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SF6 Gas Humidity Prediction Model Based on Deep Learning

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Abstract: SF6 gas is widely used in Gas Insulated Switchgear(GIS) as an insulating and arc extinguishing medium in electric power industry. However, SF6 gas humidity has a significant impact on the performance and reliability of GIS equipment. The accurate prediction of humidity level is one of the keys to ensure the long-term stable operation of GIS equipment. Traditional humidity prediction methods are often limited by model complexity and data processing ability, which is difficult to meet the actual demand. In this paper, deep learning, as a powerful data-driven approach, shows great potential in gas humidity prediction. An efficient SF6 gas humidity prediction model for GIS equipment is constructed based on deep learning algorithm. The deep learning model can learn complex feature representations from a large number of historical data, and then accurately predict SF6 gas humidity.

Keywords: SF6 gas; GIS equipment; Humidity prediction; Deep learning.

1. Introduction

GIS equipment is one of the key equipment in electric power industry, its monitoring and maintenance has been concerned. The current research has deeply discussed the status and challenges of GIS equipment monitoring and maintenance. These studies point out that during the long-term operation of GIS equipment, the change of SF6 gas humidity has an important impact on the performance and reliability of the equipment, so humidity prediction becomes an important part of GIS equipment monitoring.

In the field of humidity prediction, a series of traditional methods have been applied to GIS equipment SF6 gas humidity prediction. These methods include statistics-based models, machine learning methods, and physical models. However, the traditional method has some limitations in processing complex time series data and extracting advanced features, which is difficult to meet the needs of practical applications.

In recent years, deep learning, as a powerful data-driven method, has gradually emerged in the field of SF6 gas humidity prediction. Deep learning models can accurately predict the humidity of SF6 gas by learning complex features in large-scale data. These models are usually constructed based on deep learning algorithms such as convolutional neural networks (CNN) and recurrent neural networks (RNN), which have high flexibility and predictive performance [1].

Although deep learning has made remarkable achievements in the field of humidity prediction, its application in the GIS equipment SF6 gas humidity prediction is still in the preliminary stage. Therefore, it is of great significance to deeply study the SF6 gas humidity prediction model of GIS equipment based on deep learning, and it is expected to provide a new solution for GIS equipment monitoring and maintenance.

2. System Module Function

(1) Data input and processing module design

Data input and processing module is an important part of SF6 gas humidity prediction model of GIS equipment based on deep learning. The module is designed to achieve effective acquisition, cleaning and preprocessing of SF6 gas humidity data, and provide reliable data support for subsequent model training and prediction [2].

In the data input phase, the module will obtain SF6 gas humidity data from various data sources. These data sources can include sensor data in GIS equipment, historical data collected by monitoring systems, and external weather stations. The data input module with different data sources and real-time data acquisition.

In the data processing stage, the module will clean and preprocess the obtained SF6 gas humidity data to improve the quality and availability of the data. The cleaning process includes removing duplicate data, filling in missing values, and handling outliers to ensure data integrity and accuracy. The preprocessing involves data normalization, feature extraction and data conversion, etc., and the prepared data format is input into the deep learning model for training [3-5].

(2) The significance and implementation of time step alternate setting

The main purpose of the alternate time step setup is to explore the changes in model performance under different time steps to better understand and optimize the predictive power of the model.

The significance of time step alternate setting is reflected in the model stability and generalization ability, the exploration and adaptability of time scale, the optimization and adjustment of prediction effect, and the optimization and adjustment of prediction effect.

Therefore, the implementation of an alternate time-step setup usually consists of the following steps:

1) Data division: historical data is divided according to different time steps to form training sets, verification sets and test sets of different time scales.

2)Model training and evaluation: Data sets with different time steps are used to train and evaluate the model. In the training process, the model parameters and training strategies should be adjusted according to the characteristics of different time steps.

3)Result analysis and comparison: The prediction results of the model under different time steps were analyzed and compared to evaluate the performance of the model under different time scales. Based on the analysis results, the optimal time step setting can be selected to optimize the prediction effect of the model.

(3) LSTM network architecture definition and training process

Long Short-term Memory network (LSTM) is a kind of deep learning model commonly used for processing sequence data, which can effectively capture long-term dependency and memory information, and is suitable for modeling and forecasting time series data. In the SF6 gas humidity prediction model of GIS equipment based on deep learning, LSTM network is often selected as the main prediction model, and the LSTM network architecture is shown in Figure 1.

