www.czasopisma.pan.pl PAN www.journals.pan.pl

ARCHIVES
of
FOUNDRY ENGINEERING

ISSN (2299-2944)
Volume 21
Issue 1/2021

23 – 30

10.24425/afe.2021.136074

4/1

Published quarterly as the organ of the Foundry Commission of the Polish Academy of Sciences

Simulation and Analysis of Sintering Furnace Temperature Based on Fuzzy Neural Network Control

Zou Chaoxin [a], Li Rong [a,]*, Xie Zhiping [a], Su Ming [a], Zeng Jingshi [b], Ji Xu [a], Ye Xiaoli [a], Wang Ye [a]

[a] Guizhou Normal University, China

[b] Guizhou Zhenhua New Material Co., Ltd., China

* Corresponding author: Email address: lirong9242001@163.com

Received 01.09.2020; accepted in revised form 09.12.2020

Abstract

Aiming at the problems of delay and couple in the sintering temperature control system of lithium batteries, a fuzzy neural network controller that can solve complex nonlinear temperature control is designed in this paper. The influence of heating voltage, air inlet speed and air inlet volume on the control of temperature of lithium battery sintering is analyzed, and a fuzzy control system by using MATLAB toolbox is established. And on this basis, a fuzzy neural network controller is designed, and then a PID control system and a fuzzy neural network control system are established through SIMULINK. The simulation shows that the response time of the fuzzy neural network control system compared with the PID control system is shortened by 24s, the system stability adjustment time is shortened by 160s, and the maximum overshoot is reduced by 6.1%. The research results show that the fuzzy neural network control system can not only realize the adjustment of lithium battery sintering temperature control faster, but also has strong adaptability, fault tolerance and anti-interference ability.

Keywords: Fuzzy neural network, Furnace temperature control, PID

1. Introduction

The main processes of industrial production of lithium battery cathode materials are loading, feeding, sintering, crushing and unloading. The temperature accuracy control of the sintering furnace directly affects the storage performance and service life of the lithium battery. If the sintering temperature beyond the control range will lead to a decline in product performance and a significant increase in the rejection rate, which not only causes extreme waste of resources such as energy, raw materials and production costs, but also causes the performance of lithium batteries to fail to meet the application requirements of the current industry. The factors affecting the sintering temperature include the sensitivity of the sintering furnace temperature control system, the stability of the heating voltage, and the insulation effect of the sintering furnace lining. The mutual influence of the sintering furnace makes the sintering temperature field have a serious coupling relationship, and has the characteristics of time-varying and nonlinearity, which makes it difficult to establish an accurate mathematical model for the control of the sintering temperature [1-2]. Common types of temperature control mainly include PID control, fuzzy control, neural network control and their combined control models. PID control has the characteristics of simple algorithm and simple structure, but it relies too much on the establishment of mathematical models and manual real-time adjustment, and the parameters cannot be adjusted automatically after the model is built, which leads to the weak adaptive ability of the control system. Both fuzzy control and neural network control belong to the category of modern intelligent control. They are suitable for control occasions where it is difficult to establish precise mathematical models. They can automatically adjust and optimize control parameters, have strong adaptability and robustness, and can adapt to various nonlinear control system. But fuzzy control relies too much on expert experience and actual operating experience, and the fuzzy rules and membership functions are all manually formulated, resulting in unstable control performance and poor self-learning ability. Neural network control has problems such as lack of reasoning logic, long training time and poor dynamic adaptability [3-4].

A certain factory uses an improved PID temperature controller to control the sintering temperature of lithium battery cathode materials. However, in recent years, industrial development has placed higher and higher requirements on the performance of lithium batteries. The original PID control system is difficult to achieve precise control of the sintering temperature, resulting in production the raw materials cannot meet industrial demand. The combination of fuzzy control and neural network control can not only use the powerful self-learning and optimization capabilities of the neural network to adjust the fuzzy control rules designed by expert experience, but also apply the fuzzy control rules and fuzzy inference to the entire self-learning network [5]. To further enhance the logical reasoning ability and online self-adjustment ability of neural network. Therefore, in order to improve the temperature control accuracy of the sintering furnace in the lithium battery production process, the article proposes to combine fuzzy control with neural network control to design a fuzzy neural network intelligent temperature controller based on the principle of fuzzy neural network control. And through MATLAB establish a simulation model to verify and optimize actual production parameters to ensure that the performance of lithium batteries meets application requirements and reduce sintering energy consumption.

