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Research on anti-error operation warning of power grid dispatching based on deep bidirectional gated recurrent neural network

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Abstract

To improve the security and overall efficiency of grid scheduling work and accurately optimize scheduling decisions, a grid scheduling error-proof operation warning method based on a deep bidirectional gated recurrent neural network is proposed. This paper combines the principle of hierarchical data construction, summarizes the structured data of metadata operation tickets and maintenance plans of CIM model and OMS network frame model, and constructs the data warehouse of grid dispatching error prevention; based on the natural language processing (NLP) technology, key information and knowledge entities related to grid dispatching error prevention are automatically identified and extracted from the data warehouse. Based on the deep bidirectional gated recurrent neural network, the extracted information sequence is used as input to construct the grid scheduling operation state reconstruction model, and the error prevention warning is carried out according to the output prediction results. The experimental results show that: the data docking speed in different scheduling phases is fast with the fastest speed of 71.254MB/s, and the convergence speed of the analysis and calculation is within 0.01MB/s, indicating that the overall analysis efficiency is high, the application performance is good, and it can determine whether there is any misoperation in the process of grid scheduling and carry out highly efficient, accurate, and fast early warning.

Keywords: Deep learning; Bidirectional gating unit; Recurrent neural network; Grid dispatch error prevention; Early warning

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1. Introduction

Real-time scheduling of grid systems has been the focus of grid work, mainly involving transmission, substation, distribution, power, communication, and real-time scheduling [1-2]. Owing to the complexity, specialization, and comprehensiveness of transmission and substation operations, real-time scheduling with high accuracy has been difficult. In the process of scheduling, with the rapid development of power grid construction, grid scheduling organizations already have the ability to deal with day-to-day faults, but the scheduling staff's lack of work experience, the field technical ability is not strong, the use of equipment fault handling is not timely, and other factors, also lead to an increasing number of power scheduling errors [3]. Therefore, grid scheduling anti-misoperation early warning has gradually become an important research problem in the development of the current power field.

Literature [4] uses a novel genetic algorithm based on Extreme Learning Machine (ELM) to implement anti misoperation warning in power grid scheduling. Multiple optimization objectives are designed according to different scheduling stages, and corresponding scheduling plans are formulated to effectively ensure the accuracy and standardization of power grid scheduling operations. However, the data analysis performance of this method needs to be improved; Literature [5] proposes a state estimation method based on the smart grid measurement technology, the

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Based on the grid state estimation dataset, a smart grid scheduling strategy based on cloud computing is constructed. The conditional risk value implied by the penalty function of generation cost, grid cost and movement cost is used as the objective function of dispatch modeling to predict the action state of grid dispatch operation, and to realize the high accuracy of dispatch error prevention warning, but the dispatch operation data analysis speed of this method is slow; Literature [6] proposes a multi-agent system based grid dispatch error prevention operation validation method, which effectively realizes the grid dispatch instruction effective monitoring, but the method is unable to comprehensively analyze the timing relationship in the scheduling operation information; Literature [7] proposes an IoT-based grid scheduling anti-misoperation warning method, which adopts a partial buffer sharing mechanism, calculates the probability and classifies it according to the priority level, to realize the effective monitoring of the grid scheduling operation situation, but the application of this method is not very efficient.

Aiming at the above problems, this study proposes a grid scheduling anti-misoperation warning method based on deep bidirectional gated recurrent neural network.

2. Design of an early warning method to prevent misoperation in power grid dispatching

2.1. Grid Dispatch Error Prevention Data Warehouse Construction

To realize an effective early warning of grid dispatching error prevention and improve the overall stability and security of grid operation, it is first necessary to integrate the semi-structured data of grid dispatching error prevention and real-time power supply data, electric power distribution network scheduling data, graphic and modeling databases, and other information from different data sources, to build a grid dispatching error prevention data warehouse, to help relevant dispatchers understand the status of grid operation more effectively with the data warehouse's own complex data query and analysis functions, and to provide effective data decision support for the warning of error prevention. By virtue of the data warehouse's own complex data query and analysis functions, it can help the relevant scheduling personnel understand the operation status of the power grid more effectively and provide effective data decision-making support for the prevention of misoperation warnings.

The grid scheduling process usually involves analytical or operational processing of grid data. The analytical type refers to grid scheduling personnel through data extraction, analysis and access to certain error prevention key information. The operation type refers to dispatchers querying and modifying the data to avoid operational errors in the process of grid scheduling. The grid scheduling error prevention data warehouse essentially refers to the analysis and processing of operational data to realize the effective mining of value information in massive scheduling data [8-9]. This paper combines the principle of hierarchical data construction, summarizes the structured data of metadata operation tickets and maintenance plans of CIM model, OMS grid model, and constructs the grid dispatch error prevention data warehouse, and the layered structure of the data warehouse is shown in Figure 1.

