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A Carrying Method for 5G Network Slicing in Smart Grid Communication Services Based on Neural Network

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Abstract: When applying 5G network slicing technology, the operator's network resources in the form of mutually isolated logical network slices provide specific service requirements and quality of service guarantees for smart grid communication services. In the face of the new situation of 5G, which comprises the surge in demand for smart grid communication services and service types, as well as the digital and intelligent development of communication networks, it is even more important to provide a self-intelligent resource allocation and carrying method when slicing resources are allocated. To this end, a carrying method based on a neural network is proposed. The objective is to establish a hierarchical scheduling system for smart grid communication services at the power smart gate-way at the edge, where intelligent classification matching of smart grid communication services to (i) adapt to the characteristics of 5G network slicing and (ii) dynamic prediction of traffic in the slicing network are both realized. This hierarchical scheduling system extracts the data features of the services and encodes the data through a one-dimensional Convolutional Neural Network (1D CNN) in order to achieve intelligent classification and matching of smart grid communication services. This system also combines with Bidirectional Long Short-Term Memory Neural Network (BILSTM) in order to achieve a dynamic prediction of time-series based traffic in the slicing network. The simulation results validate the feasibility of a service classification model based on a 1D CNN and a traffic prediction model based on BILSTM for smart grid communication services.

Keywords: CNN; BILSTM; network slicing; edge network; smart grid; service classification; traffic prediction

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1. Introduction

Today, the demand for grid communication services is increasing dramatically and the types of services are diversifying, and smart grids have become the main development trend and, ultimately, the strategic goal of the electric power system. Based on different application scenarios and demands of 5G, network slicing adopts technologies based on Software Defined Network (SDN) and Network Functions Virtualization (NFV) [1,2]. Network slicing realizes an end-to-end network grouping communication function and provides the network resources required for the service through the orchestration operation of slicing. The characteristics of 5G network slicing technology are well suited to the performance requirements of a smart grid [3,4]. Its three main features of large bandwidth, low latency, and large connectivity will provide better processing capabilities for various typical services in the smart grid. Network slicing provides differentiated grid communication services for different units on demand based on the working conditions and the service requirements that are needed to meet the carrying requirements of different types of grid communication services on network slicing [5]. At present, research combining grid communication services with 5G network slicing technology is being gradually enriched and put into use.

In the electricity grid, cloud computing is now widely used [6]. But as the volume of data increases rapidly, there is a need for new ways of handling and storing those data [7]. The application of edge computing technology, which decentralises computing resources and distributes them closer to end devices, can better reduce network latency and costs [8]. Implementing edge computing through edge data centres enables more granular requirements for each edge node, resulting in more efficient resource utilisation [9]. Aiming at smart grid scenarios, edge data centres are well placed to improve resource management strategies [10,11].

Ref. [12] proposes a prediction-based 5G network slicing algorithm that uses a prediction algorithm to pre-implement resource isolation and shorten the establishment cycle of network slicing in order to accommodate the real-time requirements of 5G networks. Based on different mathematical approaches, these models are classified into game theory-based models, predictive techniques, and robustness/failure recovery models. One study [13] introduces the application of 5G network slicing technology in smart grids and presents several typical case studies. Another study [14] illustrates the application of resource allocation algorithms for network slicing in smart grids. In the work of [15], according to the demand of power services, network slice planning strategies with different isolation abilities are proposed. Based on the management requirements of refined service in the power industry, the slice identification of the power service is then proposed. The work of [16] constructs a new grid data collection system based on cloud-edge collaboration, which solves the real-time processing and response problems of edge applications while reducing the bandwidth pressure of data communication between the cloud and the edge. These preliminary studies focus on slicing scheduling algorithms and resource allocation methods that seek to improve network efficiency. In such approaches, service requirements are often abstracted into relatively fixed latency or bandwidth requirements. If the traffic changes dynamically or has many types, before slicing resource allocation, service type identification and dynamic demand prediction are achieved in advance on the edge side to realize the collection of large amounts of data in the edge nodes and the preliminary processing and analysis. Then, enter the next layer of network transmission is entered to achieve a more efficient and reasonable resource allocation and carrying scheme for grid services in 5G network slicing, which can use resources efficiently.

Communication networks are accelerating to become digitised and intelligent, and using AI technologies to enhance communication intelligence has become a development trend. To achieve this expectation, the network needs to have "endogenous intelligence", considering various artificial intelligence technologies at the beginning of the network design, such as deep learning algorithms, in order to form a perfect system architecture and enhance the network's "intelligence capability" [17]. For example, China Mobile's "Tianyan" system provides self-intelligence for many functions in the 5G core network. Compared to classical classification and recognition techniques, such as port recognition, deep message detection and recognition, and statistical feature recognition, neural network-based deep learning models can achieve higher accuracy rates while not relying on other experiences, and they can also handle tasks and data of higher complexity [18,19]. The classic traffic prediction methods, such as time series models and regression models, also perform better with deep learning models, such as neural networks. Useful features can be learned directly from the raw data, improving the accuracy and efficiency of the model [20]. The models can be better adapted to real-world scenarios and provide higher-quality prediction results [21]. Therefore, this paper proposes a neural network-based approach for carrying smart grid communication networks in 5G network slicing, which can reduce the complexity of resource allocation in the next phase of network slicing. The main contributions of this paper are as follows:

(1) The hierarchical classification matching scheme was designed by matching the different communication demand for smart grid communication services, such as bandwidth, latency, and connectivity, with the characteristics of the 5G sliced network, where the traditional 5G network slices are divided into critical and general.