2. Sintering control process and influencing factors analysis

The sintering temperature control process of the existing lithium battery cathode material is shown in Figure 1. In the figure, the factors that affect the temperature change of the furnace are heating voltage, air inlet speed and air inlet volume. Therefore, the factor that has the greatest influence on the temperature, that is, the heating voltage, is used as the input of the control system, and the air inlet speed and air volume are used as interference factors. In the control process, the PID monitoring system makes real-time adjustments according to temperature changes, and realizes the control of the sintering temperature under the combined action of manual adjustment and feedback adjustment. The sintering furnace uses high-temperature heating resistance wires to generate heat. Excessive heating voltage will cause the temperature in the furnace to rise. Excessive sintering of the raw materials will make it difficult to break during later processing, and even destroy the chemical properties of the raw materials. The heating voltage is too low and the sintering temperature cannot reach the reaction temperature of raw materials will seriously affect the pass rate of the product [6]. The inlet air volume not only provides an oxygen-rich environment for heating in the furnace, but also provides oxygen required for the mutual reaction of raw materials. The air inlet speed can affect the residence time of the heat in the furnace, and the air inlet speed in the sintering zone is relatively slow. The purpose is to ensure the uniformity and stability of the sintering temperature field and reduce heat loss. The faster air intake speed in the cooling zone is to accelerate the cooling rate and prevent the sintered agglomerate material from generating stress and causing structural damage.

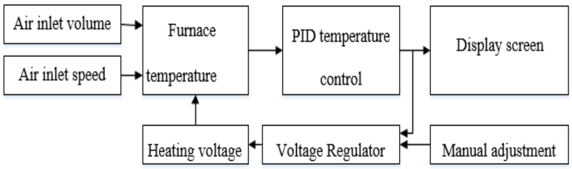

Fig. 1. Sintering temperature control process

The improved PID controller is used by a certain factory to adjust the sintering temperature in the sintering process of lithium battery cathode materials. The control principle is shown in Figure 2. PID control mainly realizes temperature adjustment through proportional (K_P), integral (K_I) and derivative (K_D) coefficients. The function of proportional coefficient is to adjust the response speed of the system and eliminate the static error in the control process. The function of integral is to adjust the overshoot of the system, the function of the differential coefficient is to adjust the stability of the system [7-8]. The control principle is as follows:

$$u(t) = K_P[e(t) + \frac{1}{T_I}\int e(t)dt + T_D \times \frac{\mathrm{de(t)}}{\mathrm{dt}}] \quad (1)$$

In formula (1), T_I and T_D are the integral and derivative time constants respectively. In actual control, real-time temperature data is collected through PID. When the control system needs the increment of input voltage, the sampled value is discretized, through numerical integration method and recursive principle [9]. The PID incremental control principle can be introduced as follows:

$$u(k) = u(k-1) + u(k) \quad (2)$$

$$u(k) = K_p[\mathrm{e}(k) - e(k-1)] + K_i e(k) + K_d[e(k) - 2e(k-1) + e(k-2)] \quad (3)$$

In formula (3), $K_i = K_p / T_I$, $K_d = k_p \times T_D$.

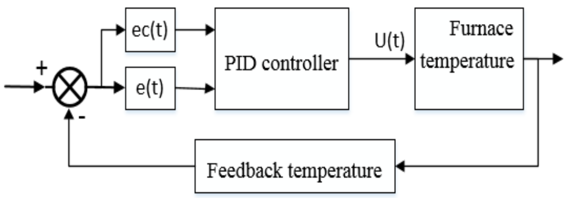

Fig. 2. PID control principle

3. Design of Fuzzy Neural Network Controller

3.1. Design of fuzzy controller

Fuzzy control is the product of the fusion of mathematical logic reasoning and classical control theory. Compared with traditional classical control theory, fuzzy control is an intelligent control theory, which is based on expert experience-based fuzzy logic reasoning and fuzzy rules. It has strong fault tolerance and can use fuzzy language variables to solve the temperature control of nonlinear systems. The principle of fuzzy control is shown in Figure 3.

