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# Research on PID Control of Marine Diesel Generator Based on Double Loops RBF Neural Network

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## Abstract

**The RBF neural network was applied to the parameter tuning of the PID for Marine Diesel Generator. In order to achieve the network output closer to the actual output, the gradient descent method is used to modify the network parameters along the negative gradient direction of the RBF neural network performance index function, so that the deviation of the network output from the actual output is minimized. Obtained the Jacobian information by RBF neural network identification, adaptively adjust the three parameters $K_p$, $K_i$ , $K_d$ of PID to meet the high-performance control requirements of the PID for marine diesel generator. The simulation results show that the controller shortens the overshoot of the speed regulation and fastens the system responses. And it has better adaptation, robustness and preventing disturbance ability.**

## Keywords

**Marine diesel generator； speed and excitation control； PID controllers； RBF neural network.**

## 1. Introduction

The traditional PID feedback control is still used in the ship diesel generator speed control system, and it is the main control method of the ship generator set. The traditional PID controller algorithm is simple. Through the deviation of the system reference value and the output value, the control quantity is composed of three links of proportional, integral and derivative to achieve the control of the controlled object. Among them, the proportional link parameter $K_p$ amplifies or reduces the deviation signal by a certain multiple to reduce the deviation; the integral link parameter $K_i$ continuously accumulates the deviation to eliminate the static error; the differential link parameter $K_d$ reflects the change direction of the deviation signal to adjust the output in advance [1]. It is difficult to further improve the power supply quality of the power system by adopting PID law for the control of diesel generator sets. With the development of marine generator sets towards large capacity and full automation, it is urgent to use some advanced control methods to improve the quality of generator control [2].

Many scholars have proposed a new PID control algorithm based on neural network. Literature [3] proposed a PID control algorithm based on expert thinking, which can effectively reduce the overshoot and steady-state error of the system, but the expert system is mainly used to solve special or difficult problems. For example, literature [4-6] proposed the application of fuzzy PID to the control of electronic speed regulation and frequency regulation of diesel generators; Literature [7] proposes a non-linear PID parameter self-tuning control method for diesel generator electronic governor; Literature [8] uses genetic algorithm and its improved particle swarm algorithm to optimize PID parameters for adaptive control method of marine diesel generator; Literature [9] proposed to apply direct feedback linearization and H∞ control theory to the control of diesel generator governors; Literature [10-11] proposed the use of fuzzy logic control methods in diesel generators and wind generators, using Fuzzy controller adjusts PI parameters, reduces load disturbance and speeds up system speed response, but it is difficult to determine fuzzy variables and fuzzy rules. This paper mainly combines traditional PID control with RBF neural network. Through the high precision of RBF neural network in function fitting and system modeling, it can train and learn the ship generator set speed control system and excitation control system well. , And then form a neural network controller. At the same time, the PID controller realizes effective control of the system on the basis of the RBF neural network.

## 2. Mathematical model of marine diesel generator system

With the continuous increase of the single generator capacity of the ship's power system, the ship's power system has become more and more complex, and the requirements for the power control system have become higher and higher. The importance of the long-term stability and control quality of ship power system control has become increasingly prominent [12].

### 2.1. Mathematical Model of Synchronous Generator

The ship diesel generator model adopts the sixth-order equation of state model [13], The model does not consider the 0-axis Park equation, and stipulates that the positive stator current produces a positive flux linkage. Nor does it consider the electromagnetic transient process of the q-axis damper winding. The two data of $T_d'$ and $T_q'$ are 0. The generator model is described by the d-q axis reference model circuit, see Figure 1. All the electrical variables are viewed from the stator side, with a tip on it is the rotor power converted to the stator side.

