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A new intelligent method based on cognitive artificial intelligence for predicting transformer remaining useful life ☆,☆☆

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A R T I C L E I N F O

Method name:
Knowledge Growing System, Backpropagation Neural Networks

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A B S T R A C T

Electricity is essential in modern life, with consumption expected to rise by 80 % by 2024, making power transformers crucial. In developing countries, monitoring old-transformer power plants is often manually and infrequently, increasing damage and reducing transformer life. The lack of data limits the accuracy of machine learning, making traditional approaches less effective. This article introduces a new perspective through Cognitive Artificial Intelligence (CAI) with the Knowledge Growing System (KGS), which builds knowledge from scratch. KGS can detect and continuously learn about transformer degradation, improving predictive accuracy. This study demonstrates KGS's ability to estimate transformer life while comparing its predictions with the Backpropagation Neural Network (BPNN) method. Enhancing decision-making in strategic planning ensures a reliable power supply and better transformer performance. It also supports the implementation of more intelligent and reliable preventive maintenance strategies.
The method is as follows:

- The KGS method demonstrates that the transformer is in satisfactory condition, with an estimated health level of 87.5 % in Semester 2 and 75 % in Semester 1.
- The BPNN method estimates the transformer's RUL at 23.42 years, achieving the RUL of 20.55 years or 7500 days with a normal loss of life of 0.0133 % per day.

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Background

For analyzing the transformer RUL, it is essential to determine accurate predictions using reliable methods. This research uses a new intelligent method based on Cognitive Artificial Intelligence (CAI), called Knowledge Growing System (KGS), to predict the transformer RUL. KGS can handle a small amount of data, apprehending that the data for predicting the transformer RUL is not easy to acquire or is very limited. KGS is a CAI method built upon how knowledge is generated within the human brain with the cognitive psychology approach. The results show that KGS successfully delivers a good prediction on the transformer RUL, showing the prospective use of KGS as a helper in predicting the useful life of electrical equipment.

On the other hand, it would be beneficial to have a comparative method, which can also support the prediction results of KGS. In this case, we selected a machine learning method called backpropagation neural networks (BPNN) to gain more insights into the two methods. The KGS method facilitates the determination of the RUL, optimizing maintenance strategies, ensuring reliability, and managing costs in power distribution systems. Accurate RUL estimation enables timely maintenance actions, minimizes the risk of failure, and improves the overall reliability and efficiency of the power grid. The significance of this estimation is particularly important in terms of economic efficiency. The scheduling of maintenance activities is optimized, resulting in periodic maintenance, which is not always economically feasible, being avoided. This approach facilitates more efficient resource management, reduced operational costs, and extended transformer life without increasing the risk of failure.

In addition to the economic benefits, RUL estimation also improves the reliability of electrical power supply. Transformers are critical assets in energy distribution, and knowledge of the RUL allows operators to ensure the electricity supply remains stable. It is particularly salient in urban environments characterized by fluctuating electricity demand, where transformer failures can precipitate significant disruptions to the power grid. In the contemporary context, integrating renewable energy sources is a significant challenge confronting power systems. Given the increasing number of renewable energy sources, such as solar and wind power, which are inherently stochastic, transformers require close monitoring to ensure reliability. The RUL estimation facilitates the management of this challenge, ensuring that transformers can adapt to load changes and remain optimally operational in modern power grids. The KGS method is effective in dealing with the significant data limitations that can impact the accuracy of RUL prediction in the system. A primary challenge pertains to the quality of data, which is frequently incomplete or inconsistent, impeding the analysis process. Errors in prediction, reduced maintenance effectiveness, and increased transformer failure risk can all result from inaccurate or limited data.

Method details

This study applies the Cognitive Artificial Intelligence (CAI) method, called Knowledge Growing System (KGS) to predict the transformer RUL. KGS shows its superiority over Artificial Neural Networks (ANN) and Fuzzy Inference Systems (FIS) in predicting the health of a transformer by assessing its faults through the interpretation of the Dissolved Gas Analysis (DGA) based on the Doernenburg Ratio method. The health is assessed by calculating various influencing factors, such as ambient temperature, oil insulation condition, loading, insulation resistance, and grounding resistance. KGS performs learning by interaction with all influencing factors to RUL to generate its knowledge and uses its knowledge to predict the transformer life. The most probable prediction is shown by the highest value of the Degree of Certainty (DoC), which is measured in probability or percentage.

On the other hand, a machine learning method called backpropagation neural networks (BPNN) was also utilized to predict the transformer RUL using its conventional mechanism. BPNN generates knowledge by adjusting its connection weights through gradient descent optimization to minimize prediction errors. Both methods aim to improve prediction accuracy and support preventive maintenance strategies, ensuring reliable transformer performance and efficient power system management. The study used Mean Square Error (MSE) to measure the average squared difference between predicted and actual values to assess the BPNN predictive performance accurately. In addition, Mean Absolute Percentage Error (MAPE) was used to evaluate the BPNN relative percentage of error, which provides insight into the model's accuracy. The KGS method estimates the percentage of the health index, which provides a qualitative assessment of the condition of the transformer.

A comparative analysis was performed to test the two methods' predictive capabilities and practical application. The validation results show that the backpropagation method achieves a mean square error of 0.00 and a MAPE of 3.16 %, with a maximum accuracy of 100 %. On the other hand, the KGS method estimates the health level of transformers at 87.5 %, which shows its reliability in assessing the useful life of transformers. These two approaches can ensure the right decisions in transformer maintenance and lifecycle management, optimizing operational performance and long-term asset utilization.

Method validation

The validation is done using a new intelligent method, the KGS, and the validation results were compared with the prediction of the BPNN method. KGS was validated directly to the operator of the Sengkaling Substation. This research presents a new approach to predicting RUL using the KGS method. The first stage of this method is processing the main parameters obtained from various sensors or transformer monitoring systems. Next, the data normalization stage is required to ensure that the data are in the appropriate range, values 0 to 1. After the normalization process is completed, the adjusted data is analyzed using the New Knowledge Probability Distribution (NKPD). The NKPD aims to form a probability distribution for transformer conditions based on the most recent data. It is continuously updated so that KGS can identify new patterns and adaptively adjust its predictions. The results of the NKPD are then used in the final step, the Degree of Certainty (DoC). DoC is used to assess the system's confidence in the decision. In addition, RUL prediction also uses a comparison method that can support the KGS prediction results.

The method used for comparison is BPNN. BPNN uses weight and bias adjustments in the network, which are iteratively adjusted until the model achieves high accuracy in detecting RUL predictions. BPNN results require a lengthy training process, so periodic model updates are necessary. As an illustration, in the first semester, the percentage of transformer health level is 75 %. After proper maintenance, according to the transformer SOP in Indonesia, the transformer health level increased to 87.5 %. According to the Health Index (HI) standard, the value range set for transformer health under excellent conditions is 85–100 %. The KGS results are compared with the BPNN method, which shows 100 % network accuracy. The BPNN results show a very long training time to achieve high accuracy with very small MSE and MAPE values. This paper shows that RUL using KGS is a new and superior method that enables more timely and effective maintenance actions. It is the most effective method to achieve faster response to transformer maintenance. The results show that the new KGS method can accurately address the failures and damage to the transformer due to a lack of real-time maintenance.

Introduction

Electricity is a vital resource for modern society, used in many aspects of daily life [1]. The contemporary lifestyle has been shown to influence electricity consumption significantly. Projections indicate that global electricity demand will increase by up to 80 % by 2024 [2,3]. The necessity for electricity has become an essential part of everyday life. The electricity demand can raise concerns about the quality of the electricity supply [4,5]. The necessity for electricity can give rise to concerns regarding the quality of the electricity supply. Ensuring the reliable distribution of electrical energy is imperative to meet the ever-increasing demand, thus underscoring the necessity for power transformers.

