A Line Loss Prediction Method of Distribution Network Based on Improved Grey Correlation Analysis and SSA-GRU Neural Network

Guangming Zhu, Dong Liang, Yunyan Xu, Shuting Wu, Wenbin Qin

Abstract—**The line loss rate represents the level of power grid operation and management, and the key to reducing the line loss rate is accurate line loss calculation. Therefore, this paper proposed a line loss prediction method for distribution network (DN) based on the improved grey correlation analytics and SSA (sparrow search algorithm) to optimize the GRU (gate recurrent unit) network. The relation between 17-electrical characteristic parameters and line loss was obtained by improving the grey correlation analysis method. In addition, the optimal electric characteristics parameter system was determined through the prediction and verification of distribution network data. Using SSA to optimize the four important hyper-parameters of GRU, the optimal unit structure of GRU was determined, thereby constructing a neural network line loss prediction model based on SSA-GRU for the line loss of distribution network predicting. Finally, through a case study of a distribution network in a certain region of Gansu Province, China, the SSA-GRU model was compared with SVM (support vector machine), GA-BP (back propagation optimized by genetic algorithm) and GRU prediction models. The results showed that SSA-GRU model had the smallest MAPE and RMSE values for line loss prediction results, compared with GRU, GA-BP and SVM models. APE was also better than the other three models, which verified that the proposed method had higher prediction precision.**

Index Terms—**Distribution network, Line loss prediction, Improved grey correlation method, SSA (sparrow search algorithm), GRU (gated recurrent unit), Deep learning**

I. Introduction

In recent years, environmental and energy issues have become increasingly prominent. Energy saving and loss reduction has become a very important strategic task for power grid enterprises. With the improvement of social generation capacity and economic development, power consumption is increasing year by year, followed by the serious problem of line loss in the distribution network. According to statistics, the line loss accounts for about 45% of the power grid total loss [1-3]. In addition to comprehensively reflecting the level of regional power grid plan formulation and operation management, reducing the line loss rate also helps to improve the economic efficiency of power supply enterprises. Although the line loss management adopts the "four division method", that is, the overall assessment is conducted from the four aspects of voltage division, zoning, line division and courts division, the final assessment is still the line loss index [4]. Therefore, the accuracy of the calculation of the line loss rate is of very importance to enhance the fine management of line loss and formulate loss reduction measures.

At present, many references have studied the calculation method of line losses. The traditional methods for calculating line loss include power flow method, equivalent resistance method and root mean square current method [5]. However, they are closely related to the power loss model of the distribution network, and the calculation accuracy is usually relatively lower, with poor real-time performance.

To reduce costs, increase efficiency and improve the fine management of line losses, the synchronous line loss management system has been vigorously promoted and applied. The data received by the synchronous line loss management system comes from multiple business systems. There are equipment operation management systems (such as PMS2.0), energy information collection systems, OMS/SCADA systems, power business management systems, electricity consumption information collection systems, and power grid GIS platforms, forming a huge database [6-8]. The multi-source heterogeneous mass data provides sufficient data support for the DN line loss calculation. However, the traditional calculation methods are difficult to explore the complex correlation between power grid line losses and massive data.

Following the utilization of artificial intelligence technology in the power system, an innovative algorithm, exemplified by artificial neural networks, has been extensively employed in the calculation of power grid losses. Reference [9] converted the theoretical line loss calculation into a regression analysis for solution and proposed an approach based on improved core vector machine for line loss calculate. Reference [10] solved the poor calculation accuracy of line losses caused by numerical dispersion by screening electrical characteristic parameters and using improved K-Means clustering and using BP neural network

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to calculate the line loss in the courts. Different from the traditional machine learning algorithm, the deep learning model has excellent nonlinear function approximation ability. By building a multi hidden layer network model, it can accurately obtain a deeper level of feature distribution in massive data [11]. At present, typical deep learning models mainly include RNN (recurrent neural network) algorithms [12], LSTM (long short-term memory) algorithms [13], GRU algorithms [14], etc. LSTM is obtained by improving RNN, while GRU further optimizes LTSM and simplifies the network structure of LSTM. GRU is one of the most competitive deep learning algorithms, which has been widely used in recent years. Reference [15] established a neural network forecast model for transformer power loss based on GRU. By constructing multi-dimensional electrical characteristic parameters as model input for training and learning, high calculation accuracy was obtained. Based on GRU neural network, reference [16] combined the interconnection information theory and hierarchy process analytic to set the influence weight of the selected electric characteristic parameters on the line loss. Additionally, the errors calculation amount of GRU neural network under different electric characteristic parameters was analyzed to set the optimal input parameters and higher calculated performance achieved. Reference [17] quantitatively analyzed the interrelation between 15-electric indexes and line loss by using the grey related coefficient analytic and proposed an adaptive algorithm to optimize the line loss rate forecast model based BP neural network, which improved the prediction accuracy, algorithm convergence and generalization ability. Reference [18] proposed a prediction model based the combination of DAE (denoising auto encoder) and LSTM, which using daily line loss rate by establishing the grey related coefficient analytic index and extracting the correlation between the recent amount of the influencing factors of DN daily line loss rate and its historical amount in the same period. Although it has low calculation speed, it has an engineering application value. Based on the grounded theory, 19-factors impacting on the DN line loss were extracted in reference [19]. An Apriori algorithm was used to derive the relationship between diverse impact factors and line losses. According to this, association rules were formulated to extract the key impact factors, and the electric indexes for calculating line loss were obtained, which was consistent with the actual distribution network topology structure. From the above reference analysis, it is evident that the precision of line loss calculation is not only depending on the advanced prediction algorithm, but also closely related to the selection of the electric characteristic parameters that actually affect line loss.

Referring to the above line loss prediction methods, this study proposed a line loss prediction approach that utilizes improved grey correlation coefficient analytic and SSA to optimize GRU neural network. First, through improving the grey correlation coefficient analytic, the relation between 17 electrical characteristic parameters and line loss was obtained. After the verification of actual data in a certain region distribution network, the optimal electrical characteristic parameter system was determined and as the prediction model input. Then, four important hyper-parameters of GRU network were optimized by SSA to determine the optimal network structure, which solved the disadvantage of relying on experience when considering multidimensional data types in GRU neural network. Finally, the SSA-GRU model was built to forecast the DN line loss. Through the calculation of 291 lines in a certain region distribution network of Gansu Province, China, the prediction results of SSA-GRU, GRU, GA-BP and SVM models were compared and analyzed, which verified that the SSA-GRU had higher prediction accuracy.

The main innovations of this paper are as follows.