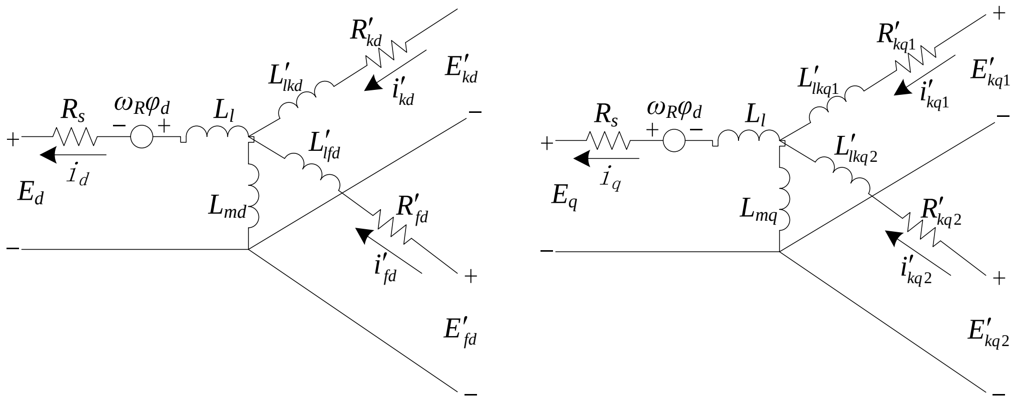


Figure 1: d-q axis equivalent circuit diagram of marine diesel synchronous generator

Parts of the circuit equations are:

$$V_d = R_s i_d + \frac{d}{dt}\varphi_d - \omega_r \varphi_q \tag{1}$$

$$V_q = R_s i_q + \frac{d}{dt}\varphi_q + \omega_r \varphi_d \tag{2}$$

$$\varphi_d = L_d i_d + L_{md}(i'_{fd} + i'_{kd}) \tag{3}$$

$$\varphi_q = L_q i_q + L_{mq} i'_{kq} \tag{4}$$

Where, *φ, V, I, L, R* represent flux linkage, voltage, current, inductance and resistance respectively. The subscripts d, q, s, r, m, l, f, k respectively represent direct axis, quadrature axis, stator, rotor, magnetization, magnetic flux leakage, excitation and damping.

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## 2.2. Mathematical Model of Speed Control System

### 2.2.1. Mathematical Model of Speed Feedback Unit

The frequency signal is calculated and converted with the voltage to obtain the speed-related voltage signal $U_f(s)$ [14], the transfer function is expressed as:

$$G_1(s) = \frac{U_f(s)}{n(s)} = K_1 \tag{5}$$

Where, $K_1$ is the feedback gain.

### 2.2.2. The mathematical model of the actuator

The control output signal is transmitted to the actuator, and the actuator controls the fuel injection volume of the diesel prime mover.

$$G(s) = \frac{L(s)}{u(s)} = \frac{K_2}{1+T_1 s} \tag{6}$$

In marine diesel generator sets, the power torque of the synchronous generator is provided by the diesel prime mover. The change of the load side will affect the speed. When the load changes, the speed control system immediately controls the diesel prime mover through the throttle actuator in the control system, so that the diesel prime mover is in a constant speed and stable operation state, ensuring that the synchronous generator maintains a stable frequency. The structure diagram of the speed control system, see Figure 2

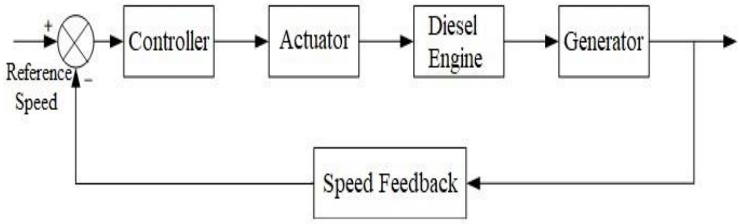


Figure 2: Block diagram of the speed control system

## 2.3. Mathematical Model of Excitation Control System

Block diagram of excitation control system, see Figure 3. The main generator of the system rotates along with the magnetic field while selecting the rotation of the magnetic field, including the armature of the rotating exciter and the diode rectifier. The ground zero voltage of the generator is Vstab, the generator d-axis voltage is Vd, the q-axis voltage is Vq, the input voltage setting reference value is Vref, and the excitation voltage is Vf. The d-q axis voltage and power factor are calculated through projection to obtain Vd and Vq, and the compound excitation voltage signal is generated through a low-pass filter. Synthesize the obtained signal and RBF neural network PID control signal and send it to the exciter for control.