Power transformers are required to have a long RUL, according to IEC 60,076, 2018 [6], of 20.55 years or 7500 days with a normal loss of life of 0.0133 % per day [2–4,7,8]. Nonetheless, many extrinsic factors can accelerate the deterioration of transformers. Consequently, to ensure reliability and preserve transformer performance, it is necessary to predict the RUL of the transformer [9,10]. In the operational context, transformers should be subjected to loads that do not exceed 80 % of their capacity. This approach is essential to ensure the transformer's continued efficiency and extend its operational useful life [4].

The extension of the service life of transformers is contingent upon maintaining their performance by implementing routine and scheduled maintenance procedures. The maintenance performed is preventative maintenance. Implementing effective maintenance practices is instrumental in enhancing the electrical system's reliability and mitigating the risk of transformer failure, thus reducing the impact on the stability of the electrical supply [11]. The maintenance of power transformers is an essential aspect of electrical engineering. It must be carried out with due consideration for factors that affect its RUL, such as operating load [12], ambient temperature, condition of the insulation oil, insulation resistance, and grounding. When a transformer operates with a load that exceeds the ideal limit, it is imperative to undertake periodic monitoring and evaluation of the loading to avert accelerated insulation degradation [13].

High temperatures have been shown to accelerate insulation degradation. Therefore, optimal cooling systems and routine inspections are required to detect potential overheating [14]. Furthermore, it is imperative to undertake insulation oil testing and maintenance to ensure the stability of its dielectric properties, thus preventing electrical failure. Considering these factors, an appropriate maintenance strategy can be implemented to extend the transformer's life and maintain the electrical system's reliability. The RUL of the transformer is predicted using two different approaches: the BPNN and the KGS method. These methods focus on integrating physical models with a data-driven approach, optimizing feature extraction, and utilizing uncertainty information. A study combining model-based and data-driven methods has the potential to overcome the limitations posed by non-linearity and small sample sizes [15,16].

Several research has predicted the RUL of transformers using the Health Index (HI) method, which numerically assesses the condition of transformers based on dielectric, thermal, mechanical, and electrical factors. The findings of these studies suggest that transformers with an HI of 0.45 at 15 years of age are likely to reach their designated useful life in 18.42 years, while new transformers are estimated to last up to 24.70 years. However, it should be noted that the accuracy of these predictions can be affected by limitations in measurement data [17]. In a separate research study, another model using a dual exponential degradation model and Gated Recurrent Units (GRU) showed improved accuracy in predicting the RUL of transformers under limited data conditions [18]. In small datasets, Data-Driven Engineering Systems (DES) are the preferred option due to their simplicity and ability to minimize overfitting.

However, it should be noted that DES is less capable of capturing complex temporal dynamics. The GRU model is more robust but is prone to overfitting and computational inefficiency when data is limited. The employment of frameworks incorporating multi-sensor data, feature fusion, and graph convolutional autoencoders has been demonstrated to enhance the interpretation and prediction accuracy of transformer RUL [19], due to inadequate infrastructure, this approach cannot be applied. In order to overcome data limitations, the transformation of historical data into a lifetime matrix allows for the integration of uncertainty, thereby improving prediction accuracy [20]. A significant proportion of the research described uses prediction of RUL with supervised and semi-supervised learning, where researchers use unlabeled data to reduce the challenges posed by data scarcity, thereby improving model robustness. In conjunction with the advancement of CAI and machine learning technologies, numerous methods have been proposed to enhance the accuracy of predicting the RUL of transformers.

Related works

In the research [21], the Health Index (HI) method was used with 33 transformers as the research's subject to identify the transformers' condition. The parameters encompassed in the study included loading, oil quality, and grounding resistance. The findings indicated that transformers exhibiting HI values ranging from 40 % to 75 % were deemed to be in a state of suboptimal condition. This factor was found to increase the probability of transformer failure. The study of [21] employed a range of HI methods (including Type I, II, III, WSS-Based, CA-Based, FL-Based, RA-Based, Pa-Based, and AI-Based) with a single transformer as the object of research to identify the monitoring of power transformer conditions. The parameters utilized encompassed the results of dissolved gas and oil (DGA) testing. The findings indicated that HI levels ranging from 70 % to 80 % signified optimal transformer conditions, as evidenced by the superiority of the AI-based algorithm in comparison to alternative methods. The AI-based method is favored because it establishes a fundamental correlation between the condition data and the transformer health index [22] .

The Enhanced Health Index (EHI) method, a development of the standard Health Index (HI) method, was utilized in the study [23] with 204 transformers as the object of research. The parameters employed encompass Dissolved Gas Analysis (DGA), Oil Quality Factor (OQF), and the transformer's average daily load. The results obtained from this study indicated that 7 transformers exhibited an HI value ranging from 50–70 % (fair condition), 78 transformers demonstrated an HI value ranging from 70–85 % (good condition), and 119 transformers showed an HI value ranging from 85 %–100 % (very good condition).

The study [24] utilized the General Regression Neural Network (GRNN) method on 30 transformers as the object of research to identify an enhancement in the accuracy of assessing the overall condition of the transformers. The parameters utilized encompass the findings of tests conducted to ascertain dielectric strength, acidity, and water content. The findings indicated that among the 30 transformers classified as good condition, 83 % exhibited satisfactory performance. This method is reliable and highly effective in automatically calculating health indices, thus facilitating the transformer condition assessment. Research [25] employs the Health Index (HI) method on Transformer 5 (T5) conditions with seven transformers under investigation to assess transformer conditions and inform maintenance decisions. The parameters employed encompass a comprehensive array of assessments, including the turn ratio test, winding resistance test, power factor test, short-circuit impedance, dissolved gas analysis (DGA), CO_2/CO ratio, dielectric strength, interfacial tension, and frequency domain spectroscopy. The obtained results indicate that the health value of Transformer 5 (T5) was 85 %, which is considered suspicious because it indicates that it is in the poor condition category.

Research by [17] utilizing model- and data-based methods has successfully overcome non-linearity and small sample sizes. The dual exponential degradation model and Gated Recurrent Units (GRU) have demonstrated enhanced accuracy in RUL prediction in circumstances where data is limited. The findings demonstrate that the proposed method exhibits robust performance in both data-leakage and non-data-leakage scenarios, surpassing the efficacy of standalone methods in producing precise RUL predictions in limited sample datasets. Finally, this study is dedicated to integrating physical and data-driven models to overcome the challenges of data irregularities in future research.

Research [19] demonstrates that for small datasets, Data-Driven Engineering Systems (DES) may be preferable due to their simplicity and reduced risk of overfitting, but this model has limitations in capturing complex temporal dynamics. Conversely, despite its enhanced robustness, GRU necessitates meticulous management to circumvent overfitting and computational inefficiency when data is limited. A framework that utilizes multi-sensor data and feature fusion improves interpretability, and graph convolutional autoencoders improve the accuracy of the RUL lifecycle. Research [11] employs the Combined Duval Pentagon (CDP) and Modified Combined Duval Pentagon (MCDP) methods to diagnose early faults in transformer isolation systems. The parameters employed encompass the concentration of furans (2-FAL), CO_2, CO, and methanol (MeOH). These variables are then used as input for the fuzzy inference model, with the output being an estimation of the insulation's degree of polymerization (DP). The findings demonstrate the efficacy of the developed fuzzy inference model, which can accurately estimate the insulation's degree of polymerization (DP). The model's performance is compared to other mathematical models, including ANFIS and previous fuzzy logic models. For instance, for transformers with a DP value greater than 1000, the model indicates that the paper insulation is in excellent condition. Conversely, for transformers with a DP value <250, the model signals that the paper insulation is approaching the end of its useful life.

