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Generative Artificial Intelligence for Panoramic Sensing and Prediction Techniques in Novel Power Distribution Systems

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ABSTRACT
This paper is based on the definition of novel distribution system panoramic perception technology under the perspective of generative artificial intelligence. The preprocessed data are put into forward GRU neurons and reverse GRU neurons as model input variables for multi-task assisted training, and the model outputs distribution system perception results to complete the task of constructing a new distribution system panoramic perception model based on BiGRU. When the distribution system current and voltage data is zero, it will lead to a reduction in the current and voltage prediction accuracy of the distribution system of the ELM model, for this reason, it is proposed to use the genetic algorithm to optimize the ELM model, to achieve the modeling of the new distribution system prediction model based on the ELM-GA algorithm. Using the model constructed in this paper, panoramic perception and prediction analysis of the new distribution system is carried out. When the BiGRU model is deployed in the new distribution system, the BiGRU network's system perception accuracy and error rate are 95.00% and 5.00%, respectively, which fully meets the user experience requirements of the new distribution system, and the relative errors of fault voltage and fault current prediction based on the ELM-GA algorithm for the new distribution system are less than 5%, which indicates that the ELM-GA distribution system prediction model has the characteristics of high robustness and high accuracy.

Keywords: BiGRU; ELM; GA; new power distribution system

1. Introduction

With the deepening of the "double carbon" work, the proportion of electric energy in the terminal energy consumption is increasing, and the user's requirements for the quality of power supply are increasing [1-2], and the distribution system, as a link in the electric power system directly facing the user, is crucial for guaranteeing the security and reliability of power supply [3-4].

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However, a large number of distributed power sources such as photovoltaic and wind power, as well as electric vehicles and power electronic devices are connected to the distribution system, which makes the relationship between the users and the distribution system increasingly complex [5-6], and brings serious challenges to the protection, control, and operation management of the distribution system [7-8].

Smart grid is built on the basis of high-speed two-way digital integrated communication network technology, through the organic combination of advanced sensing and measurement technology, advanced equipment technology, new control methods and information management technology, in order to realize the safe, reliable, economic and efficient operation of the power grid [9-11]. The smart grid of the smart grid is faced with an extremely large amount of information and data, and the smart grid-related technologies will acquire and utilize knowledge resources in the massive amount of information and data, provide decision-making support for the rapid response to various events, and intelligently coordinate and schedule the resources of the entire system [12-15].

Under the new situation, extensive attention and in-depth research are being carried out to accurately perceive the state of the distribution network, ensure the safe and reliable operation of the distribution system, improve the operation economy, and promote the local consumption of intermittent renewable energy sources, among other research objectives [16-17].

Yan, Y et al. have organized the smart grid distribution automation, metering system and smart detection modules to sort out the barriers to smart sensing, and looked forward to the development trend of smart grid sensing technology [18]. Jaech, A et al. proposed to train a neural network prediction machine based on historical outage records to enable the prediction of unscheduled outage duration practices and validated the feasibility with a simulated example analysis [19]. Chen, L designed a multi-task and multi-scale wind power trend prediction model, DRPN, and performance tests on a public wind power prediction dataset confirmed the prediction accuracy of the proposed prediction model, as well as the ability to optimize the source-grid co-operation operation of an active distribution network [20]. Kang, L et al. introduced a high-speed communication network in the smart grid substation module in order to strengthen the substation sensing capability, and at the same time, data mining analysis method was used in order to strengthen the sensing information processing capability, and ultimately to achieve the purpose of in-depth sensing of substation fault outage [21]. Lawrence, T. M et al. described the future development and research trends in data flow and modeling development for advanced control systems for smart grids, suggesting that these measures can help to integrate building park operation strategies and reduce energy consumption costs, as well as help in fault monitoring and diagnosis for smart grids [22].

In this paper, with the technical support of generative artificial intelligence, we systematically analyze the panoramic perception technology, determine the source of research data, substitute the processed research data into the shared layer in BiGRU to obtain the current and voltage feature time series of the new distribution system, and after that, we transfer it to the multitasking auxiliary training layer to carry out the auxiliary feature fusion and dimensionality reduction operation, and finally the model outputs the perception results, which realizes the BiGRU-based panoramic perception model formation for new power distribution system. Although the panoramic perception application of generative artificial intelligence in type distribution system is given, it fails to realize the fault prediction of the new distribution system, accordingly, on the level of the above research data, the GA-ELM combination algorithm is proposed to construct the prediction model of the new distribution system. The research data and the model of this paper are assembled to explore the efficacy of generative artificial intelligence for panoramic sensing and prediction application in novel power distribution systems.

