A hybrid fuzzy logic and extreme learning machine for improving efficiency of circulating water systems in power generation plant

Nur Liyana Afiqah Abdul Aziz, Keem Siah Yap, Muhammad Afif Bunyamin
Department of Electronics and Communication Engineering, College of Engineering, Universiti Tenaga Nasional
Email: yapkeem@uniten.edu.my

Abstract. This paper presents a new approach of the fault detection for improving efficiency of circulating water system (CWS) in a power generation plant using a hybrid Fuzzy Logic System (FLS) and Extreme Learning Machine (ELM) neural network. The FLS is a mathematical tool for calculating the uncertainties where precision and significance are applied in the real world. It is based on natural language which has the ability of “computing the word”. The ELM is an extremely fast learning algorithm for neural network that can completed the training cycle in a very short time. By combining the FLS and ELM, new hybrid model, i.e., FLS-ELM is developed. The applicability of this proposed hybrid model is validated in fault detection in CWS which may help to improve overall efficiency of power generation plant, hence, consuming less natural recourses and producing less pollutions.

1. Introduction

In power generation plant, there are several factors that influenced the efficiency of the power generated; type of fuels used, plant age and type, capacity utilization as well as heat sink system [1]. The CWS or heat sink system is one of the main factors in optimizing the efficiency of the power generated [2]. Heat is a form of energy lost by the system. By cooling the turbines, there will be less heat loss resulting in increases of the efficiency rate [3]. Power can be generated efficiently if the turbine works efficiently when turbine backpressure is maintained at low level [4]. This state can only be fulfilled with an efficient heat transfer process by the water circulating system. Sufficient cooling water is channeled to the turbine condensers continuously. Then, the condensing steam is discharged from the turbine through the same system. Heat transfer will become inefficient when there are blockages in the condenser due to gibberish like sand, small shells and seaweeds that able to escape the water filtering process [5]. The condenser needs to be cleaned in order to maintain the efficiency of the heat transfer to the cooling water from the exhaust steam.

This paper is organized as follows: Section 2 describes FLS and ELM as well as the hybrid FLS-ELM. The results of ELM and FLS-ELM are presents discuss in Section 3. Lastly, section 4 presents the summary and suggestion of further works.

2. The hybrid FIS-ELM model

The ELM is proven to have higher generalization performance due to its capability of having smallest training error and smallest norm of weights [6]. Almost all piecewise-continuous functions can be used
as activation functions in ELM including differential and non-differential functions as well as discontinuous functions. This feature allows ELM to be suitable for any nonlinear activation functions in addition to the ability to use fully complex functions for its activation functions. In the existing literature, it has better performance when compared to existed traditional algorithm over regression and general classification problems [7]. In general, ELM is equal to a three layer Feedforward neural network as shown in Figure 1. Consider a set of \( N \) training samples (with a input vector and respectively target output vector), \( (x_j, t_j) \in \mathbb{R}^m \times \mathbb{R}^m \), is used to training a ELM that with \( L \) number of hidden nodes. In a perfect case, the output of this ELM respectively to \( x_j \) should be

\[
 f(x_j) = \sum_{i=1}^{L} \beta_i G(a_i, b_i, x_j) = t_j \quad \text{for} \quad j = 1, \ldots, N
\]  

where \( a_i \) and \( b_i \) are the input weights and bias (learning parameters) of the hidden nodes, \( \beta_i \) is the output weights, and \( G(a_i, b_i, x_j) \) is the output of the \( i^{th} \) hidden neuron respectively to the input vector \( x_j \). Equation (2) shows the definition of the \( G(a_i, b_i, x_j) \) hidden neuron.

\[
 G(a_i, b_i, x_j) = \exp(-b_i \| x_j - a_i \|^2), \quad b_i \in \mathbb{R}^+ 
\]  

The algorithms of ELM are summarized as follows.

Step 1: Randomly assign the input weights \( a_i \) and \( b_i \) for \( j = 1, \ldots, L \).

