*Article*

# Prediction of Node Importance of Power System Based on ConvLSTM

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**Abstract:** In power systems, the destruction of some important nodes may cause cascading faults. If the most important node in the power system can be found, the important node can be protected in advance, thereby avoiding a blackout accident. At present, the evaluation algorithm of node importance is calculated based on the power flow of the power grid, so the calculation results must be lagging behind, and it does not have the ability to provide early warning for the power grid to provide protection signals. Therefore, it is necessary to predict the importance of nodes in the power system. After using a reasonable prediction model to predict the importance of nodes, we can simulate the future state of power system operation and avoid accidents for the dispatching agency of the power grid company according to the prediction results. This paper proposes a prediction model based on convolutional long short-term memory (ConvLSTM) to predict the importance of nodes. This method has obvious advantages over the long short-term memory (LSTM) network. The convolution operation is used to replace the original full connection operation of the LSTM network, which not only utilizes the advantages of convolution to extract spatial features but also retains the ability of LSTM to process time-series features. The simulation results show that the prediction of node importance using the ConvLSTM network is much more accurate than LSTM. Using statistical indicators to compare and analyze the prediction results, it can be seen that ConvLSTM has higher prediction accuracy. Therefore, using the ConvLSTM model to predict node importance has certain significance for grid dispatching agencies to accurately simulate the future state of the power system and avoid risks in advance.

**Keywords:** prediction; power system node importance; ConvLSTM; LSTM

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## 1. Introduction

### 1.1. Motivation and Incitement

Under the demand background of building a new power system, it is necessary to build a new power system fault defense system according to the requirements of safety and controllability of the new power system. On the one hand, with the gradual realization of the national energy Internet, China's power system has become one of the most complex artificial networks in the world; on the other hand, the access to new energy generation and load leads to more frequent and violent changes of power flow in the power system, which brings source load uncertainty to the power system. The power system is a complex network containing many nodes. Once an important node fails, it is very easy to cause cascading faults in the power system leading to blackouts, which brings new challenges to the safe and stable operation of the power system. At present, the algorithms for evaluating the node importance of the power system can only be used for real-time calculation. There is

a time delay between the calculation results of these algorithms and the real-time changing power system operation state; that is, the actual screening results of the algorithms lag, which is not conducive to the modeling of the future state of the power system and the prevention of cascading faults of the power system. With the support of big data theory, the power system will become a power system relying on big data processing and analysis technology in the future. With the development of time, the power monitoring department will collect and accumulate a large number of power system power flow data. Considering the advantages of the ConvLSTM algorithm in massive data processing, it is important to predict the importance of power system nodes, provide fault early warning time for the power grid, and prevent the occurrence of cascading faults.

*1.2. Literature Review and Research Gaps*

The extensive interconnection of power systems has become a trend, but although this has improved the efficiency of power use, it has also brought new challenges to the power system [1,2]. Scholars Albertlaszlo Barabasi and Reka Albert first discovered that the power system can be abstracted into a complex network in 1999. At the same time, the power system also has scale-free characteristics; that is, if an attack is applied to a node with a high degree of importance in the power system, the loss is greater than that of a random attack [3]. At present, several power outages have occurred worldwide, causing huge economic losses to society and affecting social stability [4,5]. These outages are generally caused by some nodes out of operation and gradually spread to the entire power system, which can be defined as cascading faults [6]. Therefore, predicting the important nodes in the power grid is of great significance for the power grid to avoid risks in advance and prevent cascading failures.

Reference [7] proposed the EB-SALSA algorithm to evaluate the important nodes in the power system, which not only considered the influence of the out-degree but also comprehensively considered the topology of the power system and has good evaluation performance. In this paper, the EB-SALSA algorithm is used to calculate the importance of power system nodes, which provides historical data and a comparison basis for the prediction of node importance.