2. Panoramic perception and prediction of systems under generative artificial intelligence

2.1. Generative Artificial Intelligence (AIGC)

AIGC, often referred to as Artificial Intelligence Generated Content or Generative Artificial Intelligence, represents a compelling recent advancement in the field of AI research with far-reaching implications for the design process in different fields [23-24]. As this technology continues to evolve and mature, it promises to open up new frontiers of creativity, innovation and efficiency, revolutionizing the way we design in the digital age. In this paper, we will explore the development of AIGC and its impact on panoramic sensing and prediction in novel power distribution systems, including an overview of the application space for this technology as well as common tools. Advances in generative AI have enormous potential to revolutionize content creation across different industries, providing unprecedented opportunities for innovation, efficiency, and personalization. As AIGC continues to evolve, it will undoubtedly redefine the way content is conceived, produced, and consumed in the digital age, and this paper proposes the application of neural networks to new distribution systems based on AIGC technology for panoramic perception and prediction.

2.2. New distribution system panoramic perception technology

The basis of the new comprehensive monitoring and analysis of distribution systems based on panoramic perception technology is panoramic perception technology. The so-called perception technology is literally interpreted as a meaningful impression of an object obtained by utilizing the senses. For the panoramic perception of the new distribution system, it refers to obtaining meaningful and mature data that can reflect the operation status of the new distribution system or affect the safe operation of the new distribution system through a variety of effective monitoring means, advanced communication systems and mature information processing models. For example, the changes in wire tension and meteorological data are used to sense wire ice cover, and video monitoring information is used to sense external danger sources around the new distribution system.

2.2.1. Data Acquisition and Preprocessing. In the rapidly developing smart grid era, big data composed of massive information provides a good data basis for the panoramic perception of the new distribution system, but at the same time, the complicated and messy data also causes great difficulties for the effective panoramic perception. The massive information related to the new power distribution system that can be acquired at present has significant uncertainty and redundancy, which is specifically manifested in:

1) Non-uniformity. Information of different natures and types and their forms and contents are not uniform.

2) Inconsistency. Inconsistency of information spatio-temporal relationship caused by spatio-temporal mapping distortion.

3) Inaccuracy. Differences in information accuracy caused by differences in sensor sampling and quantization methods.

4) Discontinuity. Information discontinuity due to unstable network transmission.

5) Incomprehensiveness. The information obtained is not comprehensive enough due to the limitations of the sensor's sensing domain.

6) Incompleteness. Missing information due to dynamic changes in the network and environment.

The basis of the new distribution system panoramic sensing is the technology of vertical integration and horizontal integration of big data composed of multi-source heterogeneous data, which are derived from production management information system, transmission and substation condition monitoring system, EMS/SCADA, wide-area measurement system, fault ranging system, power meteorological system, lightning localization system, vehicle localization system, material management system, and thematic map data, 3D GIS system and other different information systems. To summarize, the big data composed of massive information related to the new distribution system provides a good data basis for the panoramic perception of the new distribution system, but at the same time, the chaotic and complicated data also cause great difficulties for the effective panoramic perception. Therefore, on the one hand, it is necessary to study the effective methods of information fusion, data cleaning of uncertain information, and integrating it into certain information needed for application services. On the other hand, it is necessary to study the efficient method of information fusion, to realize the efficient perception of information through data processing methods such as data compression and data fusion, and finally to propose a complete new type of multi-source heterogeneous information integration method for power distribution system.

2.2.2. New Distribution System Perception Models:

1) Input layer. Since the distribution system voltage and current user data and the distribution system voltage related data are 2 independent data sets, they cannot be directly used as inputs to the model. In this paper, we utilize the distribution system voltage and current user data to correlate the current, voltage and other data in the distribution system voltage-related data. At the same time, in order to ensure the integrity and consistency of the data, preprocessing operations are carried out, and the preprocessed data will be used as the input X of the model, and the input data $X=[x_1,x_2,x_3,\cdots,x_n]$ of the sequence n is set.

2) BiGRU shared layer. First of all, the data X, which has been processed by the input layer, will be used as the input to the BiGRU shared layer, and after the data enters the BiGRU shared layer, it will be transported to the forward GRU neuron and the reverse GRU neuron, respectively, and will first go through the reset gate and the update gate in the GRU to utilize the temporal characteristics X of the voltage and current data samples of the power distribution system at the current time step t, and the hidden state H_{t-1} of the previous time step $t-1$, to The reset feature R_t after retaining part of the hidden state H_{t-1} and the update feature Z_t after replacing part of the current state X_t are obtained, as shown in Eqs. (1), (2):

$$R_t=\sigma\left(X_tW_{xr}+H_{t-1}W_{hr}+b_r\right) \tag{1}$$

$$Z_t=\sigma\left(X_tW_{xz}+H_{t-1}W_{hz}+b_z\right) \tag{2}$$

where: W_{xr}, W_{hr}, W_{xz}, and W_{hz} are weight matrices; b_z and b_r are biases.