1) An improved grey correlation analytic method to determine the interrelation between each electrical index and DN line losses, and to set input of the prediction model, in order to address the difficulty of selecting key factors as input parameters for calculating line losses based on expertise experience from numerous characteristic parameters that affect distribution line loss. This method is more suitable for actual line loss prediction.

2) To improve the predictive ability of GRU models, this study uses the SSA to optimize the number of hidden layers, neurons of each layer, the learning rate, and the batch size of training parameters in GRU neural networks. The optimal GRU network topology is obtained, which solves the problems of GRU neural networks relying on empirical determination when considering multidimensional data types.

3) An SSA-GRU line loss prediction model has been established to predict line losses in actual distribution networks. Through a case study of a distribution network in a certain region of Gansu Province, China, the results of different types of prediction models were compared and analyzed to verify that the proposed method has higher precision and is more suitable for predicting line losses in actual distribution networks.

This paper is arranged as follows: In Section 2, the electrical characteristic index using improved grey correlation coefficient analytic method was introduced. The SSA-GRU model was established in Section 3. The SSA-GRU model was utilized to forecast the line loss, and it was compared with GRU, GA-BP and SVM models in a real case in Section 4. In the Section 5, the conclusion is summarized and prospected.

II. Electrical Characteristic Index System build Based on Improved Grey Correlation analytic

There are several factors affecting the line losses, mainly consist of line total length, conductor type, power supply, various transformers power, and total capacity of the transformer. Nowadays, the electric characteristic indexes are generally selected by experts' experience, and there are no exact selection methods and standards, nor specific analysis and research for the actual distribution network. Therefore, this study proposed to apply an improved grey correlation analytic method to set the interrelation between each electrical feature index and the line loss, establish the electrical index of distribution network to reflect the influence of the network topology and operation state on line loss.

A. *Improved grey correlation analytic method*

The core idea of grey correlation analytic method is based on the judgment of "similarity". It reflects the strength of the correlation between system factors by calculating the degree of interrelation between the reference sequence and the comparison sequence [20]. It holds that the more similar the geometric shapes of the compared sequence and the reference sequence, the higher the correlation. Grey correlation analytic method is an effective method for dealing with uncertainty problems, especially suitable for small sample, poor information, and uncertain systems, often be used to analyze the effect of various factors on the results.

The data related to line loss prediction are characterized by large quantity and complex and diverse types, and their dimensions and orders of magnitude are usually quite different. Thereby, it has to standardize the raw data. The commonly used dimensionless methods include min-max interval normalization, arctangent standardization and Z-Score standardization [21]. The min-max normalization treatment technology was adopted in this study. Min-max normalization is to perform linear transformation on the raw data according to the principle of the relative position of the minimum and maximum values of the data index within that index, so that the final output result is between [0, 1]. The conversion equation is shown in Equation (1).

$$X = \frac{(x_{\max} - x_{\min}) \times (y - y_{\min})}{y_{\max} - y_{\min}} + y_{\min} \tag{1}$$

Where, X denotes the normalization value, y represents the original value, $y_{\max}$ and $y_{\min}$ correspond to the maximum and minimum values of the original value respectively, $x_{\max}$ and $x_{\min}$ are 1 and -1, respectively.

It is assumed that the number of electrical characteristic parameter sequences affecting the line loss of the distribution network is n_z, the line loss of the distribution network is taken as the reference sequence to normalize it to X_s. The compared sequence is X_z. The specific description is shown in Equation (2).

$$\begin{cases} X_s = x_s(1), x_s(2), \dots, x_s(n_z) \\ X_z = x_z(1), x_z(2), \dots, x_z(n_z) \end{cases} \tag{2}$$

According to the definition of relevance degree, the grey relevance degree γ between the compared sequence X_z and the reference sequence X_s is:

$$\gamma = (X_s, X_z) = \frac{1}{m} \zeta_j (X_s(j), X_z(j)) \tag{3}$$

$$\zeta_j (X_s(j), X_z(j)) = \frac{\min\limits_z \min\limits_j |\Delta_j| + \rho \max\limits_z \max\limits_j |\Delta_j|}{|\Delta_j| + \rho \max\limits_z \max\limits_j |\Delta_j|} \tag{4}$$

$$\Delta_j = X_s(j) - X_z(j) \tag{5}$$

Where, *m* is the total amount of sequence data, Δ_j is the difference between the *j*-th parameter $X_s(j)$ in the reference sequence and the *j*-th parameter $X_z(j)$ in the compared sequence, $\max\limits_z \max\limits_j |\Delta_j|$ denotes the two-stage maximum difference between sequences, $\min\limits_z \min\limits_j |\Delta_j|$ represents the two-stage minimization difference between sequences, ρ is the resolution coefficient, generally set at 0.5.

As can be seen from Equation (4), the product of the resolution coefficient ρ and $\max\limits_z \max\limits_j |\Delta_j|$ has a great influence on the calculation result of the relevance degree, and the relevance degree is different if ρ is different. The artificial setting of 0.5 in the traditional method will lead to the averaging of the calculation results, reduce the correlation distribution interval and reduce the discrimination.

Therefore, this study proposed that the concept of slope could be integrated into the traditional grey correlation analytic to solve the disadvantages of the conventional grey correlation analytic. The correlation degree calculation of the slope gray correlation analysis is shown in Equation (6). The slop of the comparison sequence X_z at the *j*-th element are defined as $Z_z(j)$, which is as follows.

$$Z_z(j) = \frac{\min\limits_z \min\limits_j |\Lambda| + \rho \max\limits_z \max\limits_j |\Lambda|}{|\Lambda| + \rho \max\limits_z \max\limits_j |\Lambda|} \tag{6}$$

$$\Lambda = \frac{x_z(j) - x_z(j-1)}{\frac{1}{n_z(m-1)} \sum\limits_{k=1}^{n_z} \sum\limits_{k=2}^{m} |x_z(j) - x_z(j-1)|} \tag{7}$$

Where, $0 \le \rho \le 1$, which is generally taken as 0.5.

After introducing the slope coefficient, a modified grey correlation analytic method is obtained. The grey relevance degree $\tilde{\gamma}$ between the two sequences of the improved grey correlation is:

$$\tilde{\gamma}(X_s, X_z) = \frac{1}{m-1} \cdot \sum_{j=2}^{m} \frac{\operatorname{sgn}(\mu)}{\frac{3}{2} + \frac{1}{2}\left(|Z_s(j) - Z_z(j)| - \frac{\min(Z_s(j), Z_z(j))}{\max(Z_s(j), Z_z(j))} \right)} \tag{8}$$

Where

$$\operatorname{sgn}(\mu) = \begin{cases} 1 & , \quad \mu \ge 0 \\ -1 & , \quad \mu < 0 \end{cases} \tag{9}$$

$$\mu = [X_s(j) - X_s(j-1)] \cdot [X_z(j) - X_z(j-1)] \tag{10}$$

It is not difficult to prove that the improved grey correlation analysis method proposed has stronger sign-preserving property and avoids the tendency of the correlation degree calculation results to average.

