Control Strategy for Energy Storage System Inverter Based on Fuzzy $PI^{\lambda}D^{\mu}$ Neural Network Controller

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Abstract. The traditional PID controller has a shortage of an-interference performance, parameters setting and time-varying control. In order to improve the output-voltage performance of the inverter and robustness of battery energy storage system power supply, this paper put forward a control method based on optimized fuzzy PID controller. Based on expounding the definition and math algorithm of fractional order controller, introduced fuzzy control rules to adjust the parameters of the controller, meanwhile, the method also combined with the self-learning ability of the neural network, adjusted and optimized the controller parameters online by improving the membership function and fuzzy control rules constantly. The simulation results show that the quality of anti-interference and robust of the optimized control system are enhanced, the controller has better construction and dynamic performance, above all, the optimized control methods are feasible for the inverter of battery energy storage system.

Introduction

Nowadays, with the large-scale development of new energy technologies and continuing maturity of distributed generation technology, together with the characteristics that uncertainty and intermittent of new energy power generation, energy storage power is paid more and more attention, which could "load shifting" to stabilize power fluctuations, enhance system stability, and improve power quality[1]. As a key component of the energy storage system, the inverter achieves a two-way flow of energy between the power and the power grid, whose topology and control methods are also varied. In the past, scholars put forward a number of control methods in the closed-loop control study of energy storage, such as dual loop control, neural network PID, hysteresis voltage control, deadbeat control and repetitive control, etc.[2-6]These control programs each have their own characteristics, but it is difficult to balance steady-state output, fast dynamic response and robust.

Based on the principle of fuzzy $PI^{\lambda}D^{\mu}$ neural network, the paper improved inverter controller. It brings the fuzzy control method into a fractional order $PI^{\lambda}D^{\mu}$ controller, combined with self-learning ability of neural networks. The method is easy to implement with strong adaptability. To further improve the performance of fractional order controllers, it also adjusted and optimized the system configuration parameters. The simulation used in the text storage power inverter control verifies the effectiveness of the method.

Fuzzy Fractional Order $PI^{\lambda}D^{\mu}$ Controller

The definition of fractional calculus. PID control, which is a mature technology, is most widely used in the field of control. The fractional order $PI^{\lambda}D^{\mu}$ controller proposed by Podlubony is a promotion to traditional concept of integer order PID controller [7]. It can be applied to nonlinear systems and achieve better results than integer order PID controller. The study object of Fractional Calculus (FOC) are the fractional integral and derivative, the operation of FOC basic operators is ${}_aD_t^{\alpha}$, in formula (1), a、t means upper and lower limits for the operation, α means the order of calculus. FOC operator can be expressed as:

$$
{}_aD_t^{\alpha} = \begin{cases} d^{\alpha} / dt^{\alpha}, & \mathrm{Re}(\alpha) > 0; \\ 1, & \mathrm{Re}(\alpha) = 0; \\ \int_a^t (d\tau)^{(-\alpha)}, & \mathrm{Re}(\alpha) < 0. \end{cases} \tag{1}
$$

Mathematicians gave different definitions according to their own understanding, such as G-L is provided as a direct basis for discrete and numerical computing; Caputo definition simplified the Laplace transform, it is helpful to discuss Equations. Compared to integer differential, fractional order differential is relative to all the history of the past, which has a memorability, but integer order differential is related to individual adjacent dots, adjacent discrete points are required to achieve linear interpolation approximation.

Fractional order $PI^{\lambda}D^{\mu}$ controller. Similar to integer order PID controller, the controller of fractional order differential equation is:

$$
u(t) = K_{\mathrm{P}}e(t) + K_{\mathrm{I}}D_t^{-\lambda}e(t) + K_{\mathrm{D}}D_t^{\mu}e(t) \tag{2}
$$

Wherein: the output of the controller is $u(t)$, the controller input is $e(t)$, the parameters of the controller are K_P 、 K_I 、 K_D , λ 、 μ are any positive real number, which are the order of FOC.