Research by [25,26] utilized the Load Curve method, employing a single-tested transformer. The parameters encompassed in the study included transformer loading, transformer oil insulation (BDV, water content, acidity, IFT, and color and appearance), and ambient temperature. The findings indicated that, among the various parameters examined, transformer loading substantially influenced the rate of decline in the RUL of the transformer. It was determined that when the load reaches 80 % of its capacity, the transformer can be said to be overheating. The findings of transformer load measurements from 2021 to 2023 demonstrate that the maximum load is anticipated in December 2023, reaching 73.00 % in the ONAF transformer type. Predictions indicate that the RUL of the transformer in 2023 is 24.48 years, decreasing to 23.51 years in 2024 and 22.53 years in 2025. To maintain the operational life of the transformer, measures to mitigate identified risks are to be implemented following the Indonesian Electric Power Transformer SOP. This mitigation includes periodic inspections to identify problems such as insulation aging, oil leaks, or signs of wear. Two distinct approaches are employed to address this challenge: the backpropagation method and the KGS. The latter can monitor the condition of the transformer by predicting its RUL.

Research method

The research is in the Sengkaling area of Malang Regency, East Java, Indonesia. The Sengkaling Substation that functions in the regional electricity network distributes electricity to the Customer Service Unit (CSU) subsystem for the Batu, Dau, Dinoyo, and Pendem areas, as well as centers of education and housing. The area is located near the banks of the Brantas River, combining residential zones, agricultural land, and educational institutions. The exact coordinates of the substation are recorded at 7°54′17 ′LS and 112°34′26′ BT. Sengkaling Substation has a medium voltage (150 kV) transmission network integrated into the Java-Bali system. Sengkaling Substation is important in providing a reliable and stable electricity supply, driving economic growth, and improving the quality of life for customers in the surrounding area.

Knowledge growing system

KGS aims to naturally mimic the human inference system's ability to develop knowledge. It is necessary to have a complete understanding of the mechanisms that occur within it. The human inference system model is illustrated in Fig. 1. In this model, the input is conceptualized as a phenomenon occurring in the environment, which can be physical or non-physical [16]. Physical inputs are characterized by their sensory properties, namely touch, sight, and perception, which facilitate recognition. Conversely, non-physical inputs, such as information obtained through communication with other individuals, are more challenging to identify due to their intangible nature. The subsequent processes within the human brain can be categorized into the three steps that have been previously delineated. The final element of the model is the system output, which manifests as new knowledge [27].

Mathematical modeling of human inference system (HIS)

The overarching objective of the human inference system is to obtain novel insights into the dynamics of the environment. The acquisition of new knowledge is a process that unfolds through three distinct phases [28,29]. Initially, there is the integration of information, wherein the data relayed by the sensory organs is amalgamated to generate a comprehensive understanding. Subsequently, the process of information inference ensues, which pertains to the mechanism through which conclusions are derived from the integrated information. Finally, the culminating step is the fusion of information inferences, where inferences derived from the amalgamated information are methodically combined to yield new knowledge [30].

The human organism is equipped with five sensory organs that enable the perception of physical and non-physical phenomena in the environment [30]. The relevant sensory organ then interprets these phenomena as information for subsequent processes. The brain then integrates the information the individual's sensory organs provide to obtain comprehensive information. In this model, we assume that each new piece of information is the product of the combined information perceived by two or more sensory organs or sensors. Based on this HIS concept, we generalize the model to a system equipped with sensors. Where λ is the number of inferences from the combined information, and δ is the number of source information or sensors [31]. In the case of humans with $\delta = 5$, there will be $(2^5 - 5) - 1 = 26$ combinations of combined information or clusters [28]. This value is obtained under the assumption that there is no merging of information for information conveyed from one pair of sense organs, such as the eyes and ears [30]. Each combination will have its own information-inference, as shown in Eq. (1).

$$\lambda = \left(2^{\delta} - \delta\right) - 1 \tag{1}$$

It is necessary to observe it periodically to comprehend a specific phenomenon. Through this method, the brain acquires new information-inference over time, which is then combined to generate knowledge about the observed phenomenon once sufficient observations have been made. In essence, the sense organs perceive the dynamics of the environment and transmit the information they collect about the perceived phenomenon to the brain [16,27,32]. The subsequent process entails the brain combining this information with its existing knowledge to formulate conclusions through reasoning. The resultant information comprises all sensory data and previously accumulated knowledge, which is then utilized as a foundation for estimating the observed phenomenon. This estimate is measured by a term called Degree of Certainty (DoC) [29], which undergoes fluctuations as additional information is received from the senses over time.

The concept of knowledge growing system (KGS)

As illustrated in Fig. 2, the growth of knowledge in KGS can be conceptualized as an extension [27,28]. The system employs sensors to perceive the environment, and the gathered information is subsequently directed to the inference system, where it is processed to generate new knowledge. This knowledge is stored in the Knowledge Base (KB) as a foundation for subsequent knowledge development steps. In each step of the knowledge development process, the system utilizes information inference fusion to acquire new knowledge. Once the observations are deemed sufficient, the latest knowledge is obtained by applying information-inference fusion.

KGS is a conceptual framework or methodology designed to facilitate knowledge growth by aggregating new information, acquiring insights from data, and improving and refining ongoing knowledge [30]. KGS typically processes information from a variety of sources, including sensors, environmental data, and human input. This information is combined with filtering, analysis, and updating mechanisms to create and improve existing knowledge [29]. In general, knowledge will be generated as information increases over time. The KGS concept emerged from observations of the mechanisms that occur in the human brain when it fuses information and references to gain new knowledge by developing the Human Inference System (HIS) model [16]. It is used as the KGS model shown in Fig. 1 and Eq. (1).

Based on Fig. 2, we develop knowledge of growth mechanisms for the designed system. It is a process to obtain new knowledge from information collected and conveyed from a phenomenon observed by the senses through a five-step process: information merging, information inference, information fusion, knowledge inference, and knowledge inference fusion. A mechanism of knowledge generation that occurs in KGS modeling, as shown in Fig. 2, shows the probability of the new knowledge called Degree of Certainty

