

The residual life prediction of power grid transformers based on GA-ELM computational model and digital twin data

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Abstract

Under the new round of power system reform, the high proportion of power electronic equipment and other issues faced by the dual carbon goal are becoming increasingly prominent, leading to increasingly complex regulation of the large power grid. Digital twin technology can provide new ways for the digital transformation of the power grid. To solve the above problems, the research first introduces digital twin technology, and then combines genetic algorithm to improve the Extreme Learning Machine. Then, considering the changes in load, a residual life prediction model for power grid transformers is designed. The research results indicated that the proposed model had a very high overlap between the predicted values and the true values, with a maximum error of only 1.76 °C. It converged at the 150th iteration, with a fitness value of 0.04. Among the hot spot temperature prediction results under different load rates, the proposed model had the highest average accuracy, at 99.97%. The average relative error, mean square error, mean absolute error, root mean square error, fitting degree, and calculation time were 2.351%, 1.381%, 7.215%, 0.1105%, 0.998%, and 0.71s, respectively, which were all superior to the performance of other mainstream models. The above results indicate that the proposed model has superior performance, which can quickly and accurately feedback simulation results to the physical entity of the transformer, thereby assisting in the optimization and decision-making of the physical entity and providing support for the smooth operation and safety of the power system.

Keywords: Transformer; Power grid; Digital twin; Genetic algorithm; Extreme learning machine

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1. Introduction

With the progress of the power system, the status monitoring and life prediction of power grid equipment are playing an increasingly important role in ensuring the stability and reliability [1]. As one of the core equipment of the power grid, the operation status of transformers directly affects the stability and reliability. However, the remaining life of transformers is influenced by various factors, including operating environment, load conditions, maintenance conditions, etc. The interaction between these factors is very complex. Therefore, accurately predicting the remaining life of transformers is a challenging task [2-4]. Digital Twin Technology (DT) is an integrated framework based on sensor updates, physical models, historical and real-time data, which can achieve real-time monitoring and data collection for physical entities [5]. In view of this, based on DT, the Extreme Learning Machine (ELM) is

optimized using Genetic Algorithm (GA). A residual life prediction model for grid transformers is constructed using GA-ELM algorithm. The significance of the research lies in providing an accurate and real-time method for predicting the remaining life of transformers, which provides scientific basis for the maintenance of power grid transformers. At the same time, it improves the efficiency and accuracy of transformer maintenance. By monitoring the operating status of transformers in real-time and predicting their remaining lifespan, potential faults can be detected in a timely manner. The maintenance and replacement can be carried out in advance to avoid power outages caused by equipment damage. The research content has four parts. The first part is a brief introduction to the research on GA, ELM, and residual life prediction models. In the second part, real-time operation data of power grid transformers are obtained based on DT. The GA-ELM algorithm is used to predict the temperature of hot spots. A remaining life prediction model

for power grid transformers is constructed considering changes in load rate. Meanwhile, due to the advantages of simplicity, strong computational capabilities and compatibility, as well as the ability to solve various numerical and non-numerical problems, this study utilizes Fortran language to develop a digital computing model and designs a software system for predicting transformer life. A software system for predicting transformer life is designed. The third part is to prove the performance of the GA-ELM residual life prediction model. The performance testing and comparative analysis experiments are conducted. The fourth part summarizes the research content. The research aims to provide new ideas for the digital transformation of transmission and transformation equipment in new power systems, solve the problems in predicting the remaining life of power grid transformers, overcome the complexity of power grid operation, and provide reference value for temperature prediction and life assessment of other transformers to prevent accidents in advance. Then it can improve economic benefits and reduce carbon emissions.

2. Related works

In recent years, the ELM algorithm has been applied in multiple fields. SHI X et al. combined boundary optimization theory with variational Bayesian inference to overcome the over fitting in ELM. A new ELM based on L1 norm was derived. The L1 term was added to the squared sum costs to form the objective value. Then a soft sensor was designed based on this foundation. The proposed soft sensor was competitive compared to existing soft sensors [6]. CHEN X et al. designed a hybrid load forecasting method based on kernel principal component analysis, Isamvy flight tree seed algorithm, and ELM. Before performing the prediction in ELM, LTSA was used to obtain the optimal parameters, which was called LTSA-ELM. Meanwhile, considering the sparsity of power load data, KPCA extraction was performed on the input data. The proposed method had superiority compared with other methods [7]. KEMICHE M et al. used ELM to recognize handwritten characters in Berber language. A fast-extreme learning machine was used to efficiently recognize Latin Berber characters. The results indicated that the handwriting recognition system based on ELM reduced computational complexity and shortened the time required in the entire recognition process [8]. To accurately obtain the strength of coal gasification slag filling materials, SUO Y et al. constructed a GA-ELM prediction model. In the model testing set, the average correlation coefficient between the predicted and actual values was 0.99. It could accurately estimate the strength of coal gasification slag based cemented filling body [9]. Warping and volume shrinkage are two common quality defects. GA optimized ELM was achieved using Moldflow software. The results indicated that the GA-ELM model could better predict defect values [10].