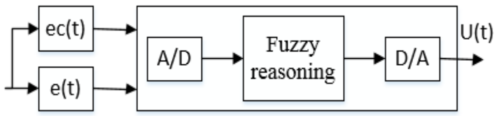

Fig. 3. Fuzzy control principle

In the figure, *e(t)* is the variation between the set value and the measured value of the sintering temperature during actual sintering, *ec (t)* is the rate of change of the difference between the set value and the measured value of the sintering temperature, and *u(t)* is the increment of system' s output and directly affects the adjustment of the sintering temperature. The process of fuzzy inference is to transform the defined variables into fuzzy language, namely A/D. Secondly, after inference by fuzzy rules, the fuzzy value output is transformed into the precise value which can directly control system, namely D/A. The inference system of fuzzy control is mainly composed of fuzzy sets, membership degrees and fuzzy rules of each variable [10]. According to the actual production parameters of sintered lithium battery cathode materials in a certain factory, a new fuzzy controller is established. Among this, *e(t)* and *ec(t)* are taken as the input of the system, and u(t) is taken as the output of the system. The fuzzy domain of e(t) is {-10,950}, the fuzzy domain of *ec(t)* is {-12,0}, and the corresponding fuzzy set is {NB,NM,NS,ZO,PS,PM,PB}[11]. According to the actual operating experience of experts, the membership function is expressed by trigonometric functions. The membership functions of *e(t)* and *ec(t)* are shown in Figure 4 and Figure 5, respectively.

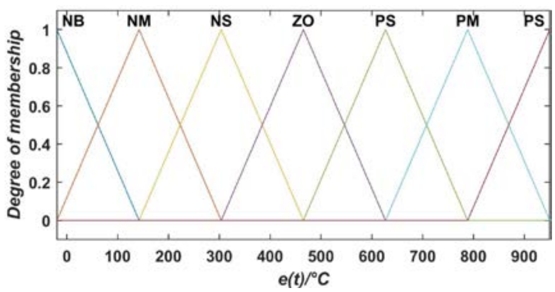

Fig. 4. Membership function of *e*(*t*)

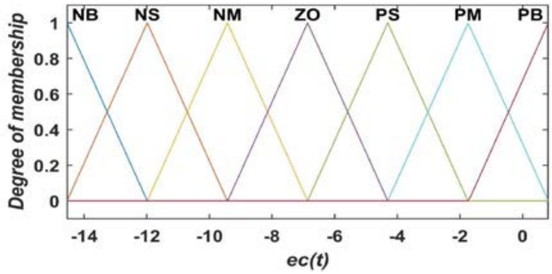

Fig. 5. Membership function of *ec(t)*

3.2. Design of fuzzy neural network controller

Neural network control is an intelligent control algorithm developed by simulating the brain nervous system. In this algorithm, a large number of neurons are connected to each other through weights. It not only has online self-adjustment and self-learning capabilities, but also can approximate any non-linear functions and solve complex non-linear furnace temperature control problems. Combining fuzzy control with neural network control can not only track and optimize control parameters online, but also increase the fault tolerance, response speed and system stability of the control system. It further makes up for the problems of poor autonomous learning ability, poor adaptability, poor optimization ability and poor generalization ability of neural network itself in fuzzy control [12]. In order to improve the temperature control accuracy in the sintering process, a dual-input single-output fuzzy neural network controller is designed, and its structure is shown in Figure 6.

