
GRU Based Time Series Forecast of Oil Temperature in Power Transformer

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Abstract

With the continuous progress of the society, the demand for electrical power is urgent. The transformer plays an important role in the power energy transmission. The oil temperature inside transformer effectively could reflect working condition of the transformer, which makes it necessary to monitor and forecast the oil temperature to monitor the operating status of the power transformer. However, the oil temperature time series data generated by the power transformer has the characteristics of being complex and nonlinear. In recent years, long and short time memory networks (LSTM) are often used to predict transformer oil temperature. Gated recurrent unit (GRU) is a new version for LSTM. In the structure of GRU, there exist two gates, which are updating gate and resetting gate, respectively. Compared with LSTM network, The structure of GRU is simpler and its effect is better. A novel predicting method for transformer oil temperature is proposed based on time series theory and GRU in this paper, which is verified on the dataset of the oil

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temperature of the transformers in the two regions. The experimental results are compared with traditional time series prediction models to demonstrate that the proposed method is effective and feasible.

Keywords: Oil temperature, power transformer, deep learning, LSTM, GRU.

1 Introduction

In the power system, the power transformer is an expensive and key equipment in the transmission and distribution network. In the process of operation, it is easy to suffer the combined impact of thermal, electrical and mechanical stresses, which results in transformer failure [1]. Therefore, the power transformer plays an important role in transmitting electricity flexibly and safely. A picture of normal power transformer is demonstrated in Figure 1. The thermal characteristic is one of the important indications for the secure and stable operation of transformer. A useful indicator to detect the thermal characteristic of transformer is the transformer oil temperature. At present, many substations still use mechanical pointer pressure gauges, whose database is established through manual periodic readings. In addition, the prediction and early warning of parameters are also completed through manual data analysis. Although the automatic collection of transformer oil temperature has been realized, its prediction and early warning are completed through manual data analysis. With the fast progress of power system automation, intelligent forecast of the temperature of power transformer oil is a research field full of research value and theoretical significance [2, 3].

Thermal circuit model calculation technology is a traditional forecast method of oil temperature in transformer, and it is fundamentally based on the thermal circuit model calculation of transformer equipment. Through the process of heat transfer inside transformer, the heat path pattern is built to predict the temperature of oil. This method requires detailed equipment parameters and operation parameters. The thermal circuit models of transformers with different types and different working modes are quite different. Incomplete parameters or inaccurate settings will lead to large prediction accuracy error.

There is a certain correlation between transformer oil temperature and other transformer monitoring parameters. Simple linear fitting method can not accurately express the relationship between oil temperature and other transformer monitoring parameters. Machine learning methods has much better nonlinear fitting capability. With machine learning based algorithms, the



1 – Tabelet; 2 – Thermometer base; 3 – Tubular oil level gauge; 4 – Low voltage bushing; 5 – HIGH voltage bushing; 6 – Gas relay; 7 – Hoisting and mixing of the body; 8 – Transformer hoisting and mixing; 9 – Tap changer; 10 – Oil tank; 11 – Oil drain valve; 12 – Grounding identification; 13 – Transformer oil number; 14 – Body; 15 – Footing.

Figure 1 A typical power transformer picture.

relationship between transformer working status and oil temperature can be well shown [4]. Commonly used machine learning models include artificial neural network method, support vector machine, etc. [5, 6]. Using machine learning algorithm for modeling, we assume that there is a good correlation between network input and network output, otherwise the model could be easily over fitted and the forecast performance will be poor. At the same time, the model dimension and the model training speed could be affected with more redundant input. Neural network algorithm is a quite significant kind of algorithm in artificial intelligence. It is self-adaptive and self-learning. Neural network algorithm has good nonlinear reflection ability and stable performance. It is more suitable for signal processing, control, pattern recognition and fault diagnosis. The forecast method of oil temperature inside transformer can be realized with neural network algorithm. Some scholars have used BP neural network to forecast the oil temperature inside transformer. He et al. [7] uses neural network to forecast the top oil temperature inside transformer, but the method is a short-term prediction. Qi et al. [8] uses a kernel limit learner and a bootstrap method to obtain top-level oil temperature prediction intervals with different confidence levels. Yu Xi et al. [3] forecast the oil temperature inside transformer with support vector machine (SVM) and the experiment data is transformer's three-phase load with real and imaginary

