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Switching Control Method for Optimal State Feedback Controller of Nuclear Reactor Power System

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Abstract

Due to the nonlinearity of the reactor power system, the load tracking situation is closely related to the initial steady-state power and the final steady-state power after the introduction of the state feedback controller. Therefore, when the initial power and the final stable power are determined, the particle swarm optimization algorithm is used to find the optimal controller parameters to minimize the load tracking error. Since there are many combinations of initial stable power and final stable power, it is not possible to find the optimal controller parameters for all combinations, so the neural network is used to take the final stable power and the initial stable power as input, and the optimal controller parameters as the output. This method obtains the optimal state feedback controller switching control method can achieve a very excellent load tracking effect in the case of continuous power change, in the power change time point, the response is fast, in the controller parameter switching time point, the actual power does not fluctuate due to the change of controller parameters.

Keywords

Optimal Status Feedback, Particle Swarm Optimization, Neural Networks, Controller Switching Control, Load Tracking

1. Introduction

In the study of reactor control, the development of appropriate load following control schemes has been a research hotspot. Reference [1] adopts the one-fuel/two-coolant model for small modular reactors, and proposes a simple state feedback control method, and the adjusted closed-loop system can achieve efficient output tracking under load following conditions. Reference [2] proposes a new feedback control method called state differential feedback control, which is based on the integral control of the control rod position and the state differential control of the control rod speed, and the equivalence between the two control systems is controlled by feedback, and applied to the reactor control system in the designed load-following operation mode, and the designed reactor power state differential feedback control system has excellent performance in the load-following mode. Reference [3] proposes a new control concept called state feedback-assisted classical control. It uses the classic output feedback control system as an easy-to-understand internal control loop and utilizes modern state feedback to enhance demand signals to achieve the goal of optimal control design. Reference [4] invents a new type of nonlinear controller called an observer-based feedback dissipative controller for single-input, single-output (SISO) generalized Hamiltonian systems that have a dissipative Hamiltonian structure and derive sufficient conditions for closed-loop progressive stability, and this novel control strategy is applied to load tracking control in nuclear reactors.

The use of neural network method to control the change of reactor power is also a new and effective means. Reference [5] proposes the use of a high-fidelity neural network surrogate model within the modular optimization framework, which is used to deal with the impurity deposition constraints in the optimization of the core loading mode of light-water reactors, which provides a powerful tool for reducing the impact of impurity deposition in the reactor core. Based on the online learning neural network, Reference [6] proposes an adaptive scheme for power level tracking of pressurized water reactor under local and global load following and emergency conditions, and the simulation results show that compared with the traditional PID controller, this scheme has better performance in smaller ISE/IAE/ITAE under load following conditions. Reference [7] Aiming at the problem of low model recognition accuracy in the model predictive control algorithm commonly used in reactor control, a new neural network predictive power control scheme suitable for small PWRs is proposed, which uses neural networks to identify core models, which has strong anti-interference ability and good load tracking performance.

In terms of particle swarm optimization algorithm, Reference [8] uses genetic algorithm and particle swarm optimization algorithm to adjust the PID gain of PWR load following, and compares the workload of the two algorithms, the results show that the particle swarm optimization algorithm achieves the optimal solution under the condition of fewer function evaluation times, in order to improve the load tracking capacity of nuclear reactors, Reference [9] uses particle swarm optimization algorithm to optimize the PID controller gain of typical pressurized water reactor power control, and the simulation results show that the closed-loop PID controller optimized by particle swarm optimization algorithm has good stability and power response ability. Reference [10] controls the motion of the control rod based on the particle swarm optimization algorithm, and designs an automatic search program for the power improvement path of the boiling water reactor. Reference [11] designs a closed-loop fuzzy controller based on particle swarm optimization algorithm for power level control of nuclear research reactors, and this control system can operate satisfactorily under most operating conditions, even at small initial power levels.

