Electricity Quality Control of an Independent Power System Based on Hybrid Intelligent Controller

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Abstract. Wind power generation is gaining popularity as the power industry in the world is moving toward more liberalized trade of energy along with public concerns of more environmentally friendly mode of electricity generation. The weakness of wind power generation is its dependence on nature—the power output varies in quite a wide range due to the change of wind speed, which is difficult to model and predict. The excess fluctuation of power output and voltages can influence negatively the quality of electricity in the distribution system connected to the wind power generation plant. In this paper, the authors propose an intelligent adaptive system to control the output of a wind power generation plant to maintain the quality of electricity in the distribution system. The target wind generator is a cost-effective induction generator, while the plant is equipped with a small capacity energy storage based on conventional batteries, heater load for co-generation and braking, and a voltage smoothing device such as a static Var compensator (SVC). Fuzzy logic controller provides a flexible controller covering a wide range of energy/voltage compensation. A neural network inverse model is designed to provide compensating control amount for a system. The system can be optimized to cope with the fluctuating market-based electricity price conditions to lower the cost of electricity consumption or to maximize the power sales opportunities from the wind generation plant.

1 Introduction

Autonomous renewable energy systems such as wind, solar, and micro-hydro require control methods to maintain stability due to the real time variation of input energy and load, while maximizing the use of the renewable resources.

Since the early eighties, wind-Diesel energy conversion system (WDECS) have been accepted and widely used as electricity generating systems for remote areas. In such cases, the WDECS serves an entire isolated load and is responsible for maintaining frequency and voltage stability. The main driving force in WDECS design was to secure both fuel saving and reliable power supply. Usually, Diesel

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generator installed capacity is sized to meet the peak power demand, but is used in practice to supply power only when the wind power output is insufficient to meet the load demand [1].

The random power disturbances at the output of wind-turbine generators can cause relatively large frequency and voltage fluctuations. In a large grid, these fluctuations can have a little effect on the overall quality of the delivered energy. However, with weak autonomous networks, these power fluctuations can have a marked effect, which must be eliminated regardless of the penetration rate [2,3]. Hence, the control of the voltage and frequency of a weak wind-Diesel system is considered more challenging than in large grids.

In this paper, fuzzy-neural hybrid controller is proposed and applied for pitch control of wind turbine. Fuzzy logic is applied for designing a feedback controller. Neural network inverse model is designed for a dynamic feed-forward controller. Therefore, fast damping from fuzzy controller and fast reference tracking can be accomplished.

2 System Description

Fig. 1 shows the prototype of a wind-diesel hybrid power system [3].

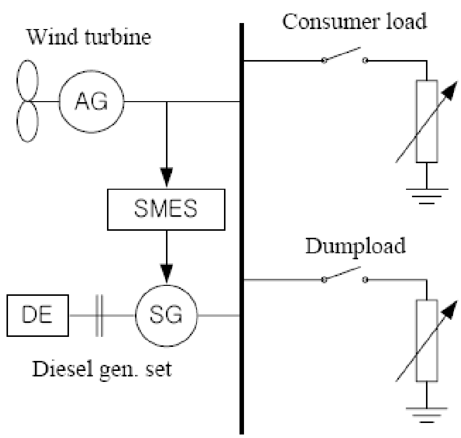

Fig. 1. The prototype of wind-diesel hybrid power system

Generator dynamics model consists of a synchronous machine driven by Diesel engine through flywheel and connected in parallel with an induction machine driven by a wind turbine.

Superconducting magnetic energy storage (SMES) [4] is a control unit for a synchronous machine. When there is a sudden rise in the demand of load, the stored energy is immediately released through power system. As the governor and pitch control mechanism start working to set the power system to the new operating condition, a SMES unit charges back to its initial value of current. In the case of sudden release of the loads, a SMES immediately gets charged towards its full value, thus absorbing some portion of the excess energy in the system, and as the system returns to its steady state, the excess energy absorbed is released and SMES current attains its normal value.

When wind power rises above the power set point and SMES unit is fully charged, the pitch control system begins operating to maintain an average power equal to the set point. The pitch control system consists of a power measurement transducer, a manual power set point control, a proportional plus integral feedback function, and hydraulic actuator, which varies the pitch of the blades. Variable pitch turbines operates efficiently over a wider range of wind speeds than fixed pitch machines. The study in this paper is focused on the designing of turbine blade pitch controller based on fuzzy logic and neural network.

