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Online Monitoring and Prediction Methodology of Lubricating Oil State in Gearbox of a Nuclear Power Plant Based on Measurement with Sensors

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Improving the reliability of the transmission gear module in the gearbox of a nuclear power plant is of considerable and far-reaching significance to ensure energy security. As a key transmission part of this specific type of power plant, this gear module often runs with heavy load in complex environments and without shutting down for a long time. In such severe working conditions, the failure of this transmission gear module is primarily caused by the deterioration of lubricating oils and the aggravated wear of gears. Once the gear module is damaged owing to the poor lubrication or serious wear of the gear, it will not only cause huge power loss, but also nuclear power accidents, seriously threatening the life of the staff. It is essential that the transmission gear module used in a nuclear power plant is not arbitrarily shut down, which makes testing and monitoring difficult. Moreover, it is very important to monitor the lubricating state of oils in the gearbox in real time by measurements with various suitable high-tech sensors. However, there were few studies concerning this issue. To solve this problem, we first designed and built an experimental test platform to simulate the real working conditions of the transmission gear module in the gearbox of a nuclear power plant. Second, an innovative online oil monitoring method was proposed on the basis of the concept of marginal values of the normal distribution theory in statistics. Finally, a real-time prediction model based on the gray system theory was established to predict the variation of the dielectric constant of lubricating oils.

1. Introduction

The transmission gear module (TGM) in the gearbox of a nuclear power plant usually works permanently with heavy load in dirty environments and cannot be arbitrarily shut down because of the specific mission of nuclear power generation. The failure of this specific TGM is mainly caused by the deterioration of lubricating oils inside the gearbox. However, thus far, few research studies on the fault diagnosis or even the health monitoring of lubricating oils inside the gearbox

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of a nuclear power plant have been conducted. To ensure the safe and long-term operation of a TGM, a comprehensive method is required to monitor the working conditions of the lubricating oils surrounding this TGM.

The commonly used monitoring methods for lubricating oils in a gearbox system include vibration monitoring, temperature monitoring, oil analysis (OA), ultrasonic detection, and acoustic emission monitoring.[1–3] Among them, the OA method that involves checking the oil level in the gearbox following comprehensive guidelines was successfully used to analyze the components of pollutants and the physical properties of lubricating oils. Thus, the performance degradation and running state of the lubricating oil in the gearbox can be detected by this method. However, the OA method adopted an offline way for data collection and sample analyses to determine the oil state.[3] This offline detection method had the disadvantages of message delay and weak timeliness, and was unable to detect real-time losses. Owing to the restriction that a nuclear power plant cannot be arbitrarily shut down once it starts running, the offline detection method is unsuitable for application to the problem of lubricating oil detection. In contrast, the online oil monitoring (OOM) method may avoid the aforementioned restriction. The OOM method adopts various sensors to instantly detect the changes in physical properties, the particle wear conditions, and the unexpected conditions of lubricating oils in the online way. Therefore, the timely diagnosis and active preventive maintenance of equipment can be conducted via the OOM method. The OOM method has received considerable attention in recent years in signal detection studies. This method was first reported in the early 1940s when an American company used an atomic emission spectrometer to successfully detect the cause of wear failure in a diesel engine.[4] After the 1970s, the United States Department of Defense began to apply the ferrography technology to study the wear state of gears.[5] Salameh *et al.*[6] developed a compact X-ray fluorescence spectrometer for the online real-time analysis of wear metals in lubricating oils. GasTOPS, a Canadian company, developed an inductive online metal abrasive detection sensor, called "MetalSCAN", which was later widely used in the online detection of lubricating oils in large equipment such as wind turbines and Apache helicopters.[7] The rapid development of various high-tech sensors has considerably broadened the application scope of the OOM method into the field of equipment condition monitoring. Dempsey[8] combined the oil abrasive grain concentration analysis with the vibration analysis scheme to monitor the lubricating condition in a gear system. Loutas *et al.*[9] studied the combination of the OOM method with vibration schemes to monitor the running state of a machine equipment. Liu *et al.*[10] established the motion equation of wear particles statistically and, accordingly, designed an online optical monitoring sensor. Sheng[11] used the OOM method to study the detection problem of the gear system in a high-power fan. Liu *et al.*[12] used the neural network scheme to deal with the chromatographic data obtained online to improve the accuracy and availability of the gear module in an electromechanical system.

In short, even if the OOM method has the disadvantage of wasting manpower and material resources, it was still the mainstream method used for oil-state detection in the gearbox of turbine machines.[13–23] On the basis of the aforementioned features of the OOM method, in our study, we intend to propose a novel online monitoring and analysis (OLMA) method that includes four phases: (1) developing an experimental gearbox system, (2) developing a sensor-based measurement system, (3) developing proper oil-state monitoring and predicting theorems, and (4) performing the experimental data analysis and management for monitoring. Through the manipulation of the proposed method, we detect the failure conditions of lubricating oils in the gearbox as early as possible and avoid huge economic losses and casualties caused by the failure of transmission gears. Details of the OLMA method are demonstrated in the following section.

