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RESEARCH ARTICLE

Attribute-driven Fuzzy Fault Tree Model for Adaptive Lubricant Failure Diagnosis

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Abstract: Lubricant diagnosis serves as a crucial accordance for condition-based maintenance (CBM) involving oil changing and wear examination of critical parts in equipment. However, the accuracy of traditional end-to-end diagnosis models is often limited by the inconsistency and random fluctuations in multiple monitoring indicators. To address this, an attribute-driven adaptive diagnosis method is developed, involving three attributes: physico-chemical, contamination, and wear. Correspondingly, a fuzzy fault tree (termed FFT)-based model is constructed containing the logic correlations from monitoring indicators to attributes and to lubricant failures. In particular, inference rules are integrated to mitigate conflicts arising from the reverse degradation of multiple indicators. With this model, the lubricant conditions can be accurately assessed through rule-based reasoning. Furthermore, to enhance its intelligence, the model is dynamically optimized with lubricant analysis knowledge and monitoring data. For verification, the developed model is tested with lubricant samples from both the fatigue experiment and actual aero-engines. Fatigue experiments reveal that the proposed model can improve the lubricant diagnosis accuracy from 73.4% to 92.6% compared with the existing methods. While for the engine lubricant test, a high accuracy of 90% was achieved.

Keywords: lubricant failure diagnosis; fuzzy fault tree; attribute guidance; rule reasoning

I. INTRODUCTION

As an essential component of mechanical equipment, lubricants are not only the source of lubrication failures but also function as a critical carrier for recording the wear degradation of friction components [1-3]. Consequently, the diagnosis of lubricant failures has become increasingly important. In particular, this promising technique has been significantly advanced by the development of sensing technologies, which provide multiple indicators to enrich the characterization integrity for lubricant conditions [4,5]. However, the diagnostic accuracy of lubricant failures remains hampered by the reverse degradation and random fluctuations of multiple lubricant indicators. Due to the greater demand for precise equipment maintenance, further development of diagnosis methods is urgent for the accurate assessment of lubricant failures.

The core of lubricant failure diagnosis lies in establishing a precise correlation between monitoring indicators and the underlying condition. Given the limitations inherent in single indicators, multi-indicators-based diagnosis methodologies have garnered significant attention for their comprehensive assessment capabilities. Early research had been focused on knowledge-driven methods, such as expert systems [6], fault trees [7], and D-S evidence theory [8]. These methods adopt symbolic representations and rule formulations to capture expert knowledge derived from historical failure events and utilize rule-based reasoning to evaluate lubricant conditions. For example, an expert system model [9] is constructed by adopting fuzzy language variables and rule combinations to diagnose lubricant failures, in which the expert knowledge is utilized to simulate human reasoning processes. Additionally, a wear state diagnosis model [10] is established based on evidence theory by using wear debris as evidence and achieves synchronous diagnosis of wear degree and wear location within the equipment. As can be observed, knowledge-based diagnosis methods provide strong interpretability by linking indicator changes to lubricant failures through rule-based reasoning, but their limited knowledge renders them less sensitive to complex lubricant failures arising from coupled factors and random fluctuations in monitoring data.

Considering the limited expert knowledge, data-driven approaches adopt intelligent algorithms such as cluster analysis [11] and support vector machines (SVMs) [12] to establish a fuzzy mapping between lubricant conditions and monitoring data. With multiple indicators such as viscosity, Fe, Cu, Cr, and acid value, a comprehensive representation space is constructed and then applied to evaluate lubricant conditions by combining the multi-layer perception (MLP) and radial basis function (RBF) network [13]. In view of the limitations of fixed diagnosis thresholds, a dynamic threshold determination method [14] is established with the decision tree and stochastic filtering to enhance model adaptability. Furthermore, the neural network is employed to develop a spectral data analysis model [15], and the genetic algorithm is adopted to optimize model weights and thresholds. These data-based models significantly improve the adaptability of lubricant failure diagnosis, but they often encounter diagnosis conflicts due to sparse samples and reverse indicator degradation in lubricant monitoring.

To enhance the assessment accuracy of lubricant failures, a novel diagnosis method is developed using an attribute-driven model. Specifically, a fuzzy fault tree

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(termed FFT) is established with logical correlations from indicators to attributes and to lubricant failures. Fuzzy evaluation and evidence theory are integrated to formulate the rule-based inference mechanism for lubricant failure deducing. Furthermore, this FFT model is optimized through the integration of both lubricant knowledge and monitoring data. For verification, a fatigue test and the maintenance data are adopted.

The rest of this paper is organized as follows: Section II contains the description of the developed model involving characterization space for lubricant conditions, FFT model construction, and model optimization strategy. The model verification and aero-engine lubricant applications are given in Section III. The conclusions are presented in Section IV.