parts. At the same time, the model parameters are optimized with particle swarm optimization (PSO). Since there exist many factors affecting oil temperature predicting, the authors introduced confidence intervals to decide the forecast results. Wei Rao, et al. [9] introduced an association rules-based oil temperature forecasting method with Bayesian network, which could enhance the predicting capability of RBF-NN. Fei Xiao, et al. [10] proposed a new intelligent forecast method with machine learning methods for timely abnormal oil temperature monitoring. The method built a dynamic association learning model with decision forests algorithm to forecast oil temperatures based on transformer parameters, power load, as well as weather condition under the normal running status.

The oil temperature data generated by the power transformer is a time series sequence. The forecast of oil temperature inside transformer is in nature a time series prediction. Time series forecast analysis is a kind of complex prediction modeling method. It predicts the data information of the event in the future from the event data generated in the past. The time series models rely on the sequence of events. If the order of values of the input changes, the forecast results of model are variable [11], which usually leads to low prediction accuracy of the above prediction method. Today, deep learning methods are widely used in various fields, and time series prediction tasks are no exception. Many DNN models perform much better simple machine learning methods. These deep neural networks (DNN) models include short-term and long-term memory network (LSTM) [12, 13] and gated recurrent unit (GRU) [13]. Three gates exist inside LSTM structure, and they are inputting gate controlling input value, forgetting gate control memory value and output gate controlling output value, respectively. GRU is a new version of LSTM network. Inside the structure of GRU, there exist two kinds of gates and they are updating gate and resetting gate. GRU has simpler structure and better effect than LSTM network, so it is a commonly used network. GRU can also solve the long dependency problem in founded in RNN networks. A major feature of GRU [13] is that it can perform prediction based on historical and current values accurately, which makes it more appropriate to deal with power transformer oil temperature time series prediction problems.

The rest of the paper contains 3 sections. In Section 2, we have a brief description of the RNN, LSTM and GRU algorithms and theories related to our research. In Section 3, we verify our method by the experiments on the dataset of the oil temperature of the transformers in the two regions. In Section 4, we summarize our work and discuss some ideas about improvements of our future work.

2 Recurrent Neural Network (RNN) and GRU Neural Network

2.1 Structure of Recurrent Neural Network (RNN)

Recurrent neural network(RNN) is different from the traditional feed-forward neural network (FNN). The RNN can process the relationship between the input data before and after the time. In the traditional neural network models, the input data starts from the input layer, through the hidden layers, and at last to the output layer. All of the layers are fully linked, but the nodes in the middle of each layer are not linked. The traditional neural networks can not solve certain problems [13]. For example, it is necessary to predict each word inside a sentence. The next word in the sentence depends on the previous word. However, the words after and before the sentence are not independent, and there is a connection between the words. For a sequence, the output of the RNN will depend on the previous output value. The specific fact is that the existing output in the RNN will remember the previous data and utilize the memorized information in the current input value. Every node in the hidden layer is linked. At the same time, the hidden layer's input contains the input value at the existing moment and the output value at the previous moment. The typical recurrent neural network structure is depicted in Figure 2. The gradient of standard recurrent neural network will disappear when the error is propagated back. To solve the gradient vanishing problem, we usually choose to use its variant models, such as LSTM [15, 16] and GRU [17]. The structure of the standard recurrent neural network is simple. Figure 3 is the internal structure diagram of the standard RNN. The status

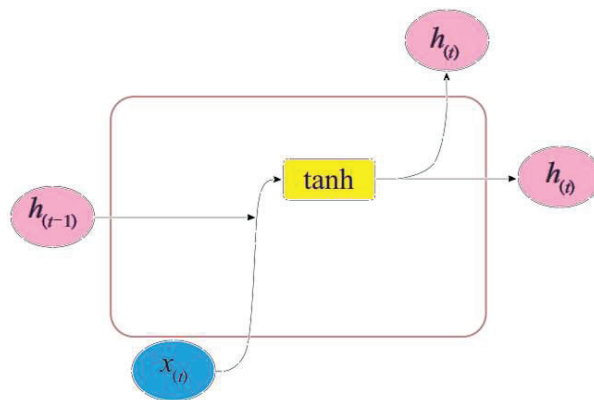


Figure 2 Internal structure of neurons in RNN.