B. Example Calculation and Analysis

To demonstrate the rationality, necessity and advantages of the improved grey correlation analytic method, a distribution network D in Gansu Province was took as the research plant for correlation analysis and compared with the traditional grey correlation analysis method. The distribution network D included 291 lines, and the monthly active power supply of public transformers accounted for 62%, of which 129 lines only had public transformers.

TABLE I. RELEVANCE DEGREE RANKING OF INDEXES AFFECTING LINE LOSS IN DISTRIBUTION NETWORK

Order	Electric index	Proposed method	Electric index	Tradition method
1	Monthly active power	0.916	Monthly active power	0.859
2	Monthly reactive power	0.876	Monthly reactive power	0.841
3	Monthly public transformer active power	0.845	Line length	0.822
4	Total transformer capacity	0.831	Total transformer capacity	0.800
5	Line length	0.824	Monthly public transformer active power	0.797
6	Monthly public transformer reactive power	0.787	Line cross-sectional area	0.760
7	Line cross-sectional area	0.774	Monthly public transformer reactive power	0.758
8	Monthly special transformer active power	0.769	Proportion of high loss transformer	0.745
9	Monthly special transformer reactive power	0.750	Reactive power compensation capacity	0.737
10	Reactive power compensation capacity	0.742	Monthly special transformer active power	0.728
11	Proportion of high loss transformer	0.738	Monthly special transformer reactive power	0.722
12	Line material	0.724	Line material	0.715
13	Trunk line total length	0.715	Trunk line total length	0.708
14	Branch line total length	0.709	Branch line total length	0.695
15	Transformer load rate	0.694	Transformer load rate	0.683
16	Public transformer load rate	0.685	Public transformer load rate	0.672
17	Special transformer load rate	0.667	Special transformer load rate	0.649

The 17- electrical characteristic parameters that can reflect the operation status and basic distribution network topology were selected. The ranking results of relevance degree calculated using improved grey correlation analytics method and traditional grey correlation analysis method are illustrated in Table 1.

From Table 1, the relevance degree value of the improved grey correlation analysis method increases overall. In particular, the line length and line cross-sectional areas are significantly correlated with the line loss, resulting in their rankings have changed. In addition, the correlation between the two indexes of the special transformer (monthly special transformer active power and its reactive power) and the line loss of distribution network is also significantly increased, indicating that when the number of special transformer users increases, the influence of the power supply of special transformers on the line loss of distribution network becomes larger. According to the actual field investigation, the above changes are consistent with the actual distribution network. So, it is very important to conduct correlation analysis on the characteristic parameters affecting the line loss.

According to the distribution network D actual data and under different electric characteristic index, the line loss prediction GRU model is established based on the correlation degree between the electrical characteristic parameters and the line loss values obtained in Table 1. The average prediction error of the distribution network D was obtained, as shown in Fig. 1. The electrical characteristic parameters obtained by the improved grey correlation analysis method are used for line loss prediction, and the average prediction error is lower from Fig.1.

Therefore, the improved grey correlation analytic method is closer to the actual distribution network than the traditional grey correlation analysis. When the index number of electric characteristic parameters is 7, the average prediction errors become to the smallest, and the performance the line loss prediction GRU model reach to the best. Therefore, different distribution networks should adopt different electric characteristic parameter.

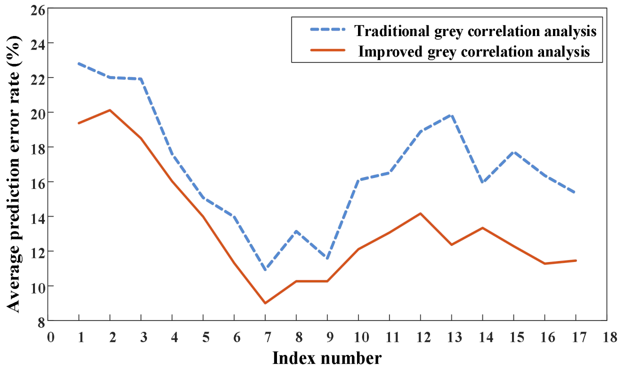


Fig. 1. Average prediction error of GRU line loss prediction model

III. LINE LOSS PREDICTION METHOD OF DISTRIBUTION NETWORK BASED ON SSA-GRU MODEL

A. GRU Neural Network

GRU inherits the superiority of RNN algorithm in time series prediction, and also has the advantages of LSTM in non-linear fitting. Furthermore, it simplifies the forgetting gate and updating gate in LSTM, greatly simplifies the model structure, shortens the model training and prediction time, improves the prediction efficiency, and avoids the gradient attenuation or explosion problems that are prone to occur during the training of RNN and LSTM [22]. The unit structure of GRU is shown in Fig. 2.

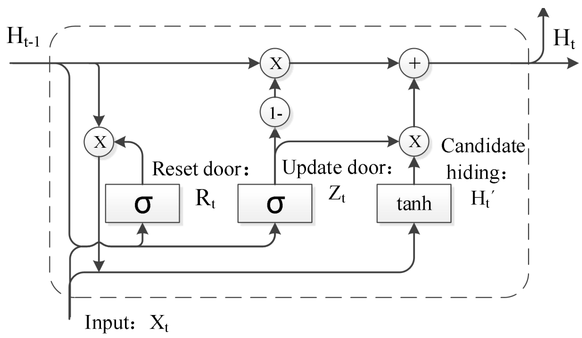


Fig. 2. Network structure of GRU

According to the unit structure of GRU, the forward calculation is shown in Equation (11).

$$\begin{cases} R_t = \sigma\left(W_r X_t + U_r H_{t-1} + b_r\right) \\ Z_t = \sigma\left(W_z X_t + U_z H_{t-1} + b_z\right) \\ H_t' = \tanh\left(W_h X_t + r_t U_h H_{t-1} + b_h\right) \\ H_t = Z_t H_{t-1} + \left(1 - Z_t\right) H_{t-1}' \end{cases} \tag{11}$$

Where, X_t represents the input at time t; W and U denote weight matrixes; b is the offset amount; R_t and Z_t are reset door and update door, respectively; H' denotes candidate hidden state; H_t denotes hidden state; σ denotes the activation function and the full connection layer. In general, the activation function is usually sigmoid function.

B. Sparrow Search Algorithm

In 2020, Xue et al. [23] put forward the Sparrow search algorithm (SSA). Subsequently, it has attracted wide attention because of its simple structure and good optimization ability. It is a swarm intelligence optimization algorithm based on sparrows' foraging skills and risk aversion behavior. This algorithm has a simple structure and good stability, making it suitable for fields such as machine learning parameter optimization. It performs well in handling complex multimodal optimization problems [24].