Secondly, the reset feature R_t and the updated feature Z_i are combined with the hidden state H_{t-1} of the previous time step $t-1$ to obtain the candidate hidden information $\tilde{H}_t$ of the time step t of the voltage and current data sample of the distribution system, and at the same time, the reset feature R_t, the updated feature Z_t and the candidate hidden information $\tilde{H}_t$ of the voltage and current data sample of the distribution system are integrated at time step t to obtain the time series feature H_t of the voltage and current data sample of the distribution system at time step t.

Finally, the temporal features $\vec{H}_t$ and $\overleftarrow{H}_t$ computed by the forward GRU neuron and the reverse GRU neuron are combined to obtain the final bidirectional temporal feature $\vec{H}_t$ of the distribution system voltage-current data sample as shown in Equations (3), (4) and (5):

$$\tilde{H}_t=\tanh\left(X_tW_{xh}+\left(R\odot H_{t-1}\right)W_{hh}+b_h\right) \tag{3}$$

$$H_t=Z_t\odot H_{t-1}+\left(1-Z_t\right)\odot \tilde{H}_t \tag{4}$$

$$\vec{H}_t=\vec{H}_t\,\|\,\overleftarrow{H}_t \tag{5}$$

Where: W_{xh} and W_{hh} are the weight matrix; b_h is the bias; $\square$ is the dot product between vectors; $\tanh$ is the activation function; $\vec{H}_t$ and $\overleftarrow{H}_t$ are the temporal features computed by the forward GRU neuron and the reverse GRU neuron, respectively [25-26].

3) Multi-task assisted training layer. In order to mine and learn the correlation features among the causes, the model in this paper sets seven auxiliary tasks to help improve the generalization ability of the main task. Among them, the main task is to obtain the main causes of the seven causes of low voltage in distribution system (low voltage in distribution system on the outlet side of the station, insufficient reactive power compensation, three-phase current imbalance, heavy overloading of distribution transformer, small average capacity of households, large supply radius, and fine diameter of low-voltage line). Bidirectional Timing Features Learned from BiGRU Shared Layer $\vec{H}_t$ Auxiliary feature fusion and dimensionality reduction operations are performed on the main task and dimensionality reduction operations are performed on the sub-tasks in the fully connected layer. The bi-directional time-series features after the full-connectivity layer operation will be used as inputs to the task layer, and the softmax activation function will be used in the task layer to compute the category probability distribution y_i of the voltage and current data features of the distribution system after dimensionality reduction, and the subscript fetch operation of the maximum value will be performed on y_t to obtain the prediction results $y_{predict}$.

After obtaining the perceptual result $y_{predict}$, the error LOSS between the prediction result $y_{predict}$ and the real result y_{true} of the main task and each subtask will be calculated using the cross-first loss function, and the overall loss Total Loss of the model will be calculated by weighting and summing the losses of the main task and each subtask according to the loss weights of the main task and each subtask W_i. In the process of Total Loss backpropagation, the task's full connectivity network of each task interacts with the BiGRU shared layer to jointly optimize the model parameters, seek the optimal solution of the model, and motivate the model to learn better representations.

2.3. New distribution system prediction model

Based on the above AI perspective, BiGRU is used to construct a new distribution system perception model to sense the faults (current and voltage faults, a detailed explanation will be given below), and it is found that the above model is able to sense, but fails to realize the intelligent prediction and diagnosis of the new distribution system. In this paper, we propose a GA-ELM combination algorithm to realize the application of generative artificial intelligence to the prediction of the new distribution system, substituting the current and voltage data collected by the BiGRU sensing model into the GA-ELM algorithm for training, and finally completing the construction of the prediction model of the new distribution system.

2.3.1. ELM algorithm (Extreme Learning Machine). ELM is a single hidden layer feed-forward neural network, compared with the traditional artificial neural network, the learning speed is faster, and the input weights and the bias of the hidden layer nodes are randomly determined, the structure of the ELM algorithm is shown in Fig. 1. Assuming that there is N set of distribution system current and voltage training data (x_i, t_i), the ELM model containing L hidden nodes and an activation function of G can be expressed as:

$$\sum_{j=1}^{L} \beta_j g\left(w_j x_i + b_j\right) = o_s, i = 1,2,3\cdots,N \tag{6}$$

Where, β_j denotes the output weight of the jnd hidden layer node. w_j denotes the distribution system current and voltage input weights of the jth hidden layer node. b denotes the threshold value of the jth hidden layer node. o_i denotes the distribution system current-voltage prediction result of the hidden layer.