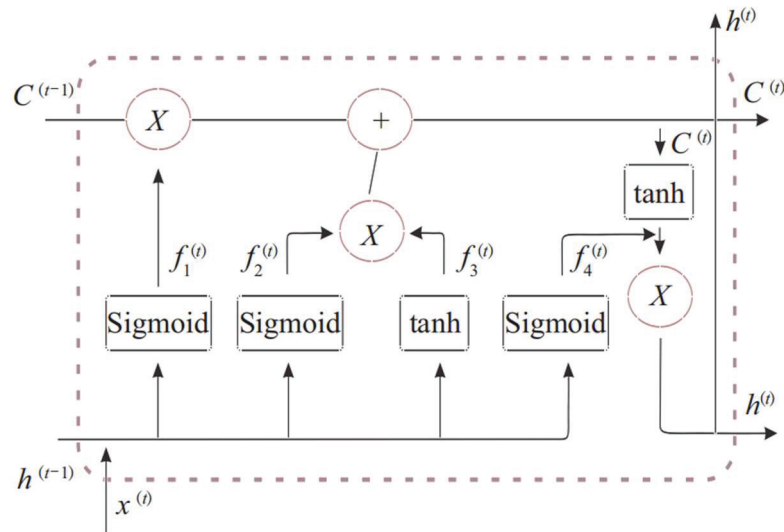


Figure 3 Internal structure of LSTM neurons.

value of the neuron at moment t is decided by the status value of the previous moment ($t-1$) and the hyperbolic tangent function value of the network input at moment t . This value will not only be used as the output of the existing neuron, but also enter the next neuron as the status value at moment t . It is difficult for the network to remember the information for a quite long range time, and can not judge the “useful” and “useless” of the input signal and the last neuron state value. When the time interval is increasing, LSTM and GRU can resolve the issue that it is very difficult for standard RNN to learn the long-distance dependency in the input sequence.

2.2 Structure of Long Short-Term Memory (LSTM) Neural Network

Different from the standard RNN neural network, LSTM and GRU introduce the concept of “gate”, including forget, input and output three gates. Compared with GRU, LSTM has one more “cell state”. Sepp Hochreiter and Jurgen Schmidhuber in 1997 proposed long short-term memory (LSTM) and it gradually improved by a few scholars who are Hasim Sak, Alex Graves, and Wojciech Zaremba. The key idea of LSTM is that the LSTM can learn the storage, and read in the long-term status from it. The LSTM signal transmission process is shown in Figure 3. When the state $c_{(t-1)}$ of

long-term across the network from left to right, it firstly passes through the forgetting gate and loses some storage, and then it adds some new memories (the memory decided by the inputting gate) through adding operation. The result is then directly sent out with no any further transition. Therefore, in every moment procedure, some information gets lost, and some information are added. Following the addition procedure, the long term state is replicated and transmitted through the tanh functionality, and the final result is then sorted out by the output gate. Then the short-term states $h_{(t)}$ is produced.

- (1) forgetting gate: as the first gate $f_1^{(t)}$ of the network, it needs to filter the network information and determine the preservation or retention of the information. It is expressed as the following:

$$f_1^{(t)} = \sigma(W_{f_1} \times [h^{(t-1)}, x^t] + b_{f_1}) \quad (1)$$

- (2) inputting gate: the inputting gate is separated into two procedures. One is to select $f_2^{(t)}$ to update the value, and another step is to determine the candidate status $f_3^{(t)}$ to transmit forward. The algorithms of $f_2^{(t)}$ and $f_3^{(t)}$ are as the following:

$$f_2^{(t)} = \sigma(W_{f_2} \times [h^{(t-1)}, x^t] + b_{f_2}) \quad (2)$$

$$f_3^{(t)} = \tanh(W_{f_3} \times [h^{(t-1)}, x^t] + b_{f_3}) \quad (3)$$

Integrate the information and update the cell status. The output is:

