing a defect decrease. The minimum value of

The minimum value of equation (2) corresponds to the condition where the condition given in equation (1) has an equal sign [5].

Results and Discussion

The 16ChH26/26 diesel engine produced by JSC "Kolomensky Zavod" was selected as the study subject, with 16 cylinders and a power output of 2650 kW (Figure 2)

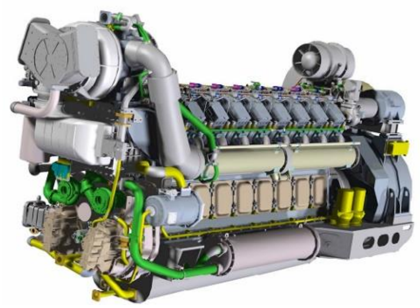

Figure 2. 16XH26/26 diesel engine

The operating manual recommends changing the M14G2 motor oil every 50-100 thousand km, and the M14D2 motor oil every 75-150 thousand km, depending on chemical and tribological characteristics of the oil. Results from an oil consumption survey study at the depot showed that 70% of the total oil was changed when it reached its maximum useful life for the diesel engine, 20% was changed due to mixing with fuel and coolant, and 10% was changed due to its physical and chemical degradation.

Analysis of wear and wear rate in diesel engine components during one maintenance cycle

When diagnosing the technical condition of a diesel engine through its lubricating oil without disassembly, it is important to carefully evaluate if the wear and wear intensity of components of the same type are consistent. Inconsistent wear intensity among components can lead to incorrect diagnostic decisions. Therefore, as part of a traditional scheduled preventive maintenance, the engine was disassembled and observations were made during routine maintenance (RM-2, RM-3). Descriptive statistics were conducted on wear and its intensity (

Table 2), and the test of normality for wear distribution was also conducted (Table 3).

Table 2.

The statistical parameters of wear in diesel engine components

Parts		N	Average	Standard deviation	Standard error	95% confidence interval of the mean		Minimum value	Maximum value	Variance of interference
						Less	More			
Piston Pins		128	0.025	0.013	0.0015	0.02	0.027	0.000	0.080	
Bronze bushing		128	0.131	0.043	0.0030	0.12	0.138	0.075	0.260	
Crank Main journals		80	0.023	0.008	0.0005	0.05	0.055	0.040	0.070	
Crank pin journals		64	0.019	0.009	0.0007	0.04	0.050	0.030	0.060	
Cylinder liner		128	0.032	0.023	0.0015	0.02	0.035	0.000	0.105	
Connecting rod bronze bushing		64	0.111	0.020	0.0014	0.10	0.114	0.070	0.145	
Pin connecting rod		34	0.032	0.014	0.0012	0.03	0.035	0.005	0.080	
Total		1190	0.071	0.056	0.0014	0.06	0.073	0.000	0.330	
Model	No random effect			0.022	0.0005	0.06	0.072			
	Random effect				0.0187	0.02	0.114			0.003

The study results on wear rate of diesel engine components showed that 95% of components experienced 0.05-0.2 mm of wear during each RM-2 maintenance, and 95% of all types of bearings experienced 0.2-0.24 mm of wear. The residual useful life of the components was found to be 0.7-0.85% based on the comparison of the wear rate to the replacement requirement specified in the routine maintenance guidelines.

Table 3.

The result of Kolmogorov-Smirnov and Shapiro-Wilk tests

Components	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df[b]	Sig.	Statistic	df	Sig.
Piston Pins	0.108	128	0.001	0.949	128	0.000
Piston bronze bushing	0.144	128	0.000	0.902	128	0.000
Crank Main journals	0.171	80	0.000	0.898	80	0.000
Crank pin journals	0.228	64	0.000	0.843	64	0.000
Cylinder liner	0.109	128	0.000	0.948	128	0.000
Connecting rod bronze bushing	0.156	64	0.000	0.936	64	0.000
Pin connecting rod	0.123	34	0.000	0.957	34	0.000

[a] Lilliefors Significance Correction, [b] Degree of freedom

The Kolmogorov-Smirnov and Shapiro-Wilk Tests were applied to test for normal distribution of wear values in the components. The results indicated a normal distribution with a probability of 0.95, indicating that the wear rate in the components is evenly distributed and ~~that~~ wear intensity of all components is equal.

