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APPLIED RESEARCH

A Fuzzy Neural Network Controller Using Compromise Features for Timeliness Problem

LEI WANG[1], LIANGXIN DONG[2], ZIWEI HUANGFU[3], AND YIYANG CHEN[4], (Member, IEEE)
[1]School of Automation, Wuxi University, Wuxi 214105, China
[2]School of Automation, Nanjing University of Information Science and Technology, Wuxi 214105, China
[3]Key Laboratory of Advanced Perception and Intelligent Control for High-End Equipment, Anhui Polytechnic University, Wuhu 241000, China
[4]School of Mechanical and Electrical Engineering, Soochow University, Suzhou 215137, China

Corresponding author: Yiyang Chen (yychen90@suda.edu.cn)

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ABSTRACT When the control rules of traditional fuzzy controller are determined, it comes to be time-consuming and laborious to adjust for different usage conditions. Therefore, the timeliness cannot be guaranteed to solve the timeliness problem, and a fuzzy controller with modifiable factors is designed. While the entire control table is affected by the modifiable factors selection table, all previous control parameters need to be reset. In light of above problems, this paper firstly proposes new fuzzy controller design methods, which retain strengths of traditional controller and controller with modifiable factors. It effectively overcomes the shortcomings of the two controllers mentioned above, and only need to adjust the compromise factor for different working conditions of proposed controller, which is more convenient and efficient. Secondly, the proposed fuzzy controller also adopts a four-layer neural network to optimize the control rules of compromise to improve control precision and system robustness. Finally, the excellent characteristics of proposed controller are verified through simulation research, and the simulation result proves the proposed fuzzy controller has the advantages of higher control precision and smaller transition.

INDEX TERMS Fuzzy controller, neural network, compromise features, control precision.

I. INTRODUCTION

Currently, fuzzy control technology is one of the advanced control technologies [1], [2], [3], which is widely and fruitfully used in various aspects of industrial processes, such as industrial engineering, robotics industry and traffic control [4], [5], [6]. Fuzzy control is an intelligent control methodology on the basis of fuzzy set theory, linguistic variable and logical inference methods etc. Comparing to classical control technology, fuzzy control is a combination product of fuzzy mathematics and control theory and it imitates experience of human experts to control the system which has difficulty in developing accurate mathematical models, so the requirement for system identification is not higher and thus easier to implement. Comparing to modern control theory and technology such as model predictive control [7], iterative learning control [8], [9], Active Disturbance Rejection Controller(ADRC) [10], [11], fuzzy control has the characteristics of simpler mathematical model, easier parameter adjustment and smaller computational resources consumption etc. The previous experiments show fuzzy control has strengths of better robustness and higher dynamic performance for controlling non-linear and complex systems [12], [13], [14].

In the process of designing fuzzy controller, the quantization factor of fuzzification is fixed so that the control precision and robustness are difficult to guarantee, which is one of the shortcomings to widely apply fuzzy controller [15], [16], [17], so neural network technology used in reference [18], [19], [20], [21], [22] can be used to promote control

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precision and robustness. The neural network technology is an intelligent control method developed by simulating human neural system, which is capable of dealing with arbitrary complex nonlinear functions, has strong robustness and fault tolerance; besides, a large number of operations can be carried out quickly with parallel distributed processing which is very efficient.

A 4-layer back propagation neural network (BPNN) is widely used to develop the fuzzy relationship, which means BPNN is used to demonstrate the input and output characteristics of the fuzzy controller. Figure 1 shows that the network 1st layer is an input layer containing 2 neurons, each of which is connected to only one input variable and acts as a bridge role. The 2nd layer consists of 10 neurons, each stands for a language variable value which would be used for calculating membership function value of each input and each language variable fuzzy set [23], [24]. The 3rd layer has 15 neurons, each represents a fuzzy rule which would be used for calculating the applicability of each rule and implementing the normalization calculation. The fourth layer is the output layer of one neuron whose function is to execute the clarification calculation. The fuzzy relations after BPNN training can be described as follow:

$$U_{BPNN} = BPNN(C, E). \tag{1}$$

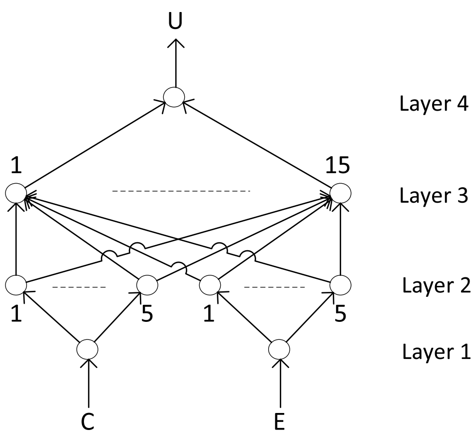

FIGURE 1. The system block diagram of a 4-layer BPNN [19].

However, the fuzzy control has various of disadvantages in practice, wherein the most important is quite troublesome and take huge time to adjust the controlling rules when the fuzzy controller rules have been determined [25], [26], [27]. In response, some improvements have been proposed, the simplest of which is to weight the inputs to the controller to construct the fuzzy controller with modifiable factors [28], [29]. As a correction to the controlling rules, its characteristic is that the weighting factor can be changed at any time according to the actual situation as a optimization of the controlling rules, and designer's experience on the control system is fully exerted in this method. While the further study reveals that this approach also has certain drawbacks, for example, almost the whole control table is affected after changing the modifiable factors, while mostly we only require changes at certain points, thus some points can satisfy the controlling demand and others not [30], [31], [32]. The disadvantage of neural network fuzzy control is that it can not handle and describe fuzzy information, besides, there are black box characteristics during learning and problem solving so that its work is not interpretable, so obviously it can not have a good usage of existing experience and experts' know-how. Moreover, through Figure 1 and Figure 2 about system block diagram of an neural network fuzzy PID controller studied in [33], [34], we can find that the neural network fuzzy controller requires higher accuracy and quantity samples which would take longer development period and higher cost for training [35], [36].

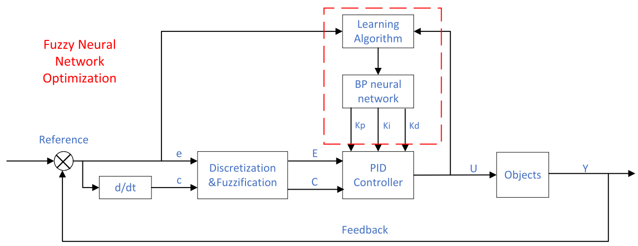

FIGURE 2. The system block diagram of a neural network fuzzy PID controller [19].

To address disadvantages of the above described fuzzy controllers, this paper proposes new design methods on basis of the principle about two outputs compromise [37], [38], [39], where only the compromise factor needs to be adjusted when the parameters of the controller need to be adjusted. It does not require a lot of effort and time to update the control rules of traditional fuzzy controllers, nor does it requires updating the control tables of fuzzy controllers when adapting to new modifiable factors. Additionally, in the development process of traditional fuzzy controller and fuzzy controller with modifiable factors [40], [41], the quantization factor of fuzzification is fixed and the control parameter resolution is not enough which leads to insufficient control precision and less robustness, so the neural network technology is adopted to optimize the compromise factor of proposed controller.

This paper selects a temperature control system with a first-order inertia link with pure delay for simulation and comparison experiments. The proposed controller defined in this paper and the compromise factor trained by neural network greatly improve the efficiency of parameters tuning and system robustness under most operating conditions compared with the traditional fuzzy controller and the fuzzy controller with modifiable factors, whereas, the proposed controller also has its own limitations especially in the requirement of system response speed, which is one of my subsequent research direction.

In Section II, an extended fuzzy controller with modifiable factors is presented, the design concept of which is the inspiration for the controller proposed in this paper. In Section III the fuzzy controller with tradeoff characteristics is developed together with the design method. The pseudo code of different algorithms introduced in this article are presented in Section IV, besides, some potential confused points about the proposed fuzzy controller algorithm details are also discussed here. In section V the temperature control system simulation results are given and the final conclusions are obtained from the simulation results. In Section VI the conclusions and our future research direction are introduced.