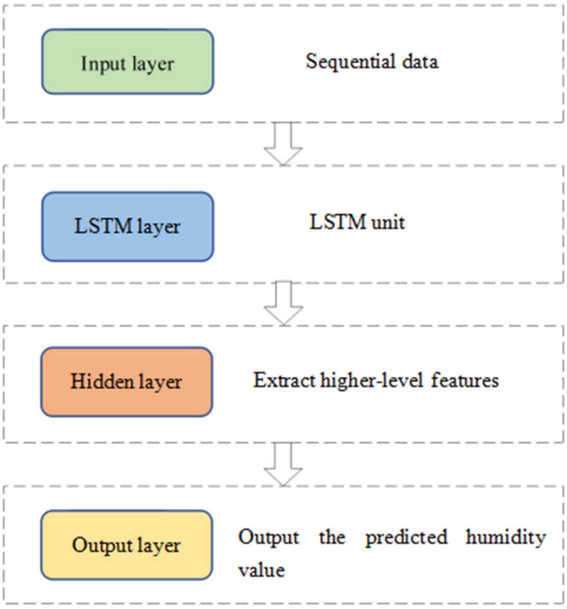

Figure 1. LSTM network architecture diagram

The LSTM network training process is shown in Figure 2.

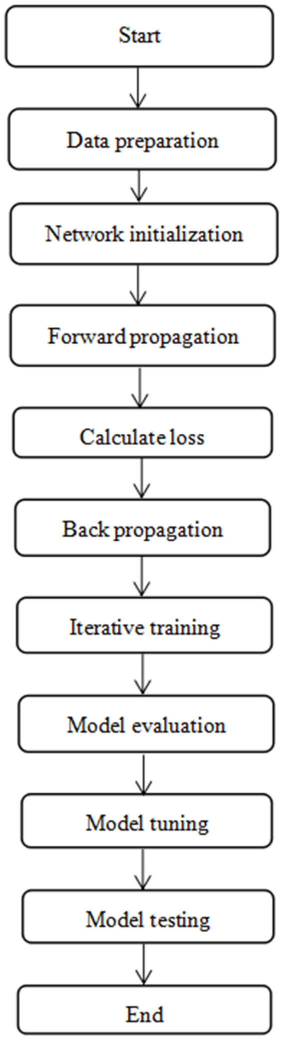

Figure 2. LSTM network training process

3. Method and Experiment

(1) Data collection and preprocessing

1)Data sources and methods of acquisition

The establishment of SF6 gas humidity prediction model requires a large amount of SF6 gas humidity data as the basis for training and verification. The data sources mainly include GIS equipment sensors, monitoring systems, weather station data and so on. Data acquisition methods mainly include real-time data acquisition, historical data query, and external data acquisition.

2)Data preprocessing procedure

Before constructing the SF6 gas humidity prediction model of GIS equipment based on deep learning, it is necessary to preprocess the original data to improve the quality and applicability of the data.

a) Missing value processing

Missing value is a common problem in data preprocessing, which may affect the performance and stability of the model. Common missing value handling methods include：

Delete missing values: In cases where there are fewer missing values, you can simply delete the sample or feature that contains the missing value.

Interpolation filling: Using the information of the existing data, the missing value is estimated by interpolation methods (such as linear interpolation, polynomial interpolation, etc.).

Fill a constant value: Replaces the missing value with some fixed constant value, such as 0 or an average.

b) Outlier detection and processing

Outliers may interfere with model training and prediction, so outliers need to be detected and processed. Common methods include:

Statistical methods: Statistical methods are used to identify outliers in the data.

Outlier detection algorithm: The outlier detection algorithm is used to automatically identify outliers.

Model-based approach: Outlier detection using machine learning models.

Delete outliers: Delete outliers from data.

Replace outliers: Replace outliers with the mean, median, or other appropriate value of the data.

c) Feature selection

Feature selection is to select the most relevant and useful features from the original features to reduce the complexity of the model and improve the prediction performance. Common feature selection methods include：

Filtering method: According to the correlation between the feature and the target variable, the commonly used indicators include correlation coefficient, Chi-square test and so on.

Packaging method: Use the performance of the model to evaluate the importance of features. Common methods include recursive feature elimination.

Embedding method: Features are automatically selected during model training. Common methods include L1 regularization, decision tree, etc.

(2) Deep learning model design and training

1)Model selection

It is very important to select the appropriate deep learning model when constructing the prediction model of SF6 gas humidity of GIS equipment based on deep learning. Common deep learning models include convolutional neural network (CNN) and recurrent neural network (RNN), which each have their own characteristics and are suitable for different types of data and problems.

Convolutional neural network (CNN) is mainly used to process image data and has good feature extraction ability. In the SF6 gas humidity prediction model of GIS equipment, if the data may have temporal and spatial characteristics (such as spatial relationship and time series) are considered, the SF6 gas humidity data can be organized into a form similar to images, and then processed by CNN. The advantage of CNN is that it can automatically extract local features and spatial correlations in the data, which is suitable for processing two-dimensional or three-dimensional data structures.

