Power System State Estimation Based on PLS-ELM

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Abstract. In order to effectively improve the computational accuracy and robustness of state estimation, a power system state estimation method based on partial least square (PLS) and extreme learning machine (ELM) is proposed in this paper, which combines artificial intelligence technology with grid data. In order to solve the problem of strong correlation between measurements, PLS is used to extract important information and select variables for each measurement, and the optimal variables are input into the ELM model, thus the PLS-ELM model of state quantities is established. Finally, this method is compared with other methods. Experimental results show that the proposed method reduces the complexity of the model, and has high estimation accuracy and strong robustness.

1. Introduction

With the rapid development of high voltage transmission technology, regional power grids are gradually interconnecting organically in China, which leads to the continuous expansion of power grids [1, 2]. Moreover, a large number of new energy power generation and distributed power generation are connected to the grid, which increases the complexity of the large power grid, and thus the power grid presents the characteristics of large and complex. All these changes put forward new requirements for the automation and intelligence level of energy management system (EMS) [3]. As the basis of EMS, the performance of state estimation directly affects the monitoring, decision-making and power system control. Therefore, it is of great significance to study state estimation and improve its scene application performance.

At present, the weighted least square (WLS) method has widely used in power system state estimation because of its low computational complexity [4]. Considering the large and complex characteristics of China's power grid, the improved state estimation algorithm and distributed state estimation have become the research hotspot, but they have only achieved good results in theoretical testing, and have not been applied and promoted. Some scholars have used neural network and back-propagation neural networks (BPNN) to estimate the state of power system [5]. In [6], the least square support vector machine (LSSVM) was used to establish the prediction model of state variables. After neural network, an extreme learning machine (ELM) based on single hidden layer feedforward neural network has emerged as the times require, which has greatly improved in training time, prediction accuracy and generalization ability [7].

Aiming at the existing problems of state estimation based on artificial intelligence technology, this paper proposes a state estimation method based on PLS and ELM. In this paper, partial least square
(PLS) is used to select the state variables of power grid, and the most valuable contribution variable is obtained.

The rest of this paper is organised as follows. The variable selection is given in Section 2. In Section 3, ELM is presented. The performance is discussed in Section 4. Finally, the conclusion is given in Section 5.

2. Variable selection

2.1. PLS

Suppose \( \{x_i,y_i\}_{i=1}^{M} \) is a sample, where \( x_i \in \mathbb{R}^{M \times p} \), \( y_i \in \mathbb{R}^{M \times 1} \), \( M \) is the number of samples, \( p \) is the number of independent variables, the variables are standardized to get the matrices \( E_0 \) and \( F_0 \). The specific steps of PLS are as follows:

Step1: The principal components \( t_1 \) and \( u_1 \) are calculated, and the principal components \( t_1 \) and \( u_1 \) are required to contain as much variation information as possible. The solution is as follows:

\[
\begin{align*}
\max & \quad <E_0w,F_0v> \wedge w_1^Tv_1 = 1, v_1^Tv_1 = 1 \\
\end{align*}
\]

The first pair of principal components is obtained by solving the above optimization problem:

\[
\begin{align*}
t_1 &= E_0 \\
u_1 &= F_0v_1 \\
\end{align*}
\]

Step2: The regression equation is established.

\[
\begin{align*}
E_0 &= t_1\alpha_1^T + E_1 \\
F_0 &= t_1\beta_1^T + F_1 \\
\end{align*}
\]

where \( \alpha_1 \) and \( \beta_1 \) are the regression coefficient vectors of (3). The expression is as follows:

\[
\begin{align*}
\alpha_1 &= \frac{E_1^TTt_1}{||t_1||} \\
\beta_1 &= \frac{F_1^TTt_1}{||t_1||} \\
\end{align*}
\]

Step3: The residual matrices \( E_0 \) and \( F_0 \) are used to solve the problem, and the second principal component \( t_2 \) is obtained, and then it is obtained in turn until the final number of principal components is determined by the principle of cross validity.

Step4: The number of principal components \( h \) is determined by cross validity, and its expression is as follows:

\[
Q_h^2 = 1 - \frac{\sum_{i=1}^{M}(y_i - \hat{y}_i(h))^2}{\sum_{i=1}^{M}(y_i - \hat{y}_{i-1}(h))^2} \\
\]

where \( y_i \) is the initial sample, \( \hat{y}_i(h) \) is the predicted value of sample \( i \) calculated by using \( h \) components, \( \hat{y}_{i-1}(h) \) is the predicted value of sample \( i \) calculated by removing sample \( i \) and using \( h \) components, and \( Q_h^2 \geq 0.0975 \) is taken as the basis to determine the number of effective principal components.