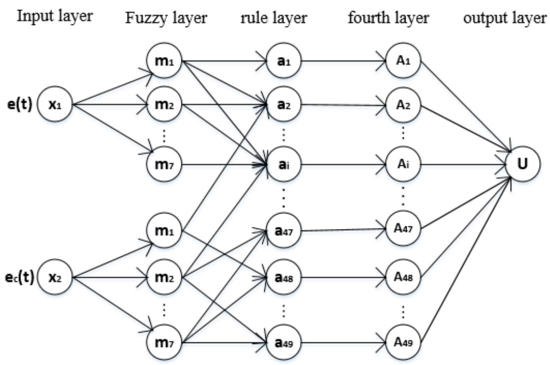

Fig. 6. The structure of the fuzzy neural controller

In this structure, the input layer has 2 neuron nodes, and the purpose is to transmit the error between the sintering temperature and the measured temperature and its rate of change to the fuzzy layer of fuzzy control. The input and output formulas are:

$$o_i(1) = x_i (i = 1, 2; k = 1, ..., 7) \qquad (4)$$

The fuzzy layer transform the precise values from the input layer to the fuzzy language recognized by the system through the fuzzy rules defined by the expert experience. According to the number of fuzzy subsets of *e(t)* and *ec(t)* in the fuzzy controller, there are 14 neuron nodes in the fuzzy layer, and they all represent the input of different membership functions, and the functions are represented by Gaussian functions. The output value of the Gaussian function is:

$$o_i(2) = -(x_i - c_{ij})^2 / 2\delta_{ij}^{\ 2} = a_i(x_i) \tag{5}$$

In formula (5), C_{ij} and δ_{ij} are the center value and width value of the table membership function, and a_i is the output of the rule layer. According to the fuzzy control rule of *u(t)*, there are 49 neuron nodes in the rule layer, and each node represents a control rule of sintering temperature, and its function is to dynamically identify and adjust the heating intensity of sintering temperature. The output formula is:

$$o_i(3) = a_1(x_1) \times a_2(x_2) \times \ldots \times a_{49}(x_{49}) \tag{6}$$

The fourth layer is the overall calculation of the variables after fuzzy inference, and the output formula is:

$$o_i(4) = A_i = a_i / \sum_{i=1}^{49} a_i (i = 1, 2, \ldots, 49) \tag{7}$$

The output layer is to re-output the precise value of *u(t)* after the fuzzy results calculated in the first layer are defuzzified. The output formula is:

$$o_i(5) = u = \sum_{i=1}^{49} c_{ij} A_i (i = 1, 2, \ldots, 49) \tag{8}$$

The fuzzy neural network controller realizes the overall regulation of the sintering temperature control by the characteristics of fuzzy inference rules, self-learning and self-adaptation. In order to reduce the temperature fluctuation of the system caused by accidental disturbance and further improve the stability of the control system, the control parameters need to be optimized. Among this, when realizing sintering temperature control, the learning objective function of the system is [13-14]:

$$y(t) = e(t) \times e_c(t) \tag{9}$$

$$e(t) = g(t) \times [u \times (t) - u(t)] \tag{10}$$

Among this formula, *y(t)* is the objective function of the control system self-learning, and *g(t)* is the control quantity function. The adjustment formula for optimization parameters is:

$$c_{ij}(t+1) = c_{ij}(t) - \eta \frac{\partial y(t)}{\partial c_{ij}(t)} \tag{11}$$

$$\sigma_{ij}(t+1) = \sigma_{ij}(t) - \eta \frac{\partial y(t)}{\partial c_{ij}(t)} \tag{12}$$

$$w_i(t+1) = w_i(t) - \frac{\partial y(t)}{\partial c_{ij}(t)} \tag{13}$$

In formula (13), w_i is the weight between each transmission layer in the control system.

4. Simulation results and analysis

4.1. Sintering temperature control function

Most of the heat generated by the resistance wire heating in the sintering furnace is used for the sintering of the positive electrode material of the lithium battery, and the remaining heat is mainly used for the absorption of the furnace body and the exchange with the environment. When the sintering temperature field meets the control requirements, the entire sintering temperature field can be regarded as a dynamic and stable system that compensates each other. At this time, the sintering furnace can be regarded as an independent temperature control system [15]. According to the law of conservation of energy, the heat calculation formula is:

$$Q = C\frac{dT}{dt} + C\frac{T - T_0}{R} \tag{14}$$

In formula (14), *Q* is the total heat, *t* is the heating time, *C* is the furnace heat capacity, *T* is the furnace temperature, *R* is the resistance, and T0 is the air temperature. The actual sintering temperature value of lithium battery cathode material is much greater than the air temperature value in the enclosed space, so the air temperature value in the heat calculation formula can be ignored, and the adjusted formula is subjected to Laplace transformation [16], the formula after transformation is as follows:

$$\frac{T(s)}{R(s)} = \frac{R}{R \times (Cs + 1)} \tag{15}$$

When the above transfer function is used in actual sintering, the delay and instability of the control system need to be considered. The formula after adding the time delay factor is:

$$G(s) = \frac{Y(s)}{U(s)} == \frac{K}{Ts + 1} e^{-\tau s} \tag{16}$$

In formula (16), *K* is the system adjustment coefficient, *t* is the system delay coefficient, and *T* is the time coefficient.

4.2. Controller structure and simulation analysis

4.2.1. Fuzzy Neural Network Controller

The different temperature zones during the sintering of the lithium battery cathode material are controlled by solid state relays, which can realize separate temperature control of the upper and lower temperature zones. The existing PID controller in the factory is a Japanese Omron E5EC intelligent instrument, which can not only automatically track the set optimal PID value, but also has temperature compensation and automatic adjustment functions. But there are problems such as poor fault tolerance, inability to realize online self-learning and optimization of PID parameters, etc. In order to improve the temperature control accuracy of the sintering furnace, a method of combining fuzzy control and neural network control is proposed, and a fuzzy neural network temperature controller is designed. Its structure is shown in Figure 7.

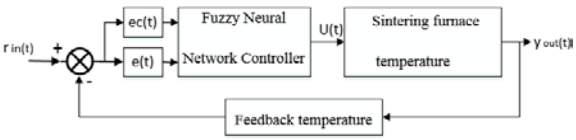

Fig. 7. Fuzzy neural controller structure

In this figure, *r in(t)* and *y out(t)* are the input signal and output value of the controller respectively, and *u(t)* is the actual heating voltage applied to the sintering furnace after the fuzzy neural network control adjustment [17]. The control process is a combination of fuzzy control and neural network control, the error value and change rate of the target expected value and the actual output value are used as input signals. The fuzzy neural control system fuzzifies the error between the feedback temperature value and the expected value and its rate of change, and then the fuzzy rules perform fuzzy inference on the fuzzified error value, and convert the fuzzy inference value into an accurate value. The system judges the precise value of the fuzzy control output according to the experience generated by self-learning, and optimizes and adjusts the width value, the center value of the membership function and the weight between each output layer through online optimization and adjustment.

4.2.2 Analysis of simulation results

Aiming at the problem of poor temperature control accuracy during solid-state sintering of lithium battery cathode materials, a fuzzy neural network controller based on fuzzy neural network control theory is designed. In order to verify whether the fuzzy neural network controller can achieve the expected results in the control of the sintering temperature of the lithium battery, first use the fuzzy neural network toolbox in MATLAB to establish the fuzzy neural network controller, and then use the SIMULINK module to establish an improved PID control system and fuzzy neural network control system. The simulation model is shown in Figure 8. In the figure, the values of K, t, and T in the transfer function are 2.618, 30, and 108, respectively. K_p, K_i, and K_d in the PID controller are 0.5, 0.005, and 5 according to the Z-N empirical formula [18]. The simulation results of the controller can be obtained as shown in Figure 9. The controller of curve 1 in the figure is a fuzzy neural network, the controller of curve 3 is PID, and the curve 2 is the target temperature. The simulation structure after adding interference only needs to switch the switch in Figure 9. The numerical value of each index of the control system is shown in Table 1.

