Reactor Coolant Pump Leakage Estimation of PWR Based on Broad Learning System

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Abstract. Loss-of-coolant accident (LOCA) of reactor coolant pump is considered as a critical issue in pressurized water reactor (PWR) accident analysis. Much work focus on the detection of LOCA, while little work has been done on leakage quantity estimation. In this paper, a reactor coolant leakage estimation model is proposed based on broad learning system (BLS) model which takes the advantages of the flatted structure and incremental learning. Considering that larger leakage is more concerned, the BLS model is improved by a weighted loss function. Dropout layer and white noise are added to improve the robustness of the model. This model is designed to estimate the coolant leakage in an online manner with high precision. The proposed model is evaluated on real leakage data of a reactor coolant pump. Experiments show that, with similar accuracy, the proposed model is significantly faster than the state-of-art deep neural networks.

1. Introduction

Reactor coolant pump (RCP), also known as the main pump, is the only revolving equipment in a PWR nuclear power plant, and is considered as safety-critical system in the reactor coolant system. The shaft seal is the key component mainly used for leakage control of reactor coolant, which directly affects the safe operation of the RCP and the plant\cite{1}. Several researches on the main pump show that about 70\% faults are caused by sealing failures\cite{2}. Corrosion or scaling phenomena in shaft seal may cause the coolant leakage to the environment, which is called loss-of-coolant accident (LOCA)\cite{3}. LOCA in the coolant system leads to depressurization, boiling of the coolant, consequent reduced cooling of the reactor core and, unless remedial measures are taken, overheating of the fuel rods\cite{4}. Real-time monitoring for coolant leakage can timely grasp the status of the shaft seal, thus effectively avoid the power loss caused by LOCA.

According to different causes and manifestations, LOCAs can be divided into various types, such as small break loss of coolant accident (SBLOCA)\cite{5}\cite{6}, large break loss of coolant accident (LBLOCA)\cite{7}\cite{8}, shaft break\cite{9}, station blackout (SBO)\cite{10}\cite{11} and seal loss of coolant accident (SLOCA)\cite{12}. Among them, SBLOCA is one of the most severe accidents in nuclear reactor, which draw increasingly attention in recent research. Nevertheless, almost all of these studies focus on the root cause analysis\cite{13}\cite{14}, faults influence or subsequent treatments\cite{5}\cite{15} and the results demonstration through simulation data or tests\cite{6}\cite{16}. The specific amount estimation of coolant leakage has not been concerned.

In this work, we focus on the data-driven models for reactor coolant leakage estimation. Leakage prediction is a regression problem in supervised learning, which requires high accuracy and timeliness.
It is well known that deep learning is designed in discovering intricate structures for high-dimensional data and obtaining high-precision models\cite{17}\cite{18}. However, a great number of hyper-parameters and complicated structures are involved in most deep-learning networks to achieve a better accuracy, which may lead to high computation burden during training process\cite{19}. In the case, broad learning system (BLS), which can effectively and efficiently update the systems (or relearn) incrementally when it deems necessary, is designed based on the idea of random vector functional link neural network (RVFLNN)\cite{19}\cite{20}. The accuracy and efficiency can be balanced well by BLS. The effectiveness and timeliness of the Broad Learning System (BLS) have been verified in various fields including fault diagnosis and prediction soon after it was proposed. For example, in \cite{21}, a new fault diagnosis method based on principal component analysis (PCA) and BLS was proposed, which proved that the BLS can take on better adaptability, faster computation speed and higher classification accuracy. And, in \cite{22}, using variational mode decomposition (VMD) and Hilbert transform (HT) in the BLS, a fault diagnosis method labeled as VHBLFD is designed for rolling bearings.

Based on the above considerations, this paper uses BLS to estimate the reactor coolant leakage of the first seal ring in PWR nuclear power plant. And, according to the actual demand, BLS is improved based on the weighted loss function and Dropout, so as to estimate the condensate leakage timely and accurately. Moreover, to demonstrate the proposed approach, a case study concerning the leakage estimation of the coolant water from the seal of a reactor coolant pump in a PWR nuclear power plant is considered.

The remainder of the paper is structured as follows. Section 2 describes the reactor coolant leakage estimation model with weighted loss function and Dropout. The application results in monitoring data from a reactor coolant pump is given in Section 3. Conclusions are drawn in Section 4, with some further research directions.

2. BLS for Reactor Coolant Pump Leakage Estimation

BLS is a single-layer incremental neural network based on RVFLNN and single-layer feedforward neural network (SLFNN). BLS maps the input data to a series of random feature spaces and determines the output weights through an optimized least squares method. Moreover, the model is optimized through incremental learning without iterative calculations, which greatly reduces the computation time\cite{19} (the structure is shown in Figure 1).

![Fig.1 The structure of BLS with incremental learning](image)

For training data \((X, Y) \in R^{K \times (P+Q)}\), where \(K\) is the number of data rows, \(P\) and \(Q\) are the dimensions of \(X\) and \(Y\) respectively, the final output of BLS is expressed as:

\[
Y = HW = \left[ Z' \right]^{E^*}W
\]

where \(H = [Z' \mid E^*]\) is the splicing of matrix \(Z'\) and \(E^*\), The matrix \(W\) is the output weights that connects \(H = [Z' \mid E^*]\) to the output layer.

\[
W = \begin{cases} 
(cI + HH^T)^{-1}Y, & K < L \\
(cI + H^TH)^{-1}H^TY, & K \geq L 
\end{cases}
\]
Here, $c$ is the regularization coefficient, $K$ is the number of the input samples, and $L = nv + m\eta$ is the number of hidden-layer nodes.

