



VALVE BARREL POSITION CONTROL BASED ON SELF-TUNING FUZZY PID WITH PARTICLE SWARM OPTIMIZATION

Zhang Haiyan, Song Lepeng* and Dong Zhiming
School of Electrical and Information Engineering
Chongqing University of Science and Technology
Chongqing 401331, P.R. China
Email: slphq@163.com

Submitted: Apr. 10, 2016

Accepted: Jul, 25, 2016

Published: Sep. 1, 2016

Abstract- This paper introduced the self-tuning fuzzy PID controller based on particle swarm optimization which aims to gain more precise control over the position of pneumatic proportional valve barrel, where particle swarm works to optimize the membership function, fuzzy rule and PID parameter in fuzzy control. The study fruits also include online optimization of the self-tuning fuzzy PID controller parameters. Comparing to the conventional control methodology, The self-tuning fuzzy PID controller with PSO optimization is proven to show better precision, dynamic performance index and more rapid tracking performance and robustness. To this end, step response was used to compare and analyze the results from the PSO algorithm optimization, providing a pragmatic method of better comprehensive performance for PID parameter optimization.

Index terms: Position Control; Particle Swarm Optimization; Fuzzy PID

I. INTRODUCTION

With air as working medium, pneumatic proportional valve barrel conveys energy and signals. Controlling signals via the proportional valve barrel has been widely used in manufacturing process automation. Owing to its environmentally friendly, safe, convenient, and economic features, the pneumatic proportional valve delivers good performance in modern control field, microelectronic and computer technology[1]. In recent years, research work on pneumatic proportional valve barrel has surged. Various types of control including PID, non-linear PID, optimal, robustness, parameter self-tuning, fuzzy control PID and fuzzy neural network, all being applied to the pneumatic proportional valve barrel[2-6]. But most control methods obtain no effective optimization. Conventional control method can hardly obtain ideal effects due to the presence of easy compression of air in the barrel, non-linearity between input and output, friction of cylinder and parameters of the valve subjected to temperature and pressure. To tackle these issues, particle swarm optimization is then taken to get fuzzy PID to enable a more precise, rapid and stable control.

II. PNEUMATIC PROPORTIONAL VALVE MODEL

The experiment system composes mainly of FESTO Company's DGPL-25-400-PPV-A-B rodless cylinder, MPYE-5-1/4-010B three-position five-path proportional valve, MLO-POT-500-TLF displacement transducer, A/D and D/A convertor commonly used in HY-6070 along with computers, as shown in Figure 1.

Basic principle of the system: A computer collects signal U_f from displacement transducer through A/D module and compares it to set signal (input voltage signal) U_e , if $U_e - U_f > 0$, the air passage of proportional valve on the left opens, followed by air pressure of the left cavity that rises to push right the cylinder piston. This is accompanied by an increasing signal U_f of displacement transducer, while deviation ΔU of $U_e - U_f$ decreases accordingly till it reaches zero. Conversely, when the signal U_f of the setpoint (input voltage signal) displacement sensor, $U_e < U_f$, ie $U_e - U_f = \Delta U < 0$, an adjustment procedure in contrast to the above may help reduce ΔU down to zero. When stability is reached, namely, $U_f = U_e = ky$, $\Delta U = 0$. $k =$ scale factor, $y =$ displacement of cylinder piston. Positioning control of input signal U_e and displacement of piston Y is realized[7].

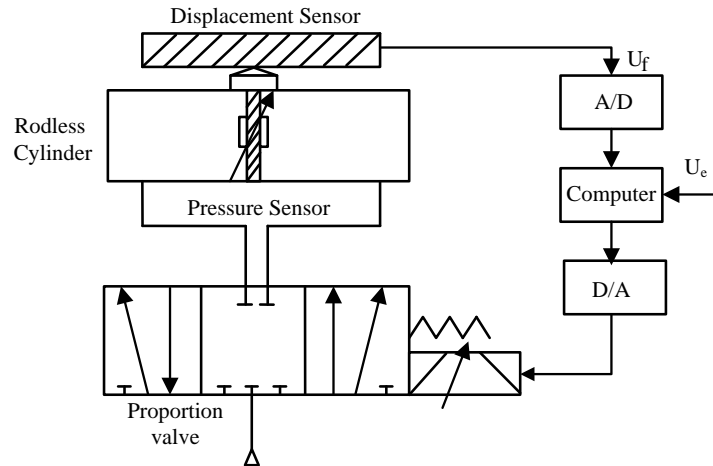


Figure 1. System Structure of Proportional Valve Barrel

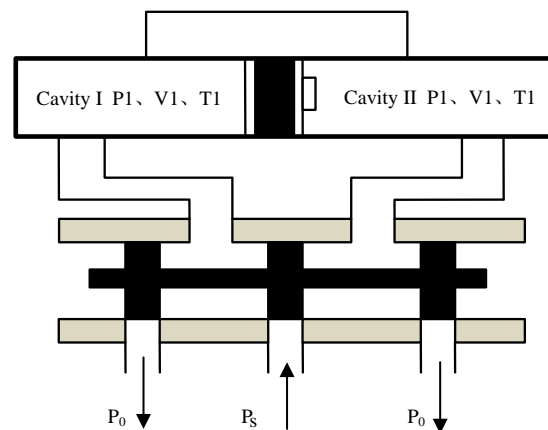


Figure 2. Diagram of Proportional Valve Barrel

Assumptions inferred from Figure2: (1) the medium of pneumatic proportional valve barrel is ideal gas, namely, $PV=MRT$; (2) constant set pressure and temperature, namely, P_S and T_S are constant; (3) the balanced gas of pneumatic proportional barrel and equal parameters in all cavities; (5) changes of all parameters during system dynamic change are minuteness.

The open-loop transfer function of pneumatic proportional valve barrel was sorted out by calculation

$$G(s) = \frac{Kv}{s(s^2 + \frac{2\zeta_n}{\omega_n}s + 1)}$$

In the experiment, air pressure is 0.6Mpa, load is 150N, cylinder lift is 500mm and piston diameter is 25mm. That is: $Kv=8.2$, $\zeta_n=0.2$, $\omega_n=39.5$ Therefore:

$$G(s) = \frac{12794.05}{s(s^2 + 15.8s + 1560.25)}$$

III. FUZZY CONTROLLER DESIGN BASED ON PARTICLE SWARM OPTIMIZATION

Fuzzy control is an advanced control technology based on language rule and fuzzy inference, also being one of the most important and active branches in intelligent control field. Fuzzy control boasts strong robustness and the capacity to control complex objects which are hard for modeling needing no precise model of controlled object, so it is widely applied in various industries such as manufacturing, agriculture, national defense and medicine.

Selection of fuzzy controller depends on system input including system error (E) and error change rate (EC), so two-dimensional fuzzy controller was chosen due to its control effect and good stability to reduce overshooting and vibration of system. Categorize after E and EC discretizing within certain range. Generally it's divided into 6 types to reduce control difficulty and complexity so as to ensure fuzzy set to better cover its domain of discourse and avoid runaway. Discriminate E, EC and change of controlled quantity by three fuzzy concepts of "big", "medium" and "small", and divide them into 7 values: Plus Big (PB), Plus Medium (PM), Plus Small (PS), Zero (0), Negative Small (NS), Negative Medium (NM) and Negative Big (NB) [8-12]. See Table 1 for fuzzy control rule compiling based on Table 1

Table 1. Fuzzy Control Rule Table

		U			E			
		NB	NM	NS	0	PS	PM	PB
EC	NB	NB	NM	NS	0	PS	PM	PB
	NM	NB	NM	NS	NS	NS	0	PS
	NS	NM	NM	NS	NS	NS	0	PS
	0	NM	NM	NS	0	PS	PS	PM
	PS	NB	NS	0	PS	PS	PM	PB
	PM	NB	NS	0	PS	PM	PM	PB
	PB	NB	NS	PS	PM	PM	PB	PB

Initialize a group of particles with no volume and mass at random, view every particle as a feasible solution after optimization which is decided by the set function. Particles move within the space of feasible solution, one speed decides its direction and distance chase the current optimal particle to search the optimal solution gradually. Meanwhile a particle of each

generation has two optimal solutions: optimal solution searched by one particle so far, and another one searched by the whole particle swarm.