Due to the two adjustable parameters, integer order and differential order, Fractional $PI^{\lambda}D^{\mu}$ controller is more flexible and has a higher degree of freedom. Laplace change on the Fractional Calculus defined by G-L is:

$$
L\left[{}_0D_t^{\lambda} f(t) \right] = s^{\lambda}F(s) \tag{3}
$$

Then, the fractional $PI^{\lambda}D^{\mu}$ differential controller can be constructed as:

$$
u(t) = K_{\mathrm{P}}e(t) + K_{\mathrm{I}}s^{-\lambda}e(t) + K_{\mathrm{D}}s^{\mu}e(t) \tag{4}
$$

Because of fractional order systems' unlimited dimension, it is relatively difficult to make the controller digital realization in the time domain, but frequency domain characteristics analysis is more convenient in the continuous domain, where we can use finite-dimensional approximation of calculus equations to complete the short-term memory implementation. According to Grünwald-Letnikov calculus definition, when binomial coefficient is sufficiently small in approaching the starting point, the time series in the past can be ignored or selectively remove. Then its limited items are chosen to approximately replace fractional derivative or integral, completing the direct research within a Z domain or time domain so as to realize digitization of the fractional order system [8-10]. The following formula is obtained:

$$
{}_0D_t^{\alpha} f(t) \approx {}_{t-l}D_t^{\alpha} f(t) \approx h^{-\alpha} \sum_{j=0}^{n(t)} \omega_j^{\alpha} f(t - jh) \tag{5}
$$

Wherein: the memory length is l , $t > l$, $n(t) = \min\{\left[\frac{t}{h}\right], \left[\frac{l}{h}\right]\}$, $\omega_j^{\alpha} = (-1)^j \binom{\alpha}{j}$ is the binomial coefficients. The formula of ω_j^{α} is:

$$
\omega_0^{\alpha} = 1 , \quad \omega_j^{\alpha} = (1 - \frac{\alpha + 1}{j})\omega_{j-1}^{\alpha} , \quad j \geq 1 \tag{6}
$$

Approximating step h by sampling time T, we discrete $D_t^{\alpha} f(t)$ and transform formula (5)、(6) in the approximately Z domain:

$$
Z\left\{ D_t^{\alpha} f(t) \right\} \approx \left\{ T^{-\alpha} \sum_{j=0}^{m} \omega_j^{\alpha} z^{-j} \right\} F(z) \tag{7}
$$

$$
\begin{aligned} U(z) \approx {} & K_{\mathrm{P}}E(z) + K_{\mathrm{I}}T^{\lambda} \sum_{j=0}^{m} \omega_j^{-\lambda} z^{-j} E(z) \\ & + K_{\mathrm{D}}T^{-\mu} \sum_{j=0}^{m} \omega_j^{\mu} z^{-j} E(z) \end{aligned} \tag{8}
$$

The formula $m = [l / T]$ represents the memory length, this method is called short-term memory digital implementation method. Through the formula (8), the smaller T and the larger m, the higher accuracy. Since the sampling period is equal to the switching cycle of switching device and the memory length m is too large, the amount of computation is greater, so the value of m should be appropriate.

Fuzzy Fractional Order $PI^{\lambda}D^{\mu}$ Controller. Similar to integer order PID controller, fractional order $PI^{\lambda}D^{\mu}$ controller does not have a parameter self-tuning function. Due to the load changes, the output voltage fluctuation factors and external environment interference, the control performance may be worse and the controller tuning method of parameter identification is not valid, when the three-phase inverter circuit works. Fuzzy control system is especially suitable for solving nonlinear and time-varying control complex issues because of its robustness and anti-jamming. Fractional controller $PI^{\lambda}D^{\mu}$ parameter tuning is combined with fuzzy control system, constructing fuzzy fractional order $PI^{\lambda}D^{\mu}$ controller, developing corresponding fuzzy control rules, to achieve the parameters of the controller K_P、λ、μ adjust automatically and make controlled object modeled difficult to obtain a better control outcome.