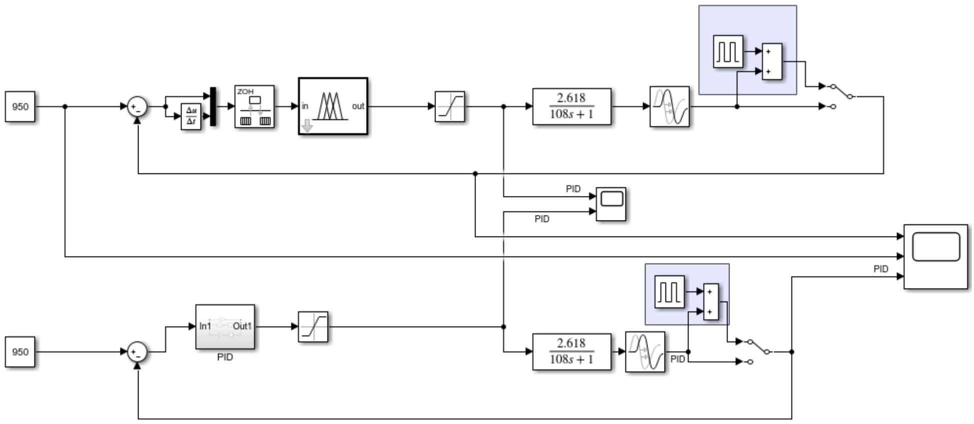

Fig. 8. Simulink simulation model

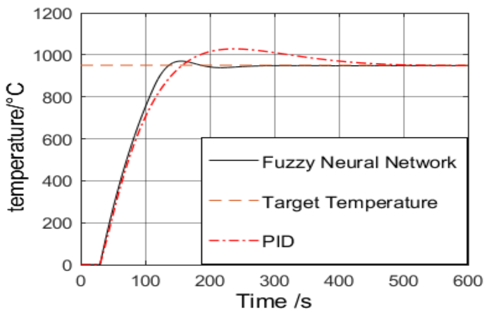

Fig. 9. Simulation curves of different controllers

The industrial production of lithium battery cathode materials generally adopts the solid-state sintering method. The sintering temperature is between 900 and 1200 °C, but the commonly used temperature is between 900 and 1000 °C. In order to make the simulation closer to the temperature control of sintering during production, the actual output value of the step response is set to 950°C. According to the analysis in Figure 9, the sintering temperature control system of the fuzzy neural network controller has the characteristics of smaller rise time, smaller overshoot, smoother and smoother curve and faster system stability than the control system of the improved PID controller. According to the analysis in Table 1, the simulation curve with the improved PID controller as the control system reaches a stable time of 600s, and the maximum overshoot is 8.2%. The simulation curve with the fuzzy neural network controller as the control system reaches a stable time as 300s, the maximum overshoot is 2.1%. Through comparative analysis, it can be seen that the fuzzy neural network control system responds faster to the sintering temperature control of lithium batteries, and the time for the system to stabilize is shorter. It further shows that the fuzzy neural network controller can not only effectively compensate for the coupling interference in different sintering temperature ranges. At the same time, it can better realize the precise control of the sintering temperature of the lithium battery.

In addition to the heating voltage, the factors affecting the sintering temperature of lithium batteries are the air inlet speed and air volume in the sintering furnace. Therefore, in order to verify the anti-interference ability of the system, a disturbance signal is added to the system when the temperature control is stable. Under the condition that other simulation settings remain unchanged, the simulation curve after adding interference is shown in Figure 10. It can be seen from the figure that when the control system adds interference at 400s, the system starts to respond after a delay of 30s. After the disturbance is added, the fuzzy neural network control system quickly recovers to stability after 32s, and the time to achieve stable adjustment is much lower than the adjustment time of the PID control system. It shows that the fuzzy neural network control system has strong anti-interference ability.

Table 1.
Numerical value of each index of the controller

	Response Time /s	Adjustment time /s	Overshoot /%
Fuzzy Neural Network	136	280	2.1
PID	160	440	8.2