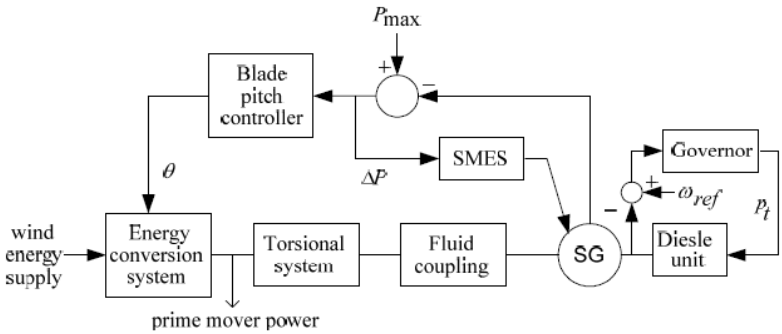

Fig. 2. The basic configuration of WDECS

3 Fuzzy-Neural Hybrid Control

3.1 Feedback Controller Based on Fuzzy Logic

Fuzzy control systems are rule-based systems in which a set of fuzzy rules represents a control decision mechanism to adjust the effects of certain system conditions. Fuzzy controller is based on the linguistic relationships or rules that define the control laws of a process between input and output [5,6]. This feature draws attention toward a fuzzy controller due to its nonlinear characteristics and no need for an accurate system modeling. The fuzzy controller consists of rule base, which represents a fuzzy logic quantification of the expert's linguistic description of how to achieve good control, fuzzification of actual input values, fuzzy inference, and defuzzification of fuzzy output.

In this paper, total of 121 rules are used for the power system under study. The general form of the fuzzy rule is given in the *if-then* form as follows:

$$\text{if } x(k) \text{ is } A \text{ and } \Delta x(k) \text{ is } B, \text{ then } y(k) \text{ is } C, \tag{1}$$

where $x, \Delta x$ are the input signals, y is controller output and A, B, C indicate the linguistic variables.

The linguistic values extracted from the experimental knowledge are NH (negative high), NL (negative large), NB (negative big), NM (negative medium), NS (negative small), ZE (zero), PS (positive small), PM (positive medium), PB (positive big), PL (positive large), PH (positive high).

In the power system under study, generator power deviation (ΔP) is chosen for the input of a fuzzy controller. The linguistic descriptions provide experimental expressions of the expert for a control decision-making process and each linguistic variable is represented as triangular membership functions shown in Fig. 3 and Fig. 4. In the fuzzy controller, the input normalization factors are chosen to represent the proper membership quantifications of linguistic values. In addition, normalization factors can be used to yield the desired response of the fuzzy controller. g_1, g_2 stand for a normalization factor for input of fuzzy controller and g_0 stands for a denormalization factor for output of fuzzy controller. Fig. 3 shows the membership function for error and change in error, Fig. 4 depicts the membership function for output.

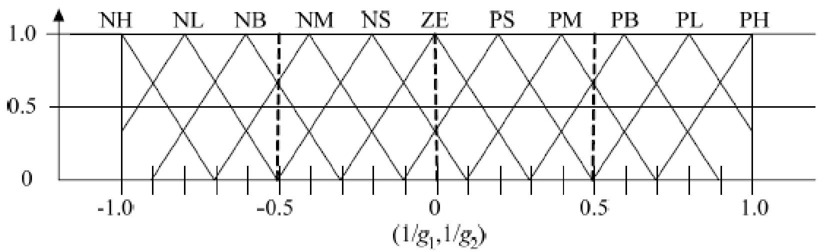

Fig. 3. Membership function of error and change in error

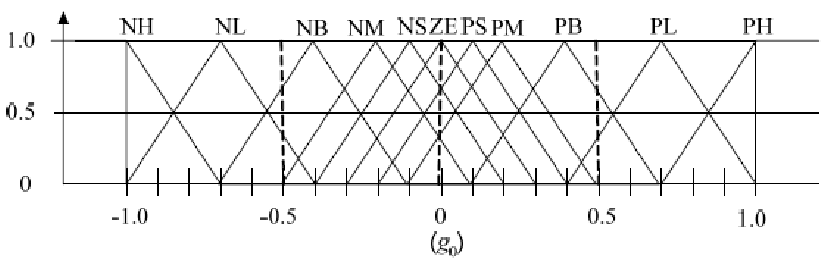

Fig. 4. Membership function of output

In Fig. 3 and Fig. 4, the membership functions are overlapped with each other to smooth a fuzzy system output and a fuzzy controller is designed to regulate a system smoothly when an error and a change in error are near zero. The rules are established to control transient stability problem for all possible cases. It is required to find the fuzzy region for the output for each rule. The centroid or the center of gravity defuzzification method [6] is used which calculates the most typical crisp value of the fuzzy set and "y is C" in (1) can be expressed by (2).

$$y = \frac{\sum_i \mu_A(y_i) \times y_i}{\sum_i \mu_A(y_i)} \tag{2}$$

where μ_A is a degree of membership function.

