Convolutional Bi-directional Long Short Term Memory Network based Dynamic Fault Diagnosis for Transformer DGA

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Abstract. Dissolved gas analysis (DGA) method is one of the important methods to detect early internal faults in transformers. Aiming at the shortcomings of feature extraction and online modelling in the analysis model based on shallow layer, a transformer DGA online fault diagnosis method combining convolutional neural network and bidirectional long short term memory network is proposed in this paper. By using multi-time characteristic gas data as the input of the diagnostic model, combined with convolution and pooling, the fault sensitive features were extracted, and the time dimension features were extracted by using the recursive neural network with gated structure. Under various evaluation criteria, it is compared with convolutional neural network, bidirectional long short-term memory (Bi-LSTM) network and dynamic support vector machine. The experimental results show that the online transformer diagnosis model proposed in this paper, which considers both time and space characteristics, has higher prediction accuracy.

Keywords: bidirectional long short-term memory, deep learning, dissolved gas analysis.

1. Introduction

Power transformer is one of the key equipment in the power system, and its operation status directly affects the safe and stable operation of the whole power system. Once the transformer stops running due to discharge or overheating and other faults, then it will cause incalculable losses to the factory production and normal life of the residents, so it is very necessary to investigate the potential faults of the transformer in the early stage [1-3]. Transformer due to long-term operation in high temperature and strong electromagnetic field environment, the internal insulation materials will be decomposed to produce a small amount of hydrogen (H₂), some hydrocarbon gases (CH₄, C₂H₆, C₂H₄, C₂H₂) and carbon monoxide (CO) and carbon dioxide (CO₂), and dissolved in the transformer oil [4]. The decomposition can be intensified if there is a latent fault inside the transformer.

In recent years, the development of deep learning has driven many applications of artificial intelligence technology in transformer DGA fault diagnosis. For example, Qin et al. [5] proposed a transformer fault diagnosis method based on convolutional neural network. Although it overcomes some problems of shallow machine learning methods, it does not mine deeper features in time. Dai et al. [6] proposed a transformer fault diagnosis method based on deep belief network, which fully exploits the features on the transformer time dimension and improves the fault tolerance of the sample...
data to a certain extent. However, it does not exploit the features on the deeper space of transformer faults.

Although the above deep learning-based transformer diagnosis methods have good diagnostic accuracy, they are mostly offline diagnosis methods. Motivated by these, this paper proposes an online transformer diagnosis method combining convolutional neural network and bi-directional long and short-term memory network (CNN-BiLSTM), where feature extraction and online modelling are performed simultaneously. The resulting network is an end-to-end trainable model by stacking the multiple layers. Experimental results show that the proposed network achieves the promising performance compared with the state-of-the-art model.

2. Convolutional neural network

Convolutional neural networks [7] are generally composed of input, convolutional, pooling, flatten, fully-connected and output layers. In order to extract feature information from the spatial structure of the data, the CNN model uses convolutional operations instead of matrix product operations in traditional networks, and reduces overfitting by compressing data and parameters. The DGA data can be represented as an ordered real-time sequence \( X = (x_1, x_2, \cdots, x_T) \), \( x_t \in \mathbb{R}^D \), \( t \in \{1, T\} \), where \( D \) is the number of characteristic gas. Assuming that the number of convolutional layers of the CNN is \( L \), the fault-sensitive DGA spatial characteristic data can be captured using a 1D filter and expressed on the convolutional layer \( l \), where \( l \in \{1, \cdots, L\} \). The feature map of the previous layer is convolved with a learnable convolution kernel and the neurons of this layer are formed from the output of the activation function, thus forming a feature extraction layer, denoted as

\[
x^l_{j,t} = f \left( \sum_{i \in M} x^{l-1}_{i,j} \ast k_{ij} + b^l_i \right)
\]

where \( x^l_{j,t} \) is the \( j \)-th feature map of the \( l \)-th layer at moment \( t \); \( f \) is the nonlinear activation function, we choose the ReLU activation function in this paper; \( \ast \) is the convolutional operation; \( k_{ij} \) is the convolutional kernel; and \( b^l_i \) is the bias term. In order to efficiently compute the activation values over a long period of time, the CNN needs to sample the output of the convolutional layer using the pooling layer, which is

\[
m_t = \max_j \{x^l_{j,t}\}
\]

3. CNN-BiLSTM model for sequential fault diagnosis

The LSTM network is a variation on the traditional Recurrent Neural Network (RNN), where a gating structure is added to the network structure to solve the problems such as gradient disappearance and gradient explosion that occur when RNNs process long time series data. The input of an LSTM cell at moment \( t \) consists of three parts: the input at the current moment (the output state \( m_t \) of the pooling layer), the state \( h_{t-1} \) of the hidden layer cell at moment \( t - 1 \) and the state \( c_{t-1} \) of the gating cell. Specifically,

\[
i_t = \sigma(W_{mi}m_t + W_{hi}h_{t-1} + b_i) \tag{3}
\]

\[
o_t = \sigma(W_{mo}m_t + W_{ho}h_{t-1} + b_o) \tag{4}
\]

\[
f_t = \sigma(W_{mf}m_t + W_{hf}h_{t-1} + b_f) \tag{5}
\]

where, \( \sigma \) is the activation function sigmoid, \( i_t, \{W_{mi}, W_{hi}\} \) and \( b_i \) are the output, weight matrix and additive bias terms of the input gate, respectively; \( \{o_t, W_{mo}, W_{ho}, b_o\} \) and \( \{f_t, W_{mf}, W_{hf}, b_f\} \) are the similar results of the output gate and forget gate, respectively. The final output state at time \( t \) is calculated as,