(2) A scheme is proposed for combining edge computing in 5G slices in order to carry smart grid communication services. Different types of data generated by electric power terminal devices are received into the edge data centre for classification and matching, while the edge data centre performs dynamic prediction of the service traffic data in the network slice.
(3) In order to adapt to the development trend of intelligence, the neural network model is used for classification matching and traffic prediction. The 1D CNN is used to extract the data features of traffic services and encode the data in order to achieve classification and matching of smart grid communication services. At the same time, with the proliferation of grid communication network traffic, the complexity of the services carried by the network has increased greatly. If a fixed rationing model is adopted, excessive network resources are often required, which is not conducive to improving network efficiency and expanding the network scale. This paper also uses BILSTM work for dynamic traffic prediction and adjustment.
(4) The experimental results show that the neural network model used can show better results in classifying the power communication network and in predicting the network traffic, which is suitable for the 5G slicing network carrying the electric power communication network.

The rest of the paper is organized as follows. Section 2 describes the system mechanism. Section 3 illustrates the algorithm model. Section 4 implements the experimental simulations. Finally, Section 5 gives the conclusions.

2. Hierarchical Dispatch Carrying Mechanism

2.1. Characteristics of Smart Grid Communication Services

The application scenario of power 5G communication service is mainly divided into two production regions, the production control region (I) and the management information region (II). The production control large area service mainly includes control class traffic, such as distribution network differential protection, intelligent distributed feeder automation (FA), and precise load control, which require low delay control [22]. The management information region mainly includes acquisition- and application-type services, involving the acquisition of various terminal data, video monitoring, etc. The acquisition objects are extended to various types of IoT terminals and multimedia scenes, with a surge in the number of connections, which is in the millions [23]. At the same time, the acquired content tends to be video-based and high-definition, and the demand for return transmission has increased greatly [24]. For these diversified power 5G services, the three scenarios of enhanced Mobile Broadband (eMBB), massive Machine Type Communication (mMTC), and ultra-Reliable and Low-Latency Communication (uRLLC) in 5G network slicing can well provide service capability for them [25,26]. The basic relationship between selected typical power 5G services and network slicing is shown in Table 1. The services of the two production regions involve three main categories, control, collection, and application, corresponding to the three application scenarios of 5G slicing. Based on the size of the specific feature data, they can be further categorized as general type and critical type.

Table 1. Features of power 5G service.

Production Region	Traffic Category	Electric Power Service	Communication Requirements		NS	Hierarchical Classification
			Delay	Bandwidth		
I	Control category	Distribution network differential protection	$\leq$10 ms	<2 Mbps	uRLLC	Delay-critical
		Distribution automation	$\leq$100 ms	<10 Mbps		Delay-general
II	Collection category	Power information collection	<3 s	10 kbps	mMTC	Connection-critical
	Application category	Mobile operation	$\leq$300 ms	$\geq$4 Mbps	eMBB	Bandwidth-general
		Robot inspection	$\leq$300 ms	20~100 Mbps		Bandwidth-critical

2.2. Neural Network-Based Hierarchical Scheduling Carrying Mechanism

The application of network slicing is greatly significant to the construction of 5G private networks in power scenarios. In the intelligent processing of the power access network, the edge access room can achieve intelligent sensing and prediction by automatically identifying different types of access terminal services, such as power distribution automation and video monitoring; by automatically adapting them to the appropriate communication lines and virtual network slices according to the different communication needs of the services; and, lastly, by achieving intelligent classification. Service traffic, flow direction and network congestion are continuously monitored and analysed, the network is dispatched based on predicted future conditions, and traffic adjustment and routing optimisation of network slices are carried out. Terminal data from different regions enter the edge data centre, and for power slicing management needs, as well as for power service needs, the power intelligent gateway is used as the edge computing node mainly responsible for receiving and forwarding data. At the same time, the characteristics of the electric power services are analysed and classified according to rules or data models, providing basic slice configuration parameters for network slice carrying planning under different conditions and generating various types of customized slices. Under the condition of considering the soft isolation of base station equipment, the mode of slice priority scheduling is proposed to ensure the resource occupation of high-priority users through the hierarchical classification of power services characteristics. Then, combined with service traffic prediction, it actively generates dynamic adjustment to improve the transmission efficiency of the whole network [27].

This paper implements feature extraction of service data based on 1D CNN and carries out service classification matching to satisfy the classification of differentiated power 5G services according to different service features and mapping deployment with power 5G slices. At the same time, the dynamic prediction of service traffic of network slices based on LSTM can better satisfy network slices according to different service conditions and service requirements for different units of differentiated power traffic network slicing services to meet the carrying of power 5G traffic network slices. At this edge computing node, the deployment of power 5G slicing service mapping for the access network is completed. Afterward, by developing a slicing network management system, network resource management and monitoring of the wireless network, bearer network, and core network for 5G slicing are all realized. In order to realize the docking of the bearer network and 5G slicing within the enterprise, a bearer network slicing device is developed in order to realize the end-to-end slicing establishment between the traffic terminal, the 5G network, the enterprise intranet and the traffic system, and the overall structure is shown in Figure 1, where the classifications and traffic forecasts mentioned are marked in red.

The 5G network slicing service carrying is the process of deploying power service to 5G slices. In the process of deployment and implementation, the demand described in the hierarchical classification of the grid service is transformed into the service level indicator of network slices in the 5G network. The network slice Service Level Agreement (SLA) is part of the service agreement signed between the operator and the network slice customer, and the network slice SLA contains the requirements of the network slice customer for the services and network provided by the operator. On the basis of the service level classification description, in order for the control equipment of the 5G network to understand the power service requirements, it is also necessary to translate the power service statute into the corresponding SLA quantitative model.