3.2 Feedforward Compensator Based on Neural Network Inverse Model

In [7], a two layer neural network is applied to obtain a dynamic feedforward compensator. In general, the output of a system can be described with a function or a mapping of the plant input-output history [7,8]. For a single-input single-output (SISO) discrete-time system, the mapping can be written in the form of a nonlinear function as follows:

$$y(k+1) = f(y(k), y(k-1), \ldots, y(k-n), u(k), u(k-1), \ldots, u(k-m)). \tag{3}$$

Solving for the control, (3) can be represented as following:

$$\begin{aligned} u(k) = g(&y(k+1), y(k), y(k-1), y(k-2), \ldots, y(k-n), \\ &u(k-1), u(k-2), u(k-3), \ldots, u(k-m)), \end{aligned} \tag{4}$$

which is a nonlinear inverse mapping of (3). The objective of the control problem is to find a control sequence, which will drive a system to an arbitrary reference trajectory. This can be achieved by replacing $y(k+1)$ in (4) with reference output y_{ref} or the temporary target $y_r(k+1)$ evaluated by

$$y_r(k+1) = y(k) + \alpha(y_{ref} - y(k)), \tag{5}$$

where α is the target ratio constant ($0 < \alpha \leq 1$). The value of α describes the rate with which the present output $y(k)$ approaches the reference output value, and thus has a positive value between 0 and 1.

In Fig. 5, the training mode is introduced, where Δ denotes the vector of delay sequence data. Fig. 6 shows the neural network inverse model (NNIM) in training mode. All activation functions in hidden layer are *tanh(x)* (described as f_j in Fig. 5) and the activation function in output layer is *x* (depicted as F_i in Fig. 6).

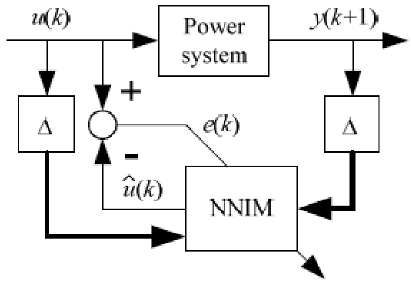

Fig. 5. Training mode of NNIM

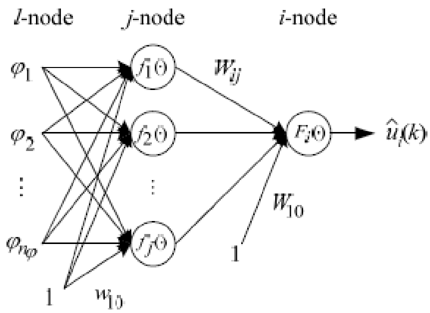

Fig. 6. Neural network inverse model (NNIM)

$$\hat{u}_i\ (k) = F_i \left[\sum_{j=1}^{n_h} W_{ij} f_j \left(\sum_{l=1}^{n_\varphi} w_{jl} \overline{\varphi} + w_{j0} \right) + W_{i0} \right], \tag{6}$$

where

$$\begin{aligned}\overline{\varphi} &= [\,y(k+1), y(k), \ldots, y(k-n), u(k-1), \ldots, u(k-m)]^T \\ &= [\varphi_1, \varphi_2, \varphi_3, \ldots, \varphi_{n_\varphi}\,]^T\end{aligned}$$

w_{jl} : weight between input and hidden layer,

n_h, n_φ : number of hidden neurons and external input,

W_{ij} : weight between hidden and output layer.

The above NNIM is trained based on the input-output data described in Fig. 5. To train the neural network inverse model, Levenberg-Marquardt method is applied which is fast and robust [7,8]. The trained NNIM is used as a feedforward compensator.