\[
\hat{c}_t = \tanh(W_{hc} \cdot h_{t-1} + W_{mc} \cdot m_t + b_c) \tag{6}
\]

\[
c_t = f_t \odot \hat{c}_{t-1} + i_t \odot \hat{c}_t \tag{7}
\]

\[
h_t = o_t \odot \tanh(c_t) \tag{8}
\]

where \( \hat{c}_t \) is the candidate cell, \( W_{hc} \) and \( W_{mc} \) denote the weight matrix of the input layer, \( b_c \) is the additive bias term of the input layer, \( h_t \) is the output result of the output layer, \( \odot \) denotes the element-wise multiplication, \( \tanh \) denotes the activation function.
Although it solves the long-term dependency problem in RNN, LSTM can only record the state information before moment $t$, but not the important state information that may exist after moment $t$. The emergence of BiLSTM is able to solve this problem. The structure of BiLSTM is shown in figure 1. The forward layer is involved in the forward operation, and the input at moment $t$ is the sequence data $m_t$ at that moment and the output at moment $t - 1$. The backward layer is involved in the reverse operation, and the input at moment $t$ is the sequence data $m_t$ at that moment and the output at moment $t + 1$. The final output result $y_t$ at moment $t$ is determined by both the forward and reverse operation results.

![Figure 1. Structure diagram of bidirectional long short term memory network](image)

4. Case study on benchmark process

Experiments are conducted on an Intel(R) Core(TM) i5-1135G7 2.40GHz CPU with 16G RAM and a Windows 10 Home Edition (64-bit) operating system to build and evaluate the models. In this paper, a total of 393 sample were collected in a DGA-based transformer, and the data were randomly disrupted. The sample data are divided into training set and test set in the ratio of 7:3.

4.1. Fault classification and performance analysis

In order to evaluate the effectiveness of the online transformer diagnosis method proposed in this paper, time-steps=20 is chosen to conduct experiments under the same experimental environment. The feature information of the transformer is extracted and normalized. The diagnosis models are constructed for comparison, including DPCA-SVM, CNN, BiLSTM and CNN-BiLSTM.

The confusion matrix of the DPCA-SVM, CNN, BiLSTM, and CNN-BiLSTM diagnostic models is shown in figure 2, where the horizontal coordinates indicate the predicted categories and the vertical coordinates indicate the actual categories. From the figure 2, we can calculate that the diagnostic accuracy of CNN-BiLSTM diagnostic model is higher than 85% except for the normal condition, and the diagnostic accuracy of each fault state is significantly higher than the other three diagnostic models, which indicates that the model is better than the other models in identifying each fault condition. This shows that the model is better than the other models in identifying each fault condition.
Figure 2. Confusion matrix under different models, (a) CNN-BiLSTM, (b) BiLSTM, (c) CNN, and (d) DPCA-SVM

Figure 3. ROC curves under different diagnostic models, (a) CNN-BiLSTM, (b) BiLSTM, (c) CNN, and (d) DPCA-SVM, where class 0-5 represent normal, partial discharge, low energy discharge, high energy discharge, medium and low temperature overheating, and high temperature overheating, respectively.

The ROC curves under different diagnostic models are shown in figure 3. From the AUC values of the micro-average ROC curve (\(AUC_{\text{CNN-BiLSTM}} = 0.98 > AUC_{\text{BiLSTM}} = 0.96 > AUC_{\text{CNN}} = 0.91 > AUC_{\text{DPCA-SVM}} = 0.87\)), it can be seen that the CNN-BiLSTM transformer diagnosis model is most sensitive, while the DPCA-SVM is less sensitive to the state of abnormal operation of the transformer. Moreover, the CNN-BiLSTM is significantly larger than the BiLSTM, CNN, and DPCA-SVM for the six operating states of the transformer and the macro-average ROC curve AUC values, indicating that the CNN-BiLSTM diagnostic model outperforms the other three diagnostic models.

In a real power system, different time-steps may have an impact on the performance of transformer online fault diagnosis models. Accordingly, the effect of the diagnostic model on the fault
identification is investigated at time steps of \{5,8,11,14,17,20,23,26,30\}. The results are shown in figure 4. The experimental results show that the CNN-BiLSTM diagnostic model outperforms the other models for fault recognition at any time step, and illustrate that the two diagnostic models, CNN-BiLSTM and BiLSTM, are less sensitive to the time step, while DPCA-SVM and CNN are more sensitive to the time step, and the diagnostic accuracy at step size 5 and step size 30 The difference is large when the step size is 30.

![Figure 4. Effect of time-step on the prediction accuracy of the test set.](image)

5. Conclusion
In this paper, we propose a CNN-BiLSTM-based online diagnosis method for DGA-based transformer application. The powerful feature extraction capability of CNN is used to extract the spatial features implied by transformer faults in the model. Meanwhile, the temporal features implied by transformer faults are mined using BiLSTM. The performance of traditional diagnostic models is experimentally compared and analysed, such as CNN-BiLSTM, BiLSTM, CNN, and DPCA-SVM. The superiority of the method is verified under various evaluation criteria of confusion matrix and ROC curve. Meanwhile, the CNN-BiLSTM diagnostic model is not sensitive to the time step, which is more conducive to online modelling and practical engineering applications.

6. References
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