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An Integrated Data and Knowledge Model Addressing Aleatory and Epistemic Uncertainty for Oil Condition Monitoring

Yan Pan [a], Yunteng Jing [a], Tonghai Wu [a,b,*], Xiangxing Kong [c]

[a] Key Laboratory of Education Ministry for Modern Design and Rotor-Bearing System, Xi'an Jiaotong University, Xi'an, 710049, China
[b] Xi'an Jinghui Information Technology Co., Ltd, Xi'an, 710049, China
[c] Aero Engine Academy of China, Beijing, 101304, China

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ABSTRACT

Reliable operation of machinery is very desirable in engineering. To achieve this objective, the assessment of the lubrication oil state is necessary. However, due to the unpredictable variations, uncertainty detection and handling in the oil state has been a bottleneck in practice. A solution strategy is proposed in this paper that integrates information from the monitoring data and expert knowledge. On the other hand, since insufficient data and limited knowledge, two types of uncertainty are present, namely, aleatory and epistemic uncertainty. To handle these uncertainties, an integrated model with a three-layer structure is constructed that incorporates both expert knowledge and data. First, for the detection of stochastic data variation, the initial connection among the layers is assigned by membership probabilities as the characterization evidence. Second, the oil state that produces a unified output with various pieces of evidence is determined by evidential reasoning with knowledge-based rules. Third, to provide consistent monitoring adaptively, a knowledge-integrated neural network is established for determining the initial parameters from measurements. The effectiveness of the proposed model is demonstrated using both simulated and real-world data from industrial vehicles.

List of Symbols

I-A-S	Indicator-attribute-state layers
KINN	Knowledge-integrated neural network
HI	Health index
H_c	The *c*-th oil state
A_i	The *i*-th oil attribute
A_i^k	The *i*-th oil attribute in the *k*-th rule
a_{ij}	Monitoring oil data of the *j*-th indicator in the *i*-th attribute
$\overline{a}_{ij}$	Normalized value of a_{ij}
$P(H_c a_{ij})$	State membership probability of monitoring data a_{ij}
$P(H_c A_i)$	State membership probability of attribute A_i
μ	Mean value of the Gaussian function
σ	Variance of the Gaussian function
w_{ij}	Weight of the *j*-th indicator in the *i*-th attribute
β_c	Belief degree for oil state H_c
β_c^I	Integrated belief degree for oil state H_c
w_k	Weight of the *k*-th rule
θ_k	Activated weight of the *k*-th rule
$\mu(H_c)$	Utility of state H_c
$y(k)$	Real value of the *k*-th oil sample
$\widehat{y}(k)$	Predicted value of the *k*-th oil sample
$x(t)$	Oil indicator data at time *t*
$g(x(t))$	Function of the increment of indicator data
$f(x(t))$	Function of the decrement of indicator data
$w(t)$	Stochastic fluctuation of the degradation process
RMSE	Root mean square error
MAE	Mean absolute error

1. Introduction

Oil condition monitoring (OCM) can provide early and comprehensive information for machine reliability and possible component failure [1]. Since the lubrication oil continuously circulates in the tribology system, the oil state can be used as a feasible indicator [2]. However, there are unavoidable uncertainties in the oil state that hinders condition monitoring and reliability assessment. Limited by the unidentified degradation mechanism and measurement difficulties in OCM, the existing uncertainties can be categorized as aleatory and epistemic types

* Corresponding author.
E-mail address: wt-h@163.com (T. Wu).

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[3,4].

Aleatory uncertainty represents the inherent variability associated with the system and environment, which stems from unpredictable and natural variations [5]. Epistemic uncertainty, also known as the subject or reducible uncertainty, arises from a lack of sufficient data that is conceptually resolvable [6]. As a probabilistic method for uncertainty characterization, the Dempster-Shafer theory (D-S theory) [4] can simultaneously handle and describe these two types of uncertainty. First, D-S theory employs multi-attributes decisions addressing the evidence, and the epistemic uncertainty is reducible with more knowledge. Second, the basic probability assignment (BPA) can provide a measurable determination for evidence combination.

Multi-attributes decisions, for OCM with D-S theory, can handle epistemic uncertainty with accumulated information. However, additional uncertainty is generated in evidence combination due to the inconsistent or conflicting decision. As an intelligent method to resolve inconsistent determination, the application of expert systems (ES) makes the assessment more systematic and repeatable in treating the uncertainty [7]. For example, Peng et al. [8] adopted ES to interpret oil condition data obtained from particle analysis. Liu et al. [9] used the “IF-THEN” rule-based method for incipient fault detection with OCM and extensively observed multiple uncertain interactions. Besides, to solve the main disadvantage of ES, which hardly handled unexpected circumstances [10], several integrated probability-based and expert-based methods were proposed. Yang et al. [11] integrated the "IF-THEN" rule and D-S theory, then proposed a belief-rule-base (BRB) model with distributed belief frameworks. Xu et al. [12] applied this framework in OCM and verified that it could identify concurrent faults. Moreover, Feng et al. [13] developed a new optimization method to solve the problem that initial parameters and rules are given by experience in the BRB. The essence to solve the uncertainty in conflicting multi-attributes decisions is the introduction of knowledge concerning the real-time monitoring data. Therefore, the above models should have the enhanced ability in handling the epistemic uncertainty in OCM.

