Extended Complex Kalman Filter Artificial Neural Network for Bad-Data Detection in Power System State Estimation

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Abstract—This paper presents an extended complex Kalman filter artificial neural network for bad-data detection in a power system. The proposed method not only can improve one-by-one detection using the traditional approach as well as enhance its performances. It uses complex-type state variables as the link weighting to largely reduce nodes number and converging speed. In other words, it not only can largely reduce the number of neurons, but also can search out the suitable and available trained variables which do not heuristically need to adjust the link weighting in the learning stage by itself. A 6-bus and IEEE standard of 30-bus power systems are used to verify the feasibility of the proposed method. The results show the convergent behavior of bad-data detection using the proposed method is better than the conventional method.

Index Terms—bad-data detection, extended complex Kalman filter, state estimation, artificial neural network.

I. INTRODUCTION

Bad-data detection in pre-estimation can help to improve state estimation [1]. State variables in state estimation are used to calculate other non-telemeter system variables. Since transient and abnormal conditions may occur in a power system, measurements may be polluted by bad data to cause estimated errors. Thus, it is necessary to accurately detect the bad data. To ensure the measured reliability, a practical state estimator should have an ability to detect and identify the bad data as well as to eliminate their effects on the estimation [2].

Generally, bad-date detection is important to guarantee the reliability of the measured data. Accurate measurements of the system states are needed to ensure the security of the system and to assist the system operator in decision makings. If one or more errors occur in power system measurements, the states of the estimated system may be biased and the safety of power supply may be potentially dangerous. To avoid this situation, several bad-data detection and identification schemes have been presented. For example, WLS (weighted least squares) was proposed in 1989 [3]. The weighted sum of squares of the measurement residuals was chosen as the objective function to be minimized. But, WLS-based state estimators were only developed by using a linearized measurement function [4] with complicated computations. Then, linear programming (LP) was proposed to improve the identification method [5]. However, the LP estimator may fail to reject the bad data and it can be attributed to the existence of leverage in the power system model [6]. Thus, Ali Abur had proposed hypothesis testing identification (HTI) to extend the case of the LP estimator. Nevertheless, it had caused computational burdens with taking the special properties of the LP estimation equations into account. Huang [4] proposed a changeable weighting matrix to identify the bad data but it only can apply for static state estimations. Nevertheless, Zhang had proposed recursive measurement error estimation identification (RMEEI) and RMEEI for bad-data identification [7]. State variables, residuals and their parameters can be updated after removing a measurement from the suspected data set to the remaining data set by using a set of linear recursive equations. With splitting the raw measurements into some parts, a set of residual equations used by the traditional methods can only apply to linear systems and it may result the operation of calculation burden and complexity because each part consists of some measurements [7].

To overcome those drawbacks, an extended complex Kalman filter artificial neural network (ECKF-ANN) is proposed in this paper. It can perform well on bad-data identification with fast computational speed in two stages. The first stage is the learning process. State variables consist of the weighting that can be learned using Kalman filter ANN to achieve the purpose of adjusting the learning of ANN constantly. As the training has been finished, a polluted value with several times of the standard deviation of the measurements was added into the measurements. The second stage uses the ECKF-ANN with the trained weighting to estimate the measurements. The rule of bad-data decision is to minimize the square difference between the measured and estimated values.

II. THE PROPOSED APPROACH

The proposed approach namely extended complex Kalman filter artificial neural network (ECKF-ANN) uses the innovation vector to minimize the difference between the input and output. The unknown link weighting w of the ECKF-ANN [8-9] can be considered mainly as state variables for estimation with its representation to be
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where

\[ w = [(w^1)^T, (w^2)^T, (w^3)^T, \ldots, (w^{M-1})^T]^T, (L \times 1) \] (1)

\[ w_i^n = [w_{i,1}, w_{i,2}, w_{i,3}, \ldots, w_{i,N_n}]^T, (N_n \times 1) \]

\[ w^n = [(w^1)^T, (w^2)^T, (w^3)^T, \ldots, (w^{N_{n+1}-1})^T]^T, \]

\[ (N_n (N_{n+1} - 1) \times 1) \]

