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Fuzzy wavelet plus a quantum neural network as a design base for power system stability enhancement

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ABSTRACT

In this study, we introduce an indirect adaptive fuzzy wavelet neural controller (IAFWNC) as a power system stabilizer to damp inter-area modes of oscillations in a multi-machine power system. Quantum computing is an efficient method for improving the computational efficiency of neural networks, so we developed an identifier based on a quantum neural network (QNN) to train the IAFWNC in the proposed scheme. All of the controller parameters are tuned online based on the Lyapunov stability theory to guarantee the closed-loop stability. A two-machine, two-area power system equipped with a static synchronous series compensator as a series flexible ac transmission system was used to demonstrate the effectiveness of the proposed controller. The simulation and experimental results demonstrated that the proposed IAFWNC scheme can achieve favorable control performance.

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1. Introduction

The nonlinear dynamics and complex characteristics of a power system can trigger low-frequency oscillations when the power system is exposed to disturbances. A power system stabilizer (PSS) is a highly efficient controller, which can be installed in the automatic voltage regulator of the generator, and PSSs are used extensively to enhance the stability of power systems. The parameters of a conventional fixed structure PSS (CPSS) are determined based on a linearized model of the power system by considering a single operating point. However, issues such as nonlinearity of the power system, changes in the operating conditions or system topology, and deviations in the system parameters all degrade the performance of CPSSs.

To address these issues, it is necessary to develop a method for operating a PSS that achieves better performance compared with the conventional approaches. Various methods are used in this field, such as adaptive control (Hussein, Saad, Elshafei, & Bahgat, 2010; Nechadia, Harmasa, Hamzaouib, & Essounboulib, 2012; Radaideh, Nejdawi, & Mushtaha, 2012), artificial intelligence (Shaw, Banerjee, Ghoshal, & Mukherjee, 2011; Talaat, Abdennour, & Al-Sulaiman, 2010), robust control (Bevrani, Hiyama, & Bevranic, 2011; Khodabakhshian & Hemmati, 2012; Ngamroo, 2012), and sliding mode control (Al-Duwaish & Al-Hamouz, 2011). In particular, methods based on adaptive control and robust control are considered better for addressing the effects of uncertainty in power systems. In adaptive control, the controller parameters are updated by identifying the plant parameters, whereas in robust control, a worst-case design scenario is considered for the plant families that correspond to different uncertainties in the system. In this study, we developed a controller based on indirect adaptive control theory. In this method, the controlled plant needs to be identified first and a controller is then designed based on the identifier. In our method, the identifier is employed to calculate the system sensitivity online based on indirect adaptive control theory.

Recently, wavelet functions have attracted much attention in areas of engineering research such as system identification (Karrari & Malik, 2005) and function approximation (Muzhou & Xuli, 2011). Based on wavelet theory, any signal or function can be closely approximated by a finite sum of the weighted wavelet functions. Wavelet neural networks (WNNs), which incorporate wavelet functions into neural networks, were proposed by Zhang and Benveniste (1992) and they have been used for identifying and controlling nonlinear systems (El-Sousy, 2011; Khan & Azizur Rahman, 2010). Activation functions such as sigmoid and Gaussian functions, which have non-local properties in time, are replaced by wavelet functions in the hidden layers of the neurons in the WNN. The output of a WNN is localized in both the time and frequency domains, thereby capturing the time–frequency localization properties of the input signal. This means that the WNN is a local

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network; therefore, during online training for any given point of the input space, a small subset of the network parameters are active, which can be updated. This maintains the generalizability of the WNN, so it has high flexibility and its training can be performed at speeds higher than that of a non-local network. Furthermore, local minima can be eliminated in the WNN. However, the WNN also has the shortcoming (Yoo, Park, & Choi, 2005) that it employs a feed-forward structure. To address this problem, self-recurrent WNNs (SRWNNs) have been proposed (Yoo et al., 2005). The SRWNN has a mother wavelet layer with self-feedback wavelets, which allows it to record previous data in the network, and thus it can adapt very rapidly to sudden changes in the configuration or condition of the controlled plant.

A fuzzy WNN (FWNN) combines WNN with the Takagi–Sugeno–Kang (TSK) fuzzy model in order to enhance the function approximation accuracy as well as the generalizability during highly complex processes. Several previous studies have considered the synthesis of a FWNN to solve problems such as forecasting, function approximation, fault diagnosis, system identification, and control problems (Abiyev & Kaynak, 2008; Dong, Xiao, Liang, & Liu, 2008; Ebadat, Noroozi, Safavi, & Mousavi, 2011; Zhang & Wang, 2012). In Dong et al. (2008), fault diagnosis for power transformers was addressed using a rough set and FWNN, which was integrated with a least squares weighted fusion algorithm. A gradient-based update rule was employed to update all of the FWNN parameters in the online mode while an adaptive learning rate (ALR) algorithm was also proposed to guarantee the convergence of the adaptive process in Abiyev and Kaynak (2008). The network obtained was used for identification and control in dynamic plants. In Ebadat et al. (2011), using a combination of TSK fuzzy models with a wavelet transform and a recursive orthogonal least squares learning algorithm, a FWNN was proposed to approximate arbitrary nonlinear functions. In Zhang and Wang (2012), a FWNN approach was introduced for forecasting long-term electricity consumption in a high energy consuming city and the rate of training was increased compared with a prediction model based on an artificial neural network.

