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Unified power flow controller based on fuzzy neural network

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Abstract: In order to allay the influence of both the experience in the design of the fuzzy rule of unified power flow controller (CPFC) and the UPFC performance with respect to the power system parameter variations, fuzzy neural networks are applied to UPFC in this paper. First, the control strategy of UPFC is briefly introduced. Second, the constructions of self-organizing fzzy neural network and fuzzy neural network based on genetic algorithms are presented. Third, the self-organizing fuzzy neural network, the fuzzy neural network based on genetic algorithms and the control strategy of UPFC are used to design two kind of UPFC. Finally, the simulating examples, done on MATLAB, are adopted to demonstrate that the proposed approaches of these UPFC will be effective.

Key words: unified power flow controller(UPFC); self-organizing fuzzy neural networks; genetic algorithms; electric current forecasting

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基于模糊神经网络的统一潮流控制器

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摘要: 为了减少先验知识对统一潮流控制器中模糊规则的设计和电力系统参数的变化对统一潮流控制器性能的影响,文中采用模糊神经网络来设计统一潮流控制器.为此首先简单介绍了统一潮流控制器的控制策略,然后阐述了自组织模糊神经网络和基于遗传算法的模糊神经网络的构造方法,接着将自组织模糊神经网络、基于遗传算法的模糊神经网络结合统一潮流控制器的控制策略应用于两种统一潮流控制器.最后通过 MATLAB 仿真例子来验证:这两种统一潮流控制器的设计方法的有效性.

关键词: 统一潮流控制器; 自组织模糊神经网络; 遗传算法; 电流预测

1 Introduction

Unified power flow controller (UPFC) can effectively control both real power flow and reactive power flow of transmission system, provide voltage support, and increase transmission line capacity and transient stability of power system. Most of the existing work on UPFC mainly deal with how to setup the mathematical model[1~5] and discuss how it affects the stability of power system[6,7]. There exist few prior studies on UPFC's new control techniques, especially the fuzzy neural network control. Recently, the application of traditional control techniques to UPFC is introduced in [3,5,7], and PID control and fuzzy control are applied to UPFC respectively. However, PID and traditional fuzzy controllers have shortcomings in themselves. The algorithm of traditional PID control cannot work well when the plant parameters change. The fuzzy control can make ratiocination, but it excessively depends on the foreknowledge and the experience. These disadvantages affect their extensive applications to UPFC. On the other hand, in the learning and training algorithms, genetic algorithms can make global search in the whole solution space, but its search speed is too low to meet the need of quick UPFC, and gradient descent method (GDM) has rapidity of convergence, but it easily converges to local optimum solution. In order to overcome the above shortcomings, two kinds of UPFC are designed here. Both of them consist of two control algorithms. The first control algorithm, which regulate active power flow and reactive power flow, are uniformly based on electric current forecasting, *d-q* axis decoupled control and voltage-space-vector pulse-width modulation (VSVPWM) technique. The second control algorithm, which maintain desired voltage profile of bus and capacitor terminals, are different for each kind of UPFC. That for the first kind of UPFC is the combination of self-organizing fuzzy neural network, *d-q* axis decoupled control and VSVPWM. That for the second kind of UPFC is the combination of fuzzy neural network, to which the genetic algorithms is applied for searching

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parameters' "quasi-optimum value" offline and the GDM is applied for speeding up the rate of convergence online, d-q axis decoupled control and VSVPWM. The numerical simulation shows that these UPFC can effectively control real power flow and reactive power flow of transmission system, maintain desired voltage profile of bus and on capacitor terminals, and that the design of UPFC does not depend on the mathematical model of power system.

2 Unified power flow controller

The plant is a single-machine infinite power system with UPFC. UPFC consists of a series transformer, a shunt transformer, two inverters and a direct current capacitor. The first inverter is connected to the series transformer, and the second inverter is connected to the shunt transformer. The first inverter produces voltage with adjustable magnitude and phase, regulating the real power flow and the reactive power flow of transmission system. The second inverter also produce voltage with adjustable magnitude and phase, maintaining zero cross-over value of reactive power between the UPFC and transmission line, and the desired voltage profile of capacitor. It also holds the attachment voltage value in constant through injecting and generating reactive power. The capacitor only injects or generates energy and transmits power. The plant's mathematical model and control strategy are depicted as follows.