In the remaining life prediction, MOHRIL R S et al. established a gradient boosting ensemble model based on

the properties of maintenance data. This model predicted the remaining life of components while considering the errors caused by maintenance personnel during the maintenance process. The results showed that the model effectively handled the uncertainty and variability of expected future task profiles, without increasing mathematical complexity [11]. To accurately predict the overall strength and remaining life of selective repair bonding structures, LIAO Y et al. established a comprehensive simulation model for crack propagation, including bonding strength. The results showed that FM94 adhesive with a thickness of 0.2-0.4 mm could reduce the stress intensity coefficient and improve the remaining life [12]. To more accurately predict the remaining life of each aged cable segment, SHAN B et al. proposed an on-site non-destructive testing method based on the principle of time temperature superposition. The results showed that the prediction error of the cable was below 3.15%. The prediction error of the remaining life was within 10% [13]. At present, there are problems in predicting the remaining life of aircraft engines. YU P et al. proposed a residual life prediction method. The experimental results indicated that it had performance advantages compared with other excellent networks [14]. LIU Y et al. utilized the real-time and accurate prediction advantages of binary Wiener processes to study the clutch remaining life prediction. Combined with the wet clutch life test, the oil change correction was performed on the spectral data. The indicator element was extracted for predicting the remaining life of the clutch. The research method exceeded traditional methods [15].

In summary, the ELM algorithm develops relatively mature. Some scholars use GA algorithm to optimize ELM algorithm. However, there is relatively little research on constructing residual life prediction models based on the GA-ELM algorithm. In view of this, the GA-ELM algorithm is applied to the residual life prediction of power grid transformers.

3. A residual life prediction model for power grid transformers

To accurately evaluate and predict the remaining life of power grid transformers, the study first uses the GA-ELM and DT to predict the hot spot temperature of transformers. Then, considering the changes in load rate, a residual life prediction model for power grid transformers is constructed. Finally, a digital computing model is written in Fortran language. A software system for predicting lifespan is designed.

3.1 The residual life assessment for transformers based on GA-ELM algorithm and DT

In recent years, a high proportion of new energy and electronic devices are being connected to the grid on a large scale. The new power system urgently needs to take on the

important responsibility. Transformers, as important energy conversion equipment in the power system, efficiently utilize their load capacity, prevent power accidents, and improve the stability of power grid operation. It is of great significance for promoting the dual carbon goal. However, the early modeling and simulation of power grid transformers are unable to depict the dynamic operation process in multi-scale time and space. The DT technology is indispensable for achieving the digital transformation of power equipment such as transformers. Its predictive, interpretive, interactive, and visual characteristics at multiple scales depict the overall structure of power equipment that traditional modeling and simulation cannot analyze, achieving full closed-loop online. The remaining life of a transformer is related to its hot spot temperature.

DT refers to a simulation process that integrates physical quantities, multiple disciplines, scales, and probabilities based on sensor updates, physical models, and operational data. It completes mapping in virtual space, reflecting the equipment's entire life cycle process. Therefore, combining DT with deep learning algorithm to predict hot spot temperatures is mainly to complete the prediction, diagnosis, and evaluation of parameters. ELM is an algorithm for single hidden layer feed-forward neural networks with fast learning characteristics. It does not require complex feature selection and parameter optimization, which can directly utilize input and output data for learning. It can be easily combined and extended with other algorithms [16-17]. In view of this, the study chooses ELM to predict the hot spot temperature of transformers. Figure 1 displays the ELM structure.

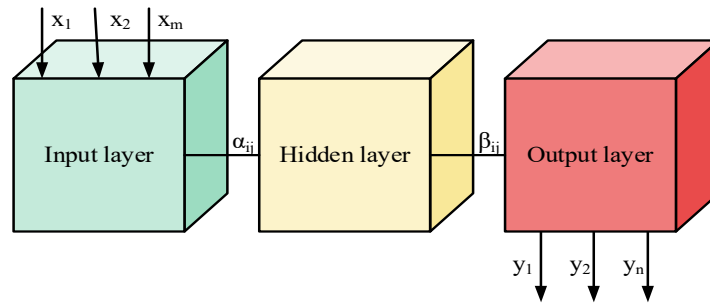


Figure 1. Neural network structure distribution of ELM

In Figure 1, the ELM structure has three parts: Input Layer (IL), Hidden Layer (HL), and Output Layer (OL). The IL is x_1, x_2, \dots, x_n . The OL data is y_1, y_2, \dots, y_n . The neurons in the OL, HL, and OL are n , l and m . w_{jk} represents the connection weight between the j -th neuron in the HL and the k -th neuron in the OL. w_{ij} represents the connection weight between the i -th neuron and the j -th neuron in the IL. The weight for the IL and HL is shown in equation (1).

$$\alpha = \begin{bmatrix} \alpha_{11} & \alpha_{12} & \dots & \alpha_{1n} \\ \alpha_{21} & \alpha_{22} & \dots & \alpha_{2n} \\ \vdots & \vdots & & \vdots \\ \alpha_{l1} & \alpha_{l2} & \dots & \alpha_{ln} \end{bmatrix} \quad (1)$$

In equation (1), α represents the weight between the IL and the HL. The weight between the HL and the OL is represented by β , as shown in equation (2).

$$\beta = \begin{bmatrix} \beta_{11} & \beta_{12} & \dots & \beta_{1m} \\ \beta_{21} & \beta_{22} & \dots & \beta_{2m} \\ \vdots & \vdots & & \vdots \\ \beta_{l1} & \beta_{l2} & \dots & \beta_{lm} \end{bmatrix} \quad (2)$$