With the continuous expansion of the power system scale, the system will accumulate a large amount of electrical information at each sampling time point. The deep learning algorithm, which is good at dealing with massive data, is gradually applied to the field of power system data processing. With its strong ability to deal with nonlinear problems, deep learning has been widely used in power system load forecasting [8]. In Reference [9], it is proposed to decompose the nonstationary wind power time series into separate stationary components by discrete wavelet transform, predict each stationary component by LSTM, and finally synthesize the prediction results to obtain the prediction results of wind power generation. In order to improve the observability of the power system and improve the sensitivity of the system to perceive the changes in electrical parameters, deep learning is applied to the field of power system state prediction [10]. The power system node importance data set also has the characteristics of big data, and the prediction of power system node importance is still in the experimental stage. This study attempts to apply the deep learning algorithm to predict the importance of power system nodes.

Once a node or a line fails, it is very easy to cause cascading faults in the power system leading to blackouts, which brings new challenges to the safe and stable operation of the power system. Therefore, the spatial characteristics of the power system must be considered when predicting the importance of power system nodes. So, this paper uses the ConvLSTM network designed by Shi et al. [11] to predict the importance of power system nodes. Compared with LSTM, its core does not change but replaces the point multiplication operation in the original LSTM model with the convolution operation. As a result, the convolution calculation is introduced into the original network so that the network can not only obtain the time-series relationship but also have the function of extracting spatial

features by the convolution layer so that the ConvLSTM network can solve the problem of spatiotemporal sequence prediction.

### 1.3. Major Contribution and Organization

The main contributions to the research on node importance prediction of the power system are as follows:

(1)  It shows the necessity of predicting the importance of power system nodes;
(2)  The importance data set of power system nodes is simulated and constructed by the EB-SALSA algorithm;
(3)  A deep ConvLSTM prediction network considering the interaction between nodes is designed;
(4)  By comparing with the LSTM prediction network, the advantages of the proposed ConvLSTM prediction network for node importance prediction are analyzed.

The following five chapters are organized as follows: Section 2 introduces the basic principles of LSTM and ConvLSTM; Section 3 introduces the work of data set preprocessing; in Section 4, the node importance of the IEEE-39 bus power system and the IEEE-118 bus power system is predicted; Section 5 is the summary of the full-text research.

## 2. Prediction Methods

### 2.1. LSTM

With the increase in the number of neural network layers in MLP, on the one hand, the optimization function is easy to fall into the local optimal solution; on the other hand, there will be the problem of gradient disappearance. DNN solves the problem of gradient disappearance, but it still has the problem of being unable to model the time series and parameter expansion. RNN solves the problem of modeling time series, but when it faces the information of long time series, it has the problem of long time dependence. Finally, an LSTM that is not easy to fall into local optimization, gradient disappearance, and long time dependence is developed. Therefore, in the face of long time-series problems, LSTM is more reliable and accurate than the above methods.

The main structure of the LSTM [12] model includes four parts: forgetting gate, input gate, output gate, and memory unit. They interact with each other in a specific relationship to filter and save information, as shown in Figure 1:
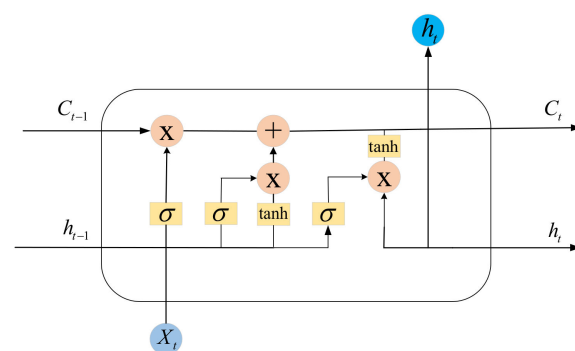


**Figure 1.** LSTM network.

In the figure, each arrow is a vector representing the output from the previous node to the input of other nodes; the circles represent point-by-point operations, the arrows merging represent connections, and the arrows bifurcating represent that their contents are copied for different purposes. The four components of LSTM are embedded in it.