$$C^{(t)} = C^{(t-1)} \times f_1^{(t)} + f_2^{(t)} \times f_3^{(t)} \quad (4)$$

- (3) Output gate: the output gate is used to output information. Information is output after processing the cell state and integrating it with the initial information, which can be divided into

$$f_4^{(t)} = \sigma(W_{f_4} \times [h^{(t-1)}, x^t] + b_{f_4}) \quad (5)$$

$$h_4^{(t)} = f_4^{(t)} \times \tanh(C^{(t)}) \quad (6)$$

where $W_{f_1} - W_{f_4}$ are random weights given by the function; $\sigma(\cdot)$ is activation function sigmoid value, $h^{(t-1)}$ is state value of the previous neuron; x^t is neuron input value at the moment, $b_{f_1} - b_{f_4}$ are bias values and $C^{(t)}$ is neuron cell state at the moment.

2.3 Structure of Gate Recurrent Unit (GRU)

The gate recurrent unit (GRU) neural network is an modified version of long short term memory (LSTM) neural network, and GRU was proposed by CHO kyunghyun (2014) [13]. The most remarkable achievement is to avoid the long dependence problem in recurrent neural networks. However, the structure of LSTM is more complicated, and there are also existing problems such as heavy training time cost and long forecast time. The gate recurrent unit improves the LSTM structure just to solve the above problems. Forgetting gate, inputting gate and outputting gate are proposed in the LSTM neural network. The design of these “Gates” is to remove or enhance the input information into the neural cell unit to control the cell state. The GRU neural network improves the structure design of the “gate”, integrates the forgetting gate and the inputting gate in the LSTM into an updating gate, which optimizes the unit structure originally composed of three gates into a unit structure composed of two gates. Meantime, the cell state has been fused and several extra enhancements have been proposed. In GRU the signal transmission process is depicted in Figure 4.

Resetting gate: $f_1^{(t)}$ is used to control whether the candidate state $f_3^{(t)}$ calculation depends on the state h_{t-1} at the previous time. The algorithm is

$$f_1^{(t)} = \sigma(W_r x_t + u_r h_{t-1} + b_r) \tag{7}$$

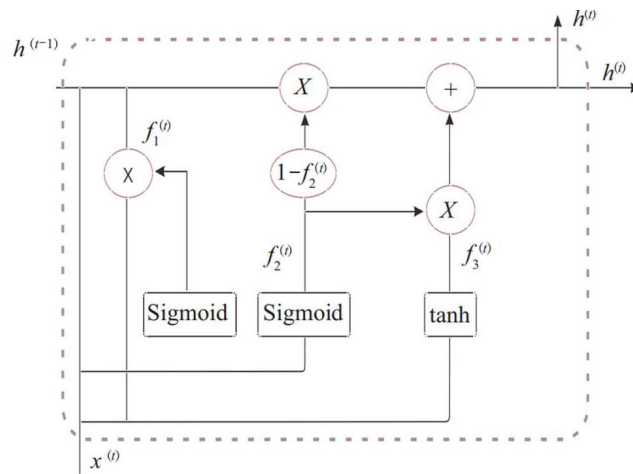


Figure 4 Internal composition of GRU unit.

The candidate status at the current time is $f_3^{(t)}$

$$f_3^{(t)} = \tanh(W_h x^t + U_h(f_1^{(t)} \cdot h_{t-1}) + b_h) \quad (8)$$

3 Experiment Results and Analysis

3.1 Power Transformer Dataset

The dataset in this manuscript adopts the ETT small data set in the power transformer data set [18]. The ETT-small data set contains data from two power transformers for two years. Each data point marked with m is recorded every minute from two regions in the same Chinese province, called ETT-small-m1 and ETT-small-m2, respectively. In addition, we use h to mark the dataset variants with one hour granularity, namely ETT-small-h1 and ETT-small-h2. Every data point has 8-dimensional characteristics, which are the recording date of the data point, the predicted value oil temperature and six different kinds of external load values. The missing values in the data have been pre-processed with the cleaning method. The data set is very important for the study of the time series data. The data is real and effective, and the amount of data is also very large. The ETT-small-h1, ETT-small-m1, the ETT-small-h2 and ETT-small-m2 dataset are used in the experiments. For each dataset 80% of the data are used as the training dataset and the remaining 20% are employed as the testing dataset for performance comparison.