In equation (2), when the node in the OL is 1, the trained result is only a single output ELM model. The expression for the threshold specified by the HL neurons is shown in equation (3) [18].

$$\gamma = [\gamma_1, \gamma_2, \dots, \gamma_l]^T \quad (3)$$

In equation (3), the bias vector γ represents the column vector of $l \times 1$. The bias element is any number in $[0, 1]$. For a training set with P samples, the expression is shown in equation (4).

$$I = \begin{bmatrix} i_{11} & i_{12} & \dots & i_{1p} \\ i_{21} & i_{22} & \dots & i_{2p} \\ \vdots & \vdots & & \vdots \\ i_{n1} & i_{n2} & \dots & i_{np} \end{bmatrix}, O = \begin{bmatrix} O_{11} & O_{12} & \dots & O_{1p} \\ O_{21} & O_{22} & \dots & O_{2p} \\ \vdots & \vdots & & \vdots \\ O_{m1} & O_{m2} & \dots & O_{mp} \end{bmatrix} \quad (4)$$

In equation (4), the input matrix is represented by I . The output matrix is represented by O . If $G(x)$ represents the activation function of the HL, the ELM output value after feature mapping is shown in equation (5).

$$f_L(x) = \sum_{i=1}^L \beta_i G(\alpha_i \cdot x_i + \gamma_i) = \sum_{i=1}^L \beta_i h(x_i) \quad (5)$$

In equation (5), the mapping value of the HL to the i -th sample is represented by $h(x_i)$. The sample is L . The expected output value is shown in equation (6).

$$T = [t_1, t_2 \dots t_p] \quad (6)$$

In equation (6), T represents the expected output. The expression that minimizes the error value is displayed in equation (7).

$$H\beta = T^T \quad (7)$$

In equation (7), β represents the weight of the OL. By obtaining the appropriate β , the minimum error can be found. After completing this step, the feature values of the predicted samples are input to obtain the corresponding simulation output values. During this process, the parameter initialization of ELM adopts a random approach, making ELM more generalizable. In the ELM model, the

expressions for the input matrix x_1 and output matrix y_1 of the transformer are shown in equation (8).

$$\begin{cases} x_1 = [K, \theta_a, \theta_{top}] \\ y_1 = [\theta_h] \end{cases} \quad (8)$$

In equation (8), the ambient temperature is θ_a . The top oil temperature is θ_{top} . The load rate is represented by K . Excessive fluctuations in the input and input parameter values of the ELM model have impacts on the learning environment. To avoid this problem, the sample data is normalized. The expression is shown in equation (9) [19].

$$y = \frac{2(x - x_{min})}{x_{max} - x_{min}} - 1 \quad (9)$$

In equation (9), x_{max} and x_{min} represent the maximum and minimum for input and output. x stands for the input and output data. y stands for the normalization result [20]. The ELM ignores the model accuracy while improving the fitting speed. In view of this, the study introduces the GA algorithm to optimize the ELM model. The GA-ELM process is displayed in Figure 2.

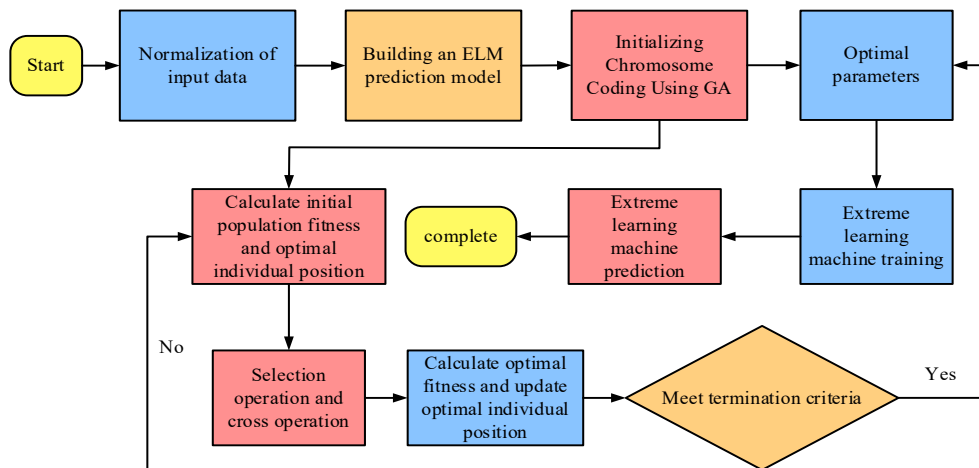


Figure 2. Running process of GA-ELM

In Figure 2, the entire process mainly consists of three parts. The first part is parameter selection in the ELM model. The second part uses the GA to optimize the random parameters in the model. The GA is a global optimization search algorithm that simulates the biological evolution

process. It searches for the optimal solution by simulating genetic principles such as natural selection, crossover, and mutation. It is usually applied to solve the optimal solution of complex problems. The third part uses ELM for prediction. The GA-ELM prediction process is shown in Figure 3.