3. Neural Network Algorithm Model

3.1. CNN Model

CNN can process input data with a grid-like structure and are widely used in the field of image processing. The part of the classification highlighted in red is shown in Figure 2, where the algorithm consists of a unique deep feed-forward network containing an input layer, a convolutional layer, a pooling layer, a global pooling layer, a fully connected layer and an output layer [28]. The dataset is obtained from the center DC, trained and the model is output to the edge DC. The input sequence can be extracted and transformed into features, and the feature vectors can be fed into a classifier for classification.

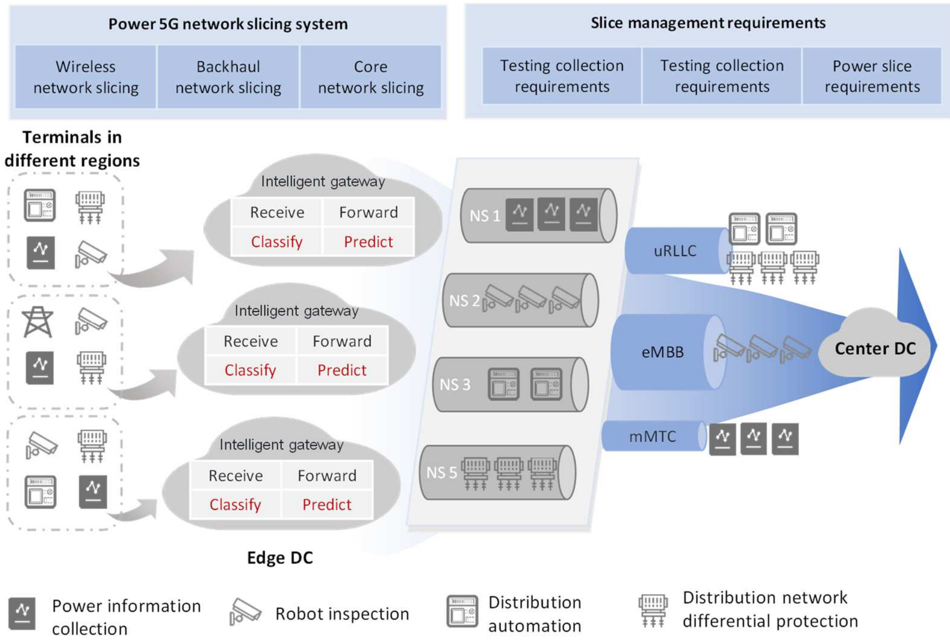

Figure 1. Structure of power grid 5G slicing system.

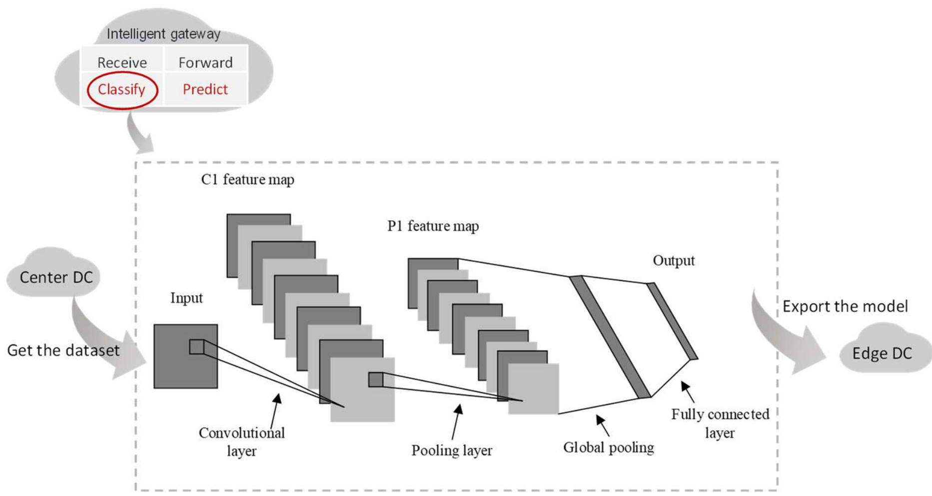

Figure 2. Structure of the CNN model.

The convolution layer is mainly used to extract local information from the temporal data, with different filters to extract different features. For a filter of length D, the output of the convolution layer is as follows [29]

$$h_i = relu(\sum_{d=1}^{D} w_d x_{i+d-1} + b) \quad (1)$$

where *relu* denotes the modified linear unit function, w_d denotes the weight vector of the filter, and b denotes the offset.

The CNN network contains multiple convolutional layers and multiple pooling layers. The combination of different layers will achieve feature extraction to obtain high-dimensional features at higher levels. This paper uses a pooling layer and a global pooling layer. In the pooling layer, the maximum pooling rule is used. The feature map is integrated into the global pooling layer and converted into a feature vector for use in classification operations.

The fully connected layer uses regularization. L2 to prevent overfitting [30], and the *softmax* logistic regression function is used to output the classification results,

$$\min_{w,b} J(w,b) = \frac{1}{m}\sum_{i=1}^{m} L(\hat{y}^{(i)}, y^{(i)}) + \frac{\lambda}{2m}\|w\|_2^2 \tag{2}$$

$$y = softmax(W^T p + b) \tag{3}$$

where *softmax* denotes the *softmax* function, and W and b are the weights and offsets of the fully connected layers, respectively.

