Robust Control for AC-Excited Hydrogenators System Using Adaptive Fuzzy-Neural Network

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Abstract. The AC-excited hydrogenerator (ACEH) is a novel type of hydraulic generation system. Concern about its integrative control strategy is increasing, owing to the features of uncertain and nonlinear as well as parameters coupling and time-variation for three parts of water flux, hydroturbine and generator. A cascade-connected self-adaptive fuzzy-neural network control strategy is proposed, which the former controller uses a self-tuning fuzzy algorithm with the intelligent weight function rulers, the latter adopts a self-adaptive neural network controller based on dynamical coupling characteristics of controlled plants. By comparison with traditional PID control, Simulation results have shown that this hydrogenerators system appears good robustness against load disturbance and system parameters uncertainty.

1 Introduction

The wide range of variable speed constant frequency (VSCF) operation, the capability of active and reactive power control make the AC-excited generator (ACEG) attractive for variable speed hydroelectric generators as well as wind power conversion system [1-4]. The stator of ACEG connects the grid directly and provides for variable speed operation by using a partially rated converter on the rotor side, which brings to some superior performances such as good power system stability, VSCF generation, stator active and reactive power regulation independently [1-6]. So the AC-excited hydrogenerator (ACEH) system can be operated round the optimal unit speed of hydroturbine by some suitable control strategies, when the water level or water flux is changed. The hydraulic efficiency and power system stabilization can be improved. The typical connection of ACEH system can be seen in [1,2,4].

The ACEH system is a more complex system including water, hydroturbine and generator portion as well as hydrotubine governing controller and generator excited system. Considering the water hammer effect, ACEH system has some distinct characteristics such as the system's nonlinear and great inertia, parameters variation, multi-variable characteristics. In order to develop the excellent operational performances of this hydrogenerator system, it is very important and necessary to study its comprehensive robust control strategies. Some methods and techniques have been researched to solve the ACEG excited control problem. Some of these methods are traditional vector control techniques based on stator flux or air-gap flux oriented frame [1-3], it is difficult to achieve the robust and stable control performances when system parameters are uncertain. To overcome the aforementioned drawbacks, the fuzzy logical control is also proposed and applied in [6], even though this kind of method is independent of the accurate plant models, it neglects the influence of the prime mover such as hydroturbine governing system.

To achieve excellent operational characteristics of ACEH system, a cascade-connected self-adaptive fuzzy-neural network (FNN) control strategy is proposed in this paper. Robust characteristics of ACEH system is studied and simulated with Matlab/Simulink.

2 Design of Fuzzy-Neural Network Controller

It is well known that the neural network technique has emerged as an attractive and powerful tool to control a wide class of complex nonlinear dynamic systems [7-13]. Considering the features of robustness and rapid convergence of fuzzy control [7,9], a novel approach of cascade–connected FNN controller is presented based on the dynamical coupling algorithm, the block diagram of which is shown in Fig. 1.

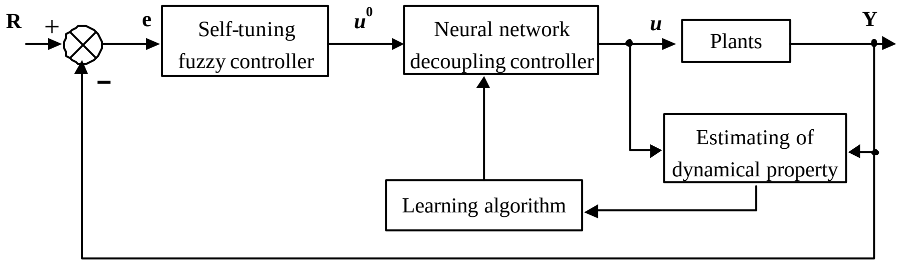

Fig. 1 Block diagram of adaptive FNN control system

This controller structure is made up of self-tuning fuzzy controller and self-adaptive neural network decoupling controller, the former is crucial to the system dynamical property, the latter is impact on the multivariable decoupling performances [8]. In the formerly fuzzy controller, the output vectors $\boldsymbol{u}^0=\{u_1^0, u_2^0,\dots, u_n^0\}$ are obtained by the error vectors $\boldsymbol{e}=\{e_1, e_2,\dots, e_n\}$. In the neural network controller, the output vectors $\boldsymbol{u}=\{u_1, u_2,\dots, u_n\}$ are achieved by the weights adaptation law, which is based on estimating the dynamical multivariable coupling property of the controlled plants.

2.1 Algorithm of Self-tuning Fuzzy Controller

In the traditional fuzzy control, the control rules and fitness function play important role in the system performances; however, the appropriate control rules and fitness function are difficult to achieve for the system uncertainty and complexity [9,11,13]. Hence, the fuzzy algorithm is adopted based on continuous intelligent weight function, the structure block diagram of the single loop is shown in Fig. 2.