During the training of the extreme learning machine, w_j and b_j are randomly generated and kept constant, and the output weights of the hidden layer are determined with the objective of minimizing the training error of the distribution system current and voltage β_j. Assuming that the extreme learning machine is capable of infinitely approximating the training samples with a very small error, it can be expressed as follows:

$$\sum_{i=1}^{X}\left\|o_i - t_i\right\| = 0 \tag{7}$$

That is, there exist β_j, w_j, b_j such that Equation (8) holds:

$$\sum_{i=1}^{L}\beta_j g\left(w_j x_i + b_j\right) = t_i, i = 1,2,3,\cdots,N \tag{8}$$

Express Equation (9) in matrix form:

$$H\beta = T \tag{9}$$

In Eq.

$$H = \begin{bmatrix} g\left(w_1 x_1 + b_1\right) & \cdots & g\left(w_L x_1 + b_L\right) \\ \vdots & \cdots & \vdots \\ g\left(w_1 x_N + b_1\right) & \cdots & g\left(w_L x_N + b_l\right) \end{bmatrix}_{N\times L} \tag{10}$$

H denotes the hidden layer matrix of the extreme learning machine.

To be able to train a single hidden layer neural network, find $\hat{W}_j$, $\hat{b}_j$, $\hat{\beta}_j$ such that:

$$\left\|H\left(\hat{W}_j,\hat{b}_j\right)\hat{\beta}_j - T\right\| = \min_{W,b,\beta}\left\|H\left(W_j,b_j\right)\beta_j - T\right\| \tag{11}$$

where $j = 1,2,3,\cdots,L$. This is equivalent to minimizing the loss function:

$$E = \sum_{i=1}^{N}\left(\sum_{j=1}^{L}\beta_j g\left(w_j x_i + b_j\right) - t_i\right)^2 \tag{12}$$

In the ELM algorithm, the distribution system current and voltage input weights w_j and the implied layer thresholds b_j are set randomly, then the output matrix H of the implied layer is uniquely determined. The output weights β_j can be found by computing the least squares solution of the system of linear equations $H\beta = T$.

$$\hat{\beta} = HT \tag{13}$$

where H' denotes the Moore-Penrose generalized inverse of the hidden layer output matrix H.

Minimization of the training error can be achieved by this method.

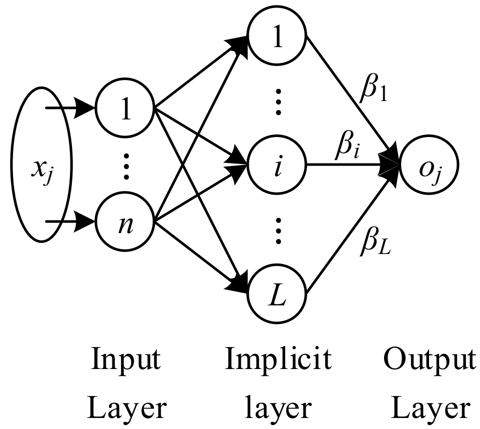


Fig. 1. Structure Chart of ELM

2.3.2. Improved ELM based on GA (Genetic Algorithm). The distribution system current and voltage input weights w_j, and the hidden layer node thresholds b_j of the ELM model are randomly generated, which makes some hidden layer nodes invalid when the distribution system current and voltage data are zero, leading to a reduction in the prediction accuracy of the distribution system current and voltage of the ELM model. Aiming at this problem, the ELM model is improved by utilizing the characteristics of the GA algorithm's fast global optimization search.

Step1: Determine the basic topology of the ELM neural network, use binary coding for the initial input weights and implicit layer thresholds of the ELM model, and construct a coding chain to generate the initial population.

Step2: Use an appropriate decoding method to decode the binary encoding, where each coding chain corresponds to an ELM neural network with specific connection weights and thresholds.

Step3: Train the population of the ELM neural network obtained in Step 2 using the training data and calculate the error function to determine the fitness of each individual (the higher the error, the lower the fitness).

Step4: According to the value of fitness function, crossover of individuals with better fitness, mutation, generate a new population, insert the selection of individuals from the sub-population into the parent population, replace the individual with the lowest fitness in the parent population, and get the new population, meanwhile, the evolutionary algebra carries out the self-subtracting one operation.