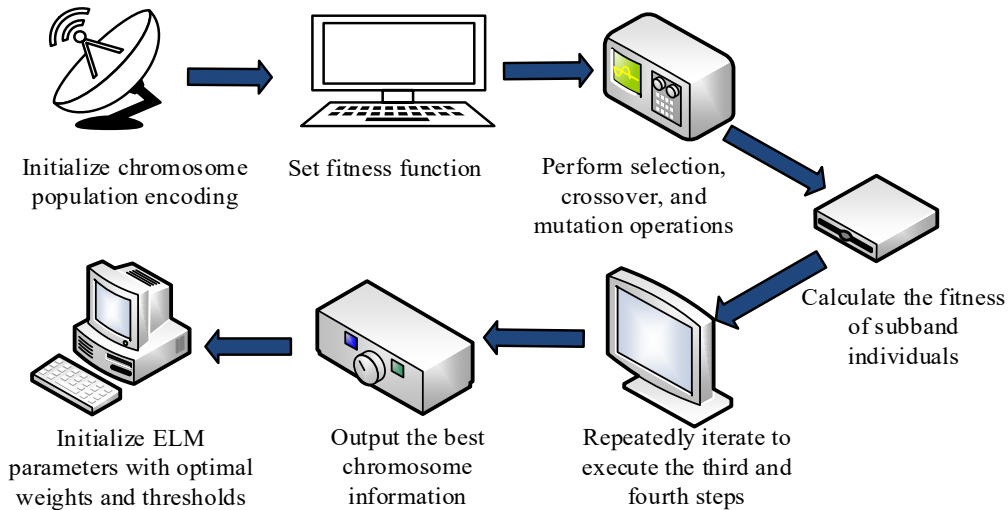


Figure 3. Prediction steps of GA-ELM model

In Figure 3, a fitness function is set within the GA framework. This function calculates the fitness value in the initial population based on the prediction output error of ELM on samples. The roulette wheel selection method is applied during the selection, crossover, and mutation stages. However, the fitness function is the mean square error, which decreases during the evolution process. When designing roulette wheel games, the fitness function is taken to the reciprocal to select individuals with "high fitness". Afterwards, the offspring individuals is merged with the parent individuals, forming a new offspring population. This process continues to iterate until the maximum iterations are reached. In the output optimal solution stage, the optimal chromosome is decoded. The decoded weight and threshold are assigned to the predicted ELM. The ELM parameters are initialized with the optimal weight and threshold, thereby obtaining the optimal network structure. The prediction

accuracy is tested. This entire process demonstrates how to optimize the ELM parameters based on the GA.

3.2 Construction of a residual life prediction model for power grid transformers based on load rate changes

The existing residual life assessment relies on the thermal life losses of power transformers during operation, that is, considering the load change rate of the transformer. When a transformer is energized, its various components generate electromagnetic losses and are prone to generating a large amount of heat. Part of the heat is lost in the air, and the remaining heat affects the temperature of the entire transformer structure. The temperature distribution of the transformer components and the overall structure are shown in Figure 4.

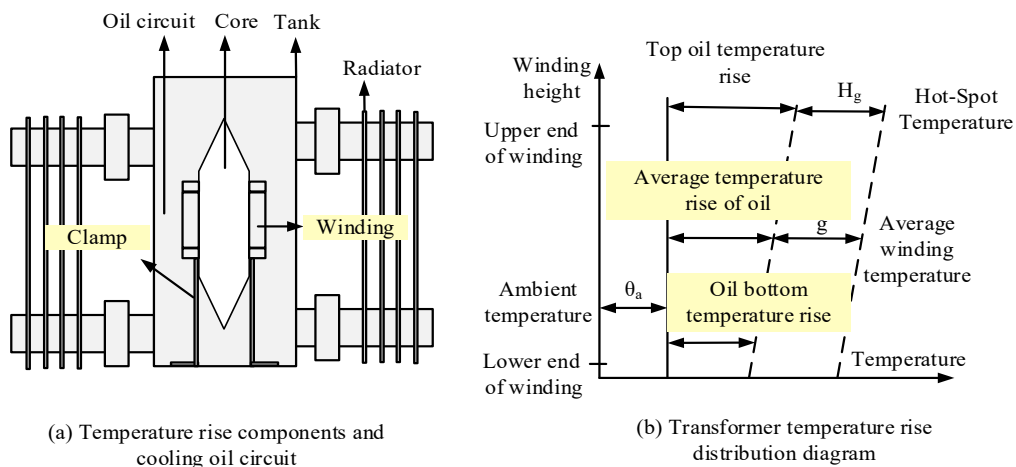


Figure 4. Transformer temperature sound components and temperature rise distribution diagram

Figure 4 (a) shows the temperature rise component and cooling oil circuit of the transformer. The poor distribution

of oil flow in the winding area often results in hot spot temperatures occurring at the upper end of high and low

voltage windings. The increase in hot spot temperature accelerates the aging of winding insulation materials. Quantitative analysis of load rate and hot spot temperature can determine the influence of load rate on the insulation thermal life. Firstly, the hot spot temperature is determined as an intermediate quantity. Then, the hot spot temperature at any load rate is calculated to quantitatively calculate and analyze the relationship between load rate and lifespan. Figure 4 (b) shows the thermal distribution diagram of the transformer described in the national standard. It details the relationship between the hot spot temperature of the winding and the ambient temperature, as well as the temperature rise of the top oil. During the overall heating process of the transformer, the winding heats up by transferring heat to the oil. Then the heat is transferred to the air through the flow and cooling of the oil. Based on this process, the average temperature rise of the winding to the air is calculated. At rated current, the temperature rise is shown in equation (10).