2.2. Importance index of independent variable

The importance index of independent variable can determine the contribution of the \( k \)th independent variable to the dependent variable \( y \). The specific expression is as follows:

\[
VIP_k = \sqrt{\frac{\sum_{h=1}^{P} r^2(y; t_h)w^2_{ik}}{\sum_{k=1}^{P} r^2(y; t_k)}} \\
\]

2
where $P$ is the number of variables and $l$ is the number of main components; $r(y; t_x)$ is the correlation coefficient between $y$ and $t_x$; $w_{th}$ is the $k$ th component of weight vector $w_h$. The larger the value of importance index is, the greater the contribution of independent variable to dependent variable is.

The importance index of each variable satisfies the following expression:

$$\sum_{i=1}^{k} VIP_i^2 = \alpha P \quad (7)$$

where $q$ is the optimal number of independent variables and $q \leq P$; $\alpha \in [0, 1]$ is the contribution factor, which determines the number of independent variables influencing the dependent variable.

### 3. ELM

ELM is a new type of feedforward neural network, which overcomes the defects of the traditional neural network and reduces the calculation time of parameter determination. Moreover, ELM has fast training speed and strong anti-interference ability. ELM has certain advantages when solving complex modeling problem, and its algorithm process is as follows:

There is a sample set $\{x_j, y_j\}_{j=1}^{N}$, where $x_j \in \mathbb{R}^m$, $y_j \in \mathbb{R}^n$, and the regression model of ELM is as follows:

$$f(x_i) = \sum_{j=1}^{L} \beta_i G(a_i, b_j, x_i) = t_j, \quad j = 1, 2, \ldots, N \quad (8)$$

where $a_i$ is the weight vector of the $i$ th hidden layer node and the input node; $b_j$ is the weight vector of the $i$ th hidden layer node and the output node; $b_t$ is the offset of the $i$ th hidden layer node; $L$ is the number of hidden layer nodes; $G$ is the hidden layer activation function, which selects the Sigmoid function; $N$ is the number of samples.

$$H \beta = T \quad (9)$$

where

$$H = \begin{bmatrix} G(a_1, b_1, x_1) & \cdots & G(a_L, b_1, x_1) \\ \vdots & \ddots & \vdots \\ G(a_1, b_L, x_N) & \cdots & G(a_L, b_L, x_N) \end{bmatrix} \quad (10)$$

and

$$\beta = (\beta_1, \cdots, \beta_L)_m \in \mathbb{R}^m \quad$$

$$T = (t_1, \cdots, t_N)_n \in \mathbb{R}^n$$

The training process of ELM network is equivalent to solving the least square solution of $H \beta = T$.

$$\|H \beta - T\| = \|HT^T - T\| = \min_{\beta} \|H \beta - T\| \quad (12)$$

The least square solution is expressed as:

$$\beta = H^T T \quad (13)$$

where $H^T$ is the Moore-Penrose generalized inverse of $H$.

### 4. Performance analysis

In this paper, IEEE14 bus system is used to generate data and grid history data, and the proposed algorithm is verified and compared with WLS, BPNN, LSSVM and ELM. The average absolute error is used to evaluate the estimation accuracy of various state estimation algorithms, and the error formula is as follows:

$$\xi(k) = \frac{1}{M} \sum_{i=1}^{M} |x'(k) - \tilde{x}(k)| \quad (14)$$
where $M$ is the number of system nodes; $\hat{x}(k)$ is the estimated value of $i$-node method at $k$ time; $x^i(k)$ is the real value of $i$-node at $k$ time. In experiment 2, the measured data of power grid is the data whose state estimation qualification rate reaches the assessment standard. Hence, the estimated value of WLS is used as the real value.

4.1. Experiment 1
In Experiment 1, the IEEE14 bus system is taken as the test object, and the load rate of the system is simulated by the superposition of linear increase mode and sinusoidal change mode, and the data samples are obtained. By changing the load, 50 groups of data samples are obtained, where the first 40 groups are used as training samples and the last 10 groups are used as test samples. The test samples are obtained by adding random noise with zero expectation and standard deviation of 2%. The input data samples are full power and voltage amplitude measurements, and the output data samples are voltage amplitude and phase angle measurements.