As shown in Figure 1, the operational database, as the bottom layer of the entire data warehouse structure, is the data source of the overall data warehouse and is used to support the data extraction operations. The extracted dynamic data are passed to the ELT layer for extraction, conversion, and loading processing to integrate the multidimensional structured grid dispatching error prevention extraction data. The data integration results are uploaded to the data warehouse base layer, and semantic information is extracted through the structural square according to the specific use of the data, which is uniformly transformed into the metadata format for storage [11-12]. Terminal devices are used to analyze the metadata, and the final data processing results are released into the visualization window of the user terminal.

Meanwhile, as shown in Figure 1, the data warehouse integrates the data used for analysis by extracting a variety of data. Data from the data warehouse are provided to the system for analysis and decision making. From the process of extracting, converting, and loading data for processing and analysis in the data warehouse, the data warehouse is divided into four layers: operational data, conversion-extraction-loading layer, data warehouse foundation layer, and online analysis and processing layer. The hierarchical construction of the data warehouse is characterized as follows:

1. Each layer plays the role of a carrier, receiving data from the lower layers and transmitting data upwards;
2. Each layer is also divided internally by layer and needs to be developed upward level by level;
3. The upper layer forms the data source for the upper layer by extracting, analyzing, and processing data from the lower layer;
4. The lower layer provides a theoretical basis for the development of the upper layer.

