An intelligent temperature control algorithm of Molecular Beam Epitaxy system based on the Back-Propagation neural network

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ABSTRACT The temperature control is a critical aspect for the semiconductor material growth of the Molecular Beam Epitaxy system. The growth rate depends on the temperature of the beam source, and the quality of epi-layers heavily depends on the temperature of the substrate. In this paper, we reported an intelligent temperature control algorithm based on the BP neural network, which is specially optimized for the MBE system. After training the BP neural network by the collected MBE temperature data, the intelligent temperature control algorithm keeps the temperature error within 0.1°C. Moreover, this intelligent algorithm achieves a better control effect, reduces the regulation time of the system and makes the system overshoot to zero.

INDEX TERMS Back propagation neural network, molecular beam epitaxy, PID algorithm

I. INTRODUCTION

THE Molecular beam epitaxy (MBE) is an ultrahigh vacuum technique for growing very thin epitaxial layers of semiconductor crystals. Because it is inherently a slow growth process, extreme dimensional control over both major compositional variations and impurity incorporation can be achieved [1].

The basic principle is to spray atoms or molecules of material onto the target substrate with appropriate reaction temperature and lattice orientation in an ultra-high vacuum environment. Atoms or molecules react on the substrate surface, forming high-quality thin crystal film as shown in Figure 1.

In effect, the MBE requires a precise temperature control. If the temperature is too low, polycrystalline or amorphous layer will grow. If the temperature is too high, the adsorbed atoms will evaporate again and break away. In addition, the MBE source is usually provided by Knudsen effusion cells, where the flux of the molecular beam is adjusted by the cell operation temperature, resulting in an appropriate range of
growth rate.

Therefore, it is an urgent problem in the research and practice of MBE, how to control the growth temperature effectively and accurately. Two important features of the temperature control in MBE system are required, i.e., high accuracy and fast response. The accuracy of temperature control determines the accuracy of growth rate. The fast response will be beneficial to shorten the time of growth interruption which is needed for temperature adjustment and stabilization.

The temperature control is a method aims to heat the system up to delimited temperature, afterward hold it at that temperature in stable manner. Active electric heating method with Proportional-Integral-Derivative (PID) control strategy is one of the common means to achieve high-precision temperature control for thermal control systems. PID control is widely used in various industrial controls due to its simple structure, easy implementation, and strong robustness. But the choice of its proportional, integral and differential parameters, for ordinary PID temperature control method, depends on experience. It has defects of large overshoot, low steady-state accuracy if the parameters are inappropriately selected [7], [8].

Although the PID is hard to deal with the control of complex nonlinear systems, the back-propagation neural network (BPNN) and the fuzzy logic system (FLS) can identify and learn unknown nonlinear variation. Thus, the control method based on BPNN or FLS provides an effective method to resolve these issues present in uncertain systems [9], [10]. Both BPNN and FLS deal with important aspects of knowledge representation, inferencing and learning process, but they use different approaches and have their own strengths and weaknesses. The FLS is capable to perform approximate reasoning, but usually is not self-adaptive. The BPNN can learn from sample data automatically, but lack of explanation ability [11]. Given all kinds of complex problem, the design of an intelligent temperature controller for the MBE system remains a tremendous issue.

Wang Liang et al. [12] used three methods to predict the deformation temperature of coal ash based on the relationship between the composition and the melting characteristic temperature of coal ash, and they illustrated that prediction results of BPNN can achieve good accuracy according to comparison of the traditional linear regression, Factsage calculation, and BPNN calculation. Yan-Ming Cheng et al. [13] introduced intelligent control strategy applied to the phase shifting full-bridge converter, furthermore their simulation results showed that back-propagation neural network PID control (BP-PID), compared with traditional PID control strategy, has higher response speed, less overshoot, shorter time to enter the steady state and strong immunity. Yuwen Zhou et al. [14] combined BPNN to improve the PID controller in MOCVD parameter control and proved that BPNN controller can obtain a better control effect, reduce the regulation time of the system and make the system overshoot to zero. Minmin Wang et al. [15] proposed an intelligent optimization control method based on BP-PID to keep the ideal output of Microbial fuel cell (MFC) under different load disturbances and demonstrated that it can effectively eliminate the influence of complex and changeable interference in the MFC control process. Hui Liang et al. [16] designed a heater auto-tuned, which performed high-precision temperature control in a variety of constantly changing weather conditions without advance knowledge of the weather variation range, and showed BP-PID also can achieve a high-precision control effect under complex conditions.