2. OLMA Method

2.1 Procedure

The manipulation procedure of our proposed novel OLMA method includes six steps as follows.

Step 1: Designing and establishing an experimental test platform that includes a gearbox system and a bypass-sensor-based monitoring and measurement system.

Step 2: Establishing an OOM model based on the marginal-value theorem of statistics.

Step 3: Establishing an online oil prediction model based on the gray system theory (GST).

Step 4: Exploring the software including the human–machine interface for monitoring and predicting the state of lubricating oils in the gearbox system.

Step 5: Executing online experiments and measurements via the experimental test platform based on various physical sensors.

Step 6: Analyzing the acquired experimental data and displaying the assessment results in real time through software calculations.

Moreover, to execute the monitoring experiment of lubricating oils using the proposed OLMA method, we adopt the ISOAJD (the uppercase letter of the first word in six steps) procedure, as explained in the following and illustrated in Fig. 1.

Step 1: Inputting the lubricating oil into the experimental test platform.

Step 2: Starting and running the experimental test platform for a preset long period of time without stopping.

Step 3: Online sampling and measuring the physical properties of oil using various physical sensors. The following two types of online measurements are performed: lubrication measurement for analyzing oil performance and wear measurement for analyzing abrasive grains.

Step 4: Analyzing the obtained data with the proposed monitoring and prediction models in real time.

Step 5: Judging the oil state and displaying judgement results. According to the analysis results in Step 4, the oil state can be divided into three situations: “Normal”, “Abnormal”, and “Shut down alert”. “Abnormal” situations can be further divided into “Attention signal” and “Warning signal”. All judgement results are displayed on screen.

Step 6: Decision options. We have two final decision options: “Repair” and “Maintenance”; these depend on whether the analysis results of the lubricating oil conditions are deemed acceptable or not.

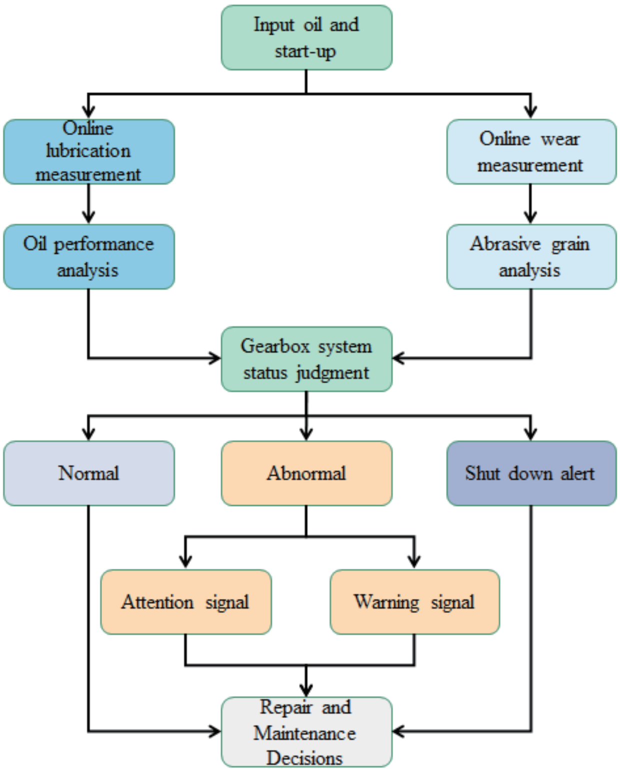


Fig. 1. (Color online) Manipulation procedure of ISORJD.

2.2 Parameters affecting lubricating oil state

From the above discussions, we know that there are strict requirements on the performance level of the lubricating oil during usage in the gearbox of a nuclear power plant. Generally, the main factors that affect the lubrication performance of oils in the gearbox are the physical quality of lubricating oils, the number of wear particles in oils, the wear condition of gear surfaces, the pollution degree of oils, and the effective oil amount during lubrication. Among them, we select the physical quality of lubricating oils and the pollution degree of oils as the investigation parameters that are commonly used as the physical indicators in oil state examinations. Moreover, it is found from our test results that the other factors do not change apparently during our experiments. Therefore, we only analyze three physical factors of lubricating oils in our test experiments: the dynamic viscosity, the dielectric constant of small particles, and the oil contamination degree.

2.3 Design of experimental test platform

On the basis of the actual operation situation of the transmission gears in the gearbox system of a nuclear power plant, we accordingly design an experimental test platform for simulations and measurements, as shown in Fig. 2. The designed experimental test platform contains four major parts: the scale model of a gearbox system (scale 1:5, No. 1), the bypass pipe system (No. 2), the monitoring and measurement module (No. 3), and the electrical cabinet. One end of the bypass pipe system is connected to the oil outlet of the gearbox system and the other end is connected to the monitoring and measurement module. In the monitoring and measurement module, we install various high-tech sensors, the data acquisition and calculation module, and the display equipment.

