Fault Prediction of Street Lamp Power Distribution System Based on Sliding Time Window with Attenuation of AR-ELM

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Keywords: Street lamp power distribution system, Machine learning, Extreme learning machine, Fault prediction.

Abstract. Aiming at the street lamp power distribution system, a fault prediction method based on the improved online limit learning machine is designed, which is integrated into the AR Model to enhance the temporal correlation analysis of the ELM model, into the attenuation sliding time window to speed up the efficiency and accuracy of the model learning. The application showed that the method can prevent a wide range of lines and distribution problems caused by the street lamp power distribution system failure.

Introduction

With the street lamp power distribution system continues to expand, maintenance costs are continuing to grow. However, relying solely on fault detection for screening later maintenance way, often makes it hard for fault area lighting in a relatively short period of time to repair. In this paper, the fault prediction model of street lamp power distribution system plays a great role on positive economic and social benefit. In recent years, the emerging online learning method can effectively combine the new data update model, which is more suitable for predicting the trend of data in the near future. It is an important research direction for the application of machine learning method in the field of fault diagnosis and prediction of future lighting system[1], such as a special Neural Network, Extreme Learning Machine[2].

Based on the improved method of limit learning, this paper builds the fault prediction model with integrating the Autoregressive Model, and introduces the learning algorithm with the attenuation time window to enhance the practicability and accuracy of the fault prediction model.

Based on the AR-ELM with the Attenuation of the Sliding Window of the Street Lamp Power Distribution System Prediction Model and the Specific Steps

Prediction Model Construction of Self-regression Limit Learning Machine

In this paper, the Autoregressive Model[3] is integrated into the Extreme Learning Machine to solve the problem by combining the nonlinear mapping of the neural network excitation function and its fitting characteristics of any continuous function[3]. The model is called AR-ELM model.

The resulting model structure of power distribution network failure in urban lighting area is shown in Figure 1.
The AR-ELM model has a time delay layer in the input layer, that is $B^{-1}, B^{-2}, \ldots, B^{-s}$ in the figure, in which $B$ indicates that the time delay is delayed by one interval. At the time of $t$, the distribution of the network attribute value $X$ in the urban lighting area passes back to the time delay layer and passes an AR Model of s order as input to the subsequent model. For a hidden layer node, the AR Model parameters $\varphi_k$ and $\alpha$ are randomly generated, and because there are $L$ actual hidden layer nodes, the model form $L$ random AR Model function mapping in which the relationship between data sequences are included through the hidden layer node.

**Learning Algorithm with Decaying Sliding Time Window**

On the one hand, the ELM online updating process is used to make the model have the ability of online learning. On the other hand, with the model characteristics in time series analysis, the algorithm is introduced in the online process of ELM.

The learning algorithm with the attenuation sliding time window is as follows:

**Learning Algorithm with Attenuation Sliding Time Window**

**Input:**
- $\lambda$: Attenuation coefficient (adjusted by training data);
- $W_{Size}$: Slide window size (adjusted by training data);
- $\beta$: Current model output weight;
- $K$: The intermediate storage of the algorithm;
- $W_{Sample}$: The data of the sliding window;
- $AR_{Sample}$: The last input of AR Model;
- $Samples$: The running data entered in chronological order;

Combine the previous AR data and the newly introduced Sample to assemble the AR data $AR_{Sample}$ of the current moment;

If $W_{Size}$ > the number of $W_{Sample}$

**Algorithm:**

1. $K_{k+1} = 2^2 K_{k} - \lambda^2 K_{k} H_{k+1}^T (I + \lambda^2 H_{k+1} K_{k} H_{k+1}^T)^{-1} H_{k+1} \lambda^2 K_{k}$, calculate intermediate results $K_{k+1}$; Through the formula,

2. $\beta_{k+1} = \beta_{k} + K_{k+1}^{-1} H_{k+1}^T (T_{k+1} - H_{k+1} \beta_{k})$, (among them, $K_{k+1}^{-1} = K_{k}^{-1} - K_{k}^{-1} H_{k+1}^T (I + H_{k+1} K_{k} H_{k+1}^T)^{-1} H_{k+1} K_{k}^{-1}$)

calculate the current model parameters $\beta$;

else

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remove the oldest data in WSample O_Sample; AR_Sample is added after WSample; To attenuate the data in Wsample; Calculate the output of discarded data corresponding to the output $H_{k+1}$ of the hidden layer; Calculate the newly added data corresponding to the output $H_{k+1}$ of the hidden layer; Through the formula

\[
K_{k+1}^{-1} = \lambda^2 K_k^{-1} - \lambda^2 K_k^{-1} \left( I + \left[ \frac{H_{k-s+1}}{H_k} \right] \lambda^2 K_k^{-1} \left[ \frac{H_{k-s+1}}{H_k} \right]^T \right)^{-1} \left[ \frac{H_{k-s+1}}{H_k} \right] \lambda^2 K_k^{-1},
\]

(3)
calculate intermediate results $K_{k+1}$; Through the formula $^{[10]}

\[
\beta_{k+1} = \beta_k + K_{k+1}^{-1} \left[ \frac{H_{k-s+1}}{H_k} \right] \left( \frac{T_{k-s+1}}{T_k} \right) - \left[ \frac{H_{k-s+1}}{H_k} \right] \beta_k,
\]

(4)

(among them,
calculate the current model parameters beta;
end if

**Output:** WSample; $K_{k+1}$; beta

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**Failure Prediction Model Workflow and Verification**

**Workflow**

The paper constructs the AR Model as the input of the input layer of the classic ELM. At the same time, a sliding window is maintained during the training of the algorithm to monitor the change of the sample data for a period of time. Then, when the amount of data arrives in turn to determine whether the window is sliding, constructed incremental and decrement update algorithm respectively.