The input, output, and state of LSTM are all one-dimensional vectors, and the key formulas are shown in (1) to (5):

$$i_t = \sigma(W_{xi}X_t + W_{hi}H_{t-1} + W_{ci} \circ C_{t-1} + b_i) \tag{1}$$

$$f_t = \sigma\left(W_{xf}X_t + W_{hf}H_{t-1} + W_{cf} \circ C_{t-1} + b_f\right) \tag{2}$$

$$C_t = f_t \circ C_{t-1} + i_t \circ \tanh(W_{xc}X_t + W_{hc}H_{t-1} + b_c) \tag{3}$$

$$o_t = \sigma(W_{xo}X_t + W_{ho}H_{t-1} + W_{co} \circ C_t + b_o) \tag{4}$$

$$H_t = o_t \circ \tanh(C_t) \tag{5}$$

In the formula, $\sigma$ is the sigmoid or tanh function, $W_{xi}$, $W_{xf}$, $W_{xc}$, and $W_{xo}$ are the node weight matrices of the input gate, forget gate, memory unit, and output gate, respectively, and $b_i$, $b_f$, $b_c$, and $b_o$ are the node threshold matrices, respectively. $X_t$ is the input of the neuron at time $t$; $H_{t-1}$ is the output of the neuron at the time $t-1$; $W_{xi}$, $W_{xf}$, $W_{xc}$, and $W_{xo}$ are the weights of $X_t$ in different convolution operations, respectively; $W_{hi}$, $W_{hf}$, $W_{hc}$, and $W_{ho}$ are the weights of $H_{t-1}$; $b_i$, $b_f$, $b_c$, and $b_o$ are the bias values of the convolution operation. $i_t$ controls the input gate, which uses the sigmoid function to select the new input data and the output of the previous neuron to determine the input information of the neuron. $f_t$ controls the forgetting gate, the input parameters are the same as the input gate, and the output of the previous neuron is forgotten in proportion; that is, how much information is retained from the previous neuron to enter the neuron. $C_t$ is the cell state of the neuron at time $t$, which combines the cell state of the previous neuron and the new data input at time $t$ to form a new cell state. The last is the output gate. Through the gate control setting, the current cell state is output proportionally; that is, $H_t$, the current cell output.

### 2.2. ConvLSTM

Considering the spatial correlation of power system data, this paper proposes to use the ConvLSTM [11] network designed by Shi et al. to predict the importance of power system nodes, expecting to achieve better prediction results than LSTM. The main structure of the ConvLSTM network is shown in Figure 2:
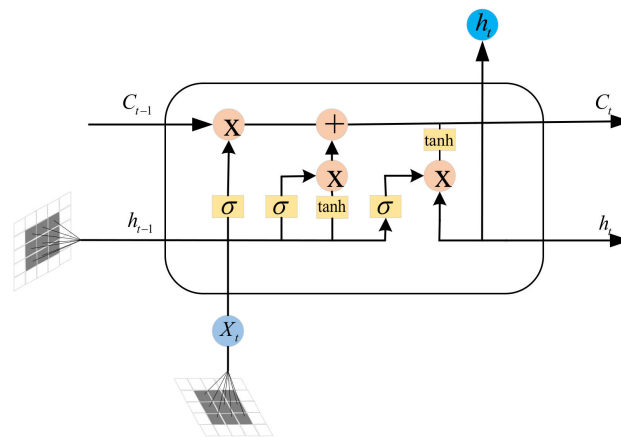


**Figure 2.** ConvLSTM network.

The core essence of ConvLSTM is still the same as LSTM. The difference is that the ConvLSTM model introduces convolution calculation based on the LSTM model so that the model can not only obtain the time-series relationship but also extract spatial features like the convolution layer. In this way, the spatiotemporal sequence features can be obtained so that the ConvLSTM network can solve the spatiotemporal sequence prediction problem. The following are the key formulas of the ConvLSTM network.

$$i_t = \sigma(W_{xi} * X_t + W_{hi} * H_{t-1} + W_{ci} \circ C_{t-1} + b_i) \tag{6}$$

$$f_t = \sigma\left(W_{xf} * X_t + W_{hf} * H_{t-1} + W_{cf} \circ C_{t-1} + b_f\right) \tag{7}$$

$$C_t = f_t \circ C_{t-1} + i_t \circ \tanh(W_{xc} * X_t + W_{hc} * H_{t-1} + b_c) \tag{8}$$

$$o_t = \sigma(W_{xo} * X_t + W_{ho} * H_{t-1} + W_{co} \circ C_t + b_o) \tag{9}$$