SSA relies on sparrow individuals distributed in the solution space to search for the best foraging position to achieve the purpose of optimization [25]. Sparrows that reach the foraging area preferentially are "discoverers", corresponding to better fitness values, leading the remaining "participants" in the population to move to better foraging positions. Some sparrows are selected as vigilantes in the population to drive the population to walk randomly to avoid the risk of predation [26]. SSA continuously updates the location of discoverers, participants and vigilantes by comparing the fitness of the models to find targets.

During the iterative calculation, the position of the discoverer is updated as:

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j} \exp\left(-\dfrac{i}{\alpha S_{\max}}\right), & R_2 < ST \\ X_{i,j} + Q \cdot L & , R_2 \geq ST \end{cases} \tag{12}$$

Where, $S_{\max}$ denotes the maximum number of iterations; $X_{i,j}$ is the location information of the i-th sparrow in the j-th dimension; α is a random number between 0 and 1, $R_2 \in [0,\ 1]$ denotes the warning value, $ST \in [0.5,\ 1]$ denotes the safety value; Q is a random number that follows normal distribution; L is a $1 \times d$ matrix whose elements are all 1.

$R_2 < ST$ indicates that there are no predators around the foraging environment, and the discoverer conducts overall search. On the contrary, $R_2 \geq ST$ indicates that some sparrows in the population have discovered predators and alerted other sparrows. At that time, all sparrows needed to quickly migrate to a safe place for feeding.

Those who forage by tracking the discoverer are the participants. The participant position can be update as follows.

$$X_{i,j}^{t+1} = \begin{cases} Q \cdot \exp\left(-\dfrac{X_W - X_{i,j}^t}{i^2}\right) & , i > \dfrac{n}{2} \\ X_p^{t+1} + \left|X_{i,j} + X_p^{t+1}\right| L A^+ & , other \end{cases} \tag{13}$$

Where X_p is the optimal location forthe discoverer, X_W is the worst position, A is a $1 \times d$ matrix whose elements are randomly set 1 or -1, and $A^+ = A^{\mathrm{T}}\left(AA^{\mathrm{T}}\right)^{-1}$.

When $i > n/2$, it shows that the i-th participant can't obtain food and is in a state of hunger with low fitness. Therefore, it is necessary to migrate to other places for feeding to obtain more energy.

If the vigilante perceives the insecurity, it sends out a warning signal and produces the anti-predator behavior. The expression of its position is:

$$X_{i,j}^{t+1} = \begin{cases} X_b^t + \beta\left|X_{i,j}^t + X_b^t\right| & , f_i > f_b \\ X_{i,j}^t + K\left|\dfrac{X_{i,j}^t + X_b^t}{\left(f_i - f_W\right) + \varepsilon}\right| & , f_i = f \end{cases} \tag{14}$$

Where, X_b denotes the global optimal position, β is a random number, which follows a normal distribution with a mean of 0 and a variance of 1. $K \in [0,\ 1]$ is a random number. f_i is the fitness, f_b and f_W denote the current global best and worst fitness respectively. ε is a constant. If $f_i > f_b$, it shows that the current sparrow is vulnerable because it is at the edge of the population. The discoverer then conducts the next round of search.

C. Establishment of SSA-GRU Line Loss Prediction Model

In GRU, the batch size, learning-rate, the number of hidden layers and their neurons is the key parameters affecting the prediction accuracy. The four parameters determine the network unit structure of GRU. It varies greatly in the prediction ability of the model trained with different parameters. Therefore, a novel SSA-GRU model was established. The SSA is applied to optimize the number of hidden layers and their neurons, learning rate and batch size of GRU. The steps for SSA optimize GRU as follows.

Step1: The electrical characteristic parameters selected according to the improved correlation analysis method were standardized by Min-Max to get the sample set.

Step2: Set the value range of batch size, learning rate, hidden layers and neurons, and also randomly initialize the sparrow position.

Step3: Initialize the population. Set the number of iterations, and set the number of predators, discoverers, and entrants. The individual fitness of sparrow population was calculated and ranked.

Step4: Calculate the early alert value. Update the position of the discoverer according to the calculated value.

Step5: The position of the participant was updated referring to Equation (13).

Step6: Update the position of the vigilante perceives. The sparrow that sensed danger approached other sparrows according to Equation (14).

Step7: Calculate the fitness value of the sparrow's new position and save the optimal and worst position values in the population.

Step8: Proceed to the next step if the iteration number condition was satisfied; otherwise, return to step (4).

Step9: At the end of the iteration, the global optimal sparrow individual position was output, which was the optimal parameter group of the GRU model training.

D. Implementation Process of Line Loss Prediction

The line loss prediction process based on SSA-GRU model is shown in Fig. 3.

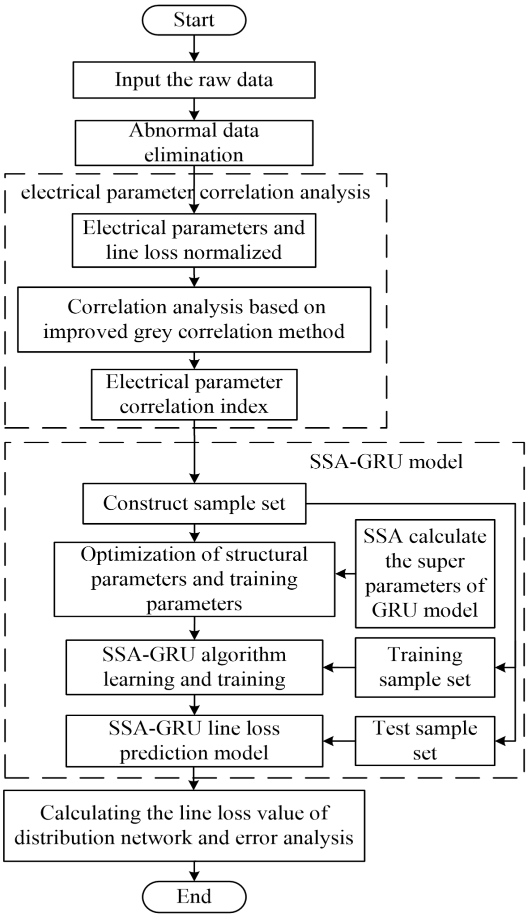


Fig. 3. The flowchart of line loss predication process

The specific steps of line loss prediction based on SSA-GRU are as follows.

Step1: Input the original data and preprocess the data, including elimination of duplicate data and abnormal data and filling of vacant data.

Step2: Normalize the data, including electrical characteristic parameters and line loss data.

