Research Article

An Improved Prediction Model of IGBT Junction Temperature Based on Backpropagation Neural Network and Kalman Filter

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With the rapid development of emerging technologies such as electric vehicles and high-speed railways, the insulated gate bipolar transistor (IGBT) is becoming increasingly important as the core of the power electronic devices. Therefore, it is imperative to maintain the stability and reliability of IGBT under different circumstances. By predicting the junction temperature of IGBT, the operating condition and aging degree can be roughly evaluated. However, the current predicting approaches such as optical, physical, and electrical methods have various shortcomings. Hence, the backpropagation (BP) neural network can be applied to avoid the difficulties encountered by conventional approaches. In this article, an advanced prediction model is proposed to obtain accurate IGBT junction temperature. This method can be divided into three phases, BP neural network estimation, interpolation, and Kalman filter prediction. First, the validities of the BP neural network and Kalman filter are verified, respectively. Then, the performances of them are compared, and the superiority of the Kalman filter is proved. In the future, the application of neural networks or deep learning in power electronics will create more possibilities.

1. Introduction

The insulated gate bipolar transistor (IGBT) is the main power electronic energy conversion device and transmission device. It combines the merits of MOSFET and BJT with low drive power and low saturation voltage. The IGBT has become the pivotal supporting technology to alleviate energy shortages and reduce carbon emissions since it is highly efficient, energy-saving, and environmentally friendly. Nowadays, it is widely utilized in communication, rail transit, smart grid, aerospace, electric vehicles, and new energy power generation [1]. Given the significance of the IGBT, it is essential to maintain safety and reliability during the IGBT device's operation.

One of the most important factors affecting the technical progress and development of the IGBT is operating temperature. The high junction temperature resulted from large heat fluxes will significantly deteriorate the performance and reliability of the IGBT device [2]. The electronics prognostics supplied by the NASA AMES Laboratory also pointed out that overheating of the IGBT die is one of the main causes of

the failure [3]. In a related survey on the power device's reliability, the failure rate due to junction temperature is as high as 55% and doubles for every 10°C increase [4]. Thus, ensuring the IGBT junction is maintained at a controllable temperature is the cornerstone of keeping the IGBT device's stability. Monitoring IGBT junction temperature during the operation has become the major challenge and top priority at present.

There have already been many approaches to monitor junction temperature, including optical, physical, and electrical methods [5, 6]. The optical method measures the energy change of lattice photons to infer the junction temperature using infrared (IR) cameras [7], IR sensors [8], IR microscope [9], and optical fiber [10]. This method can directly and accurately obtain the junction surface temperature map, but the implementation usually requires expensive instruments and extra modification on the standard module package. The typical physical method is the electrothermal model, which uses thermistors or thermocouples to physically contact the IGBT chip and infer the junction temperature [11, 12]. However, this method's

response time is usually long because of the thermal capacitance of thermistors and thermocouples [5]. Besides, the physical method relies too much on complex physical models. The accuracy of prediction will be greatly reduced once the physical models change for some reason. The electrical method uses temperature-sensitive electrical parameters (TSEPs) such as gate threshold voltage (V_{th}) [13], on-state voltage (V_{CEon}) [14], short circuit current (I_{sc}) [15], and peak gate current (I_{Gpeak}) [16] to calculate or infer the junction temperature. It can be found either in the scientific literature or the device datasheet published by the manufacturer that there is good linearity between TSEPs and junction temperature. A major benefit of using the electrical method is that the junction temperature can be obtained without modifying the standard module package, which is also the main reason it is used more now. This article will focus on the approach of using on-state voltage (V_{CEon}) at a high current.

The conventional V_{CEon} (high-current) TSEP method attempts to build a temperature model using linear equations. However, the relationship between on-state voltage and junction temperature does not perform absolute linearity. There is always an error between the real value and the calculated value [17]. Dong and coworkers recently proposed a new junction temperature prediction model using an artificial neural network (ANN) [18]. They applied the backpropagation (BP) neural network to predict the junction temperature using on-state voltage and collector current. The results are compared with the conventional TSEP method, and the feasibility of the BP neural network is proved. However, because of the inherent data, randomness during the training process, and intrinsic nonidentifiability of the model, the prediction results are prone to strong instability [19]. This article proposes a new method using the Kalman filter based on BP neural network and interpolation to stabilize the prediction. The flowchart of this approach is shown in Figure 1.