3.2. LSTM Model

3.2.1. Structure of the LSTM and BILSTM Models

LSTM introduces self-loops to produce paths where gradients flow continuously over long periods. The algorithm can predict dynamically changing sequences of numbers. The LSTM model contains three gating units, the input gate, the forget gate, and the output gate, which control the flow of information [31]. The internal structure of the LSTM model is shown in Figure 3.

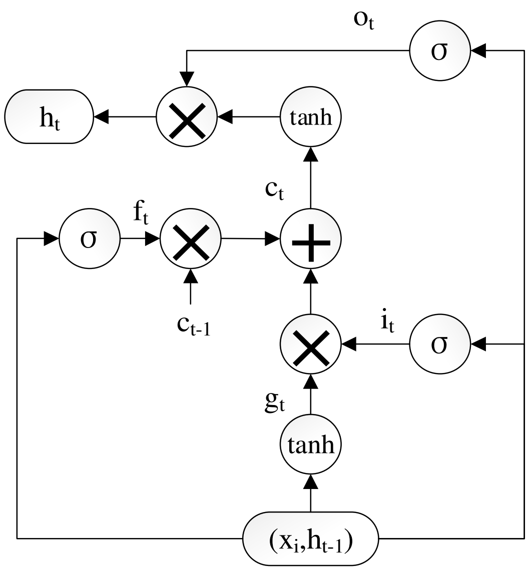

Figure 3. Structure of the LSTM model.

The relationship between the three gating units and the candidate memory states is as follows:

$$i_t = \sigma(W_{ii}x_t + b_{ii} + W_{hi}h_{t-1} + b_{hi}) \tag{4}$$

$$f_t = \sigma(W_{if}x_t + b_{if} + W_{hf}h_{t-1} + b_{hf}) \tag{5}$$

$$o_t = \sigma(W_{io}x_t + b_{io} + W_{ho}h_{t-1} + b_{ho}) \tag{6}$$

$$g_t = tanh(W_{ig}x_t + b_{ig} + W_{hg}h_{t-1} + b_{hg}) \tag{7}$$

The relationship between h_t and c_t is as follows

$$c_t = f_t c_{t-1} + i_t g_t \tag{8}$$

$$h_t = o_t \cdot tanh(c_t) \quad (9)$$

where i_t indicates the output of the input gate; f_t denotes the output of the forgetting gate, controlling the importance of the memory state at the previous moment; o_t denotes the output of the output gate, controlling the output of the memory state; g_t indicates the activation value of the input at the current moment; c_t indicates the memory state of the current moment, used to store historical information; h_t indicates the output value of the current moment for passing to the next moment; σ denotes the sigmoid function; tanh denotes the hyperbolic tangent function; and W, b denote the weight and offset, respectively.

BILSTM is an extended LSTM model that considers not only historical input information from the current moment but also information from future moments. It has greater expressiveness and model generalization capabilities.

The BILSTM model processes the input sequence from front to back and from back to front in two different LSTM layers and concatenates their outputs to obtain the final output. In the forward LSTM layer, the LSTM model receives the original input sequence, i.e., in left-to-right order. In the backward LSTM layer, the LSTM model receives the inverted input sequence, i.e., in right-to-left order. The structure of both the LSTM and the BISTM are shown in Figure 4.

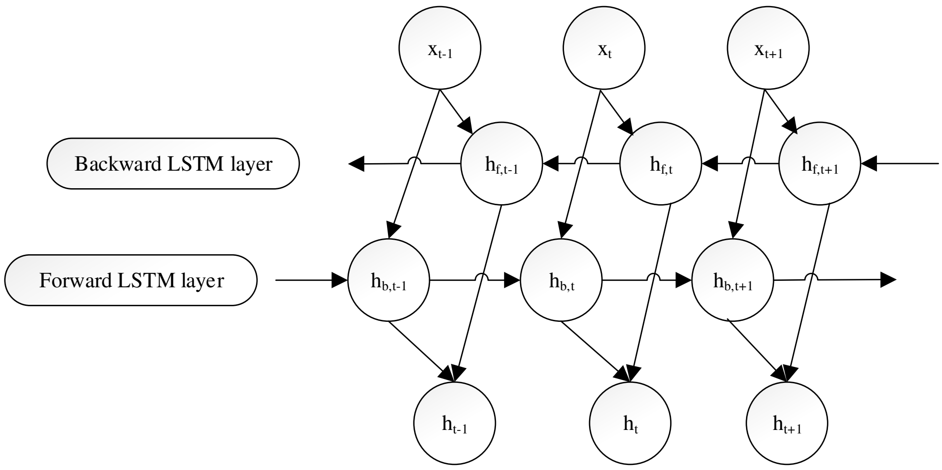

Figure 4. Structure of the BILSTM model.

h_f represents the hidden state output of the forward LSTM layer. H_b represents the hidden state output of the backward LSTM layer; and h_t denotes the output value at the current moment, which is a concatenation of the outputs of the forward and backward LSTM layers. Suppose the hidden state of the forward LSTM output is $h_{f,t}$, the hidden state of the backward LSTM output is $h_{b,t}$, and the input at the current moment is x_t. Then, outputs can be expressed as follows, respectively, the output of the final forward and backward LSTM are dot productively stitched together at moment in order to obtain the output of the BILSTM model at that moment as

$$h_{f,t} = LSTM(x_t, h_{f,t-1}) \quad (10)$$

$$h_{b,t} = LSTM(x_t, h_{b,t-1}) \quad (11)$$

$$h_t = h_{f,t} \oplus h_{b,t} \quad (12)$$

where $\oplus$ represents the splicing operation of vectors, and the activation function is chosen as *relu*.