II. EXTENDED FUZZY CONTROLLER WITH MODIFIABLE FACTORS

The traditional fuzzy controller design process is to develop a serious of controlling rules firstly based on the characteristics of the fuzzy language variables and the operator's actual experience of the manufacturing process. Secondly to constitute a control table and stored it in the computer through reasoning and composition operation. Finally to obtain the control output by comparing the actual measured data with the control table to achieve real time control of the manufacturing process [42], [43], [44].

Figure 3 shows the traditional fuzzy controller system frame. Firstly the computer gets precise value of the controlled target through sampling and A/D conversion, then obtains the fuzzy subsets E and C by fuzzy quantization of error e and error change rate c between reference output and the actual output; secondly calculates the total fuzzy relationship according to the fuzzy subsets E, C and fuzzy controlling rules; finally, fuzzy controlling rules and corresponding applicable algorithm are used to defuzzify the fuzzy output U used for the system. U can be the control input of the actual actuator or the parameters used to calculate the control input, such as Kp, Ki, Kd, etc.

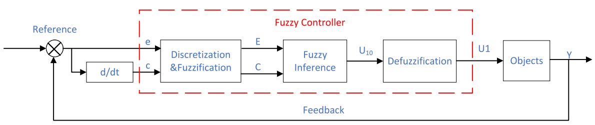

FIGURE 3. The system block diagram of a traditional fuzzy controller [2].

However, the controlling rules need be updated in some cases, such as parameter optimization for optimal control systems, parameter adjustment for adaptive systems, system identification for fuzzy control models and part of control requirements change in the manufacturing processes. As mentioned earlier, it is a troublesome and time consuming task, and it brings great difficulty to the development and use of fuzzy controllers. Hereto, the fuzzy controlling rules with modifiable factors is used to improve [45], [46].

For a two inputs and one output fuzzy controller, the modifiable factors based fuzzy controlling input is

$$\begin{cases} E = a * e \\ C = (1-a) * c \end{cases} \tag{2}$$

where a is real number between [0,1]. The input to formula expressed in (2) are the original input deviation e and the corresponding change rate c. The essence of (2) is that the inputs are on weight of different performance requirement. So we can have a conclusion that the inputs of the fuzzy controller expressed in (2) are not confined to e and c, and any other inputs or multiple inputs are suitable for this controller. Figure 4 shows the system frame of the fuzzy control system with modifiable factors.

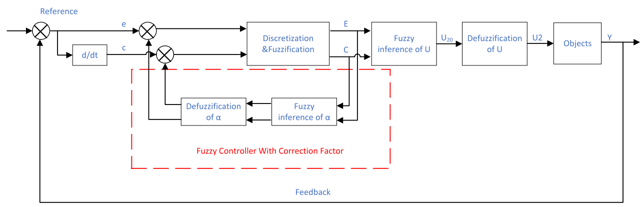

FIGURE 4. The system frame of a fuzzy controller with modifiable factors.

If we use mathematical expression for the fuzzy control rule to describe Figure 5, an extended fuzzy controlling rule with modifiable factors can be described as follows:

$$W = [k * Z_1 + (1-k) * Z_2] \tag{3}$$

where k is real number between [0,1], Z_1, Z_2 are fuzzy sets of any input, and W is output of the fuzzy controller, Figure 5 demonstrates a frame of fuzzy controller with any two inputs as an example.

FIGURE 5. The block diagram of a two inputs fuzzy controller.

III. PROPOSED FUZZY CONTROLLER WITH TRADEOFF CHARACTERISTICS

Set the system desired output in time domain to be R, deviation E and the corresponding change rate C are obtained through comparing R to the measured output Y. After inference and synthesis with fuzzy control decision table summarized on the basis of operator's experience shown in Table 1, the control action U_{10} is obtained which is abbreviated to as Algorithm 1 hereafter; the control action U_{20} obtained after inference and synthesis similarly, in addition to a control decision table of the modifiable factors a shown in Table 2 and a corresponding membership function which a is the output, this control rule is abbreviated to be Algorithm 2. Then we set the questions as follow:

(1) Are U_{10} and U_{20} same?

(2) If not, which one is closer to reality?