When fuzzy controller works, the deviation between signal actual output and the expected value is adjusted through fuzzy $PI^{\lambda}D^{\mu}$. The modulated wave created by analyzing the deviation is modulated with triangular carrier, generating a suitable PWM wave to control inverter bridge, so that the system output is close to expectations. The system uses a two-dimensional fuzzy control, u is the control, u_o is the amount of sampled voltage, e is the error signal, ec is the error rate of change. e and ec are chosen as the input of controller. Firstly, fuzzy processing them into blur E、EC, and then fuzzy output is obtained by fuzzy inference algorithm, the exact values ΔK_P、$\Delta\lambda$、$\Delta\mu$ are given after defuzzification. The input-output relationship is shown as formula (9):

$$\begin{cases}\Delta K_{\mathrm{P}} = f_{\mathrm{P}}(E,EC)\\ \Delta\lambda = f_{\lambda}(E,EC)\\ \Delta\mu = f_{\mu}(E,EC)\end{cases} \tag{9}$$

Where f_P、f_λ and f_μ represent the input and output of a binary function.

Fractional controller architecture based on fuzzy control diagram is shown in Figure1. Firstly, utilizing standardized design method proposed by Mamdani, set the basic domain of e、ec and u as [-6 6], discrete the domain of in-output to 13 levels, adjust e和ec in both directions respectively. The system fuzzy subset are [NB, NM, NS, ZE, PS, PM, PB], respectively corresponding to the [negative large, negative, and negative small, zero, positive small, middle, large].

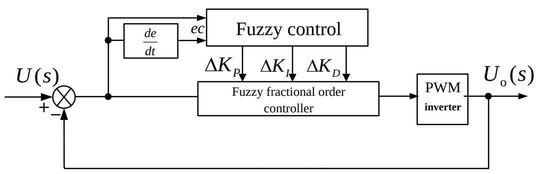

Fig.1 Structure of fuzzy neural fractional order controller

Based on actual experience, the fuzzy inference rule is: When the output voltage deviation $|E|$ is larger, in order to make the system posses better tracking performance and could shorten the settling time, the value ΔK_P and value $\Delta\mu$ should be larger. $\Delta\lambda$ should not be too small to avoid large overshoot; when $|E|$ and $|EC|$ are medium, in order to ensure that the system has a smaller overshoot, the value ΔK_P and values $\Delta\mu$ should be smaller; when the $|E|$ is small, in order to make the system get a good steady performance, the value $\Delta\lambda$ and values ΔK_P should be larger. After repeated tests, utilizing the membership function in the form of a triangle, the exact value of ΔK_P、$\Delta\lambda$、$\Delta\mu$ are obtained when output fuzzy subset defuzzification method using gravity, and the formula(10) gives the controller parameters. Wherein, K_P^0、λ^0、μ^0 are the initial set value of fractional order $PI^{\lambda}D^{\mu}$ controller, thus determining the controller parameters.

$$\begin{cases} K_\mathrm{P} = K_\mathrm{P}^0 + \Delta K_\mathrm{P} \\ \lambda = \lambda^0 + \Delta\lambda \\ \mu = \mu^0 + \Delta\mu \end{cases} \quad (10)$$

Fuzzy neural Fractional order $PI^\lambda D^\mu$ controller

Structure of Fuzzy Neural Network. The traditional fuzzy control system's membership functions and control rules can't be changed once confirmed, leading to non-ideal control effect [11]. In this paper, T-S fuzzy neural network which belongs to the local approximation of feed forward networks is adopted. The in-output node of network represents respectively the in-output of fuzzy control, and the node of hidden layer represents membership functions and control rules.