The forward loop transfer function is:

$$G_1(s) = \frac{k_a(t_c s+1)}{(t_a s+1)(t_b s+1)(t_e s+k_e)} \tag{7}$$

The feedback transfer function is:

$$G_2(s) = \frac{k_f s}{t_f s + 1} \tag{8}$$

Where, $k_a$ is the magnification of the main regulator, $t_a$ is the time constant, $t_b$ and $t_c$ are the time constants of the lead and lag compensation, respectively, and $k_f$ and $t_f$ are the magnification and time constants of the feedback damping link, respectively.

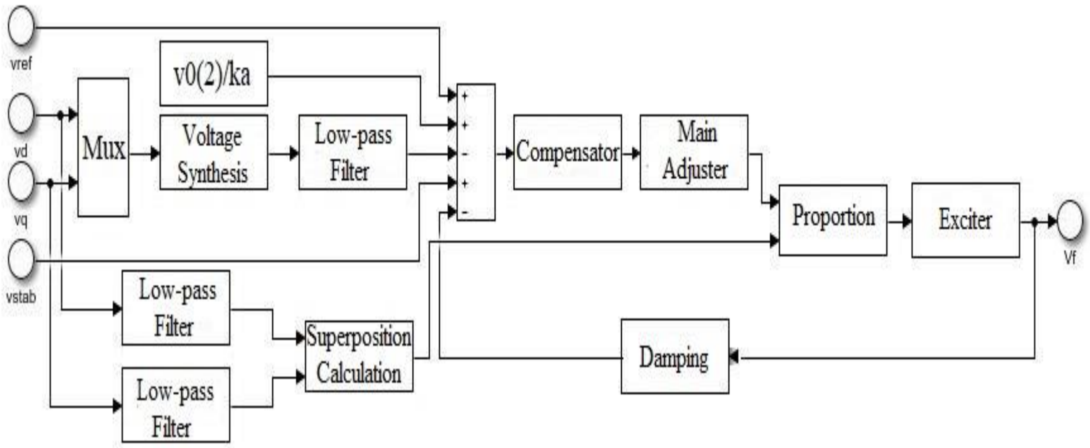


Figure 3: Block diagram of excitation control system

## 3. RBF neural network model

The RBF neural network is a 3-layer feedforward network with a single hidden layer. It has been proved that the RBF network can approximate a continuous function with arbitrary precision [15]. There is no weight connection between the input layer and the hidden layer. You can directly pass the input vector to the hidden layer, and perform a linear weighted summation on the output results of the hidden layer to get the output of the RBF neural network [16], The RBF network structure used in this paper is shown in Figure 4.

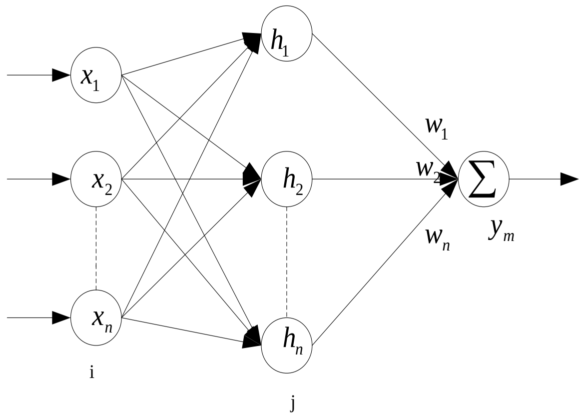


Figure 4: RBF neural network structure

In the network structure of RBF neural network [17], $X$=$[x_1, x_2,...,x]^T$ is the input vector of the network input layer, $H$=$[h_1, h_2,...,h_n]^T$ the radial direction of the hidden layer of the network The basis vector, where $h_j$ is the Gaussian function and $n$ is the number of hidden layer nodes.

$$h_j = \exp\left(-\frac{\|X - C_j\|^2}{2b_j^2}\right),\ j = 1,2,\ldots,m \tag{9}$$