II. MATERIALS AND METHODS

Multi-source fusion is the foundation of lubricant failure diagnosis, relying fundamentally on the coupling mechanism of multiple indicators. Therefore, a FFT-based model is adopted to illustrate the inducement mechanism from indicator to failure. Specifically, attributes are introduced to serve as the mediation layer, and the lubricant failure is inferred layer by layer with the fuzzy evaluation and D-S theory. Furthermore, the FFT model is optimized with both knowledge and data to be more adaptive.

A. PRINCIPLE

Essentially, lubricant refers not just to the oil itself but also to vital information during the lubrication process [16-18]. Accordingly, a comprehensive lubricant characterization space is established, incorporating three critical attributes: physico-chemical property, contamination, and wear. Each attribute consists of several representative indicators. The sketch of this construction is illustrated in Fig. 1. With this framework, the lubricant condition can be deduced from the monitoring indicators.

In considering both the representativeness and measurability, the indicators for each attribute are defined as follows. Viscosity stands as a pivotal indicator for the physico-chemical attribute and is sensitive to the lubricant's aging degree [19]. The contamination attribute can be represented by several indicators including the particle count (PC) and the water content (WC) [20]. The wear attribute can be represented by wear debris concentration (WDC) and the proportion of large debris (PLD) [21]. Moreover, the changing rate of each indicator is also considered to amplify the sensitivity of the characterization space. In view of this, a range of indicators involving viscosity, WC, PC, WDC, PLD, and their changing rates are selected to characterize the lubricant condition.

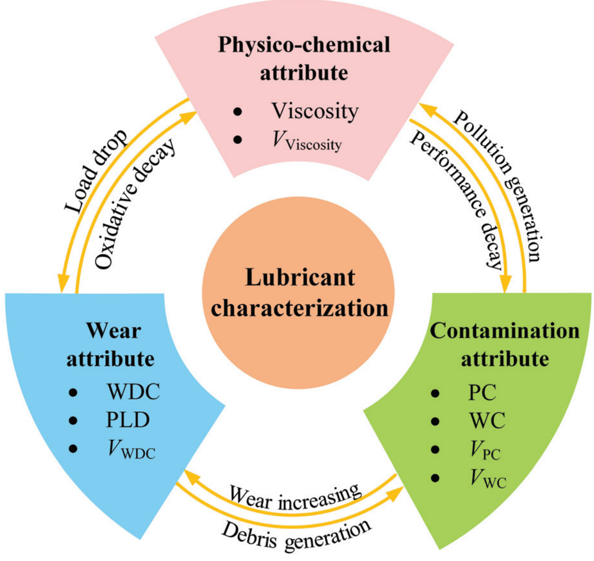

Fig. 1. Comprehensive characterization space for lubricant conditions.

While the characterization space provides a theoretical basis for assessing lubricant conditions, there are distinct gaps in applications. Foremost, the monitoring data is often susceptible to random fluctuations due to the manual operation in lubricant sampling, analysis, etc., which are very common in regular lubricant inspections. Second, indicators may exhibit reverse trends during lubricant degradation, for example, the decrease in viscosity may be accompanied by an increase in wear. This inconsistency may induce conflicting conclusions for failure diagnosis. All these challenges are addressed in the proposed diagnosis method.

B. MODEL CONSTRUCTION

Compared to machine learning methods, the fault tree model [22] can conduct top-down event deduction to describe coupling effects among multiple lubricant indicators, thereby providing a high interpretability of diagnosis results. Given this, the fault tree is adopted to establish the lubricant diagnosis model. Among fault-free (FT) models, FFT models [23] introduce fuzzy theory to address issues arising from unclear failure mechanisms and uncertain failure probabilities. In view of this, a FFT model is proposed with the lubricant characterization space, involving two main parts: the FFT model and inference rule formulation.

1) MODEL SKETCH. Referring to the FFT principle [23], the FFT lubricant failure diagnosis model is constructed as shown in Fig. 2. The top event of the fault tree is the lubricant failure conclusion, which is determined by three attribute branches: physico-chemical, contamination, and wear. Excessive degradation of any one of these three attributes will lead to lubricant faults. Therefore, their effects on the top event can be represented by an OR operation. The details for each branch are described as follows.

Physico-chemical degradation involves two viscosity-related mechanisms: exceeding the standards and rapid change; thus, these two mechanisms are designated as basic events with equal impact. Naturally, viscosity and its changing rate are the bottom inputs of this branch. Similarly, exceeding the standards and rapid change are also suitable for the other two attributes. For the second branch, the basic events of contamination exceeding standards can be determined jointly by two indicators: PC and WC. The second basic event of rapid change is represented by the changing rates of these two indicators. In the third branch, the basic events also consist of wear exceeding standards and rapid change. WDC is selected as the characterization indicator of exceeding standards, while the changing rate of the WDC and the PLD are chosen as the characterization indicators of the second events.