T-S fuzzy neural network is a five-layer structure. The first layer is the input layer, including voltage error e and error rate of change ec ; the second layer is a layer of input membership functions, calculating the input vector membership functions u_i^j via nodes. m_i is the number of fuzzy divisions of x_i. n indicates the dimension of input. The system parameter values are determined as follows：n=2； x_i=E； x_i=EC； m_1=7； m_2=7; and membership function is:

$$u_i^j = \exp(-(x_i - c_{ij})^2 / \sigma_{ij}^2) \quad (11)$$

Where c_{ij} and σ_{ij} represent the center and width of membership functions respectively.

The third layer is the fuzzy rule layer, whose each neural network node represents a fuzzy rule. Its role is to match antecedent fuzzy rules and generate applicable of each fuzzy control rules:

$$a_j = \min\left\{u_1^{i_1}, u_2^{i_2}\right\} \quad (12)$$

Wherein: $\begin{cases} i_1 = \left\{m_1, m_{2,} ..., m_i\right\} \\ i_2 = \left\{m_1, m_{2,} ..., m_j\right\} \\ j = 1, 2, ..., m, m = \prod_{i=1}^{n} m_i \end{cases}$

The fourth layer is the normalized layer, and the number of its nodes is the same with the third layer, normalization is calculated as follows:

$$\bar{a}_j = a_j / \sum_{i=1}^{m} a_i \ , \quad j = 1, 2, ..., m \quad (13)$$

The fifth layer is a back piece network, which includes r parallel sub-networks, and each sub-network generates an output, calculating back piece of each rule:

$$v_{ij} = p_{j0}^i + p_{j1}^i x_1 + ... p_{jn}^i x_n = \sum_{k=0}^{n} p_{jk}^i x_k \quad (14)$$

Relationship between back piece network layers is linear, the system output is:

$$v_i = \sum_{j=1}^{m} \bar{a}_j v_{ij} \ , \quad i = 1, 2, ..., r \quad (15)$$

Learning Training of Fuzzy Neural Network. T-S fuzzy neural network fuzzy inference is achieved by former member networks. Voltage error e and error rate of change ec are being as the network inputs, specific training steps are as follows:

Step1: The fuzzy neural network off-line training is connected with control system as an adaptive controller;

Step2: Output of the controlled object is sampled to obtain the output data acquisition $Y(k)$;

Step3: The control amount is gotten by analyzing in-output relationship fuzzy fractional $PI^\lambda D^\mu$ neural network, the system output value $Y(k+1)$ is calculated through the formula (15);

Step4: According to the performance index that is a function of the total input of the error function, network rules of fractional fuzzy $PI^{\lambda}D^{\mu}$ neural network are corrected online by utilizing the steepest gradient learning algorithm so as to achieve the purpose of adaptive control;

Step5: Update the system status and check the maximum number of iterations. If the termination condition is satisfied, the cycle ends, otherwise $k = k + 1$, go to step2.

Simulation

In MATLAB / Simulink7.1 environment, the T-S fuzzy neural network is trained off-line, and the trained fuzzy neural network controller is packaged into the simulation circuit. Switching frequency of simulation system is f_s=10kHz; output filter inductor is L=250μH; output filter capacitor is C=350μF; sampling period T is set to 0.001s. Domain of basic error is [-35V , 35V]. The error rate of change in the basic domain is [-5 , 5]. The control output of the basic domain is [-40V , 40V]. Fuzzy factor are $k_e = 0.2$, $k_{ec} = 0.02$, $k_u = 6.5$; integer order PID controller parameters in the simulation experiment are set to K_P=8、 K_I=2.5、 K_D=0.0005; parameter of fuzzy fractional $PI^{\lambda}D^{\mu}$ controller are set to λ=0.6、 μ=0.65、 K_P=8、 K_I=2.5、 K_D=0.0006; parameter of fuzzy neural fractional controller is set to λ=0.6、 μ=0.65、 K_P=8、 K_I=2.