$$H_t = o_t \circ \tanh(C_t) \tag{10}$$

In the formula, $*$ represents the convolution operation; $X_t$ is the input of the neuron at time $t$; $H_{t-1}$ is the output of the neuron at time $t-1$; $W_{xi}$, $W_{xf}$, $W_{xc}$, and $W_{xo}$ are the weights of $X_t$ in different convolution operations; $W_{hi}$, $W_{hf}$, $W_{hc}$, and $W_{ho}$ are the weights of $H_{t-1}$; $b_i$, $b_f$, $b_c$, and $b_o$ is the bias value of the convolution operation. $i_t$ controls the input gate, which uses the sigmoid function to select the new input data and the output of the previous neuron to determine the input information of the neuron. $f_t$ controls the forgetting gate, and the input parameters are the same as the input gate, which can determine how much information from the previous neuron enters the neuron. $C_t$ is the cell state of the neuron at time $t$, and at the same time, new data are input, and the two are reorganized into a new cell state. Finally, the output gate is gated to output the cell state according to a certain proportion; that is, the current cell output $H_t$ is obtained. It should be noted that $X$, $C$, $H$, $i$, $f$, and $o$ are all three-dimensional tensors, and their last two dimensions represent the spatial information of rows and columns.

## 3. Preparations before Forecasting

### 3.1. Evaluation Method of Node Importance

In order to realize the prediction of node importance, we first need to select the algorithm to evaluate the node importance. In this study, the EB-SALSA algorithm is selected to evaluate the node importance.

When evaluating the importance of power system nodes, the comparison between each part of the power system, Internet, and complex network is shown in Table 1.

**Table 1.** Comparison between each part of power system, Internet, complex network.

| Internet | Power System | Complex Network |
|----------|--------------|-----------------|
| Webpage | Bus | Node |
| Hyperlinks | Transmission line | Edge |

Both the power system and the Internet can be abstracted as complex networks, so the nodes in the power system are abstracted and compared with the web pages on the Internet. Different from the Internet evaluation of important web pages, the Internet is abstracted as a directed weighted graph. In order to fully evaluate the impact of operation mode on the importance of power system nodes in the EB-SALSA algorithm, the power system needs to be abstracted as a directed weighted graph evaluation; that is, the power flow is regarded as the weight assigned on the edge abstracted from the corresponding transmission line.

The calculation flow of the EB-SALSA algorithm is shown in Figure 3.

The authoritative value of a node is related to the number of nodes and the size of the hub value. Similarly, the hub value of a node is related to the number of nodes pointed to by the node and the size of the authority value. According to the topology of the power system to be evaluated, the original directed graph is obtained. In order to meet the conditions of power balance of the whole system, the generation and load nodes are added to obtain the complete adjacency matrix of the whole system. Next, considering the penetration of nodes in the global topology, the final authority value is obtained through iterative operation. Considering the out-degree of nodes in the global topology, the final hub value is obtained through iterative operation. Finally, the sum of the authority value and the hub value is taken as the final node importance value.
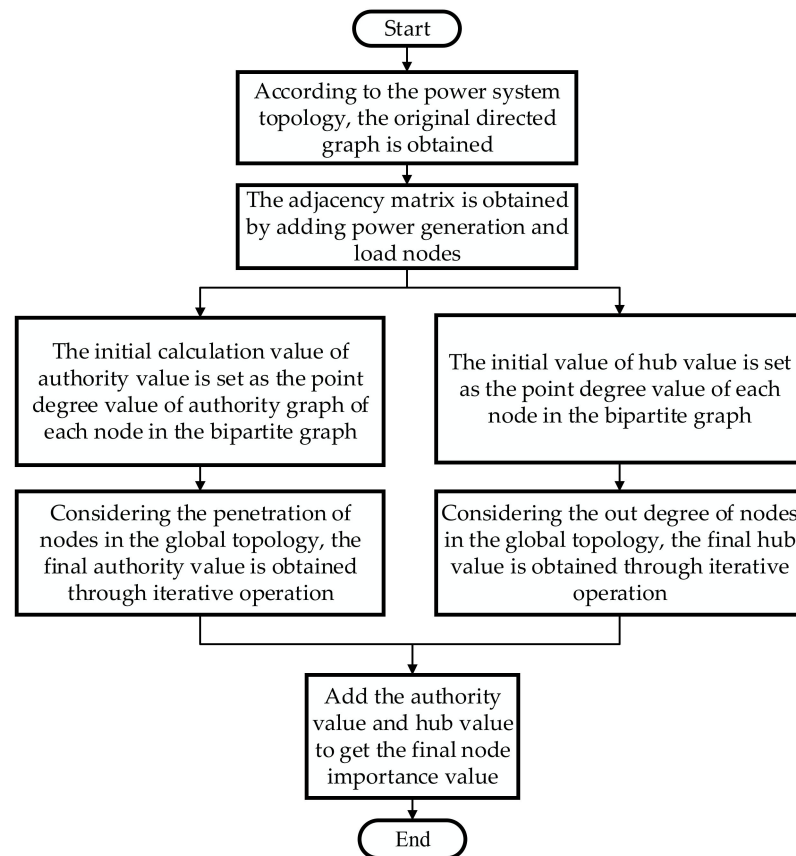
```
┌─────────────┐
│    Start    │
└─────────────┘
       │
┌──────────────────────┐
│ According to the power│
│ system topology, the  │
│ original directed     │
│ graph is obtained     │
└──────────────────────┘
       │
┌──────────────────────┐
│ The adjacency matrix  │
│ is obtained by adding │
│ power generation and  │
│ load nodes            │
└──────────────────────┘
```