Above all, these previous studies show that the PID temperature control based on BPNN is an effective method to resolve nonlinear parameter issues. Although the combination of temperature control and back-propagation neural network on the MBE system has not been reported in public literature yet, it can be reasonably inferred that the MBE temperature control system based on BP-PID algorithm not only can provide accurate temperatures to improve the theoretical reference, but also be used for the follow-up scientific research of temperature control, which has a broad application prospect.

Moreover, this paper proposed an intelligent temperature control system of the MBE system. This intelligent control system consisting of the basic structure of the MBE, a PID temperature controller, a four-layer-structure back-propagation neural network and different groups of samples was developed and numerically modelled. The temperature-control performance of the MBE system was trained and tested under millions of datasets which contained a variety of temperatures and parameters. In addition, the optimal choice of proportional, integral and differential parameters could also be selected automatically. Finally, the comparison of traditional PID control and BP-PID control in the MBE system was studied.

II. THE STRUCTURE OF MOLECULAR BEAM EPITAXY SYSTEM

The MBE is a technique for epitaxial growth via the interaction of one or several molecular or atomic beams that occurs on a surface of a heated crystalline substrate. In Figure 2, a scheme of a typical MBE system is shown. The solid sources
The purity of the raw materials is between 99.9999% and 99.999999%. The cleanliness of the furnace, especially at high temperature, is very important. The rate of gas evolution from the materials in the chamber has to be as low as possible. So pyrolytic boron nitride (PBN) is chosen for the crucibles which gives low rate of gas evolution and chemical stability up to 1400 °C, molybdenum and tantalum are widely used for the shutters, the heaters and other components, and only ultrapure materials are used as source.

B. EFFUSION CELL
The effusion cells used in MBE systems exploit the evaporation process of condensed materials as molecular flux source in vacuum. The molecular beam is used to spray the raw materials in the crucible through high-temperature heating. The purity of the raw materials is between 99.9999% and 99.999999%. The cleanliness of the furnace, especially at high temperature, is very important. The rate of gas evolution from the materials in the chamber has to be as low as possible. So pyrolytic boron nitride (PBN) is chosen for the crucibles which gives low rate of gas evolution and chemical stability up to 1400 °C, molybdenum and tantalum are widely used for the shutters, the heaters and other components, and only ultrapure materials are used as source.

C. MONITOR SYSTEM
The UHV environment provides in-situ monitoring conditions for the growth of molecular beam epitaxial materials. Reflective high energy electron diffraction (RHEED) and quadrupole mass spectrometer (QMS) provide real-time information for in-situ monitoring crystal growth quality, measuring growth rate and residual gas content in vacuum chamber. This plays an important role in improving the quality of epitaxial materials. The computer-controlled temperature system can automatically control the temperature and monitor it in real time to provide the temperature required for growth.

D. THE TEMPERATURE CONTROL MODEL
The MBE system’s electric heating furnace is a common heating equipment in the process of scientific experiment and industrial production. Due to the different specifications of furnaces and different heating objects, the systems constitute vary greatly. From the perspective of control, most electric heating furnaces are controlled objects with hysteresis, inertia and characteristic parameters varying with temperature. Therefore, we decided to establish an accurate model for MBE temperature model by using a flying method instead of difficult traditional methods.