When the test platform starts running, some of the lubricating oils in the gearbox system (oil samples) flow through the bypass pipe system and then into the monitoring and measurement module. Next, the physical properties of these oil samples can be detected via the preset high-tech sensors. Moreover, these properties can be analyzed with a specific software program developed in this study. Finally, the monitoring results including warning and related messages are presented in a terminal screen. After that, these oil samples flow out the online measurement module and back to the gearbox system through a return pipe. The designed test platform has the function of pressure self-adjustment to ensure the system's safety and reliability during tests.

2.4 Analysis method

Many methods of analyzing lubricating oils in a gearbox were proposed.(1–3) Among them, the physical analysis method was simple for determining the oil quality level, the spectral analysis method was frequently used to accurately obtain the concentrations of various elements in oil samples, and the ferrographic analysis method was appropriate for the detection of large abrasive particles. However, these analysis methods were all characterized by the defects of low

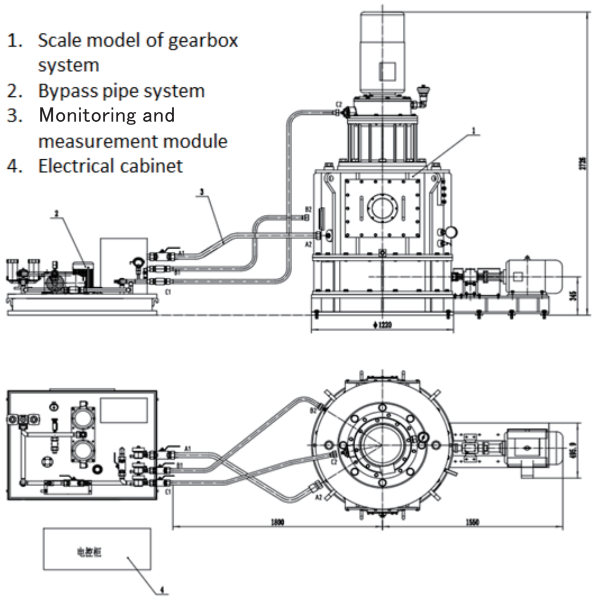


Fig. 2. Configuration of designed sensor-based gearbox test platform.

detection speeds, tedious operation procedures, and high dependence on usage experiences. If we can develop an integral method that combines their merits, then both the detection accuracy as well as the usage convenience can be markedly improved. To overcome these defects, we now develop the bound-limit and gray system theories for dealing with the aforementioned three factors, namely, the dynamic viscosity, the contamination degree, and the dielectric constant of small particles in lubricant. The following is a brief introduction of the theories used in the monitoring and prediction of lubricating oils.

It is essential that, in the data collection stage, the dynamic viscosity of lubricating oils must be determined for an entire oil-change period because the measured physical oil properties usually fluctuate. In contrast, the dielectric constant should be determined randomly by eliminating the abnormal outlier technique.

2.4.1 Monitoring: Bound-limit theory for monitoring the dynamic viscosity and contamination degree of lubricating oils

Using statistical methods to study the variations of oil properties to judge the state of lubricating oils in a gearbox was popular.[1] From the statistical viewpoint, the long-time collected data of oil properties should statistically conform to the normal distribution with a probability density function as

$$f(X|\mu,\sigma)=\frac{1}{\sigma\sqrt{2\pi}}e^{\frac{(X-\mu)^2}{2\sigma^2}}, \tag{1}$$

$$\mu=\lim_{n\to\infty}\frac{1}{n}\sum X, \tag{2}$$

$$\sigma=((\sum(X-\mu)^2)/n)^{1/2}, \tag{3}$$

where n is the sample number, X is the property of oil samples, μ means the overall average of X, and σ is the overall standard deviation of X. In this study, we propose a bound-limit theory as the monitoring scheme of lubricating oils based on the concept of the normal distribution of statistics. Details of the bound-limit theory are introduced as follows.

Since the measured sample data is finite, n will not become infinity. We assume that the sample data collected at different times (t_1, t_2, ..., t_n) are expressed as $Y(y_1, y_2, ..., y_n)$, μ is replaced by A, and σ is replaced by S, then Eqs. (2) and (3) can be expressed as

$$A=\frac{1}{n}\sum_{i=1}^{n}y_i, \tag{4}$$

$$S=\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(A-y_i)^2}. \tag{5}$$

Our bound-limit theory is based on the above two equations where the standard deviation S can be dynamically adjusted according to actual situations. To ensure calculation accuracy, the sampling space should be as large as possible. By examining the data distribution conditions of oil samples, together with the trial-and-error method, we may reasonably set the normal and warning bound limits as $A \pm 2S$ and $A \pm 3S$, respectively, as shown in Table 1.