The belief degree in D-S theory can provide remedies for aleatory uncertainty, and it is critical to establish a suitable probability distribution function. Traditionally, the setting of BPA is based on expert experience or off-line samples, which cannot meet the demand for real-time updates. Artificial neural networks (ANN) provide real-time adaptive acquisition from data, which have been frequently applied in OCM, such as the identification of wear debris [14], the prediction of wear performance [15,16], and the assessment of system reliability [17,18]. Nevertheless, the neural network is regarded as a black-box, which is unable to provide interpretable outcomes. Therefore, many improved models have been proposed to explain the results in the process of handling uncertainty. First, tandem models were developed, in which each unit operates independently. For example, Drieschner et al. [19] combined fuzzy logic and ANN to overcome the computational cost of uncertainty propagations. Valis et al. [17] considered that the oil data is uncertain and applied a fuzzy inference system (FIS) and neural networks to acquire the condition information. Second, embedded models were used to obtain comprehensive and associated outcomes. Zio et al. [20] verified a high rate of correct and interpretable classification with a neuro-fuzzy approach for pattern classification. Kari et al. [21] presented an incipient fault diagnosis based on an integrated adaptive neuro-fuzzy inference system, and further enhance fault diagnosis consistency and accuracy. Besides, Xu et al. [22] fused multiple data-driven models, including an ANN model, a BRB model, and an ER rule model, for oil fault diagnosis at the decision level. The drawback of the above studies is that the knowledge essentially stems from the data, which is insufficient to provide a traceable description of the oil degradation mechanism.

Correspondingly, this work aims to develop a quantitative characterization model that addresses uncertainty by integrating both data and expert knowledge. Specifically, a three-layer structure is constructed for modelling the oil state. To deal with the aleatory and epistemic uncertainties aforementioned, the distributed probabilities between each layer are computed by the membership function. With the D-S theory, knowledge-based rules are combined to infer the oil state. Considering adaptive continual monitoring, a knowledge-integrated neural network (KINN) is designed. Finally, the well-trained intelligent model is examined with both simulated and real-world data sets. The main contributions of the work are as follows.

1) To deal with the epistemic uncertainty of choosing indicators, the indicators with representative attributes are used to characterize oil state quantitatively. The introduction of expert knowledge solves the problem of conflicting results. This strategy provides a multi-attributes decision to assure the accurate oil assessment.
2) To detect the aleatory uncertainty from dynamic data mining, a probability-based model is proposed. It adaptively extracts the parameters from the real-time data. The model adapts to the stochastic volatility of the monitoring data and makes the characterization outcomes interpretable.

The rest of the paper is organized as follows. Section 2 gives a mechanism-based model for oil state characterization. Section 3 presents a knowledge-integrated neural network for the initial parameter optimization. In Section 4, the proposed model is verified through two groups of data. Section 5 contains the conclusion.

2. Mechanism-based model for oil state characterization

The degradation of the lubrication oil can be treated as the changes in its physicochemical property. It is a gradual process and can be assessed as a series of grades. Accordingly, the grades can be arranged as the sequence for the full lifecycle monitoring samples. Then the sequence is used as the evaluation metric of the oil with a description of the degradation extent.

Before describing the model structure, some terminologies are defined as follows:

1) Grade set: $H = \{H_c\}$, $c = 1, \cdots, N$, where N is the numbers of oil grades.
2) Attribute set: $A = \{A_i\}$, $i = 1, \cdots r$, where r is the numbers of attributes.
3) Indicator set of the i-th attribute: $A_i = \{a_{ij}\}, j = 1, \cdots g$, where g is the numbers of indicators of the i-th attribute.

The grades can qualitatively describe the degradation of oil. Meanwhile, mechanisms for oil degradation can provide a mapping between the monitoring data and oil state. The oil attributes is the bridge connecting the monitoring data and oil state. Furthermore, the oil state can be the integration of all attributes regarding the oil properties. The oil indicator can also be grouped as the same attribute to be evaluated. It should be noticed that characterization is influenced by complicated oil degradation mechanisms. Although the monitoring data contains randomness the latent mechanism at a particular stage is relatively stable.

A three-layer modelling structure is constructed with probabilistic inferences. It includes the indicator layer, the attribute layer, and the state layer, denoted as I-A-S and is illustrated in Fig. 1. In the indicator layer, the data of the corresponding indicators are used to match the predefined grades. In the attribute layer, the attributes describe the oil property by combining the inclusive indicators. In the state layer, the oil state is synergistically determined based on knowledge and data.

There are two processes in the initialization stage: probability assignment of evidence and knowledge-based state inference. First, the corresponding indicators are transformed into the probabilistic description with membership functions. Then the indicators of the same attribute are evaluated to obtain the weighted probabilities. Second, the inference integration rules are constructed by the knowledge and data,

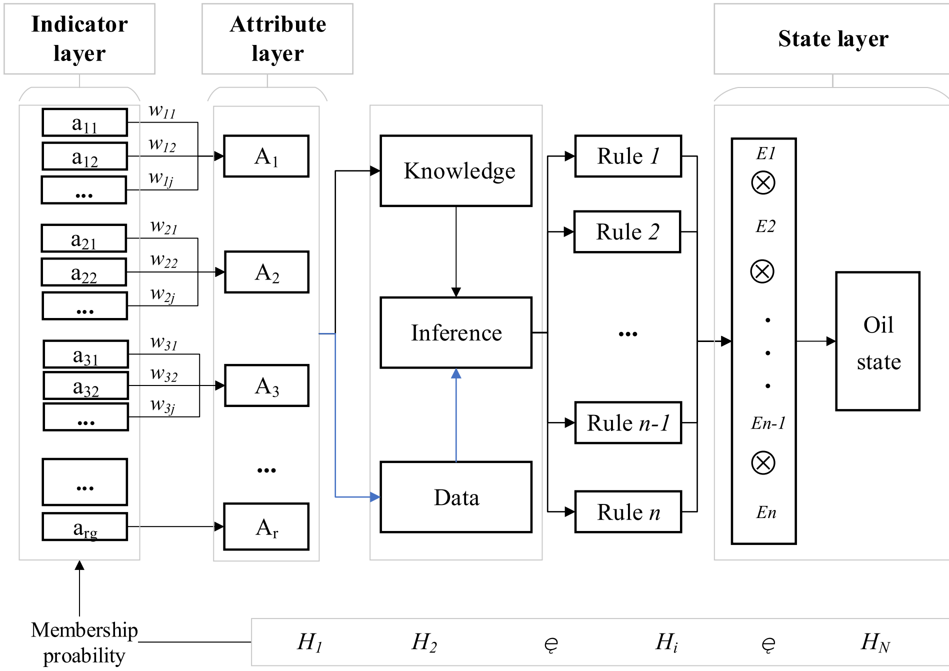

Fig. 1. The three-layer structure of oil state characterization, where ⊗ denotes the of evidence combination operator.

and is further combined by D-S theory. The comprehensive oil state is hence characterized.