This article is organized as follows: Section 2 describes the object of study and simulation environment. Section 3 introduces three methods used to predict junction temperature and their parameter settings. The results are given in Section 4. The validities of the BP neural network and Kalman filter are verified. There is also a comparison between the errors of the three predicting methods in this section. Section 5 discusses the superiority of the Kalman filter prediction and the possibility of improvement. Finally, the conclusion is drawn.

2. Simulation Settings

This article's research object is Infineon IKW75N65ET7 IGBT discrete (650 V, 75 A) and the simulation is based on LTspice. The SPICE model downloaded from Infineon has already included the temperature module. The on-state voltage test circuit is built to measure the on-state voltage V_{CEon} of the IGBT discrete. The test circuit includes current source, power load, IGBT discrete, control system, and voltmeter, as shown in Figure 2. The junction temperature extraction can be carried out without modifying the

standard package even under the real experimental environment.

In LTspice, set the global temperature to a certain value, which is also assumed to be the junction temperature. Next, set the output of the current source I_s and drive IGBT discrete with a single pulse. Then measure the on-state voltage under this condition. Afterward, tune the collector current I_C and junction temperature T_j (global temperature) to obtain the on-state voltages V_{CEon} under different conditions. In the simulation, this task can be completed quickly by using the sweep function. The value range of collector current I_C is from 5 A to 75 A, and junction temperature T_j is from 25°C to 175°C. The sample intervals are one ampere (1 A) and one-degree centigrade (1°C), respectively. Hence, 10721 groups of data in total can be obtained. One thousand groups for the training set and 20 groups for the test set are randomly assigned, respectively. Random sampling intends to check the neural network's robustness, but it is recommended to sample evenly in the real experiment.

3. Methods

This section introduces three methods, including backpropagation (BP) neural network, interpolation, and the Kalman Filter. The BP estimation and interpolated value are used as the Kalman filter measurement and prediction model, respectively. The setup and application of each method are also drawn.

3.1. Backpropagation Neural Network. Backpropagation (BP) neural network is a multilayer feedforward neural network trained according to the error backpropagation algorithm. It is capable of classifying arbitrary complex patterns and mapping multidimensional functions. The BP neural network base is the gradient descent method, which uses gradient search to minimize the mean square error between the actual and the expected output. The inputs are transmitted from the input layer to the output layer after being processed by the hidden layers during forward propagation. If the actual output is inconsistent with the expected output, then move to backpropagation. During backpropagation, the output is back transmitted to the input layer somehow, and the error is distributed to all units of each layer. Then, each layer's error can be obtained, which is used to correct the weight of each unit. With the continuous correction of the error, the network's accuracy will be improved step by step [20].

The junction temperature prediction model can be regarded as a complex nonlinear system, which is difficult to be accurately modelled with a single mathematical method. In this case, BP neural network can be constructed to express it. On-state voltage V_{CEon} and collector current I_C of IGBT discrete are chosen as the inputs. The junction temperature T_j is chosen to be the output. When the signal is transmitted, the inputs V_{CEon} and I_C act on the output node through the hidden layer. After the nonlinear transformation, the prediction of junction temperature T_e is generated from the output layer. If the actual output T_e is equal to the expected

FIGURE 1: Block diagram of the methods for predicting junction temperature.

FIGURE 2: The simulation circuit for measuring on-state voltage.

output T_j , then propagation is terminated. Otherwise, the error will be allocated to all nodes in each layer through backpropagation. The neural network's weight and deviation are updated in the fastest increasing direction to minimize the error.

The structure of the BP neural network in this article is shown in Figure 3. As the figure shows, the neural network consists of two inputs, one output, and one hidden layer including ten neurons. For a complex task, choose 0.01 for learning rate and 0.9 for the momentum parameter to achieve high performance [20]. The other parameter settings for training the neural network are listed in Table 1, and the implementation is based on the MATLAB "neural network training toolbox." It is worth mentioning that, before starting the training, the dataset should be normalized to avoid possible numerical problems [21]. The BP estimation will be used in Section 3.3 as the measurement model of the Kalman filter.

3.2. Interpolation Method. The interpolation method interpolates the continuous function based on the discrete data. The continuous curve passes through all data points, which is a vital approach to approximate discrete functions. It can estimate the approximation of other points by analyzing the function value of finite points.

Use the interpolation function in MATLAB to generate an interpolation graph composed of on-state voltage V_{CEon} , collector current I_C , and junction temperature T_j , as shown in Figure 4. Because of the resolution limitation, the

extracted temperature will be slightly different from the real junction temperature. On top of that, the personal error also probably exists during the extraction. The interpolated value will be used in Section 3.3 as the prediction model of the Kalman filter.