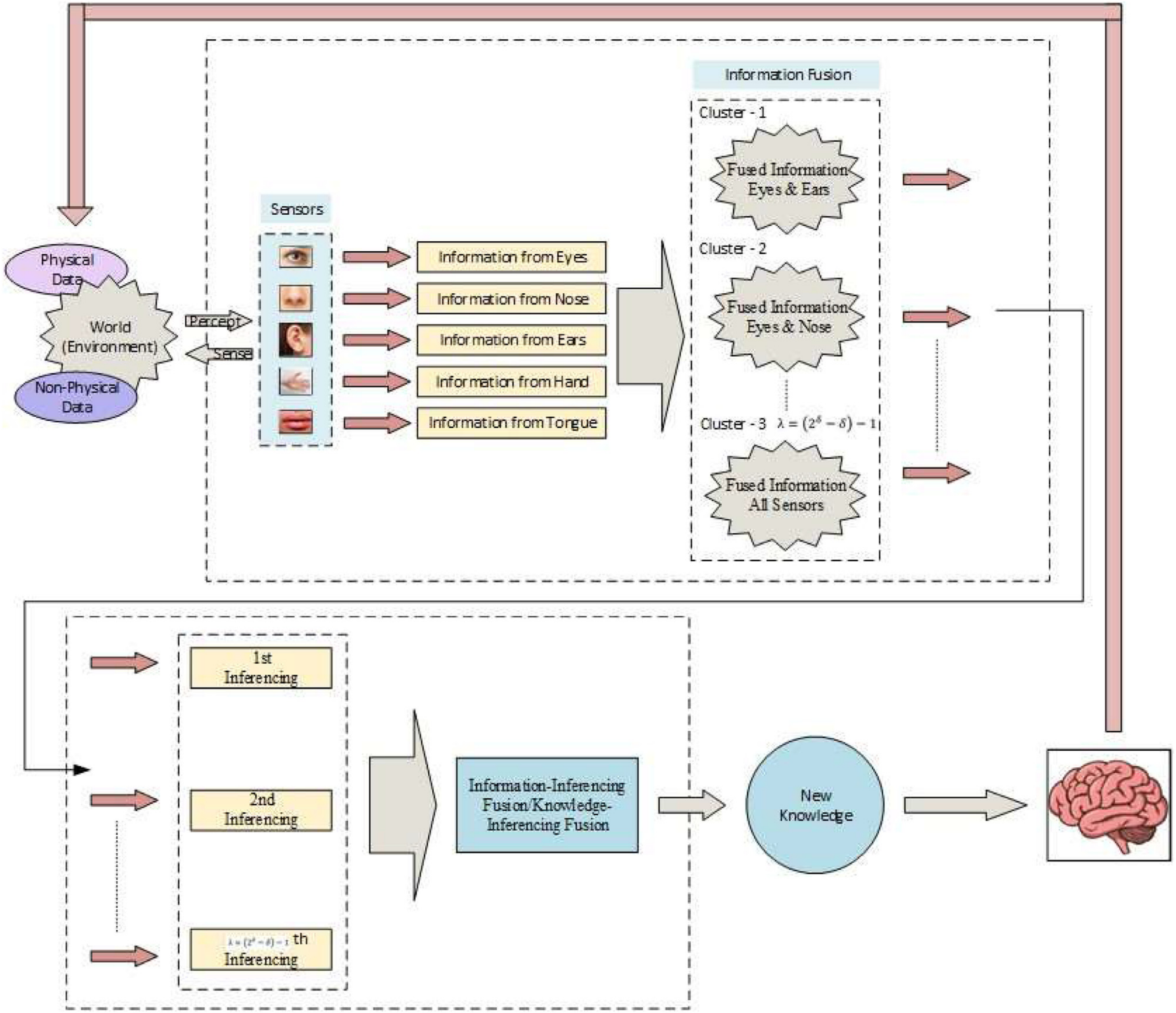

Fig. 1. A simplified illustration of a human inference system.

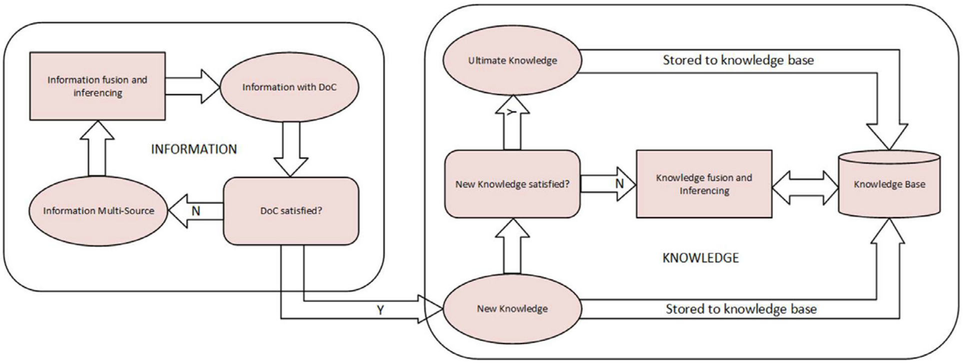

Fig. 2. The Concept of Knowledge Growing System.

(DoC). DoC is a value that determines the certainty of new knowledge about the observed phenomenon. DoC can be obtained by applying the ASSA2010 (Arwin Sumari-Suwandi Ahmad) information-inferencing fusion method. Several steps must be taken to develop knowledge, such as knowledge base and fusion mechanisms. The combination is done by integrating the information received with pre-existing knowledge or information [30,33]. This knowledge results from a combination of new and existing information, known as processed or posterior information. The ASSA2010 version that considers the time parameter in its calculation is called OMASSA2010 (Observation Multi-time Arwin Sumari-Suwandi Ahmad) information-inferencing fusion method.

For each step, the following will be applied [16].

(1) Process 1 (P-1)

Implementing the Bayes Inference Method (BIM) achieves the fusion of information received from sensors [27]. The rationale behind the development of a methodology termed ASSA2010 information-inferencing fusion is outlined below [30]. This methodology will be employed in the subsequent process to derive inference from the information fusion resulting from P-1. The ASSA2010 method is outlined in Eq. (2).

$$P\left(\psi_i^j\right) = \frac{\sum_{j=1}^{\delta} P\left(v_i^j\right)}{\delta} \tag{2}$$

Data is collected using parameters and then compared with established standards and relationships. In this context, NKPDT is knowledge developed during interaction time, while $P(\psi_i^j)$ is the NKPD indicated by the notation '1' The decision taken from the NKPDT is referred to as the Estimated NKPD and is measured by the DoC [29].

(2) Process 2 (P-2)

The KG mechanism will be carried out from time to time on P-2, where inferences collected over a period will be combined and then summarized to obtain final inferences. This inferencing is also obtained by applying Eq. (3). This final inference will be expressed as new knowledge because of KGS learning over time.

$$P\left(\psi_\tau^j\right)\text{estimate} = \odot\left[P\left(\psi_\tau^j\right)\right] \tag{3}$$

Meanwhile, $P(\psi_\tau^j)$ estimate is knowledge obtained from the NKPD and is indicated by the notation '1', while for binary representation of $P(\psi_\tau^j)$ in preparation for a multi-time knowledge generation. Decisions will be made based on the highest DoC in the NKPDT matrix shown in Eq. (2) and (3) [16,27,32,33]. A two-time process uses the OMASSA2010 [31].

Backpropagation neural networks (BPNN)

The BPNN method is an algorithm used for training artificial neural networks to reduce output errors when predicting the RUL of transformers [34]. This algorithm can adjust the weights based on the error gradient, with each training step dedicated to reducing overall error [30,35]. This advantage allows the application of backpropagation to various problems, including classification, regression, and pattern recognition. The BPNN algorithm accurately defines the relationship between independent variables [16]. In the context of predicting the RUL of a transformer [36], the independent variable is considered a function of the input layer, the hidden layer, which processes and transforms the input data, and the output layer, which represents the dependent variable [37], in the backpropagation topology shown in Fig. 3.

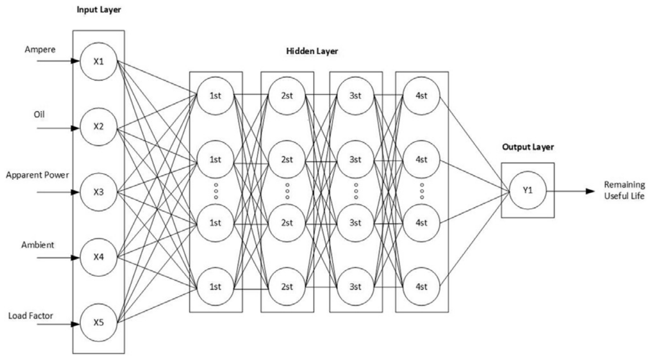

Fig. 3. Backpropagation topology.

Table 1
Data collection of transformer.