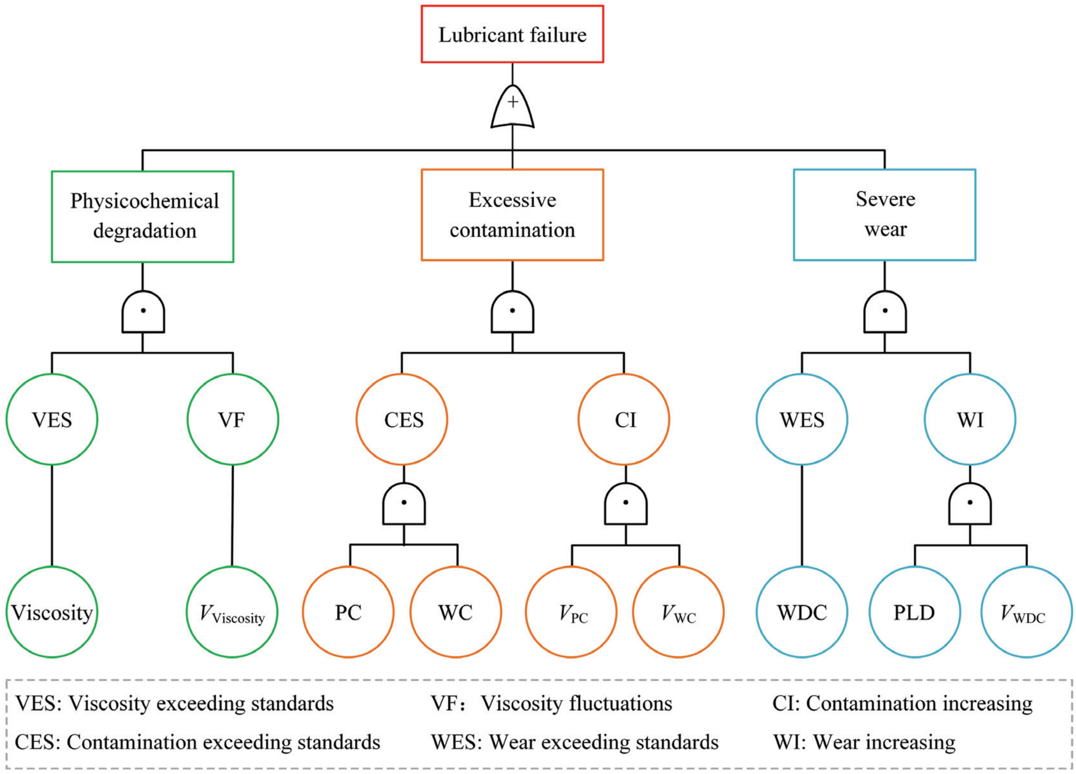

Fig. 2. Framework of the FFT lubricant failure diagnosis model.

As can be observed from Fig. 2, the basic events are determined by the monitoring indicators and then used to deduce the top events. It should be noted that AND operations and OR operations represent reasoning rules, which will be described in the following sections.

2) INFERENCE RULES. The small number of samples and reverse indicator degradation in lubricant monitoring data pose significant challenges to the applicability of FT models. To address this issue, the lubricant indicators are transformed into probabilistic form through fuzzy evaluation, and inference rules are formulated to reduce the diagnosis uncertainty of lubricant failures.

(1) Fuzzy characterization. The essence of fuzzy evaluation [24] is to transform deterministic values into probabilistic forms through membership functions. However, traditional lubricant failure diagnosis methods are constrained to binary assessments of health/failure states, thereby incapable of providing the lubricant degradation degree. In this work, lubricant conditions are divided into four levels based on expert knowledge [25,26], namely healthy, warning, mild fault, and severe fault. These levels are symbolically characterized by $\{HS_1, HS_2, HS_3, HS_4\}$. Considering that the random fluctuations and inconsistencies of monitoring indicators will increase the diagnosis uncertainties for lubricant conditions, the membership function is introduced to transform lubricant indicators into a fuzzy manner according to the fuzzy theory. Compared to trigonometric and trapezoidal functions, the Gaussian membership function offers a more precise depiction of complex membership relationships through the fine-tuning of key parameters. Therefore, the Gaussian membership function is employed to calculate the membership probabilities of monitoring indicators corresponding to the lubricant condition levels, as defined in Eq. (1):

$$\mu_{HS_j}(x_i) = \exp\left(-\left(\frac{x_i - a_j}{\sigma_j}\right)^2\right) \tag{1}$$

where x_i represents the i-th indicator involving its value and changing rate, $\mu_{HS_j}(x_i)$ represents the membership probability of the indicator x_i to the condition level HS_j, $i = 1,2,\ldots,n$, n is the total indicator number, j represents the j-th lubricant condition, and a_i and σ_j are the mean and standard deviation of the membership function of the j-th condition level.