2.1 Mathematical model of the plant

The mathematical model of the plant consists of synchronous motor equations, d-q axes decoupled control equations of series transformer and shunt transformer, and dynamic equations of capacitor terminal voltage.

Synchronous motor equations are second order differential equations.

After discretized with forward-difference method, the d-q axes decoupled control equations of series transformer is

$$u_{sed}(k) = u_{sd}(k) - u_{td}(k) + R_z i_{sed}(k) - \omega L_z i_{seq}(k) + L_z[i_{sed}(k+1) - i_{sed}(k)]/T_s, \tag{1}$$

$$u_{seq}(k) = u_{sq}(k) - u_{tq}(k) + R_z i_{seq}(k) + \omega L_z i_{sed}(k) + L_z[i_{seq}(k+1) - i_{seq}(k)]/T_s \tag{2}$$

and the d-q axes decoupled control equations of shunt transformer is

$$u_{shd}(k) = u_{td}(k) - R_{sh} i_{shd}(k) + \omega L_{sh} i_{shq}(k) - L_{sh}[i_{shd}(k+1) - i_{shd}(k)]/T_s, \tag{3}$$

$$u_{shq}(k) = u_{tq}(k) - R_{sh} i_{shq}(k) - \omega L_{sh} i_{shd}(k) - L_{sh}[i_{shq}(k+1) - i_{shq}(k)]/T_s. \tag{4}$$

By considering the charge and discharge process of capacitor, the dynamic equation of capacitor terminal voltage is

$$\mathrm{d}u_d/\mathrm{d}t = (P_{sh} - P_{se})/Cu_d. \tag{5}$$

The parameters of equations (1) ~ (5) can be described as follows: u_s is the infinite system voltage, u_t is the bus voltage, u_d is the capacitor terminal voltage, R_{se}, L_{se}, u_{se} are respectively the resistance, the inductive resistance and the voltage of series transformer, R_{sh}, L_{sh}, u_{sh} are respectively the resistance, the inductive resistance and the voltage of shunt transformer, R_l, L_l are respectively the line resistance and the line inductive resistance, $R_z = R_{se} + R_l$, $L_z = L_{se} + L_l$, C is the capacitance of capacitor, P_{sh}, P_{se} are respectively the injecting and generating real power of capacitor, T_s is sampling period, ω is power system frequency.

2.2 Control strategy of unified power flow controller

The control strategy of UPFC includes the control technique of the switching element of inverter and the control scheme of power flow and voltage.

The switching element of UPFC's inverter uses VSVPWM technique. The key part of VSVPWM is the conversion from the ideal three-phase voltage source to d-q axis two-phase rotational coordinates, please refers to [3,8] for the conversion formula and operation process.

The control strategy of power flow and voltage of proposed UPFC is divided into two sections. The first section, which adopts electric current forecasting and d-q axis decoupled control[3], adjusts the real power P and reactive power Q. The second section, which uses fuzzy neural network and d-q axis decoupled control adjusts the bus voltage and capacitor terminal voltage. The detail control method is shown as Figs.1,2.

The decoupled control scheme of real power P and reactive power Q is shown in Fig.1.

For

$$S = P + jQ = \bar{V}\bar{I} = (u_d + ju_q)(i_d - ji_q). \tag{6}$$

It can be obtained

$$\begin{aligned} i_d^{obj} &= (u_d P + u_q Q)/(u_d^2 + u_q^2), \\ i_q^{obj} &= (u_q P - u_d Q)/(u_d^2 + u_q^2). \end{aligned} \tag{7}$$

In formula (1),(2), the predictive value $i_{sed}(k+1)$ and $i_{seq}(k+1)$ are $i_{sed}(k+1) = i_d^{obj}$, $i_{seq}(k+1) = i_q^{obj}$.