By testing the Molecular Beam Epitaxy system (DCA P600) , the temperature control gain of MBE is 1.01db, the pure lag time of the controlled object is 10s, and the process inertia time constant of the controlled process is 120s. According to the flying method [14], the transfer function can be obtained as equation (1):

\[ G(s) = \frac{1.01}{120s + 1} e^{-10s} \]  

III. BP NEURAL NETWORK PID CONTROL ALGORITHM
In order to achieve good control results, the conventional PID control algorithm should be realized by adjusting three coefficients: proportional, integral and differential (herein after referred to as P parameter, I parameter and D parameter). This combination of PID parameters does not necessarily exist linear relation [17], so it is difficult for the conventional PID to find the relationship between the three parameters of optimal control. However, the neural network has the ability to approach any nonlinear function. [18], [19] Through the network adaptive and learning ability [20]–[22], we can find the optimal proportional, integral and differential coefficients under the given conditions.

The PID controller of the BP neural network consists of two parts: the PID control part and the BP neural network part. According to the running state of the system, the parameters of the PID controller are adjusted. Through the self-adaptive and self-learning ability of the neural network synchronously, it achieves a good control effect and overcomes the inherent shortcomings of conventional PID control, such as large overshoot and large inertia [23]. The system structure is shown in Figure 3.
In equation (3), \(k_p\) is the proportional coefficient, \(T_i\) is the integral time coefficient and \(T_d\) is the differential time coefficient. After discretization of the PID control algorithm, the following results can be obtained:

\[
u(k) = K_p e(k) + K_i \sum_{j=0}^{k} e(j) + K_d [e(k) - e(k - 1)] \quad (4)
\]

In equation (4), \(e(k)\) is the temperature error of the MBE system at \(k\) time, \(e(k-1)\) is the error at \(k-1\) time, \(K_p\), \(K_i\), \(K_d\) represent P parameter, I parameter, D parameter in the MBE temperature control system.

The incremental PID algorithm can be obtained by \(u(k) - u(k - 1)\) of the PID algorithm in equation (4). As the incremental PID does not need to store the deviation generated by each sampling period, the required storage space is greatly reduced, which is more convenient for computer processing. So the incremental PID algorithm is shown as follow equations:

\[
\Delta u(k) = u(k) - u(k - 1) \quad (5)
\]

\[
\Delta u(k) = K_p [e(k) - e(k - 1)] + K_i e(k) + \frac{K_d}{2} [e(k) - 2e(k - 1) + e(k - 2)] \quad (6)
\]

The MBE system need a high precision manufacturing process, while the BP neural network is used to further optimize PID the control algorithm.

**B. BP NEURAL NETWORK ALGORITHM**

The BP neural network algorithm is comprised of forward propagation and backward propagation.

Forward propagation: the input signal is propagated from the input layer, via the hide layer, to the output layer. During the forward propagation of operating signal, the weight value and offset value of the network are maintained constant and the status of each layer of neuron will only exert an effect on that of next layer of neuron. In case that the expected output can not be achieved in the output layer, it can be switched into the back propagation of error signal.

Back propagation of error signal: the difference between the real output and expect output of the network is defined as the error signal; in the back propagation of error signal, the error signal is propagated from the output layer to the input layer in a layer-by-layer manner. During the back propagation of error signal, the weight value of network is regulated by the error feedback. The continuous modification of weight value and offset value is applied to make the real output of network more closer to the expected one.

In the Figure 4, the BP neural network’s input layer can be defined as:

\[\text{net}_j^{(1)} = a_1^{(1)} + a_2^{(1)} + a_3^{(1)} + a_4^{(1)} + a_5^{(1)} \quad (7)\]

In equation (7), \(a_1^{(1)}\) is the temperature error, \(a_2^{(1)}\) is the input temperature, \(a_3^{(1)}\) is the output temperature, \(a_4^{(1)}\) is the constant \(c_1\) and \(a_5^{(1)}\) is the constant \(c_2\). The input of the first hidden layer can be expressed as:

\[\text{net}_j^{(2)} = \sum_{i=1}^{5} [w_{ij}^{(1)} * a_i^{(1)}] + b_j^{(1)} (j = 1, 2, ..., 4) \quad (8)\]