Traditional proportional-integral-derivative (PID) controllers have problems such as large overshoot and long adjustment time in the core power control process. In order to make full use of the performance advantages of different types of controllers, a fuzzy switching controller based on TS-type fuzzy rules is designed by combining proportional-integral-derivative (PID) controller and fuzzy controller in [12], which is more suitable for core power control under core reactive step disturbance and core coolant inlet temperature step disturbance compared with traditional PID controller. Reference [13] designed a fuzzy PID compound controller to solve the problem of molten salt fuel fluidity in liquid Molten salt reactor. This composite controller combines the advantages of fuzzy controller and PID controller, and can automatically switch between the two control methods based on the error range to control the system. The simulation results show that the fuzzy PID composite controller combines the advantages of two control methods, and its synthesis quality is superior to that of ordinary PID controllers and basic fuzzy controllers

2. Numerical Modeling

2.1. Establishment of Mathematical Models

The nuclear fuel in the reactor undergoes a neutron fission reaction, and the presence of slow neutrons prolongs the reaction cycle of the reactor, making the control of the nuclear reactor possible. When establishing the reactor mathematical model, considering that the reactor power control mainly studies the characteristics of the change of reactor power with time, and does not consider the influence of spatial effects too much, the point reactor model is used to ignore the spatial effect, and the six groups of slow-onset neutron point reactor model equations without considering the temperature effect are:

$$\begin{cases} \dfrac{dn(t)}{dt} = \dfrac{\rho - \beta}{\Lambda} n(t) + \sum_{i=1}^{6} \lambda_i c_i(t) \\ \dfrac{dc_i(t)}{dt} = \dfrac{\beta_i}{\Lambda} n(t) - \lambda_i c_i(t) \end{cases} \quad i = 1, 2, \ldots, 6 \tag{1}$$

The neutron density $n(t)$ and the concentration of slow-emitted neutron pioneer nuclei in group $ic_i(t)$ were normalized, and the relative neutron density was introduced $n_r(t) = n(t)/n_0$ and the relative concentration of group i slow-emitted neutron precursor nuclei $c_{ri}(t) = \dfrac{c_i(t)}{c_{i0}}$, where n_0 is the neutron density during the initial steady-state operation of the reactor and c_{i0} is the concentration of the slow-emitted neutron precursor nucleus of group i during the initial steady-state operation, as follows:

$$\begin{cases} \dfrac{dn_r(t)}{dt} = \dfrac{\rho-\beta}{\Lambda} n_r(t) + \sum_{i=1}^{6} \lambda_i c_{ri}(t) \\ \dfrac{dc_{ri}(t)}{dt} = \dfrac{\beta_i}{\Lambda} n_r(t) - \lambda_i c_{ri}(t) \end{cases} \quad i = 1, 2, \ldots, 6 \tag{2}$$

In order to simplify the model and reduce the order of the system model, the multi-group slow-emitting neutron point heap equation is approximated as a point heap model with equivalent single-group slow-emitted neutrons, and introduce $c_r = \sum_{i=1}^{6} c_{ri}$ and $\lambda = \beta / \sum_{i=1}^{6} \dfrac{\beta_i}{\lambda_i}$, and the system at the initial steady state there is $\dfrac{\beta_i}{\Lambda} n_{r0} = \lambda_i c_{ri0}$, then the point stack dynamics equation for a single group of slow-emitted neutrons can be expressed as:

$$\begin{cases} \dfrac{dn_r(t)}{dt} = \dfrac{\rho-\beta}{\Lambda} n_r(t) + \lambda c_r(t) \\ \dfrac{dc_r(t)}{dt} = \lambda n_r(t) - \lambda c_r(t) \end{cases} \quad i = 1, 2, \ldots, 6 \tag{3}$$

In the reactor power control, the control rod is a main means to adjust the reactor reactivity, the introduction of the control rod can increase the absorption section inside the reactor, thereby reducing the reactivity in the reactor, and the speed of the control rod determines the rate of change of reactivity. Combining the reactivity rate of change equation yields the reactor power model:

$$\begin{cases} \dfrac{dn_r(t)}{dt} = \dfrac{\rho-\beta}{\Lambda} n_r(t) + \lambda c_r(t) \\ \dfrac{dc_r(t)}{dt} = \lambda n_r(t) - \lambda c_r(t) \qquad i = 1, 2, \ldots, 6 \\ \dfrac{d\rho_r}{dt} = G_r z_r \end{cases} \tag{4}$$