The control scheme of bus voltage u_t and capacitor terminal voltage u_d is shown in Fig. 2, where the input variables of multi-input and single-output FNN1 are the capacitor terminal voltage error $\Delta u_d = u_d^{\text{obj}} - u_d$ and its change rate $\mathrm{d}\Delta u_d/\mathrm{d}t$, the output variable is $i_{\text{sh}d}^{\text{obj}}$; the input variables of multi-input and single-output FNN2 are bus voltage error $\Delta u_t = u_t^{\text{obj}} - u_t$ and its change rate $\mathrm{d}\Delta u_t/\mathrm{d}t$, the output variable is $i_{\text{sh}q}^{\text{obj}}$. In Eqs. (3),(4), the predictive value $i_{\text{sh}d}(k+1)$ and $i_{\text{sh}q}(k+1)$ are $i_{\text{sh}d}(k+1) = i_{\text{sh}d}^{\text{obj}}, i_{\text{sh}q}(k+1) = i_{\text{sh}q}^{\text{obj}}$.

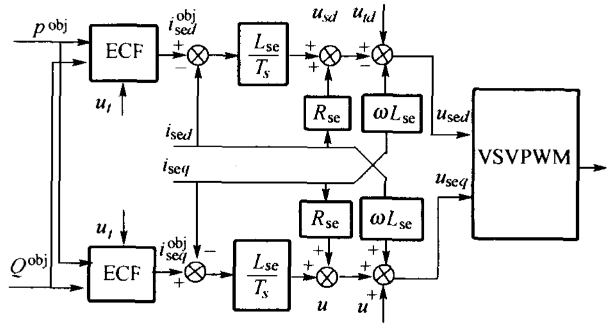

Fig. 1 Control scheme in serial part

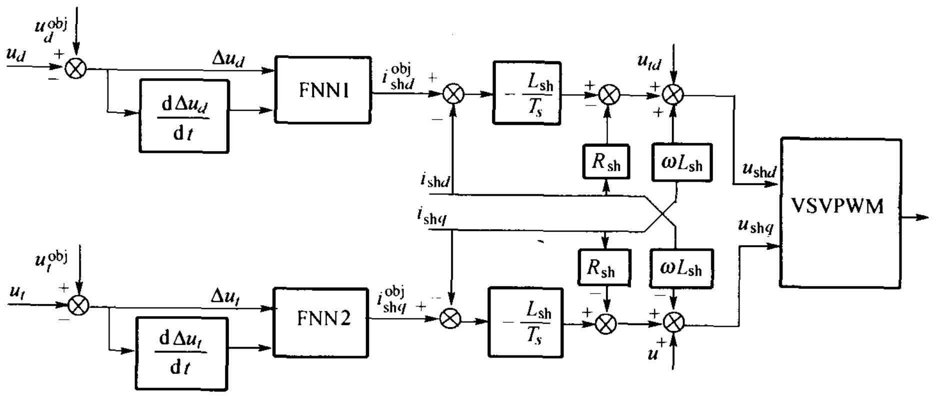

Fig. 2 Control scheme in shunt part

3 Self-organizing fuzzy neural networks

In Fig.2, FNN1, FNN2 of the first UPFC are self-organizing fuzzy neural networks SOFNN1, SOFNN2. This SOFNN consists of input layer, fuzzifier layer, fuzzy logic layer, fuzzy normalized layer and output layer, and its connecting weight coefficient only exists between fuzzy normalized layer and output layer. The structure and node connection is dynamically varying. The detail description about self-organizing fuzzy neural networks was given in [9].

The learning of SOFFN implements the training of the parameters of membership function and connecting weight coefficient. Their training algorithms adopt gradient decent methods, the objective function is

$$J = \frac{1}{2}(y_i^{\text{obj}} - y_i)^2, \tag{8}$$

where, for SOFNN1, y_i^{obj} is u_d^{obj}, y_i is u_d; for SOFNN2, y_i^{obj} is u_t^{obj}, y_i is u_t.