The experiment was conducted on 20 engines' used oil through 319 tests during each technical maintenance (TM), routine maintenance (RM), oil changes, and as necessary. The oil analysis was performed in the Mongolia Techonomics LLC lab, a branch of the Australian Techenomics International Company, accredited by the

Diagnostic parameters

MNS/IES 17025 standard, using ASTM D6595 standard.

A model was created to estimate the amount of wear in components by using the concentration of wear elements in engine oil. This model was based on the equation of (2). The model assumes constant speed of wear elements entering the oil and filtration parameters.

The oil was changed 3-5 times or every 75,000 km, according to the physical and chemical specifications, during the 16ChH26/26 engine's routine maintenance (300,000 km). The total mileage for complete oil change was divided into periods I-IV and the concentration of wear elements (g/ton) and its descriptive statistical parameters were determined by spectral analysis in used oil (Figure 3; Table 4).

Table 4.

Statistical analysis of wear element concentration (g/ton) in used engine oil: Periods I-IV of total mileage

Periods	Statictics	Symbol				
		Fe	Pb	Al	Cu	Cr
I	*Count*	33	33	33	33	33
	Mean	20.1	1.1	3.8	2	1
	SD	11.38	1.24	1.79	1.29	0.82
II	*Count*	36	36	36	36	36
	Mean	30.5	1.8	4.9	3.7	1.7
	SD	17.7	2.23	2.48	2.29	0.99
III	*Count*	25	25	25	25	25
	Mean	34.4	2.1	5.4	4.3	1.9
	SD	15.94	1.08	2.48	3.17	1.44
IV	*Count*	16	16	16	16	16
	Mean	32.3	2.2	5.2	6.3	2.5
	SD	13.37	0.98	1.6	4.63	1.38

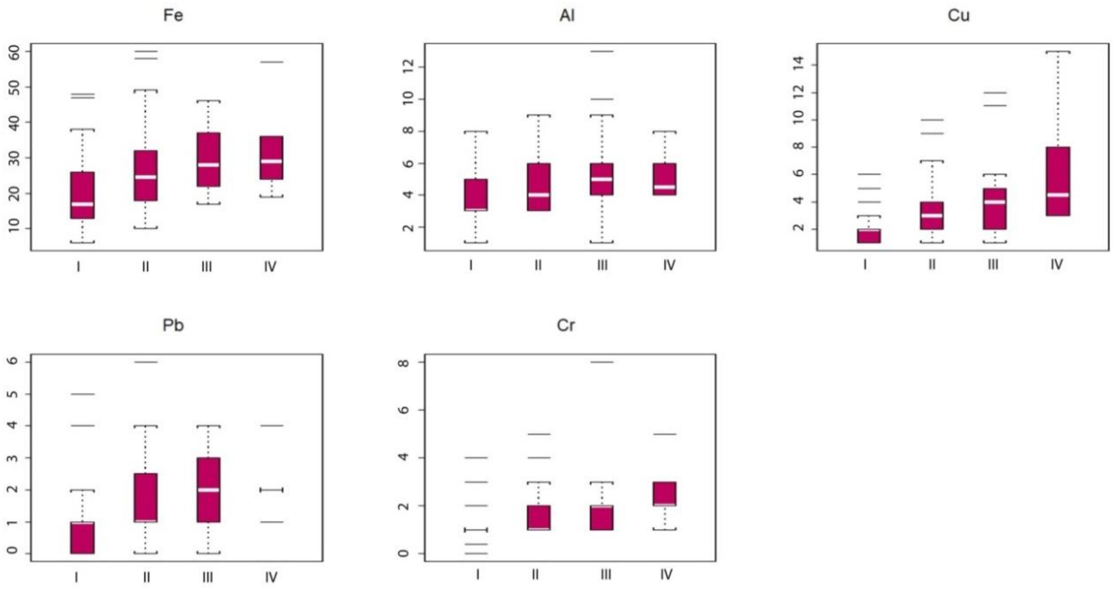

Figure 3. The changes in the concentration of wear elements in used oil in periods I-IV of mileage for complete oil change; g/ton

A histogram of the concentration of wear elements of iron, copper, aluminum, chromium, and lead in oil was produced (Figure 4 and Figure 5). The normal distribution function K/D_1 can be used as the engine was found to be normal or undamaged during its disassembly check through routine maintenance.