(2) Inference rule formulation. Regarding the AND operation in the FFT model in Fig. 2, the weighted fusion is adopted to calculate the membership probability of basic events or intermediate events corresponding to the condition levels, as defined in Eq. (2):

$$\mu_{HS_j}(X_i) = w_{i1}\mu_{HS_j}(x_{i1}) + w_{i2}\mu_{HS_j}(x_{i2}) \tag{2}$$

where w_i is the weight corresponding to the i-th fused monitoring indicator or the basic event, X_i, x_{i1}, and x_{i2} represent the comprehensive variation, monitoring value, and changing rate of the i-th fused monitoring indicator or the basic event, respectively.

Regarding the OR operation in the FFT model in Fig. 2, D-S theory [30] is introduced to fuse multi-source lubricant information. Specifically, the membership probability of intermediate events belonging to different condition levels is adopted as evidence for deducing the occurrence probability of the top event. The D-S theory employs the set-theoretic concept to assign probabilities for inputs. For example, assuming a set $A = \{\alpha_1, \alpha_2, \ldots, \alpha_n\}$, the probability assignment function satisfies the mapping $2^A \to [0,1]$; thus, the basic probability assignment (BPA) of the set A can be calculated using Eq. (3):

$$\begin{cases} m_x(\phi) = 0 \\ 0 \leq m_x(\alpha_i) \leq 1 \\ \sum_{x \subseteq A} m_x(\alpha_i) = 1 \end{cases} \tag{3}$$

where ϕ is the null set, $m_x(\alpha_i)$ represents the assigned probability of the intermediate event x to the set α_i, and α_i represents the condition level HS_i.

To reduce the indicator uncertainty effect on fusion results, a weight coefficient is introduced to measure the credibility of the fused evidence, as defined in Eq. (4):

$$a_k = \hat{a} \times \left(\frac{w_k}{w_{max}}\right) \tag{4}$$

where a_k is the weight coefficient, w_k is the evidence weight of intermediate events, and $\hat{a}$ is the weight measurement parameter.

Furthermore, the calculations for the BPA and uncertainty Θ are presented in Eqs. (5) and (6), in which the uncertainty Θ represents the unassigned probability that does not belong to any lubricant condition level:

$$m_{M_k}(HS_j) = \hat{a} \times \frac{w_k}{w_{max}} \times \mu_{S_j}(M_k) \tag{5}$$

$$m_{M_k}(\Theta) = 1 - \sum_{k=1}^{4} \hat{a} \times \frac{w_k}{w_{max}} \times \mu_{S_j}(M_k) \tag{6}$$

Using Eqs. (2) to (6), the OR operation for deriving probabilities from intermediate events to top events can be performed with the probability assignment function $m(HS)$ for intermediate events to different condition levels. Specifically, assuming the evidence to be fused are M_1, M_2, and M_3, the first step is to fuse the evidence M_1 and M_2. Taking the fusion of condition levels HS_n and HS_{n+1} as an example, the fusion rules are presented in Table I. The fusion result $m_{(12)}$ is further fused with evidence M_3 using the same process and ultimately outputs the BPA of the top event across different lubricant condition levels.

The evidence fusion for lubricant failure diagnosis is presented in Eq. (7):

$$\begin{cases} m_{(2)}(HS) = \frac{\sum_{M_1 \cap M_2 = HS} m(M_1)m(M_2)}{1-K} \\ K = \sum_{M_1 \cap M_2 = \phi} m(M_1)m(M_2) \end{cases} \tag{7}$$

where $m_{(2)}(HS)$ is the fusion result of two evidences and K is the conflict coefficient.

After the evidence fusion of the OR operation, the obtained BPA can be defuzzified referring to the utility interval [31] and then acquire a quantitative failure probability HS for overall lubricant condition, as defined in Eq. (8):

$$HS = \sum_{j=1}^{4} m(HS_j) \times u(HS_j) \tag{8}$$

where $m(HS_j)$ and $u(HS_j)$ are the membership probability and utility interval corresponding to the j-th condition level, respectively.

C. OPTIMIZATION STRATEGY

Considering limited knowledge and the scarcity of lubricant monitoring samples, a hybrid approach is developed to optimize the parameters of the FFT model through the knowledge-related analytic hierarchy process (APH) and data-related entropy weight method. By this means, the FFT model can be optimized for accurate lubricant failure diagnosis.