$$\Delta\theta_1 = \Delta\theta \left(\frac{1 + RK^2}{1 + R} \right)^x \quad (10)$$

In equation (10), $\Delta\theta_1$ represents the average temperature rise of transformer oil to air. R represents the ratio of load loss to air loss. K represents the load rate. x is a constant, representing the oil index. At any load rate, the hot spot temperature difference of the transformer and the top oil temperature is displayed in equation (11).

$$\Delta\theta_2 = H_{gr} K^y \quad (11)$$

In equation (11), H_{gr} represents the temperature difference of the oil immersed transformer. y represents the exponential power of current to load rate. The hot spot temperature of the transformer is expressed as equation (12).

$$\Delta\theta_h = \theta_a + \Delta\theta_1 + \Delta\theta_2 = \theta_a + \Delta\theta_{or} \left(\frac{1 + RK^2}{1 + R} \right) + H_{gr} K^y \quad (12)$$

In equation (12), θ_a represents the ambient temperature of the transformer during operation. The calculation process for the remaining life of transformers is shown in Figure 5.

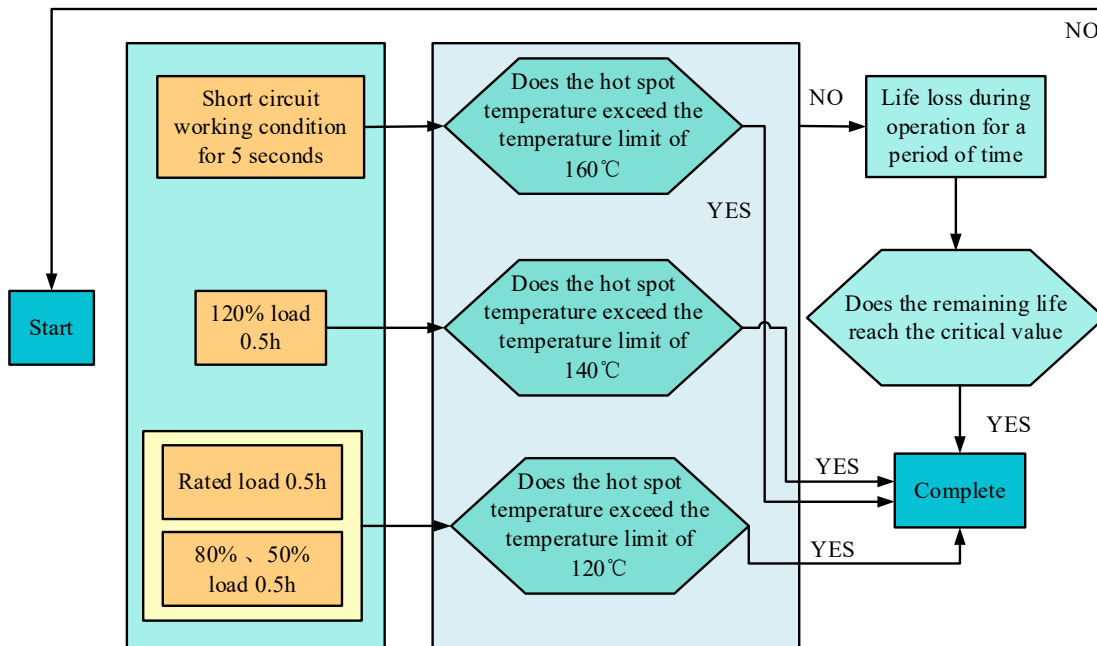


Figure 5. Remaining life calculation process

In Figure 5, the remaining life of the power transformer is determined under fixed ambient temperature and rated load conditions. The study assumes five load conditions, including rated load, 50% load, 80% load, 120% overload, and short circuit conditions. The study stipulates that the operating time for each load condition is 10 hours, while the operating time for short-circuit condition is 5s. A program is developed to calculate the transformer aging under various working conditions within one cycle. When the running time is below the specified value, the calculation will stop.

During continuous operation, under rated load and below load conditions, the maximum hot spot temperature is below the 120°C, which is the temperature limit. Under overload conditions, the maximum temperature of the hot spot is below 140°C. During short circuit, the temperature limit during the duration is 160°C. The above temperature limits serve as critical conditions. Once the temperature exceeds the specified limit, it is considered that the transformer insulation is damaged. A mathematical calculation model for transformer thermal life is developed using Fortran

language. The main functions of the software are shown in Figure 6.

