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Erroneous measurement detection in substation automation system using OLS based RBF neural network

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ABSTRACT

With the development of communication and information technology over the past decades, Electronic Instrumental Transducer (EIT) and broadband communication network have been prevalent within Substation Automation System (SAS) and power utilities. Since mal-function of EIT and broadband communication network within SAS can produce dangerous erroneous measurements, the risk for the protection system to receive these erroneous measurements and thereafter to mis-operate increase. Pattern identification can be utilized to detect erroneous measurements. In order to achieve satisfying pattern identification precision within time limit imposed by protection systems, Radial Basis Function Neural Network (RBFNN) are investigated in the paper. Orthogonal Least Square (OLS) learning algorithm is used to prune network scale in order to mitigate contradictory requirements of high precision and low time delay. Simulation results show OLS based RBFNN can achieve satisfying performance within limited time.

1. Introduction

With the development of communication and information technology over past decades, broadband communication network has been prevalent in power systems. As a protocol to regulate communication within Substation Automation System (SAS), IEC 61850 is becoming popular in recent years. Several hundreds of projects using the new protocol at different stages of realization have been reported during 2006 CIGRE session and pilot substations have been operated for several years [1].

Unlike traditional SAS where Intelligent Electronic Devices (IEDs) are hardwired linked to implement data acquisition and carry out their function, development of Electronic Instrumental Transducer (EIT) and prevalence of communication and information technology have led to a revolution in SAS using new protocol. In the network based SAS, current and voltage are measured with EIT and the output is sent to secondary equipments as numerical signals via broadband communication networks [2–4]. Thereafter, the numerical measurements can be utilized conveniently for controlling and protection applications of SAS. However, as two edges of a sword, the risk emerges is erroneous measurement that may be introduced in the signal (voltage and current) acquisition and measurement transmission. Erroneous measurement received by protection system may lead to its mis-operation. Generally speaking, the major causes are mal-function of EIT and broadband communication network.

The outstanding merit of EIT is that it has much better linearity than traditional electromagnetic instrumental transducer [2,5]. However, the structure of EIT is much more complicated than its predecessors and a typical EIT contains optic fiber, power source, and A/D module with digital output [2,6]. Therefore, it is less reliable. Mis-operations of protection relay due to mal-function of EIT do happen in real world application [7]. In February 2004, the busbar protection of 500 kV Jianglin Convertor substation in China, which has a coordination of 100 A, detect the fault with average differential current of consecutive 20 measurement and output the tripping signal with a delay of 25 ms, has kept mis-tripping the busbars repeatedly. Field Investigation showed the cause is the defect of the EIT. When the system operates without disturbance, the EIT randomly outputs pulse of thousand amperes which last for less than 3 ms. Consequently, the residual current exceeds constraint current significantly and the relay operated "correctly" based on this erroneous measurement. In order to mitigate this defect, the delay to output the tripping signal is prolonged to 60 ms to prevent from mis-operation of relays. However, this is not a general effective countermeasure and may not work for other scenarios. Similarly, the erroneous measurement due to communication system may also lead to mis-operation of protection relays.

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As a tool for pattern identification, Neural Network (NN) has been used in protection systems [8–10]. In [11], pattern identification based approach is proposed to detect fake measurement due to cyber security problem. The scheme operates on the premise that when short circuit occurs, most instrument transducers around faulted section will feel the events by deviation of voltage, current, and apparent resistance. When protection system detects a fault with measurements of a single or pair of EIT, measurements of the whole substation are fed to the network to validate the tripping signal. Thereafter, the measurement that deviates significantly from known fault pattern can be detected and mis-operation upon highly suspicious measurements can be blocked. Obviously, the approach can also work on erroneous measurement detection due to mal-function of EIT.

Ref. [11] implements pattern identification with a Probability Neural Network, which is a branch of Radial Basis Function Neural Network (RBFNN). However, there are contradictory requirement for higher pattern classification precision and less process time imposed by protection system. In RBFNN, a complex network with more nodes in the hidden layer will generally have better generalization and pattern identification precision at the cost of longer process time. In order to achieve higher precision with less process time, the paper proposes to construct Orthogonal Least Square (OLS) learning algorithm based RBFNN for erroneous measurement detection in SAS using IEC 61850. The scale of the network can be determined by speed requirement of protection system. The organization of this paper is as follows. Section 2 introduces RBFNN and OLS learning algorithm. Configuration of simulated power system and preparation of correct/erroneous training/testing dataset is described in Section 3. Comparative simulation results are given in Section 4. Section 5 concludes the paper.