3.2 Experimental Results Comparison and Analysis

In this manuscript, we use the structure of RNN network in Pytorch to build the LSTM and GRU models. No matter which network structure of RNN, LSTM or GRU, they have unified requirements for input, and the input data are sequential data. The hyper parameters setting are that input_dim is 15, hidden_dim is 2048, num_layers is 1 and output_dim is 1. The loss function use MSELoss() and the optimizer uses Adam. The learning rate used is 0.00001. The proposed method diagram is shown in Figure 5.

In order to verify the correction and effectiveness of the proposed method, we employ the oil temperature of power transformers described Section 3.1 and compare the results of LSTM and GRU with seasonal auto-regressive integrated moving average (SARIMA) model, which is one of the commonly used time series prediction and analysis methods. SARIMA model has fast calibration calculation and self-learning ability [19–21]. It is very suitable for

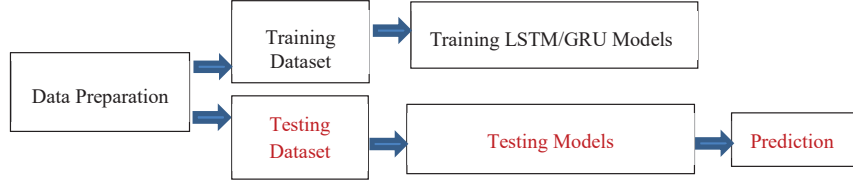


Figure 5 The block diagram of the proposed method.

Table 1 Prediction accuracy comparison results on data set ETT-small-h1

	RMSE	MAE	MAPE(%)
SARIMAX	1.3903	1.0000	5.5051
LSTM	1.5414	1.2598	6.7398
GRU	0.9766	0.6236	3.4506

online real-time prediction and analysis, and is widely used in the prediction scenarios of time series in various fields. At last, the prediction results are analyzed. According to the error analysis in statistics, we mainly use the root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) to measure the effectiveness of the compared methods. We assume that O_i and P_i are the ground truth and label and the forecast values, separately. These indicators can be formulated as follows.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (P_i - Q_i)^2} \quad (9)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |P_i - Q_i| \quad (10)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \frac{|P_i - Q_i|}{Q_i} \quad (11)$$

Tables 1, 2, Figures 6 and 7 show the prediction accuracy comparison results, with SARIMAX, LSTM and GRU methods, on data set ETT-small-h1, ETT-small-m1, respectively.

Tables 3, 4, Figures 8 and 9 show the prediction accuracy comparison results, with SARIMAX, LSTM and GRU methods, on data set ETT-small-h2, ETT-small-m2, respectively.

From Tables 1 to 4 and Figures 6 to 9, it can be demonstrated that our proposed GRU based prediction method has the best performance. The

Table 2 Prediction accuracy comparison results on data set ETT-small-m1

	RMSE	MAE	MAPE(%)
SARIMAX	1.0267	0.7891	1.9594
LSTM	0.6977	0.5213	1.2951
GRU	0.6971	0.5221	1.2978

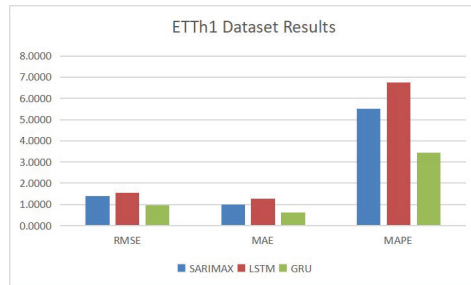


Figure 6 Comparison results on dataset ETTh1.

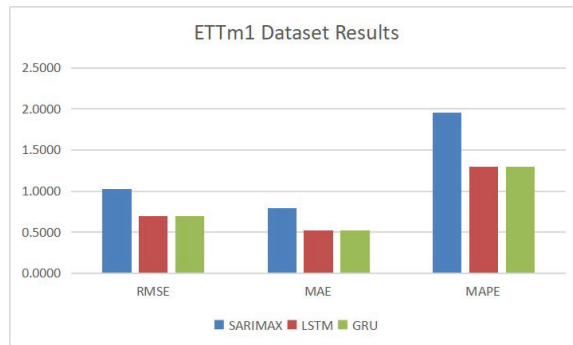


Figure 7 Comparison results on dataset ETTm1.