Step3: Use the improved grey correlation analytics method to calculate the relevance degree of 17 kinds of electrical characteristic parameters, select the characteristic parameter set that had the greatest impact on the line loss, and build the index system.

Step4: Input training data-set and test sample data-set. The SSA-GRU was trained to obtain the SSA-GRU prediction model.

Step5: The SSA-GRU model was used to the actual line loss prediction. To comprehensively evaluate the predictive performance and precision of the model, an error assessment is carried on its prediction results.

IV. EXAMPLE ANALYSIS

A. Determine Electrical Characteristic Parameters and Model Evaluation Indexes

Taking a distribution network D in Gansu Province as a case, the SSA-GRU model was used to forecast its line loss, and compared with SVM, GA-BP and GRU models.

According to the proposed slope grey correlation analytic method, seven electric characteristic parameters were set for the distribution network, which were monthly active and reactive power, monthly active power of public transformer, total capacity of transformer, line length, monthly public transformer reactive power and line cross-sectional area, and they were taken as inputs of SSA-GRU model. The line loss prediction value y was the output of SSA-GRU.

To quantitatively illustrate the accuracy and superiority of the SSA-GRU model, APE (absolute percentage error), MAPE (mean absolute percentage error) and RMSE (root mean square error) were introduced as the evaluation indexes to assess the calculation accuracy of line losses in distribution networks.

$$APE=\left|\frac{y_i-\overline{y}_i}{y_i}\right|\times 100\% \tag{15}$$

$$MAPE=\frac{1}{m}\sum_{i=1}^{m}\left|\frac{y_i-\overline{y}_i}{y_i}\right|\times 100\% \tag{16}$$

$$RMSE=\sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(y_i-\overline{y}_i\right)^2} \tag{17}$$

Where, y_i denotes the prediction value through the GRU neural network; $\overline{y}_i$ denotes the true line loss value corresponding to the test data of the i-th line; m denotes the number of samples tested.

B. Parameter Optimization Analysis of SSA-GRU Model

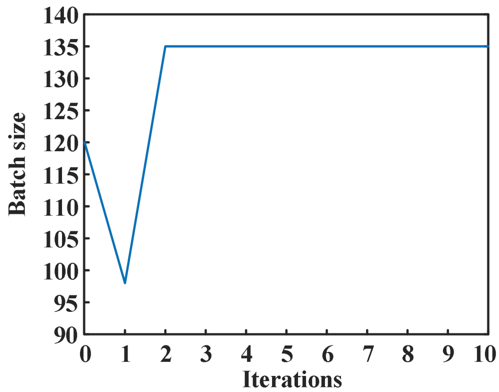
The determined seven electrical characteristic parameters were input into the SSA-GRU model, and the SSA algorithm was used to iteratively optimize the most important training parameters in the GRU model. The optimization process is shown in Fig. 4.

From Fig.4, the best size of the training batch is 135. The learning rate is less than 0.005, converging to 0.0015. The result of SSA iteration is 3 layers, and more layers will increase the training time, which may lead to over fitting. The number of neurons in each layer is 5, 9 and 6 respectively, and the optimal super parameters of SSA-GRU can be obtained.

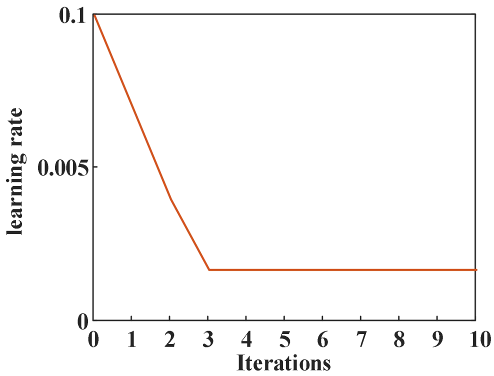
C. Analysis of Line Loss Prediction Results Based on SSA-GRU Model

There are 291-line data in distribution network D, with a data sampling interval of 15 minutes. To analyze the generalization and accuracy of the proposed SSA-GRU model, K-fold cross validation was used. Divide data of 291 -line into 5 sub sample sets on average, take turns using 1 sub sample set as the test set, and the remainder 4 groups as the test sample set, and repeat 5 times.

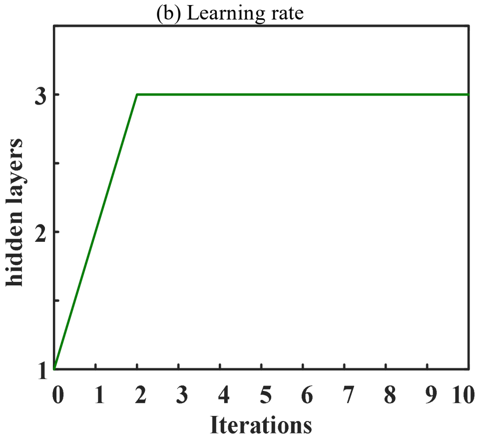
As an evaluation index of neural network, loss function often is applied to measure the difference or error between the neural network output and the real value. To better illustrate the prediction accuracy of SSA-GRU model, it is compared with SVM, GA-BP and GRU models. Under the same data set, set the number of model super parametric training rounds to 250, and the learning rate is 0.0015. The loss values of the four training models are shown in Figure 5.



