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Performance comparison of neural networks for intelligent management of distributed generators in a distribution system

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ABSTRACT

The Multilayer Perceptron (MLP) neural network has been proven to be a very successful type of neural network in many applications. The MLP activation function is one of the important elements to be considered in neural network training in which proper selection of the activation function will give a huge impact on the network performance. This paper presents a comparative study of the four most commonly used activation functions in the neural network which include the sigmoid, hyperbolic tangent and linear functions used in the MLP neural network and the Gaussian function used in the Radial Basis Function (RBF) network for managing active and reactive power of distributed generation (DG) units in distribution systems. Simulation results show that the sigmoid activation functions give better performance in predicting the optimal power reference of the DG units. However, the RBF neural network gives the fastest conversion time compared to the MLP neural network.

Introduction

Distributed generation (DG) technology which mainly utilized renewable energy resources had become attractive recently due to their capabilities and sustainabalities. With regard of energy shortage, fossil fuel exhaustion, and other worsening environmental issues these promising technology could bring great impact to enhance conventional electrical power generation. Considerably, DG units will be optimally located near the loads side due to the presence of dynamic load i.e. inductive loads which make voltage profiles worsen. Else, they would offer some improvement technically and economically to yield power loss reduction, voltage profile enhancement and low capital investment. Nowadays, research on expanding DG system in a Smart Grid (SG) concept has received great attentions and become remarkable in current electricity generation sector. In achieving a SG concept, dissemination of a large number of DG units in distribution networks are necessary to participate in improving the reliability and the quality of the electricity [1].

Conceptually, SG technology is defined as "an electricity network that can intelligently integrate the actions of all users connected to it such as generators, consumers and those that do both, in order to efficiently deliver sustainable, economic and secure electricity supply" by the Smart Grids European Technology Platform [2]. In SG concept, all the information and signals at the load demand will be process bidirectionally by the management system and they must react to any event that occured optimally so as to ensure efficient transmission and distribution network ongoing successfully [3]. By intelligently managing the active and reactive power of DG units installed in the distribution network, further reduction of losses can be achieved with regard proper coordination among the DGs themselves.

A number of publications have discussed the aspect of managing reference power of the DG units in the distribution network [4–6]. Communication's infrastructures definitely become ultimate key to realize the SG technology in distribution network. Such poor communication affects the process to coordinate the DG units in order to compensate reactive power with local voltage controller [4]. Thus with high technology of communication management among the power networks, a group of DG units can be centrally controlled as they are known can improved several problems faced by current networks for instance power loss and voltage stability issues. Loads variation and power congestion will increase the lines impedance thus more reactive power needed to regulate the voltages and secure power transfer indeed. There are several optimization techniques which are suitable for managing the reference power such as in [5–6] as way to achieve optimal operation. By coordinating all DG units with other voltage controlled devices

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via optimization techniques, an optimal value of voltage and reactive power can be realized. Abrupt changes of the optimization operation are required for every load changing situation to take the effect of local voltage and reference power regulation. Therefore, by repeating the optimization process, any changes in load demands can be compensated successfully in short period of time and this is to meet the real time online operation in the future.

A solution to avoid repetitive optimization process, the application of artificial neural network (ANN) is demonstrated [7]. Main target is to reduce the operational cost of DG units subject to fuel and electricity tariff. In conjunction, this study only focuses only single unit of DG and the ANN process is applied to manage the cost of the network with regards the tariff and load demands become the input to the ANN. In the proposed technique, ANN was trained using an optimal database extracted from optimization process. The procedure is suitable for online management of active and reactive power flow for a group of DG units with the objective of minimizing the total power losses in the system [7].

In this paper, DG's active and reactive power references are managed using ANN techniques incorporating the optimization algorithm with the objective of minimizing power losses in a system and maintaining the voltage profile within its acceptable limit. Type of neural network and multiple activation functions used in the network training were focused. In fact, Multilayer Perceptron (MLP) and Radial Basis Function (RBF) neural networks are the widely used in ANN architectures and their roles affect the network performance. Many researchers have investigated a variety of methods in improving ANN performance such as optimizing training methods, learn parameters and also determining decision borders [8–9]. Besides that, determining the types of activation functions is also important in improving ANN performance because a careful selection of the activation function has a huge impact on the ANN classification and prediction performance. Activation functions can be categorized into three basic families which are linear, logistic and radial basis function [10]. The mathematical and theoretical basis of different MLP activation functions, including RBF, can be found in [10]. Comprehensive surveys of various activations function are provided in [11]. Nowadays, performance comparison of MLP and RBF neural networks in various applications has been attracted the attention of many researchers [12–15]. There is no comparison has been made on intelligent management of reference power for a group of DG in distribution system. This paper will focused on comparing the activation functions such as sigmoid, hyperbolic tangent, linear (MLP) and Gaussian (RBF) for managing active and reactive powers of DGs in distribution system.