The workflow of the forecast model is as follows:

Step 1. After cleaning and normalization of data, the whole process is arranged according to time series, and a sample data is transmitted to the algorithm each time;

Step 2. The algorithm first is based on the p-order AR model to input data collation;

Step 3. Then determine whether the current model of the training sample meets the maximum window requirements;

Step 4. When the sample size has not reached the window size, the model is updated according to formula 1 (that is, formula (1) and formula (2)). On the contrary, according to formula 2 (that is, formula (3) and formula (4));

Step 5. Each time the intermediate value and the weight are updated, the model predicts the failure of the next time, and calculates the prediction performance of the current model, that is, the prediction residual. When all the data are transmitted in turn, the algorithm verifies the end.

**Model Validation and Result Analysis**

To illustrate the accuracy and validity of the model proposed in this paper, the influence of the Autoregressive Model and the influence of the attenuation window on the prediction performance are verified respectively in the model verification, and compared with the prediction effect of the prediction model constructed by the classic ELM.

**The Effect of the Autoregressive Model on the Prediction Effect.** Four kinds of commonly used excitation functions Sigmoid, Hardlim, Sin and RBF build prediction model on the classic ELM, in which the model constructed by RBF function has the best prediction effect. Therefore, in the model validation, the RBF activation function builds prediction model in the classic ELM as the Figure 2 shows and in the regional distribution system introducing Autoregressive Model as the
Figure 3 shows, calculates the predicted value and the actual value of the deviation of the predicted point, and calculates the predicted error value over the entire time span, namely the RMSE.

![Figure 2. Classic ELM Mod.](image1)

![Figure 3. AR-ELM Model.](image2)

In the figure, the abscissas are the number values after the data is sorted by time, and the ordinates indicate the absolute deviation between the predicted fault value and the actual fault value. The more the model is distributed over \( y = 0 \), the more serious the case of misclassification, and the larger the \( y \) coordinate of each point, the greater the error of the predicted value.

It can be seen from the figure that the model introduced by the autoregressive model can further reduce the situation of misclassification points. In order to further illustrate the improvement of the model, this paper makes a statistical error (RMSE) for different configurations (Table 1).

<table>
<thead>
<tr>
<th>Using model</th>
<th>Activate function</th>
<th>Prediction error (RMSE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classic ELM</td>
<td>Sigmoid</td>
<td>0.1865</td>
</tr>
<tr>
<td></td>
<td>Sin</td>
<td>0.1732</td>
</tr>
<tr>
<td></td>
<td>Hardlim</td>
<td>0.2420</td>
</tr>
<tr>
<td></td>
<td>RBF</td>
<td>0.1226</td>
</tr>
<tr>
<td>Autoregressive ELM</td>
<td>RBF</td>
<td>0.0552</td>
</tr>
</tbody>
</table>

It can be seen that the autoregressive ELM Model proposed in this paper can predict the problem of regional distribution system fault prediction with higher accuracy than traditional mode-type.

**Impact of the Introduction of the Decay Time Window on the Prediction Effect.** This paper validates respectively the decay time window size with 0, 20, and 40 as shown in the Figure 3, Figure 4, Figure 5, on the basis of the previous section.

![Figure 4. Window size of 20.](image3)

![Figure 5. Window size of 40.](image4)

It can be seen from the figure that the introduction of the sliding window greatly reduces the error prediction situation, and the model's prediction is more accurate and accurate with the expansion of the time window. In order to more clearly compare the degree of optimization of the model, this paper statistics RMSE in three cases, as shown in Table 2.

<table>
<thead>
<tr>
<th>Using model</th>
<th>Windows number</th>
<th>Prediction error (RMSE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Autoregressive ELM with attenuation window</td>
<td>20</td>
<td>0.0521</td>
</tr>
<tr>
<td></td>
<td>40</td>
<td>0.0296</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>0.0552</td>
</tr>
</tbody>
</table>

It can be seen from the table that the autoregressive ELM prediction model with decay time window can predict the fault of the regional distribution system with polar prediction error with the increase of the number of windows.
Conclusion

In the paper, the predicting model is presented firstly. Secondly, the learning algorithm with decay time window is expounded. Finally, the workflow of the fault prediction model of the street lamp power distribution system is introduced. In the model validation and analysis of the results, we compare the prediction results before and after the introduction of Autoregressive Model and the decay time window. The results show that the proposed method can greatly improve the prediction effect of the prediction model and reduce the prediction error.

Acknowledgement

This work is supported by the National Natural Science Foundation of China (71671026) and also supported by Science & Technology Department of Sichuan Province under Grant 2016GZ0312.

References