The initial calculation value of authority value is set as the point degree value of authority graph of each node in the bipartite graph

The initial value of hub value is set as the point degree value of each node in the bipartite graph

Considering the penetration of nodes in the global topology, the final authority value is obtained through iterative operation

Considering the out degree of nodes in the global topology, the final hub value is obtained through iterative operation

Add the authority value and hub value to get the final node importance value

```
┌─────────────┐
│     End     │
└─────────────┘
```

**Figure 3.** EB-SALSA algorithm flow chart.

### 3.2. Preprocessing the Node Importance Dataset

According to the definition of importance by the EB-SALSA algorithm, node importance = authority value + pivot value. Among them, the authority value is only related to the in-degree of the node, and the pivot value is only related to the out-degree of the node.

The importance data of the power system nodes used in this paper is large and fluctuates greatly, which will limit the running speed of the model. In order to speed up the network convergence and improve the prediction accuracy, it is necessary to perform min–max normalization on the original data. The formula is as follows:

$$X = \frac{X_0 - X_{\min}}{X_{\max} - X_{\min}} \tag{11}$$

In the formula, $X_0$ is the initial value, and $X$ is the result after data normalization; $X_{\max}$ and $X_{\min}$ are the maximum and minimum values of the sample data. After preprocessing, the data are mapped to the range of 0 to 1, and the volatility of the data is weakened. It is beneficial to speed up the iteration of the network and improve the prediction accuracy.

### 3.3. Prediction Dataset Structure Reshaping Suitable for ConvLSTM Networks

According to the structural requirements of the ConvLSTM network for input data, it is necessary to reshape the two-dimensional node importance data set into a five-dimensional structure of [sample, time step, row, column, channel]. The power system is a complex network containing many nodes. Each node is connected with several adjacent nodes. With the access of distributed generation or load switching, the line power flow in the power system will change. Any change in line power flow will cause a change in the importance of each node, and the change in the importance of any node will also affect other nodes. Therefore, when reshaping the data set, it is necessary to consider the influence relationship between each node. Therefore, reshape the data set into a [sample, 1, 1, l, n] structure, in

which the time step is set to 1, the row is set to 1, the column representing the predicted time length is set to 10, and the number of channels represents the number of factors affecting the change in the importance of a node. It can be seen from the characteristics of the power system that each node in the power system affects each other, so in the IEEE-39 bus system, set the number of channels to 39; in the IEEE-118 bus system, set the number of channels to 118.