Assuming: a particle swarm formed by M particles in a D -dimension search space, particle's state in time t is as follows:

Position:

$$x_i^t = (x_{i1}^t, x_{i2}^t, \dots, x_{id}^t)^T, x_{id}^t \in [ld, ud],$$

Speed:

$$v_i^t = (v_{i1}^t, v_{i2}^t, \dots, v_{id}^t)^T, v_{id}^t \in [v_{\min}, v_{\max}],$$

Individual optimal position:

$$P_i^t = (P_{i1}^t, P_{i2}^t, \dots, P_{iD}^t)^T;$$

Global optimal position:

$$P_g^t = (P_{g1}^t, P_{g2}^t, \dots, P_{gD}^t)^T,$$

including

$$1 \leq d \leq D, 1 \leq i \leq M.$$

Then position and speed of particle in time $t+1$ changes to:

$$v_{id}^{t+1} = \omega v_{id}^t + c_1 r_1 (P_{id}^t - x_{id}^t) + c_2 r_2 (P_{gd}^t - x_{id}^t)$$

$$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1}$$

r_1 and r_2 are random numbers within $[0,1]$, c_1 and c_2 are learning factors, also called accelerated factor, usually $c_1=c_2=2$.

ω is inertia weight, whose value decides the particle's inheriting of current speed.

The first part is inheriting from previous speed, keeping on inertia motion relying on particle's own speed;

The second part is the cognition part of particle, i.e. particle's thought on itself. Integrate particle's own path and experience then to make further decision, which is a self-learning process of particles.

The third part is the social part, namely, information sharing and cooperation between a particle and other particles. Implementation steps are as follows [13,14]:

Step 1: Initiate population's position and speed; Step 2: Calculate particle's objective function value; Step 3: For each particle, compare the fitness value of optimal position P having

been found by particles so far and that of themselves, choose the better one as the optimal position; Step 4: For each particle, compare the fitness value of global optimal position P having been found by particles so far and that of themselves, choose the better one as the global optimal position; Step 6: refresh the speed and position of particles based on formula (3), (4); Step 7: If the above calculation cannot meet the requirement, go back to Step 2 [13, 14].

Key of particle swarm optimization is the setting of objective function. Adopt ITAE method to use particle swarm to optimize objective function. Optimize dynamic and static index of the system[15,16].

$$J_{itac} = \int_0^{+\infty} t |e(t)| dt \quad (1)$$

In the formula, e(t) is error. PID algorithm utilizes error's ratio, integral and differential to form linear combination and controller, and PID regulator input can be described as:

$$U(t) = K_p [e(t) + \frac{1}{T} \int_0^t e(t) dt + \frac{T_D de(t)}{dt}] \quad (2)$$

In the formula, KP = proportion magnification factor, T = integral time constant, TD = differential time constant; and K1 = KP/KD, KD = KPTD; e(t) is the feedback deflection of the system. The central part of facilitating particle swarm to optimize and set parameters of self-tuning fuzzy PID is to utilize error optimization algorithm, error change rate and the optimal position of $\theta=[KP, KI, KD]$, enabling dynamic and static index of PID control to comply with the requirement. The essence is a process for objective function to pursue optimization[17,18].

IV. SIMULATION EXPERIMENT AND RESULTS ANALYSIS

Figure 3 is system editor of fuzzy inference, Figure 4 is membership function curve of input variable (e), Figure 5 is membership function curve of input variable (ec), Figure 6 is membership function curve of output variable (kp), Figure 7 is membership function curve of output variable (ki), Figure 8 is membership function curve of output variable (kd), Figure 9 is the editor window of fuzzy control rules, Figure 10 is graphic of rules observer, Figure 11 is graphic of surface observer (kp), Figure 12 is graphic of surface observer (ki), Figure 13 is graphic of surface observer (kd), Figure 14 is membership function curve of input variable after optimization (e), Figure 14 is membership function curve of input variable after optimization (e), Figure 15 is membership function curve of input variable after optimization (ec), Figure 16 is membership function curve of output variable after optimization (kp), Figure 17 is membership

function curve of output variable after optimization (ki), Figure 18 is membership function curve of output variable after optimization (kd). Table 2 is control rule table after optimization (kp), Table 3 is control rule table after optimization (ki), Table 4 is control rule table after optimization (kd). Figure 19 is fuzzy PID system simulation model after optimization, Figure 20 is fuzzy PID simulation oscillogram of fuzzy control and simulation model after optimization. From the result, self-tuning fuzzy controller optimized by particle swarm is proven to own stable and rapid control performance. Conventional PID simulation results show: larger system overshoot, briefly longer rising time and regulation time[19]. Simulation results of fuzzy PID controller optimized by particle swarm were: shorter rising time and regulation time of simulation model, while simulation result of PSO optimization model overshoot was poor but stable, with longer system recovery time than that of PID control simulation under the influence of step disturbance, Self-tuning fuzzy model optimized by particle swarm has better disturbance -rejection capacity than non-linear typical model. It is shown that the controller is applicable to situation requiring high stability, which is most important in control system. No stability, no system. So PSO optimization result has an advantage in overshoot optimization and wide application in control field.

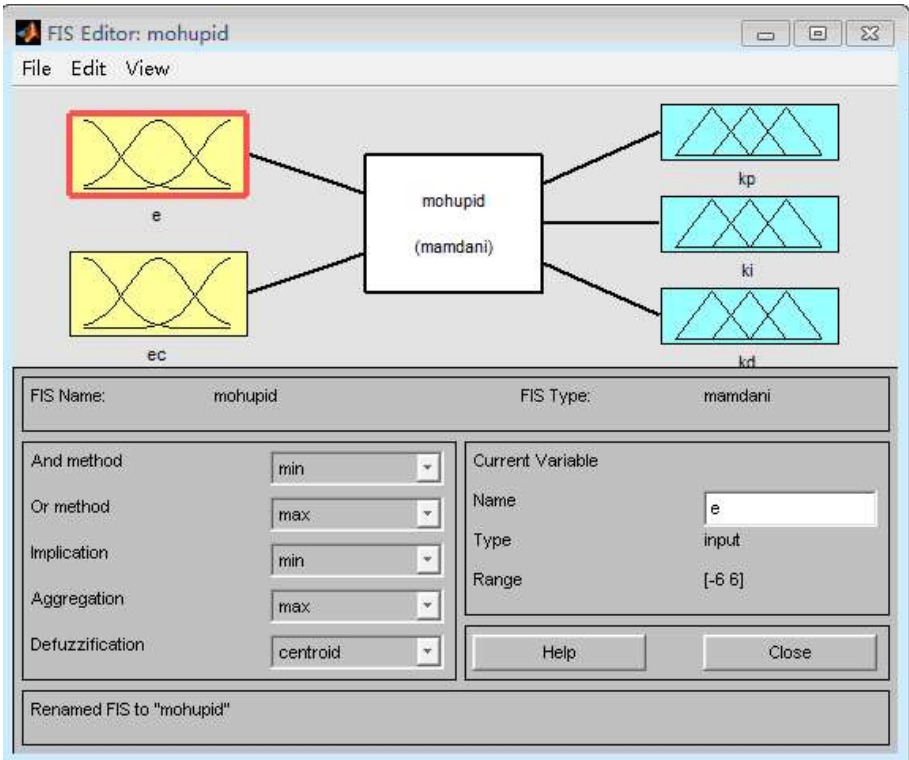


Figure3. System editor of fuzzy inference.