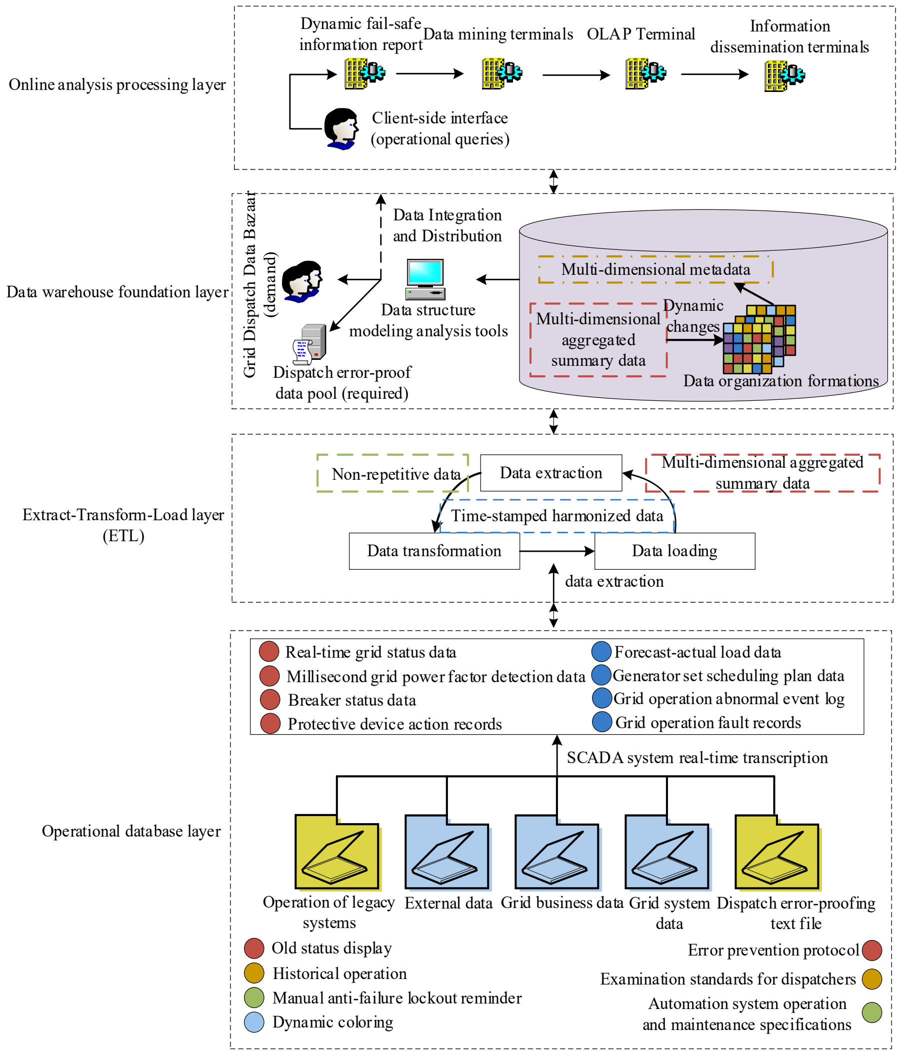

Figure 1. Layered structure of grid dispatch error-proof data warehouse

2.2. Grid Dispatch Error Prevention Knowledge Entity Extraction

Based on the error prevention data warehouse shown in Figure 1, the knowledge information of grid dispatch error prevention in the form of metadata is available in the underlying database. To accurately identify and extract the knowledge entities related to grid dispatch error prevention operations from the data warehouse, and to transform unstructured or semi-structured grid dispatch data into a structured data format, it is necessary to automatically identify and extract the key information and knowledge entities related to grid dispatch error prevention from the data warehouse based on Natural Language Processing (NLP) technology as a means of providing an in-depth bidirectional gating loop neural network to provide richer and more accurate input data.

Entity and relations are key technologies in natural language processing. Through entity recognition, the electrical equipment name information in the error-proof operation instructions can be extracted, while relation extraction can process two or more entities simultaneously, so as to obtain deep text information. In other words, entity recognition is the basis of relational extraction [13-15]. In natural language processing, entity recognition is categorized as a sequence annotation task. Defining the sample set of metadata in the data warehouse of Figure 1 as and the data size of the sample set as, the sample set can be further represented as:

$$A=\{(a_1,o_1),(a_2,o_2),\ldots,(a_m,o_m)\} \quad (1)$$

In Formula 1: a denotes a sample of data; o denotes grid scheduling error-proofing knowledge labels

Based on the interaction relationship between the sample and the set of labels in Eq. (1), the sample extraction instance is represented as:

$$\widehat{a}_{\gamma_1}^{\gamma_2} = \left(a_1', o_1'\right), \gamma_1 \leq m, \gamma_1 < m, a_1' \in a, o' \in o \tag{2}$$

In Formula 2: γ_1 denotes the length of the text; γ_2 denotes the size of the labeled entity information; a_1' denotes the sample information in the extraction instance; o_1' denotes the real labeling information in the extracted instance.

Based on the instance transformation process in Eq. (2), the entity recognition task is abstractly represented as an NER task and the task generation process is regarded as a parametric learning problem. In the task execution process, the CRF model is used to design its objective to minimize the negative log-likelihood of the conditional probability, and identify key entities, such as device names and operation commands, from the sample set, and the specific process is:

$$L(\theta) = -\sum_{a=a_1'}^{m} \ln mP\left(o_1' \middle| T_a, \theta\right) \tag{3}$$

In Formula 3: $L(\cdot)$ denotes the conditional probability negative log-likelihood loss function; θ denotes the CRF mathematical model parameters; $P(\cdot)$ denotes the probability distribution function, i.e., the data distribution predicted by the CRF mathematical model; T_a denotes the feature information given in the sample of extracted instances.

On the basis of obtaining the actual sample feature information and real label information, the SVM model is used to design the decision function for relationship extraction, and the extraction process is:

$$F\left(T_a\right) = \sum_{a=1}^{m'} \alpha \left\|o_1' + T_a\right\|^{m'} \hat{F}\left(a, a_0'\right) + b_0' \tag{4}$$

In Formula 4: $F(\cdot)$ denotes the decision function, which is used to determine whether an input feature belongs to a certain relational category or not; m' denotes the number of support vectors; α denotes the Lagrange multiplier; $\hat{F}(\cdot)$ denotes the kernel function, which is used to compute the similarity between two vectors (training text and actual text) in the feature space; a_0' denotes the training sample; b_0' denotes the bias factor.

Considering that knowledge entity-relationship extraction is essentially a spatial mapping process of sample feature information [16], feature engineering techniques and TF-IDF methods are used to correspond to the extraction of structured data and textual data features, respectively:

$$\delta_{a_0'}^1 = \sum_{a=1}^{m'} \frac{1}{m'} \left(a - a_0'\right) \tag{5}$$

$$\delta_{a_0'}^2 = \sum_{a=1}^{m'} \frac{1}{m'} \left(a_0' - \delta_{a_0'}^1\right)^2 \tag{6}$$

In Formula 5-6: $\delta_{a_0'}^1$ denotes the structured data sample mean eigenfactor; $\delta_{a_0'}^2$ denotes the coefficient of variation characterizing the sample variance of the structured data; m' denotes the number of support vectors, but is mapped here to the total number of structured data points.