No	Date	Current (A)	Oil	Apparent power (MVA)	Ambient	K	RUL (Year 2023)	RUL (Year 2024)	RUL (Year 2025)
1.	21/01/2021	876	50	31.08	30	0.52	24.98	23.98	22.98
2.	22/01/2021	1060	50	37.19	30	0.62			
3.	23/01/2021	1120	50	39.41	30	0.66			
4.	21/02/2021	892	50	31.48	30	0,52			
5.	22/02/2021	937	50	32.95	30	0.55			
6.	23/02/2021	1072	50	37.78	30	0.63			
7.	21/03/2021	1041	50	36.50	30	0.61			
8.	22/03/2021	1027	50	36.00	30	0.60			
9.	23/03/2021	1052	50	37.11	30	0.62			
10.	21/04/2021	906	50	31.87	30	0.53			
11.	22/04/2021	1027	50	36.00	30	0.60			
12.	23/04/2021	1023	50	36.12	30	0.60			
13.	21/05/2021	901	50	31.77	30	0.53			
14.	22/05/2021	1009	50	35.41	30	0.59			
15.	23/05/2021	998	50	35.27	30	0.59			
16.	21/06/2021	950	50	33.44	30	0.56			
17.	22/06/2021	998	50	35.05	30	0.58			
18.	23/06/2021	1206	50	42.35	30	0.71			
19.	21/07/2021	975	50	34.23	30	0.57			
20.	22/07/2021	1002	50	35.19	30	0.59			
21.	23/07/2021	1195	50	41.97	30	0.70			
22.	21/08/2021	931	50	32.75	30	0.55			
23.	22/08/2021	896	50	31.58	30	0.53			
24.	23/08/2021	1200	50	42.14	30	0.70			
25.	21/09/2021	931	50	32.75	30	0.55			
26.	22/09/2021	902	50	31.77	30	0.53			
27.	23/09/2021	1208	50	42.42	30	0.71			
28.	21/10/2021	992	50	34.82	30	0.58			
29.	22/10/2021	1037	50	36.40	30	0.61			
30.	23/10/2021	1208	50	42.42	30	0.71			
31.	21/11/2021	1000	50	35.12	30	0.59			
32.	22/11/2021	1008	50	35.39	30	0.59			
33.	23/11/2021	1204	50	42.32	30	0.71			
34.	21/12/2021	1000	50	35.12	30	0.59			
35.	21/12/2021	1023	50	35.90	30	0.60			
36.	23/12/2021	1256	50	44.05	30	0.73			

The proposed methodology consists of the following steps:

(a) Data Collection:

The data set used includes data from Current (A), Oil, Apparent Power (MVA), Ambient, and Load Factor (K). It is collected for use in Backpropagation model training.

The data presented in Table 1 and Fig. 3 contains parameters of the electrical network that record current (Amps), power (MVA), ambient temperature, and load factor K, which may be related to the operating condition or aging of the transformer. From the table, the operational load varies between 31.08 MVA and 44.05 MVA, while the ambient temperature remains at 30 °C. The IEC 60,076, 2018 [38] standard asserts that the RUL of transformers is significantly influenced by operating temperature and load. The

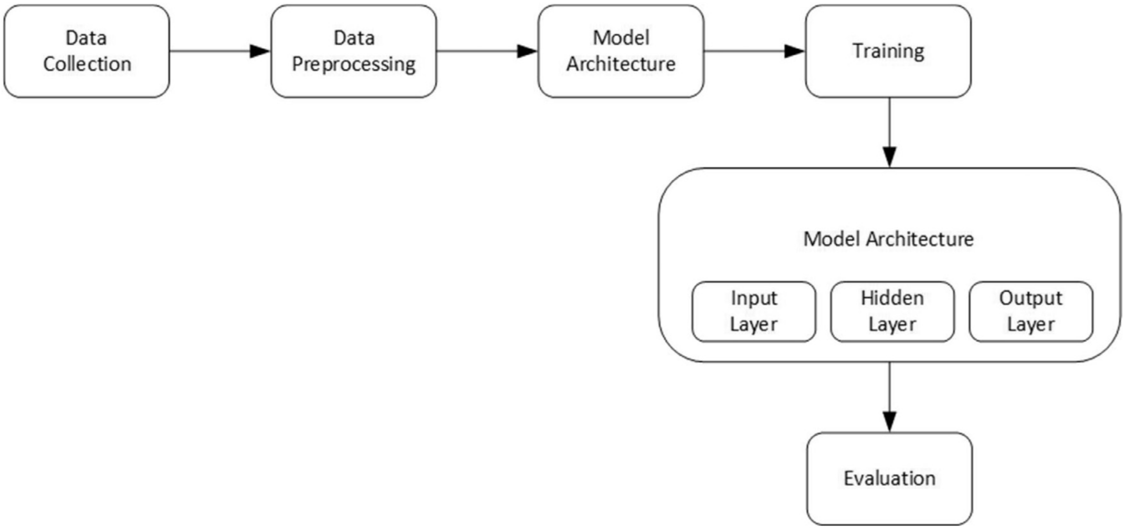

Fig. 4. Methodology followed.

IEC stipulates that the maximum oil temperature should not exceed 98 °C, and the maximum winding temperature should be below 110 °C to ensure the insulation remains in optimal condition. Exceeding these limits has been shown to lead to a marked increase in the rate of insulation degradation, which in turn accelerates the aging process of the transformer.

Furthermore, the K factor, which is presented in tabular form, has a range of 0.52 to 0.73. It can be indicative of the rate of acceleration of transformer aging. The IEC 60,076, 2018 guidelines utilize a hotspot factor to determine the impact on the insulation life. Higher K values may indicate harsher operating conditions, accelerating the transformer's useful life decrease. The data analysis in the table indicates several instances where the loads are near or exceed the standard capacity, particularly at MVA values greater than 40. The concomitant increase in winding temperature can accelerate the insulation aging process. Additional data, including oil and winding temperatures and maximum load history, are required to achieve a more accurate analysis of the RUL.

(b) Data Preprocessing:

A normalization process standardizes input features and target variables, ensuring a uniform scale. In addition, the dataset is partitioned into different training and testing sets.

(c) Model Architecture

The model architecture used in the Backpropagation method consists of several main layers: the input, hidden, and output layers. The input layer receives the normalized data, which is then passed to one or more hidden layers. Each neuron in the hidden layer uses a nonlinear activation function, such as Rectified Linear Unit (ReLU), to capture complex relationships in the data [39]. The model also uses batch normalization after each hidden layer to improve training stability. In addition, a dropout layer is applied as a regulatory technique to prevent overfitting by randomly ignoring several neuron units during training. At the output layer, the model generates predictions using linear activation [40–43].

(d) Training

The training phase uses an optimizer with a learning rate set to 0.01. Training is carried out over several epochs until the model converges or the error does not change significantly. After training, the model is evaluated using a validation set, and parameters such as learning rate or number of neurons can be adapted to improve model performance, as shown in Fig. 4.

(e) Evaluation

Model evaluation is performed on a test set to measure predictive performance. Several performance metrics, including Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and R-squared, are calculated to assess the model's effectiveness, as presented in Table 2.

Result and discussion

RUL using the KGS method

This research uses the KGS method to predict the RUL transformer in the substation. This research is in the Transmission Service Unit and Substation (ULTG) and Transmission Service Unit (UPT). The data used in this research were obtained from PT PLN (Persero)

Table 2
MAPE value.

MAPE	Evaluation
MAPE ≤ 10 %	High Accuracy Forecasting
10 % < MAPE ≤ 20 %	Good Forecasting
20 % < MAPE ≤ 50 %	Reasonable Forecasting
MAPE	Inaccurate Forecasting

Table 3
The data represents the normalized transformer RUL prediction.