The total number of the link weighting of ANN is given to be

\[ L = \sum_{n=1}^{N} N_n (N_{n+1} - 1) \] (2)

Assuming the output \( O^n(t) \) of the nodes at the \( n \)th layer can be written to be

\[ O^n(t) = [O^n_1(t), O^n_2(t), \ldots, O^n_{N_n}(t)]^T, (N_n \times 1) \] (3)

and the desired output \( d(t) \) is given to be

\[ d(t) = [d_1(t), \ldots, d_{N_n}(t)]^T, (N_M \times 1) \] (4)

As a result, the model of multilayered neural network can then be expressed by nonlinear equations as below:

\[ w(t+1) = w(t) \]

\[ d(t) = O^M(t) + v(t) \] (5)

where \( O^M(t) \) is the output layer of ANN at an instant time \( t \), \( M \) is the output of the last layer, \( v(t) \) is a random noise with covariance \( R_v(t) \). Learning algorithms of the ECKF-ANN can be summarized to be as follows:

\[ \hat{w}(t) = \hat{w}(t-1) + \hat{K}(t)[d(t) - \hat{O}^M(t)], (L \times 1) \] (7)

\[ K(t) = P(t-1)H(t)H(t)P(t-1) + R_v(t)]^{-1} (L \times N_M) \] (8)

\[ P(t) = P(t-1) - K(t)H(t)P(t-1), (L \times L) \] (9)

where \( K(t) \) is the Kalman gain, \( H(t) \) is the measurement matrix, \( H(t)^H \) is the Hermitian matrix of \( H(t) \) called the Jacobian matrix, \( \hat{w} \) is the estimated value of \( w \) and \( P(t) \) means the expectation values of the residual of the \( \hat{w}(t) \) and \( \hat{w}(t-1) \). One can further write the \( P(t) \) and \( H(t) \) to be as below:

\[ P(t) = E\{[(\hat{w}(t) - \hat{w}(t-1))(\hat{w}(t) - \hat{w}(t-1))^H]\} \] (10)

\[ H(t) = (\frac{\partial O^M(t)}{\partial w})_{w=\hat{w}(t-1)} \] (11)

Note that \( H(t) \) can be obtained by using the Taylor series expansion with respect to the initial state vector as the higher-order terms are neglected.

The structure in the \( n \)th neuron of the \( L \) layer is shown in Fig. 1. The input complex signal can be separated into real and imaginary parts. The output is a complex-type by operating with the activation function \( f(\bullet) \) to suppress the varying range of the input signal. The relation of input and output of the neuron is written to be

\[ O^L_n = f(S^L_n) = f(S^L_{n,R}) + jf(S^L_{n,I}) \] (12)

Note that \( O^L_{n,R} \) and \( O^L_{n,I} \) as shown in Fig. 1 are the real and imaginary parts of the output neuron \( O^L_n \), respectively.

Similarly, \( S^L_{n,R} \) and \( S^L_{n,I} \) are the real and imaginary parts of the input neuron \( S^L_n \), respectively. \( S^L_n \) is a linear combination of the output of the prior layer and is represented by the following equation.

\[ S^L_n = S^L_{n,R} + jS^L_{n,I} = \sum_{m=1}^{N} O^L_{m} W^L_{mn} \] (13)

In (13), \( W^L_{mn} \) denoted the weighting of the prior layer is also a complex-type. Its operating structure is shown in Fig. 2 and the relation of the input data and the weighting is written to be

\[ O \ast W = (O_R + jO_I)(W_R + jW_I) \]

\[ = (O_R \ast W_R - O_I \ast W_I) + j(O_R \ast W_I + O_R \ast W_I) \] (14)

Substituting (14) into the activation function \( f(\bullet) \), one can obtain

\[ f(O \ast W) = f(O_R \ast W_R - O_I \ast W_I) \]

\[ + jf(O_R \ast W_I + O_R \ast W_I) \] (15)

To satisfy the conditions of the activation function, a complex activation function is obtained by conforming to a special property which it is analytic and bounded everywhere in the
complex plane [10]. This paper selects the function of \( \tanh(z) \) as an activation function, where \( z \) is a complex value.