In equation (8), \(w_{ij}^{(1)}\) is the weight coefficient between the input layer and the first hidden layer, \(b_j^{(1)}\) is the bias of the input layer. Therefore, the output of the first hidden layer is:

\[O_j^{(2)} = f[\text{net}_j^{(2)}] \quad (9)\]

\[f(x) = \text{tanh}(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (10)\]

In equation (9), \(f(x)\) is the activation function. Compared to the Sigmoid function, the \(\text{tanh}(x)\) function has faster convergence speed and better practical training effect, which expresses in equation (10). Similarly, we could deduce the input of the second hidden layer:

\[\text{net}_k^{(3)} = \sum_{j=1}^{4} [w_{jk}^{(2)} * O_j^{(2)}] + b_j^{(2)} (k = 1, 2, 3) \quad (11)\]

In equation (11), \(w_{jk}^{(2)}\) is the weight coefficient between the first hidden layer and the second one, and \(b_j^{(2)}\) is the bias of the first hidden layer. Correspondingly, the output of the second hidden layer is:

\[O_k^{(3)} = f[\text{net}_k^{(3)}] \quad (12)\]

Then, the input of the output layer could be shown as:

\[\text{net}_l^{(4)} = \sum_{k=1}^{4} [w_{kl}^{(3)} * O_k^{(3)}] + b_j^{(3)} (l = 1, 2, 3) \quad (13)\]

In equation (13), \(w_{kl}^{(3)}\) is the weight coefficient between the second hidden layer and the output layer and \(b_j^{(3)}\) is the bias of the second hidden layer. Thus, the output in the output layer is:

\[O_l^{(4)} = f[\text{net}_l^{(4)}] \quad (14)\]
As shown in equation (15), the predicted result can be regarded as $Y$, and $y_1$, $y_2$ and $y_3$ can represent the predicted value of $k_p$, $k_i$, $k_d$.

$$Y = \begin{cases} y_1 = O_1^{(4)} \\ y_2 = O_2^{(4)} \\ y_3 = O_2^{(4)} \end{cases} \quad (15)$$

The actual value can be regarded as $R$, and $r_1$, $r_2$, $r_3$ can represent the actual value of $k_p$, $k_i$, $k_d$. In equation (16), we defined the cost function:

$$J(x) = \frac{1}{2} \sum_{n=1}^{3} [Y_n(x) - R_n(x)]^2 \quad (16)$$

In order to achieve the best weight coefficient, we used the gradient descent method to find the global minimum in the case of adding a minimal inertial term, through iterating and adjusting the negative gradient direction of the weight coefficient, as shown in equation (17).

$$\Delta w_{kl}^{(4)} = -\eta \frac{\partial J(x)}{\partial w_{kl}^{(4)}} + \rho \Delta w_{kl}^{(4)}(x - 1) \quad (17)$$

In equation (17), $\eta$ is the learning rate and $\rho$ is coefficient of inertia, $\frac{\partial J(x)}{\partial w_{kl}^{(4)}}$ also can be expressed as equation (18).

$$\frac{\partial J(x)}{\partial w_{kl}^{(4)}} = \frac{\partial J(x)}{\partial y(x)} \cdot \frac{\partial y(x)}{\partial u(x)} \cdot \frac{\partial u(x)}{\partial O_l^{(4)}(x)} \cdot \frac{\partial O_l^{(4)}(x)}{\partial w_{kl}^{(4)}} \quad (18)$$

So it could be deduced that the correlation between BP neural network and incremental PID equation is as follows:

$$\begin{cases} \frac{\partial u(x)}{\partial O_l^{(4)}(x)} = e(x) - e(x - 1) \\ \frac{\partial y(x)}{\partial u(x)} = e(x) \\ \frac{\partial u(x)}{\partial O_l^{(4)}(x)} = e(x) - 2e(x - 1) + e(x - 2) \end{cases} \quad (19)$$