And, when $p$ additional enhancement nodes are inserted in the network, the new hidden layer is defined as:

$$H^{n+\Delta} = \left[H^*\|\xi(Z^*W_{m\eta} + \beta_{\eta m})\right]$$

The new output weights matrix can be derived as follow:

$$W^{n+\Delta} = \left[\begin{array}{c}
W^n - DB^TY \\
B^TY
\end{array}\right]$$

with $D = (H^*)^\dagger \xi(Z^*W_{m\eta} + \beta_{\eta m}), B' = \begin{cases}
(C), & C \neq 0 \\
(D' + D')^\dagger D'(H^*), & C = 0
\end{cases}$ and $C = \xi(Z^*W_{m\eta} + \beta_{\eta m}) - H^*D$.

The pseudo inverse of previous nodes can be used directly, and only the pseudo inverse of the additional enhancement nodes needs to be calculated. Thus, the training process is greatly accelerated. Therefore, BLS based reactor coolant leakage estimation of PWR nuclear power plant can quickly retrain the model in combination with the current engineering environment, with low calculation complexity. Moreover, in hydraulic seal system, the amount of coolant leakage is generally kept in a controllable range. When the leakage is low, diversified ways can make up for the leakage. When the leakage exceeds the critical value, the PWR nuclear power plant must be shut down instantly. Thus, operators are more concerned of correctly identifying the leakages of large magnitude than small. Correspondingly, the accuracy is more important for large amount of leakage than that for small amount. However, as the PWR is highly reliable, most of the recorded data relates to the low amounts of leakage, in comparison with the data on large amounts of leakage. In this work, the proposed weighted-MSE is adopted as the loss function for estimating and optimizing the BLS model. To improve the stability and robustness, white noise and Dropout layer are also considered in the model.

For the convenience of operation and low cost of calculation, the weighted-MSE and Dropout layer are all considered as a matrix to multiply the original input $X$ and the final input $H = [Z^*E^n]$ respectively. Assume that the weight matrix related to leakage is $Q$, and the Dropout probability matrix is $\Lambda$ ($Q$ and $\Lambda$ are respectively square matrices with the same number of rows as $X$ and $H$). Thus, the original input $X$ is transformed into $X' = Q^*X$, new final input is calculated by $X''$ in the same way and recorded as:

$$H' = \Lambda^* [Z''E'']$$

Then, the new output weights matrix is:

$$W = \begin{cases}
[H'^T(cI + H'H')^TY], & K < L \\
(cI + H'H')^T H'^TY], & K \geq L
\end{cases}$$

Here, $c$ is the regularization coefficient, $K$ is the number of the input samples, and $L = nv + m\eta$ is the number of hidden-layer nodes.

### 3. Application results

In this section, the effectiveness of the proposed model is verified based on the actual reactor coolant monitoring data from a pump in PWR. Sensors are installed to monitor the temperature, pressure, bearing speed, flow of coolant water, etc and 16 factors in total related to the leakage are recorded. These factors are obtained based on expert experience and monitoring difficulty, which provides information on leakage estimation. For the purpose of confidentiality agreement, these variables are not listed in details here. Based on BLS and the popular deep neural networks (artificial neural network and convolutional neural network, ANN and CNN), the reactor coolant leakage estimation model is constructed with the 16 factors as inputs. Based on the weighted MSE and Dropout layer, different models are applied to estimate the coolant leakage of the main pump in the same environment. All the experiments are carried out using PYTHON (3.6) on a 1.60 GHz intel(R)
Core(TM) i5-8250U CPU with 31.9 GB RAM.

**Fig.2 The key steps of the contrast experiment**

The key steps of this experiment are as demonstrated in Figure 2. After data cleansing, the variables are normalized with 0-means to eliminate the influence of scale, and the cost matrix $Q$ is set according to the actual experience. To avoid the influence of random factors, the average results of 5-fold cross-validation are listed in this section. In addition, the depth and nodes in BLS, ANN, and CNN gradually increase until the generalization error is basically unchanged or increased. And, the Dropout layer is set according to a specific model. Thus, the position and structure of Dropout layers in BLS, ANN and CNN are completely different. (ANN and CNN use `keras.layers` in PYTHON (3.6) to set up the Dropout layers). Moreover, Gaussian white noise is added to the training data group to improve the robustness of the model.

With 5-fold cross-validation, the outputs of the models include the average training time, testing time and testing MSE. The experiment results are shown in Table 1:

|          | BLS       | ANN       | CNN       |
|----------|-----------|-----------|-----------|
| Generalization MSE | 0.0143    | 0.0161    | 0.0148    |
| training time(s)   | 1.4064    | 35.6874   | 88.6049   |
| testing time(s)    | 0.1249    | 0.1093    | 0.1093    |

It can be seen that when the generalization MSE accuracy is similar, the training time of BLS is much shorter than that of ANN and CNN. It only takes 1.4064 seconds to retrain the BLS model. In practical application, the model can be updated in time to ensure the accuracy of leakage estimation and greatly reduce the cost of operation and maintenance.

**4. Conclusions**

Real-time monitoring of coolant leakage can grasp the state of the shaft seal in time, thereby effectively avoiding losses caused by LOCA. In this paper, a reactor coolant leakage estimation model is proposed based on BLS. And, Weighted loss function and Dropout layer are applied to improve the model. Compared with ANN and CNN, this model can quickly and accurately estimate the amount of coolant leakage, so it has extremely high application value. At the same time, we note that the
uncertainty in the actual scenario needs to be properly evaluated to further improve the effectiveness of the model, and BLS can be applied to short-term fault prediction. These ideas will be deeply considered in the future research.

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