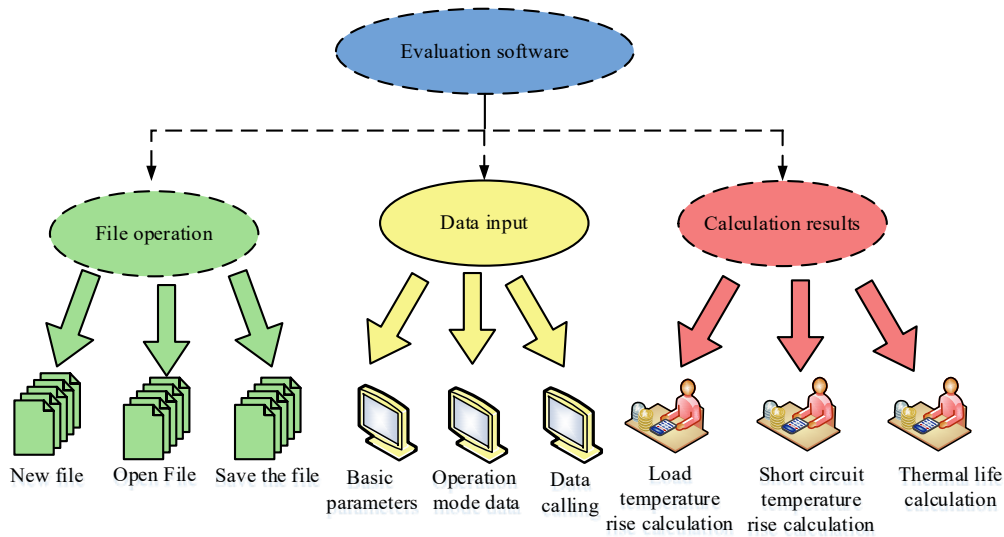


Figure 6. Main functions of the software

In Figure 6, the software allows users to directly input or modify parameter data. Meanwhile, it can also call data files of different formats from the system, which greatly improves the operation convenience. In terms of functionality, this software can fully automatically read the hot spot temperature, thermal life loss, short-circuit impedance, magnetic field distribution and other parameters of transformer DTs, and update data in real-time. The calculation results can be directly used to guide the operation and maintenance work of engineering personnel, which have extremely high practical value.

4. Result analysis of residual life prediction model for power grid transformers

To verify the predictive performance of the GA-ELM on transformers, performance testing experiments are first conducted. The accuracy, error, and fitness values of the research method are tested. Then the research model is

applied to actual transformers. Compared with other models, the performance and applicability are further validated.

4.1 Performance testing of GA-ELM model

To avoid errors caused by different experimental environments, the experiment is conducted on the same computer. The CPU is Intel Xeon E5-2680 v2, the RAM is 16GB, the operating system is Windows 10 Home, and the memory is 10GB. The top oil temperature, different load rates, and ambient temperature are used as output parameters. The hot spot temperature is used as the output parameter. A random combination generates 500 twin data samples, with 400 samples as the training set, and 100 samples as the testing set. To verify the superiority of the ELM prediction model, it is compared with the commonly used Back Propagation (BP) model in residual life prediction models. The error results are shown in Figure 7.

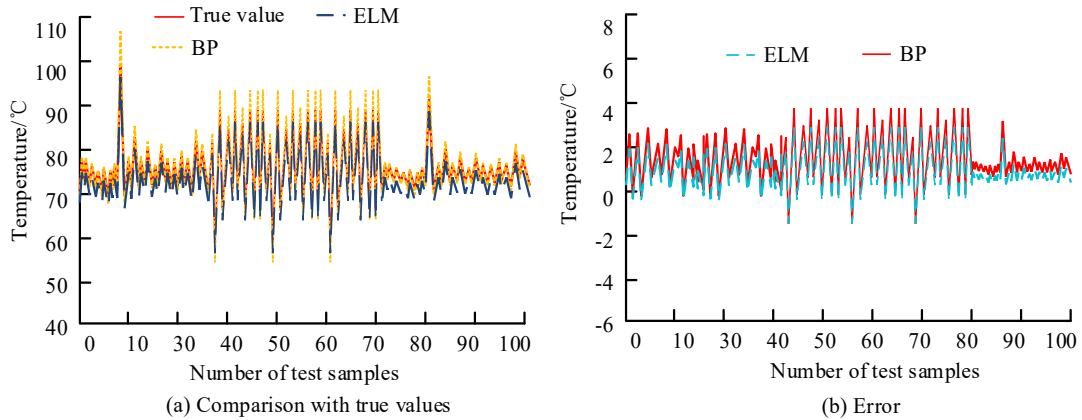


Figure 7. Comparison between predicted and true values

Figure 7 (a) displays the fitting curves between the true and predicted values. The two models had a high fitting degree. In Figure 7 (b), the error of the BP was within 4°C, and the ELM was within 3°C. The accuracy of the BP and the ELM was generally high, but the ELM had higher accuracy. To verify the improvement effect of introduced GA on the ELM model, the optimized ELM model is compared with the ELM model. Figure 8 displays the comparison results.

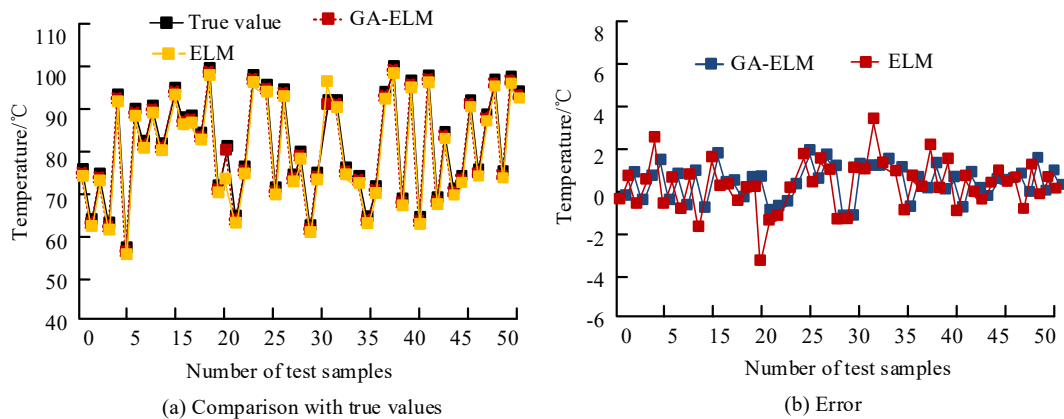


Figure 8. Comparison between predicted and true values before and after model improvement