Fig 2 to Fig 4 shows respectively the rectified output voltage waveform generated by using of integer order PID controller, fuzzy fractional order $PI^{\lambda}D^{\mu}$ controller and fuzzy nerve fractional order $PI^{\lambda}D^{\mu}$ controller in resistive load. Seen from the waveform, integer order PID control system became stable at 0.012s, transient time of three-phase output voltage waveform was relative long, overshoot amount was large, and there was a big fluctuation about output voltage waveform up to 310V after entering the steady-state process; output voltage waveform overshoot under fuzzy fractional order $PI^{\lambda}D^{\mu}$ controller was too large and became stable at 0.007s; transient time of output voltage waveform under fuzzy nerve fractional $PI^{\lambda}D^{\mu}$ controller was short, improving the response speed and control accuracy of the system. The output voltage waveform fluctuation was small and the system came into stable after entering the steady-state process.

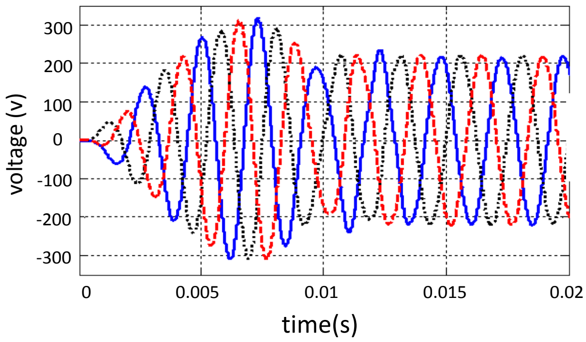

Fig.2 The output voltage waveform by controllers with integer order

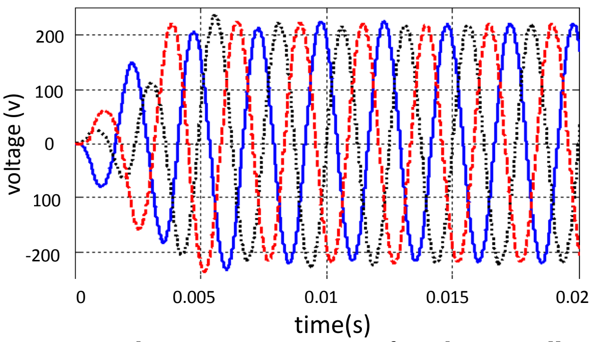

Fig.3 The output voltage waveform by controllers with fuzzy fractional order

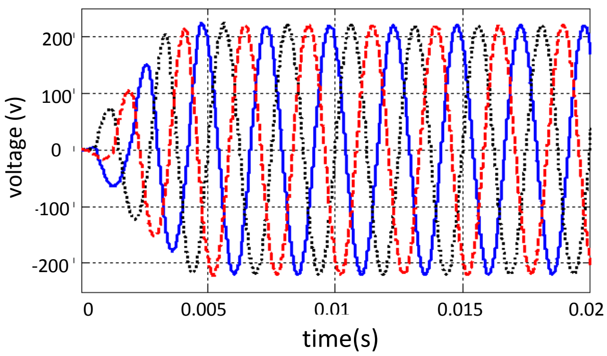

Fig.4 The output voltage waveform by controllers with fuzzy neural network fractional order

Summary

The optimization fuzzy PID control method proposed in the paper combines the neural network and fractional $PI^{\lambda}D^{\mu}$ control, both of which are applied to energy storage power inverter to perfect fuzzy PID control. T-S fuzzy neural network structure employed in the method blends fuzzy control and neural network, making inference significantly faster. The system can continue to modify and improve the fuzzy control rules under work, making the controller parameters adjust and optimize on-line; combined with steady performance of fractional order $PI^{\lambda}D^{\mu}$ control, it expands the order of differentiation and integration to any order, so that the steady-state and overshoot of the system is greatly improved.

The simulation results show that the fuzzy neural fractional order $PI^{\lambda}D^{\mu}$ controller is suitable for energy storage power inverter research, and the controller based on the control method possesses more flexible structure, better robustness, greater anti-interference ability, good dynamics and adaptability. It provides a powerful reference for applying the controller to nonlinear and time-varying system.

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