3.2.2. Evaluation of the LSTM and BILSTM Models

Formula (13) represents Mean Absolute Percentage Error (MAPE) and is a common metric used to evaluate LSTM and BILSTM models, which indicates the difference between the predicted and the actual values of the LSTM and BILSTM models, and the smaller the value of the metric, the higher the prediction accuracy of the model

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (13)$$

where n indicates the sample size, y_i indicates the actual value, and $\hat{y}_i$ indicates the predicted value.

4. Results and Discussion

The neural network algorithm was built using the TensorFlow framework in the simulation experiments. The hardware environment consisted of an AMD Ryzen 7 5800H CPU, 16×3.2 GHZ cores, 16G RAM and an NVIDIA GTX 1650 GPU with 4G video memory.

4.1. Classification of Grid Services Based on 1D CNN

The data messages generated by power communication services have relatively fixed frame formats, and the characteristics of different types of electric power services are more obvious, which can be abstracted into $1 \times$ N pixel images, and then identified using CNN-based image algorithms. Based on 1D CNN, the data features of the traffic service are extracted and encoded in order to achieve power service identification and classification matching. The data collected from various types of power terminals first enter the input layer data, which is a 1×1024 two-dimensional matrix after pre-processing. In the pre-processing of the data, the dataset used in the experiments are transformed into an input format with the same structure. This mainly consists of data encoding, normalisation processing, and array dimensionality reduction. The acquired data are used to convert them to integers according to the ASCII table and turn them into a 1×1024 two-dimensional matrix.

In the simulation, the tagged sample dataset obtained from packet capture in the operational network is used, with 146 service types in total and 100 sample service packet data for each class. Each sample service packet data intercepts the net data load of the application layer message and presents it in the form of a hexadecimal code stream. The data processing flow based on the CNN model is shown in Figure 5.

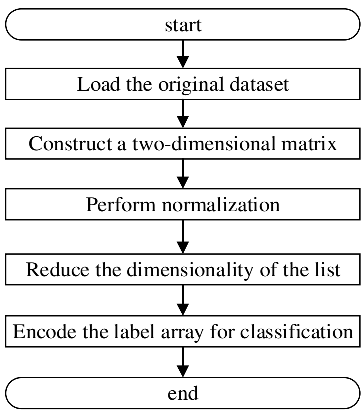

Figure 5. Flow chart of data processing in CNN model.

The accuracy of the operational recognition is related to the training sample parameters, the convolutional layer parameters and the activation function. For the parameters of the convolutional layer, the value of the number of convolutional kernels, FILTER, was chosen to be adjusted. The corresponding accuracies for different filters is shown in Table 2. It can be seen that the best combination of parameters is the number of the FILTERs of 128 and 256, which are indicated by underline.

Table 2. The effect of the number of filters on accuracy.

FILTER		Accuracy/%
128	256	82.72
512	1024	82.68
256	512	82.34
64	128	81.42
128	128	79.09
256	256	77.93
32	64	78.49
64	64	77.32

Figure 6 shows the results of the test set training tests with the best combination of parameters. It can be seen that the test accuracy increases and gradually stabilises as the number of epoch iterations increases over time. The accuracy of the test increases with the number of iterations and stabilizes at around 83%. The recognition accuracy can be further improved when the number of samples per class of service is increased, limited by the fact that the number of samples per class of service is only 100. Therefore, we obtained Table 3 by repartitioning the number of entries of training set and test set data for each type of data. It can be seen that as the number of training data entries within the dataset increases, the accuracy of the model is subsequently increased.

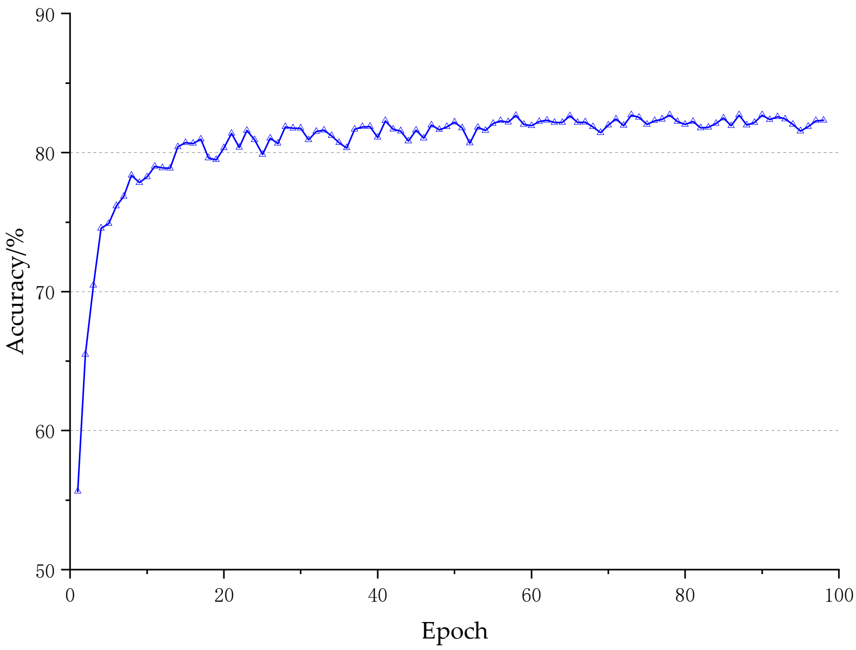

Figure 6. Accuracy of classification with the best combination of parameters.