Where, the center vector of the $j$ node of the network is $C_j$=[$C_{j1}$, $C_{j2}$,...,$C_{jm}$]$^T$, $i$=1,2,...n. Suppose the base width vector of the network is $B$=[$b_1$, $b_2$,...,$b_m$]$^T$; the weight vector of the network is $W$=[$w_1$, $w_2$,...,$w_m$]$^T$.
The output of the identification network is as follows:

$$y_m(k) = w_1 h_1 + w_2 h_2 + \ldots + w_m h_m \tag{10}$$

Performance index function of network approximation:

$$E(k) = \frac{1}{2}(y(k) - y_m(k))^2 \tag{11}$$

In order to achieve the optimal PID parameter tuning, the correction of the RBF neural network parameters should follow the direction of negative gradient decline to minimize the performance index function.
Weight values updating:

$$\Delta w_j(k) = -\eta \frac{\partial J}{\partial w_j} = \eta(y(k) - y_m(k))h_j \tag{12}$$

Base width parameter updating:

$$\Delta b_j = (y(k) - y_m(k)) w_j h_j \frac{\left\| X - C_j \right\|^2}{b^3{}_j} \tag{14}$$

$$b_j(k) = b_j(k-1) + \eta \Delta b_j + \alpha(b_j(k-1) - b_j(k-2)) \tag{15}$$

Hidden layer center updating:

$$\Delta c_{ji} = (y(k) - y_m(k)) w_j \frac{x_i - c_{ji}}{b^2{}_j} \tag{16}$$

$$c_{ji}(k) = c_{ji}(k-1) + \eta \Delta c_{ji} + \alpha(c_{ji}(k-1) - c_{ji}(k-2)) \tag{17}$$

Where, $\eta$ is the learning rate, $\alpha$ momentum factor, $\eta \epsilon [0,1]$, $\alpha \epsilon [0,1]$. In this paper, the number of hidden layer neurons is $m$=6, and the learning parameters of the network are $\alpha$=0.5 and $\eta$=0.5.

## 4. PID parallel control design based on RBF neural network

The block diagram of PID control structure based on RBF neural network is shown in Figure 5.

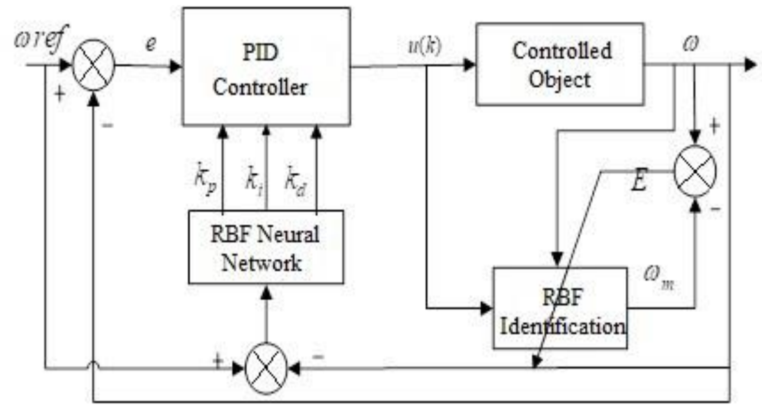


Figure 5: Block diagram of PID control structure based on RBF neural network

This paper uses incremental PID control, so the control error:

$$e(k) = \omega ref(k) - \omega(k) \tag{18}$$

The three input quantities of the RBF neural network PID controller:

$$xc(1) = e(k) - e(k-1)\ ,\ xc(2) = e(k)\ ,\ xc(3) = e(k) - 2e(k-1) + e(k-2) \tag{19}$$

The control algorithm of RBF neural network PID controller:

$$u(k) = u(k-1) + \Delta u(k) \tag{20}$$

$$\Delta u(k) = k_p(e(k) - e(k-1)) + k_i e(k) + k_d(e(k) - 2e(k-1) + e(k-2)) \tag{21}$$