### III. BAD-DATA DETECTION

For bad-data detection, complex-type data obtained from power flow calculations are used in this paper. The data learned by the ECKF-ANN are used to train the variety of the weightings and the architecture of Kalman filter is applied to estimate the polluted measurements.

Since the difference between the measured value \( X_i \) and the estimated value \( O_i \) at a particular measurement point is larger than a pre-specified detection threshold in the ECKF-ANN, the decision rule based on ANN is given by

\[
(X_i - O_i)^2 > r_i^2, \quad i = 1, \ldots, n
\]

where the parameters \( i \) and \( r \) represent the measurement index and the threshold value, respectively. An appropriate threshold is important to determine the bad data, but it is not an easy task. Many trials have to be made in order to determine the best values. Generally, the square value of 10 times standard deviation is chosen for each measurement index. Bad data can be flagged when the square of the residual between the measured and estimated values is larger than the corresponding threshold. Thus, the bad data can be detected. The procedure of bad-data detection is described as follows:

Step 1) Inputting normal measurement from a telemeter instrument at a control point such as voltages or power flows in a power system.

Step 2) Executing the forward phase of ANN.

\[
S_n^{(L)} = \sum_{m=0}^{N^{(L)}} W_{nm}^{(L)} X_m^{(L-1)}
\]

Step 3) Performing the learning phase of ANN, (i.e., estimating the link weighting by the extended complex Kaman filter.)

Step 4) Completing the learning in the same way as the residual is smaller than the accepted range during constant training of ANN by the past historical data.

\[
E = \sum_{n=1}^{N} ((D_{nR} - O_{nR}) + (D_{nI} - O_{nI}))^2
\]

where \( D_{nR} \) and \( D_{nI} \) are the real and imaginary parts of the designed value, respectively. \( O_{nR} \) and \( O_{nI} \) are also the real and imaginary parts of the output of ANN, respectively.

Step 5) Inputting the polluted measurement and executing the ECKF-ANN algorithm for measurement estimation.

Step 6) Determining bad data by squaring the difference between the estimated and measured values with the decision rule as shown in (16).

Step 7) Using the estimator to directly estimate with no bad-data existing. If bad data have occurred, the original measured value can be replaced by the estimated value and state estimation can be executed again.

The whole process of estimations as mentioned above may continue until the measurement index is beyond the time point obtained from the raw measurement.

Performance of the simulation results is evaluated by the index of the standard deviation as below:

\[
\sigma = \sqrt{\frac{1}{n} \sum_{i=1}^{n} |X_i - O_i|^2}
\]

where \( n \) is the maximum measurement index. When the value of \( X_i \) is near to \( O_i \), the standard deviation \( \sigma \) is small. This means the detection process is good, i.e., a small index of \( \sigma \) reveals that the algorithm would obtain a better detection.

### IV. SIMULATION RESULTS

Two test systems including a 6-bus and IEEE standard of 30-bus power systems are used in this study. ANN configurations include input, hidden and output layers. The 6-bus system as shown in Fig. 3 consists of 6-bus voltage magnitude \( |V_i| \), 3 pairs of active and reactive generations, 3 pairs of active and reactive loads \( P_i, Q_i \), and 22 pairs of active and reactive line flows \( P_{ij}, Q_{ij} \). Total of 62 data are measured in this system. Since the active and reactive power flows can be combined to be as a complex-type, the total measured data can be reduced to 34. As for the IEEE standard 30-buses power system, it consists of 24 load busses, 5 generator buses and 1 reference (swing) bus as shown in Fig. 4. The Fig. 4 can be divided into five areas. As a result, using a complex-type to represent the measured data, this system will only need to measure total of 142 data.
Three methods are tested to simulate bad-data detection, including ECKF-ANN, real back-propagation artificial neural network (RBP-ANN) and complex back-propagation artificial neural network (CBP-ANN). Moreover, the convergence condition and noises rejection of these three methods are performed to assess their efficiency on bad-data detection. Comparison of the convergent behavior for detecting the 6-bus system using the three methods is shown in Fig. 5. As seen from Fig. 5, the squared error is 0.60726 at the 2\textsuperscript{nd} training number using the ECKF-ANN. However, the squared errors reach 0.94414 and 0.93272 at the 70\textsuperscript{th} and 40\textsuperscript{th} training number for the RBP-ANN and CBP-ANN, respectively.