Setp5: The termination condition determines whether the maximum number of evolutionary generations is reached. If the maximum number of evolutionary generations is reached, go to step 6, otherwise go to step 2.

Setp6: Decode the corresponding parameters to get the optimal input weight w_j and hidden layer node threshold b_j.

3. Analysis of new distribution system sensing and prediction algorithms

3.1. Example analysis of a new distribution system sensing model

3.1.1. Assessment of indicators. In the distribution system perception problem, indicators such as accuracy, recall, precision, and P-R curve are generally used to evaluate the performance of the model in this paper. In this paper, the training model is used the cross-entropy loss function Loss and accuracy Accuracy as the evaluation index of the model training performance, which is calculated as:

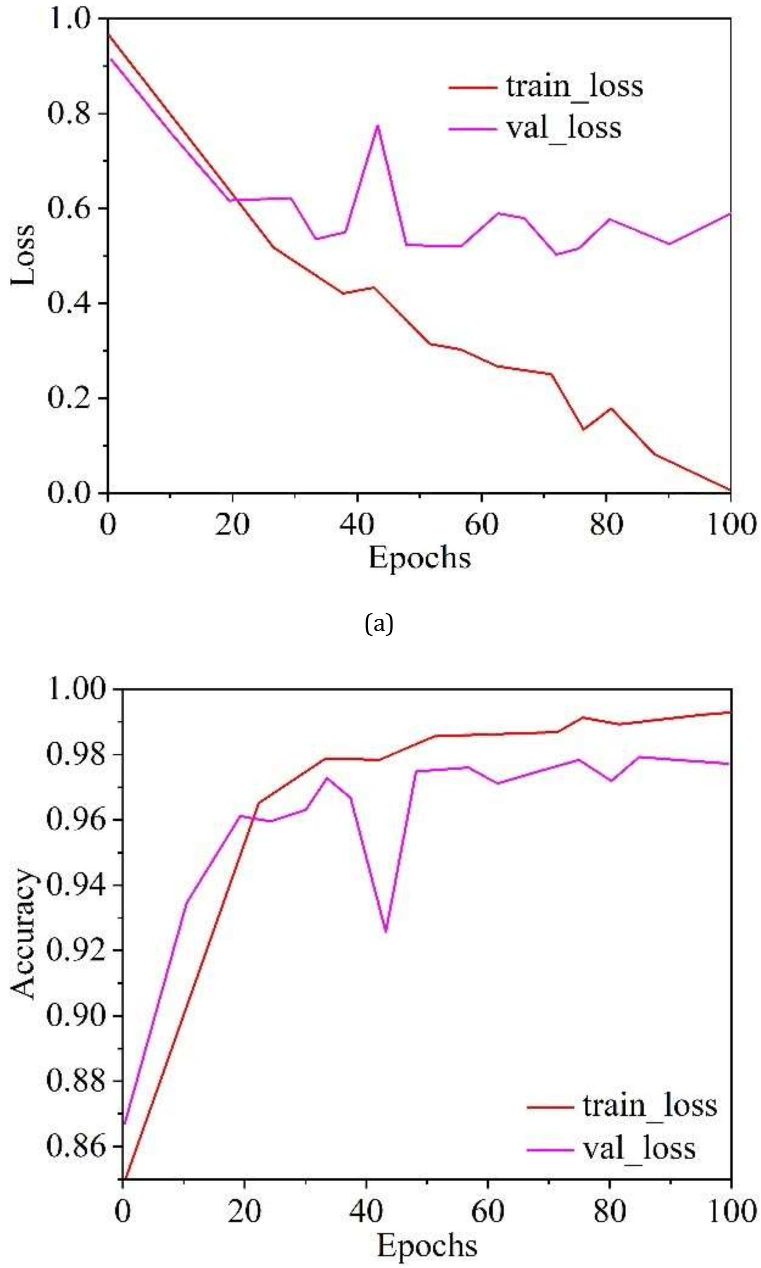
$$H_p(q) = \sum_x q(x)\log_2\left(\frac{1}{p(x)}\right) = -\sum_x q(x)\log_2 p(x) \tag{14}$$

$$Acc = \frac{R}{N} \tag{15}$$

where $p(x)$ represents the true distribution of the probability, $q(x)$ represents the distribution of the fitted probability, and $H_p(q)$ represents the value of the loss function, the smaller the result, the better the model perceives. R represents the amount of correct data perceived by the model, and N represents the total amount of data.