For question (1), U_{10} may be different from U_{20} even if both fuzzy controllers are well designed and repeatedly validated due to unavoidable differences of determining a factor and summary of different operational experience. For question (2), it is also difficult to conclude, because U_{10} has great practical sense, however, U_{20} has a good mathematical model and conforms to realistic experiment. So it could be concluded that there is a difference between U_{10} and U_{20}, while it is impossible to judge which one is more superior.

TABLE 1. **Fuzzy decision table of *U*.**

U \ C, E	NB	NM	NS	0	PS	PM	PB
NB	PB	PB	PB	PB	PM	0	0
NM	PB	PB	PB	PB	PM	0	0
NS	PM	PM	PM	PM	0	NS	NS
N0	PM	PM	PS	0	NS	NM	NM
P0	PM	PM	PS	0	NS	NM	NM
PS	PS	PS	0	NM	NM	NM	NM
PM	0	0	NM	NB	NB	NB	NB
PB	0	0	NM	NB	NB	NB	NB

TABLE 2. **Fuzzy decision table of *a*.**

a \ C, E	NB	NM	NS	0	PS	PM	PL
NL	VB	VB	VB	S	VS	VS	0
NM	VB	VB	MB	SB	S	S	S
NS	VB	B	B	MB	VS	MB	SB
0	B	B	VB	0	VB	B	B
PS	SB	MB	VS	MB	B	B	VB
PM	S	S	S	SB	MB	VB	VB
PL	ZE	VS	VS	S	VB	VB	VB

To resolve the above problems, is it possible to imagine to merge U_{10} and U_{20} into a new fuzzy controller since both of them can reflect the objective reality, to obtain new output using two new inputs and some other operation, then this new output will efficiently eliminate difference of the two?

We define system output of Algorithm 1 to be U_1, and system output of Algorithm 2 to be U_2. If U_1 and U_2 are taken as the input of the proposed fuzzy controller with compromise factor α (Algorithm 3 for short hereafter), the functional block diagram is shown in Figure 6, then system output of Algorithm 3 is

$$U = [\alpha * U_1 + (1 - \alpha) * U_2] \tag{4}$$

where α is real number between [0,1], and α is obtained from the neural network.

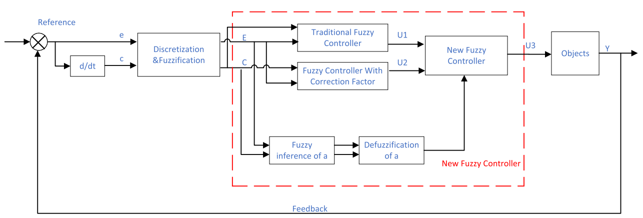

FIGURE 6. **The block diagram of proposed fuzzy controller.**

This definition shows that Algorithm 3 takes output of Algorithm 1 and Algorithm 2 as new inputs and reweights the output through a control rule of compromise factor α. The compromise factor α can completely reflect the weight of U_1 and U_2, then the suitable value can efficiently eliminate the deviation of adopting U_1 or U_2. Therefore, Algorithm 3 is much simpler and more practicable. Besides,even if the formats of (3) and (4) are the same, there are essential differences. In (3), $Z1$, $Z2$ and W are fuzzy sets, instead, U_1, U_2 and U in (4) are all fuzzy quantities.

Algorithm 1 Traditional Fuzzy Controller [2], [3], [12]

Input: Fuzzy controller reference output R, actual output Y, A/D sampling period T_s.
Output: Fuzzy output U_1.

1. Initialization: Actual output $Y = y$ after A/D sampling, reference output $R = r$.

2. Discretization: Obtain the fuzzy input e in time k, $e(k) = r(k) - y(k)$, obtain the fuzzy input c in time k, $c(k) = (e(k) - e(k-1))/T_s$.

3. Fuzzification: Obtain the value $E(k)$ according to the appropriate fuzzy subset and fuzzy input $e(k)$, obtain the value $C(k)$ according to the appropriate fuzzy subset and fuzzy input $c(k)$.