Figure 8 (a) shows the fitting curve between the true and the predicted value. The fit degree before and after improvement was relatively high. The predicted value curve of the GA-ELM model almost completely coincided with the true value curve. The ELM model showed significant differences between sample 20 and sample 31. In Figure 8

(b), the error of the ELM was within 3°C. The GA-ELM was within 2°C, with a maximum error of 1.76°C. The improvement effect of the research method is good. The accuracy of the GA-ELM is relatively high. To further demonstrate the superiority of the GA-ELM, the absolute error values are compared. 50 samples are used for testing again. The test results are shown in Figure 9.

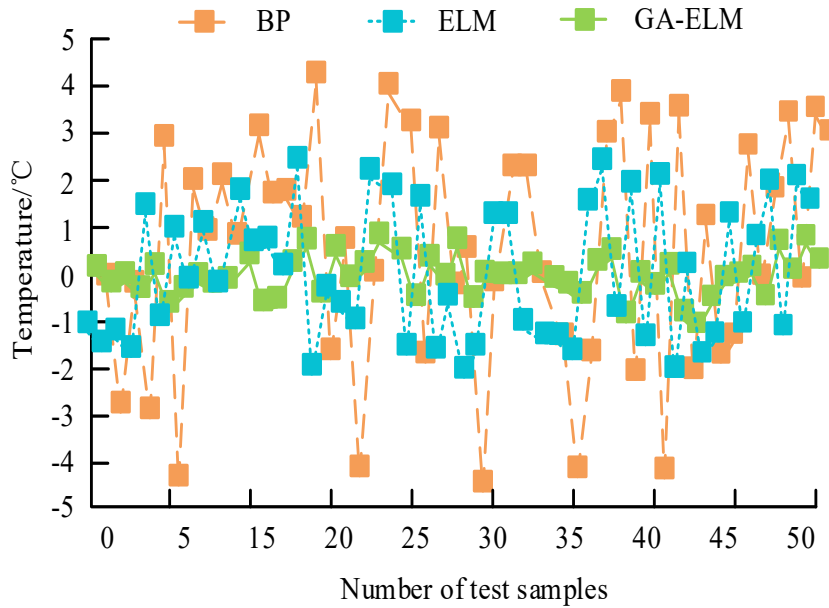


Figure 9. Comparison of absolute errors among three types of models

In Figure 9, the GA-ELM error curve was relatively flat, with small fluctuations. The error was still controlled within 1°C. The error curves of the BP and ELM both fluctuated significantly. The BP was controlled within 5°C, with a maximum error of 4.76°C. The ELM was controlled within 3°C, with a maximum error of 2.84°C. In summary, the improved GA-ELM has higher accuracy and smaller error, indicating its superiority in predicting hot spot temperatures. The Long Short-Term Memory Network (LSTM) model is introduced for comparison. The convergence curves of fitness values and iteration times are tested, as shown in Figure 10.

In Figure 10, the fitness value first rapidly decreased with the increase of iteration number. Then, after a certain iteration, the fitness value tended to stabilize, and the change was relatively small. The fitness value of the research model decreased the fastest. When the iteration number was 100, the fitness value of the research model was 0.07. The fitness value of the BP model was 0.18, and the LSTM was 0.12. The fitness curves of the BP model and LSTM model converged at 265 and 275 iterations, respectively. The research model converged at around 150, with a lower fitness value of 0.04. A low fitness value indicates a low error in the method. Figure 8 shows that the training effect of the research model is good, with stable hot spot temperature prediction ability and strong robustness.

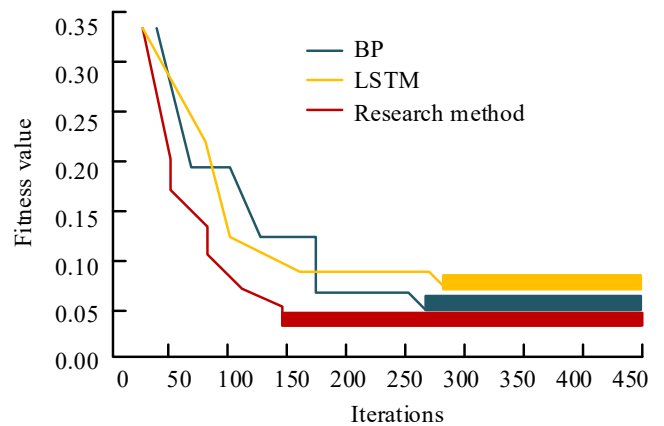


Figure 10 Fitness curve

4.2 Application and comparison of residual life prediction models for power grid transformers

To verify the superiority of the method, it is applied to the actual life prediction of power grid transformers. A comparison is made between the BP and the ELM. The sample data results from different algorithms are displayed in Table 1.