In processing text data using TF-IDF, the text keyword extraction process is:

$$\text{TF-IDF}\left(s_a, \vec{a}\right) = \text{TF}\left(s_a, \vec{a}\right) \times \text{IDF}\left(s_a\right) \tag{7}$$

$$\text{TF}\left(s_a, \vec{a}\right) = \frac{C_{\vec{a}}^{s_a}}{S_{\vec{a}}'} \tag{8}$$

$$\text{IDF}\left(s_a\right) = \log \frac{\breve{m}}{\kappa} \tag{9}$$

In Formula 7-9: $\text{TF-IDF}(\cdot)$ denotes the importance score calculation function; s_a denotes the keyword from which the sample was drawn; $\vec{a}$ denotes the text document in the extraction sample; $\text{TF}\left(s_a, \vec{a}\right)$ denotes the frequency of occurrence of the keyword in the text document; $\text{IDF}\left(s_a\right)$ denotes the importance of the keyword in the whole document collection; $C_{\vec{a}}^{s_a}$ denotes the number of times the keyword appears in the text document; $S_{\vec{a}}'$ denotes the total number of words in the text document; $\breve{m}$ denotes the total number of documents in the document collection; κ denotes the number of documents containing the keyword in the extracted sample.

Based on the grid scheduling error prevention knowledge entity extraction and feature extraction logic in Eqs. (3)-(9), iterates through all the metadata items in A, generates the grid scheduling error prevention information sequence containing key entities, relationships and features [17-19], and outputs the knowledge subject extraction and identification result $\vec{A} = \left\{\vec{a}_1, \vec{a}_2, \vec{a}_3, \ldots, \vec{a}_m\right\}$, where $\vec{a}$ denotes an element in the grid scheduling error prevention information sequence, which may represent an entity, a relationship or a feature.

2.3. Grid dispatching anti-misoperation warning based on deep bidirectional gated recurrent neural network

Modeling of operational state reconstruction for deep bidirectional gating recurrent neural networks

The grid scheduling operation is a continuous process, and each step of the operation has a close chronological relationship with the previous operation, showing a significant correlation before and after the overall operation. Simultaneously, because grid scheduling involves multiple devices and links, the operation is complex and highly correlated, and part of the misoperation will affect the overall scheduling security of the grid. In this study, based on a deep bidirectional gated recurrent neural network, we analyze the sequence of operation steps in the grid scheduling process by considering the bidirectional (past-future, i.e., forward RNN and backward RNN) information flow, identifying the misoperation and potential risk information [20-22], and providing timely warning. The overall architecture of the network model constructed in this study is illustrated in Figure 2:

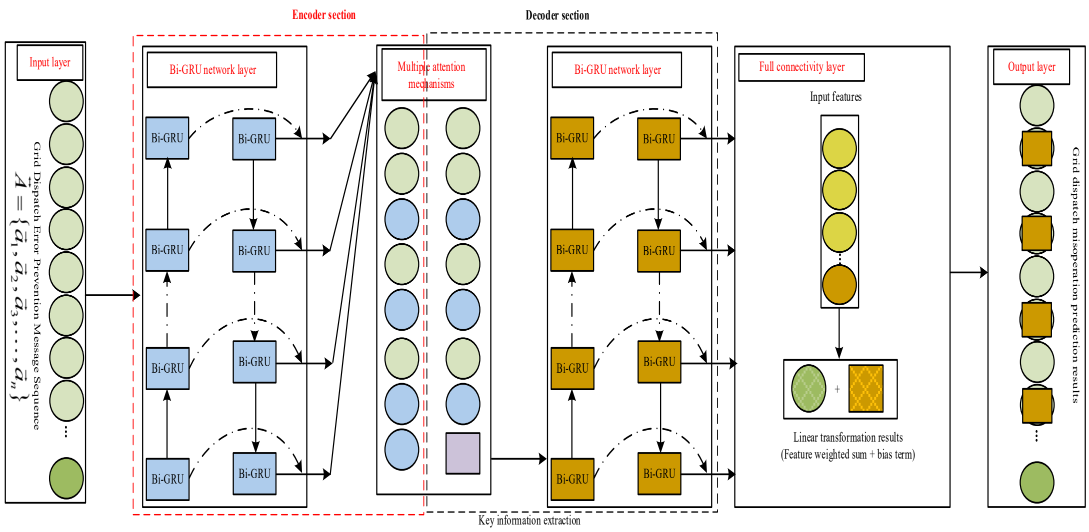

Figure 2. Deep bidirectional gating recurrent neural network anti-misoperation state prediction model