The total control scheme is indicated in Fig. 7. Δ denote the vector of delay sequence data. The total control input is $u(k) = u_{fb}(k) + u_{ff}(k)$. $u_{fb}(k)$ is the output of fuzzy controller and the output of the feedforward controller, $u_{ff}(k)$ can be represented as following:

$$\begin{aligned} u_{ff}(k) = g(&y_r(k+1), y_r(k), y_r(k-1), \ldots, y_r(k-n), \\ &u_{fb}(k-1), u_{fb}(k-2), \ldots, u_{fb}(k-m)). \end{aligned} \tag{7}$$

In Fig. 7, once a signal of a feedforward compensator is given into the control system, the fuzzy controller provides a signal that minimizes the inputs of controller, which contains a compensated system output. This control scheme can be a soft way of generating a control signal to minimize the tracking error and improve a system performance in the point of view of giving compensating signal in advance [9]. This implies the optimization of existing controller, which is the main purpose of a feedforward controller in a hybrid control scheme.

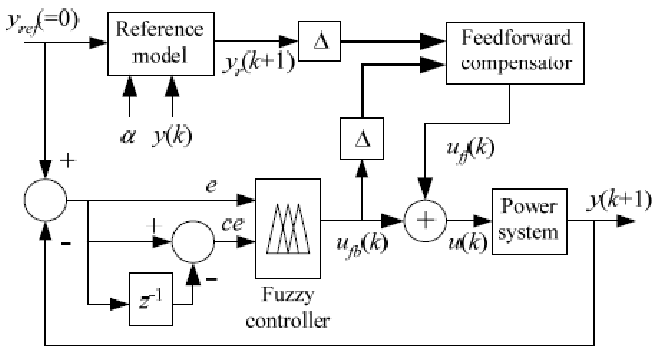

Fig. 7. The fuzzy-neural hybrid control

4 Simulation

First, a fuzzy controller is designed for a feedback controller and an NNIM is obtained for a feedforward compensator. In this paper, α is 0.1 and g_1, g_2, g_0 are 5, 50, and 5 by trial and error, respectively. Levenberg-Marquardt method is applied to train an NNIM. The sampling time is 0.01 sec. for the proposed control action.

The proposed fuzzy-neural hybrid controller (Fuzzy+NNIM) is tested in a wind-Diesel autonomous power system (WDAPS). Two cases are considered: first, the sudden step load increase of 0.01 [p.u.] and SMES is in discharging mode (rectifier) mode). Second, the SMES fully discharged and there is sudden step load increase. In this case, SMES is in recharging mode (inverter mode).

4.1 Case 1: A Sudden Step Load Increase

A load is suddenly increased by 0.01 [p.u.]. The SMES releases the charged current (2 p.u.). The governor and pitch mechanism start operating for charging current of SMES and damping of WDAPS. Fig. 8 shows improvement of the system frequency oscillations and power deviations.