2.1. Probability assignment of evidence

For the indicators with positive effects on the oil, e.g., total alkali value and additive content, they are defined as the value-type indicators I_1. For others with negative effects, e.g., viscosity change rate, wear metal content, they are defined as cost-type indicators I_2. Furthermore, to bound indicators in the same magnitude range, the oil data is normalized. The normalization of oil data is given by Eq. (1),

$$\overline{a}_{ij}=\begin{cases}\dfrac{a_{\mathrm{Max}}-a_{ij}}{a_{\mathrm{Max}}-a_{\mathrm{Min}}}, & a_{ij}\in I_1\\ \dfrac{a_{ij}-a_{\mathrm{Min}}}{a_{\mathrm{Max}}-a_{\mathrm{Min}}}, & a_{ij}\in I_2,\end{cases} \tag{1}$$

where a_{Min} is the minimum value representing the initial state of oil, a_{Max} is the maximum value representing the failure state of the oil. These two bounding values can be obtained from the full-range dataset. The variable $\overline{a}_{ij}$ is the normalized value of the oil indicator.

The evaluation of the indicator adopts the fuzzy approach [23], then the membership probabilities are calculated. The Gaussian function [24] is selected as the membership function, as shown in Eq. (2),

$$P(H_c a_{ij}) = \exp\left(-\left(\frac{\overline{a}_{ij}-\mu}{\sigma}\right)^2\right), \tag{2}$$

where μ and σ are respectively the mean and variance of the Gaussian function, $P(H_c a_{ij})$ is the state membership probability of data a_{ij}; specifically, μ and σ are the parameters to be optimized.

The attribute is composed of indicators that reflect the same property of the oil. In order to quantify the probability of the attribute associated with the corresponding grade, the membership probability is obtained from Eq. (3),

$$P(H_c A_i) = \sum_{j=1}^{g} w_{ij} P(H_c a_{ij}) \tag{3}$$

where $P(H_c A_i)$ denotes the membership probability that A_i belongs to H_c; w_{ij} is the weight of the indicator, which is also the parameter to be optimized.

2.2. Knowledge-based state inference

The membership probability provides the quantitative assessment of the oil, which is also used to handle the aleatory uncertainty. Then knowledge-based rules are formed to resolve the epistemic uncertainty of the oil state. To aggregate the activation rules, the evidential reasoning (ER) algorithm is applied to generate the final decision.

2.2.1. Rule formulation

Based on expert knowledge, the "IF-THEN" rule database is adopted to formulate n inference rules. The "IF" part is the antecedent of oil attributes. The "THEN" part, the consequent, generates the inference of the rule. The k-th rule takes formulate as:

IF: A_1^k is H_1 and … A_i^k is H_c and … and A_r^k is H_N,
THEN: $\{(H_1,\ \beta_1^k),\cdots,(H_c,\ \beta_c^k),\cdots,(H_N,\ \beta_N^k)\}$,

where A_i^k represents the i-th oil attribute in the k-th rule antecedent, β_c^k denotes the belief degree of inference, which indicates the probability that the oil state belongs to H_c. Moreover, β_c in the activated rules are the parameters to be optimized.

The rule database includes n rules, and the activated rules should be measured. The activated weight of the k-th rule, which represents the importance of activated rules, is calculated as follows,

$$\theta_k = \frac{w_k \prod_{i=1}^{N} P(H_c A_i)_k^i}{\sum_{l=1}^{n} w_l \prod_{i=1}^{N} P(H_c A_i)_l^i}, \tag{4}$$

where θ_k denotes the activated weight of the k-th rule, N is the numbers of oil grades, n is the numbers of rule, w_k is the weight of the k-th rule, which is the parameter to be optimized.

2.2.2. Rule aggregation

The ER algorithm [25] is applied to the aggregation of the activated rules. Consequently, the belief degree, the measurement of oil state with probability, can be obtained based on the D-S theory, specified in Eq. (5),

$$\beta_c^I = \frac{K\left[\prod_{k=1}^n\left(\theta_k\beta_c^k + 1 - \theta_k\sum_{j=1}^N\beta_j^k\right) - \prod_{k=1}^n\left(1 - \theta_k\sum_{j=1}^N\beta_j^k\right)\right]}{1 - K\left[\prod_{k=1}^n(1-\theta_k)\right]}, \tag{5}$$

$$K^{-1} = \prod_{k=1}^n\left(\theta_k\beta_c^k + 1 - \theta_k\sum_{j=1}^N\beta_j^k\right) - (N-1)\prod_{k=1}^n\left(1 - \theta_k\sum_{j=1}^N\beta_j^k\right), \tag{6}$$

where β_c^I represents the integrated belief degree of oil state; K is the normalization coefficient and is calculated by Eq. (6). The final determination of oil state H can be expressed as follows,

$$H = \left\{\left(H_c, \beta_c^I\right), c = 1, \cdots, N\right\}, \tag{7}$$

So far, the oil state is expressed by the belief degree combining the grade interval. To describe the gradual degradation, it is desirable to produce a continuous health index (abbreviated as *HI*) for the training of the model, so the concept of expected utility is introduced [26]. Assume that $\mu(H_c)$, $c = 1, \cdots, N$ are the utilities of the states. Because the distributed assessments of oil state are all complete, whose corresponding utility values are equal, the quantified output *HI* can be simplified, as shown in Eq. (8),

$$HI = \sum_{c=1}^N \beta_c^I \mu(H_c). \tag{8}$$

Finally, *HI* is formed from the combination of knowledge and data. However, the initial parameters of the model are traditionally set depending on experience, which is not suitable for the intelligently updated data.

3. KINN for initial parameter optimization

Parameter initialization of the I-A-S model is infeasible for gradual oil degradation due to limited knowledge. The adaptive learning from continuously updated data can provide a solution. Moreover, with more updated information, epistemic uncertainty of the oil state can be reducible. Therefore, an adaptive optimization strategy is proposed.