2.2. The Stability of the Model

In the absence of input, Equation (4) can be expressed as $\dot{x} = f(x)$ where $x = [n; c; \rho]$, Jacobi matrix for the nonlinear system of reactor point reactor power system:

$$J(x) = \frac{\partial f(x)}{\partial x^{\mathrm{T}}} = \begin{bmatrix} \dfrac{\rho-\beta}{\Lambda} & \dfrac{\beta}{\Lambda} & \dfrac{n}{\Lambda} \\ \lambda & -\lambda & 0 \\ 0 & 0 & 0 \end{bmatrix} \tag{5}$$

Constructing scalar functions $V(x) = f^{\mathrm{T}}(x) f(x)$.

$V(x)$ is definite and $\dot{V}(x)$ is also definite. This proves that the system was originally unstable, so a state feedback controller is designed to make the system stable.

$$\dot{x} = f(x) - BFx + Bv \tag{6}$$

The flowchart of its introduction into the controller is shown in **Figure 1**.

Wherein $G = F(1) + F(2)$.

3. Controller Design

Under the premise of stabilizing the system, the parameters of the controller are designed. After introducing a state feedback controller, the phase diagram of the relative concentration of neutrons and the concentration of delayed neutron precursor nuclei is shown in **Figure 2**.

It can be seen that under the same controller parameters, if the initial stable power is the same but the final stable power is different, the initial path of the phase diagram is consistent. When the initial stable power is different and the final stable power is the same, the final path of the phase diagram is consistent.

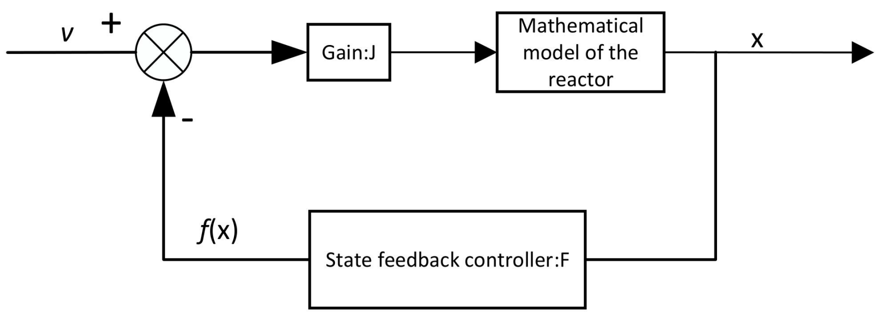

Figure 1. Controller flowchart.