### 3.4. Building a ConvLSTM Prediction Model

In view of a large number of nodes in the power system, the importance of each node changes synchronously. Based on the ConvLSTM network, a deep ConvLSTM network prediction model with a total of 11 layers is designed. Considering that the operation mode of the power system changes rapidly, and the node importance data with a long time interval have no reference value for predicting the node importance at a certain time in the future, 5 layers of ConvLSTM layers are used to reduce the learning data. Data features can be accurately learned in the case of less historical data. With 1 pooling layer, the pooling layer can reduce the model size while preserving the main features. The transition from the convolutional layer to the fully connected layer is completed with a flatten layer, and finally, 4 fully connected layers are used to enhance the nonlinear expression ability of the model, and the output dimension is converted into the dimension of the label vector. The importance of nodes changes with the power flow and the operation mode of the power system. In order not to miss the data, the sliding step size is set to 1 in this simulation.

The structure of the deep ConvLSTM prediction model proposed in this paper is shown in Figure 4:
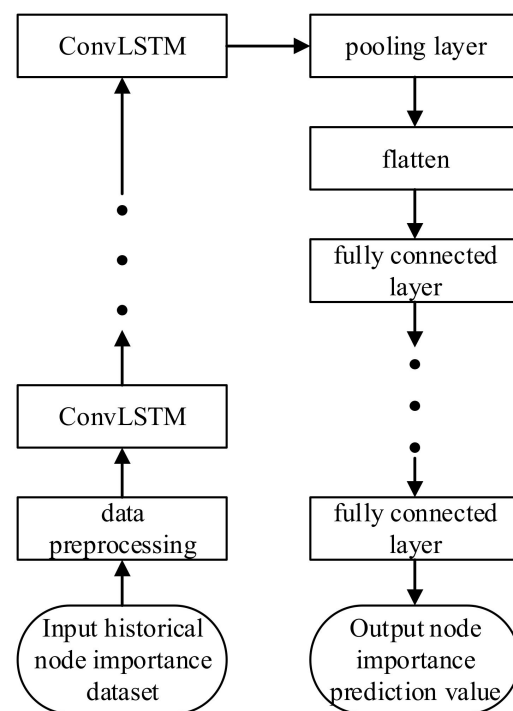


**Figure 4.** Deep ConvLSTM network model.

After completing the four preparations given in Section 3, the data set can be sent to the ConvLSTM network for node importance prediction. The complete process of node importance prediction is shown in Figure 5:
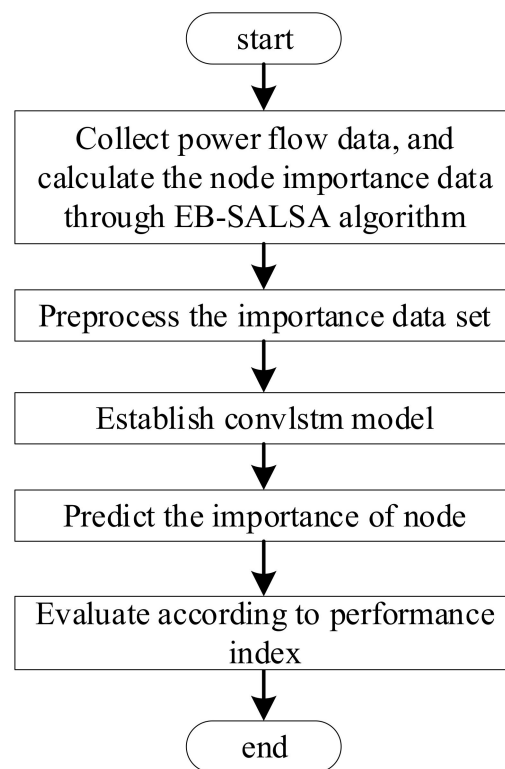
**Figure 5.** Complete forecasting process.