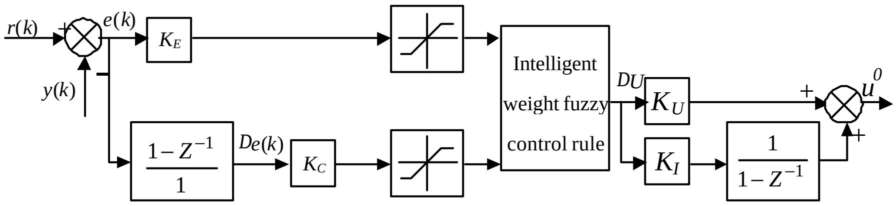

Fig. 2 Block of fuzzy controller with continuous intelligent weight functions

The fuzzy values of error $e(k)$ and differential error $\boldsymbol{\Delta}\, e(k)$ are acquired as follows

$$\left.\begin{aligned} E &= K_E \cdot e(k) \\ E_C &= K_C \cdot \Delta e(k) \end{aligned}\right\} \tag{1}$$

Where K_E is error coefficient, K_C is differential error coefficient.

The self-tuning control rule is presented by the two-weight coefficients a_e, a_c

$$\left.\begin{aligned} a_e &= |E| / (|E| + |E_C| + e) \\ a_C &= |E_C| / (|E| + |E_C| + e) \end{aligned}\right\} \tag{2}$$

Where e is a discretionary small positive constant.

The self-tuning rule of fuzzy controller is updated as follows [13]

$$\Delta U = a_e E + a_C E_C \tag{3}$$

The output of the self-tuning fuzzy controller is obtained as follows

$$u_i^{\,0}(k) = K_U \Delta U + K_I \cdot \sum \Delta U \tag{4}$$

Where K_U is proportional coefficient, K_I is integral coefficient.

2.2 Self-adaptive neural network controller

Three input-output structure of the self-adaptive neural network controller is shown in Fig. 3, the output vector of neural network controller is given as follows.

$$u_j(k) = \sum_{i=1}^{n} w_{ij}(k) u_i^0(k) \quad (j = 1, 2, 3, \cdots, n) \tag{5}$$

Where $\boldsymbol{\omega}_{ij}(k)$ is weight value, $u_i^{\,0}(k)$ is output of the above fuzzy controller.

Considering the minimization of the mean square error between the factual output and the desired output, the system cost function is defined as follows

$$E(k) = \frac{1}{2} \sum_{i=1}^{n} (r_i(k) - y_i(k))^2 \qquad i = 1, 2, \cdots, n \tag{6}$$

The weights of the neural network controller is updated as follows:

$$w_{ij}(k+1) = w_{ij}(k) - h \frac{\partial E(k)}{\partial w_{ij}(k)} = w_{ij}(k) + h \sum_{i=1}^{n} (r_i(k) - y_i(k)) \frac{\partial y_i(k)}{\partial u_j(k)} u_i^0(k) \tag{7}$$

Where h is the learning-rate parameter; $\frac{\partial y_i(k)}{\partial u_j(k)}$ is dynamical coupling degree of the j^{th}

input to the i^{th} output value.

3 FNN Control for AC-Excited Hydrogenators System

3.1 Description of Control System for AC-Excited Hydrogenerators

In order to control independently active and reactive power for this hydrogenerator, the stator active power P_1, active power Q_1 and slip s are considered as input variables of the controller, respectively, the excited voltage components U_{rd}, U_{rq} based on synchronous rotational frame and hydrotubine regulation valve u are taken as output variables. The proposed FNN control system for ACEH system is shown as Fig. 3.

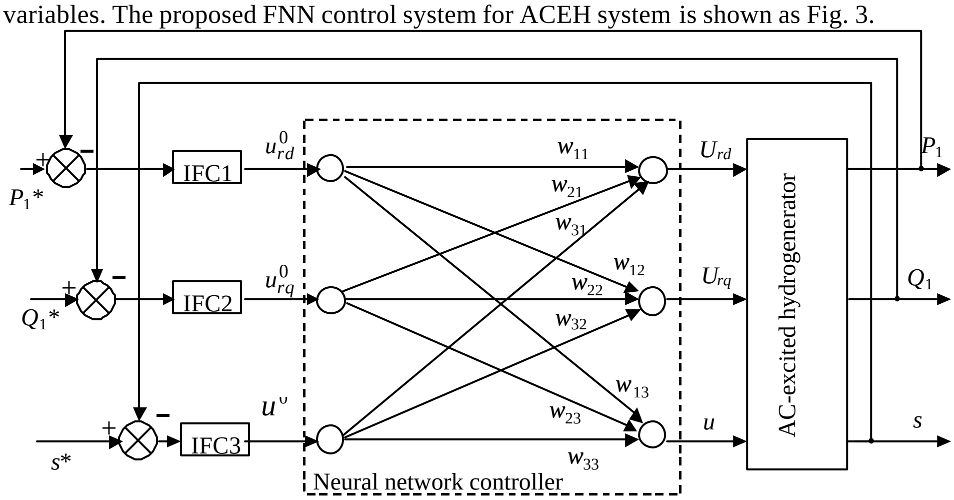

Fig. 3 Block of FNN control for AC-excited hydrogenerator system

As it can be seen, IFC1, IFC2 and IFC3 denote self-tuning fuzzy controller based on intelligent weight function, respectively, the mathematical models of ACEH are described in [2,4], where P_1*, Q_1* and s* denote the given value of stator active power, stator reactive power and slip, respectively.