3.1. Network architecture

According to the I-A-S model, a 7-layer knowledge-integrated neural network (KINN) is proposed, as shown in Fig. 2. The main components of the model include 1) data structure with indicator-attribute-state layers; 2) knowledge structure with inference rules and weights.

The critical elements of KINN are neurons and parameters, which are summarized in Table 1. The neurons in KINN are set by referring to the numbers of indicators, attributes, states, and rules. And the parameters of the neural network are selected referring to the parameters in I-A-S. Seven parameters, which traditionally rely on empirical settings, need to be optimized. The connection relationship of the network is shown in Fig. 3.

Furthermore, the KINN is trained with the back-propagation algorithm, with the mean square error (MSE) as the loss function, as shown in Eq. (9).

$$\varepsilon(P) = \frac{1}{s}\sum_{k=1}^s\left(y(k) - \hat{y}(k)\right)^2, \tag{9}$$

where $y(k)$ represents the real value as labelled data, $\hat{y}(k)$ represents the predicted value, s is the number of samples, P is the parameter vector to be optimized.

3.2. Optimization strategy

The optimization in the KINN is for two types of parameters, 1) the data-related parameters including μ, σ, w_{ij} and $\mu(H_c)$, and 2) the knowledge-related parameters of w_k and β_c.

3.2.1. Data-related parameter optimization

In the optimization of data-related parameters, $y(k)$ denotes the real value of the oil state, which has been labelled based on expert recog-

Table 1
Optimization parameters and neurons of KINN layer.

Layer	Indicator	Attribute	Grade	Rule	Belief	State
Number of neurons	r × g	r	N	n	1	1
Parameters	μ, σ	w_{ij}	-	w_k, β_c	-	$\mu(H_c)$

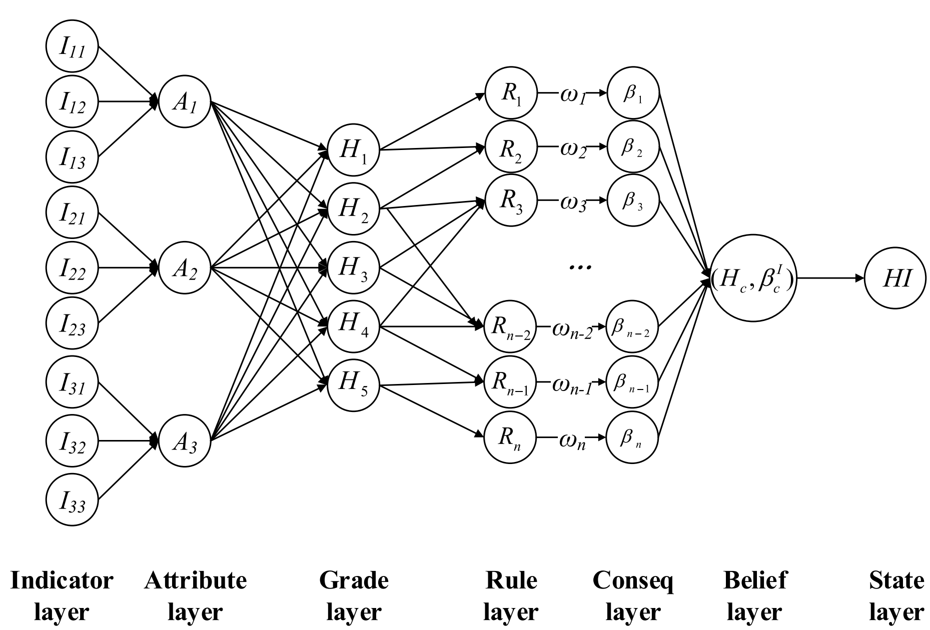

Fig. 2. The structure of KINN characterization and quantization of oil state.

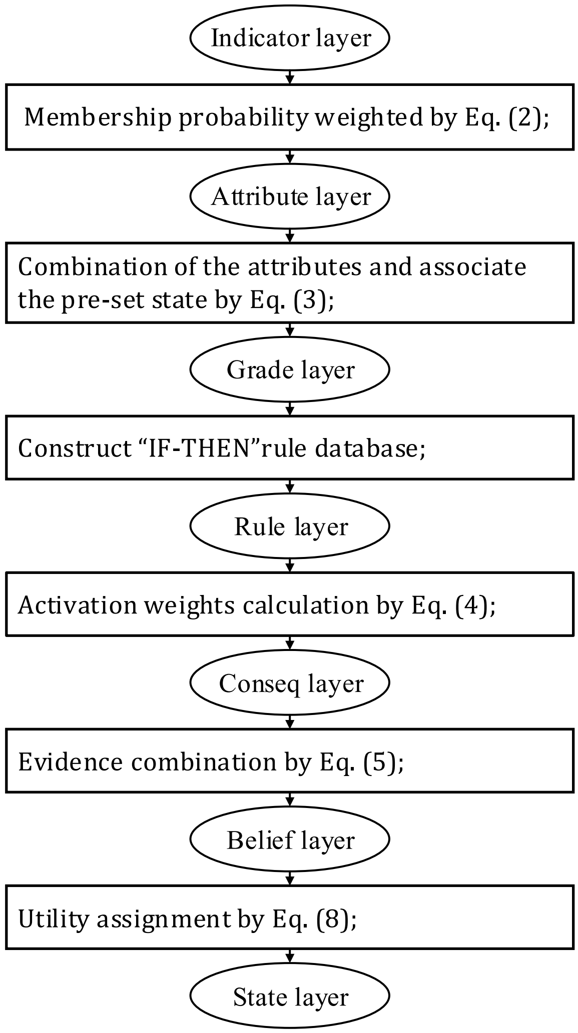

Fig. 3. The connect relationship of the layers in KINN.

nition. The predicted value $\widehat{y}(k)$, the output of the I-A-S model, is iteratively updated through the comparison with the real value $y(k)$. When the minimum loss function $\varepsilon(P)$ in Eq. (9) is searched by the gradient descent optimization algorithm (GDA) [27], the optimization of the model parameter vector $(\mu,\ \sigma,\ w_{ij},\ \mu(H_c))$ is then obtained. The schematic diagram is detailed in Fig. 4.