3.3. Kalman Filter. Kalman filter (KF) is an algorithm using the linear system's state equation to predict the system state through measurement. Since the measurement includes some noise and disturbance, the optimal estimation can also be regarded as a filtering process [22]. The first step is to predict the current state based on the previous state and control vector. The state equation from time $k-1$ to k is defined as

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1}, \quad (1)$$

where A and B are the state transition matrix and control-input matrix, respectively, A is set as identity matrix I , and control vector u_{k-1} is set as zero since the temperature does not change in a short time. The w_{k-1} is the noise during the prediction process. It is assumed to be white Gaussian noise with mean zero and covariance Q , denoted as $w_{k-1} \sim N(0, Q)$. Because of the limited resolution and personal error, the interpolated value will have some fluctuations. Hence, it can be considered to satisfy the Gaussian distribution with covariance Q .

The measurement equation defines the relationship between the state and the measurement at the time k as follows:

$$z_k = Hx_k + v_k, \quad (2)$$

where v_k is the noise from the measurement. It is assumed to be white Gaussian noise with mean zero and covariance R , denoted as $v_k \sim N(0, R)$. The measurement will be directly loaded from the BP estimations. The neural network's estimations can also be considered to satisfy the Gaussian distribution with covariance R since it has the oscillation around a fixed point.

When both the prediction and measurement model satisfy Gaussian distribution, their product will also be Gaussian distribution. The fused Gaussian distribution has a higher probability density and smaller variance, as shown in Figure 5. Kalman algorithm is a recursive prediction-update method and can be divided into prediction stage and correction stage. The prediction stage calculates the state variable's prior estimate based on the posterior estimate of the

previous moment. It can be described in the next two equations:

$$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_{k-1}, \quad (3)$$

$$P_k^- = AP_{k-1}A^T + Q, \quad (4)$$

where P is the state error covariance; it represents the credibility of the prediction stage.

The correction stage combines the prior estimate with the new measurement variables to construct the optimal estimate. It can be described in the following three equations:

$$K_k = \frac{P_k^- H^T}{H P_k^- H^T + R}, \quad (5)$$

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-), \quad (6)$$

$$P_k = (I - K_k H) P_k^-, \quad (7)$$

where R is the covariance of the measurement noise; it represents the measurement stage's credibility.

The implementation of the Kalman filter is based on the MATLAB code. Use the interpolated value as the prediction and 100 different BP estimations to measure the Kalman filter, respectively. R and Q 's values need to be tuned to obtain the most appropriate result, that is, make the optimal estimation closer to the expected value.

4. Results and Discussion

This section provides the validities of the BP neural network and the Kalman filter. Also, the detailed results of the three methods introduced in Section 3 are given. In the end, the experimental conclusions are also drawn.

4.1. Inflection Point of IGBT. Based on the simulation's collected data, the relationship between on-state voltage V_{CEon} , collector current I_C , and junction temperature T_j is drawn. Figure 6 shows that these coordinate points can make up a smooth surface. It is apparent that the value of V_{CEon} is affected by both I_C and T_j , which verifies the correctness of selecting V_{CEon} and I_C as the inputs of the temperature prediction model.

Figure 7 indicates that on-state voltage increases with the increment of junction temperature in the above three conditions but decreases below three conditions. This normal phenomenon is caused by the manufacturing process, which is known as the inflection point. The curves with positive and negative temperature coefficients intersect at this point.

By checking the data table obtained from simulation, the inflection point is found around 42 A. On-state voltage and junction temperature have a positive correlation when the collector current is larger than 42 A and a negative correlation when the collector current is smaller than 42 A. Consequently, the next sections' analysis will be divided into two parts ($I_C < 42$ A and $I_C > 42$ A). Limited to the

FIGURE 3: The flowchart of the BP neural network for estimating junction temperature.

TABLE 1: BP neural network training parameters.

Items	Parameters
Nodes in input layer	2
Nodes in hidden layer	10
Nodes in output layer	1
Activation function	Tansig
Output function	Purelin
Training function	Levenberg–Marquardt
Learning rate	0.01
Maximum epochs	1000
Performance goal	10^{-5}
Validation failures	6
Momentum factor	0.9

article's length, this article's analysis will focus on the condition when the collector current is larger than 42 A. Still, the result of both conditions will be given in Section 4.5.

4.2. Validity of BP Neural Network. Sometimes, the BP neural network can only accurately predict specific but not all test sets because of contingency. To avoid that, it is necessary to pick different training and test sets to check the validity [23]. In this case, three completely different training and test sets are used to construct and evaluate the neural network. Each training set contains 1000 groups of data, and each test set includes 20 data groups. Besides, the parameter settings of the three control groups are the same.