The equation of the output weight could be generalized from equation (17) and (18):

$$\Delta w_{kl}^{(4)} = \eta \delta_{l}^{(4)} O_k^{(4)}(x) + \rho \Delta w_{kl}^{(4)}(x - 1) \quad (20)$$

$$\delta_{l}^{(4)} = \frac{\partial J(x)}{\partial y(x)} \cdot \frac{\partial y(x)}{\partial u(x)} \cdot \frac{\partial u(x)}{\partial O_l^{(4)}(x)} \cdot f'(net_l^{(4)})(l = 1, 2, 3) \quad (21)$$

For the same reason, the equation of hidden layer weight is shown in the following equation (22) and (24):

$$\Delta w_{jk}^{(3)} = \eta \delta_{j}^{(3)} O_k^{(2)}(x) + \rho \Delta w_{jk}^{(3)}(x - 1) \quad (22)$$

$$\delta_{j}^{(3)} = f'(net_j^{(3)}) \cdot \sum_{l=1}^{3} \delta_{l}^{(4)} w_{kl}^{(4)}(k = 1, 2, 3) \quad (23)$$

$$\Delta w_{ij}^{(2)} = \eta \delta_{j}^{(2)} O_i^{(1)}(x) + \rho \Delta w_{ij}^{(2)}(x - 1) \quad (24)$$

$$\delta_{j}^{(2)} = f'(net_j^{(2)}) \cdot \sum_{k=1}^{3} \delta_{k}^{(3)} w_{ij}^{(3)}(j = 1, 2, 3, 4) \quad (25)$$

At last, the optimal weight coefficient could be obtained by gradient descent method.

IV. RESULTS

The designed intelligent temperature control system of the MBE system was shown in Figure 5.

A. TRAINING AND TESTING

The intelligent temperature control system trended to go through 3 phases, including collecting, training and testing. Therefore, we begin with collection of PID datas. Approximately 1685 groups of samples were collected through a PID simulator, and each group had 10000 datas which contained actual temperatures, setting temperatures, parameter $P$, parameter $I$, parameter $D$ and so on.

In the second phase, we constructed a BP neural network which adopted a four-layer structure, herein 5-20-10-3 structure. This structure had single input layer, single output layer and two hidden layers. Besides, the five nodes of input layer are the input temperature $vin$, the output temperature $vout$, the temperature error $e$, the constant $c_1$, which measures whether the system produces overshoot (if the system has overshoot, $c_1$ is set to 0, otherwise it is set to 1), and the constant $c_2$, which evaluates whether the system’s temperature meets the requirement (if the system temperature reaches the setting temperature, $c_2$ is set to 1, otherwise it is set to 0). Likewise, the parameter $k_p$, $k_i$, $k_d$ are the nodes of output layer.

Then we started the training. 1000 groups of samples were used for training, besides each trained group was regarded as 1 epoch, also there were 1000 iterations in per epoch. The training details has been shown in Figure 6 and Table 1.
We found that there was little overshoot phenomena, in the Figure 6, when trained epoch was 200. When trained epoch was 600, a satisfactory result was achieved. When trained epoch was closer to 1000, the temperature was closer to the setting temperature.

In the final phase, one of the 685 groups of sample was applied to test the trained model. The results were shown in Figure 7, 8 and table 2. It was obvious that there was about 0.1 °C error between setting temperature and actual temperature, and this error was within a reasonable range. Therefore, we thought the set of parameters was the one of the best choices in PID parameters.

B. ANALYZING

The comparison of response curves between the BP-PID and the conventional PID control algorithm are shown in Figure 9 and Figure 10. By comparing the conventional PID algorithm with BP-PID control algorithm based on neural network, the heating process from 200 °C to 800 °C has been simulated. Moreover, the interference was added in the system after setting temperature had been achieved. It is beyond dispute that the time required for BP-PID to eliminate the influence of interference is less than that of PID. Thus it can be proved that BP-PID has better robustness.

From Figure 9, the final temperature of the conventional PID algorithm is 798.662 °C, and that of the BP-PID algo-
rithm can reach is 800.093 °C. The time taken by the conventional PID algorithm, to achieve the setting temperature (800 °C), is almost close to that of the BP-PID algorithm, but the BP-PID algorithm avoids the overshoot phenomenon in the PID algorithm. It could be concluded that the PID control algorithm with BP neural network has higher precision after the same period of time.