Table 3 Prediction accuracy comparison results on data set ETT-small-h2

	RMSE	MAE	MAPE(%)
SARIMAX	2.3971	2.1312	7.4880
LSTM	1.6407	1.3934	4.8557
GRU	0.8549	0.6616	2.3561

Table 4 Prediction accuracy comparison results on data set ETT-small-m2

	RMSE	MAE	MAPE(%)
SARIMAX	0.6013	0.4183	0.8476
LSTM	1.1991	1.1356	2.4082
GRU	0.5007	0.3450	0.6774

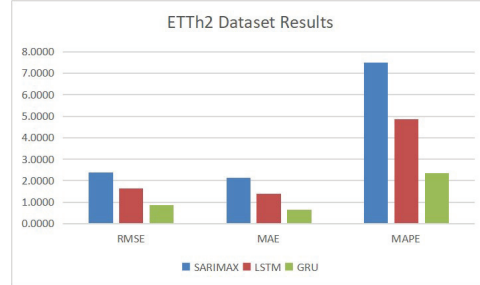


Figure 8 Comparison results on dataset ETTh2.

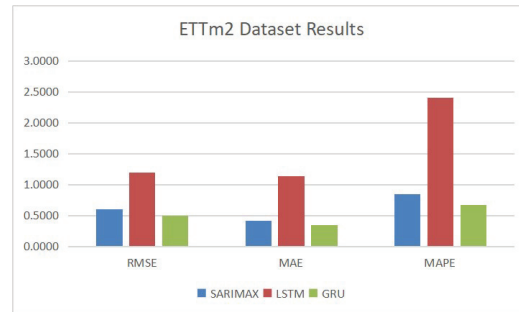


Figure 9 Comparison results on dataset ETTm2.

specific reasons are analyzed as following. The transformer oil temperature has characteristics of randomness, fluctuation and uncertainty, which is a typical nonlinear unstable sequence. The nonlinear mapping ability of neural networks, LSTM and GRU, can setup the mapping relationship for output and input under the premise of uncertain specific functional relationship. Therefore, LSTM and GRU methods have potential advantages in training and predicting transformer oil temperature time series, because the neural network has better nonlinear mapping capability and generalizing ability. Neural network can establish the mapping relationship between input and output without a thorough understanding of the system. Traditional SARIMAX model is a static regression model in nature, but the transformer oil temperature time series is nonlinear and dynamic. In addition, the current time series prediction value will be affected by the current input information and historical information, and GRU model has a unique gate cycle structure, which is not available in the traditional neural network structure. Due to the

advantages of the GRU model, the proposed prediction method also can be employed in other time series prediction problems.

4 Conclusion

Power transformer plays a crucial role in the whole power grid and its normal operation decides the regular operation of the whole power grid. The oil inside the transformer is important [22, 23]. In order to accurately predict the working condition of transformer, the oil temperature prediction method is often used to provide a reference for the working condition of transformer. As the power transformer oil temperature time series is nonlinear and dynamic, LSTM and GRU based methods have potential advantages in predicting transformer oil temperature time series, because the neural network has better nonlinear mapping capability and generalizing ability. GRU is a new version of LSTM network. In GRU model, there exist only two gates which are updating gate and resetting gate. GRU has simpler structure and better effect, compared with LSTM network, so GRU is also a very useful network, currently. GRU can fix the long dependency problem too in RNN networks. A new method for predicting transformer oil temperature was proposed based on time series theory and GRU in this paper, which is verified on the dataset of the oil temperature of the transformers in the two regions. Finally, the results demonstrated that the proposed method can better learn the features of the oil temperature data, and have a good generalization.

In future, more dataset could be used to verify the effectiveness of the proposed method in this paper. In addition, the combination of different algorithms will be studied to predict to the power transformer oil temperature.

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