4. Fuzzy Inference1: Obtain the individual fuzzy implication relation $R_n(k)(n = 1, 2, 3\ldots)$ according to $E(k)$, $C(k)$ and applicable combination in fuzzy rules table, then obtain the total fuzzy implication relation $R(k)$ from combining the individual fuzzy implication relation.

5. Fuzzy Inference2: obtain the fuzzy subset of U_1 based on total fuzzy implication relation R and membership function of output.

6. Defuzzification: Obtain $U_1(k)$ according the fuzzy subset of U_1 and defuzzification method, such as maximum membership method, area barycenter method and area bisection method etc.

IV. DISCUSSION ABOUT ALGORITHMS

Before discussing the advantage of Algorithm 3, the main computational logic of Algorithm 1, 2 and 3 is described below, and the main differences between them are illustrated, which can also be better understood by combining Figure 3, 4 and 6.

We can find from the different algorithms that Algorithm 2 has an additional modifiable factors a comparing to Algorithm 1, then the original input e multiply by a and c multiply by $(1-a)$ as the new input for fuzzification, and Algorithm 3 has a compromise factor α which can be adjusted as per input e and c. The value of α is obtained according to the algorithm trained by the neural network technology, and the cost function is defined by combining the system simulation dynamic performance (rise time, overshoot, steady-state time) and static performance (static error) with different weights. The output $U1$ from Algorithm 1 and $U2$ from Algorithm 2 are inputs of Algorithm 3, then the output U can be obtained according to (4). We know from the above demonstration that Algorithm 3 can take the advantage of Algorithm 1 and 2 with suitable compromise factor α, so we need to further discuss the questions as follow:

A. SELECTION OF COMPROMISE FACTOR α

There can be a variety of methods to choose, such as according to experience summary, performing experiments to determine etc., or through online or offline optimization.

Algorithm 2 Fuzzy Controller With Modifiable Factors [28], [29]

Input: Fuzzy controller reference output R, actual output Y, A/D sampling period T_s, initial modifiable factors $a(0)$.
Output: Fuzzy output U_2.

1. Initialization: Actual output $Y = y$ after A/D sampling, reference output $R = r$.
2. Discretization: Obtain the fuzzy input e in time k, $e(k) = r(k) - y(k)$, obtain the fuzzy input c in time k, $c(k) = (e(k) - e(k-1))/T_s$.
3. Fuzzification: Obtain the value $E(k)$ according to the appropriate fuzzy subset and fuzzy input $e(k) * a(k)$, obtain the value $C(k)$ according to the appropriate fuzzy subset and fuzzy input $c(k) * (1 - a(k))$.
4. Select $a(k+1)$: Obtain modifiable factors $a(k+1)$ according to $E(k)$, $C(k)$, applicable combination in modifiable factors fuzzy rules table and membership function of a.
5. Fuzzy Inference1: Obtain the individual fuzzy implication relation $R_n(k)(n = 1, 2, 3\ldots)$ according to $E(k)$, $C(k)$ and applicable combination in fuzzy rules table, then obtain the total fuzzy implication relation $R(k)$ from combining the individual fuzzy implication relation.
6. Fuzzy Inference2: obtain the fuzzy subset of U_2 based on total fuzzy implication relation $R(k)$ and membership function of output.
7. Defuzzification: Obtain $U_2(k)$ according the fuzzy subset of U_2 and defuzzification method, such as maximum membership method, area barycenter method and area bisection method etc.

Algorithm 3 Proposed Fuzzy Controller

Input: Fuzzy controller reference output R, actual output Y, A/D sampling period T_s, initial modifiable factors $\alpha(0)$, Output U_1 from Algorithm 1, Output U_2 from Algorithm 2
Output: Fuzzy output U_3.

1. Initialization: Actual output $Y = y$ after A/D sampling, reference output $R = r$.
2. Discretization: Obtain the fuzzy input e in time k, $e(k) = r(k) - y(k)$, obtain the fuzzy input c in time k, $c(k) = (e(k) - e(k-1))/T_s$.
3. Fuzzification: Obtain the value $E(k)$ according to the appropriate fuzzy subset and fuzzy input $e(k)$, obtain the value $C(k)$ according to the appropriate fuzzy subset and fuzzy input $c(k)$.
4. Select $\alpha(k+1)$: Obtain modifiable factors $\alpha(k+1)$ according to $E(k)$, $C(k)$, applicable combination in the algorithm trained by the neural network.
5. Obtain output: Obtain $U_3(k)$ via formula $\alpha(k) * U_1(k) + (1 - \alpha(k)) * U_2(k)$.