Methodology

A smart grid is designed in a way that it is integrated with advanced coordinated control for managing DG units, sensors, and all equipment through highly developed communication facilities. The smart grid system will employ coordinated control, which means that the voltage, as well as the active and reactive powers will be centrally controlled. The control will be based on the wide area coordination to achieve optimum active and reactive power flows for a day load forecast and DG output planning. The application of the ANN is a relatively simple technique with a rapid response time and the technique is considered suitable for smart grid applications. By employing ANN-based optimization; optimal active and reactive power references for the DG inverters can be coordinated by minimizing the total power losses in a smart grid. Thus, by coordinating the DG units in a smart grid, the distribution system can operate economically when subjected to the load variation or unexpected disturbances. The ANN-based intelligent control and optimization proposed in this study is suitable for use in an on-line energy management scheme. The comparison between on-line and off-line control managements is described as shown in Table 1.

The study aims at comparing the predictive performance of different activation functions of MLP and RBF neural networks in predicting active and reactive power references of several DG units in a distribution network. For the MLP neural network, Levenberg–Marquardt (LM) is used as the training algorithm since by adopting the LM algorithm in the network, the training process converges quickly as the solution is approached. For this study, the three main activation functions in MLP which are sigmoid, hyperbolic tangent and linear are applied in the learning process because the derivative of the three activation functions is easy to compute and can be expressed directly as a function of the net input.

Artificial neural network system

MLP neural network models are used widely in most of the research applications in engineering, medicine, classification etc. [16]. In the MLP architecture, the weight sum of the input data and selected bias are passed through a transfer function in order to produce the output data. The MLP configuration is arranged in a layered feed-forward topology and it consists of an input layer, one or more hidden layers and output layer. The number of hidden layers can be altered depending on the problem data under the training procedure. The common training process for the MLP is by supervised learning with the standard back propagation algorithm. In this paper, the MLP consists of three-layers of neurons which means that only one hidden layer is involved and three types of activation function are used in the hidden layer and there are seven inputs with five outputs in the study; this is as shown in Fig. 1 and the equation for the output of the MLP neural network is shown in [15].

The RBF neural network is a simpler network structure and has been widely used in many science and engineering applications [17]. The RBF also consists of three-layers similar to the MLP but the input values are each allocated to a node in the input layer and sent directly to the hidden layer without the existing of weights. Data transferred will be transformed from the input space to the hidden space by the hidden layer and the hidden nodes are determined by a parameter vector called 'center' and a scalar called 'width'. The activation function used in the hidden layer is the Gaussian density function and shown in Fig. 2. One of the advantages of the RBF is that it can be trained using a fast two-stage training algorithm without the need for the time consuming non-linear optimization techniques. A supervised least mean square (LMS) algorithm is used to determine the connection weights between the hidden layer and the output layer.

Levenberg–Marquardt training algorithm is typically the most stable and the fastest training algorithm with a combination of two minimization methods which are the gradient-descent method and Gauss–Newton method [18]. The LM methods act more like the Gauss–Newton method when the current solution is close to their optimal value, and it acts more like the gradient-descent when the current solution is far from the optimal value. The LM algorithm, which was independently developed by Kenneth Levenberg and Donald Marquardt, is an iterative technique that locates the minimum of a function for non-linear least-squares problems [19]. By applying the LM algorithm in the ANN technique, the training procedure converges immediately as the solution is approached and it is suitable for training small and medium sized problems. The updated rule of LM algorithm is presented in Eq. (3) as follows:

$$\boldsymbol{w}_{k+1} = \boldsymbol{w}_k - \left(\boldsymbol{J}_k^T \boldsymbol{J}_k + \mu \boldsymbol{I}\right)^{-1} \boldsymbol{J}_k \boldsymbol{e}_k \tag{3}$$