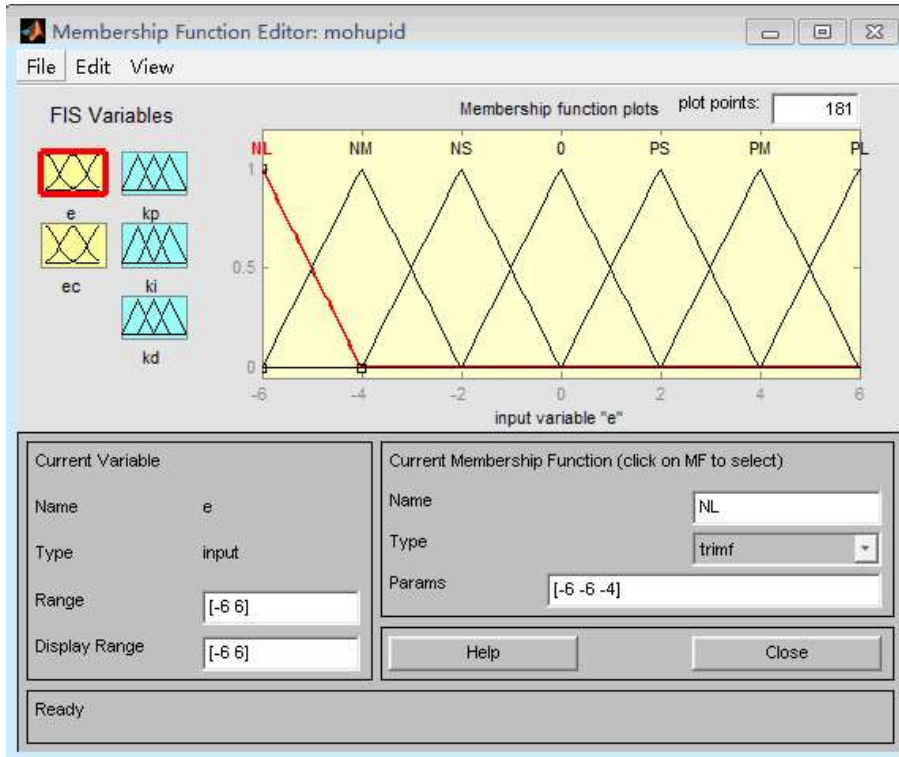


Figure4. Membership function curve of input variable (e)

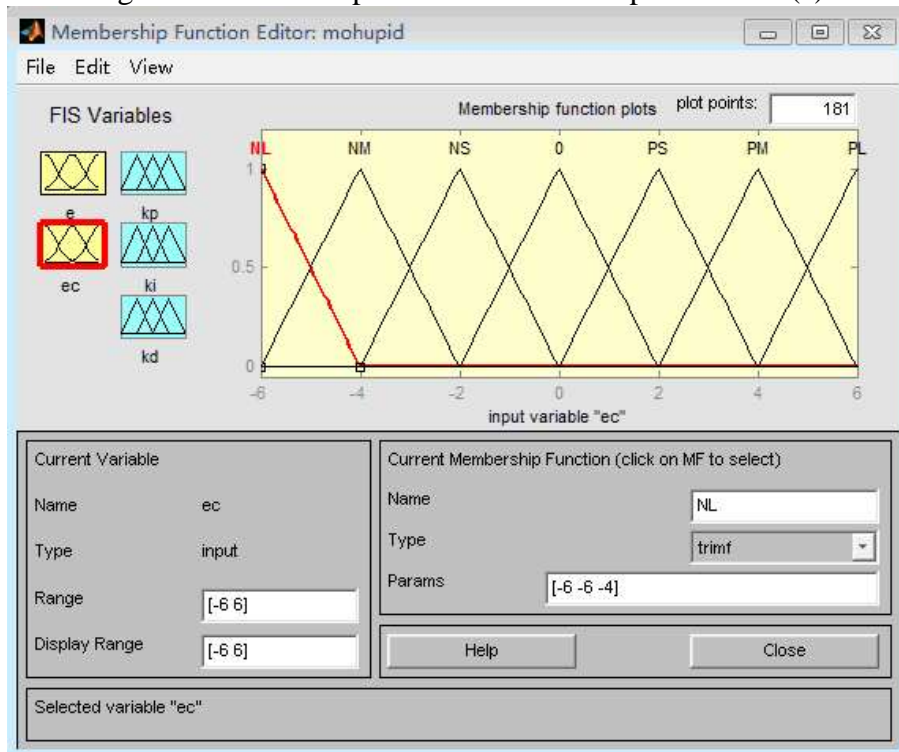


Figure5. Membership function curve of input variable (ec)

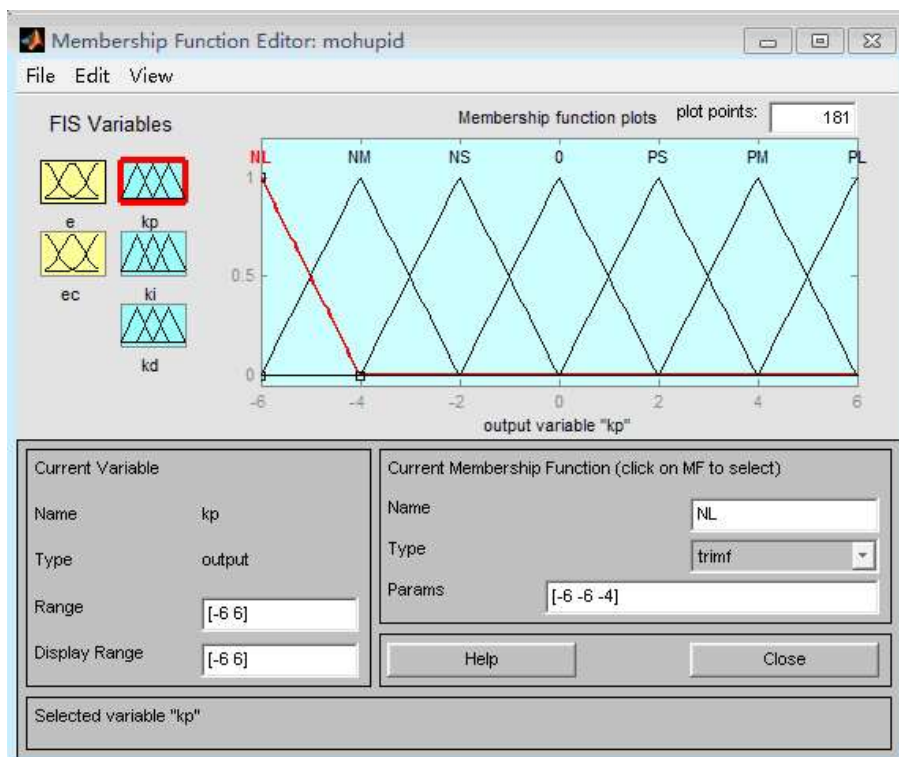


Figure6. Membership function curve of output variable (kp)