In order to reduce the dimension of input samples, the first 40 groups of data are used as training samples. The variables of training samples are selected and important features are extracted by (1)-(9), and the projection important indexes of input variables are sorted from large to small, and $\alpha = 0.9$. When the variables cannot be integer, the number of variables is integer, and the first $q$ variables are determined as the input variables of ELM.

Using the samples obtained by the above method, the optimal influence variables of voltage amplitude and voltage phase angle of each node are taken as the inputs of ELM, and the state estimation method based on PLS-ELM is obtained. In order to demonstrate the performance of the proposed method, it is compared with the state estimation methods based on WLS, BPNN, LSSVM and ELM. The average estimation error of voltage amplitude and phase angle of 10 groups of test samples by each method is shown in Table 1.

| Method                  | WLS   | BPNN  | LSSVM | ELM   | Proposed method |
|-------------------------|-------|-------|-------|-------|-----------------|
| Voltage phase angle/10^{-4} | 7.3   | 15.2  | 11.6  | 10.8  | 8.7             |
| Voltage amplitude/10^{-4}  | 6.8   | 12.8  | 4.8   | 4.4   | 2.7             |

It can be seen from table 1 that the estimation errors of the proposed method for voltage amplitude and phase angle are significantly smaller than those of BPNN, LSS-VM and ELM state estimation methods, and the proposed method has higher estimation accuracy. Especially in the estimation of voltage amplitude, the effect is more obvious, and the change of estimation error is relatively stable, which also shows that PLS-ELM is suitable for state estimation to a certain extent. Compared with WLS, the proposed method has more advantages in voltage amplitude estimation and slightly disadvantages in voltage phase angle estimation. In addition, the PLS-ELM method with variable selection has higher accuracy than the ELM method without variable selection. At the same time, the number of modeling variables is compressed, which can avoid the influence of bad data on the overall power grid state estimation to a certain extent.

4.2. Experiment 2
The voltage amplitude model of 500 kV bus is established. Considering that the bus coupler switch of section I bus and section II bus is closed, section I bus is selected for research. In this paper, one bus is selected for research, which is recorded as A bus. When the qualification rate of state estimation of a local dispatching station reaches the assessment standard, 50 groups of actual data of power grid are collected from SCADA system and EMS system at 5 min interval. Among them, the first 40 groups of data are used as training samples, and the last 10 groups of data are used as test samples. Some data of A bus voltage amplitude modeling are given in this paper, as shown in Table 1. Based on the above data, the voltage amplitude model of a bus is established.
In order to fully explain the superiority of the state estimation method proposed in the paper, it is compared with BPNN, LSSVM and ELM without variable selection. The average error values of training sample and test sample are shown in Table 2.

It can be seen from the table that the estimation accuracy of the proposed state estimation method is higher than that of other methods, which indicates that the estimation accuracy of the model is improved through variable selection. In addition, the number of input variables is optimized, which is helpful to limit the bad data to the local and reduce the impact on the whole power grid state estimation.

Table 2. Error comparison of five state estimation methods.

| Method           | WLS  | BPNN | LSSVM | ELM  | Proposed method |
|------------------|------|------|-------|------|-----------------|
| Training sample | /kV  |      |       |      |                 |
| 0.001            | 0.28 | 0.003| 0.002 | 0.00042 |
| Test sample      | /kV  |      |       |      |                 |
| 0.41             | 0.63 | 0.45 | 0.52  | 0.32  |

5. Conclusion
In this paper, the artificial intelligence technology is combined with power grid data, and a power system state estimation method based on PLS and ELM is proposed, which is verified by IEEE14 bus system data and actual power grid historical data. By using PLS to select variables, the accuracy of state estimation is improved, the number of variables needed for modeling is compressed, and the dimension and complexity of the model are reduced. Moreover, the bad data can be limited locally to reduce the impact on power grid state estimation. Compared with WLS, BPNN, LSSVM and ELM, PLS-ELM has higher estimation accuracy and stronger robustness. The proposed PLS-ELM state estimation method can effectively resist the bad data in measurement, and has strong ability to resist gross error, which has a certain reference significance for engineering application.

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