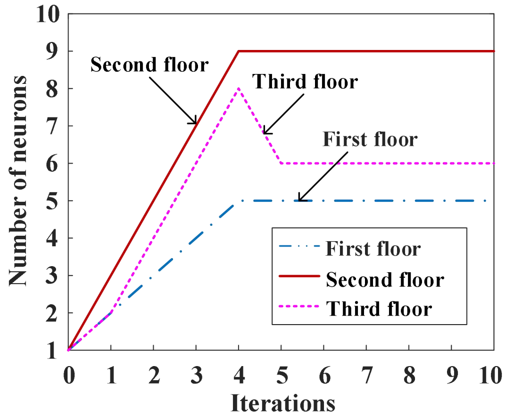
(a) Batch size



(b) Learning rate

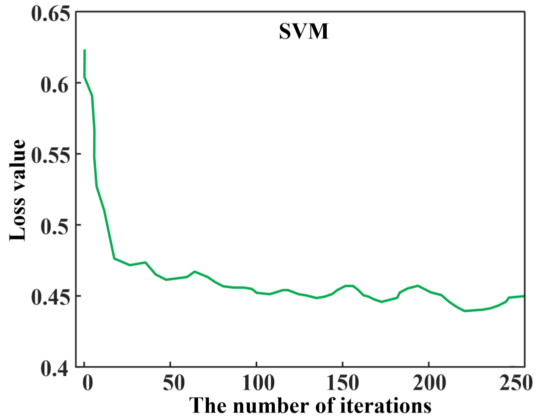


(c) Number of hidden layers

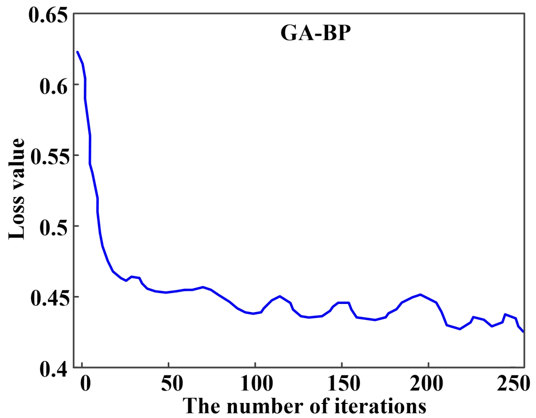


(d) Number of neurons

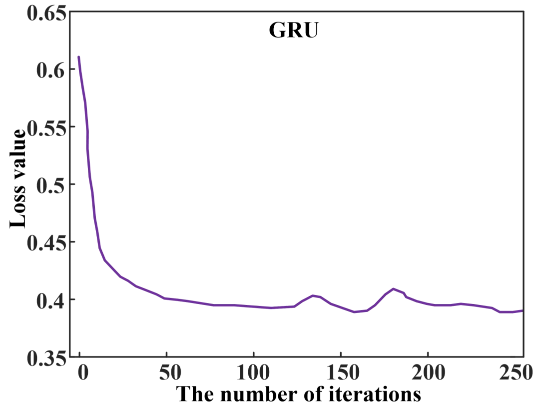
Fig.4. Optimization process of optimal parameters of SSA-GRU network



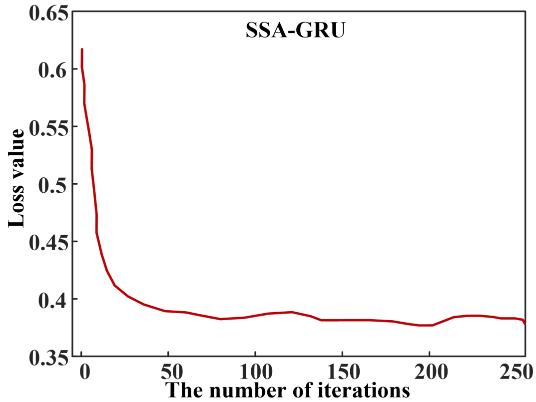
(a) Loss value curves of SVM models



(b) Loss value curves of GA-BP models



(c) Loss value curves of GRU models



(d) Loss value curves of SSA-GRU models

Figure 5. The loss values of four prediction models

From Fig.5, SVM, GA-BP, GRU and SSA-GRU models have all achieved small loss values under this training set, and the final loss value of SSA-GRU model is below 0.4, with small fluctuation, and the best training result is obtained. The final predicted value of LSTM is close to 0.4, and the loss value fluctuates slightly. The final loss values of SVM and GA-BP prediction models are all below 0.45, but their loss values fluctuate greatly. To sum up, the data fitting effect of SSA-GRU is better, and the error between the neural network output and the real value is smaller.

To validate the generalization and accuracy of SSA-GRU model for line loss prediction, the evaluation indexes MAPE and RMSE were used to evaluate the forecast accuracy of the four models. The model evaluation indexes MAPE and RMSE of SSA-GRU, GRU, GA-BP and SVM on the test sample set are displayed in Table 2 and 3, respectively.

TABLE II MAPE VALUES OF 5 TEST SETS IN 4 PREDICTION MODELS

Test set	SSA-GRU	GRU	GA-BP	SVM
Test set1	4.88%	9.48%	11.25%	11.32%
Test set2	4.22%	9.21%	11.89%	13.13%
Test set3	5.17%	10.33%	12.61%	12.18%
Test set4	4.85%	8.02%	11.08%	13.03%
Test set5	4.10%	8.56%	12.31%	12.33%
Average value	4.64%	9.12%	11.83%	13.20%

It is clear that the SSA-GRU model has the highest prediction accuracy among the models from Table 2, with an average MAPE of 4.64% for the five test sets. In Test Set 2 with the largest error, its MAPE value is 4.12%.

TABLE III RMSE VALUES OF 5 TEST SETS IN 4 PREDICTION MODELS

Test set	SSA-GRU	GRU	GA-BP	SVM
Test set1	15.78	32.53	53.61	64.69
Test set2	14.70	30.26	47.81	55.73
Test set3	17.67	52.65	65.42	79.94
Test set4	17.24	49.99	52.15	73.11
Test set5	16.60	35.67	50.69	67.62
Average value	16.40	40.22	53.94	68.22

From Table 3, it can be seen that the performance of GA-BP and SVM is similar, with RMSE mean values of 53.94 and 68.22 for their five test sets, respectively. The performance of SSA-GRU significantly superior to GRU, GA-BP, and SVM models, with an average RMSE of 16.40. SSA-GRU has the best distribution line loss prediction performance, because the larger RMSE value, the greater the error between the predicted value and the true value.

To better illustrate the accuracy of SSA-GRU model, the proposed method was compared with GRU, GA-BP and SVM models. Fig. 6 shows the line loss prediction results for each line in the test sample set. It can be seen that the SSA-GRU model's line loss prediction curve is closest to the actual curve. The prediction results of SVM and GA-BP models have a large deviation in line 82 and line 59 respectively, and the GRU model also has significant deviations from the actual values in line 59.

One of the main indicators for assessing the economic efficiency of power system operation is the line loss rate. The line loss rate results of each line in the test sample set are shown in Fig. 7.