As shown in Figure 2, the entire model consists of an input layer, a coding layer, a decoding layer (Bi-GRU recurrent network structure + multi-head self-attention mechanism), a fully-connected layer and a reconstructed output layer. The input layer represents the sequence of grid scheduling error prevention information containing key entities, relationships and features, and at the same time, the input sequence data is also preprocessed by this layer, including the elimination of abnormal data and the standardization of data; the coding layer consists of a 2-layer Bi-GRU recurrent neural network (with a symmetric structure), which compresses and downsizes the data, and fully extracts the internal information of the time series; in order to conduct deep mining for the association relationship of power scheduling entities, the decoding layer is composed of a Bi-GRU recurrent neural network (with symmetric structure). To deeply mine the association relationship of power dispatch entities and directly establish a connection between any two positions in the sequence [23-24], it is necessary to add a multi-attention mechanism after the coding layer to capture the long-distance dependence of the downscaled grid scheduling error prevention feature information; the downscaled feature information with long-distance dependence needs to be passed through the decoding layer and the fully-connected layer in turn, and the output of the fully-connected layer is the reconstructed time series; according to the presentation of the time series, the time series is reconstructed by the Bi-GRU loop neural network in a symmetric structure; the data are compressed and downscaled to fully extract the internal information. The output of the fully connected layer is the reconstructed time series; according to the results of the time series presentation, the output layer outputs the final misoperation type prediction results containing the misoperation occurrence time sequence information, realizing the grid scheduling misoperation prevention and warning.

Grid dispatching anti-misoperation warning based on deep Bi-GRU recurrent neural network

Specifically, the recurrent neural network model designed in this study mainly includes the input layer, coding layer, decoding layer, fully connected layer, and output layer. This study uses the form of a stacked self-encoder to construct the coding and decoding module in the network model, the main structure of which is shown in Figure 3:

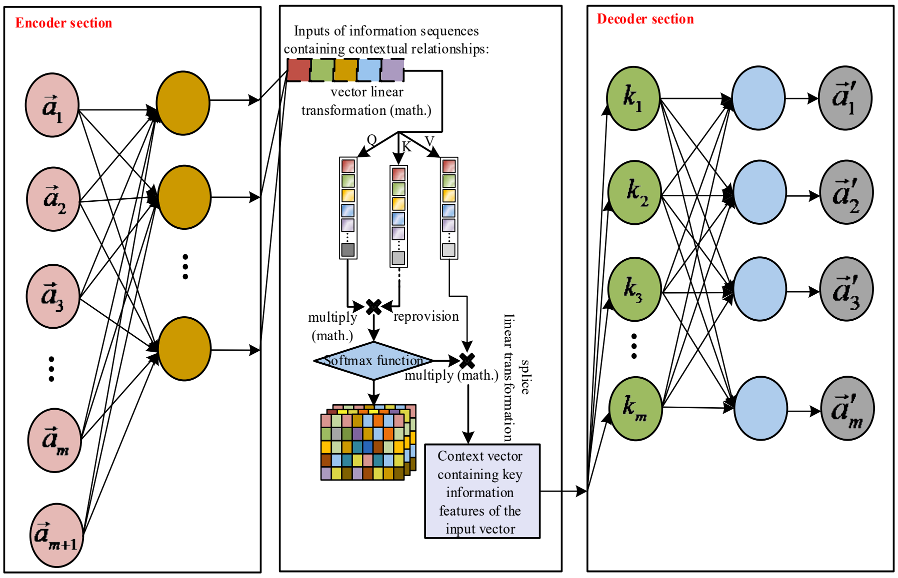

Figure 3. Self-encoder main structure

As can be seen from Figure 3, the self-encoder applied in the design model of this paper mainly consists of a coding part, a multi-head attention mechanism and a decoding part. Where, $\{\vec{a}_1,\vec{a}_2,\vec{a}_3,\ldots,\vec{a}_n,\vec{a}_{n+1}\}$ is the input variable of the self-encoder, $\{k_1,k_2,k_3,\ldots,k_m\}$ is the encoded output matrix element (containing contextual information), and $\{\vec{a}'_1,\vec{a}'_2,\vec{a}'_3,\ldots,\vec{a}'_n\}$ denotes the variable reconstructed by the self-encoder.

The codec training operation is performed in the form of stacked encoders, and the training process uses a layer-by-layer greedy algorithm to complete the construction of the entire stacked self-encoding network. The coded output of the first self-encoder is mainly used as the input of the second self-encoder, and the coded output of the second self-encoder is obtained after training. After the end of the multilayer forward propagation, we obtain the features that have been downgraded layer by layer, and then the features are input to the same network as the encoding process for decoding, and the final reconstructed output is obtained after training.