3.1.2. Data analysis. In this paper, BiGRU model is trained based on the previously collected dataset, in order to prove the effectiveness of the novel panoramic perception model of distribution system based on BiGRU in this paper, VGG-19 is used as a comparison model, and the training and fine-tuning are performed on the novel distribution system dataset through the method of migration learning, and the following Loss and Accuracy curves are obtained:

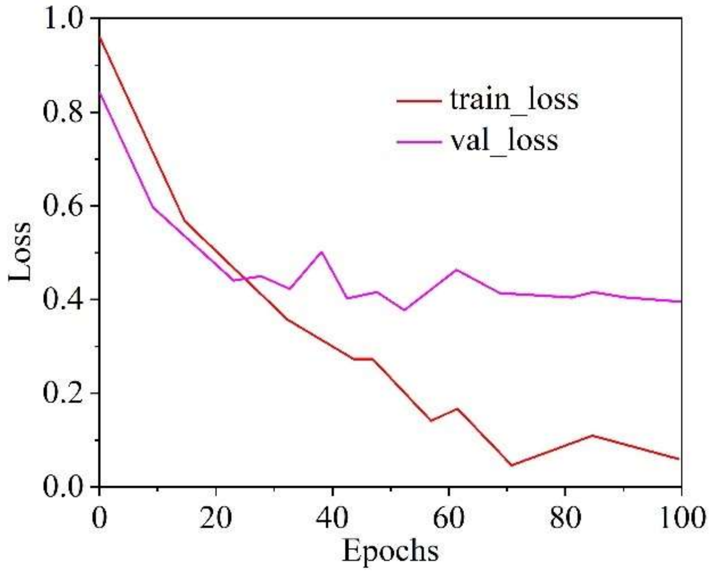
Loss represents the value of the loss function, i.e., the error function between the true value and the predicted value, and the Loss will become smaller and smaller as the training process proceeds.Acc represents the model prediction accuracy, which represents the proportion of the data that the trained model predicts correctly for the dataset as a percentage of the overall dataset, and the training process and model performance can be reflected with the help of Loss and Acc curves.The VGG-19 network The Loss and Accuracy curves of VGG-19 network are shown in Fig. 2, and the Loss and Accuracy curves of BiGRU network are shown in Fig. 3. It can be seen that the training accuracy of VGG-19 with the increase in the number of iterations, the training error continues to decrease, infinitely close to the error value of 0.01, Acc training curve trend wirelessly close to 1. However, the error value of the validation data basically ceased to decline after about 0.53, and the accuracy no longer rises around 0.99, and a large fluctuation, indicating that the network has overfitting phenomenon, which indicates that the network has overfitted. That is, it performs well in the training set and is less robust in the test. Compared with the VGG-19 network, the BiGRU proposed in this paper achieves even better performance, the starting value of Loss is substantially lower than that of the VGG network, and the training error tends to be close to 0.001, although after several iterations, the validation set also suffers from the problem of the error no longer decreasing, but the final error is about 0.1, which is much lower than that of the VGG network, and the validation accuracy is also greater than 0.98, infinitely close to 1. By comparison, it can be seen that the new panoramic perception model of power distribution system based on BiGRU in this paper has more excellent performance.



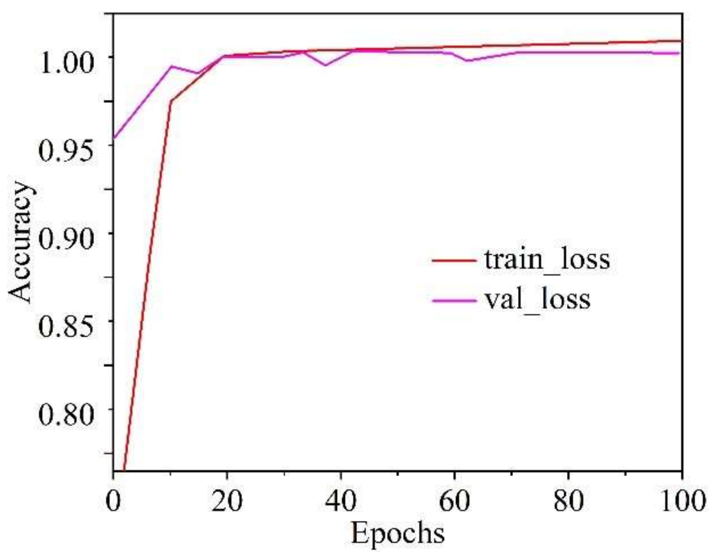
(a)

(b)

Fig. 2. VGG-19 Network Loss and Accuracy curve



(a)



(b)