1) APH WEIGHT ASSIGNMENT. AHP [32] decomposes multi-criteria problems into a hierarchical structure of the goal level, criterion level, and scheme level and assigns weights based on the indicator relevance to each layer. In view of this, AHP is introduced into the proposed FFT model for weight assignment. Specifically, a transformation from FFT to AHP is constructed, where the top event "lubricant failure" corresponds to the goal level, the intermediate events to the criterion level, and the basic events and monitoring indicators to the scheme level. For multiple criteria at the same level, pairwise comparisons are conducted to assess each importance across a nine-point scale {1,2,3,4, 5,6,7,8,9}, where "1" indicates equal importance between two criteria and "9" represents the utmost importance of one criterion over the others. Subsequently, these scores are adopted to obtain an importance matrix $\boldsymbol{U}$ for weight assignment. Notably, the fusion weights of multiple lubricant indicators are set with different importance matrices.

The rationality of matrix $\boldsymbol{U}$ can be evaluated through a consistency check (CR), as defined in Eq. (9). If the CR is less than the accepted threshold of 0.1, the assignment of matrix $\boldsymbol{U}$ is considered reasonable, thereby passing the consistency check; otherwise, corrections to matrix $\boldsymbol{U}$ are necessary to improve consistency. After performing the consistency check, each column of matrix $\boldsymbol{U}$ undergoes element accumulation, followed by normalization to calculate the weight matrix α of different attributes, namely the prior weights of physico-chemical, contamination, and wear information at the criterion level. By repeating this process, the importance assessment of each indicator can be conducted in the scheme layer and applied to acquire prior knowledge weights for lubricant indicators:

$$CR = \frac{\lambda_{max} - m}{RI(m-1)} \tag{9}$$

where λ_{max} is the maximum eigenvalue of matrix $\boldsymbol{U}$, m is the order of matrix $\boldsymbol{U}$, and RI is a random index associated with the matrix order.

2) ENTROPY WEIGHT OPTIMIZATION. The knowledge-related APH approach provides fixed weights for the FFT model but poses limitations in adaptability when applied to

TABLE I. Relevant rules of evidence synthesis for intermediate events

Evidence to be fused		Evidence M_2: HS_n	Evidence M_2: HS_{n+1}	Evidence M_2: Θ
Evidence M_1	HS_n	$m_1(S_n)m_2(S_n)$	$m_1(S_n)m_2(S_{n+1})$	$m_1(S_n)m_2(\Theta)$
	HS_{n+1}	$m_1(S_{n+1})m_2(S_n)$	$m_1(S_{n+1})m_2(S_{n+1})$	$m_1(S_{n+1})m_2(\Theta)$
	Θ	$m_1(\Theta)m_2(S_n)$	$m_1(\Theta)m_2(S_{n+1})$	$m_1(\Theta)m_2(\Theta)$

random lubricant monitoring data. To address this issue, a data-related optimization strategy is proposed based on entropy weighting. This strategy takes normalized lubricant monitoring data as input and calculates the weight β_j for each indicator through information entropy, as defined in Eq. (10). The larger the information entropy of an indicator, the higher its weight. Conversely, the smaller the information entropy of an indicator, the lower its importance. By this means, the knowledge-related weights can be dynamically adjusted according to lubricant monitoring data:

$$\beta_j = \frac{1 - e_j}{n - \sum_{j=1}^{n} e_j} \tag{10}$$

where n is the total number of lubricant indicators.

3) KNOWLEDGE AND DATA INTEGRATION. For comprehensive optimization of the FFT model, knowledge-related weights and data-related weights are integrated, as defined in Eq. (11):

$$P_{ij} = \frac{\alpha_i + \beta_{ij}}{\sum(\alpha_i + \beta_{ij})} \tag{11}$$

where α_i represents the knowledge-related weight of the i-th indicator and β_{ij} represents the data-related weight of the j-th group for the i-th indicator.

Through the measures described above, an FFT lubricant failure diagnosis model can be constructed by integrating the indicators from physico-chemical, contamination, and wear attributes. Furthermore, model parameters are optimized using the knowledge and data-integrated strategy for adaptive diagnosis of lubricant failures.

III. VERIFICATION AND APPLICATIONS

For verification, the constructed FFT model is tested with actual lubricant degradation data from a fatigue test of harmonic reducer. Subsequently, the method is applied to the evaluation of aero-engine lubricants.

A. VERIFICATION

1) DATA ACQUIREMENT. A harmonic reducer fatigue tester is adopted to obtain full-length lubricant degradation samples, as shown in Fig. 3. The harmonic reducer consists of three core components: the rigid gear assembly, the flexible gear assembly, and the wave generator assembly. To accelerate lubricant degradation, the lubricant properties are artificially modified in accordance with lubricant replacement standards. Concretely, the high temperature is adopted to heat the lubricant for aging failure acceleration. Different levels of water contamination and non-metallic particle pollution are simulated by adding varying concentrations of water (ranging from 0% to 0.2%) and silica particles (ranging from 0 to 200 ppm) into the lubricant, respectively. Moreover, additional iron particles and high operational load are integrated to accelerate the wear process. Each lubricant sample is then served as the lubricating medium of the harmonic reducer to simulate typical lubricant conditions. Furthermore, a lubricant monitoring system is employed, integrating an online ferrography (OFE) sensor, a lubricant physico-chemical (LPC) sensor, and a particle count (PCO) sensor to acquire six types of indicators.