In general, if we regard Algorithm 1 and 2 as system's equivalent reflection, then α shall be preliminarily selected to be 1/2, then (4) becomes

$$U = (U_1 + U_2)/2. \tag{5}$$

If we just take α to be 1/2 and it stays the same forever, Algorithm 3 comes to be meaningless, so α must be adaptable. When some system situations are changed, it is easier to modify the control rules of Algorithm 2, then α shall be updated correspondingly too after modifying Algorithm 2. Hence the output of Algorithm 3 at this time is actually modified two times, especially the second correction is more significant which is one of the key characteristics of this controller.

B. ABOUT FUZZY OUTPUT U

From (5) we can find that there are following questions if Algorithm 3 is applied in practice: (a) when U_1 is odd and U_2 is even, or the opposite that U_1 is even and U_2 is odd, while both are positive or negative, depending on the general control table rounding method when U is a decimal, on this condition it will lose the characteristics of the fuzzy controller either taking U_1 or U_2; (b) when U_1 and U_2 have the same value but opposite sign, then U comes to be 0. The condition is obviously not true, because if either U_1 or U_2 is true, then U is wrong; (c) When U_1 is odd, U_2 is even, or the opposite that U_1 is even and U_2 is odd, and they are different sign, what is U should be?

For (a), the author puts forward the method of redividing the domain of control output U to subdivide U to fuzzy fields with decimals, which would not only resolve existing problem in (a), but also optimize control precision and reduce transition. For (b) and (c), the author puts forward following solutions: it may be because of incomplete summary of controlling rules or incorrect definition of membership function in Algorithm 1, or modifiable factors of Algorithm 2 is not properly selected causing condition (b) and (c), so we should go back to review Algorithm 1 and 2. If the issue still can not be eliminated, the author believes that although it can not be completely eliminated, it will certainly prevent them from occurring at a large level, and it only exists at a small level. As control characteristic of Algorithm 2 is more superior comparing to Algorithm 1, the effectiveness of output U can be equivalent to that of U_2.

As a summary, the author proposes Algorithm 3 on the basis of Algorithm 1 and 2. With combination of (4) and discussion about above problems, it can be concluded that control characteristics of Algorithm 3 are more superior than others.

V. SIMULATION RESULTS

Set the control object be a temperature control system with a pure lag first-order inertial link, for example,

$$G(s) = e^{-\Theta S}/(T_0 S + 1). \tag{6}$$

In Algorithm 1 we define theoretical fuzzy field to be (-6, 6) and the control table remains as Table 1. Algorithm 2 defines theoretical fuzzy field to be (-6, 6) and modifiable

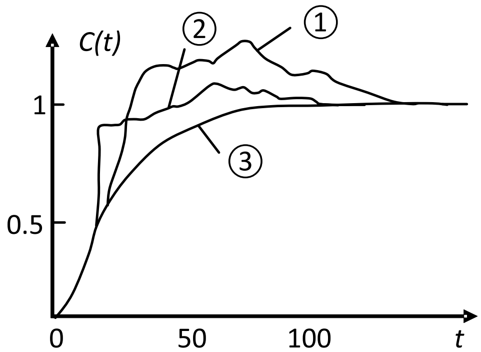

FIGURE 7. Step response curve of $M = 1, T_0 = 100s, T_S = 3s$.