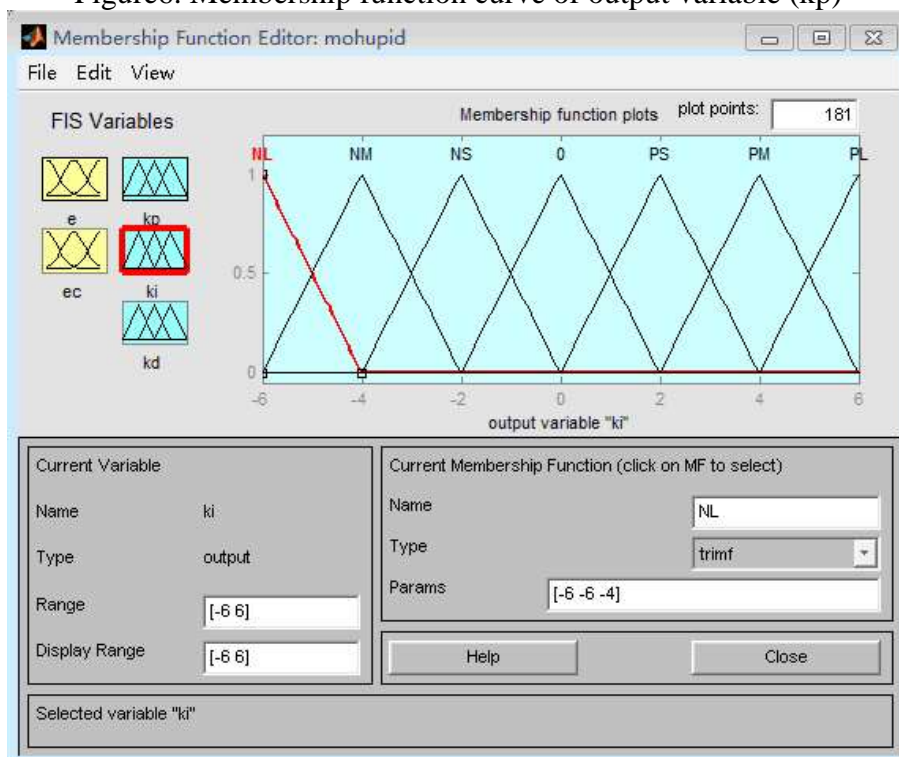


Figure7. Membership function curve of output variable (ki)

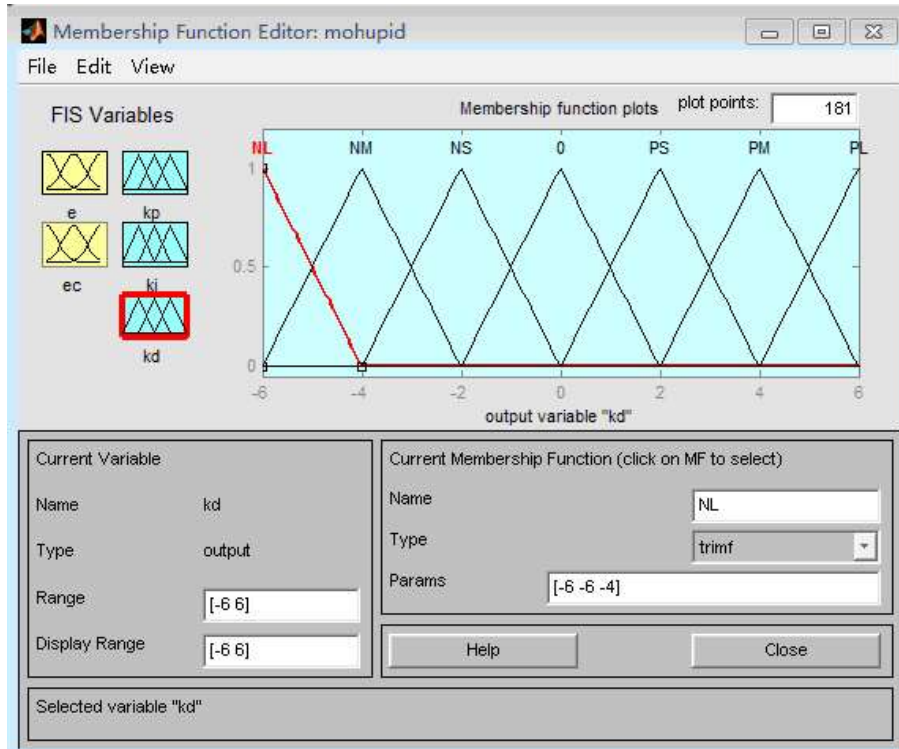


Figure8. Membership function curve of output variable (kd)