Prediction	Observation Time	Year RUL	Parameters of transformer							
			Ambient Temperature	Insulation of transformer oil				Loading	Insulation resistance	Grounding resistance
				BDV	Acidity	IFT	Color and appearance			
S1	y_1	2021	0.50	0.00	0.94	1.00	0.00	0.00	1.00	1.00
	y_2	2022	1,00	0.37	0.00	0.12	1.00	0.52	0.00	0.00
	y_3	2023	0,00	1.00	1.00	0.00	0.22	1.00	0.00	0.00
S2	y_1	2021	0.00	0.00	0.94	1.00	0.00	0.00	1.00	1.00
	y_2	2022	0.13	0.37	0.00	0.12	1.00	0.03	0.00	0.00
	y_3	2023	1.00	1.00	1.00	0.00	0.22	1.00	0.00	0.00
Average	y_1	2021	0.25	0.00	0.94	1.00	0.00	0.00	1.00	1.00
	y_2	2022	0.57	0.37	0.00	0.12	1.00	0.27	0.00	0.00
	y_3	2023	0.50	1.00	1.00	0.00	0.22	1.00	0.00	0.00

Table 4
Converted transformer RUL prediction data for KGS input (NKPD).

Prediction	Observation Time	Year RUL	Parameters of transformer							
			Ambient Temperature	Insulation of transformer oil				Loading	Insulation resistance	Grounding resistance
				BDV	Acidity	IFT	Color and appearance			
S1	y_1	2021	1	1	1	1	1	1	1	1
	y_2	2022	1	1	1	1	1	1	1	1
	y_3	2023	0	1	1	1	1	1	1	1
S2	y_1	2021	0	1	1	1	1	1	1	1
	y_2	2022	0	1	1	1	1	0	1	1
	y_3	2023	1	1	1	1	1	1	1	1

UPT Malang and the Meteorology, Climatology and Geophysics Agency. The parameters analyzed include ambient temperature, transformer oil insulation characteristics (BDV, Acidity, IFT, Color and Appearance), Loading, Insulation Resistance, and Grounding Resistance. The data was collected over a certain period, as shown in Table 3.

The KGS method processes the learning-by-interaction data to predict the transformer's RUL more accurately. The prediction results are expected to assist in decision-making related to transformer maintenance and replacement, thereby improving the electrical system's reliability at the substation.

The data results for the Knowledge Growing System are obtained by applying the methodology described in Table 4 to the predicted RUL of the transformer. The mean value per year is then utilized as a threshold to calculate the predicted RUL of the transformer at each location (x_{ij}). This value is then converted into binary data '0' or '1', depending on the value. The results of this conversion are presented in Table 6 and form the basis for applying the equation in the KGS, as illustrated in Eq. (2). The initial step in this process aims to identify the value of '1' that will be used in the probabilistic learning method to improve prediction accuracy.

The dataset utilized in this study is presented in Table 4 and encompasses the outcomes of employing the KGS formula in the form of NKPD. The calculation in KGS refers to the inference fusion method introduced in ASSA2010. In this context, the symbol δ represents the number of sensory organs or sensors that observe a particular phenomenon in an area. The variable $P(v_i^j)$ is employed to assess the characteristics of phenomenon i compared to hypothesis j. Furthermore, the results of the NKPD model at time t for initial interaction are represented by the variable $P(\psi_\tau^\delta)$. When multiple examples are present at a given time, the value '1' is adjusted to reflect the relevant interaction [44].

Following acquiring the NKPD's mathematical model, the existing data will be transformed into a (DoC model, as shown in Table 5 and Eq. (4).

$$\mathrm{DoC} = \left|P(\psi)\mathrm{estimate} - P\left(\upsilon_j^i\right)\right| \mathrm{x}100\% \tag{4}$$

Table 5
Prediction data of remaining useful life of DoC results.

Prediction	Observation Time	Year RUL	Parameters of transformer							
			Ambient Temperature	Insulation of transformer oil				Loading	Insulation resistance	Grounding resistance
				BDV	Acidity	IFT	Color and Appearance			
S1	y_1	2021	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
	y_2	2022	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
	y_3	2023	0.09	0.13	0.13	0.13	0.13	0.13	0.13	0.13
S2	y_1	2021	0.07	0.13	0.13	0.13	0.13	0.13	0.13	0.13
	y_2	2022	0.06	0.14	0.14	0.14	0.14	0.11	0.14	0.14
	y_3	2023	0.07	0.14	0.14	0.14	0.14	0.11	0.14	0.14

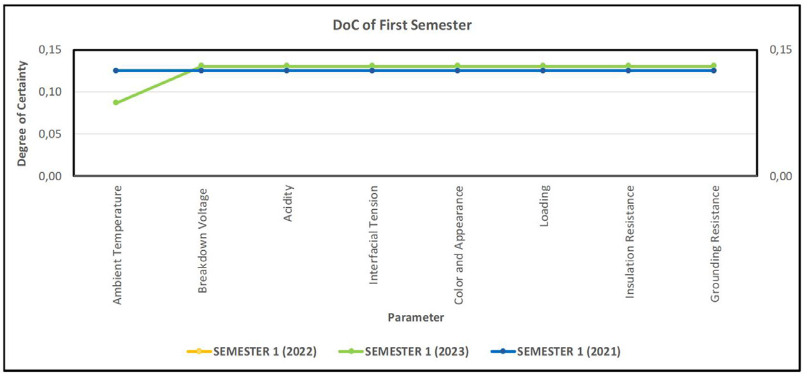

Fig. 5. Remaining Useful Life Chart for S1.

This transformation aims to improve the accuracy of analysis and decision-making based on probabilistic learning results. The KGS method enables the system to adaptively increase its knowledge and understanding of the transformer's RUL patterns, which can ultimately be used in preventive maintenance strategies.

The analysis of the DoC results in Table 5 in Fig. 5, 2 indicates that each parameter plays a significant role in predicting the RUL of transformers at substations, as observed in S1 (Semester 1). A notable pattern emerges in the prediction of the RUL of the transformer in the period from 2021 to 2023, as shown in the graph of the first semester results. The values obtained are nearly identical during this period, indicating a proportional relationship between the parameters. The transformer's RUL is calculated using eight main parameters, namely ambient temperature, transformer oil insulation quality (BDV, acidity, IFT, color, and appearance), load, insulation resistance, and grounding resistance. The calculation results indicate that the transformer is estimated to have a RUL of 23.42 years, while its current operational age is approximately ±7 years. It is imperative to note that the findings are contingent on the condition of the transformer at the specific substation where the observation was conducted.

The RUL of a transformer is 23.42 years, which can be affected by several factors, one of which is a reduction in ambient temperature. While a temperature decrease can lead to a reduction in the RUL of a transformer, this factor does not have a significant direct effect on the RUL. As shown in Table 5 and Fig. 5, although some factors remain stable, other parameters can accelerate changes in the RUL. The graph indicates that the ambient temperature is the primary factor contributing to the decline, thereby affirming the satisfactory condition of the substation transformer, with its health level reaching 87.5 % of 100 % during the initial semester. Fig. 6 reveals a change in the condition of the transformer in the second semester compared to the first. This change can be attributed to a decrease in two main factors: ambient temperature and load. The decline in load was attributed to the onset of the rainy season in the final months, which resulted in an increase in electricity consumption in the household sector compared to the industrial sector. The increased utilization of space heaters, water heaters, clothes dryers, and supplementary lighting in the home during the rainy season has been identified as contributing to the increased electricity demand. This analysis underscores the significance of considering a broader array of factors that can influence the residual value of a transformer's useful life. The graph presented indicates that the two most significant parameters are ambient temperature and load, this suggests that the substation transformer is operating within an acceptable range of performance, with a calculated RUL of approximately 75 % of 100 %.