![Temperature Simulation Without Overshoot](image)

From Figure 10, the final temperature of the BP-PID algorithm is 799.921 °C, as the same as that of the conventional PID algorithm without overshoot phenomenon. But the conventional PID algorithm, to achieve the setting temperature (800 °C), has taken more time than twice as long as the BP-PID algorithm. It could be concluded that the PID control algorithm with BP neural network takes less time to reach the setting temperature.

When the actual temperature surpasses the set temperature, the adsorbed atoms will evaporate again and break away. When it takes a long time to get the set temperature, polycrystalline or amorphous will grow. Thus the BP neural network PID algorithm is more suitable for the MBE temperature control system.

V. CONCLUSION

The MBE growth temperature affects the film quality obviously. In the process of film growth, it is necessary to accurately control the temperature of the source furnace. In our paper, we proposed a BP neural network PID control algorithm, which could analyze the MBE temperature intelligently. The PID control algorithm with BP neural network is based on the prediction of the overall operation status of the object to determine the future operation status, so as to determine the control quantity. It is suitable for complex temperature control process which is difficult to establish an accurate mathematical model. The BP neural network PID control algorithm is designed, by adjusting the parameters of the PID controller. From the simulation results, the BP neural network PID algorithm control shows the temperature error between 0 and 1 °C, however the temperature error of PID control often is between 0 and 3 °C. Therefore, the designed intelligent temperature system has a better performance than the conventional PID algorithm control, which presents a quick response speed and an excellent adaptive ability. The results achieved are expected to the MBE temperature control system requirements. This research not only could provide accurate temperature control for the production process to improve the theoretical reference, but also be used for the follow-up scientific research of control algorithm, which has a broad application prospect.