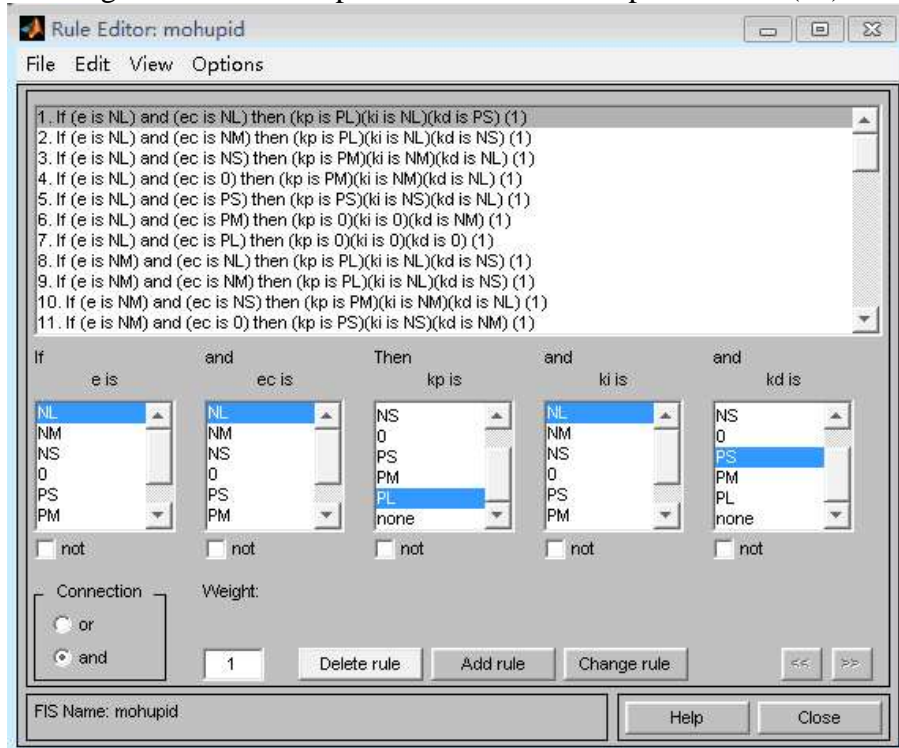


Figure9. The editor window of fuzzy control rules

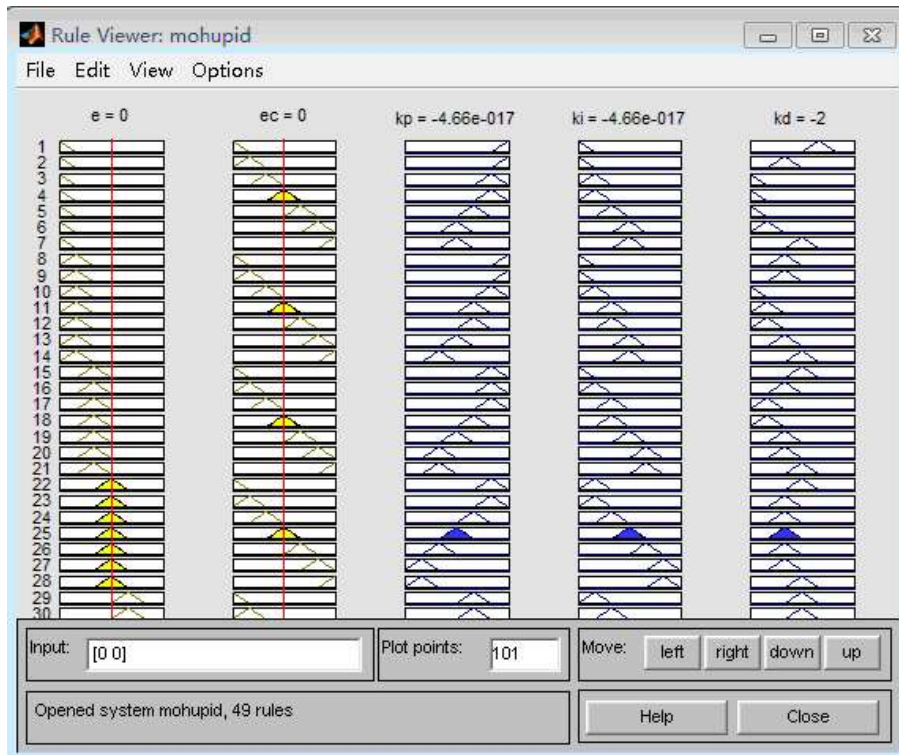


Figure10. Graphic of rules observer

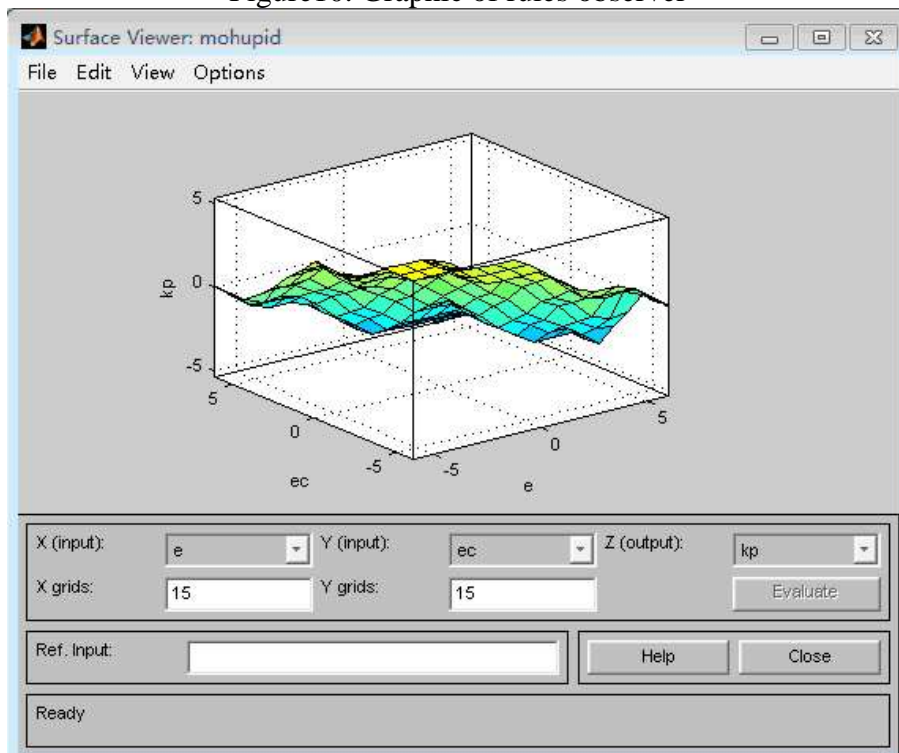


Figure11. Graphic of surface observer (kp)

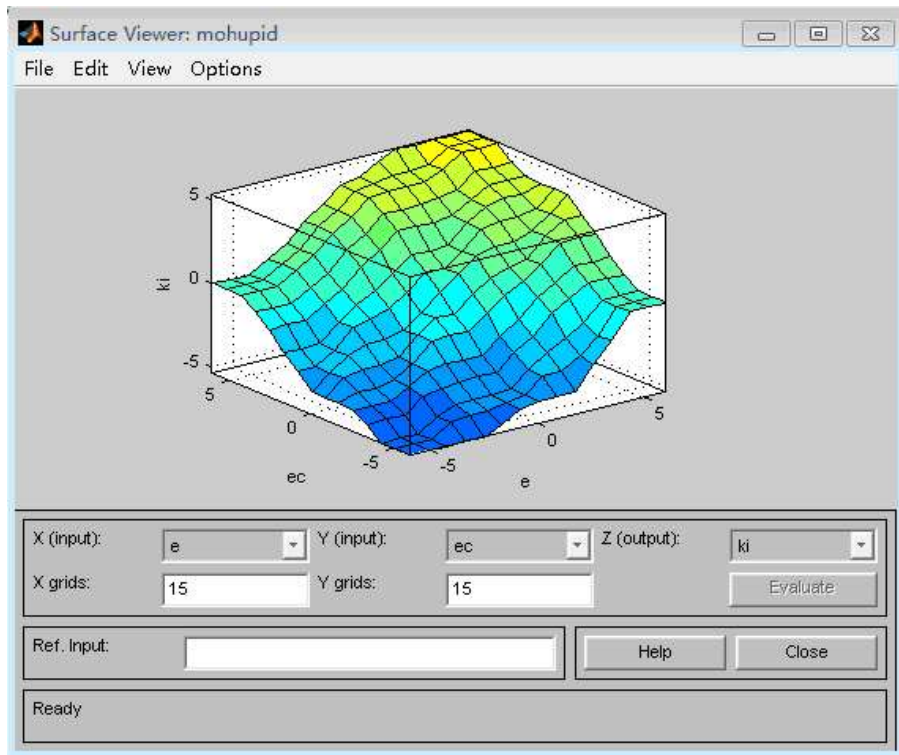


Figure12. Graphic of surface observer (ki)

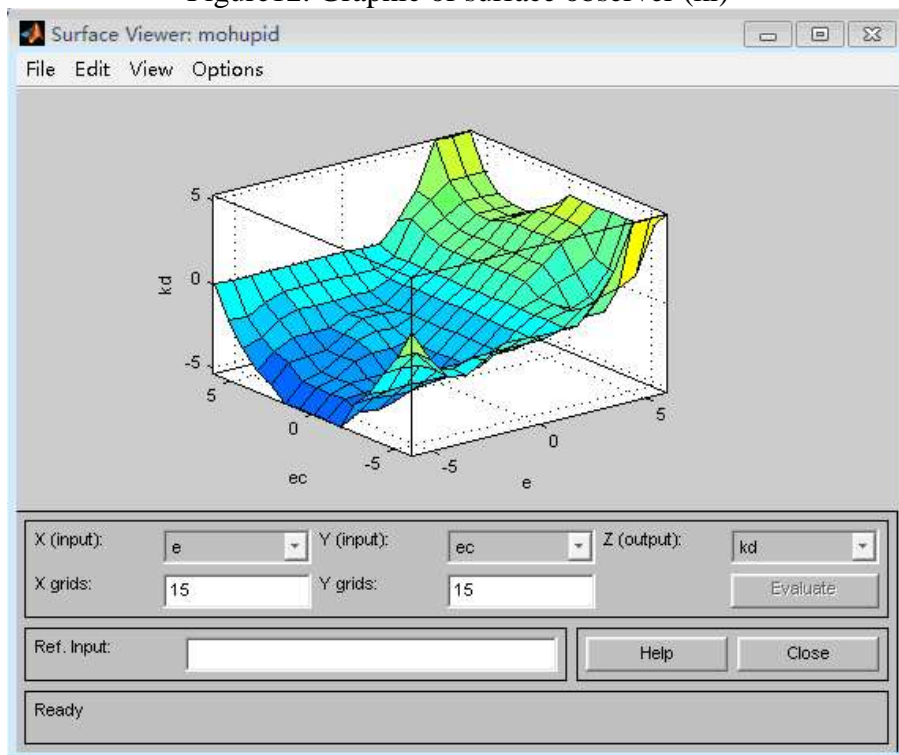


Figure13. Graphic of surface observer (kd)