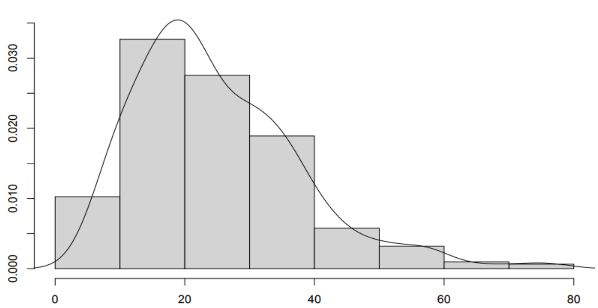

Figure 4. A Histogram of iron concentration in the used engine oil tested

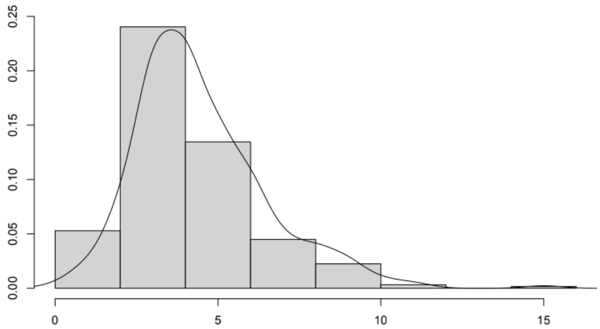

Figure 5. A Histogram of aluminum concentration in the used engine oil tested

Acceptable limit values of diagnostic parameters were determined based on statistical data on the concentration of wear elements in used oil, with confidence between 0.9-0.975 using a nonparametric statistical method.

Table 5.

Acceptable limit values of diagnostic parameters

Wear elements; g/ton	Probability in confidence interval			
	0.9	0.925	0.95	0.975
Iron	41	43	50	58
Copper	7	8	8	9
Aluminum	5	6	7	10
Chrome	3	3	3	4
Lead	3	3	3	4

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The relative frequency approach was used to estimate the probability that all diagnostic parameters simultaneously meet the requirements of the 0.95 confidence interval probability.

$$P = \frac{n_0}{n} = \frac{214}{312} = 0.68$$

where,

n_0 : number (value) obtained by all parameters,

n : random number (value).

The number of all parameters n_0 is defined as

$$n_0 = \sum_{i=1}^{n} I(k_{1i} < 50) \cdot I(k_{2i} < 7) \cdot I(k_{3i} < 8) \cdot I(k_{4i} < 3) \cdot I(k_{5i} < 3)$$

using the indicator function

$$I(K > K_0) = \begin{cases} 1, if\ K < K_0 \\ 0, if\ K \le K_0 \end{cases}$$

where,

k_{1i} : iron concentration in measurement number i,

k_{2i}- : copper concentration in measurement number i,

k_{3i}- : aluminum concentration in measurement number i,

k_{4i}- : chrome concentration in measurement number i,

k_{5i}- : lead concentration in measurement number i.

The parameters (values) of the concentration of wear elements are indicated as k_1, k_2, k_3, k_4, k_5. These elements were transformed by linear transformation as followings:

$$Y_1 = a_{11}k_1 + a_{12}k_2 + a_{13}k_3 + a_{14}k_4 + a_{15}k_5$$
$$Y_2 = a_{21}k_1 + a_{22}k_2 + a_{23}k_3 + a_{24}k_4 + a_{25}k_5$$
$$Y_3 = a_{31}k_1 + a_{32}k_2 + a_{33}k_3 + a_{34}k_4 + a_{35}k_5$$
$$Y_4 = a_{41}k_1 + a_{42}k_2 + a_{43}k_3 + a_{44}k_4 + a_{45}k_5$$
$$Y_5 = a_{51}k_1 + a_{52}k_2 + a_{53}k_3 + a_{54}k_4 + a_{55}k_5$$