Table 3. The effect of the number of training sets on accuracy.

Number of Training Sets	Number of Test Sets	Average Accuracy/%
10	20	44.71
20	20	58.88
30	20	66.31
40	20	68.67
50	20	73.19
60	20	75.26
70	20	75.35
80	20	77.86

When applying this method to the power communication network, the training of the recognition model can be carried out centrally in the data centre, and the sample pool can be continuously updated and expanded to dynamically improve the accuracy of the model. The training results of the model can be loaded onto the smart gateway devices in the edge network stations or server rooms using the edge computing mode to automatically classify the services before they are adapted into 5G slices.

The traffic types and characteristics of power communication networks are relatively stable and less diverse than those of ordinary communication networks. Therefore, in this type of traffic context, traffic identification can be carried out separately for different services within the grid area, which can improve the accuracy of the dataset identification. In order to analyse the impact of traffic types on the accuracy of the dataset, scenarios with different numbers of types were set up and trained five times randomly in this paper, and the classification average accuracy of the test data of the training model was obtained as shown in Figure 7. In each of the five training sessions, datasets corresponding to the number of species were randomly selected for training and testing. Figure 8 shows the confusion matrix heat map of the results of one of the experiments when the number of types of datasets is 10. Var-1 to val-10 represent each of the 10 different data types. It can be seen that the traffic classification accuracy increases greatly when the number of types of datasets is reduced, and the recognition accuracy reaches up to 95% when the number of types of datasets is reduced to 10.

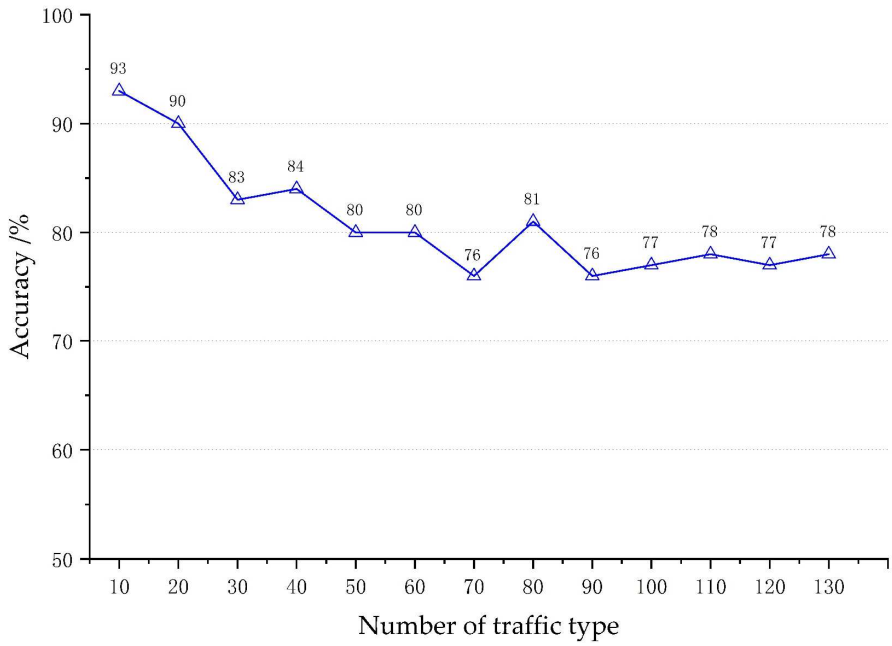

Figure 7. The impact of traffic type number on classification accuracy.

In combination with edge computing, as represented in Figure 2, the data in the central data centre are trained and the already trained model is stored separately on the edge side. Then, the terminal data are brought in to classify it. In the simulation, the edge-smart gateway is simulated by separating the training and validation of the model. The accuracy obtained in the end is virtually unchanged from the accuracy values obtained when training and testing are performed together.

4.2. Grid Service Traffic Prediction Based on LSTM

In traffic services, especially for the grid service, current traffic may be influenced by the previous moments. LSTM can capture the long-term dependencies in sequential data and handle the temporal relationships between input data. By training, it can learn the periodicity, trend, and special events in traffic, and then use these features for prediction.

The LSTM model performs well in traffic prediction tasks. It is applied to dynamically predict service traffic in the power 5G network slice, thereby adjusting the service carrying requirements of the network slice.

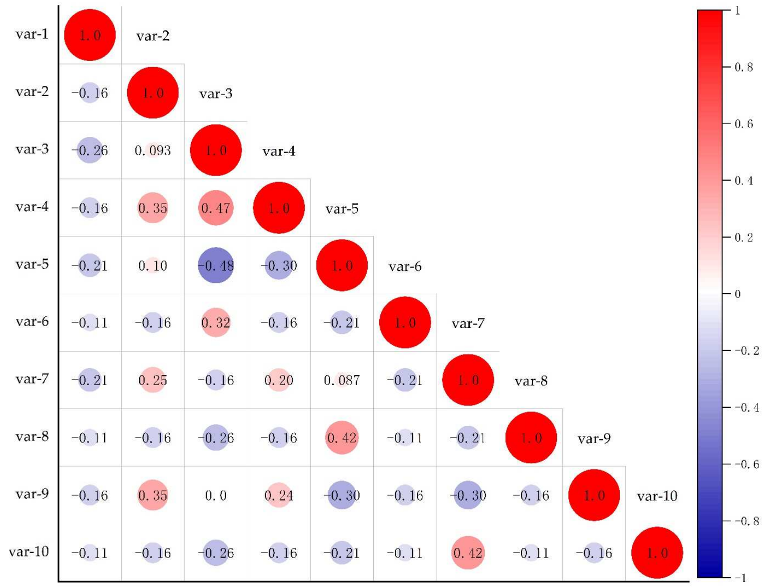

Figure 8. Heat map of the confusion matrix at 10 for the category.