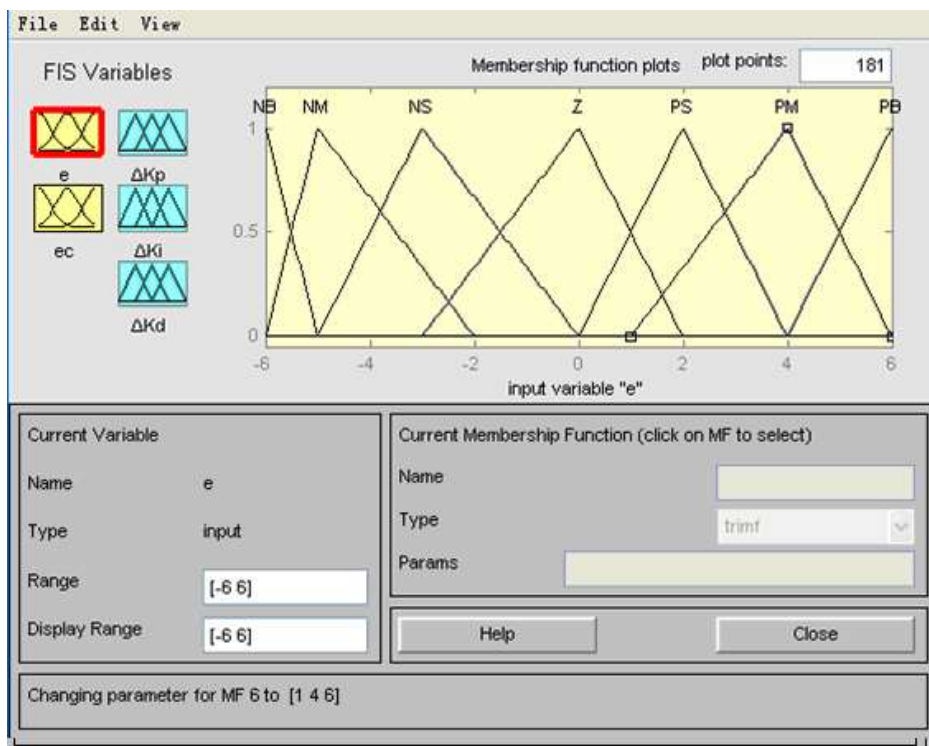


Figure14. Membership function curve of input variable after optimization (e)

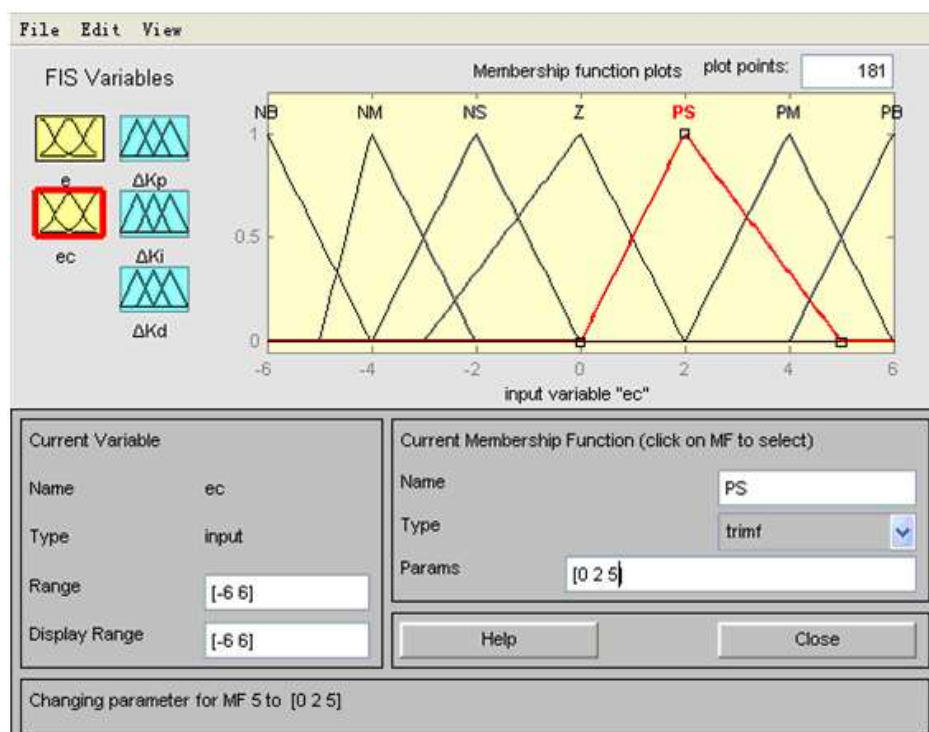


Figure15. Membership function curve of input variable after optimization (ec)

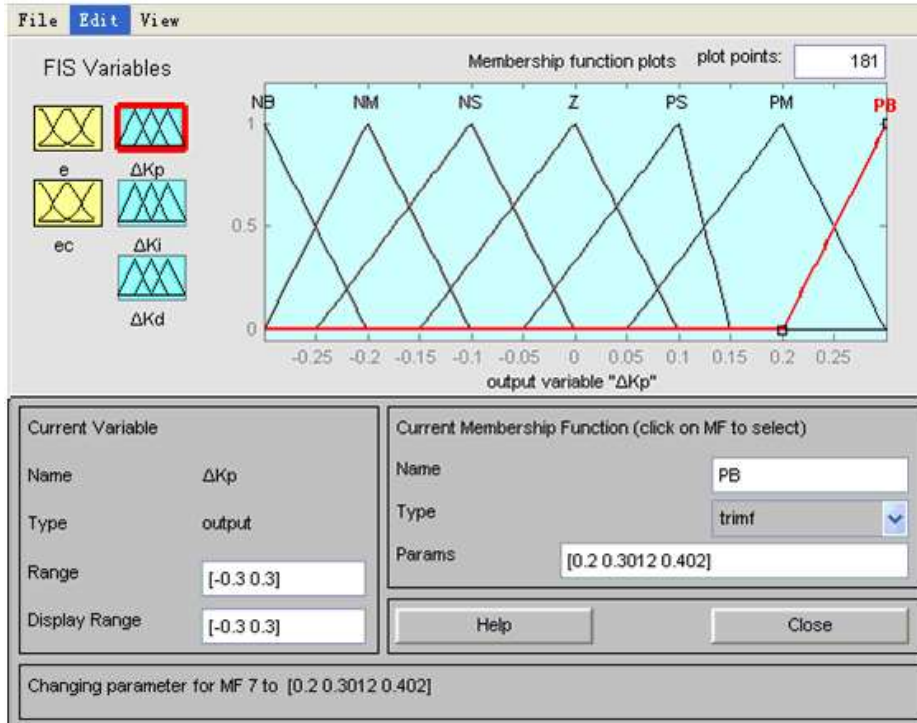


Figure16. Membership function curve of output variable after optimization (kp)