REFERENCES

[1] M. B. Panish, “Molecular beam epitaxy,” *Science*, vol. 208, no. 4446, pp. 916–922, 1980.
[2] V. Dubrovskii, G. Cirinl, I. Soshnikov, A. Tonkikh, N. Shibirev, Y. B. Samsonenko, and V. Ustinov, “Diffusion-induced growth of GaAs nanowiskers during molecular beam epitaxy: Theory and experiment,” *Physical Review B*, vol. 71, no. 20, p. 205325, 2005.
[3] G. Cirinl, V. G. Dubrovskii, Y. B. Samsonenko, A. Bouravleuv, K. Durose, Y. Y. Proskuryakov, B. Menedes, L. Bowen, M. Kaliteevski, R. Abram et al., “Self-catalyzed, pure zincblende GaAs nanowires grown on Si (111) by molecular beam epitaxy,” *Physical Review B*, vol. 82, no. 3, p. 035302, 2010.
[4] S. R. Provence, S. Thapa, R. Paudel, T. K. Truttman, A. Prakash, B. Jalan, and R. B. Comes, “Machine learning analysis of perovskite oxides grown by molecular beam epitaxy,” *Physical Review Materials*, vol. 4, no. 8, p. 083807, 2020.
[5] M. Tchernycheva, J. Harmand, G. Patriarche, L. Travers, and G. E. Cirlin, “Temperature conditions for GaAs nanowire formation by an-assisted molecular beam epitaxy,” *Nanotechnology*, vol. 17, no. 16, p. 4025, 2006.
[6] M. J. Manfra, “Molecular beam epitaxy of ultra-high quality AlGaAs/GaAs heterostructures: enabling physics in low-dimensional electronic systems,” *Ann. Rev. Condens. Matter Phys.*, vol. 5, no. 1, pp. 347–373, 2014.
[7] J.-I. Song, W.-I. Cheng, Z.-M. Xu, S. Yuan, and M.-H. Liu, “Study on pid temperature control performance of a novel ptc material with room temperature cure point,” *International Journal of Heat and Mass Transfer*, vol. 135, pp. 1038–1046, 2016.
[8] K. H. Ang, G. Chong, and L. Yun, “PID control system analysis, design, and technology,” *IEEE Transactions on Control Systems Technology*, vol. 13, no. 4, pp. 559–576, 2005.
[9] L. Liu, Y.-J. Liu, A. Chen, S. Tong, and C. P. Chen, “Integral barrier lyapunov function-based adaptive control for switched nonlinear systems,” *Science China Information Sciences*, vol. 63, no. 3, pp. 1–14, 2020.
[10] Y.-J. Liu, W. Zhao, L. Liu, D. Li, S. Tong, and C. P. Chen, “Adaptive neural network control for a class of nonlinear systems with function constraints on states,” *IEEE Transactions on Neural Networks and Learning Systems*, 2021.
[11] Y. Yuan and S. Suarga, “On the integration of neural networks: and fuzzy logic systems,” in 1995 *IEEE International Conference on Systems, Man and Cybernetics. Intelligent Systems for the 21st Century*, vol. 1, IEEE, 1995, pp. 452–457.
[12] W. Liang, G. Wang, X. Ning, J. Zhang, Y. Li, C. Jiang, and N. Zhang, “Application of bp neural network to the prediction of coal ash melting characteristic temperature,” *FUEL*, vol. 260, p. 116324, 2020.
[13] Y.-M. Cheng, C. Liu, J. Wu, H.-M. Liu, J.-K. Lee, J. Niu, J.-P. Cho, K.-W. Koo, M.-W. Lee, and D.-G. Woo, “A back propagation neural network with double learning rate for pid controller in phase-shifted full-bridge soft-switching power supply,” *Journal of Electrical Engineering & Technology*, vol. 15, no. 6, pp. 2816–2822, 2020.
[14] Y. Zhou, K. C. Chang, K. C. Chu, D. K. Amnesimenu, and A. Omer, “Advanced 5g system chip mcvd process parameter control and simulation based on np neural network and smith predictor,” in 2020 *IEEE International Conference on Artificial Intelligence and Information Systems (ICAIS)*, 2020.
[15] M. Wang and A. An, “An adaptive pid control based on np neural network for the voltage of mfc,” in 2020 *Chinese Automation Congress (CAC)*, 2020.
[16] H. Liang, Z.-K. Sang, Y.-Z. Wu, Y.-H. Zhang, and R. Zhao, “High precision temperature control performance of a pid neural network-controlled
heater under complex outdoor conditions,” Applied Thermal Engineering, p. 117234, 2021.

[17] J. Li, J. H. Cheng, J. Y. Shi, and F. Huang, Brief Introduction of Back Propagation (BP) Neural Network Algorithm and Its Improvement. Advances in Computer Science and Information Engineering, 2012.

[18] R. Hecht-Neilsen, “ii. 3-theory of the backpropagation neural network*,” Neural Networks for Perception, pp. 65–93.

[19] J. Chen, K. Li, K. Li, P. S. Yu, and Z. Zeng, “Dynamic planning of bicycle stations in dockless public bicycle-sharing system using gated graph neural network,” ACM Transactions on Intelligent Systems and Technology (TIST), vol. 12, no. 2, pp. 1–22, 2021.

[20] Y. Dou, “An improved prediction model of ight junction temperature based on backpropagation neural network and kalman filter,” Complexity, vol. 2021, 2021.

[21] J. Chen, K. Li, K. Bilal, K. Li, S. Y. Philip et al., “A bi-layered parallel training architecture for large-scale convolutional neural networks,” IEEE transactions on parallel and distributed systems, vol. 30, no. 5, pp. 965–976, 2018.

[22] J. Chen, K. Li, H. Rong, K. Bilal, K. Li, and S. Y. Philip, “A periodicity-based parallel time series prediction algorithm in cloud computing environments,” Information Sciences, vol. 496, pp. 506–537, 2019.

[23] J.-l. Song, W.-l. Cheng, Z.-m. Xu, S. Yuan, and M.-h. Liu, “Study on pid temperature control performance of a novel ptc material with room temperature curie point,” International Journal of Heat and Mass Transfer, vol. 95, pp. 1038–1046, 2016.

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