Moreover, the constraints of the parameters in I-A-S are constructed for indicator weight w_{ij}:

$$\begin{gathered}0\leq w_{ij}\leq 1, i=1,\ldots,r,\ j=1,\ldots,g,\\ \sum_{j=1}^{g}w_{ij}=1.\end{gathered}\tag{10}$$

For utility (H_c):

$$\begin{gathered}\mu(H_c)\geq 0, c=1,\ldots,N,\\ \mu(H_j)>\mu(H_i),\ j>i.\end{gathered}\tag{11}$$

3.2.2. *Knowledge-related parameter optimization*

In the optimization of knowledge-related parameters, it is difficult to obtain global convergence due to the interaction between parameters. In traditional methods, the setting depends on limited expert experience. To this end, the particle swarm optimization (PSO) algorithm is used to optimize the knowledge-related parameters from the data. As a member of metaheuristic algorithms, PSO searches for the optimal solution by iteratively refining the intermediate solutions [28].

3.2.3. *Stepwise parameter optimization strategy*

To prevent redundancy and over-fitting in the iteration process, a stepwise optimization strategy is proposed, in which two types of parameters are separately optimized step-by-step. First, the parameter set $\{\mu,\ \sigma,\ w_{ij},\ \mu(H_c)\}$ is obtained based on the data-related parameter optimization. Second, the knowledge-related parameters with the data-related parameters are searched by the PSO algorithm for global convergence. Finally, the parameters $(\ w_k, \beta_c)$ are generated. The specific process is shown in Fig. 5. The summarization of optimization information for different methods is shown in Table 2.

4. Model verification

To verify the performance of the proposed model, simulated data and real-world data are used. The simulated data is originated from the state-space model based on the degradation mechanism of lubricating oil, and the real-world data is collected from the real machines. Especially, the real-world data has been acquired from moving construction vehicles. Besides, the possible application objects beyond the presented case include large equipment with circulating lubrication systems, such as wind turbine, ship, nuclear power, mining equipment, etc.

4.1. *Verification with simulation data*

To simulate the lubricating oil degradation processes, the degradation tendency of viscosity [29], TBN [30], Fe content, Cu content [31], and Zn content [32] are developed. The mechanism model of oil indicator degradation is constructed according to the solution of the state-space model [33] shown in Eq. (12),

$$\frac{d(x(t))}{dt}=g(x(t))-f(x(t))+w(t),\tag{12}$$

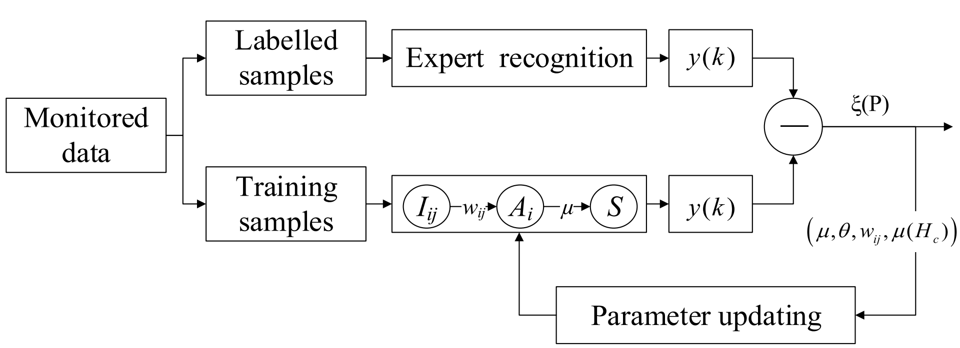

Fig. 4. Schematic diagram of parameter optimization for the I-A-S.

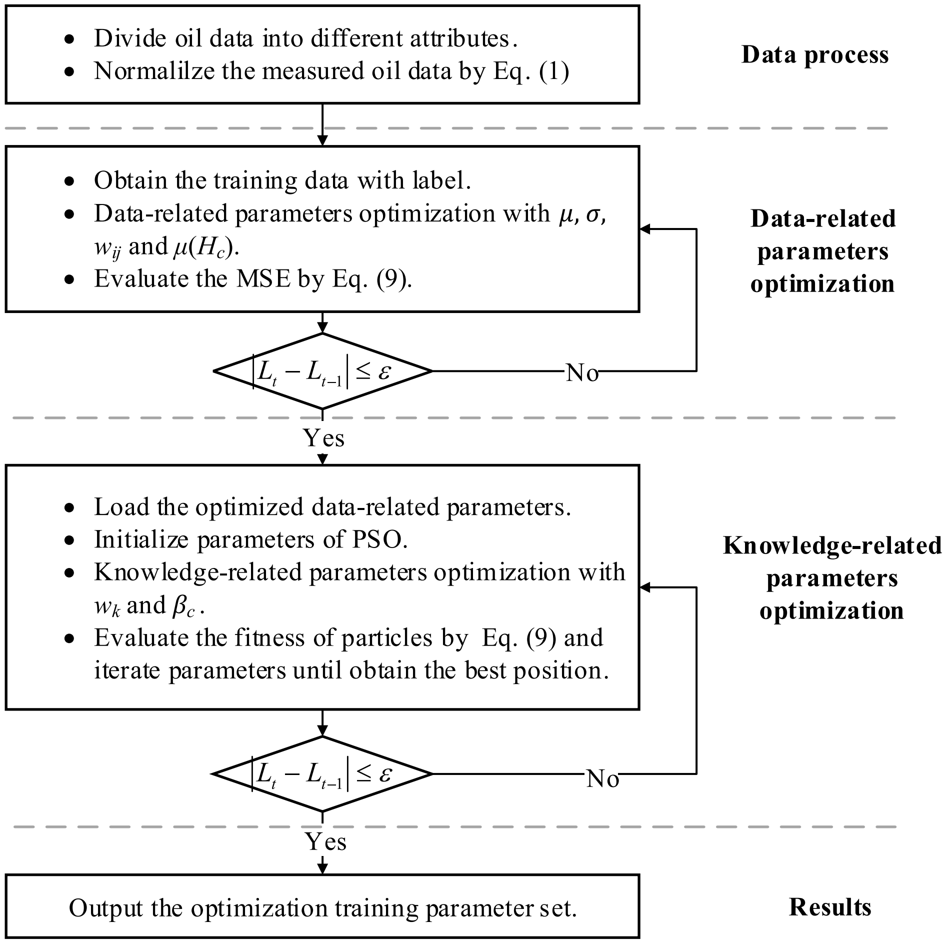

Fig. 5. Flowchart of the KINN training process.