## 4. Case Analysis

### 4.1. IEEE-39 Bus System

The IEEE-39 bus system includes 39 buses and 46 transmission lines, and its topology is shown in Figure 6:
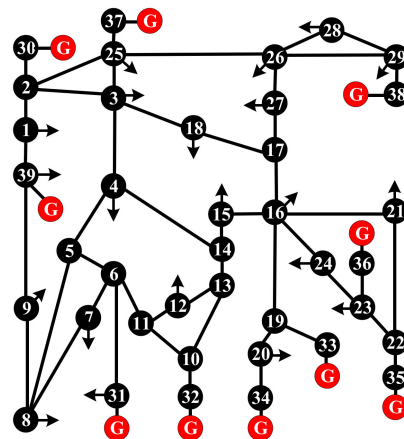


**Figure 6.** IEEE-39 bus power system.

The parameters of the deep ConvLSTM model used to predict the node importance of the IEEE-39 bus power system are listed in Table 2:

**Table 2.** Deep ConvLSTM model parameters for IEEE-39 bus power system.

| Power System Scale | Parameter Setting |
| --- | --- |
| IEEE-39 | 2×2-128; 2×2-128; 2×2-128; 2×2-128; 2×2-128 |

The 39 × 1500 node importance data set is obtained by repeated operations of the EB-SALSA algorithm for the training of the prediction model. For the prediction model, the status of 39 nodes is equal, so the importance of one of the nodes is used for prediction. Use the ConvLSTM model and the LSTM model to predict the importance of power system nodes, respectively, and obtain the ConvLSTM predicted value, the LSTM predicted value, and the real value of the power system node importance on the time scale of the broken line comparison chart, as shown in Figure 7:
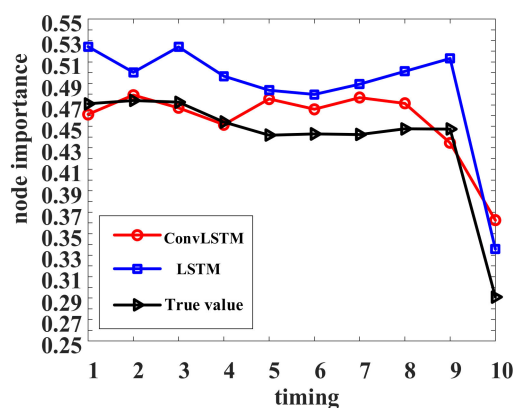


**Figure 7.** Comparison of prediction values of node importance of IEEE-39 bus system.

The EB-SALSA algorithm needs to calculate the node importance after the power grid company collects the power flow data of the power system, which makes the important nodes evaluated by the EB-SALSA algorithm lag behind the real-time changing operating state of the power system. The deep ConvLSTM network proposed in this paper uses the historical data set of node importance to establish a prediction model so as to realize the prediction of node importance without waiting for the power grid company to collect the power flow data of the power system.

As shown in Figure 7, the prediction through the deep ConvLSTM network can obtain the node importance before collecting the power flow data of the power system, and compared with LSTM, the predicted value is closer to the real value. It can provide a data basis for the power grid company dispatching agency to simulate the future state of power system operation. In the future state, the prediction results can be verified and fed back to the prediction model for correction. Second, if a power system failure is simulated in the future state, measures can be taken in advance to avoid accidents and minimize losses. Therefore, the more accurate the prediction of node importance is, the more the future state model built is more connected to the real situation, and the more beneficial it is to prevent the occurrence of power system failures.

It can be seen from Table 3 that when the ConvLSTM model and the LSTM model are used for node importance prediction, the mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE) of the former are less than those of the latter. Therefore, it can be considered that the ConvLSTM model has better performance than the LSTM model when used for node importance prediction.

**Table 3.** Comparison of node prediction results of IEEE-39 bus system.

| Model | Performance Evaluation Index | | |
|---|---|---|---|
| | MAE | RMSE | MAPE |
| LSTM | 0.0464 | 0.0475 | 1.0433 |
| ConvLSTM | 0.0222 | 0.0298 | 0.3081 |

### 4.2. IEEE-118 Bus System

The IEEE-118 bus system includes 118 buses and 186 transmission lines, and its topology diagram is shown in Figure 8:
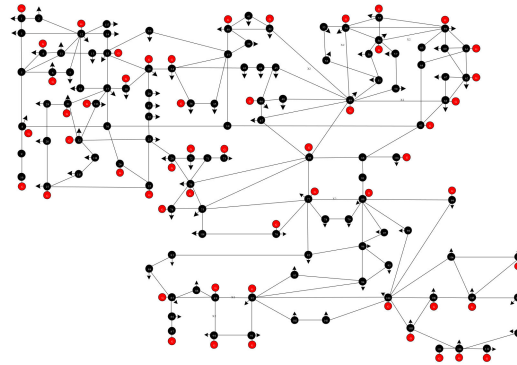