Normally, the standard deviation obtained from the measured values at the first 100 time points of the data is used to generate the bad data. However, 20 to 100 times of the standard deviation was used as the error to add into the measurement in order to generate the bad data [11]. However, this paper uses 20 times of the standard deviation of the measured values to pollute the measurements. Three of the polluted data will be used for bad-data detection and they are described as below.

![Comparison of the convergent behavior for three methods.](image)

To avoid interfering bad-data detection, the ability of noises injection is tested by applying above three methods and the results are shown in Fig. 6. As seen from Fig. 6, the squared error of the RBP-ANN reaches 0.45 at the noise of 18 dB. However, the squared errors of the CBP-ANN and ECKF-ANN reach only 0.0014461 and 0.00016034 at the noise of 20dB, respectively. Thus, performance on noise injection using the ECKF-ANN is the best among the three methods.

For the 6-bus test system, the data of 150 time points can be obtained from the original power flow calculation and the first 100 time points are used as the training data of the neural network. For convenient observations, the last 20 time points of the data will be used for bad-data detection. The standard deviations of 0.01 and 0.02 for the bus voltages and the rest of measured data at the last 20 time points will be used for evaluating bad-data detection of ANN during the time duration of the last 20 time points. Similarly, the data measured at the power system of IEEE standard 30-buses will also use the last 20 time points.

![Comparison of the capacity of noise rejection for three methods.](image)

**Case 1: Single bad data**

**Situation A: 6-bus power system**

A bad-data is assumed to occur at the 12\textsuperscript{th} time point of the real power of the bus 4 (i.e., P\textsubscript{4}) for the measurement number 10. The threshold value used to identify the bad data is predetermined to be 0.046454 and the standard deviation is computed to be 0.021553. Comparison of the squared error in this system using the three methods is shown in Fig. 7. The squared errors using the ECKF-ANN and CBP-ANN methods are 0.14813 and 0.16725, respectively. Although the squared error using the ECKF-ANN method is smaller than that of the CBP-ANN method, it is good enough to distinguish the bad data. In other words, the ECKF-ANN and CBP-ANN methods can be used to effectively detect the bad data of power signals. However, as seen from Fig. 7(b), the squared errors of measurements at the 12\textsuperscript{th} time point using the RBP-ANN method are all beyond the threshold value. This means this method cannot be used to detect the bad data in this case.

Additionally, detection of the imaginary part of complex state variables with a single bad-data is tested. The bad-data is assumed to occur at the 2\textsuperscript{nd} time point of the reactive power of the bus 6 (i.e., Q\textsubscript{6}) for the measurement number 18. The threshold value used to identify the bad data is predetermined to be 0.039747 and the standard deviation is computed to be 0.019937.