The RBF neural network tuning index :

$$E(k) = \frac{1}{2}e(k)^2 \tag{22}$$

Where, $K_p$、$K_i$、$K_d$ are proportional gain, integral coefficient, and differential coefficient, respectively. The adjustment of $K_p$、$K_i$、$K_d$ is realized by gradient descent method, namely

$$\Delta k_p = -\eta\frac{\partial E}{\partial k_p} = -\eta\frac{\partial E}{\partial \omega}\frac{\partial \omega}{\partial \Delta u}\frac{\partial \Delta u}{\partial k_p} = \eta e(k)\frac{\partial \omega}{\partial \Delta u}xc(1) \tag{23}$$

$$\Delta k_i = -\eta\frac{\partial E}{\partial k_i} = -\eta\frac{\partial E}{\partial \omega}\frac{\partial \omega}{\partial \Delta u}\frac{\partial \Delta u}{\partial k_i} = \eta e(k)\frac{\partial \omega}{\partial \Delta u}xc(2) \tag{24}$$

$$\Delta k_d = -\eta\frac{\partial E}{\partial k_d} = -\eta\frac{\partial E}{\partial \omega}\frac{\partial \omega}{\partial \Delta u}\frac{\partial \Delta u}{\partial k_d} = \eta e(k)\frac{\partial \omega}{\partial \Delta u}xc(3) \tag{25}$$

Where, the sensitivity information of the output of the controlled object to the change of the control input, that is, the Jacobian matrix algorithm is:

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$$\frac{\partial \omega(k)}{\partial \Delta u(k)} \approx \frac{\partial \omega_m(k)}{\partial \Delta u(k)} = \sum_{j=1}^{m} w_j h_j \frac{c_{ji} - x_1}{b_j^{\,2}} \tag{26}$$

Where, $x_1 = \Delta u(k)$

## 5. Simulation Design of PID Speed and Excitation Double-loop Based on RBF Neural Network

When both the speed control and excitation control system of marine diesel generator sets are controlled by RBF neural network PID, ANN is used for control in both loops, which can make the system control more coordinated and control performance higher [18]. The experimental simulation diagram is shown in Figure 6.

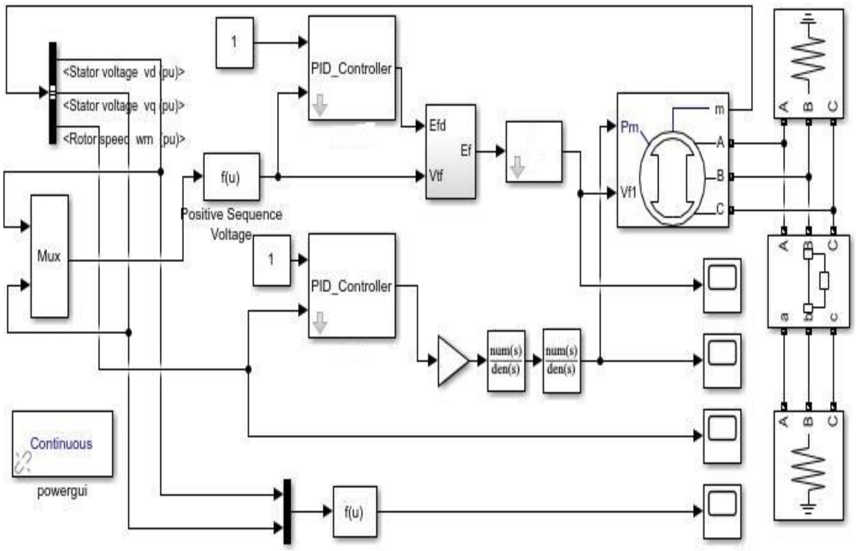


Figure 6: Diagram of PID control simulation system of marine diesel generator based on neural network