All the indicators are listed in Table II. Particularly, PC-5μm and PC-15 μm are selected to comprehensively characterize the PC. The reason can be attributed to the fact that the significance of particles to the contaminant levels varies with their sizes, where large particles signify a higher contaminant level. Through accelerated experiments, 274 sets of lubricant condition deterioration data are collected, encompassing six kinds of samples: normal, aging failure, wear failure, water contamination, non-metallic particle pollution, and composite failure samples.

2) RESULT EVALUATION. To validate the effectiveness of the proposed FFT model, 274 sets of real lubricant samples are randomly sampled, with 180 sets used for training and the remaining 94 sets for testing. Diagnostic results of the testing samples are presented in Fig. 4, where the true lubricant condition is determined based on expert experience and oil change standards [25,26]. As can be observed, the proposed model achieves a diagnostic accuracy of 92.6%, demonstrating high consistency with the true lubricant conditions.

3) OPTIMIZATION STRATEGY VALIDATION. For the knowledge and data-integrated optimization strategy, a comparison is made between the FFT model and a new GD-FFT model, which utilizes a gradient descent (GD)

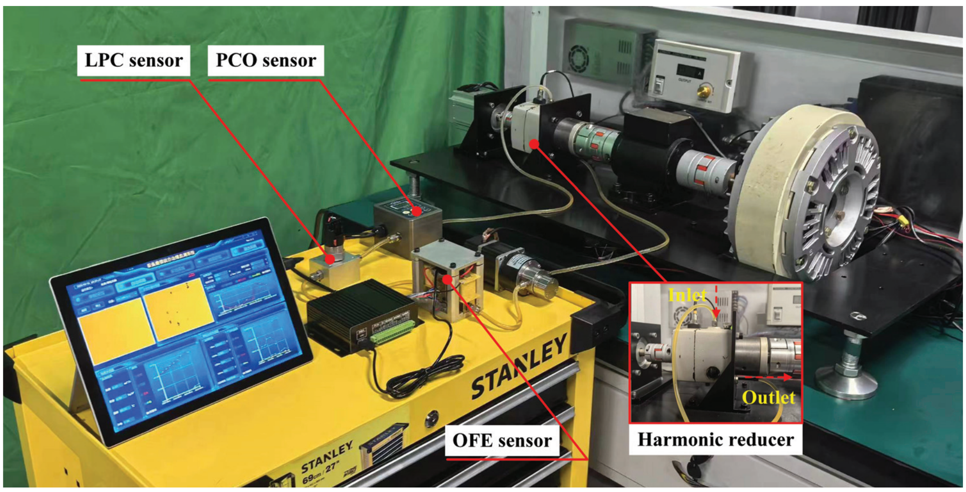

Fig. 3. Fatigue test rig for lubricant degradation.

Table II. Part of lubricant degradation samples (Note that PC-5 μm represents the count of particles with size >5 μm, and PC-15 μM represents the count of particles with size >15 μM)

Number	Service time (h)	Viscosity (cP)	PC-5 μm (piece/ml)	PC-15 μm (piece/ml)	WC (ppm)	WDC	PLD
1	7	25.98	38900	3200	29.84	0.12	0
2	11	26.43	12300	400	39.74	0.01	0
3	15	26.36	14400	300	40.01	0.03	0
4	21	26.63	12800	2400	32.98	0.24	0
…	.	…	…	…	…	…	…
91	61	25.61	273400	45450	31.29	8.15	0.023
92	45	27.20	264750	27050	95.31	8.66	0
93	55	29.30	160050	6000	66.82	8.27	0.019
94	40	29.60	335250	6400	34.06	0.61	0

