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Adaptive scheme for local prediction of post-contingency power system frequency

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ABSTRACT

The power system frequency always should be kept upper than a minimum threshold determined by the limitations of system equipments such as synchronous generators. In this paper a new method is proposed for local prediction of maximum post-contingency deviation of power system frequency using Artificial Neural Network (ANN) and Support Vector Regression (SVR) learning machines. Due to change of network oscillation modes under different contingencies, the proposed predictors adjust the data sampling time for improving the performance. For ANN and SVR training, a comprehensive list of scenarios is created considering all credible disturbances. The performance of the proposed algorithm is simulated and verified over a dynamic test system.

1. Introduction

Under frequency load shedding (UFLS) is a common practice for electric power utilities to prevent frequency decline in power systems after disturbances causing dangerous imbalance between the generation and load [1]. Depending on the size of the frequency deviation experienced, emergency control and protection schemes may be required to maintain power system frequency at a safe range. The small frequency deviations can be attenuated by the governor natural autonomous response (primary load frequency control) and secondary automatic generation control system. For larger frequency deviations, the emergency control and protection schemes must be used to restore the system frequency.

Frequency prediction could be used either in UFLS relays for improving relay decisions or in local dispatching centers to trigger corrective actions [2]. Different kinds of UFLS protection schemes have been proposed including traditional, semi-adaptive and adaptive schemes [3,4]. The role of rate of frequency change (df/dt) in designing effective under frequency load shedding (UFLS) plan has been discussed in [1,4,5]. The main advantage of adaptive UFLS schemes is that the load shedding is carried out based on the severity of disturbance. A systematic method for setting under frequency load shedding relays has been proposed using a mixed integer linear technique [6]. The ability of a regression tree method for estimation of the frequency decline following a generator outage is examined in [7]. In [8] a genetic algorithm (GA) has been employed to determine and minimize the amount of load to be shed at each stage for under frequency load shedding relays. In [9] a computational method is presented using the Monte-Carlo simulation approach for the calculating settings of under frequency load shedding relays [9]. In this paper, Artificial Neural Network (ANN) and Support Vector Regression (SVR) techniques are developed for predicting post-contingency deviations of power system frequency. A data base of input–output pairs is constructed considering credible contingencies. The best time for sampling input frequency of the system is determined using small signal stability analysis. The sampling time of frequency trajectory for predictor machines is adjusted to present the minimum error of prediction.

The rest of this paper is organized as follows: The fundamentals of load frequency control are described in Section 2. Artificial neural network is discussed in Section 3. The fundamentals of SVR method are discussed in Section 4. Simulations results of applying ANN in different contingencies and the small signal stability analysis are presented in Section 5. Also in Section 5 the results of ANN and SVR implementation in predicting post-contingency frequency are compared. Finally, Section 6 concludes the paper.

2. Fundamentals of load frequency control

The application of under frequency load shedding relays in substations throughout the load area to remove specific amount of

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loads at predetermined frequency thresholds, is the simplest automatic load shedding plan. Relay settings can be optimized to shed the minimum load amounts to arrest system frequency decay at a safe operating level [10]. An adaptive under frequency load shedding plan should be designed according to the following issues:

1. Prediction of the magnitude of the disturbance
2. Disturbance localization
3. Derivation of control action
4. Distribution of control action throughout the power system

Assume that the swing equation of the *ith* generation unit is expressed as follows [3]:

$$\frac{2H_i}{f_n}\frac{df_i}{dt} = p_{mi} - p_{ei} = \Delta p_i \tag{1}$$

where p_{mi} is the mechanical turbine power in p.u., p_{ei} is the electrical power in p.u., Δp_i is the load generation imbalance in p.u., H_i is the inertia constant in second, f_i is the frequency in Hz and f_n is the rated value of frequency. By combining N_g swing equations, the following expression is obtained for the total load generation imbalance:

$$\Delta p_d = \sum_{i=1}^{i=N_g} \Delta p_i = \frac{2\sum H_i}{f_n}\frac{df_c}{dt} = \zeta\frac{df_c}{dt} \tag{2}$$

where

$$f_c = \frac{\sum H_i f_i}{\sum H_i} \tag{3}$$

$$\zeta = \frac{2}{f_n}\sum H_i \tag{4}$$

Parameter f_c is the frequency of the equivalent inertial center, and ζ is a constant which can be calculated in advance [1,11].