## 6. Simulation analysis of PID control of marine diesel generator set based on neural network

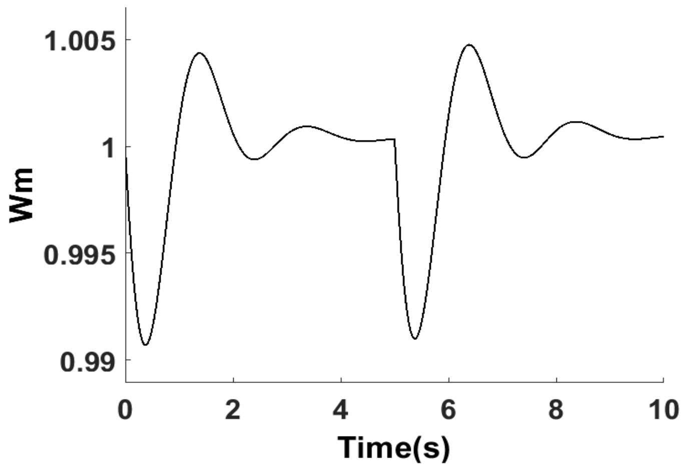


Figure 7: Traditional PID speed response

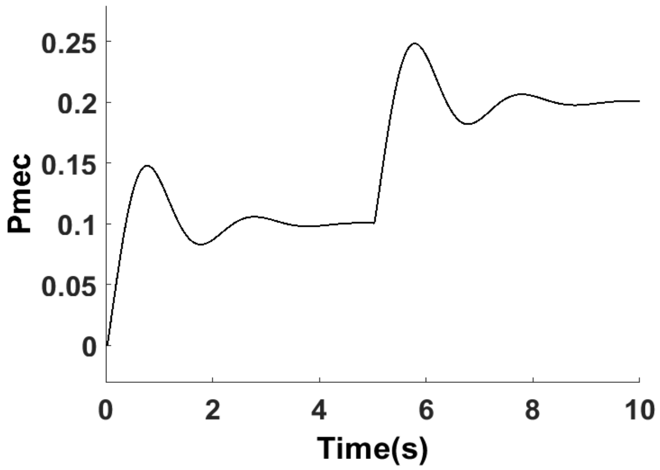


Figure 8: Traditional PID torque power

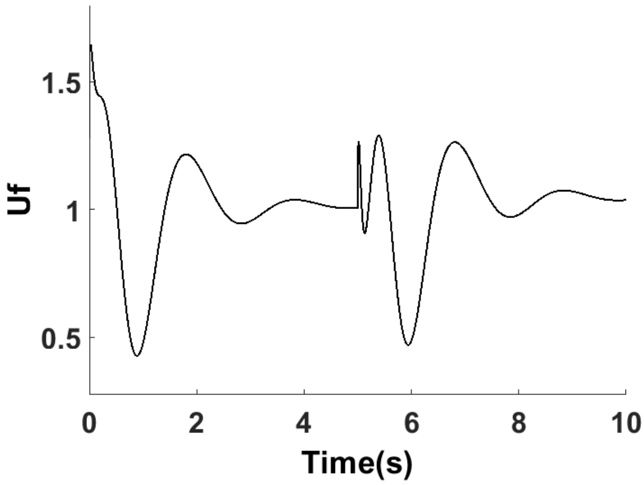


Figure 9: Traditional PID excitation voltage

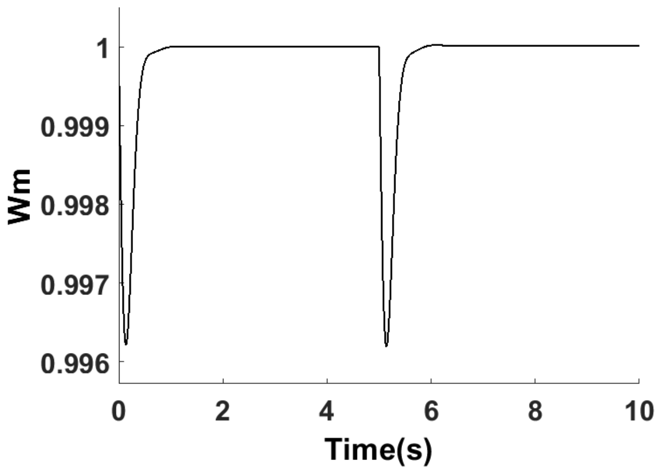


Figure 10: Neural network PID speed response

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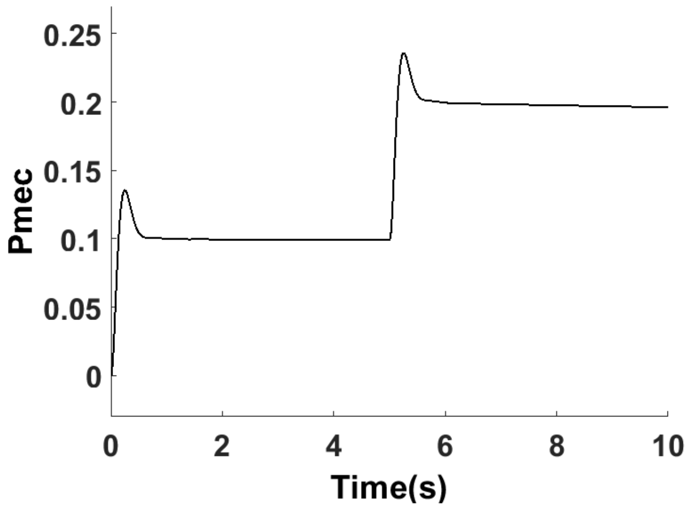

Figure 11: Neural network PID torque response

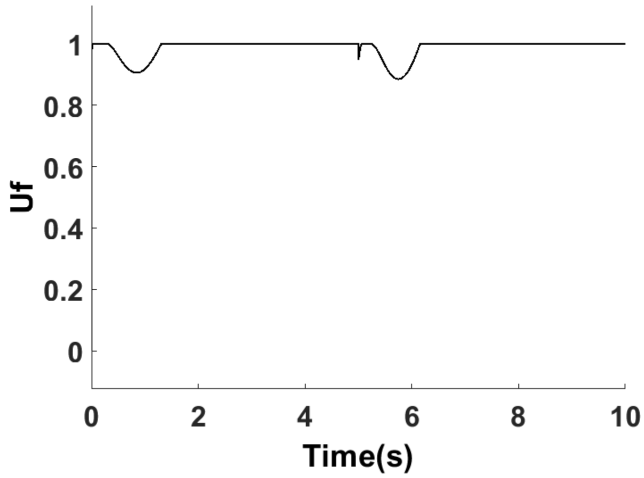

Figure 12: Neural network PID excitation voltage

In this paper, the dynamic characteristics of marine diesel generators under traditional PID control are simulated. After that, the dynamic characteristics of marine diesel generator set under RBF neural network PID control are simulated. The marine diesel generator set control system starts normally when the load is 0.725MW, and the system suddenly reduces the load by 0.3125MW in the 5s, and the system runs for 10s. The simulation results of the traditional PID control system are shown in Figure 7, Figure 8, and Figure 9, which are the speed, torque power and excitation voltage response curves of the generator set under the traditional PID control. When the generator set is started and the load changes, in Figure 7, the system's speed overshoot is relatively large. In Figure 8, the torque power of the generator has obvious spikes. In Figure 9, there are more excitation voltage spikes and slower adjustment. When the traditional PID control system restarts and reduces the load suddenly, the fluctuation is large and the response is slow. The simulation results of the RBF neural network PID control system are shown