Table 1. Calculation results of sample data from different algorithms

Number	Load rate $K(I/I_N)$	Ambient temperature ($\theta_{top}/^{\circ}C$)	Top oil temperature ($\theta_a/^{\circ}C$)	$\theta_h/^{\circ}C$			True value
				BP	ELM	GA-ELM	
1	0.4	21.6	18.5	41.2	41.2	41.2	41.2
2	0.9	20.3	21.4	45.3	45.3	45.3	45.3
3	0.9	25.4	34.5	51.7	51.7	51.7	51.7

4	0.8	27.1	39.2	67.3	67.3	67.3	67.3
5	0.4	21.6	34.5	72.5	70.5	72.5	72.5
6	0.8	25.4	18.5	43.6	48.6	48.6	48.6
7	0.4	20.3	34.5	64.1	63.4	64.1	64.1
8	0.5	20.3	39.2	72.4	77.4	76.4	77.4
9	0.9	27.1	18.5	58.3	58.3	58.3	58.3
10	0.7	25.4	21.4	48.8	47.8	48.8	48.8
11	0.4	21.6	39.2	71.5	75.5	75.4	75.5
12	0.6	27.1	21.4	58.6	58.6	58.6	58.6
13	0.4	20.3	18.5	99.0	99.0	99.0	99.0
14	0.7	27.1	34.5	80.2	81.2	81.2	81.2
15	0.9	25.4	21.4	83.2	81.9	83.2	83.2
16	0.4	21.6	39.2	64.4	69.4	69.4	69.4
17	0.9	25.4	34.5	74.3	75.3	75.2	75.3
18	0.8	20.3	18.5	69.5	66.5	69.5	69.5
19	0.4	21.6	39.2	44.4	49.4	49.4	49.4
20	0.9	25.4	21.4	48.9	48.9	48.9	48.9

In Table 1, the GA-ELM model had good predictive performance for hot spot temperatures under different load rates, with an average accuracy of 99.97%. The BP had an average accuracy of 97.12%, and the ELM was 98.96%. Compared with the BP and ELM, the GA-ELM improved accuracy by 2.85% and 1.01%, respectively. Moreover, for GA-ELM, the prediction error was relatively stable. There

was no significant deviation, making it suitable for predicting the hot spot temperature of transformers. The evaluation indicators Mean Relative Error (MRE), Mean Square Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), fit, and calculation time are introduced for evaluation. The results are displayed in Table 2.

Table 2. Comparison of prediction parameters for different models

Performance evaluation index	BP	ELM	LSTM	GA-ELM
MRE	6.409%	5.124%	7.219%	2.351%
MSE	2.612%	3.415%	6.617%	1.381%
MAE	14.16%	11.17%	24.31%	7.215%
RMSE	0.1928	0.1821	0.2623	0.1108
Fitting	0.981	0.992	0.987	0.998
Computing time (s)	1.23	0.15	1.13	0.71

In Table 2, for GA-ELM, MRE, MSE, MAE, RMSE and fitting degree were 2.351%, 1.381%, 215%, 0.1108, and 0.998, respectively. Each evaluation parameter of the research model was superior to other models. Under the optimal preset parameters of each algorithm, the evaluation results were ranked from best to worst as GA-ELM, ELM, BP, and LSTM. The calculation time of the ELM model was the shortest, only 0.15s. Although the GA-ELM was 0.71s, it exceeded the ELM. However, compared with the BP and LSTM, GA-ELM still had temporal superiority. This indicates that GA-ELM sacrifices computational speed while pursuing higher accuracy. Overall, in the comparison of various model errors, the GA-ELM has the best evaluation performance and the lowest error. This indicates that the GA-ELM has higher accuracy and certain

advantages in predicting the hot spot temperature of transformers.

5. Conclusion

To accurately evaluate and predict the residual life of power grid transformers, a prediction model for the remaining life of power grid transformers is constructed based on the GA-ELM. According to the results, in the comparison between the ELM and the BP, the ELM had higher accuracy, with an error controlled within 3°C. It had higher fitting degree with the true value curve. In the comparison between the GA-ELM and the ELM, the predicted value curve of the GA-ELM almost completely coincided with the true value curve. The GA-ELM was within 2°C. The highest

error was only 1.76°C. The GA-ELM converged with a fitness value of 0.04 at 150 iterations. The GA-ELM model had good predictive performance for hot spot temperatures under different load rates. The average accuracy reached 99.97%. Compared with the BP and ELM, the GA-ELM method improved accuracy by 2.85% and 1.01%, respectively, with small and stable prediction errors. For GA-ELM, MRE, MSE, MAE, RMSE and fitting degree were 2.351%, 1.381%, 215%, 0.1108, and 0.998, respectively. Each evaluation parameter of the research model was superior to other models. The calculation time of the GA-ELM was 0.71s, which was better than the BP and LSTM model. The experimental results verify the superiority of the research method, indicating that the constructed model has high accuracy and stability. At the same time, it indicates that the research model has certain application value in the remaining life assessment and prediction of power grid transformers. However, there are still shortcomings in this study. When considering changes in transformer load rate, only a small part of the load conditions is considered. There are various complex situations in the actual operation of transformers. In future research, overload and various short circuits will be considered.

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