Fig. 3. BiGRU Network Loss and Accuracy curve

In order to further test the effectiveness of the practical application of the model, the model is deployed in the power distribution system, and the performance of the practical application of the model is evaluated based on the accuracy and false judgment rate of the panoramic perception discrimination using the model. The accuracy and false judgment rate are calculated as follows:

$$precision_1 = \frac{M_{11}}{\sum_{m=0}^{1} M_{1,m}} \tag{16}$$

$$error_1 = \frac{M_{11}}{\sum_{m=0}^{1} M_{1,m}} \tag{17}$$

$m,n = \{0,1\}$ represents normal, error respectively. M_{ij} represents the number of actual labels as i and predicted labels as j. The accuracy and misperception rates of the distribution system are tested 100 times according to the accuracy and misperception rate formulas, respectively. The results of distribution system sensing accuracy rate based on BiGRU network are shown in Table 1, and the results of distribution system sensing misjudgment rate based on BiGRU network are shown in Table 2. Based on the data in the table, it can be seen that the panoramic perceptual discrimination accuracy of BiGRU network for power distribution system is:

$$precision_1 = \frac{95}{100} = 95.00\%$$

The panorama-aware discrimination error rate of the BiGRU network for the distribution system is:

$$error_1 = \frac{M_{00}}{\sum_{m=0}^{1} M_{1,m}} = \frac{5}{100} = 5.00\%$$

That is to say, it shows that the accuracy of BiGRU network for panoramic sensing of distribution system is 95.00% and the corresponding error rate is 5.00%, and the method in this paper can satisfy the user's demand for panoramic sensing of distribution system.

Table 1. Accuracy results

Time	Result	Time	Result	Time	Result	Time	Result
1	1	26	1	51	1	76	1
2	1	27	1	52	1	77	1
3	1	28	1	53	1	78	1
4	1	29	1	54	1	79	1
5	1	30	1	55	1	80	1
6	1	31	2	56	1	81	1
7	1	32	1	57	1	82	1
8	1	33	1	58	1	83	1
9	2	34	1	59	0	84	1
10	1	35	1	60	1	85	1
11	1	36	1	61	1	86	1
12	1	37	1	62	1	87	1
13	1	38	1	63	1	88	1
14	1	39	1	64	1	89	1
15	1	40	1	65	1	90	0
16	1	41	1	66	1	91	1
17	1	42	1	67	1	92	1
18	1	43	1	68	1	93	1
19	1	44	1	69	1	94	1
20	1	45	1	70	1	95	1
21	1	46	1	71	1	96	1
22	1	47	1	72	1	97	1
23	1	48	1	73	1	98	1
24	1	49	1	74	1	99	0
25	1	50	1	75	1	100	1

Table 2. Error rate result

Time	Result	Time	Result	Time	Result	Time	Result
1	1	26	1	51	1	76	1
2	1	27	1	52	1	77	1
3	1	28	1	53	1	78	1
4	1	29	1	54	1	79	1
5	1	30	1	55	1	80	1
6	1	31	1	56	1	81	1
7	1	32	1	57	1	82	1
8	1	33	1	58	1	83	1
9	1	34	1	59	0	84	1
10	1	35	1	60	1	85	1
11	1	36	1	61	1	86	1
12	1	37	1	62	1	87	1
13	1	38	1	63	1	88	0
14	1	39	1	64	1	89	1
15	1	40	1	65	1	90	1
16	1	41	1	66	1	91	1
17	1	42	1	67	1	92	1
18	1	43	1	68	1	93	1
19	0	44	1	69	0	94	1
20	1	45	1	70	1	95	1
21	1	46	1	71	1	96	1
22	1	47	1	72	1	97	1
23	1	48	1	73	1	98	1
24	1	49	0	74	1	99	1
25	1	50	1	75	1	100	1

3.2. Example analysis of a new distribution system forecasting algorithm

In order to check the prediction performance of the prediction model of this paper in a new type of distribution system, the fault voltages and currents in the distribution system are taken as examples, and the specific analysis process is as follows:

3.2.1. Training samples. In this paper, the number of hidden neurons is chosen to be N=10, while the activation function of the extreme learning machine is Equation (6). In order to facilitate the processing of the later data, to avoid the appearance of singular data, and also in order to make the program speed up the convergence at runtime, therefore the input data of the experiment is normalized, i.e., the input data is uniformly normalized to the range of [0, 1]. In addition, in order to make the order of magnitude of the output consistent with the order of magnitude of the peak short-circuit current taken in the simulation, the output is then back-normalized. In the normalization process, it is calculated according to the formula: y = (x - MIN)/(MAX -MIN), where x is the value before the normalization process, y is the value after the normalization process, and MAX and MIN are the maximum and minimum values within the same set of data as x, respectively.