The training algorithms of the center point value and width $m_{i,j}, \sigma_{i,j}$ (that is mean and variance) of Gaussian membership functions is

$$m_{i,j}(k+1) = \begin{cases} m_{i,j}(k) + \lambda_1 (y_i^{\text{obj}}(k) - y_i(k)) \operatorname{sgn}(\dfrac{\partial y_i(k)}{\partial u}) \displaystyle\sum_l \frac{w_l - u}{\sum_l c_l^{(3)}} c_l^{(3)} \frac{2(x_i - m_{i,j})}{\sigma_{i,j}^2}, & \text{node } i \text{ connects with node } 1, \\ m_{i,j}(k), & \text{node } i \text{ does not connect with node } 1, \end{cases} \tag{9}$$

$$\sigma_{i,j}(k+1) = \begin{cases} \sigma_{i,j}(k) + \lambda_2 (y_i^{\text{obj}}(k) - y_i(k)) \operatorname{sgn}(\dfrac{\partial y_i(k)}{\partial u}) \displaystyle\sum_l \frac{w_l - u}{\sum_l c_l^{(3)}} c_l^{(3)} \frac{2(x_i - m_{i,j})}{\sigma_{i,j}^3}, & \text{node } i \text{ connects with node } 1, \\ \sigma_{i,j}(k), & \text{node } i \text{ does not connect with node } 1, \end{cases} \tag{10}$$

where $\lambda_1 = \eta_1 |\partial y_i/\partial u|, \lambda_2 = \eta_2 |\partial y_i/\partial u|$, η_1, η_2 are the varying learning factors, λ_1, λ_2 are the actual learning factors, which are constant.

The connecting weight coefficient training algorithm of

SOFNN is as follows:

$$w_i(k+1) = w_i(k) + \lambda_3(y_i^{\text{obj}}(k) - y_i(k))\text{sgn}(\partial y_i(k)/\partial u)c_j^{(4)}. \tag{11}$$

$\lambda_3 = \eta_3|\partial y_i/\partial u|$, η_3 is the varying learning factor, λ_3 is the actual learning factor, which is constant.

As shown in formula (9) ~ (11), the training algorithms of SOFNN1 and SOFNN2 only need the variable of $\text{sgn}(\partial y_i(k)/\partial u)$, they do not need exact mathematical model of the plant.

4 Fuzzy neural networks based on genetic algorithms

Genetic algorithm is a global stochastic optimum search method based on organic evolution. Its search process does not depend on initial value, and the search result is a global optimum value; however, the speed of convergence of genetic algorithms is low. GDM is actually an algorithm that obtains the optimum solution in local area. If fuzzy neural networks are trained by GDM, their parameters may be locally optimum, and their initial value easily affects the convergence of training process during the optimization of parameters. Compared with the genetic algorithm, GDM has higher speed of convergence, it is more suitable for the system required high control speed. Here, genetic algorithm is adopted to train fuzzy neural networks offline, which obtains the "quasi-optimum value" of parameters, then the GDM is used to trained fuzzy neural networks online, which obtains the "optimum value", at last the obtained fuzzy neural networks are applied to the second UPFC to improve the self-learning capability and robustness. FNN1 and FNN2 of the second UPFC shown in Fig.2 are fuzzy neural networks based on genetic algorithms GAFNN1 and GAFNN2.

GAFNN has the same structure as SOFNN, and their node functions are also the same, but GAFNN nodes and their connection are invariable. The premise of fuzzy logic rule behaves Gaussian membership function, and the conclusion variable is the connecting weight coefficient. The node function of input layer, fuzzifier layer, fuzzy logic layer, fuzzy normalized layer and output layer is $c_i^{(1)} = x_i$, $c_{i,j}^{(2)} = \exp\{-(c_i^{(1)} - m_{i,j})^2/\sigma_{i,j}^2\}$, $c_i^{(3)} = c_{1,k}^{(2)}c_{2,l}^{(2)}, \cdots, c_{n,m}^{(2)}$, $c_i^{(4)} = c_i^{(3)}/\sum_{j=1}^{N(3)} c_j^{(3)}$, and $c^{(5)} = \sum_{i=1}^{N(4)} c_i^{(4)}w_i$, respectively, The connecting weight coefficient only exists between fuzzy normalized layer and output layer. The training process is depicted as follows.