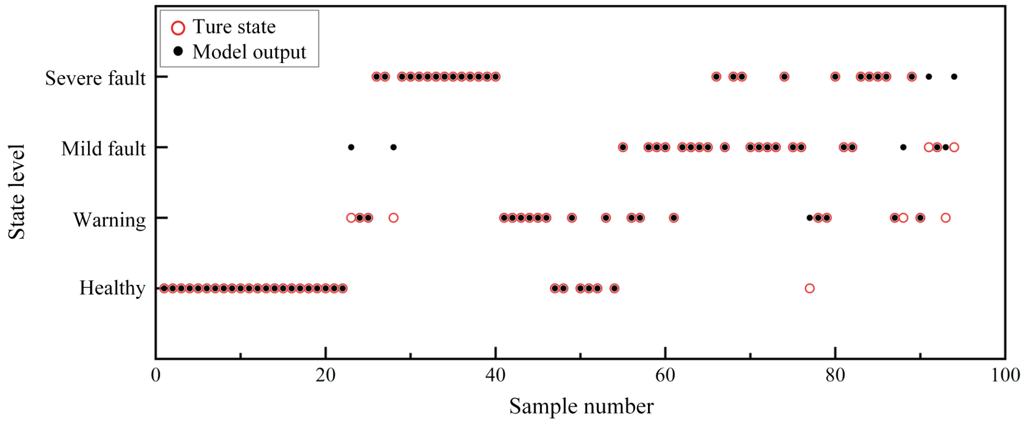

Fig. 4. Diagnostic results of the testing samples based on the FFT model.

optimization algorithm [33] instead of the integrated optimization strategy. It should be noted that the training samples and initial parameters for these two models are consistent. The weight variations applied by the two methods on the testing samples are visualized in Fig. 5, where distinctively colored boxes denote the indicator weights calculated by the integrated optimization strategy, whereas the red dashed line signifies the weights calculated by the GD algorithm.

As can be observed from Fig. 5, the proposed integrated optimization strategy, in contrast to the GD algorithm, can adaptively adjust the indicator weights according to the data variations of testing samples. Furthermore, the GD-FFT model is applied to evaluate the 94 sets of testing samples, and its diagnostic accuracy is 85.1%, which is lower than that of the FFT model. This lower accuracy may be attributed to the limitation of the GD-FFT model in dynamically adjusting parameters.

4) ACCURACY COMPARISON. Using the 94 sets of testing samples, the FFT model is compared with the fuzzy evidential reasoning (FER) model [34], the SVM model [12], and the GD-FFT model. Among them, the SVM model employs nonlinear mapping to transform the sample space into a high-dimensional feature space and then seeks an optimal hyperplane to distinguish different lubricant conditions. For the FER model, multiple lubricant indicators can be synthesized through fuzzy membership evaluation and evidence integration for multi-attribute decision-making of lubricant conditions. The diagnostic accuracy of the four methods is presented in Table III. As can be observed, the proposed FFT model achieves higher recognition accuracy than the comparative models. In particular, compared to the most popular SVM model, the diagnostic accuracy has been improved from 73.4% to 92.6%, which may be attributed to the fact that rule-based reasoning and integrated optimization strategy are introduced to enhance the model adaptability.

B. APPLICATIONS

To evaluate the model practicability, the constructed FFT model is applied to diagnose the lubricants from actual aero-engines. The tested lubricants are collected from three operational states of aero-engines, including normal testing, return-to-factory maintenance, and overhaul. A total of 40 aero-engine lubricant samples are collected from various locations, including the oil sump, front cavity, accessory gearbox, etc. Part of the detected data is shown in Table IV.

The 40 sets of aero-engine lubricant samples are input into the FFT model, and the diagnosis results are illustrated in Fig. 6. As can be observed, an accuracy of 90.0% has been achieved, and only four samples are mistakenly recognized.