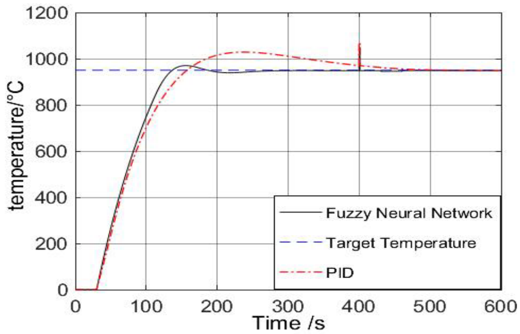

Fig. 10. Simulation curve after adding interference

The main factors affecting the stability of the lithium battery sintering temperature control system are heating voltage, air intake, air intake speed, conversion rate of materials inside the furnace, insulation effect of materials inside the furnace, and mixing degree of sintered materials. Therefore, the sintering temperature control system for lithium batteries actually changes all the time, that is to say, the values in the transfer function model established according to the characteristics of the industrial furnace and the delay link are not accurate. In order to verify the fault-tolerant ability of the fuzzy neural network control system and the adaptive ability to deal with model errors, a verification experiment was performed when the increments of K and T in the transfer function were within 2% [19]. When the size of K and T are 2.65 and 110, the simulation results to verify the adaptability of the controller are shown in Figure 11.

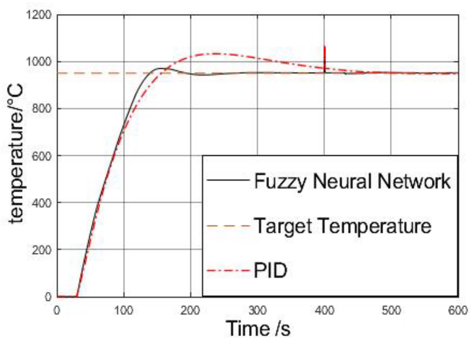

Fig. 11. Simulation curve to verify the adaptability of the controller

From the analysis of the figure, after the fuzzy neural network control system changes the transfer function, the stable time is 290s, the response time to reach the standard temperature is 138s, the maximum overshoot is 2.1%, and the time for the system to stabilize again after adding interference is 26s. Compared with the simulation results output by the original fuzzy neural network controller for the control system, the initial stabilization time of the system is 10s longer, the response time is different by 2s, and the maximum overshoot is not different, but the time to stabilize the system after anti-interference is shortened by 4s. The comparative analysis verifies that the fuzzy neural network control system can not only quickly realize the accurate control of the sintering temperature of the lithium battery, but also has strong adaptability and fault-tolerance.

5. Conclusions

1) The article analyzes the influence of heating voltage, air inlet speed and air inlet volume on the sintering temperature of lithium batteries and the performance of sintered products. Aiming at the delay and instability of the existing PID temperature controller, a fuzzy neural network controller that can realize temperature control of the nonlinear system is designed.
2) The characteristics of the fuzzy neural network control system. On the one hand, the neural network performs online training and optimization of fuzzy control rules and membership functions for lithium battery sintering temperature control. On the other hand, the fuzzy reasoning of fuzzy control enhances the reasoning ability of neural network control. The combination of the two improves the dynamic response characteristics, robustness and error control accuracy of the lithium battery sintering temperature control system.
3) The simulation model of fuzzy neural network controller and improved PID controller is established through MATLAB. The simulation results show that the fuzzy neural network controller can effectively solve the problems of nonlinearity and delay in sintering temperature control, and further enhance the adaptability, fault tolerance and anti-interference ability of the temperature control system.

Acknowledgments

This research was financially supported by a Major Project of Guizhou Province, China (QKH [2019]3003). Moreover, this research was also financially supported by the Guizhou Industry Simulation Design & Innovation Center (QKZYD NO. [2016]4006). This research is also support by Doctoral Research Foundation of Guizhou Normal University (2017).

References

[1] Li, H.S., Miao, Q. & Zhou, R.M. (2014). Research on control algorithm of ceramic kiln temperature control system. *Journal of Wuhan University of Technology*. 36(10), 135-139. DOI: 10.3963/j.issn.1671-4431.2014.10.024.

[2] Zhu, D.Q. & Jiang, K.R. (2009). Design and simulation of fuzzy neural network controller for drying process. *Journal of System Simulation*. 21(15), 4768-4771. DOI: 10.16182/j.cnki.joss.2009.15.079.

[3] Zhang, Z.M., Zhang, J.Y. & Feng, X.G. (2019). Design of hot blast stove temperature control system based on RBF neural network tuning. *Journal of Hebei University of Science and Technology*. 40(06), 503-511. DOI: 10.7535/hbkd.2019yx06007.