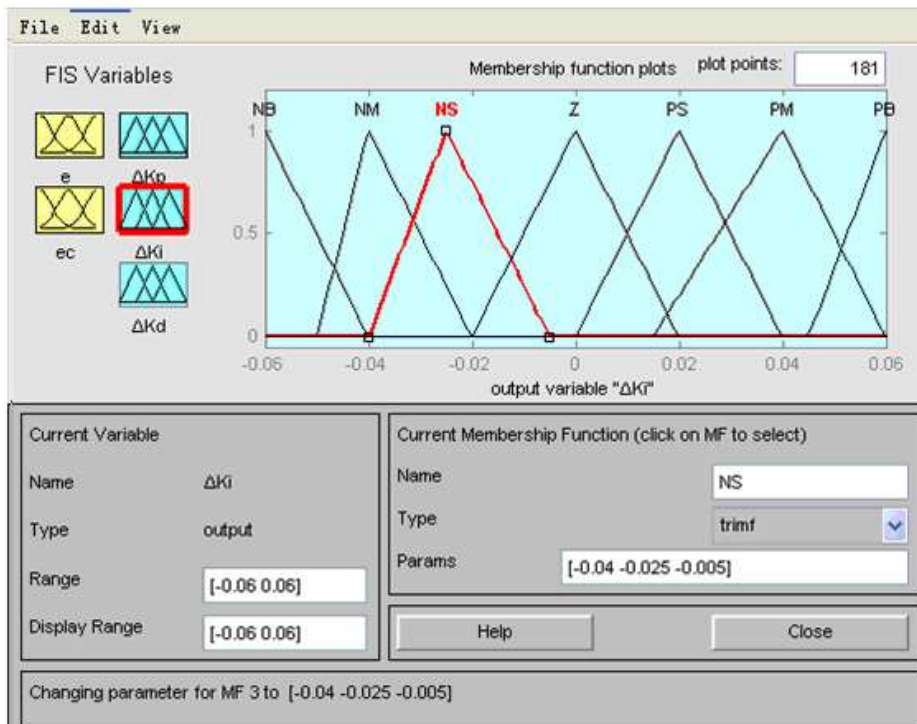


Figure17. Membership function curve of output variable after optimization (ki)

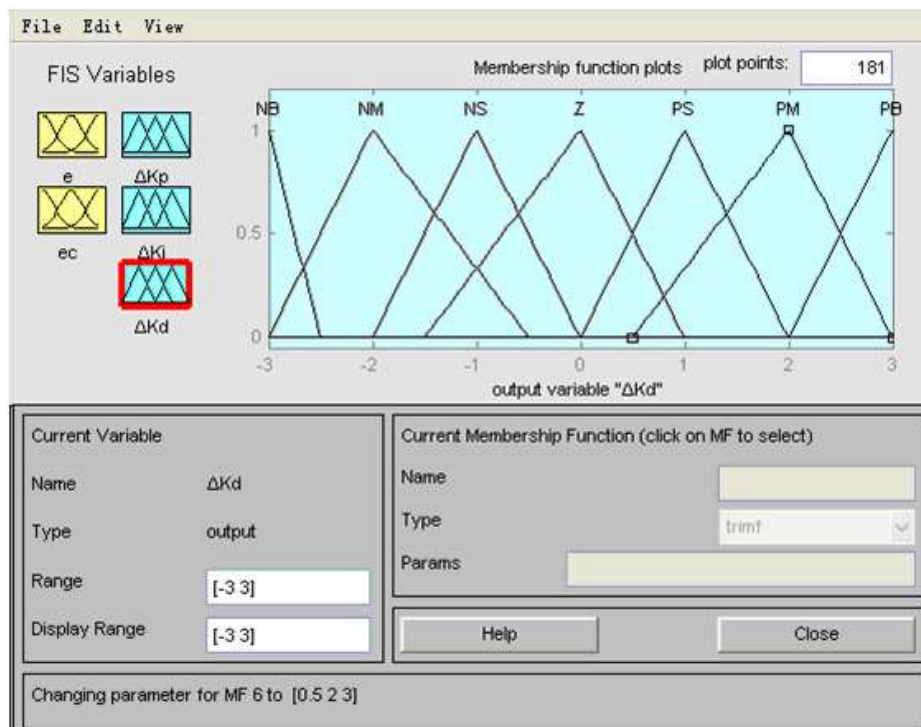


Figure18. Membership function curve of output variable after optimization (kd)

Table 2. Control rule table after optimization (kp)

EC	E						
	NB	NM	NS	Z	PS	PM	PB
NB	NM	NB	NM	NB	PB	PM	NM
NM	Z	PS	PM	NB	PM	NB	NB
NS	NM	NS	PM	PB	PM	PM	NS
Z	NM	PS	PM	PB	PB	NB	Z
PS	NB	Z	PB	PM	PM	PM	NM
PM	PM	NM	PB	NB	NB	PM	NM
PB	PS	PS	NB	NM	PS	Z	NB

Table 3. Control rule table after optimization (ki)

EC	E						
	NB	NM	NS	Z	PS	PM	PB
NB	PB	PB	NB	NB	Z	PS	PM
NM	PB	NM	NB	PM	NB	NS	PB
NS	PB	PN	NM	PS	NS	NB	PB
Z	PB	NB	NS	Z	Z	NM	PM

PS	PS	NB	NB	PB	PM	Z	NB
PM	NB	NB	NB	PM	NM	NS	NB
PB	PM	PM	Z	NS	NB	NB	PM

Table 4. Control rule table after optimization (kd)

EC	E						
	NB	NM	NS	Z	PS	PM	PB
NB	PM	PS	NS	PB	NB	NB	NM
NM	PM	PM	NB	PB	NB	NB	NM
NS	PS	PM	NB	Z	PM	Z	NM
Z	Z	Z	PS	NM	PM	NB	PS
PS	Z	NM	PS	PB	PB	PB	NB
PM	NS	NM	NS	NB	PM	NM	NB
PB	NS	NM	Z	NS	PM	PS	NB