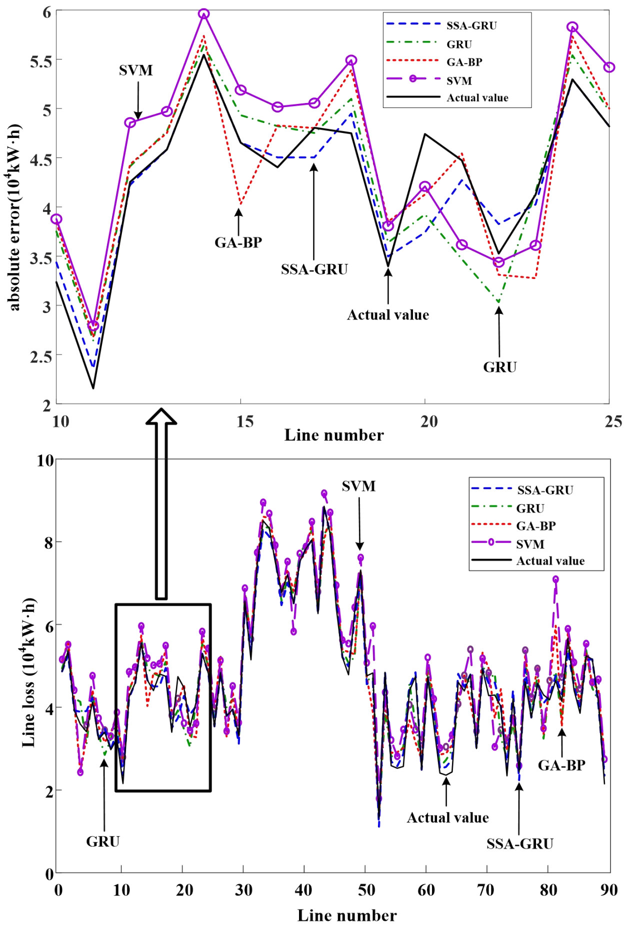


Fig. 6. Comparison of predication results of line loss of four models

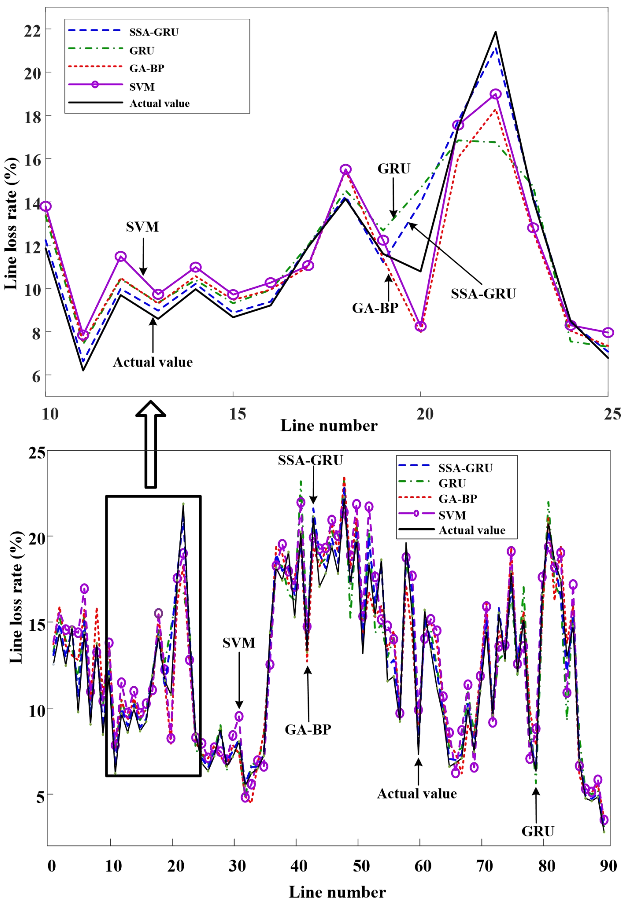


Fig. 7. Comparison of line loss rate predication results of four models

From Fig.7, the line loss rate prediction curve of SSA-GRU model fits the actual line loss rate curve to the highest degree. The prediction results of SVM and GA-BP models have a small deviation on the 21st line and the 53rd line respectively, and the GRU prediction model has a minimum deviation on the 84th line.

Comparing Fig. 6 and Fig. 7, the 52nd line has a higher line loss rate and a lower power quantity loss. The 79th line has a lower line loss rate and a higher power quantity loss. By comparing the actual operation of distribution network, it is found that this is because the 52nd line has a lower total transformer capacity and a longer line, while the 79th line has a higher total transformer capacity and a shorter line, indicating that the seven electrical characteristic parameters selected can not only fit the change of line loss well, but also reflect the actual operation of the distribution network, which validates the accuracy and scientific of the slope grey correlation method.

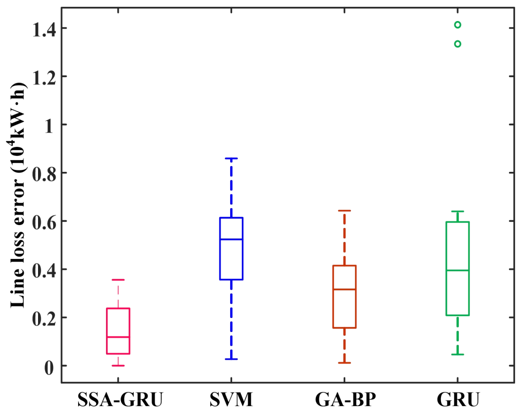


Fig. 8. The line loss absolute error boxplot of four models

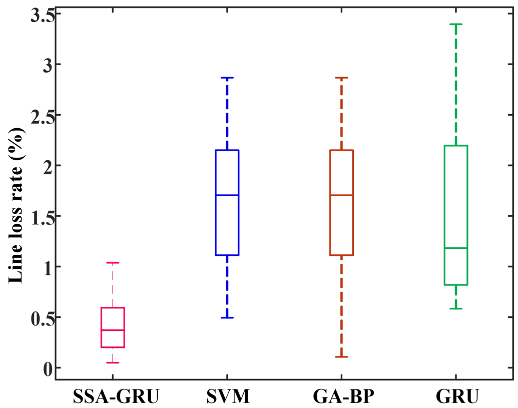
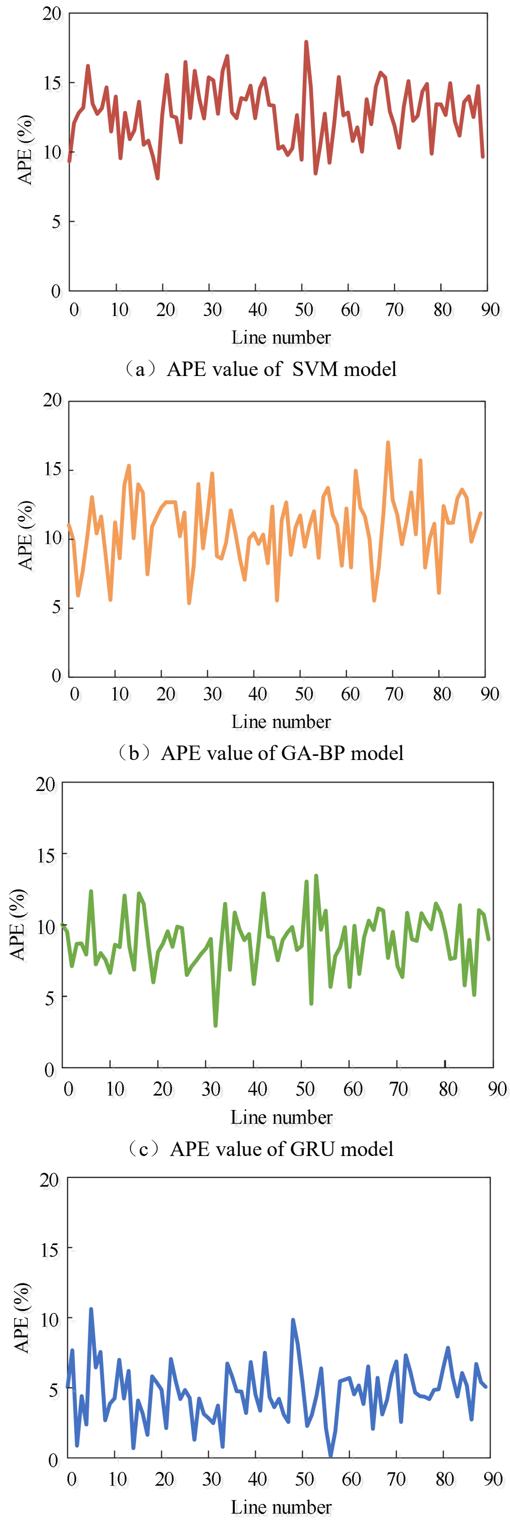