The traffic prediction algorithm utilizes a publicly available dataset from Internet source providers (ISP) to verify the effectiveness of the prediction model [32]. Each traffic data point in the dataset is measured at one-hour intervals, resulting in a total of 1232 data points. After reading in the dataset, the traffic data are normalized and split into training and testing datasets with an 8:2 ratio [33]. Time series data are then created, and the time series length is set. Based on TensorFlow, LSTM and BILSTM models are established and trained on the training dataset, obtaining the loss values for both the training and the testing datasets during the training process. Finally, predictions are made and the denormalized results are compared to the true values. The data processing flowchart for the BILSTM model is shown in Figure 9.

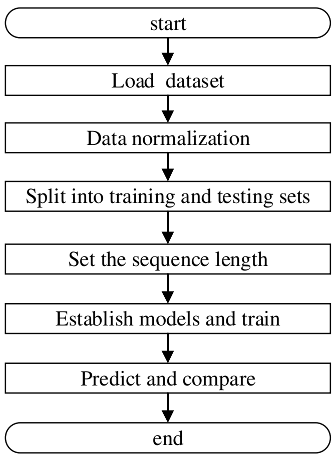

Figure 9. Flow chart of data processing in LSTM and BILSTM model.

Figure 10 shows the loss values of the LSTM and BILSTM as the model is continuously trained. Figure 10a shows the loss values for the training set and Figure 10b shows the loss values for the test set. It can be seen that the loss values in both the training and test sets gradually decrease, with the loss values in both the training set being lower than those in the validation set. Loss and val_loss represent training error and testing error, respectively. At the same time, the loss values of the BILSTM model were both lower than those of the LSTM model. Therefore, the use of the BILSTM model for prediction is more effective and can basically satisfy the task of traffic prediction in the power network slicing.

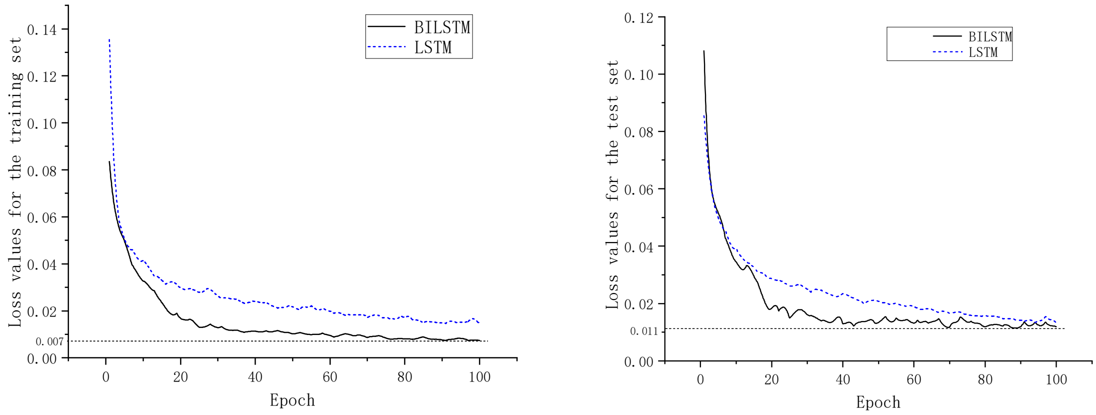

Figure 10. Training loss values of LSTM model and BILSTM model. (**a**) Loss values for the training set. (**b**) Loss values for the test set.

As shown in Table 4, multiple predicted values were obtained by changing the time series length. According to the comparison results of MAPE, it can be seen that the smallest error was obtained when the time series length was set to 10. The comparison chart of the predicted results and actual values shown in Figure 11 was based on the BILSTM model with a time series length set to 10. At this point, the MAPE of the BILSTM model was 6%. The red solid line shows the actual values of the test set and the black dashed line shows the predicted values based on the BILSTM model. As can be seen from the figures, the two curves are in good agreement. Figure 12 shows a statistical histogram of the different relative errors and it can be seen that about 90% of the predicted data have a relative error of less than 10%. Table 5 and Figure 13 show the comparison of MAPE under the BILSTM method used in this paper with the four methods mentioned in [32]. From the table and bar chart, it can be seen that the use of BILSTM method has reduced the MAPE of this dataset and gives better and stable prediction results.

Table 4. MAPE corresponding to different time series lengths.

Length/h	MAPE/%
5	9.18
10	6.32
30	8.58

Table 5. MAPE values for different methods.