During monitoring, when the collected real-time data of parameters of the lubricating oil were between $A - 2S$ and $A + 2S$, the lubricating oil is considered to be in a normal state with good running conditions. When the data of parameters of the lubricating oil were between $A + 2S$ and $A + 3S$, the lubricating oil should be closely monitored and their sampling period should be shortened. Moreover, when the data of parameters of the lubricating oil were beyond $A + 3S$, the lubricating oil is viewed as in an abnormal state, and we should stop the operation of the gearbox system and check the lubricating oil immediately.

2.4.2 M(1,1) model for oil state prediction

According to the GST proposed by Deng [24] in 1982, the GM(1,1) model of GST is as follows. Firstly, we assume a non-negative sequence:

$$X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)\}, \tag{8}$$

where $x^{(0)}(k) \geq 0$, $k = 1, 2, ..., n$. Then, we define a new sequence $X^{(1)}$, called the first accumulating generation operator sequence of $X^{(0)}$, where

$$X^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)\}, \tag{7}$$

and

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i),\ k = 1, 2, ..., n. \tag{8}$$

Moreover, we define a mean sequence $Z^{(1)}$, called the mean generation of consecutive neighbors sequence of $X^{(1)}$, where

$$\begin{aligned} Z^{(1)} &= \left\{z^{(1)}(2), z^{(1)}(3), ..., z^{(1)}(n)\right\}, \\ Z^{(1)}(k) &= \frac{1}{2}\left[x^{(1)}(k) + x^{(1)}(k-1)\right], k = 2, 3, \cdots, n. \end{aligned} \tag{9}$$

Table 1
Bound-limit values for normal and warning states.

	Normal limit	Warning limit
Two-side limit	$A \pm 2S$	$A \pm 3S$
Upper bound	$A + 2S$	$A + 3S$
Lower bound	$A - 2S$	$A - 3S$

Assuming that sequence $Z^{(1)}(k)$ follows the equations

$$X^{(0)} + bZ^{(1)}(k) = u \tag{10}$$

and

$$B = \begin{bmatrix} -Z^{(1)}(2) & 1 \\ -Z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -Z^{(1)}(n) & 1 \end{bmatrix}, \tag{11}$$

$$y_N = [x^{(0)}(2), x^{(0)}(3), x^{(0)}(4), \cdots, x^{(0)}(n)]^T, \tag{12}$$

$$\hat{b} = (b, u)^T = (B^T B)^{-1} B^T y_N. \tag{13}$$

Then, Eq. (10) can be expressed simply as

$$y_N = B\hat{b}. \tag{14}$$

Equation (10) is a first-order differential equation in which it is usually called a gray differential equation and denoted as GM(1,1). The white differential equation of Eq. (10) can be written as

$$\frac{dX^{(1)}}{dt} + bX^{(0)} = u. \tag{15}$$

By solving Eq. (15), we obtain

$$\hat{X}^{(1)}(k+1) = \left[X^{(0)}(1) - \frac{u}{b} \right] e^{-bk} + \frac{u}{b}. \tag{16}$$

Eventually, $\hat{X}^{(0)}(k+1)$ is obtained through the operation of an accumulation subtraction from $\hat{X}^{(1)}(k+1)$ as

$$\hat{X}^{(0)}(k+1) = X^{(1)}(k+1) - X^{(1)}(k). \tag{17}$$

2.4.3 Data calculation and display-software development

To record, display, preserve, and analyze the measured data in a convenient manner, we developed an online-monitoring software set that contains the functions of data calculation for oil properties and the human–machine interface. Figure 3 shows a real-time measurement and analysis result at a certain moment by using our developed specific software program. This

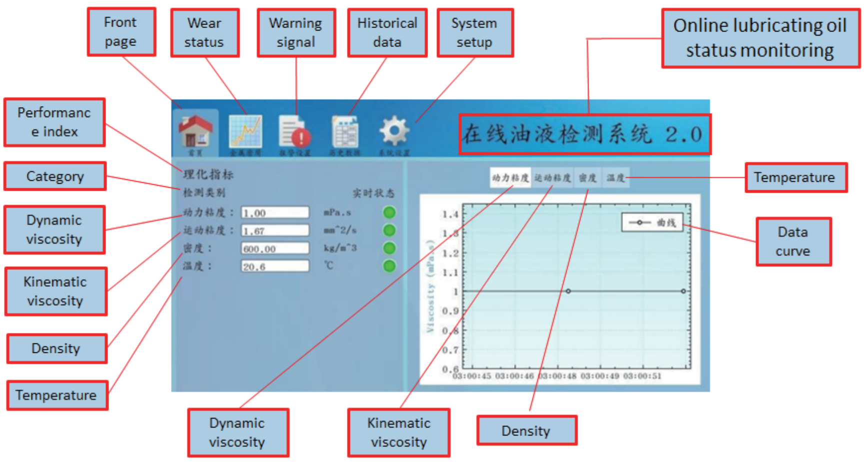


Fig. 3. (Color online) Illustration of explored software program.

software program has the function of monitoring the changes in oil properties, pollution degree, wear content, and some other properties of lubricating oils in real time. Moreover, it may also be used to exhibit the measured data in the form of curves or tables so as to provide users real-time messages about the state of the lubricating oil in the gearbox. At the same time, we may arbitrarily set the upper and lower bounds of the concerned properties of lubricating oils in this software program.