Fig. 9. The line loss rate error boxplot of four models

Boxplot is a statistical chart applied to display the dispersion of data, which can reveal the features of data distribution. Boxplot is based on actual data and does not need to preset distribution assumptions or strict regulations, which visually show the original distribution of the data. The median of the box illustrates the trend of data concentration. The box length shows the degree of data dispersion. The longer the box length, the more scattered the data will be. The dotted line extended from the boxplot represents the maximum and minimum values within the normal range, and the data points beyond the normal range are abnormal values (represented by circles).



(a) APE value of SVM model

(b) APE value of GA-BP model

(c) APE value of GRU model

(d) APE value of SSA-GRU model

Fig. 10. APE value of each line under different models

To more intuitively demonstrate the significant advantages of the SSA-GRU model, the boxplots were used to analyze the errors of SSA-GRU, GRU, GA-BP and SVM prediction methods. According to the predicted data and actual line loss data test set of 90 lines, draw the boxplot of the absolute error of line loss power of SSA-GRU, GRU, GA-BP and SVM models, as illustrated in Fig.8, and the boxplot of line loss rate error is illustrated in Fig. 9.

From Fig. 8, the SSA-GRU model shows better performance in line loss prediction. Compared with the GRU, GA-BP and SVM methods, the SSA-GRU model does not have an excessive error value, and the error is mostly concentrated within the range of 0~0.3×104kW·h, and the overall level of forecast error is smaller than that of the other three methods.

From Fig. 9, compared with other methods, the SSA-GRU model does not have an excessive error value, and the prediction error is mostly concentrated within the range of 0~0.7%. The performance of the SSA-GRU model in predicting the line loss rate is also more prominent, and the overall level of forecast error is smaller than that of the other three methods. In addition, From Fig. 8 and Fig. 9, the SSA-GRU model prediction error data set has symmetrical data distribution and no abnormal values.

In summary, from the above analysis, the boxplot intuitively shows that the actual line loss data has similar data distribution features in the line loss data can forecast by SSA-GRU prediction method, and SSA-GRU can accurately forecast line loss.

To intuitively show the error between the predicted line loss value and the actual value, the APE value of the line selected by SSA-GRU, GRU, GA-BP and SVM prediction models. The calculation results are shown in Fig. 10.

From Fig.10, in the selected 90 lines, the APE values of SVM model and GA-BP model fluctuate between 5% and 18%, and the APE values of SVM and GA-BP reach the maximum in the 52nd and 70th lines, which are 17.031 and 17.941 respectively. The APE value of GRU prediction model fluctuates between 2% and 14%. The maximum APE value appears on the 54th line, with a value of 13.459%. The SSA-GRU model proposed performs best on this data set, with the fluctuation range within 11%. The maximum APE value appears on the sixth line, which is 10.61%.

For the convenience of analysis, Table 4 also shows the prediction error results of some main lines.

TABLE IV. COMPARISON OF 4 MODELS OF SOME LINES

Sequence number	Prediction result error (%)			
	SSA-GRU	GRU	GA-BP	SVM
2	7.673	9.523	9.935	12.085
12	6.997	8.616	8.622	9.557
25	4.202	9.887	10.219	10.697
37	4.760	10.867	10.488	12.438
47	3.104	8.938	11.362	10.420
58	1.902	7.820	11.803	11.988
66	2.077	9.654	10.016	12.005
75	4.664	8.890	13.406	12.250
84	4.381	11.384	11.202	12.199

In conclusion, compared with GRU, GA-BP and SVM algorithms, SSA-GRU algorithm had the smallest MAPE and RMSE values for line loss prediction results. APE was also better than the other three algorithms, indicating that SSA-GRU algorithm had higher accuracy and smaller errors in the line loss forecast.

V. CONCLUSIONS

This study delves into the prediction method of distribution network line losses and proposes a prediction method of DN line losses based on slope coefficient grey correlation analytics and SSA-GRU model, which is applied to the line loss calculation in a certain area. The DN line loss prediction mostly relies on expert experience and traditional correlation degree analysis model, which lacks accuracy and theoretical basis. Therefore, this paper proposes an improved grey correlation analytic method. Through the correlation degree analysis of 17-electrical characteristic parameters of distribution network, it verifies the superiority of the proposed slope coefficient grey correlation analytic method compared with the traditional grey correlation analysis method, thus solving the low predication accuracy caused by the wrong selection of electrical characteristic parameters. The SSA-GRU model is established, SSA is used to adaptively optimize the super parameters of GRU model, and the optimal parameter set is obtained to avoid the effect of parameter setting on the line loss prediction accuracy. Finally, through the calculation of a regional distribution network in Gansu Province, the SSA-GRU model is compared with GRU, GA-BP and SVM prediction models. The results show that the MAPE and RMSE values of SSA-GRU model are significantly lower than GRU, GA-BP and SVM models, which verifies that the SSA-GRU method has higher prediction accuracy.

The line loss prediction accuracy is not only closely related to advanced prediction algorithms, but also to the topology structure of the actual distribution network. There are a large number of distributed generations integrating into today's distribution network, such as distributed photovoltaic, wind power and electric vehicles, etc., has made the flow of power in the distribution network bidirectional, increasing the difficulty of predicting line losses. Therefore, in the future, it is necessary to further study the topology recognition approaches of distribution networks containing distribution power sources based on artificial intelligence and deep learning methods, research the line loss prediction technology under the dynamic changes of distribution network topology structure, study the abnormal identification and positioning method of line loss, and apply it to actual distribution networks, so as to fulfill the goal of energy conservation, loss reduction, and carbon reduction in the power grid.

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