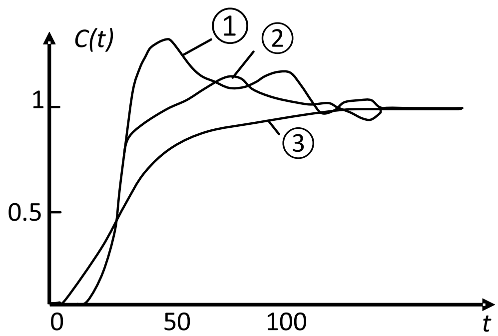

FIGURE 8. Step response curve of $M = 2, T_0 = 100s, T_S = 3s$.

factors a is taken as 0.7, the control tables referring to Table 1 and 2. The time unit is second in this experiment, we set parameters as $T_S = 3$ (sample time), $T_0 = 100$, $M = 1$, $\Theta = M * T_S$. The step input is $R = 1$, simulation time $T = 200$, and compromise factor $\alpha = 0.7$ for Algorithm 3. For the convenience of analysis, the response curves obtained by the three algorithms are plotted on a single graph, where below (1), (2), and (3) are the response curves of Algorithm 1, 2 and 3 respectively with step input.

(1) $M = 1, 2$ and other parameters are fixed, step response comparison shown in Figure 7 and 8. From the comparison in the figures, we can conclude that Algorithm 3 outperforms Algorithms 1 and 2, especially on the condition that system has big hysteresis. Algorithm 1 and 2 show serious oscillations and fail to stabilize at the target value, while Algorithm 3 has almost no oscillations and higher steady-state precision. Besides, Algorithm 3 is basically free of dead zones when the hysteresis is large.

(2) $T_0 = 80, 120$ and other parameters are fixed, step response comparison shown in Figure 9 and 10. We can conclude from the graphs that Algorithm 3 is better than Algorithms 1 and 2 in several aspects including smooth rise and short regulation time without overshoot.

(3) $M = 2$, $T_0 = 120$, other parameters are fixed, step response comparison shown in Figure 11. We can draw a conclusion from the figure as follow: when hysteresis and time constants change at the same time, the control performance of proposed fuzzy controller is more superior than those of the other two controllers.

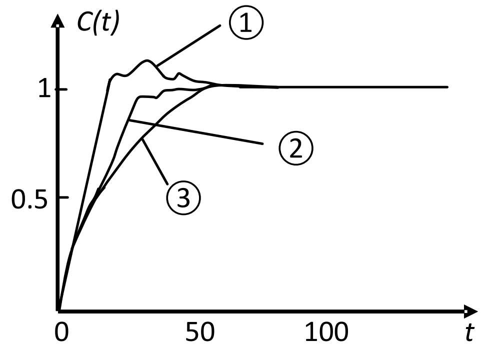

FIGURE 9. Step response curve of $M = 1, T_0 = 80s, T_S = 3s$.

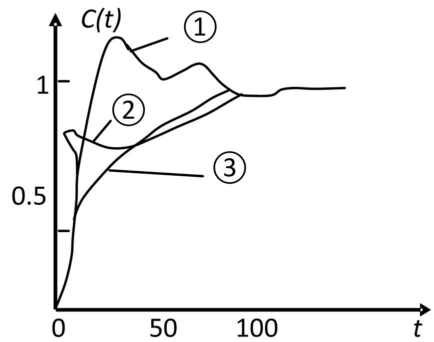

FIGURE 10. Step response curve of $M = 1, T_0 = 100s, T_S = 3s$.

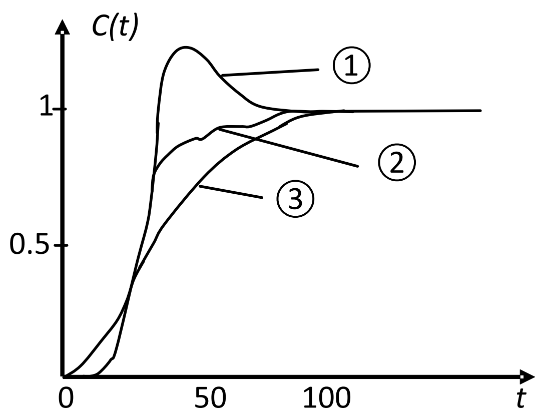

FIGURE 11. Step response curve of $M = 2$, $T_0 = 120s$, $T_S = 3s$.