**Figure 8.** IEEE-118 bus power system.

The parameters of the deep ConvLSTM model used to predict the node importance of the IEEE-118 bus power system are listed in Table 4:

**Table 4.** Deep ConvLSTM model parameters for IEEE-118 bus power system.

| Power System Scale | Parameter Setting |
|---|---|
| IEEE-118 | 2×2-256; 2×2-256; 2×2-256; 2×2-256; 2×2-256 |

The $118 \times 1500$ node importance data set is obtained through repeated operations of the EB-SALSA algorithm for the training of the prediction model. For the prediction model, the 118 nodes have the same status, so the importance of one of the nodes is used for prediction. Use the ConvLSTM model and the LSTM model to predict the importance of power system nodes, respectively, and obtain the ConvLSTM predicted value, LSTM predicted value, and the real value of the power system node importance on the time scale of the broken line comparison chart, as shown in Figure 9:
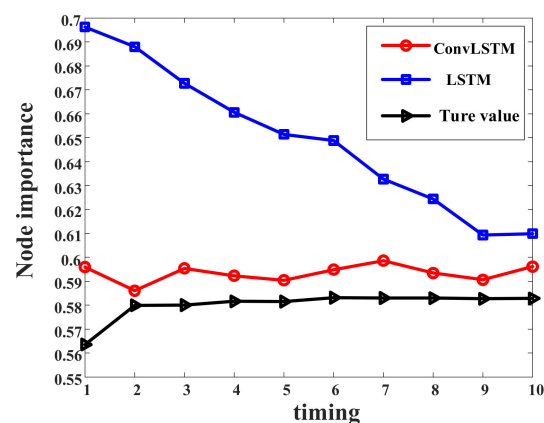


**Figure 9.** Comparison of prediction values of node importance of IEEE-118 bus system.

As can be seen from Figure 9, when the scale of the power system expands, the prediction results of the deep ConvLSTM network are still better.

It can be seen from Table 5 that when comparing the ConvLSTM model and the LSTM model for node importance prediction of IEEE-118 bus power system in an expanded network, the MAE, RMSE and MAPE are less than those of the latter. Therefore, it can be considered that the ConvLSTM model has better performance than the LSTM model when

used for node importance prediction, and the prediction model has universality. It can be applied to power systems of different scales.

**Table 5.** Comparison of node prediction results of IEEE-118 bus system.

| Model | Performance Evaluation Index | | |
|:---:|:---:|:---:|:---:|
| | **MAE** | **RMSE** | **MAPE** |
| LSTM | 0.0693 | 0.0768 | 1.1901 |
| ConvLSTM | 0.0133 | 0.0150 | 0.2274 |

## 5. Conclusions

The power system is widely interconnected and has become larger and larger, and its safe and stable operation is very important, so the necessity of fault defense is self-evident. The premise of fault defense is to find the weak links in the operation of the power grid and then take measures to protect it. Therefore, it is very necessary to predict the importance of nodes in the power system to find the weak links of the power grid. Since the power system node importance data have the characteristics of time and space sequence, in order to consider both time and space information, this paper uses ConvLSTM to predict the power system node importance. In this method, the fully connected weights in LSTM are changed to convolution, which takes into account the local spatial features, thereby improving the prediction accuracy. The prediction accuracy of LSTM and ConvLSTM are compared in the IEEE-39 bus system and the IEEE-118 bus system, respectively. The prediction accuracy of ConvLSTM and LSTM is evaluated by using statistical indexes MAE, RMSE, and MAPE. The results show that the prediction error of the former is less than that of the latter. The simulation results and the accuracy evaluation of statistical indexes prove the rationality and effectiveness of ConvLSTM in node importance prediction.

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## Abbreviations

| | |
|---|---|
| ConvLSTM | Convolutional long short-term memory |
| LSTM | Long short-term memory |
| MAE | Mean absolute error |
| RMSE | Root mean square error |
| MAPE | Mean absolute percentage error |

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