3. Results and Discussion

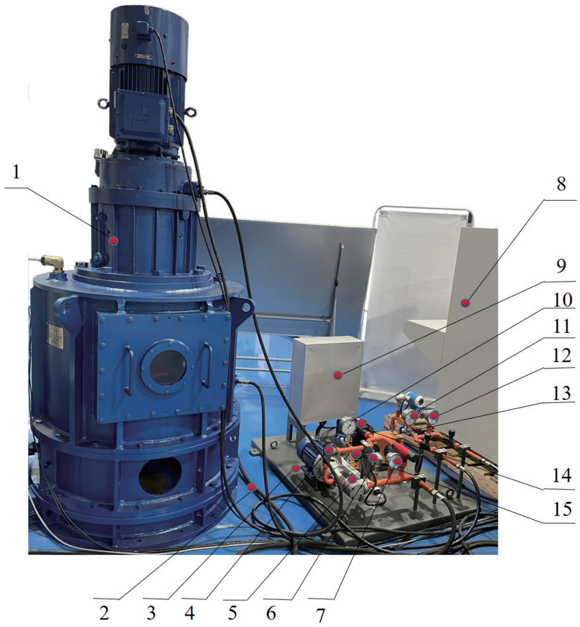
3.1 Experimental system

3.1.1 Experimental test platform and sensor arrangement

As described in Sect. 2.3, according to the shape, material, and even dimensions of an actual gearbox system, we designed an experimental test platform that contains a gearbox model with the size reduced by 80%, connection pipes, and a bypass monitoring and measurement system with numerous and various sensors to simulate the actual work conditions and meanwhile perform the nonstop measurement and analysis of lubricating oils in real time during one oil-change period.

The accomplished experimental test platform is shown in Fig. 4, the major components of which include a power transmission device (1), a connection pipe (2), an oil pump (3), a check valve (4), a screw-type pump (5), a PT-100 thermometer (6), a bimetallic thermometer (7, 12), an electric control cabinet (8), a display screen (9), two pressure gauges with sensors (10, 11), a fan-type cooler (13), a pressure regulator with sensor (14), and an oil filter (15).

The temperature of the lubricating oil at the pump inlet can be directly measured using the bimetallic thermometer. Units (8) and (9) are used to control the working conditions of the air



1. power transmission device
2. connection pipe
3. oil pump
4. check valve
5. screw-type pump
6. PT-100 thermometer
7. bimetallic thermometer
8. electric control cabinet
9. display screen
10. pressure gauge with sensor
11. pressure gauge with sensor
12. bimetallic thermometer
13. fan-type cooler
14. pressure regulator with sensor
15. oil filter

Fig. 4. (Color online) Configuration of experimental test platform.

cooler. A system pressure regulating circuit is installed near the pump outlet. The check valve (4) and pressure regulator (14) are used to ensure that the pressure of the lubricating oil is always safe and normal under any operation circumstances.

The lubricating oils are first pumped through an oil filter (15), a differential pressure controller (14), and an air cooler (13). Then, they flow into two branches of the main pipeline. Every branch is equipped with a throttle valve, a pressure gauge sensor, a pressure transmitter (10, 11), a bimetallic thermometer (7, 12), and a Pt100 thermal resistor (6). The pressure transmitters are connected to a pressure control unit (8, 9) for pressure monitoring. In a similar manner, the Pt100 thermal resistor is connected to the temperature control unit (8, 9) for temperature monitoring.

3.1.2 Consistency tests of experimental platform

To test the reliability as well as the consistency of our designed experimental test platform, we now carry out three test cases through this test platform as follows: Case 1: test run at a normal pumping speed, Case 2: test run at a super pumping speed (120% of normal pumping speed), and Case III: test run at the rated pumping speed without load, lasting for 48 h. The test conditions and associated test results for these three cases are discussed as follows.

Case I: test run at a normal pumping speed

In this case, the experimental test platform works at a preset normal pumping speed of 176 rpm. The measurement results obtained with various sensors together with the required conditions are listed in Table 2. It is seen that all our measured physical parameters including speed, temperature, pressure, and flow rate match well with the required conditions. The test duration is 10 min.