Recurrent neural network (RNN) are neural network structures specifically designed to process sequence data with memory and dynamic modeling capabilities. In the SF6 gas humidity prediction model of GIS equipment, SF6 gas humidity data are usually collected in time order, which is sequential and series-dependent, so RNN is a natural choice. With RNN, models can automatically capture temporal correlations in data, model historical data, and make future predictions.

2) Model architecture design and optimization

When designing the architecture of a deep learning model, key factors such as the number of layers of the network, the number of nodes in each layer, and the choice of activation functions need to be taken into account. These factors directly affect the representation ability, complexity and prediction performance of the model.

The number of layers of the network determines the depth of the model, and deep networks are often able to learn more complex feature representations, but are also prone to problems such as disappearing gradients or explosions. When choosing the number of layers, you need to make trade-offs based on the complexity of the data and the difficulty of the problem. Typically, you can start with a shallower network initially and gradually increase the number of layers until you reach a stable point of performance.

The number of nodes in each layer affects the capacity and complexity of the network. The more nodes, the stronger the expression ability of the network. However, too many nodes can lead to overfitting problems, while too few nodes can lead to underfitting. When selecting the number of nodes, we can find the appropriate number of nodes to balance the performance and generalization ability of the model through cross-validation and other methods.

Activation function plays the role of nonlinear mapping in neural network, which can increase the expressive power of the network. Common activation functions include ReLU, Sigmoid, Tanh, and so on. When selecting the activation function, it is necessary to consider the problems such as gradient disappearance and gradient explosion, and make appropriate selection according to the actual situation.

In addition to architectural design, regularization and optimization techniques need to be considered. Regularization methods such as Dropout and L2 regularization can be used to prevent overfitting, and optimization techniques such as Adam and SGD can be used to accelerate network convergence and improve training efficiency.

Finally, it is necessary to optimize the hyper parameters of the model, including learning rate, batch size, optimizer selection, etc. Through cross-validation and other methods, the optimal combination of hyper parameters can be found to further improve the performance of the model.

(3)Model performance evaluation and result analysis

1) Experimental Settings

When evaluating the performance and analyzing the results of SF6 gas humidity prediction model of GIS equipment based on deep learning, it is necessary to carry out appropriate experimental Settings, including the division of data sets and the selection of evaluation indicators.

Among them, data set partitioning mainly includes training set, verification set, test set and so on. The Training Set is used to train the model and usually accounts for the majority of the total data, which can be around 70% to 80% of the data. Validation sets are used for the tuning and parameter selection of the model and can account for around 10% to 20% of the total data as needed. Test sets are used to ultimately evaluate the performance of the model and cannot be used for training and tuning of the model, usually accounting for about 10% of the total data. The randomness and representations of samples should be taken into account in the partitioning of data sets to ensure the objectivity and reliability of model evaluation.

In terms of the selection of evaluation indicators, root mean square error (RMSE) is the most commonly used regression model evaluation indicator to measure the deviation between the predicted value and the actual value. The formula is shown in Equation 1.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2} \qquad \text{(Equation 1)}$$

Then, the mean absolute error (MAE) is used to measure the mean absolute deviation between the predicted value and the actual value of the model, as shown in equation 2.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y_i}| \qquad \text{(Equation 2)}$$

Correlation Coefficient is used to measure the degree of linear correlation between the predicted value of the model and the actual value, and the value range is [-1, 1]. The closer the value is to 1, the better the prediction effect is. Finally, Goodness of Fit (R-squared) measures the fitting degree of the model to the data, and the value range is [0, 1]. The closer the value is to 1, the better the fitting effect of the model is.

2) Model training and evaluation

During model training and evaluation, data is first prepared, loaded according to the previously divided training set, verification set and test set, and necessary preprocessing is carried out, such as data normalization and standardization. Secondly, model initialization initializes the structure and parameters of the deep learning model, and selects the appropriate optimizer and loss function. The process is then trained, the training set is input into the model, and the model parameters are constantly adjusted through a back-propagation algorithm to minimize the loss function. At the same time, the validation set is used to verify the model and monitor the performance of the model. In the training process, the parameters and weights of the model are saved regularly, so that the model can be restored and the training can continue when the training is interrupted. At the end of the training, when the model achieves satisfactory performance on the verification set, the training process is stopped and the optimal model is saved.

In the model evaluation, the test set evaluation is carried out first, and the trained model is evaluated with the test set. The predictive performance indicators of the model on the test set, such as RMSE and MAE, are calculated. Secondly, the result analysis analyzes the prediction results of the model on the test set, compares the difference between the predicted value and the real value, discusses the advantages and limitations of the model, and further optimizes the model or improves the prediction method. Then the visualization analysis can be carried out by drawing the prediction curve, residual diagram and other ways to visualize the model to show the prediction effect of the model. Finally, model comparison. If there are multiple models, their performance on the same data set can be compared, and the optimal model can be selected for practical application.