Method	Naïve	Holt-Winters	ARIMS	NNE	BILSTM
MAPE	65.67%	50.60%	26.96%	23.48 ± 0.49%	6.32%

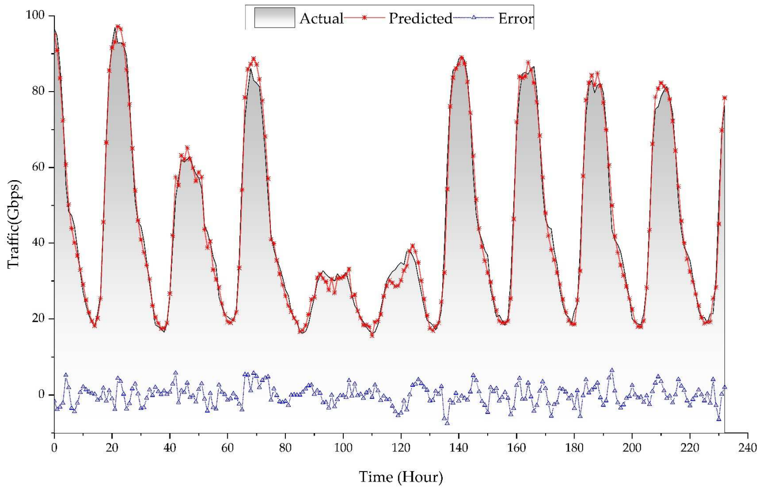

Figure 11. Comparison of flow forecast results.

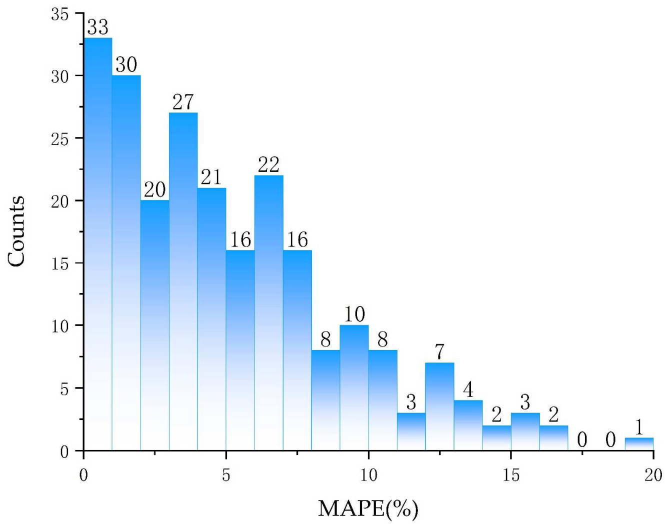

Figure 12. Histogram of statistics corresponding to MAPE values.

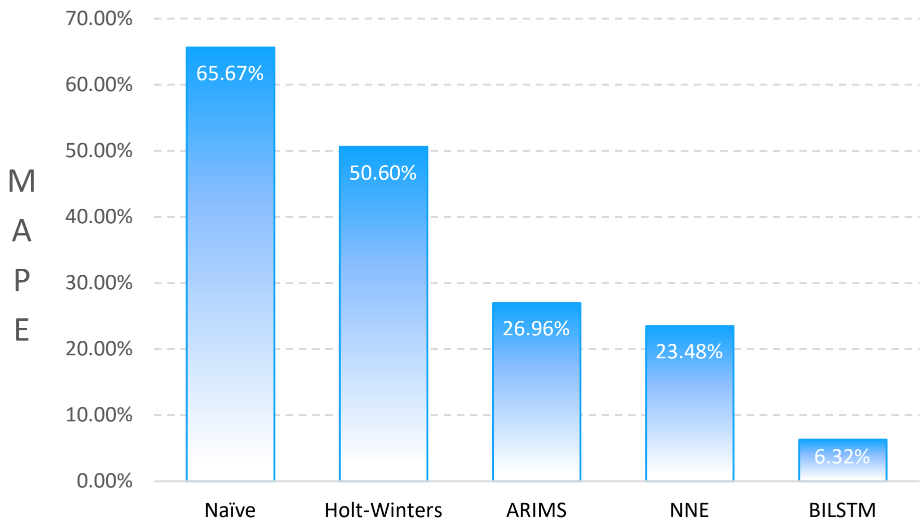

Figure 13. MAPE values for different methods.

5. Conclusions

The 5G network slicing technology is a good solution to the complex service needs of grid systems. The network slicing technology enables the isolation of electric power services from other services whilst also meeting specific service requirements and quality of service guarantees. This paper combines 1D CNN and BILSTM to extract data features of traffic services and encode the data, which proposes a neural network-based power 5G slicing service carrying method to achieve electric power services classification matching and dynamic traffic prediction. Through simulation verification, we can show that, based on the 1D CNN neural network model, the features of electric power services are extracted, classified, and matched. The recognition accuracy can reach up to 95% when the type of dataset is 10, and the recognition can be carried out separately for the services in different grid areas, which can improve the accuracy of dataset recognition and meet the mapping deployment of 5G power network slicing. Meanwhile, combined with the BILSTM-based service traffic prediction, the model training loss value is small, the value of each evaluation index is optimized compared with the BILSTM model, and the error of more than half of the prediction values is less than 10%. This enables the scheduling configuration of services at the edge nodes and meets the service-carrying requirements of 5G network slicing.

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Abbreviations

Acronym	Definition
1D CNN	One-Dimensional Convolutional Neural Network
5G	5th Generation Mobile Networks
BILSTM	Bidirectional Long Short-Term Memory Neural Network
CNN	Convolutional Neural Network
DC	Data Centre
eMBB	Enhanced Mobile Broadband
FA	Feeder Automation
ISP	Internet Source Providers
LSTM	Long Short-Term Memory Neural Network
MAPE	Mean Absolute Percentage Error
mMTC	Massive Machine Type Communication
NFV	Network Functions Virtualization
SDN	Software Defined Network
SLA	Service level Agreement
uRLLC	Ultra-Reliable and Low-Latency Communication

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