in Figure 10, Figure 11, and Figure 12, which are the speed, torque power and excitation voltage response curves of the generator set under the RBF neural network PID control. It can be seen from the simulation results that when the marine diesel generator set is just started up under the control of the RBF neural network, since the RBF network is still in the initial learning stage, the initial control effect is not very satisfactory. However, the RBF neural network quickly changed the control effect through learning. The system output curve shows that the continuity and smoothness of the waveform have been greatly improved, and the overshoot of the system dynamic process is reduced. The continuity of the transition process characteristics has been significantly improved, and there is no obvious spike mutation; the accuracy of the system has been greatly improved, the maximum dynamic deviation has been reduced to a certain extent, and the stability of the system has also been greatly improved.

## 7. Conclusion

This paper studies the PID control of marine diesel generator set based on RBF neural network, uses the self-learning ability of neural network to modify the parameters of RBF neural network, realizes the rapid adjustment of PID parameters, and solves the problem of traditional PID controller due to the difficulty of parameter adjustment. Satisfy the problem of high-performance regulation of marine diesel generator set control system. Through simulation analysis, the control method in this paper makes up for the shortcomings of traditional PID control. The marine diesel motor starts stably, basically has no overshoot, speed response is faster, and has better anti-interference effect after sudden load reduction.

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