(4) The author also had a survey about step response with the addition of step disturbance, random disturbance and both disturbances separately. Adding step disturbance $G = 1$ and random disturbance $F = 1.2 * RND(0)$ to input of the system at one time, as seen in Figure 12, the anti-interference capability of Algorithm 3 is much better than both Algorithms 1 and 2. The simulation results prove the previously proposed assumption as follows: control performance of Algorithm 3 is superior to the other two algorithms, particularly when the key parameters of control system changed. Algorithm 3 is also superior to Algorithm 1 or Algorithm 2 in the aspect of robustness theoretically and practically, and the Algorithm 3 is more adaptive in systems with large inertia and large lag type objects, besides, the stability, non-oscillating feature and control precision of Algorithm 3 are also much better comparing

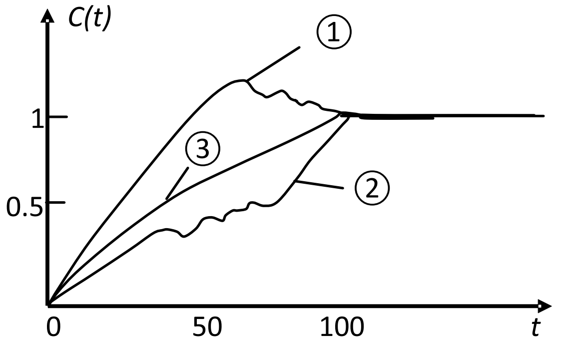

FIGURE 12. Step response curve of $M = 1$, $T_0 = 100$s, $T_S = 3$s and two kinds of disturbance.

to Algorithm 1 and 2. However, through simulation studies, we can also see that Algorithm 3 has the problem of slow rise rate, caused on the one hand by the subdivision of the control volume and on other hand by the fact that it is a compromise and correction of Algorithm 1 and 2. As a consequence, the proposed fuzzy controller also has certain usage restriction about rise speed requirement.

VI. CONCLUSION AND FUTURE WORK

This paper employs a new fuzzy controller design method to compromise the outputs from traditional fuzzy controllers and fuzzy controller with modifiable factors as a new output, which does not need to spend a lot of effort and time to deal with the parameters or use case change of traditional fuzzy controllers or fuzzy controller with modifiable factors, and only the compromise factor needs to be adjusted instead. Through simulation and comparison experiments of a temperature control system with a first-order inertia link with pure delay, we can get the conclusion that the proposed fuzzy controller is more robust and adaptive, especially in systems with large inertia and large lag type objects, besides, the stability, non-oscillating feature and control precision are also much better comparing to the other two controllers.

While we can also find from the simulation results that the proposed fuzzy controller has the problem of slow rise rate, so it is mainly proposed to be applied in systems that require higher control precision, no oscillation overshoot, no output dead zone and no high requirements for rise speed. Of course, this problem could be improved with a better understanding of the subject, more comprehensive experience and better selection of modifiable factors, which is also the focus of our future research. Besides, we will also try to apply this algorithm to other models for more computational experiments to verify the effectiveness.

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LEI WANG received the Ph.D. degree in control science and engineering from Jiangnan University, China, in 2021. From 2018 to 2019, he studied at the University of Zielona Góra, Poland. He is currently a Lecturer with the School of Automation, Wuxi University, China. His research interests include intelligent control and advanced control theory.

LIANGXIN DONG received the bachelor's degree in material science and engineering from the Harbin University of Technology. He is currently pursuing the master's degree in electronic information with the Wuxi Graduate School, Nanjing University of Information Science and Technology. His scientific research achievements include two SCI journals published, two utility model patents have been authorized, and two invention patents have been submitted.

ZIWEI HUANGFU received the bachelor's degree in automation from Wuxi University. She is currently pursuing the master's degree in control engineering with Anhui Polytechnic University. Her main research interest includes iterative learning control algorithm optimization.

YIYANG CHEN (Member, IEEE) received the M.Eng. degree from Imperial College London, London, U.K., in 2013, and the Ph.D. degree from the University of Southampton, Southampton, U.K., in 2017. After that, he worked as a Research Fellow in control systems (2017–2018) and in traffic signal control (2018–2020) with the University of Southampton. He joined the School of Mechanical and Electrical Engineering, Soochow University, as an Associate Professor, in 2020. He has published several papers in top control conferences and journals. His research interests include iterative learning control, optimization, artificial intelligence, image processing, and robotic systems.