Table 2
Key parameters of the optimization methods.

Method	Algorithm	Optimize parameters	Default parameters	Default parameter source
GDA	GDA	$\mu, \sigma, w_{ij}, \mu(H_c), w_k, \beta_c$	–	–
KINN-1p	PSO	w_k	$\mu, \sigma, w_{ij}, \beta_c, \mu(H_c)$	Expertise
KINN-2p	PSO	w_k, β_c	$\mu, \sigma, w_{ij}, \mu(H_c)$	Expertise
KINN-overall	PSO	$\mu, \sigma, w_{ij}, \mu(H_c), w_k, \beta_c$	–	–
KINN-stepwise	PSO and GDA	w_k, β_c	$\mu, \sigma, w_{ij}, \mu(H_c)$	Data-related parameter optimization

where $x(t)$ is the oil indicator data at time t, $g(x(t))$ is the function representing increment of indicator data, $f(x(t))$ is the function as the decrement of indicator data, and $w(t)$ is the random noise in the data acquisition process.

After integrating Eq. (12), we have

$$x(t) = a\exp(ct) - b\exp(dt) + w(t), \tag{13}$$

where a, b, c, and d are unknown parameters of model, $w(t)$ denotes the stochastic variation of the degradation process that is subject to the Gaussian distribution $N(\mu, \sigma^2)$.

The parameters of degradation models need to be determined to obtain simulation data. Then the interpolation least-squares method [34] is applied for parameter estimation based on the simulated data, and the estimation result is shown in Table 3.

In the training data simulation, it is assumed that oil degradation time is 2000 hr, and the sampling period is 10 hr. Consequently, 201 groups of oil data are simulated. These data are grouped as a training set, then the state of each sample is labelled. In the test data simulation, the oil running time is configured as 2000 hr and the sampling period is 16 hr. Totally 122 sets of oil simulation data within the 2000 hr operating cycles are produced, and all the simulation data are labelled with existing expert knowledge.

Table 3
Parameter estimation in the oil indicator degradation model.

	a	b	c	d	μ	σ
Viscosity	-0.1265	0	0.4407	0	2.7910 × 10-4	0.0116
TBN	2.6914	2.6536	0.1916	0	6.9523 × 10-7	0.0358
Zn	-9.5193	16.769	0.5091	0	4.9500	4.5977
Fe	25.067	0.6752	21.666	0.6869	0.0089	0.3368
Cu	0.1665	-0.7399	-1.0484	0.6373	3.5412 × 10-6	5.1607

4.1.1. Verification of the optimization strategy

Different optimization algorithms are examined by using the training data. The particle initialization of PSO is generated randomly, so the training data are trained six times repeatedly. The resultant (mean square error) MSE is shown in Fig. 6, where the thick line represents the mean value of several optimizations.

The GDA algorithm and PSO algorithm are compared for training all parameters in KINN. Their resultant MSE shows that the PSO algorithm presents much better performance. Furthermore, considering the PSO algorithm, the KINN-1p, KINN-2p, and KINN-overall methods with different parameters are compared. The KINN-2p algorithm has the minimum MSE. Finally, Comparing to the KINN-2p with the best performance, the KINN-stepwise presents improved performance and is selected as the optimization strategy.

4.1.2. State Characterization

The continuous value *HI*, which describes the degradation of the oil state, is obtained by training and testing the simulation data. The specific steps are shown in Algorithm 1 below.

The results using the test data set are shown in Fig. 7. It can be seen that the *HI* calculated by KINN can effectively represent oil degradation and the maximum absolute error is 0.05. The oil degradation tendency is accompanied by the increase of time, which proves that the oil is in a state of gradual evolution.

4.2. Verification with real-world data

As a comparison, the proposed method is verified by real-world data collected from 20 industrial vehicles for more than 1.5 years of monitoring. The target objects include engine oil, hydraulic oil, and gear oil flowing in the transmission system. Oil samples are periodically collected once a month, then the data from 5 indicators are selected from multiple indicators of off-line testing.

4.2.1. State Characterization

The indicator set $I = \{I_{11}, I_{12}, I_{21}, I_{22}, I_{31}\}$ and attribute set $A = \{A_1, A_2, A_3\}$ are constructed from multi-attribute oil data. Oil indicators including viscosity, TBN, Fe element content, Cu element content, and Zn element content, are used to construct the corresponding indicator set *I*. Oil attributes including physicochemical attribute, wear attribute, and additive attribute, are related to elements in the attribute set *A*. The collecting of some monitoring data is shown in Fig. 8.

In order to verify the robustness of the model, the training set is randomly selected from 425 sets of real-world data, which consists of 295 sets of training data, and the rest is used for validation. The results of the test data calculated by KINN are shown in Fig. 9. The predicted values of 130 sets of test data return high accuracy as compare to the real label. It illustrates that the KINN can accurately predict the uncertain oil state and obtain quantified *HI* for oil state characterization.