Case II: test run at a super pumping speed (120% of normal pumping speed)

In this case, the experimental test platform works at a super pumping speed of 211 rpm (120% of normal pumping speed). The measurement results obtained with various sensors together with the required conditions are listed in Table 3. Similar to the results in Case I, all our measured physical parameters including speed, temperature, pressure, and flow rate match well with the required conditions. The test duration is 10 min.

Case III: test of running at the 48 h rating speed without load

In this case, the experimental test platform works at the rated pumping speed of 745 rpm without load, lasting for 48 h. The obtained results of the measured parameters and their corresponding required qualities are shown in Table 4. It is evident that all the physical parameters of lubricating oils obtained by sensor measurement, including speed, temperature,

Table 2
Test conditions and results of Case I (preset normal pumping speed).

Test parameter	Required condition	Measurement result
Pumping speed (rpm)	176	176
Inlet oil temperature (°C)	49	48
Tank temperature (°C)	49–56	51
Temperature of upper guiding bearing (°C)	<70	60.4
Temperature of lower guiding bearing (°C)	<70	30.3
Temperature of trust bearing (°C)	<95	59.9
Working pressure (Mpa)	>0.2	0.2
Lift pressure (Mpa)	1–25	20
Leakage	No	No
Flow rate (L/min)	>330	348.5
Pressure difference in filter (Mpa)	<0.1	0.02

Table 3
Test conditions and results of Case II.

Test parameter	Required condition	Measurement result
Pumping speed (rpm)	211	211
Inlet oil temperature (°C)	49	47
Tank temperature (°C)	49–56	48
Temperature of upper guiding bearing (°C)	<70	51.5
Temperature of lower guiding bearing (°C)	<70	30.6
Temperature of trust bearing (°C)	<95	52.4
Working pressure (Mpa)	>0.2	0.216
Lift pressure (Mpa)	1–25	16.8
Leakage	No	No
Flow rate (L/min)	>330	378
Pressure difference in filter (Mpa)	<0.1	0.01

Table 4
Test conditions and results of Case III.

Test parameter	Required condition	Measurement result
Pumping speed (rpm)	745	745
Inlet oil temperature (°C)	49	49
Tank temperature (°C)	49–56	52
Temperature of upper guiding bearing (°C)	<70	53.3
Temperature of lower guiding bearing (°C)	<70	31.7
Temperature of trust bearing (°C)	<95	59.6
Working pressure (Mpa)	>0.2	0.209
Lift pressure (Mpa)	1–25	20
Leakage	No	No
Flow rate (L/min)	>330	355
Pressure difference in filter (Mpa)	<0.1	0.02

pressure, and flow rate, are well within the required specifications. The test duration is 30 min.

In short, the comparison of the required and measured conditions of the related oil parameters for the above three cases reveals that our designed experimental test platform is working well with a high degree of consistency with the actual gearbox system in a nuclear power plant and all the measured data are reliable.

3.2 Monitoring and prediction

3.2.1 Analysis of kinematic viscosity

During the one oil-change period, we measure the variation of the kinematic viscosity of the lubricating oil via a multifunction viscosity sensor in the experimental test platform. Moreover, we randomly choose 200 sets of kinematic viscosity v values detected at different times so as to carry out further statistical analyses. The obtained results are shown in Fig. 5.

On the basis of the sampled 200 sets of data and the calculations via Eqs. (4) and (5), we obtain the overall mean and standard deviation of the kinematic viscosity as 138.29 and 42.53 m^2/S, respectively. Then, a normality analysis is carried out for these data. Since the kinematic viscosity of lubricating oils is decreasing with increasing running time during one oil-change period, it is reasonable to hypothesize that the kinematic viscosity distribution has negative skewness. Moreover, from statistics, the skewness of the sampled data is calculated as $\beta_s = 0.2328$. When the number of samples considered is small, the significance level α is 0.05, then the quantile p should be less than 0.28. Previous calculation results of skewness $\beta_s = 0.2328$ reveal that it satisfies the condition of $p \leq 0.28$. Therefore, the previously assumed null hypothesis is not rejected and the bound limit of the kinematic viscosity can be set by using the normal distribution method. Accordingly, when we monitor the state of lubricating oils, the upper and lower bound limits of the kinematic viscosity are set as $138.29^{+85.07}_{-85.07}$ m^2/s for attention and $138.29^{+127.6}_{-127.6}$ m^2/s for warning, as shown in Fig. 6.

Figure 6 shows that, as determined by sensor measurements, the obtained kinematic viscosity of lubricating oils does not exceed warning limits (upper and lower warning bound values, shown in red lines). In other words, the sensor-measured data of μ are all within the normal range.