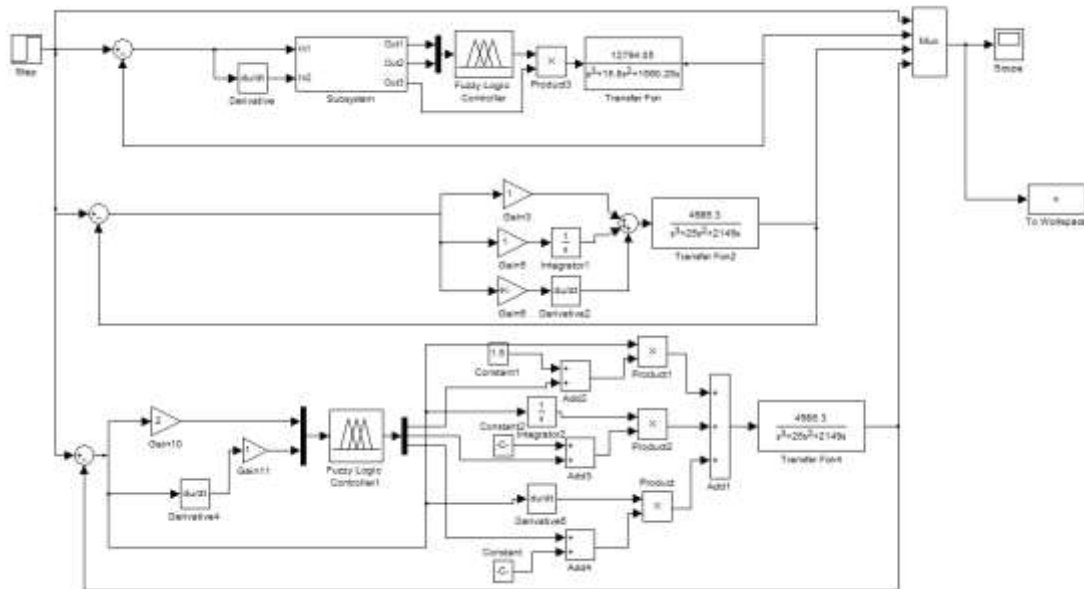


Figure19. Fuzzy PID system simulation model after optimization

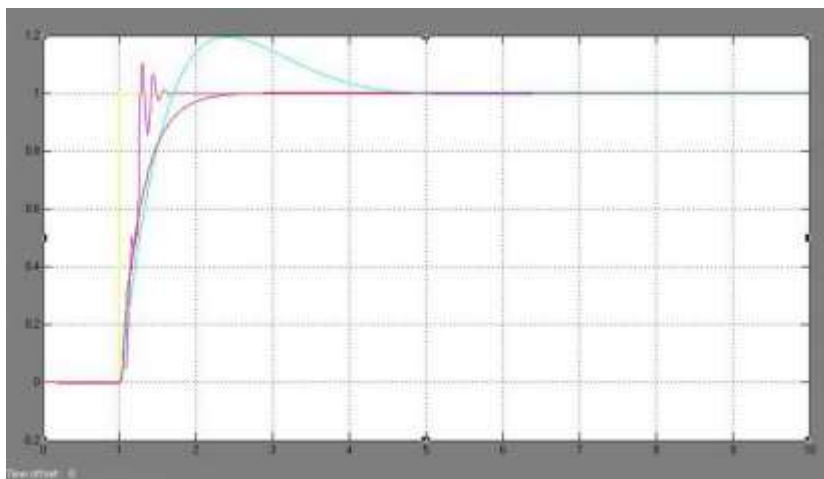


Figure20. fuzzy PID simulation oscillogram of fuzzy control and simulation model after optimization.

V. CONCLUSION

This paper is here concluded by applying the particle swarm optimization to pneumatic proportional valve barrel control system, conducting parameter optimization on E, EC and KP, KI, KD of fuzzy PID controller, which were compared with those of conventional PID simulation results. It is impressive that the dynamic effect of the former is better than regular ones. Fuzzy PID controller makes a feature of speediness, smaller overshoot, stronger robustness and is more applicable to online control and parameter setting of complex objects. The results appeared that particle swarm optimized pneumatic proportional valve barrel enjoyed more advantage than traditional controllers.

ACKNOWLEDGEMENTS

This work was financially supported by the Project of Natural Science Foundation Of China (61174015), Application and Development Projects of Chongqing (cstc2014yykfA80012), Project of Natural Science Foundation Of Chongqing Education (KJ131416、KJ133501), Research Foundation of Chongqing Education Committee, Foundation Number: KJ1501325. Natural Science Foundation of Chongqing. Foundation Number: cstc2014jcyjA70001

REFERENCES

- [1] Kong Xiangzhen, Liu Yanjuan, Wang Yong, "Research on System Friction Compensation of Pneumatic Proportional Valve", *Lubrication and Seal*, 2007, 31(2): 135-138.

- [2] Shi Bingcun, Yao Xiaoning, "Research on Position Control Precision Experiment of Pneumatic Proportional Valve", *Hydraulic and Pneumatic Research*, 2007, 25(6): 28-30.
- [3] Wen Dongsheng, Wu Guangqiang, Wang Leilei, "Application of Genetic Algorithm PID in Automatic Transmission Proportional Valve", *Saic Motor*, 2011, 30(11): 40-43.
- [4] Jiang Jimin, Zhang Lei, Shi Jingzhuo, "Position Control of Pneumatic Proportional Valve Barrel System Based on Immune Principle", *Electric Drive*, 2012, 42(5): 30-32.
- [5] Zhu Chunbo, Bao Gang, Cheng Shukang, Wang Zuwen, "Research on Neural Network Control Method of Pneumatic Servo System Based on Proportional Valve", *China Mechanical Engineering*, 2001, 12 (12), 1412-1414.
- [6] Luo Yanlei, Chen Lunjun, Li Yuan, Qiu Xue, Bai Yuzhu, "Research on Fuzzy PID Control Method Optimized by Pneumatic Proportional Position System", *Chinese Journal of Construction Machinery*, 2010, 8(1): 56-61
- [7] Zhang Yanyan, Han Jianjun, Zhao Shushang, Li Jilei, "Cylinder Position Servo Control System Based on FUZZY-PID", *Hydraulics Pneumatics & Seals*, 2008, 28(4): 11-15.
- [8] Bo Yanhong, Li Xiaoning, "Improvement of Feedback Control of Cylinder Position Servo Control System State", *Chinese Journal of Mechanical Engineering*, 2009. 45(8): 101-105.
- [9] Wang Yongfu, Chai Tianyou, "Research Review of Self-tuning Fuzzy Control Principles", *Control Engineering*, 2006, 13(3): 193-198.
- [10] Li Jian, Liu Weimiao, Xu Chang'an, Sun Yanwei, Li Hongwei, "Precise Positioning Control of Fuzzy PID Method Applying to Hydraulic Proportion Valve", *Heavy Machinery*, 2012, (1): 14-16.
- [11] Wen Shengping, Zhao Guoping, Cai Kangxiong. "Fuzzy Control Self-tuning Algorithm in Variable Domain", *Control Theory and Applications*, 2009, 26(3): 265-268.
- [12] Liu Zhizhuang, Hong Tiansheng, Li Zhen, Song Shuran, Yue Xuejun, Fan Zhiping, "Flow Control Valve Simulation Based on Fuzzy Control", *Transactions of the Chinese Society of Agricultural Engineering*, 2009, 25(2): 83-86.
- [13] Su Yi, Xu Xiao'ang, "Research on Speed Regulation of Double Closed-Loop DC Motor Based on Particle Swarm Algorithm Improvement", *Colliery Mechanical & Electrical Technology*, 2012, 28(4), 03-08.
- [14] Zhou Songhua, Ouyang Chunjun, Liu Changxin, Zhu Ping, "Self-Tuning Fuzzy Particle Swarm Optimization Algorithm", *Computer Engineering and Applications*, 2010, 46(33): 46-48.
- [15] Payman Moallem, Mohammad Ali Abdollahi, and S. Mehdi Hashemi, "Compensation Of Capacitive Differential Pressure Sensor Using Multi Layer Perceptron Neural Network", *International Journal on Smart Sensing and Intelligent Systems*, Vol. 8, No. 3, pp 1443-1463, September 2015.
- [16] Adam Funnell, Xiaomin Xu, Jize Yan, Kenichi Soga, "Simulation Of Noise Within BOTDA And COTDR Systems To Study The Impact On Dynamic Sensing", *International Journal on Smart Sensing and Intelligent Systems*, Vol. 8, No. 3, pp 1576-1600, September 2015.

[17]Xing Haihua, Yu Xianchuan, Hu Dan and Dai Sha, “Sensitivity Analysis Of Hierarchical Hybrid Fuzzy - Neural Network”, International Journal on Smart Sensing and Intelligent Systems, Vol. 8, No. 3, pp 1837-1854, September 2015.

[18]H. Ozaki and Y. Omura, “An Advanced Nonlinear Signal Model To Analyze Pulsation-Derived Photoplethysmogram Signals”, International Journal on Smart Sensing and Intelligent Systems, Vol. 8, No. 2, pp 921-943, June 2015.

[19]Zhongwei CUI, Yong ZHAO, Daoyun XU, and Yu ZUO, “An Energy efficient Routing For Vehicular Ad Hoc Networks Using Real-Time Perception Of Node Information”, International Journal on Smart Sensing and Intelligent Systems, Vol. 8, No. 2, pp 1142-1161, June 2015.