The coding and decoding part of the model in Figure 2, in addition to including the self-encoder structure, the coding and decoding part of the model incorporates a bi-directional gated recurrent neural network containing gated recurrent units [25-26]. The gated recurrent unit (GRU) network is a type of recurrent neural network, which is a variant of the long-short-term memory (LSTM) network, with a simpler structure. Its effect is similar to that of the long-short-term memory network, but with a faster operation speed. However, different from LSTM, GRU network controls the information by introducing update gate and reset gate, in which update gate is responsible for the retention of historical information, and reset gate is responsible for adjusting the combination of the current input information and historical information, and the specific computational process is as follows:

$$r_1 = \mu\left[\varpi_1\left(x_{t-1}, y_t\right) + \vec{b}_1\right] \tag{10}$$

$$r_2 = \mu\left[\varpi_2\left(x_{t-1}, y_t\right) + \vec{b}_2\right] \tag{11}$$

$$r_3 = \otimes\left[\varpi_3\left(r_1 x_{t-1}, y_t\right) + \vec{b}_3\right] \tag{12}$$

$$r_4 = x_{t-1}\left(1 - r_2\right) + r_2 r_3 \tag{13}$$

In Formula 10-13: r_1、r_2 denotes reset gate and update gate; μ denotes the Sigmoid activation function; ϖ_1、ϖ_2、ϖ_3 denotes the fully connected layer weights for computing the reset gate, update gate, and candidate outputs in the GRU network; x_{t-1} denotes the hidden layer output at a particular moment in time; y_t denotes the GRU network input at a specific moment in time; $\vec{b}_1$、$\vec{b}_2$、$\vec{b}_3$ denotes the fully connected layer bias coefficients of the reset gate, update gate, and candidate outputs; r_3 denotes the candidate output at a particular moment in time; $\otimes(\cdot)$ denotes the hyperbolic tangent function; r_4 denotes the implicit layer output at a particular moment in time.

The GRU neural network can only read the historical information from the time series, whereas the bi-directional recurrent neural network can utilize both historical and future information of the time series data. Therefore, based on the derivation process of Eqs. (10)-(13), this study utilizes two GRU neural networks with the same structure and opposite propagation directions in the network model to construct a Bi-GRU neural network. The network establishes the connection between the input grid scheduling error prevention information sequence and the predicted value at the next moment, and covers both the past and future data information of the sequence, thus improving the capacity and feature learning intensity of the design model.

Based on the overall operation principle of the deep bi-directional gated recurrent neural network dispatch operation anti-misoperation state prediction model, the design of the grid dispatch anti-misoperation warning process is shown in Figure 4:

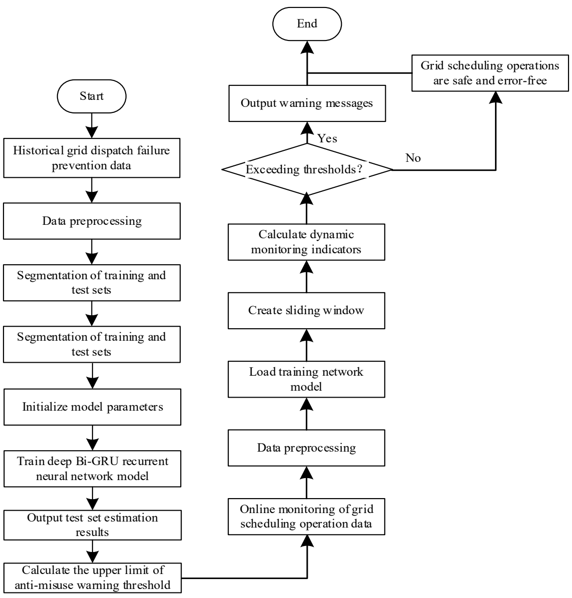

Figure 4. Grid dispatching anti-misoperation warning based on anti-misoperation state prediction model

3. Experimental analyses

3.1. Experimental environment setup

To verify the practical application performance of the design method, a smart grid dispatching system in a certain region is used as an aid, the SOP process is used to manage the dispatching operation ticket, and the performance of the design method is tested according to the current grid operation data, as well as a way to simulate the real smart grid normal dispatching situation.

During the experiment, the experimental environment configuration information is as follows: communication network transmission speed is 30MB/s, half-duplex bus adopts RS485 type, grid scheduling software running server CPU: Intel Xeon Gold 6230, 20 cores, 2.1 GHz, memory: 128GB DDR4 ECC RAM, storage: 2TB NVMe SSD + 8TB SATA HDD, Network Interface: Dual-port 10GbE SFP+ NIC. Workstations for grid scheduling and monitoring by operators CPU: Intel Core i7-10700K, 8 cores, 3.8 GHz, Memory: 32GB DDR4 RAM, Graphics: NVIDIA Quadro P2200, 5GB GDDR5X, Monitors: two 27-inch 4 K monitors. The error simulation software is MATLAB-2019 version and the electronic design automation (EDA) software is Proteus 8.6.