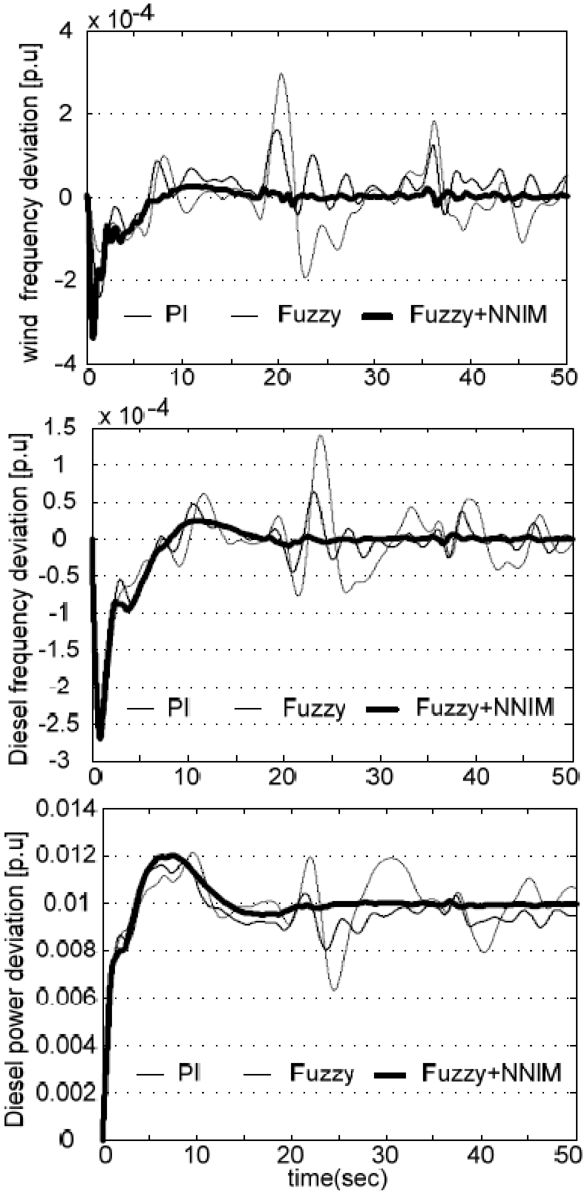

Fig. 8. Comparison of system response among PI, Fuzzy, and Fuzzy-NNIM

4.2 Case 2: Sudden Step Load Increase with Fully Discharged SMES

In this case, the SMES is fully discharged (0 p.u.). Then, the SMES needs to recharge current to set point (2 p.u.). The wind power generation from the wind turbine is assumed as not sufficient. Fig. 9 also shows that the Fuzzy-NNIM performance is much better than the PI and the Fuzzy controller.

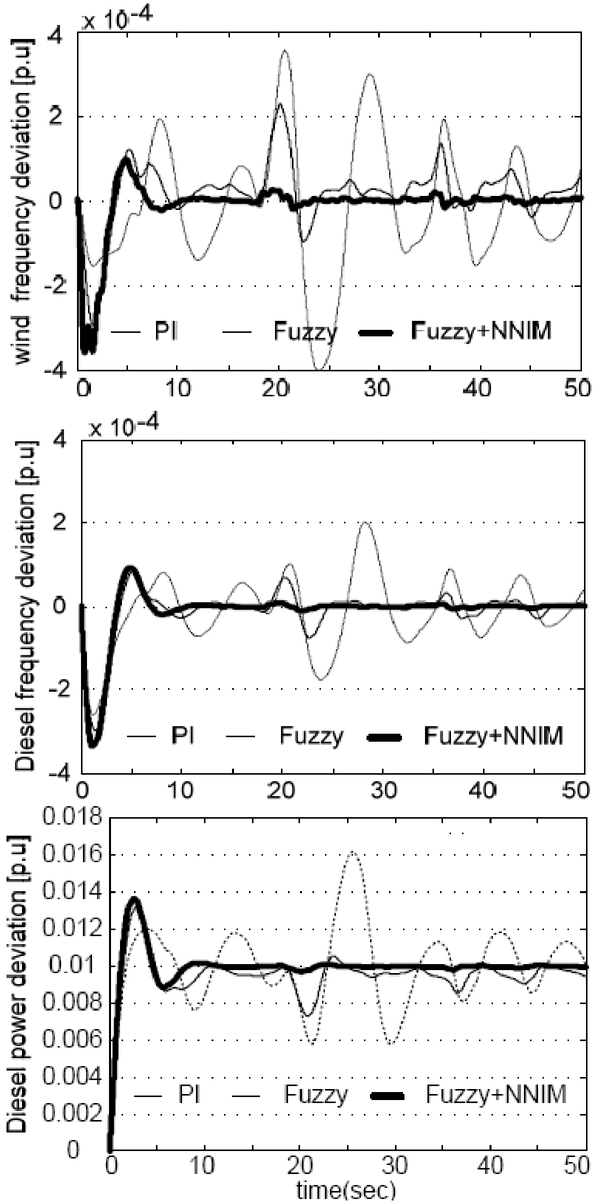

Fig. 9. Comparison of system response among PI, Fuzzy, and Fuzzy-NNIM

5 Conclusions

In this paper, the fuzzy-neural hybrid controller for electricity quality control of wind power generation plants is presented. The main idea of hybrid control is that the ynamic feedforward control can be used for improving the reference tracking while feedback is used for stabilizing the system and for suppressing disturbances. Feedforward controller is a neural network inverse model (NNIM), which is trained by Levenberg-Marquardt method and feedback controller is a fuzzy controller. The Fuzzy-NNIM was tested in a wind-Diesel autonomous power system and compared with the conventional PSS and the fuzzy controller. In all cases, the Fuzzy-NNIM out-performed the conventional PSS and the fuzzy controller. The Fuzzy-NNIM provides quite small frequency deviation and fuel saving of Diesel system. Thus, the usefulness of Fuzzy-NNIM based controller design is demonstrated.

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