When dealing with load shedding planning, several issues must be considered including the definition of the minimum allowable operating frequency for secure system operation, the number of load shedding steps, the frequency thresholds and the amount of load to be shed at each step.

The minimum allowable frequency is determined considering the operational limitations of system equipments, specifically, the elements that are more sensitive to frequency drops such as generators, auxiliary services and steam turbines. In fact, they begin to malfunction at a frequency of 57 Hz (47.5 Hz at 50 Hz), while the situation becomes critical at 53–55 Hz (about 44–46 Hz at 50 Hz). It is needed to avoid the frequency decline below 57 Hz (47.5 Hz at 50 Hz) [12–14]. In this paper a new method is proposed based on the predictor models including Artificial Neural Network and Support Vector Regression to estimate frequency changes under sever contingencies such as load and generation switching. If the estimated steady-state frequency was upper than the minimum allowable frequency, the applying of under frequency load shedding schemes are ignored and the power system frequency is restored to its primary value with activation of generators governor system and also secondary frequency controls (i.e. AGC actions).

3. Artificial Neural Network

A typical Artificial Neural Network consists of input and output layer with one or more hidden layers of activating nodes as illustrated in Fig. 1. In this paper a Multilayer Perceptron (MLP) is used as Artificial Neural Network. Each node in one layer connects with a certain weight W_{ij} to every other node in the following layer. The number of neurons in the input layer is equal to the number of input features. In this paper the number of neurons

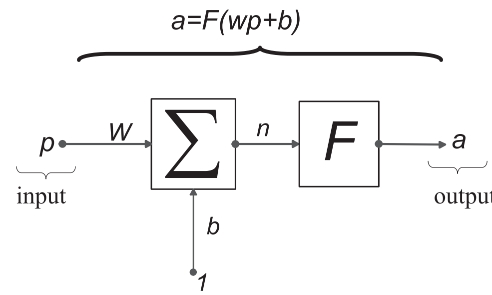

Fig. 1. The structure of a typical neuron.

in hidden layer is chosen to 5 neurons with '*hyperbolic tangent sigmoid*' activation function. This algorithm uses the gradient of the performance function to determine how to adjust the weights to minimize the prediction error. The gradient is determined using a technique called *backpropagation*. The network is trained with Levenberg Marquardt backpropagation algorithm [15]. A neuron with a single scalar input and bias is shown in Fig. 1.

The scalar input *P* is transmitted through a connection that multiplies its strength by the scalar weight *W* to form the product *WP*. It can be seen that the bias *b* is added to the product *WP* by the summing junction or as shifting the function *f* to the left by an amount *b*. Multilayer Perceptron is a feed-forward neural network model that maps sets of input data onto a set of appropriate output. MLP network is more powerful than the perceptron as it can distinguish data that is nonlinearly separable. The basic structure of a multilayer perceptron network used for simulation is shown in Fig. 2 [16–18].

The task of learning a neural network is to determine the optimal estimation of *W* vector that yields the minimum error over training input–output pairs. The prediction error could be measured as a function of deviation of the actual output from the estimated output. Therefore some indices could be used including Mean Square

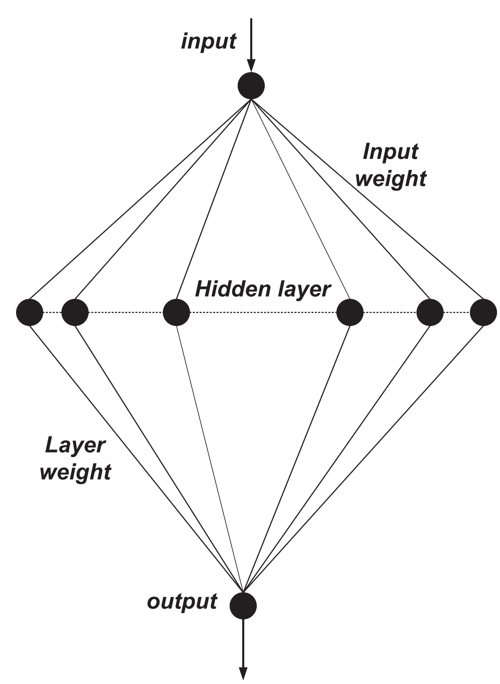

Fig. 2. Structure of Multilayer Perceptron (MLP).