The model simulation parameters are as follows: the number of iterations is 100, the number of codec layers is 2-2, Word_dim is 30, the initial learning rate is 0.0012, and the number of Bi-GRU neurons in the codec layer is [64,128].

In the historical grid scheduling information warehouse of the region, some anti-misoperation entity information is extracted, as shown in Table 1:

Table 1. Grid scheduling error prevention information extraction, identification results

Entity type	Entity Extraction Elements	Recognition Role
Equipment entity	Generator, transformer, circuit breaker, disconnect switch, busbar, capacitor, reactor scheduling attribute elements	Identify key attribute information such as name, model, capacity, rated voltage, rated current, etc. of these devices to ensure the error-proof attributes of dispatching operations
Operation entity	Primary equipment commissioning, shutdown, paralleling, de-paralleling, trend adjustment behavioral elements	Capture the specific behavior, execution conditions, and execution time of operation information.
Fault entity	Elements of equipment failure, line failure, short-circuit, and disconnection failure	Identify the type, location, phenomenon, and cause of grid operation faults.
Rule entity	Grid dispatch operation safety rules, operation rules, constraints	Capture the specific content, scope of application, and execution requirements of grid scheduling rules to

		ensure that scheduling operations are in compliance with the regulations and to avoid misoperation.
Time entity	Dispatch operation, time labeling of fault occurrence	Recognize time attributes such as time stamps and time intervals of abnormal events
Location entity	Grid topology describing the connectivity and spatial location of equipment in the grid	Identify geographic elements such as substations, lines, busbars, etc. in the power grid, and analyze the multi-source connection relationship of power grid equipment

Based on Table 1, two different operation tasks are designed: one is the operation task under normal conditions and the other is the operation task when the grid is faulty. The dispatcher writes the dispatching operation ticket according to the grid operation, performs the operation preview after writing the ticket, issues the preorder, transmits the dispatching preorder through the dispatching data network, realizes the data docking and instruction flow, and files the dispatching operation ticket after its execution.

For the above content of the grid failure, for the historical data in the double fault as an example, the grid scheduling received fault information is shown in Table 2:

Table 2. Grid dispatch fault information

Serial number	Early Warning Information
1	Differential protection (main protection bus)
2	Right side circuit breaker 5 tripped
3	Line left near backup protection
4	Left side of line 3 fiber differential protection
5	Breaker 7 tripped
6	Breaker 9 control power loss
7	Circuit breaker 9 communication abnormality

3.2. Methods anti-misoperation warning accuracy analysis

In order to verify the practical application effect of the design method, literature [4], literature [5] method is introduced as a comparison method to compare the different methods in the same number of iterations (100 times) to obtain the grid scheduling anti-misoperation state prediction results with the actual grid scheduling operation state of the degree of fit, a higher degree of fit indicates that the method of anti-misoperation early warning accuracy is higher, the results of the different methods of early warning accuracy analysis are shown in Figure 5 The results of different methods are analyzed as shown in Figure 5:

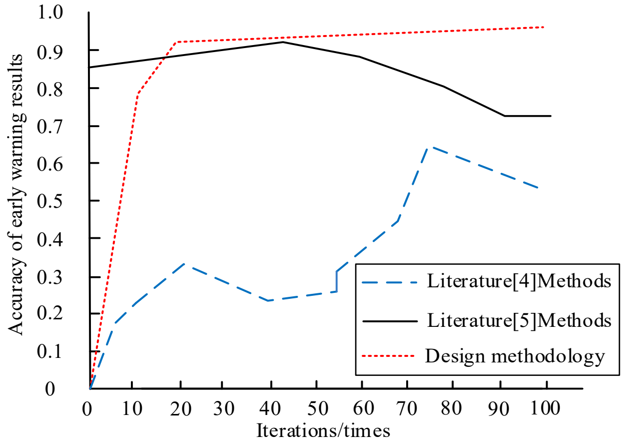

Figure 5 Results of the analysis of the accuracy of different methods of early warning

As can be seen from Figure 5, the prediction results of the grid scheduling anti-misoperation state obtained by using the design method have a high degree of fit with the actual grid scheduling operation state, and can effectively determine whether there is misoperation in the actual scheduling task, and in the process of continuous iteration, the average value of the anti-misoperation warning accuracy is 0.87, which is higher than that of the other two methods. It can be seen that the design method has a stronger error prevention performance in the actual application process, which can effectively prevent the dispatcher from making mistakes when operating the grid and provide timely and accurate warnings for the operations that have already made mistakes.