In the last decade, neural networks have attracted increasing attention from researchers in various application areas. Neural networks have considerable computational advantages, but they also have some problems in practice. For example, they are not suitable for performing simulations in a reasonable time on classical computers due to the massively parallel characteristics of neural networks. Quantum computing is a likely candidate for improving the computational efficiency of neural networks because it has been very successful in dealing with a selected set of computational problems. In this framework, several quantum neural networks (QNNs) have been proposed in previous studies (Kouda, Matsui, & Nishimura, 2002, 2004; Kouda, Matsui, Nishimura, & Peper, 2005).

In this study, we developed an indirect adaptive fuzzy wavelet neural controller (IAFWNC) for stabilizing the inter-area oscillations in a multi-machine power system. Based on the fact that quantum computing is an efficient tool for improving the computational efficiency of neural networks, we developed an identifier based on a QNN to train the IAFWNC in our proposed scheme. A back-propagation algorithm with a Lyapunov-based ALR (LALR) scheme is also proposed to update all the parameters of the consequent parts of each fuzzy rule during online operation A two-machine, two-area power system equipped with a static synchronous series compensator (SSSC) as a series flexible ac transmission system (FACTS) was used to demonstrate the effectiveness of the proposed controller. The results of these studies demonstrated that the inter-area oscillations were successfully damped by the IAFWNC. In brief, the main contributions of this study are summarized as follows.

a. The main disadvantage of FWNN is that the application domain is limited to static problems due to its feed-forward network structure. Therefore, we propose to use a SRWNN in the consequent part of the FWNN, thereby solving the control problem for chaotic systems.
b. Our proposed structure requires fewer wavelet nodes than networks with a feed-forward structure due to the dynamic behavior of the recurrent network.
c. Finding the optimal learning rate is a challenging task for classic gradient-based learning algorithms. Hence, in our proposed framework, all of the learning rates are determined optimally based on Lyapunov stability theory.
d. We developed an identifier based on a QNN to train the proposed controller.
e. We developed a controller based on the proposed network structure, which we use to damp oscillations in a multi-machine power system.

The remainder of this paper is organized as follows. A brief introduction to the SRWNN structure is presented in Section 2. Section 3 describes the architecture of the proposed FWNN with a self-recurrent consequent part. The design process for the IAFWNC is discussed in Section 4. In Section 5, we present the results of the comprehensive stability study. The results of nonlinear time-domain simulations are provided in Section 6. Finally, the discussion and our conclusions are given in Section 7.

2. The SRWNN structure

A detailed structure of SRWNN with N_{in} inputs, one output, and $N_{in} * N_w$ mother wavelets is illustrated in Fig. 1. The network inputs are passed directly to the second layer, i.e., the mother wavelet layer. 3. Note that different choices of wavelet prototypes are possible for use as the elementary building blocks when constructing WNN models. Specific choices can be applied effectively to certain problems but there is no systematic approach. However, in practice, these choices only lead to marginal differences. In our method, the first derivative of a Gaussian function $\varphi(x) = x.\exp(-0.5x^2)$ is selected as the mother wavelet function, which has the universal approximation property (Wai, 2002), although the proposed framework can easily be adapted to operate with other wavelet functions. According to the mother wavelet selected, each wavelet $\varphi_{r\ell}$ in the second layer, which is a translated and dilated version of the mother wavelet, is represented as:

$$\varphi_{r\ell}(z_{r\ell}) = z_{r\ell}\exp\left(-0.5 \cdot z_{r\ell}^2\right), \quad (1)$$
$$\forall z_{r\ell} = \left(\left(u_{r\ell} - t_{r\ell}\right)/d_{r\ell}\right), \quad r = 1 : N_w,\ \ell = 1 : N_{in},$$

where for discrete time k,

$$u_{r\ell}(k) = x_\ell(k) + \varphi_{r\ell}(k-1)\,\theta_{r\ell}, \quad r = 1 : N_w,\ \ell = 1 : N_{in}, \quad (2)$$

where $t_{r\ell}$ and $d_{r\ell}$ represent the wavelet translation and dilation parameters, respectively; and $\theta_{r\ell}$ is the weight of the self-feedback loop, which can be treated as a storage coefficient. The subscript $r\ell$ denotes the ℓth input term of the rth wavelet. The product of the wavelets is then calculated in the product layer as follows:

$$\psi_r = \prod_{\ell=1}^{N_{in}} \varphi(z_{r\ell}) = \prod_{\ell=1}^{N_{in}} \left[z_{r\ell} \cdot \exp\left(-0.5 \cdot z_{r\ell}^2\right)\right], \quad (3)$$
$$\forall\, r = 1 : N_w.$$

The SRWNN output υ is finally rendered by the output layer:

$$\upsilon(k) = \sum_{r=1}^{N_w} w_r \cdot \psi_r, \quad (4)$$

where w_r is the connection weight between the product and the output layers.

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