2. OLS based RBFNN

2.1. RBFNN

RBFNN is a pattern classification tool that has been used in a wide variety of engineering applications [12–16]. In comparison to the other types of NN used for pattern classification like back propagation feed forward networks, the RBFNN requires less computation time for learning and has a more compact topology [13]. The Gaussian RBFNN is found suitable not only in generalizing a global mapping but also in refining local features. A typical RBFNN has a feed forward structure consisting of a single hidden layer of n_h locally tuned hidden nodes which are interconnected to an output layer of n_o linear output nodes as shown in Fig. 1.

$$O_k = \exp(-[x - c_k]^T[x - c_k])/2\sigma_k^2) \tag{1}$$

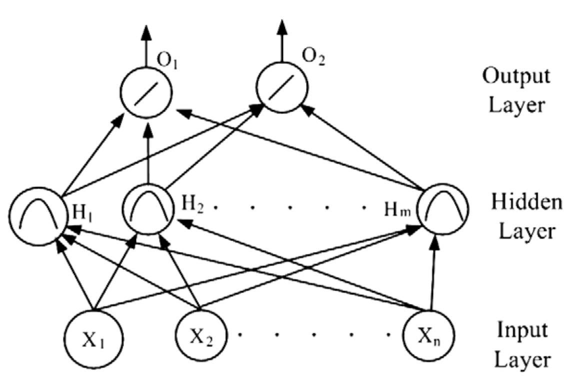

Fig. 1. Architecture of the RBFNN.

All hidden nodes receive the n_i dimensional input vector. The input vector is passed to the hidden nodes. The hidden layer consists of a set of radial basis functions. Functions like spline, multi-quadratic, and Gaussian functions, may be used as the transfer function of the hidden nodes. The Gaussian RBFNN is used in the paper. Associated with *i*th hidden node is a vector, c_i denotes a center. The hidden node calculates the Euclidean distance between the input vector and the center and then passes the result to the radial basis function. The hidden layer performs a nonlinear transformation and maps the input space onto a new space. The output layer gives its result based on a linear combiner on this new space. Thus, the network represents a map from the input to output space according to Eq. (2):

$$d_i = \sum_{j=1}^{n_h} \exp(-\|x - c_j\|^2/2\sigma^2) * \theta_{ji} + \varepsilon_i \quad 1 \le i \le n_h \tag{2}$$

where

$i = 1, 2, \ldots, n_o$, and $j = 1, 2, \ldots, n_h$. d_i denotes the desired output of i th output node. x denotes the input vector. n_h denotes the number of hidden nodes. θ_{ji} denotes the weight between the *j*th hidden node and the *i*th output node. c_j denotes the center of the *j*th hidden node. σ denotes the correct constant of spread factor. ε_i denotes the error between the desired output and the actual output.

The linear coefficients between the hidden and output layers affect the output deviation from the desired output and it can be tuned using the linear least squares (LS) method. Performance of RBFNN relies on selection of node in the hidden layer, configuration of spread σ and coefficients between the hidden and output layers. The spread is configured as the maximum distance between the input vector and the center of the RBFNN to get better generalization in the paper.

2.2. OLS based learning procedure

The task of learning procedure is to optimize the RBFNN with appropriate hidden nodes and then determine the corresponding coefficients based on a set of training inputs and outputs. The hidden nodes of RBFNN are selected from training exemplars and it is a problem of subset model selection [16]. The full model is defined by considering all the training exemplars as candidates for hidden nodes [17]. Eq. (1) can be expressed in the matrix form as:

$$\boldsymbol{D} = \Phi\Theta + \boldsymbol{E} \tag{3}$$

where

$$\boldsymbol{D} = [d_1, \ldots, d_{n0}]$$
$$d_i = [d_i(1), \ldots, d_i(N)],\ i = 1, \ldots, n_0$$
$$\Phi = [\Phi_1, \ldots \Phi_M], \text{where } M \text{ is the data window}$$
$$\Phi_{\boldsymbol{i}} = [\Phi_i(1), \ldots, \Phi_i(N)]^T$$
$$\Theta = [\theta_1, \ldots, \theta_{n0}]$$
$$\theta_j = [\theta_j(1), \ldots, \theta_j(N)]^T, \quad j = 1, \ldots, M$$
$$\boldsymbol{E} = [\varepsilon_1, \ldots, \varepsilon_{n0}]$$
$$\varepsilon_i = [\varepsilon_i(1), \ldots, \varepsilon_i(N)],^T \quad i = 1, \ldots, n_0$$

The parameter matrix Θ can be solved by using the LS principle. The regressors Θ_js form a set of basis vectors. An orthogonal transformation is performed to transfer from the set of Θ_j into a set of orthogonal basis vectors by decomposing Θ_j as (4)

$$\Phi = \boldsymbol{WA} \tag{4}$$