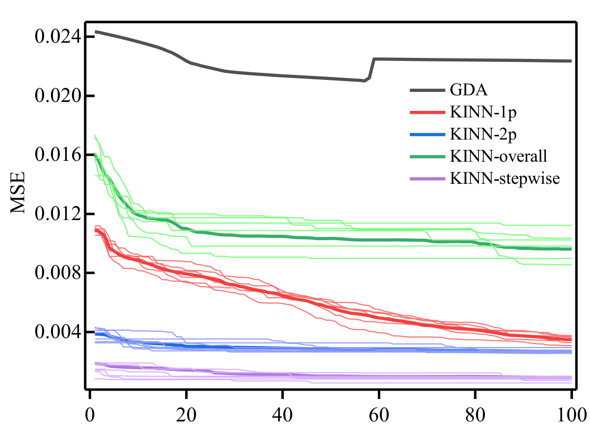

Fig. 6. The results of different optimization strategies.

Algorithm 1
The procedures of KINN of data training and testing.

Input: $A_i = \{a_{ij}\},\ i = 1, \cdots, r,\ j = 1, \cdots, g,\ y(k),\ \hat{y}(k),\ k = 1, 2, \cdots, s.$

1) Normalize the data according to Eq. (1), and the threshold value is selected according to the oil change standard.
2) Label each sample data based on expertise.
3) Train sample data with I-A-S parameter optimization, then obtain data-related parameters $\mu,\ \sigma,\ w_{ij},\ \mu(H_c)$.
4) Assign the trained parameters to the KINN, then optimize knowledge-related parameter vector $w_k,\ \beta_c$ with the PSO algorithm.
5) End training if $|L_t - L_{t-1}| \le \varepsilon$, where $\varepsilon = 10^{-6}$.
6) Compute the test data in the trained model to obtain the prediction value.
7) Compare the error between the predicted value and the real value.

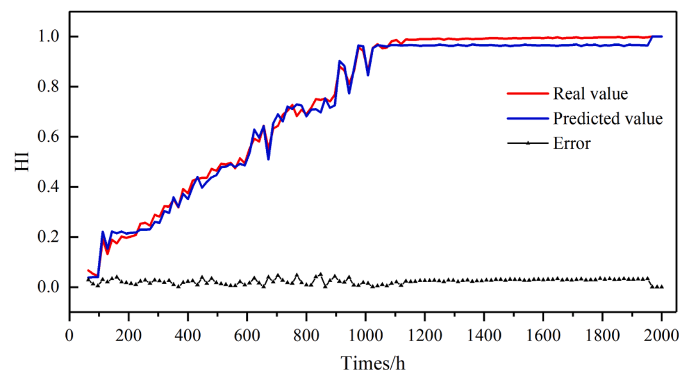

Fig. 7. The validation results of simulation data.

4.2.2. Performance evaluation

For the comparison of state modelling methods, performance indexes are used according to Eqs. (14) and (15). i.e., the root mean square error (RMSE) of the training set and the mean absolute error (MAE) of the test set.

$$RMSE = \sqrt{\frac{1}{s}\sum_{i=1}^{s}\left(y(k) - \hat{y}(k)\right)^2}, \tag{14}$$

$$MAE = \frac{1}{s}\sum_{i=1}^{s}\left|y(k) - \hat{y}(k)\right|. \tag{15}$$

Different methods of state characterization, including the dynamic evidential reasoning method (DER) [26], fuzzy inference system (FIS) [17], Adaptive Network-based Fuzzy Inference System (ANFIS) [21], and KINN with different strategies, are used for comparison. In the training process, the parameter optimization of DER, ANFIS, and KINN uses the same real-world data. Due to the inability to optimize, the setting of parameters in FIS is referred to KINN-stepwise instead of expertise. The evaluations of the comparison are shown in Table 4.

It can be seen that the proposed model presents the minimum RMSE after the training process. The weakness of the DER method is mainly caused by the negligence of conflicting judgments. In the traditional ANFIS, the rule database is formulated based on expert knowledge, so the result is better than DER. However, the RMSE result from its training set is larger than the KINN method due to the lack of enough information from the small oil sample set. Comparing the KINN methods with different optimization parameters, the KINN-stepwise method obtained the minimum RMSE as shown in Table 4.

The MAE of the test set presents a consistent tendency as the RSME in training. The KINN-stepwise and DER methods respectively obtain the minimum and the maximum MAE. The FIS method obtains the best optimization result except for the KINN-stepwise methods due to the suitable parameters, indicating that the trained parameters possess universality. To visualize all sample test errors, the absolute error is

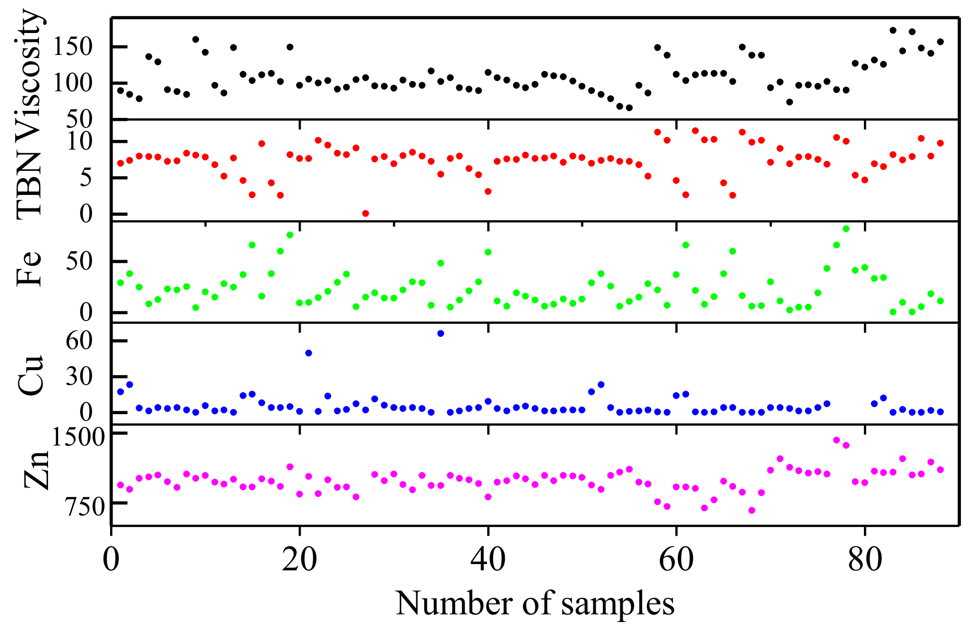

Fig. 8. The original data of hydraulic oil with five indicators.