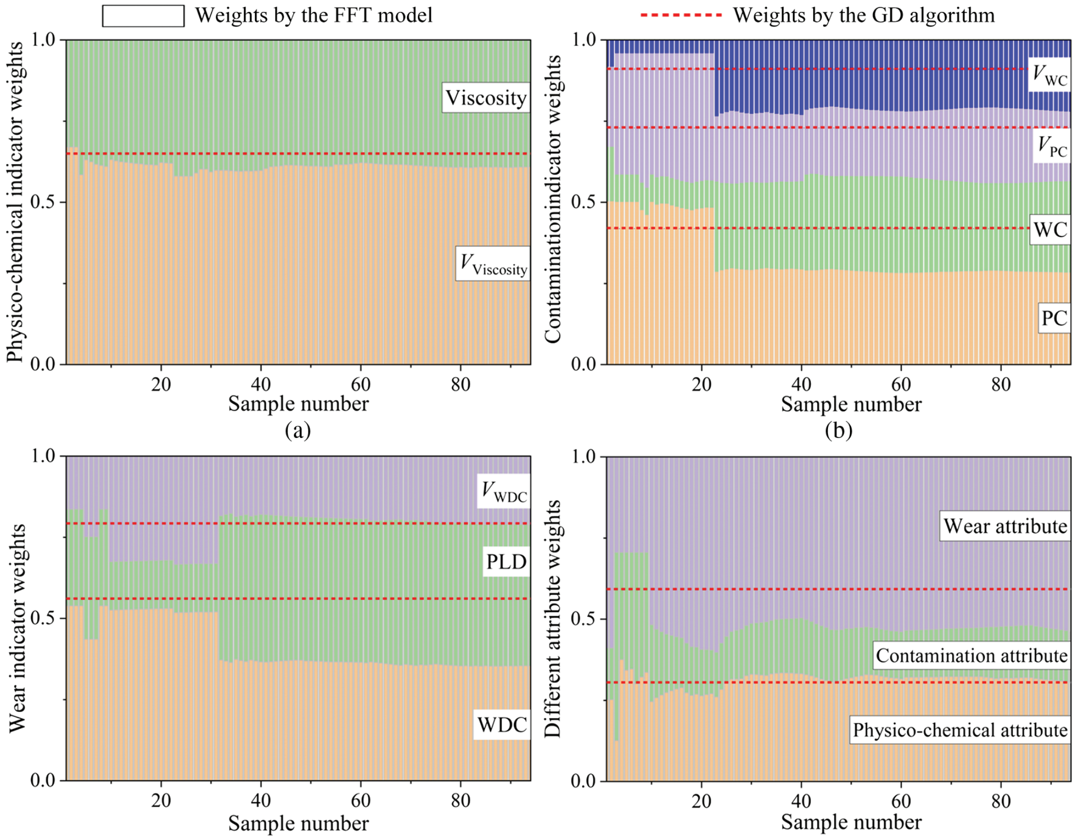

Fig. 5. Weights calculated by optimization strategies: (a) physico-chemical indicator weights, (b) contamination indicator weights, (c) wear indicator weights, and (d) different attribute weights.

Table III. Accuracy comparison of various methods for lubricant failure diagnosis

Model	Accuracy
FFT	92.6%
GD-FFT	85.1%
FER	76.6%
SVM	73.4%

With the satisfied test results, the FFT model can be considered as an effective means for assessing lubricant conditions even with limited samples. Furthermore, the proposed FFT model can be applied to evaluate different lubricants, and a small number of failure samples are required to optimize model parameters for accurate lubricant condition diagnosis. Nevertheless, the proposed FFT model requires further optimization to accommodate special application conditions involving lubricant replacement, equipment start–stop cycles, and temperature alternating changes. Lubricant condition prediction provides

Table IV. Part of the detected data from aero-engine lubricants

Number	Service time (h)	Viscosity (cP)	PC-5 μm (piece/ml)	PC-15 μm (piece/ml)	WC (ppm)	WDC	PLD
1	5	26.53	9600	0	38.39	0.03	0
2	10	26.39	14400	300	39.01	0.02	0
3	15	25.91	16800	1400	38.8	0.01	0
4	20	26.93	13100	900	35.66	0.185	0
5	25	26.99	16300	1200	35.28	0.222	0
...	.	...	...	...	...	...	...
37	240	24.99	228900	3650	92.82	0.888	0.033
38	260	24.46	301500	13700	94.65	2.368	0
39	285	29.2	314000	65200	34.2	2.96	0
40	300	28.45	251600	52200	34.06	1.776	0.02

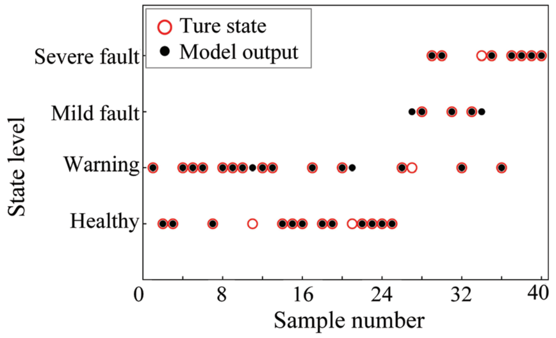

Fig. 6. Diagnosis results for aero-engine lubricant samples.

significant support for the predictive maintenance of equipment. Another direction of interest will focus on the remaining useful life prediction of lubricants by integrating time-series monitoring data with degradation mechanisms.

IV. CONCLUSIONS

In this study, an FFT model incorporating rule-based reasoning has been developed and implemented to diagnose lubricant failures. The following key contributions have been made:

An attribute-driven model has been developed: The FFT model has been embedded to illustrate the logical correlation from indicators to attributes and lubricant failures.

Knowledge and data have been integrated: The lubrication condition diagnosis model has been designed to fuse both lubricant analysis knowledge and monitoring data, effectively addressing the issues associated with small sample sizes in traditional models.

Diagnostic accuracy has been significantly improved: Compared to existing representative methods, the proposed model has enhanced diagnostic accuracy from 73.4% to 92.6%. Further application in aero-engine lubricant diagnosis shows an average of 90%.

Overall, this model represents a significant advancement in lubricant failure diagnosis, providing a robust and adaptable solution for practical applications.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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