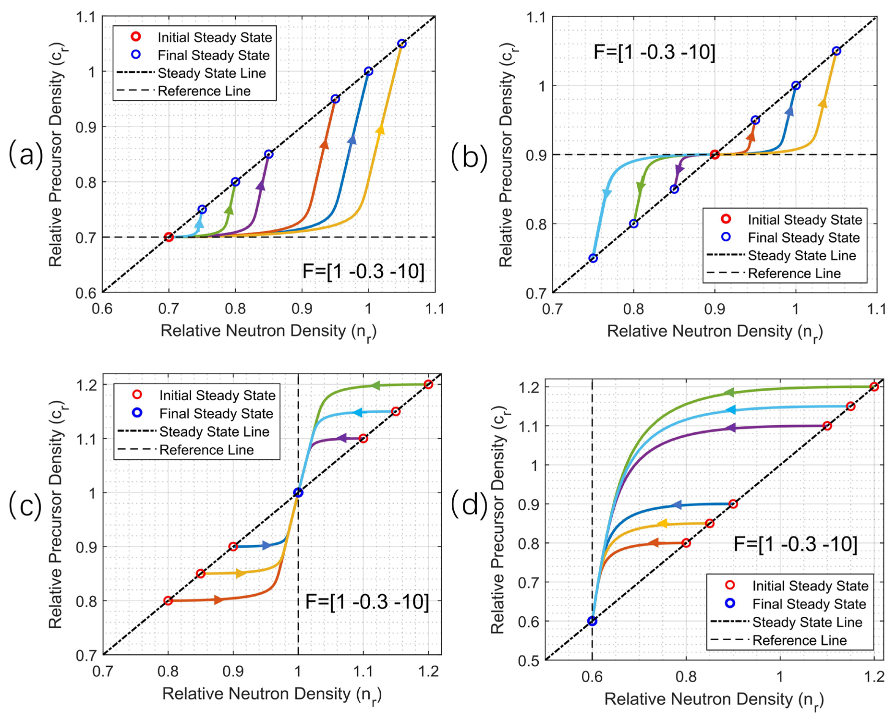

Figure 2. Neutron relative concentration and delayed neutron precursor nuclear concentration chart.

Therefore, suitable controller parameters can be designed based on the given initial power and final power to make its path the optimal path.

According to **Figure 3**, it can be seen that the designed optimal state feedback controller has very good performance when given the initial equilibrium power and final stable power. However, when the initial power and final stable power change, the same controller parameters do not have as good load tracking performance. When the initial equilibrium point and final equilibrium point are different, the corresponding optimal state feedback controller parameters are also different.

The Particle swarm optimization algorithm can find the optimal controller parameters of the given initial balance point and final balance point. Therefore, the Particle swarm optimization algorithm is designed to switch the parameters of the state feedback controller when the expected power changes, so as to ensure that the state feedback controller can minimize the tracking error every time the power changes. The flowchart is shown in **Figure 4**.

However, the time taken to search for the optimal parameters using particle swarm optimization is too long, and the optimal corresponding time is much shorter than the time taken by particle swarm optimization to search for the optimal parameters. In other words, the switching time of controller parameters is slower than the response time of the state, which cannot achieve the desired effect of parameter switching. Therefore, using optimization algorithms to guide controller parameter switching is not feasible. Therefore, neural networks can be used to guide parameter switching. Specify 90 sets of initial equilibrium points and final equilibrium points as inputs, and each set is used for particle swarm optimization algorithm to seek the optimal state feedback controller parameters,

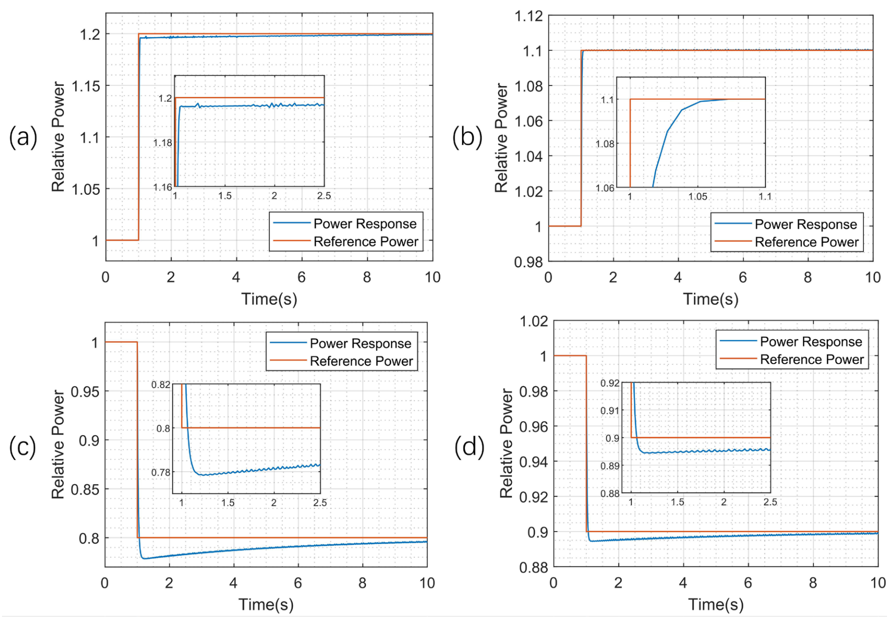

Figure 3. Reference power and power response when using optimal state feedback controller.

and the parameters are used as outputs. The trained neural network is used to guide the switching of controller parameters, and the flowchart is shown in **Figure 5**.