3.2.2. Results and analysis. The input and output data in the ELM-GA prediction model are shown in Tables 3 and 4. It can be seen more clearly that the peak short-circuit currents predicted with the ELM-GA distribution system prediction model are very close to the peak short-circuit currents taken in the simulation, and none of their relative errors exceeds 1%, which indicates the effectiveness of the

ELM-GA distribution system prediction model based on the ELM-GA distribution system prediction model in the prediction of current and voltage faults.

Table 3. Training sample

N	Initial fault phase Angle/(°)	Fault voltage /N	short-circuitPeak current /A
1	10	0.825	1277.59
2	20	0.844	1237.74
3	30	0.837	1179.04
4	40	0.824	1094.08
5	50	0.753	986.26
6	60	0.672	859.19
7	70	0.579	716.32
8	80	0.463	533.49
9	90	0.341	404.36
10	100	0.208	249.49
11	110	0.091	135.08
12	120	-0.112	-1337.08
13	130	-0.237	-1336.06
14	140	-0.384	-1338.47
15	150	-0.509	-1335.23
16	160	-0.617	-1324.21
17	170	-0.707	-1315.26
18	180	0.773	-1303.17

Table 4. Test sample and its accuracy

N	Initial fault phase Angle/(°)	Fault voltage /V	Peak short circuit current /A	Predicted currentPeak value /A	Relative error (%)
1	10	0.817	1284.24	1284.08	0.0125%
2	20	0.837	1251.16	1251.16	0.0000%
3	30	0.844	1193.44	1193.42	0.0017%
4	40	0.812	1114.39	1114.46	0.0063%
5	50	0.763	1012.79	1012.81	0.0020%
6	60	0.704	891.13	891.08	0.0056%
7	70	0.609	746.23	746.26	0.0040%
8	80	0.445	594.19	594.27	0.0135%
9	90	0.353	435.09	434.12	0.2229%
10	100	0.227	287.38	284.53	0.9917%
11	110	0.082	154.49	156.33	1.1910%
12	120	-0.073	-1341.64	-1337.12	0.3369%
13	130	-0.205	-1341.19	-1341.33	0.0104%
14	140	-0.348	-1335.08	-1335.08	0.0000%
15	150	-0.472	-1333.12	-1328.22	0.3676%
16	160	-0.583	-1325.41	-1325.41	0.0000%
17	170	-0.688	-1321.31	-1321.36	0.0038%
18	180	-0.758	-1304.75	-1304.39	0.0276%

According to the above-mentioned ELM-GA distribution system prediction model, under the same fault initial phase angle, the input characteristic quantities are tested 50 times respectively, and the relative error of each fault is obtained, and the maximum relative error under the initial phase angle of each fault is found out and recorded, and the maximum relative error under the initial phase angle of each fault is shown in Table 5. When the fault voltage is used as the input characteristic quantity, the maximum relative error exists when the initial phase angle of the fault is 3°: 3.8458%, and the error under the rest of the initial phase angles is even less than 3%; and when the fault current is used as the input characteristic quantity, its maximum relative error, although slightly larger than that of the fault voltage, is also within the scope of the engineering error (5%), so it can be seen that the ELM-GA distribution system prediction model has a strong robustness, high accuracy.

Table 5. The maximum relative error at the initial phase Angle of each fault

Initial fault phase Angle/(°)	Maximum relative error in 50 tests (%)	
	Input characteristic: fault voltage/%	Input characteristic: fault current
10	3.8458	3.7212
20	2.7368	3.1999
30	2.6323	3.1637
40	1.9127	2.591
50	1.8887	2.5616
60	1.8836	2.5383
70	1.8791	2.2218
80	1.7345	2.116
90	1.715	2.0395
100	1.6707	1.8219
110	0.8844	1.328
120	0.4707	0.8815
130	0.412	0.5228
140	0.3499	0.501
150	0.3304	0.4954
160	0.1919	0.3117
170	0.1189	0.2789
180	0.0047	0.0037

4. Conclusion

According to the characteristics of generative artificial intelligence technology, this paper proposes to construct a new distribution system panoramic perception and prediction model using BiGRU network and ELM-GA algorithm respectively, combining with the operation of the new distribution system, and using the model in this paper to perform perception and prediction analysis of the new distribution system. When BiGRU network is applied to the actual distribution system, the perception accuracy of the distribution system at this time is 95.00%, and the perception discrimination error rate is 5.00%, that is, BiGRU network is capable of performing the task of distribution system panoramic perception. The relative error of current and voltage fault prediction based on ELM-GA distribution system prediction model is not more than 5%, which proves that the ELM-GA distribution system prediction model based on ELM-GA distribution system prediction model has excellent performance in current and voltage fault prediction.

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