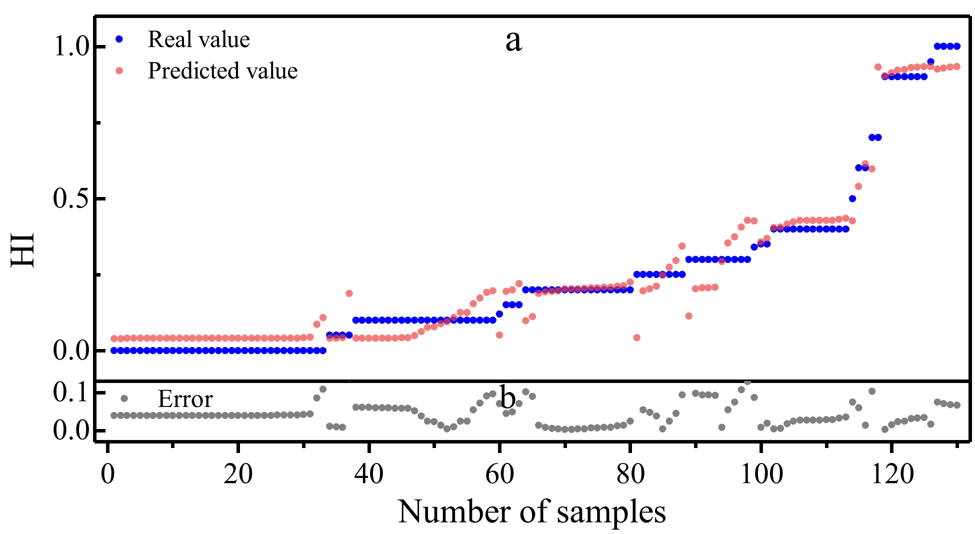

Fig. 9. The comparison of real data and predicted data, where a represents the results of the test data and b represents the error.

Table 4
The comparison of the training and test results of different methods.

Methods	Input	RMSE	MAE
DER	Viscosity, TBN, Fe, Cu, Zn	0.0354	0.1170
FIS	Viscosity, TBN, Fe, Cu, Zn	-	0.0481
ANFIS	Viscosity, TBN, Fe, Cu, Zn	0.0226	0.0756
KINN-overall	Viscosity, TBN, Fe, Cu, Zn	0.0153	0.0618
KINN-stepwise	Viscosity, TBN, Fe, Cu, Zn	0.0073	0.0460

defined as $|y(k) - \hat{y}(k)|$, and the comparison of errors is shown in Fig. 10. The maximum errors are coloured in dark blue. It is observed that the KINN-stepwise method presents the best consistency and the strongest robustness.

5. Conclusions

Due to the lack of sufficient data and their prior knowledge, the uncertainty in lubrication oil severely constrains the application of OCM in reliability assessment. Addressing the aleatory and epistemic uncertainties in oil state characterization, a new model is developed that integrates both the data and knowledge, which realized the mechanism-based state modelling and the dynamic data evolution detection. To handle the uncertainty of multi-attribute decision making, expert knowledge and mechanism knowledge were introduced to characterize the oil state. To be adaptive for continuous monitoring, the parameters of the model were optimized by the KINN model. Consequently, the proposed method was evaluated with various oil data sets. The main conclusions are as follows. 1) A mechanism-based three-layer structure model including indicator, attribute, and the state is proposed with the assigned probability distribution and knowledge-based rule inference. 2) To be adaptive to oil monitoring, a knowledge-integrated neural network is adopted for optimizing the model parameter. 3) The proposed model shows high performance in the experiment with both the simulated and real-world data.

There are still some limitations in the proposed method, and whether

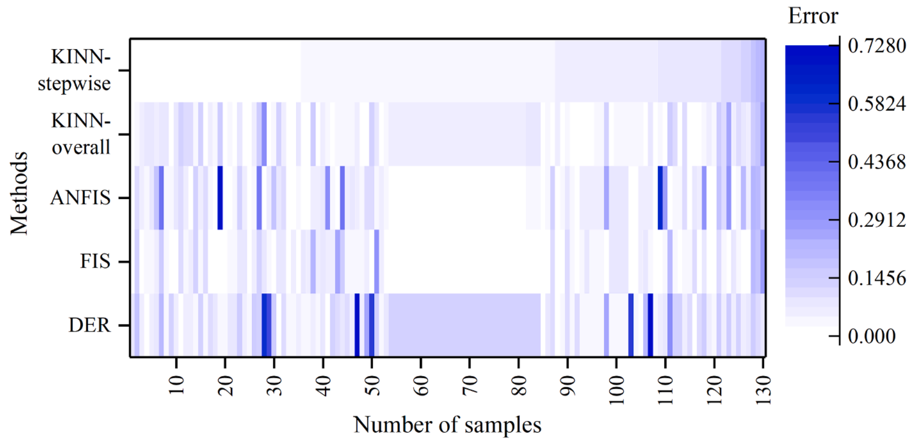

Fig. 10. The comparison of the errors of deferent methods.

the model works effectively relies on the detection of data tendency. Decision-making based on the laws of big data is plausible, but there are two challenges in practice. 1) It is difficult to obtain a large number of samples, especially the failure samples. 2) The accumulation of data is accompanied by the increase of uncertainty, which hinders accurate assessment. Therefore, in the future, we will conduct research on the generation of simulated data based on the oil degradation mechanism and real-world data. It is vital to explore the hidden information from the data and can provide the basis for reliability assessment.

Author Statement

Yan Pan: Conceptualization of this study, Methodology, data curation, Writing - Original draft preparation.

Yunteng Jing: Data curation, Software.

Tonghai Wu: Conceptualization of this study, Methodology, Writing - reviewing.

Xiangxing Kong: Data curation.

We would like to declare on behalf of the co-authors that there is no conflict of interest in the submission of this manuscript, and the manuscript is approved by all authors.

Declaration of Competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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