According to **Table 1**, it can be seen that the time required for the trained neural network to switch controller parameters is much shorter than the time required for state response. Given the initial and final equilibrium states, the state feedback parameters obtained using particle swarm optimization algorithm are compared with the controller parameters obtained using neural networks. The results are shown in **Figure 6**.

Selecting some data and using these parameters for simulation, it can be seen that the error between the simulation curve of the controller parameters obtained by the neural network and the simulation curve of the controller parameters

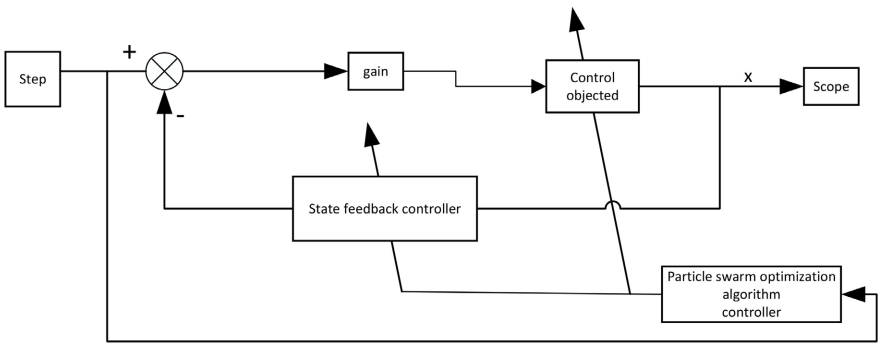

Figure 4. Controller flow chart using Particle swarm optimization algorithm.

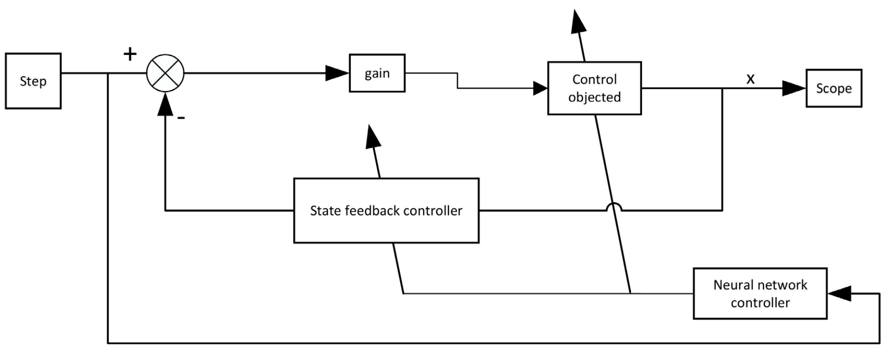

Figure 5. Controller flowchart using neural networks.

Table 1. The parameter time and state response time of neural network switching controller.

Initial equilibrium point	Final equilibrium point	PSO T	NN T	XY T
1	1.1	2.280029	0.016309	0.8281
1	0.9	2.112923	0.015789	0.1296
0.9	0.8	2.603124	0.017611	0.1059
0.8	1	2.001808	0.018749	0.9557
0.7	1.2	1.995561	0.017354	0.6348