3.2 Simulation

In order to testify the FNN control quality of the ACEH system, the operation performances of robustness against load disturbance and system parameters variation and uncertainty are simulated, respectively. The base region of controlled variables are set with [-1,1] in fuzzy controller, the initial learning-rate of neural network controller is set to 0.01, the initial weights are given as $w_{ij}(0) = 1 \quad (i = j)$; $w_{ij}(0) = 0 \quad (i \neq j)$. The main parameters of ACEH are described in Table 1.

Table 1. Main parameters of AC-excited hydrogenerator systems

Main parameters	Value
stator resistance R_s (p.u.)	0.00706
rotor resistance R_r (p.u.)	0.005
stator leakage inductance X_s (p.u.)	0.171
rotor leakage inductance X_r (p.u.)	0.156
mutual inductance X_m (p.u.)	2.9
system moment of inertia H (s)	5.04
time constant of hydraulic pressure driver system T_y (s)	5
time constant of water flux inertia T_w (s)	2

A. *Robustness against Load disturbance*

The water flux variation and grid power fluctuations can be considered as load disturbance DP_m. When DP_m is 0.3 p.u. from the time of 2 to 3 seconds, system operational performances are shown and compared as Fig. 4. (The thick real curve denotes the simulation result of the FNN control, while the thin real curve denotes it of the traditional PID). As it can be seen that the generating system has good robust ability with the FNN control, however it occurs more fluctuation of power and speed by using the conventional PID control.

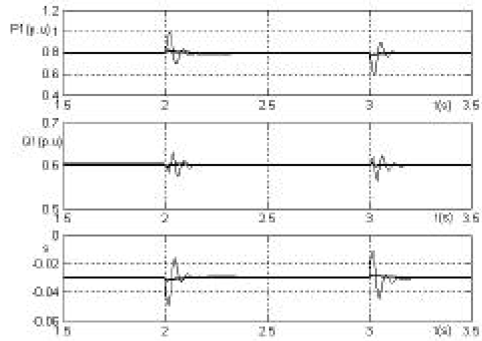

Fig. 4 Characteristics of against load disturbances

B. Robustness against parameters variation

The rotor resistance value is changed to 2 times with the original value in ACEG models, which is kept by original value in system control models, the active power regulation characteristics with rotor resistance variation is shown in Fig. 5. In the same way, when the constant time of water flux inertia T_w is set to 10 times with the

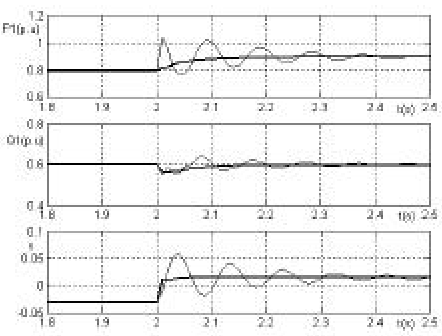

Fig. 5 Robustness when R_r is uncertain

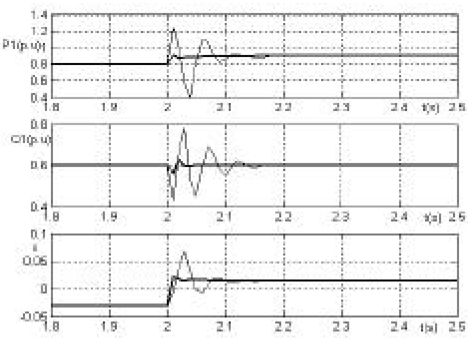

Fig. 6 Robustness when T_w is uncertain

original value, the active power regulation is also shown in Fig. 6. From the two figures, it can be seen that the ACEH system performance is seldom affected by the generator parameters variation or water flux time constant uncertainty by using FNN control, however the system occurs more fluctuation or unstable by using the conventional PID control, which is usually dependent on accurate plants models [13].

4 Conclusion

Based on the complex characteristics of uncertain and nonlinear as well as parameters coupling and time-variation for ACEH system, the integrated control strategies of a cascade-connected self-adaptive FNN is proposed in this paper. The strong robustness is achieved by simulation, no matter what is the load disturbance and uncertainty of generator rotor resistance parameter or water flux time constant.

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