The transformers are still in relatively good operating condition. Nevertheless, to ensure optimal performance and prolong the transformer's useful life, it is necessary to carry out regular monitoring and maintenance, such as strict load monitoring and, if necessary, operational adjustments. The failure to implement these measures may result in a more rapid degradation of the transformer's performance than expected, potentially reducing the RUL of the transformer. The results of the analysis in Fig. 5 and Fig. 6 show that long-term use of transformers can cause gradual wear and damage to their components, which can lead to a reduction in the

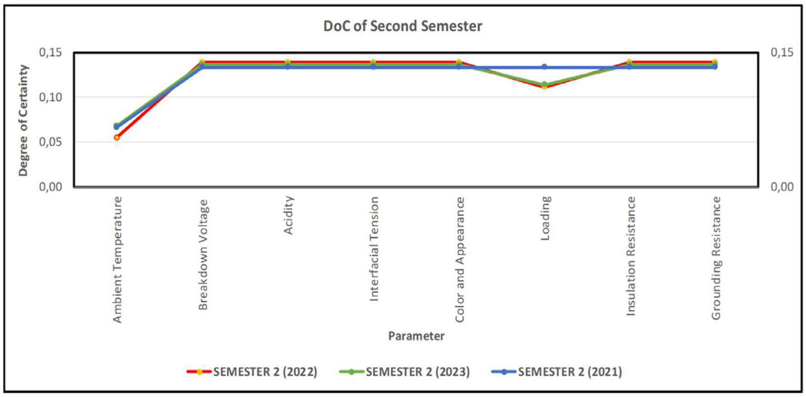

Fig. 6. Remaining Useful Life Chart for S2.

Table 6
Prediction of RUL Transformer.

Prediction	Age of use (year)	RUL (year)
2023	6	24,98
2024	7	23,98
2025	8	22,98

overall performance of the transformer. While effective ambient temperature management can mitigate the risk of failure, the impact of transformer performance degradation remains an issue that cannot be avoided entirely.

In the event of transformers continuing to operate under conditions of load that are lower than their optimal capacity, it is to be expected that their power utilizations will not be maximized. This is especially true in cases where there is an increase in electricity demand that the existing system cannot meet. While operating transformers at lower loads can extend their lifespan and mitigate the risk of failure, regular monitoring remains essential. Maintenance by following industry standards and manufacturer recommendations is imperative, encompassing regular condition monitoring, preventive maintenance, and replacement of worn or damaged components. Consequently, for transformers with a RUL of >20.55 years, rigorous monitoring and maintenance are required to maintain proper operation. The implementation of periodic maintenance is paramount to ensure the continued optimal functioning of transformers and to avert damage that could have repercussions for the electrical system. This analysis suggests a potential opportunity to enhance the power capacity accepted by transformers. However, effective strategic planning is essential to ensure sufficient power availability and enhance operational efficiency in the future.

RUL using the BPNN method

In this research, the BPNN is employed as a comparison method to the new intelligent CAI-based method using the KGS method applied to transformer RUL prediction. The selection of BPNN as a comparison method is predicated on its status as a prominent artificial neural network-based machine learning method, which is readily implementable in prediction applications. The BPNN training is performed using the Levenberg-Marquardt algorithm (trainlm), with MSE as the primary metric for evaluation. The findings from the training process demonstrate that the BPNN model attains a low MSE value, thereby signifying its capacity to predict with a high degree of accuracy.

The predicted RUL of the transformer, as presented in Table 6, shows that the model predicts a steady decrease in the RUL each year. The prediction table shows an increase in the age of use of the transformer, with a gradual increase from 6 years in 2023, 7 years in 2024, to 8 years in 2025. Concurrently, the predicted RUL shows a steady decrease from 24.98 years in 2023, 23.98 years in 2024, to 22.98 years in 2025. This pattern of decline can be attributed to the fact that, annually, the transformer will accrue a year of age due to factors that affect it. Despite this decline, the analyzed transformer is still classified as good. The model accurately predicts transformer degradation, exhibiting minimal or no prediction errors.

The RUL prediction provides a reliable basis for transformer maintenance planning, indicating a residual lifespan of over 20.55 years, eliminating the need for immediate replacement. However, continuous monitoring is essential to address external factors like overloading, high temperatures, or humidity that may accelerate degradation. Implementing a Preventive Maintenance strategy is recommended to maintain optimal performance and extend lifetime. Additionally, the model aids in long-term degradation analysis, allowing for early detection of deviations from expected trends. Thus, it is a prediction tool and a health monitoring system for optimizing operations and infrastructure planning.

As illustrated in Table 7, the model's performance in predicting the RUL of the transformer for the years 2023, 2024, and 2025 is shown. In 2023, the model performed 354 iterations with a processing time of 1 s, resulting in a regression value 1.00, indicating perfect prediction accuracy. The Mean Squared Error (MSE) was recorded at 0.00, while the Mean Absolute Percentage Error (MAPE)

Table 7
Performance of RUL transformer.

Prediction	Iteration	Time progress	Regression	MSE	MAPE	Accuracy (%)
2023	354	0:00:01	1.00	0.00	3.82 %	100 %
2024	289	0:00:00	1.00	0.00	3.39 %	100 %
2025	310	0:00:01	1.00	0.00	2.28 %	100 %

Table 8
Validation of RUL transformer.

Aspects	In 2023	In 2024	In 2025
Optimal Number of Epochs	354	289	310
Best Validation Performance	6.6722 x 10^{-10}	9.9021 x 10^{-10}	3.8651 x 10^{-10}
Curve Stability	Stable, no spikes	Stable, no spikes	Slight fluctuations around epoch 150 before converging
Prediction Accuracy	Very high	High, but MSE is larger than the others	Highest because it has the smallest MSE
Overfitting Risk	None	None	None

was documented at 3.82 %. The model demonstrated an accuracy of 100 % in this prediction. In 2024, the model completed 289 iterations with a speed of less than one second. The regression value remains at 1.00, indicating that the prediction remains accurate without deviation. The MSE registered at 0.00, while the MAPE registered at 3.39 %, slightly lower than the previous year. The model demonstrated an accuracy of 100 % in this prediction. In 2025, the model performed 310 iterations with a running time of 1 s. The regression value remained consistent at 1.00, indicating that the model remained reliable in predicting the RUL of the transformer. The mean square error (MSE) remained at 0.00, and the MAPE decreased to 2.28 %, indicating an enhancement in the model's precision in forecasting transformer degradation on an annual basis. The model demonstrated an accuracy of 100 % in this prediction.

From the three graphs presented, the prediction model used can estimate the transformer's RUL with 100 % accuracy. The absence of deviation between the predicted results and the target value confirms that this model can be relied upon to optimally support transformer maintenance and replacement planning. One of the main factors that ensure the reliability of this model is the selection of the appropriate best validation performance in the training process. The best validation performance determines the optimal point to keep the model accurate and avoid overfitting. This value reflects the lowest validation error before it increases, indicating that the model has achieved its best performance in recognizing the data pattern without being trapped by the unique characteristics of the training data. Therefore, this optimal point is crucial to balance prediction accuracy and the model's generalization ability. With this approach, the model can provide highly accurate prediction results and remain effective under various operational conditions, as shown in Table 8.