Step 2: Calculate the initial hidden layer output matrix, \( H \), as follows.

\[
 H = \begin{bmatrix}
 G(a_1, b_1, x_1) & \cdots & G(a_L, b_L, x_L) \\
 \vdots & \ddots & \vdots \\
 G(a_1, b_1, x_{N_0}) & \cdots & G(a_L, b_L, x_{N_0}) 
\end{bmatrix}_{N \times L}
\]  

Step 3: Estimate the initial output weights, \( \beta \) by following equations,

\[
 \beta = (H^T H)^{-1} H^T T
\] 

where \( T = [t_1, \ldots, t_N] \) is the respective targeted output vectors.

For the proposed FLS-ELM model has the similar algorithms as ELM but the equation (3) is redefined as
where function $F(.)$ represents the operation of a Fuzzy Inference System (FIS) (refer to Figure 2). A FIS can be summarized 4 sub modules, i.e., fuzzification, rule based, inference engineer and defuzzification. Note that for the fuzzification module of FIS, the membership for an input attribute, $x$, is defined as

$$u(x) = \exp\left(-\frac{(x-c)^2}{2\sigma^2}\right), \quad (6)$$

where $c$ and $\sigma$ are the centre and standard deviation respectively. The full details of a FIS can be found in [5] and [8].

3. Experiments and Results
The collected dataset of CWS consists of 2500 data samples, each of them with 12 input features (parameters of CWS, mainly temperatures and pressures along CWS) and two output classes (normal and fault). They are divided into three subsets, i.e., 1000 data for training, 500 data for validation and 1000 data for test. Experiments are conducted for both ELM and FLS-ELM. For ELM, the best validation accuracy rate was obtained for $L = 1000$ (number of hidden neuron), i.e., 97.132%. With the ELM trained with the best validation rate, the accuracy rate to the test set is 96.610%.

For FIS-ELM, searching of the best validation accuracy rate is through a grid search method, i.e., number hidden neuron (number rules) and standard deviation ($\sigma$) of membership function. Table 1 shows the validation results of FLS-ELM.

Table 1. Validation Accuracy rates of FLS-ELM for difference number of rules and standard deviation

| $\sigma = 2^n, n =$ | 1     | 2     | 3     | 4     | 5     |
|---------------------|-------|-------|-------|-------|-------|
| No. of Rules =       |       |       |       |       |       |
| 200                 | 97.156| 97.168| 97.268| 97.216| 97.220| 97.244|
| 210                 | 97.200| 97.288| 97.228| 97.356| 97.332| 97.248|
| 220                 | 97.248| 97.320| 97.204| 97.376| 97.284| 97.324|
| 230                 | 97.236| 97.212| 97.224| 97.344| 97.336| 97.228|
| 240                 | 97.300| 97.244| 97.352| 97.284| 97.216| 97.364|
|                     |       |       |       |       |       | 97.260|
The validation results suggested the best number of rules (number of hidden neuron) is 250 and the standard deviation of membership function is \(2^1 = 2\). The FLS-ELM with the highest validation accuracy rate is further used to classify test data. The test accuracy rate is 96.988%. In conclusion, FLS-ELM is better than ELM, i.e., has better test accuracy rate (96.988% vs. 96.610%) and smaller number of hidden neuron (250 vs. 1000).

4. Summary

In this research, a new hybrid FLS-ELM model has been developed and applied in the fault detection of power generation plant. The experimental results show the proposed model able to perform well in fault detection which will increase the efficiency of power generation plant. With the higher efficiency, both consumption on natural resources and pollutions due to power generation expected to be reduced. The results of the proposed model is slightly higher than ELM, however it has a new feature, i.e., potentially to be used for discovery the explicit knowledge from the raw data into the form of “If-then” rules as it was developed based on fuzzy logic. Other further works can be focus on the implementing proposed model on other application domains to further evaluate its applicability.

Acknowledgement

The authors would like to thank Dr. S. C. Tan (Multimedia University, Malaysia) for sharing the dataset.

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