4.1 Offline learning algorithm

The initial values of fuzzy logic parameters ($m_{i,j}\sigma_{i,j}w_i$) in GAFNN are trained offline by genetic algorithm. The process is: firstly to choose individual adaptability function and objective function, and to determine decision variables and their constraint conditions; secondly to choose the encoding and decoding methods of decision variables; thirdly to choose basic genetic operators such as regeneration, crossing and aberrance for the individual operation; and finally to evaluate the individual according to the objective function and to obtain the optimum decision variable, namely the quasi-optimum value of fuzzy logic parameter in GAFNN which is the initial value.

The individual adaptability function is

$$F = (u_t^{\text{obj}} - u_t)^2 + (u_d^{\text{obj}} - u_d)^2 + (\omega^{\text{obj}} - \omega)^2. \tag{12}$$

The objective function is

$$J = 1/F. \tag{13}$$

The detail process is as follows:

1) To stochastically produce n individuals(binary system character strings), each individual represents a set of GAFNN parameters ($m_{i,j}\sigma_{i,j}w_i$), where the relationship between character strings(y_i is integer represented by k bit binary character)and parameters x_i is

$$x_i = x_i^{\min} + \frac{y_i}{2^k - 1}(x_i^{\max} - x_i^{\min}). \tag{14}$$

2) The plant is controlled according to the set of GAFNN parameters obtained in first step, then to compute the adaptability and objective function of each individual, and to search the individual with best performance.

3) According to the existing probability of each individual $p_i = f_i/\sum f_i$, by which individual will be regenerated in next generation, new individual will be regenerated until total number of new generation is n, and a new colony Q is obtained.

4) After selected the individuals Q_i and Q_k in the new colony, the individuals Q_i and Q_k will cross at cross probability p_c, then the new $n-1$ individuals Q_i' and Q_k' are obtained, and the new colony Q' consists of $(n-1)$ new individuals and the individual with best performance obtained in Step 2).

5) The individuals Q_i' and Q_k' are selected in the new colony, the individuals Q_i' and Q_k' carry out aberrance at aberrance probability p_m, and then the new $n-1$ individuals Q_i'' and Q_i'' are obtained.

6) The new generation colony Q'' consists of the $n-1$ new individuals and the individual with best performance

obtained in Step 2).

7) Return to Step 2), until one of the individuals meets the control demand. The individual with best adaptability in this colony is the initial value (quasi-optimum values) of GAFNN parameters.

4.2 Online learning algorithm

Online learning algorithm is GDM, input variable, output variable, objective function, training algorithms of Gaussian membership and connecting weight coefficient are the same as SOFNN.

5 Simulation result

The disturbance and the parameters of single-machine infinite power system in the numerical simulation are shown as follows. At $t = 3.2$ s, the real power P increases from 0.2 pu to 0.4 pu, the reactive power Q increases from 0.2 pu to 0.3 pu, at $t = 9.6$ s, the real power increases from 0.4 pu to 0.6 pu, the reactive power increases 0.3 pu to 0.5 pu. $L_{sh} = 0.01, R_{sh} = 0.1, L_{se} = 0.01, R_{se} = 0.1, L_l = 0.03, R_l = 0.3, X_q = 0.18, X_{d1} = 0.16$. The learning rate of SOFNN1 in UPFC is $\lambda_1 = \lambda_2 = \lambda_3 = 0.08$, sgn(·) is positive, the learning rate of SOFNN2 is $\lambda_1 = \lambda_2 = \lambda_3 = 0.06$, sgn (·) is positive. After the times of learning they can obtain satisfactory control result. The learning rate of GAFNN1 in UPFC is $\lambda_1 = \lambda_2 = \lambda_3 = 0.2$, sgn(·) is positive, the learning rate of GAFNN2 is $\lambda_1 = \lambda_2 = \lambda_3 = 0.15$, sgn (·) is positive, the cross probability is $p_c = 0.6$, the aberrance probability is $p_m = 0.001$. After 200 generations of learning they can be used to online control the power system at once. The response curves of two kinds of UPFC are shown in Figs. 3 ~ 6. From the simulation results it can be seen that these UPFC can realize the decoupled control of real and reactive power, which have no obvious difference in control results, that these UPFC can control the capacitor terminal voltage ranging between 1 ± 0.07 pu, but the adjusting result of UPFC based on SOFNN is better than that of UPFC based on GAFNN, and that these UPFC can control the bus voltage ranging between 1 ± 0.05 pu, but the adjusted result of UPFC based on GAFNN is better than that of UPFC based on SOFNN. In a word, these UPFC can effectively maintain desired voltage profile of bus and capacitor terminal.