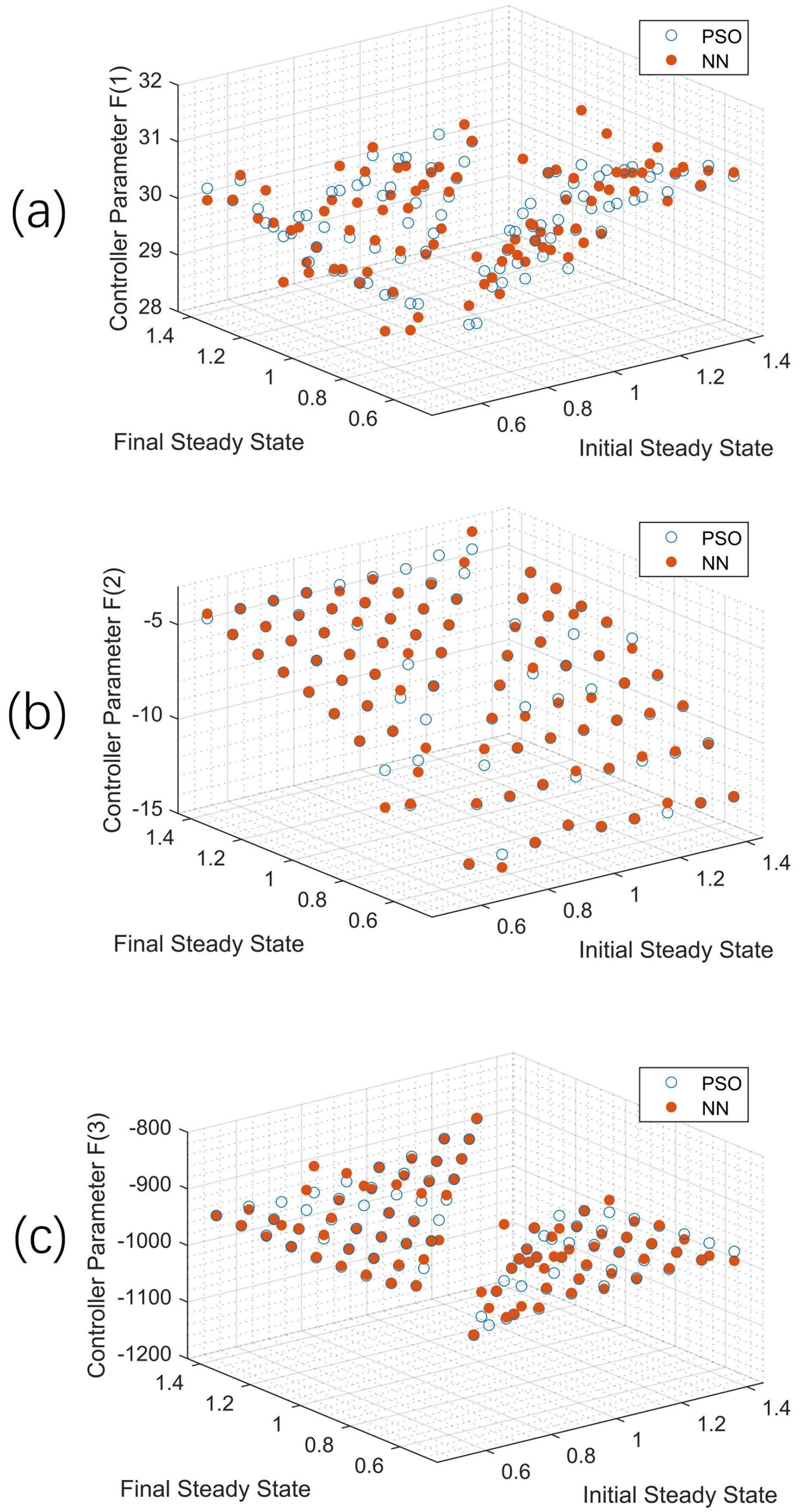

Figure 6. Comparison of state feedback parameters obtained by particle swarm optimization and neural network algorithms.

Table 2. Neural network simulation curve error and particle swarm optimization simulation curve error.

Initial equilibrium point	Final equilibrium point	PSO		NN	PSO E	NN E
		K	V	K		
1	1.1	29.9; −5.4;−896	25.5	29.8815; −5.4080; −896.8610	0.00043422	0.00043372
1	0.9	29; −7.5;−1039	21.5	29.0255; −7.1099; −939.520	0.00045068	0.00044262
0.9	0.8	29; −8.3;−1025	20.7	29.0004; −8.3276; −1024.2689	0.00046572	0.00047128
0.8	1	29.9; −6.1;−923.5	23.7	29.8980; −6.0757; −924.8245	0.00091605	0.00095319
0.7	1.2	29.6; −5.1;−943.5	24.5	29.6295; −5.3106; −940.6148	0.0026155	0.0028439

obtained by the particle swarm optimization algorithm is very small, as shown in **Table 2**.