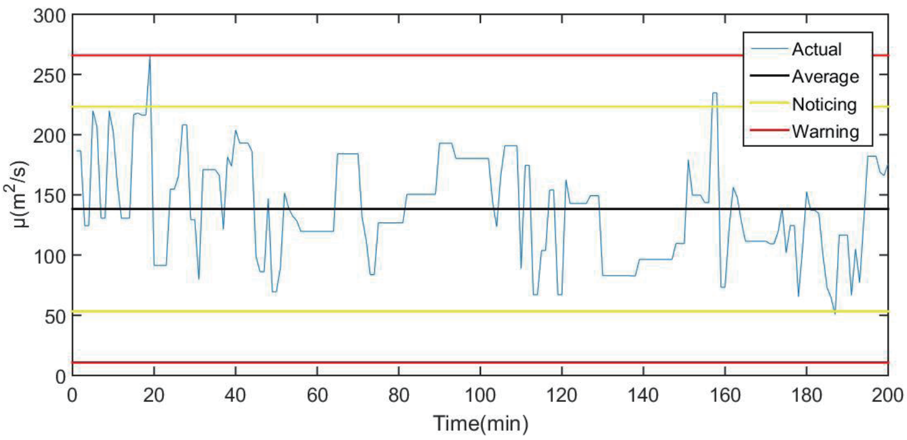


Fig. 5. (Color online) Measured kinematic viscosity of lubricating oils.

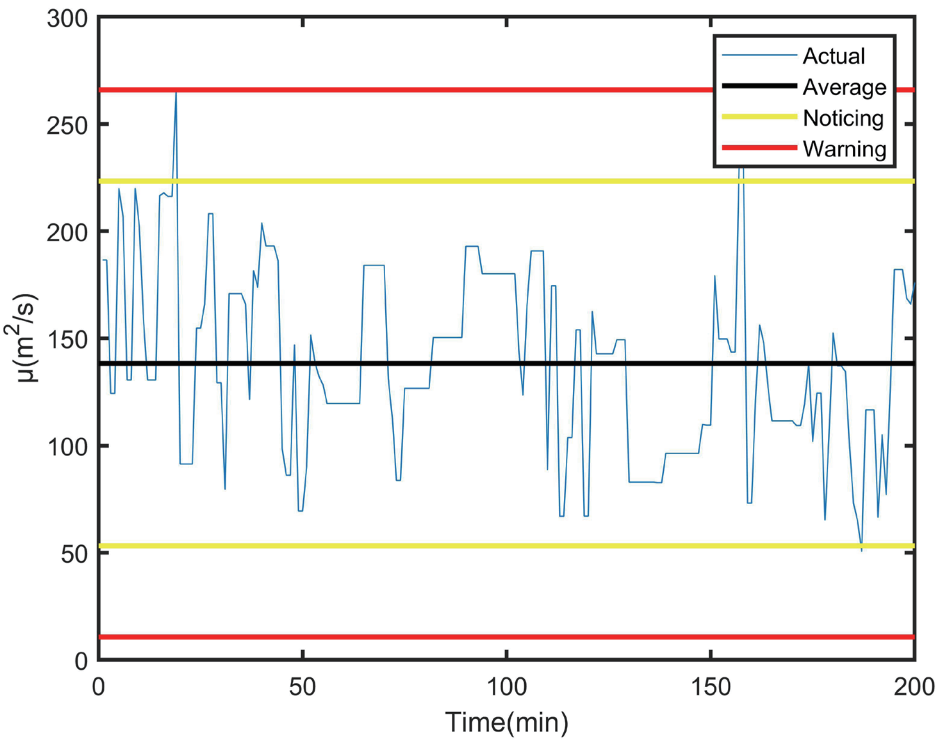


Fig. 6. (Color online) Upper and lower bound limits of the kinematic viscosity of lubricating oils for attention and warning during operation.

3.2.2 Analysis of oil contamination level

For clearly examining the oil quality, we adopt a significant physical parameter of the oil contamination index to express the oil contamination level in a gearbox, which is defined as the concentration of detected abrasive particles with diameters greater than 14 μm[22] in lubricating oils and denoted as D_L (number per milliliter). From measurements via the metal abrasive sensor for ten lubricating oil samples, we obtain the oil contamination index distribution, as shown in Table 5.

Through calculations, we further obtain the overall mean and standard deviation of D_L for the collected lubricating oil samples, which are 1.92 and 0.3225, respectively. Eventually, according to the normal distribution rule of statistics, the upper and lower bounds of attention and warning values of D_L for the lubricating oil samples are set as 1.92 ± 0.65 and 1.92 ± 0.97, respectively, as shown in Fig. 7.

3.2.3 Prediction of dielectric constant using GST

For an oil lubrication system, the dielectric constant (τ) is a comprehensive parameter that can be used to describe the performance degradation, pollution state, and wear state of lubricating oils. Once the lubricating oil is polluted or aged, the number of abrasive particles in oils will markedly increase, and therefore, the dielectric constant of lubricating oils will also change accordingly.[23,24] We now measure, via a multifunction sensor, the variation of the dielectric constant of the lubricating oil in one oil-change period. The collected data of the dielectric constant for ten oil samples are shown in Table 6. It is seen that τ varies in the range from 1.9 to about 3. Note that the dielectric constant of vacuum is 1 and that of air is 1.00059.