In 2023, the model achieved the best validation performance at epoch 354 with an MSE value of 6.6722e x 10^{-10}. The training and validation curves appear stable with no spikes, indicating that the model learns well without experiencing instability. The prediction accuracy of this model is very high, and there is no risk of overfitting, making it a reliable model for predicting the RUL of transformers. In 2024, the model performs best with the best validation at epoch 310 and the smallest MSE value of 9.9021e x 10^{-10}. This means the model has the highest prediction accuracy compared to models from previous years. However, there is a slight fluctuation around epoch 150 before the curve finally converges. Despite the slight instability, the model does not suffer from overfitting and can still be used for more accurate predictions than previous years' models. In 2025, the model shows the best performance with the best validation at epoch 310 and the smallest MSE value, which is 3.8651e x 10^{-10}. This means the model has the highest prediction accuracy compared to models from previous years.

However, there is a slight fluctuation around epoch 150 before the curve finally converges. Despite the slight instability, the model does not suffer from overfitting and can still be used to make more accurate predictions than previous years' models. Overall, the 2025 model performs best as it has the lowest MSE, although it requires monitoring of initial training fluctuations. The 2023 model is also excellent, with high stability, while the 2024 model converges faster but with slightly lower accuracy. It shows that when choosing a model to predict the RUL of a transformer, it is important to consider the balance between several epochs, MSE value, curve stability, and prediction accuracy. A very small MSE value indicates that the model can accurately predict the RUL of a transformer before significant performance degradation. For example, if a transformer has operated for eight years, the model can estimate how many more years it will function optimally. This high accuracy is crucial for power system operators to schedule maintenance or replacements effectively. The low error values and consistent convergence patterns ensure reliable predictions, supporting informed operational decisions. Ultimately, this model helps plan preventive maintenance, minimize failure risks, and enhance the efficiency and reliability of the power system.

Comparison of KGS and BPNN methods

The KGS and machine learning methods are used for learning and decision-making but with different approaches. BPNN is an algorithm used to adjust weights based on errors generated in artificial neural networks, while KGS focuses on dynamic knowledge

Table 9
Comparison of knowledge growing systems and machine learning (BPNN) adapted from [48] with some adjustments.

Measuring parameter	KGS	Machine learning (BPNN)
Foundation science	Cognitive psychology	Neuroscience
Data	Data is obtained when interacting directly	The data must be provided in advance
Approach	Emulate brain mechanism when a human think	Emulate brain's neutral network works
Knowledge generation paradigm	Learning by interaction	Learning by past data or experiences
The way of generation of knowledge	Information-Inferencing Fusion	Updating synapse weight
Knowledge generation method	ASSA2010	Various neural-like computations depended on the problem
Knowledge generation time	Very short	Can be very long depended on the amount of data
Knowledge generation paradigm	Unsupervised with told-information at the end	Supervised
Mathematical Models	Simple	Complex
Number of data	Very little	Massive
Data collection	No required	Required
Data annotation	No required	Required
Computing power	Low	High
Training Phase	No required	Required
Retrained	No	Yes
Architecture Structure	Simple	Complex

development with learning by interaction [45,46]. The comparison between these two methods includes the scientific basis, the type of data used, data labeling, adaptation to change, learning paradigms, advantages of each method, accuracy comparisons, and ways of forming knowledge, as shown in Table 9.

The comparison between these two methods aims to understand their respective advantages and limitations in different application scenarios. BPNN is more suitable for systems that need to learn from large amounts of data with complex patterns, while the KGS is more effective in systems that require adaptive and fast decision-making [47]. By comparing these two methods, researchers and practitioners can determine the most appropriate approach based on the specific needs of the CAI [30,31].

In this research, to further evaluate the generalization ability of the two proposed methods, a new intelligent method, KGS, is compared with the comparative method, BPNN. It is important to note that both methods belong to the CAI and machine learning-based approaches. Table 9 presents the model results from KGS and BPNN in predicting the RUL of the transformer, thus enabling an analysis of the performance difference between the two methods. KGS is a new intelligent method that was developed and compared with BPNN in predicting transformer RUL. The objective of this comparison is to ascertain the superiority of the method or to develop CAI and machine learning approaches with the aim of enhancing the reliability of predictions. The utilization of more accurate predictions is expected to prevent the premature failure of transformers and optimize maintenance strategies, thereby enhancing the efficiency and reliability of the electricity system.

As shown in Table 9, KGS focuses more on interaction and inference-based approaches derived from cognitive psychology [49]. This method has been shown to generate predictions more rapidly, as it does not require large amounts of data and does not rely on a lengthy training process. This approach facilitates the efficient prediction of the RUL of a transformer, even with limited data available. Furthermore, KGS does not necessitate data annotation or a complex retraining process, thus facilitating its application in industrial settings, prioritizing speed and efficiency. However, given the KGS model's simplicity and inference-based nature, the accuracy of the resulting predictions may be limited compared to data-driven methods, such as machine learning. In circumstances involving more complex or unstructured data patterns, these methods may encounter limitations in detecting deeper relationships between variables. Consequently, while KGS demonstrates notable strengths in speed and efficiency, its selection should be considered case-by-case, mainly when high accuracy is a top priority in predicting transformer lifetime.

Conversely, the machine learning approach employs an artificial neural network methodology, necessitating substantial data and considerable computing capabilities. In predicting the RUL of a transformer, this method requires a substantial amount of historical data, a protracted training process, and readjustment in the event of alterations in the data pattern. The capacity to learn from experience enables machine learning to identify patterns and long-term trends that are challenging to detect by inference-based methods such as KGS. Overall, KGS is more suitable for systems with limited data and fast prediction needs, as it does not require many resources. In contrast, machine learning excels in accuracy but requires much data and higher computing power. Therefore, the selection of methods should be tailored to specific needs, data availability, and computational capacity to provide optimal prediction results for the RUL of the transformer.

Conclusion

The conclusion of this research shows that mimicking the human ability to recognise objects with only a few trials faced with a small amount of data and low computational power has become a challenge for machine learning techniques. KGS has advantages for systems that require real-time adaptation without relying on previously collected historical data. This method allows the system to learn directly from its operating environment, making it more flexible in dealing with changing conditions. When predicting the RUL of a transformer, KGS can consider various factors such as ambient temperature, oil insulation quality, load, insulation resistance, and grounding resistance that dynamically affect the useful life of the transformer. The analysis of this method shows that the transformer is still in good condition, with a health level of 87.5 % in the first semester (S1) and about 75 % in the second semester (S2). It can be said that with only a few interactions with a small computational power, KGS can present itself as a fast object recogniser. By using the comparison method, BPNN method with machine learning approach, there are different parameters in temperature and load variations, the transformer can still operate efficiently with an estimated RUL of about 24.98 years in 2023. The main advantage of KGS is its ability to continuously adjust predictions based on current conditions, making it a more adaptive method than approaches based on historical data. If we look at it from a comprehensive perspective, the comparison of KGS and machine learning can mimic the development of knowledge or knowledge generation in the human brain, learning through interaction and learning through past data or experience.

Limitations

None.

Ethics statements

The authors confirm that no experiments involving human subjects or animals were conducted in connection with the present work, and that no data from social media platforms were used.

CRediT author statement

Nur Avika Febriani: Software, Formal Analysis, Writing-Original Draft, **Ika Noer Syamsiana**: Conceptualization, Methodology, Writing-Review & Editing, Supervision, **Arwin Datumaya Wahyudi Sumari**: Software, Writing-Review & Editing, Validation, **Rachmat Sutjipto**: Project Administration, Investigation, **Mohammad Noor Hidayat**: Resources, Data Curation, Validation, **Hendri Febrianto**: Resources, Data Curation.

Supplementary material *and/or* additional information [OPTIONAL]

IEC 60,076, "Loading guide for mineral-oil-immersed power transformers." 2018.

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.

Data availability

Data will be made available on request.

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