Finally, the neural network is adopted to guide the parameter switching of the state feedback controller.

4. Simulation Result

The final change in power decreases from 1 step to 0.8, increases to 1.1, decreases to 0.9, and increases to 1. Provide a time point line diagram of power change and demonstrate the changes in controller parameters.

The optimal state feedback controller switching scheme designed based on the above scheme should be simulated for complex power changes. The expected power change is to operate at an initial relative power of 1 for 5 seconds, then step down to 0.8, and then step up to 1.1 at 10 seconds, then decrease to 0.9 at 15 seconds. The power returns to 1 at 20 seconds, and quickly steps between 0.9 and 1.1 between 25 and 30 seconds. Finally, the relative power returns to the initial state at 31 seconds. The simulation results are shown in **Figure 7**. From this, it can be seen that at each time point of power change, the role of the optimal state feedback controller is very obvious, and the load tracking situation is as excellent as expected. Even if the power switches quickly within a certain period of time, its load tracking effect is also very good.

During the time period of controller parameter switching, the power runs smoothly and does not fluctuate due to changes in controller parameters. Frequent switching of con troller parameters has no impact on stable power. Comparing the actual power change with optimal state feedback switching control with the actual power change of the controller without switching, it can be found that the load tracking effect of switching controller parameters is better than that of not switching parameter load.

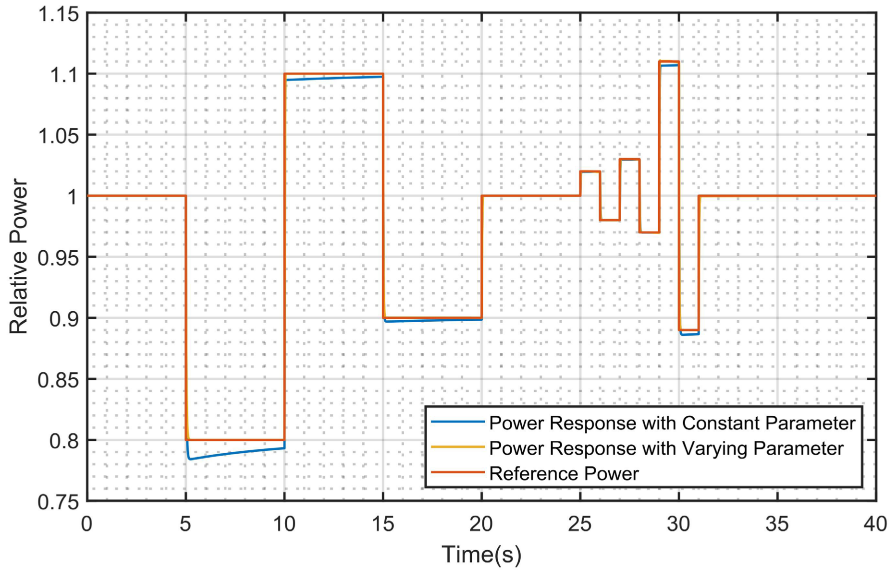

Figure 7. Power changes and controller parameter changes.

5. Conclusion

According to the analysis of the system, in the absence of input, the steady-state power is the only equilibrium point of the system. With input, the final steady-state power is the only equilibrium point of the system. By adjusting the parameters of the state feedback controller, the optimal path between the two equilibrium points can be achieved in reality. Through actual simulation comparison, it can also be seen that the load tracking effect of controller parameter switching is much better than that of pure state feedback load tracking. Combining the reactor power mathematical model and the principle of the state feedback controller, and through the simulation of the load tracking effect of power changes, the following conclusions can be drawn for the switching control method of the optimal state feedback controller:

- Introducing a state feedback controller can achieve the optimal load tracking effect;
- The design of optimal state feedback controller parameters is related to the initial stable state of power and the final stable state of power;
- Using neural networks to switch controller parameters is faster than using optimization algorithms to switch;
- The power does not fluctuate during controller parameter switching.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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