The first two principal components of the sample, calculated using SPSS software, account for 80.66% of the total variance. The first component, Y_1, has a variance of 57.7% and is described by the equation $Y_1 = 0.881k_1 + 0.875k_2 + 0.751k_3 + 0.783x_4 + 0.410x_5$. The second component has a variance of 22.96% and is described by the equation $Y_2 = -0.210k_1 - 0.158k_2 + 0.424k_3 - 0.435k_4 + 0.843k_5$. These two components are considered representative of the entire sample.

Therefore, using the first and second components, an analytical range with a 5% probability of a type 1 error can be established as $Y_1 \leq 60.02$; $Y_2 \leq 1.004$.

The wear state of engine parts can be assessed as normal if their diagnostic range for the concentration value of metal elements in the operating oil is within the limits determined by the linear equations Y_1 and Y_2, as established through principal component analysis. This information can then be used to make informed maintenance decisions.

Results of the diagnostic parameters in maintenance systems

Attempts to adjust the maintenance schedule provided by the manufacturer of the diesel locomotive using the concentration of elements in used oil and newly established diagnostic parameters were successfully conducted. For example, according to the manufacturer's technical documents, routine maintenance-2, which involves partial disassembly of the diesel engine, is recommended at 300,000 km and routine maintenance-3, which requires complete disassembly and repair of the diesel engine, is recommended at 600,000 km. It was found that routine maintenance-2 can be postponed if the concentration of wear elements in used oil is not at the maximum level of the diagnostic parameters established in the study. This occurred for 30% of all locomotives and reduced maintenance costs by 20% per million kilometers.

Conclusion

By understanding the critical diagnostic parameters for diesel engines in locomotives in Mongolia, the railway transportation system can be optimized for performance and efficiency, reducing operating costs and increasing the lifespan of diesel engines. Improved diagnostic parameters can inform maintenance practices, enabling technicians to address potential issues early, before they become bigger problems. This also can lead to a reduction in the cost and frequency of maintenance, and increase the lifespan of diesel engines in locomotives.

Additionally, with aging locomotives and diesel engines, there is a growing need to address technical challenges such as outdated technology, limited automation and diagnostics, and the need for refurbishment or replacement. By understanding the critical diagnostic parameters, technical challenges can be addressed and prevented, enhancing the overall efficiency and sustainability of railway transportation in Mongolia. Overall, studying diagnostic parameters for diesel engines in locomotives in Mongolia is crucial for improving the performance, reliability, and sustainability of railway transportation in the country.

This paper presents the following findings of a study aimed at determining the diagnostic parameters for 16XH26/26 diesel engine used in 2TE116Um locomotive:

1. It was found that the wear intensity of diesel engine components has a normal distribution, which was determined through routine maintenance-2 or every 300,000 km.
2. Additionally, the study determined diagnostic parameters for diesel engines without disassembling components, which were analyzed using the principal component method. The results of the study provide important insights for the efficient maintenance and repair of diesel engines used in locomotives, particularly in Mongolia where the engines are operated at reduced power.

In future research, it is important to analyze cost-effectiveness of condition-based maintenance systems, particularly predictive maintenance technology, for diesel engines of locomotives. This could include exploring alternative, less expensive retrofit options using sensors and monitoring equipment, as well as examining the potential for integrating these systems with existing infrastructure. Moreover, a study on the practicality and benefits of predictive maintenance for lubricant oil analysis in diesel engines would provide valuable insight and contribute to the advancement of diesel engine maintenance practices.

Conflict of Interests
The authors declare no conflict of interests.

Authors' Contribution
S.G. Performed quantitative and qualitative analysis of wear products in the working oil of the diesel engine, collected quantitative data on the amount of wear of diesel engine parts, conducted preliminary data processing; P.J-O. Performed statistical analysis of the quantitative data, determined diagnostic parameters based on the analysis; N.O. Edited and revised the manuscript

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