Comparison of the squared errors for the bad-data detection using the prior three different methods and RMEEI method is shown in Fig. 8. As seen from Fig. 8, the squared errors obtained from the prior three methods are beyond the
threshold value. However, the squared error obtained from the RMEEI method is smaller than the threshold value. This result is similar to the prior test when the squared error of each measurement using the RBP-ANN method is all beyond the threshold value and the bad data cannot be detected. Nevertheless, the ECKF-ANN and CBP-ANN methods can be used to detect the bad data at the 2nd time point of the measurement value. As a result, the RMEEI method cannot be easily to detect the bad data because its squared errors of each measurement are all lower than the threshold value. Although the squared error obtained from the ECKF-ANN method (i.e., 0.162860) is smaller than that of the CBP-ANN method (i.e., 0.168560), it is still greater than the threshold value. Thus, the ECKF-ANN method can be used to detect the bad data. Fig. 9 shows the performance comparison of using three different methods. As seen from Fig. 9, the standard deviation of the ECKF-ANN method is smaller than those of the other methods.

Situation B: IEEE standard of the 30-bus power system

A bad-data is assumed to occur at the 12th time point of the first area in the P13 (i.e., P13 is the real power of the transmission line flow from bus 1 to bus 3) for the measurement number 10. The threshold value used to identify the bad data is predetermined to be 0.0009874 and the standard deviation is computed to be 0.0031423. The test result using the ECKF-ANN method is shown in Fig. 10. As seen from Fig. 10, the squared error is near 0.02 at the 12th time point of the first area and it is greater than the threshold value. Thus, it can be used to detect the bad data occurred in the P13.

Case 2: Multiple bad data

Situation A: 6-bus power system

Bad data are assumed to occur in the P6, P23 and P24 of the measurement value at the 8th time point. The numbers 12, 22 and 30 are real-type measurements and the numbers 12, 16 and 24 are complex-type measurements. The threshold value used to identify the bad data is predetermined to be 0.013938 and the standard deviation is computed to be 0.011806 in the P23 measurement value. Comparison of the test results using the ECKF-ANN and CBP-ANN methods is shown in Fig. 11. As seen from Fig. 11, the squared errors in the P6, P23 and P24 of both methods are all greater than the threshold value. However, the results using the CBP-ANN method for detecting other measurements are all beyond the threshold value. Thus, the detected results were interfered. This situation will not occur to the ECKF-ANN method. As seen from Fig. 10, the squared error of other measurements is smaller than the threshold value. This means the ECKF-ANN method is more useful for bad-data detection in power signals.

Similarly, detection of the imaginary part of complex state variable with multiple bad data is tested. The bad data are assumed to occur in the Q6, Q14 and Q41 of the measurement value at the 12th time point. As seen from Table 1, the squared errors for detecting Q6, Q14 and Q41 are all beyond the threshold value. However, the squared errors in the Q14 and Q41 using the ECKF-ANN method are greater than those of using the CBP-ANN method. As a result, bad-data detection using the ECKF-ANN method is better than the CBP-ANN method since it has higher squared error.
distinguishing the bad data. In other words, the ECKF-ANN method is better for detecting the combination of different types of bad data than the CBP-ANN method.

Table 2: Numerical results for detecting the combination of different types of bad data occurring in P2-21.

<table>
<thead>
<tr>
<th>Methods</th>
<th>Measured value</th>
<th>Estimated value</th>
<th>Squared error</th>
</tr>
</thead>
<tbody>
<tr>
<td>CBP-ANN</td>
<td>-0.051971</td>
<td>0.056848</td>
<td>0.011842</td>
</tr>
<tr>
<td>ECKF-ANN</td>
<td>-0.051971</td>
<td>0.076853</td>
<td>0.016596</td>
</tr>
</tbody>
</table>

Note: The threshold value is 0.014329 and the standard deviation is 0.01197.

Situation B: IEEE standard of the 30-bus power system

Bad data are assumed to occur in the measurements of P2, P5-7 and P9-10 at the 10th time point since their squared errors are all beyond the threshold value.

The proposed method with the ECKF learning algorithm based ANN has been developed in this paper to identify the bad-data occurred in a power system. Complex state variables were applied for the ECKF-ANN method as a link weighting. The proposed method not only can largely reduce node numbers of neurons, but also can search out the suitable and available training variables. Moreover, the ECKF-ANN method converges faster than the traditional algorithms and its capacity of noise rejection is better than the traditional algorithms.

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