3) Result analysis and discussion

The LSTM network architecture is defined and trained, and the single step prediction is realized by using LSTM network.The prediction results are compared with the actual data. The 300 predictive trainings are shown in Figure 3, and the 300 test results since 2000 are shown in Figure 4.

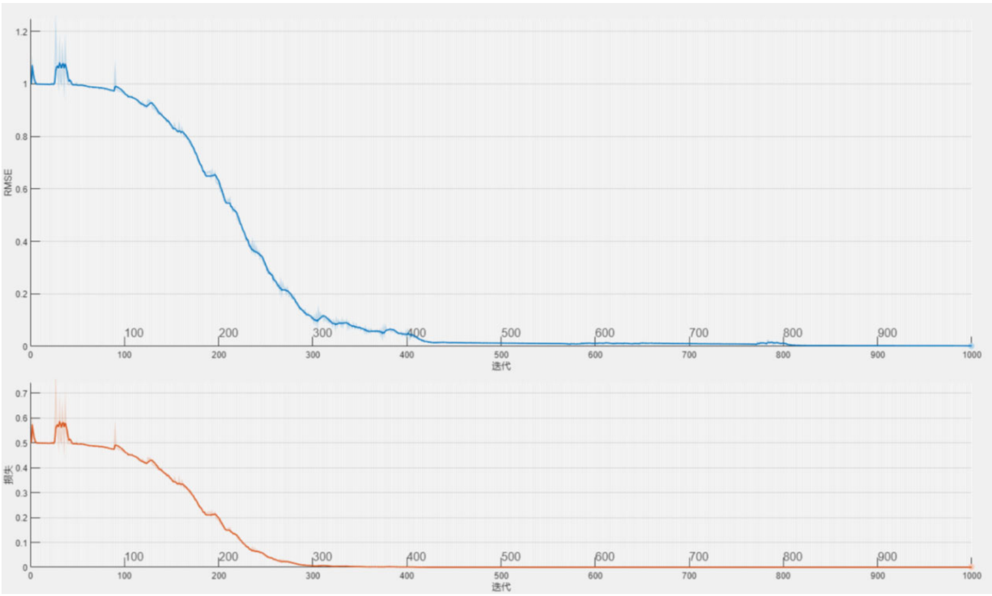

Figure 3. Prediction training diagram

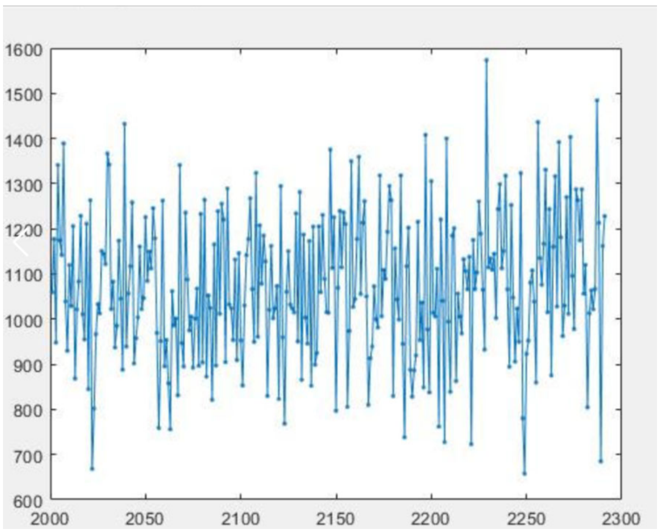

Figure 4. Test result diagram

As can be seen from Figure 4, in the prediction process, the model predicted 300 data points after 2000 data points, and the data points verified the training results of the neural network, showing that the results were good

4. Conclusion

Through the construction of GIS equipment SF6 gas humidity prediction model based on deep learning, some results and enlightenment have been obtained. In the process of model design and training, the advantage of deep learning algorithm is fully utilized, and the accurate prediction of SF6 gas humidity is realized through LSTM network and other models. In the experiment and result analysis, it is found that the model has good performance in the forecasting process, and can predict the future humidity level more accurately.

However, there are still some challenges and shortcomings in the construction and training of deep learning models. For example, the prediction accuracy of the model is limited by the quality and quantity of training data, and the processing of complex scenarios and anomalies needs to be further improved. In addition, the generalization ability and stability of the model also need to be further improved to adapt to the actual application requirements in different environments.

In future studies, it is necessary to continue to optimize the design and training methods of deep learning models to further improve the performance and stability of predictive models. At the same time, more data sources and feature representation methods will be explored to improve the adaptability and generalization ability of the model. With the continuous progress of technology and in-depth research, GIS equipment SF6 gas humidity prediction model based on deep learning will play an increasingly important role in the monitoring and maintenance of power industry.

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