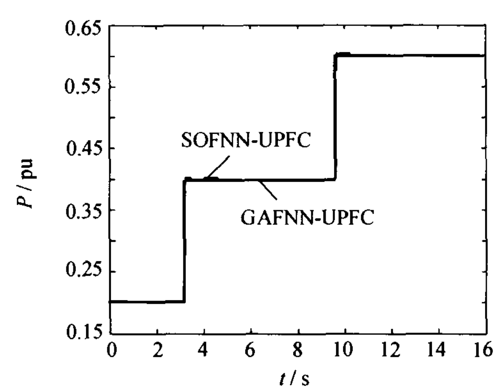

Fig. 3 Response curve of active power

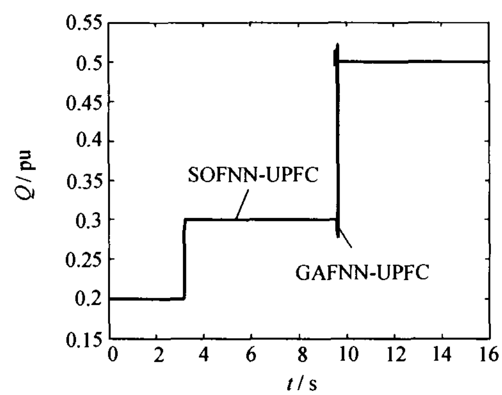

Fig. 4 Response curve of reactive power

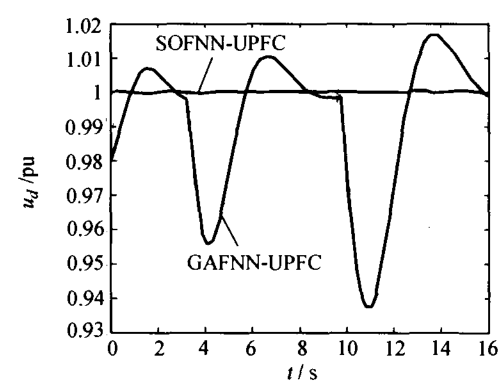

Fig. 5 Response curve of capacitor terminal voltage

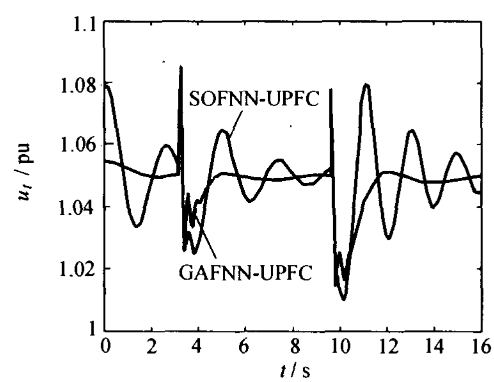

Fig. 6 Response curve of bus voltage

6 Conclusion

These UPFC proposed in this paper can adjust fuzzy rules and have the online learning capability, it does not depend on the foreknowledge and the experience of the designer. And the design of these training algorithms do not need exact mathematical model of power system. In addition, The UPFC adopting SOFNN can self-generate fuzzy logic rule. They can effectively realize the decoupled control of real and reactive power, and maintain desired voltage profile on bus and direct current capacitor. These show the validity of proposed two kind of UPFC.

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