3.3. Speed of analysis of dispatching operations under normal operation of the grid

In order to verify the practical application effect of the design method, the literature [4], literature [5] method is introduced as a comparison method to the normal operation of the power grid as the scheduling operation environment, to analyze whether there is misoperation in the process of grid scheduling, and the performance of the analysis of the operation data is shown in Table 3:

Table 3. Performance of data analysis of method operation under normal operation of the grid

Methodology	Scheduling phase	Computational convergence Speed/(MB/s)	Data Docking Speed/(MB/s)
Design Methods	Checking stage	0.0047	60.353
	Ticket writing stage	0.0024	64.207
	Dispatch instruction flow phase	0.0032	70.563
Literature [4] Methods	Checking stage	0.0091	10.328
	Ticket writing stage	0.0074	9.576
	Dispatch instruction flow stage	0.0105	9.332
Literature [5] method	Checking stage	0.0104	8.577
	Ticket writing stage	0.0111	8.968
	Dispatch instruction flow stage	0.0106	9.032

As can be observed from Table 3, under the normal operation of the power grid, the data docking speed of the literature [4] method and the literature [5] method in different scheduling phases is relatively slow, and the convergence speed of the analysis and calculation process is relatively slow. However, the design method has fast data docking speed in different scheduling phases, with the fastest speed of 71.254MB/s, and the convergence speed of analyzing and calculating is within 0.01MB/s, which indicates that the overall analyzing efficiency is high, the application performance is good, and it can determine whether there is any misoperation in the process of grid scheduling and carry out highly efficient, accurate and fast warning.

3.4. Speed of analysis of dispatching operations under normal operation of the grids

In the case of grid anomalies, to prevent the dispatcher from executing wrong operations leading to the aggravation of grid problems or triggering a wider range of faults, it is necessary to analyze the scheduling operations in real time and provide timely warnings against misoperation. To verify the practical application effect of the design method, literature [4] and literature [5] method are introduced as a comparison method to analyze whether there is misoperation in the process of grid scheduling by taking the abnormal grid operation (the existence of faults) as the scheduling operation environment, the performance of which is shown in Table 4:

Table 4. Performance of data analysis of method operation under abnormal operation of the power grid

Methodology	Scheduling phase	Computational convergence Speed/(MB/s)	Data Docking Speed/(MB/s)
Design Methods	Checking stage	0.0045	75.332
	Ticket writing stage	0.0026	71.254
	Dispatch instruction flow phase	0.0031	73.563
Literature [4] Methods	Checking stage	0.0093	45.324
	Ticket writing stage	0.0075	46.103
	Dispatch instruction flow stage	0.0103	41.781
Literature [5] method	Checking stage	0.0105	38.752
	Ticket writing stage	0.0113	40.088
	Dispatch instruction flow stage	0.0107	39.762

As can be observed from Table 4, under abnormal grid operation (presence of faults), there is a decrease in the data docking speed of the design method, literature [4] method, and literature [5] method in different scheduling stages. However, the data docking speed of the design method decreases to a lesser extent, and the overall speed is above 60MB/s. In addition, the convergence speeds of the analysis calculations for each analysis method do not differ significantly from the results in Table 3, indicating that the presence of faults does not have a significant impact on the convergence speed. It can be seen that the use of the design method can quickly realize the effective docking of real-time scheduling operation data and historical data, and the data analysis speed is faster, which can effectively determine whether the dispatcher's operation in the abnormal situation of the power grid has errors, and carry out accurate alarms.

4. Concluding remarks

In summary, this study designs a grid scheduling anti-misoperation warning method based on a deep bidirectional gated recurrent neural network that can effectively predict whether there is a misoperation situation in the grid scheduling task, which can reduce human operation errors to a greater extent. In this study, by combining the principle of hierarchical data construction, a grid scheduling error prevention data warehouse is constructed, and the scheduling error prevention operation metadata in the database is used as the data basis for knowledge entity extraction and identification. Simultaneously, based on the deep bidirectional gated recurrent neural network, the grid scheduling operation state reconstruction model is constructed, and the error prevention warning is carried out according to the output prediction results. The experimental results show that the designed method has stronger error prevention performance in the actual application process, which can effectively prevent the dispatcher from making errors when operating the grid and provide timely and accurate warnings for the operations that have already made errors.

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