[4] Bai, G.Z. & Yu, J.H. (2016). PID parameter self-tuning based on improved fuzzy neural network. *Computer Application Research*. 33(11), 3358-3363+3368. DOI: 10.3969/j.issn.1001-3695.2016.11.035.

[5] Li, C.L. & Huang, C.Z. (2010). Design of temperature control system based on fuzzy neural network. *Microcomputer Information*. 26(07), 75-76+98. DOI: 10.3969/j.issn.2095-6835.2010.07.031.

[6] Li, G.Q., Tong, S.H. & Lu, L.X. (2013). Analysis of the temperature field in a continuous sintering furnace for solar cells. *Computer Simulation*. 30(01), 188-192+218. DOI: 10.3969/j.issn.1006-9348.2013.01.043.

[7] Huang, B., Xie, G.J., Liang, W.S. & Zhang, J.W. (2018). Application of heating furnace temperature control system based on hybrid fuzzy PID. *Electric Drive*. 48(02), 43-46. DOI: 10.19457/j.1001-2095.20180208.

[8] Zhou, G.L., Peng, Y.F. & Dong, H.S. (2007). Design of adaptive fuzzy PID controller based on T-S model. *Industrial Instrumentation and Automation*. 2, 22-25. DOI: CNKI: SUN: GYZD.0.2007-02-005.

[9] Tan, M., Cheng, C.H. & Lu, C. (2006). Research on the temperature control system of vacuum sintering furnace based on neural network. *Measurement and Control Technology*. 2, 31-32+53. DOI: 10.19708/j.ckjs.2006.02.010.

[10] Wang, J.P. & Ku, M.S. (2010). Application of FNN on atmospheric heating furnace of distillation unit. *Computer Measurement and Control*. 18(11), 2649-2651. DOI: 10.16526/j.cnki.11-4762/tp.2010.11.003.

[11] Chen, B.F., Yin, P.L. & Ma, L. (2010). Research on temperature control system based on fuzzy neural network. *Computer and Digital Engineering*. 38(07), 54-57. DOI: 10.3969/j.issn.1672-9722.2010.07.016.

[12] Li, M.H. & Li, Z.Q. (2012). Research on Decoupling Control Strategy of Injection Molding Machine Barrel Temperature Based on Neural Network. *Ceramics*. 4, 17-19. DOI: 10.19397/j.cnki.ceramics.2012.04.004.

[13] Hu, Y.N. & Ma, W.M. (2017). Research and application of paper quantitative moisture control strategy based on FNN decoupling. *China Paper*. 36(07), 48-53. DOI: 10.11980/j.issn.0254-508X.2017.07.009.

[14] Zhang, L., Zhang, J.C., Han, H.G. & Qiao, J.F. (2020). Process control of biochemical phosphorus removal in sewage treatment based on fuzzy neural network. *CIESC*

Journal. 71(03). 1217-1225. DOI: 10.11949/0438-1157.20191514.

[15] Tao, X.M., Luo, L. & Liu, Z.G. (2015). Research and simulation of injection molding machine barrel temperature control algorithm based on segmented PID. *Plastics.* 44(03), 68-70. DOI: CNKI: SUN: SULA.0.2015-03-022.

[16] Zhou, P.Q. (2016). Research on synchronization control technology of double winches based on fuzzy neural network. *Machine Design and Manufacture*. 9, 64-68. DOI: 10.19356/j.cnki.1001-3997.2016.09.017.

[17] Li, J.J., Xu, Y., Zhang, G., Wei, Z.Y. & Zhang, Y.B. (2015). Irrigation controller design based on BP neural network prediction and fuzzy control. *Machine Design and Research.* 31(05), 150-154. DOI: 10.13952/j.cnki.jofmdr.2015.0207.

[18] Luo, C.N., Hao, R.K. & Yang, W. (2018). Boiler temperature control simulation in industrial production process. *Computer simulation.* 35(09), 358-362. DOI: 10.3969/j.issn.1006-9348.2018.09.074.

[19] Zhao, J. & Xu, H. (2016). Computer simulation study on segmental control of barrel temperature of injection molding machine. *Synthetic Resin and Plastics.* 33(05), 61-63. DOI: 10.3969/j.issn.1002-1396.2016.05.018.