Table 5
Detected contamination index of collected oil samples.

Sample group	1	2	3	4	5	6	7	8	9	10
D_L (μm)	1.4	1.8	1.6	1.9	2.4	2.2	1.7	2.1	1.8	2.3

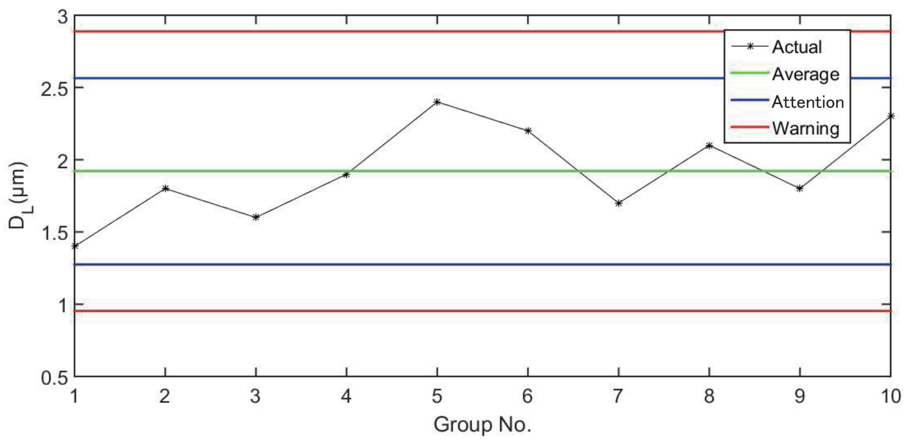


Fig. 7. (Color online) Upper and lower bound limits of attention and warning of lubricating oil samples.

Table 6
Measured dielectric constants of lubricating oil in one oil-change period.

No.	1	2	3	4	5	6	7	8	9	10
τ	1.900	1.965	2.251	2.284	2.470	2.637	2.783	2.812	2.876	2.925

Table 7
Predicted dielectric constants of lubricating oils.

No.	6	7	8	9	10	Average
Measured τ	2.637	2.783	2.812	2.876	2.925	
Predicted τ	2.6518	2.8394	3.0403	3.2554	3.4858	
Residue	0.0148	0.0564	0.2283	0.3794	0.5608	0.086
Relative accuracy	99.44%	97.97%	99.97%	86.82%	80.83%	98.7%

Using Eqs. (6)–(17) introduced in Sect. 2.4.2, we now establish a prediction model for the dielectric constant of the lubricating oil using the GM(1,1) model and the first five data listed in Table 6 as the formulation base:

$$\hat{X}^{(1)}(k+1) = 28.5082e^{0.0684k} - 26.6082. \tag{18}$$

On the basis of Eq. (18), the sixth to tenth dielectric constants of the lubricating oil are calculated. The obtained predicted data together with the respectively measured data are shown in Table 7.

It is seen that, for the sixth and seventh predicted τ values, the average residual and relative accuracies are 0.013 and 98.7%, respectively. Clearly, the prediction results are satisfactory. However, the relative residuals of eighth to tenth data are slightly large because the GST is unsuitable for long-term predictions owing to the increasing interference of data uncertainty. As for the overall (the sixth to tenth terms) predictions, it is seen from the data in the last two rows that the overall average residual and relative accuracies are 0.086 and 91.39%, respectively. As a consequence, we may dynamically add the real-time measured data of τ into the GM(1,1) model using only three terms for better prediction.

4. Conclusion

To appropriately diagnose the lubricating oil state in the gearbox used in a nuclear power plant, we first developed a novel OLMA method based on sensor measurements. Our proposed OLMA method mainly involves the analysis of possible failure modes of transmission gears, designing an experimental test platform, setting a bypass sensor measurement system, measuring and analyzing the parameters affecting the state of lubricating oils, and building the bound theory of attention and warning based on the normal distribution principle of statistics for monitoring the dynamic viscosity and oil contamination index. Moreover, we built a dynamic three-term GM (1,1) gray prediction model for monitoring the dielectric constant of lubricating oils. Furthermore, on the basis of this method, we accomplished a decision-making strategy to monitor the state of lubricating oils in the gearbox of a nuclear power plant. The developed manipulation procedure of this strategy is called ISOAJD. The proposed innovative real-time OLMA method together with the ISOAJD strategy solves the severe problem that the oil state cannot be monitored in real time in the gearbox of a nuclear power plant where the lubricating oil usually works in heavy-load and complex environments and cannot be shut down arbitrarily for a long time.

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