The three control groups' error and percentage error are shown in Figures 8(a) and 8(b). It is observed that the absolute errors are mostly below 10°C and the percentage errors are mostly below 15%. The neural network performs well with each dataset, which also confirms its strong generalization ability.

4.3. Oscillation of BP Neural Network Estimations. Because the BP neural network model is initialized when built, the estimated value will differ each time. Pick three test data and put them in 100 different neural networks. The results are shown in Figure 9, and three test data are coloured differently. It is observed that the BP estimations are unstable but oscillate around their mean values. The oscillation appears because the initial weights and thresholds are

FIGURE 4: The interpolation graph which is composed of the training set.

FIGURE 5: The working principle of Kalman filter from time $k - 1$ to time k .

FIGURE 6: The three-dimensional space which is composed of junction temperature, collector current, and on-state voltage.

FIGURE 7: The relationship between junction temperature and on-state voltage with different collector currents.

FIGURE 8: (a) The temperature errors of 20 samples. (b) The percentage errors of 20 samples.

generated randomly. Most of the points are close, but a few are far from the mean value. In other words, the closer to the mean, the higher probability of a point occurs. It indicates that the BP estimations used as the Kalman filter measurement model conform to the Gaussian distribution approximately. It is also found that the mean value of estimations becomes stable after around 15 repetitions. Thus, using the mean value is a feasible way to stabilize the oscillation. However, the estimation given by BP neural network can be further treated to increase the accuracy.

4.4. Validity of Kalman Filter. The BP estimations obtained from Section 4.3 are used as the measurement of the Kalman filter. The interpolated value obtained from Section 3.2 is used as the initial estimate of the Kalman filter. Pick one test data randomly to check the performance of the Kalman filter based on BP and interpolation. The results are shown in Figure 10.

The figure shows the performance comparison between interpolation, BP neural network, and Kalman filter. It is observed that the curve of Kalman filter prediction moves

FIGURE 9: The temperature estimations of three samples with 100 times repetition.

FIGURE 10: Performance comparison with 100 times of repetition.

towards where the BP estimations occur more frequently. Also, it converges after about 85 iterations and will be finally stabilized around the expected value. In this case, Kalman filter prediction has a big advantage over the other two methods in both stability and accuracy.

4.5. Performance Comparison between Three Predicting Methods. Check the Kalman filter's performance on all test data and compare the result with the mean value of BP estimations and the interpolated value. As shown in Figures 11(a) and 11(b), the Kalman filter greatly stabilizes the BP estimations and interpolated values. In both conditions ($I_C < 42$ A and $I_C > 42$ A), the errors are mostly below 5°C. The detailed predicted values in the two

conditions are given in Tables 2 and 3. In most cases, the Kalman filter prediction is between the BP mean and interpolated value because the nature of the Kalman filter is the weighted average.

The comparison of errors is shown in Table 4. In condition $I_C < 42$ A, RMSE and MAPE of Kalman filter prediction are 2.6415 and 0.0166, respectively, which are smaller than the other two predicting methods. In condition $I_C > 42$ A, RMSE and MAPE of Kalman filter prediction are 4.8282 and 0.0284, respectively, which are also smaller than the other two predicting methods. The results indicate that the Kalman filter has a significant advantage in predicting junction temperature. The feasibility of using the Kalman filter based on BP neural network and interpolation has been further confirmed.

FIGURE 11: (a) The comparison of errors when $I_C < 42$ A. (b) The comparison of errors when $I_C > 42$ A.

TABLE 2: The numerical comparison of three methods when $I_C < 42$ A.

Test data	Real	BP mean	Interpolation	Kalman
1	173	172.9056	166	169.9133
2	99	94.4629	104	99.1401
3	174	171.5643	170	170.9382
4	102	102.3818	106	104.1974
5	142	139.1298	144	140.889

TABLE 3: The numerical comparison of three methods when $I_C > 42$ A.

Test data	Real	BP mean	Interpolation	Kalman
1	153	155.5118	155	155.267
2	76	75.2725	77	75.8904
3	47	46.5827	48	47.303
4	117	117.3351	115	116.39
5	139	140.2383	146	142.9634

5. Discussion

In Section 4.2, the validity of the BP neural network has been confirmed. The absolute errors of estimation are mostly less than 10°C , but the oscillation still impedes the accurate prediction of junction temperature. Calculating their mean can reduce the error and stabilize the oscillation to some extent. As Table 4 shows, the RMSE and MAPE of BP estimation are 3.6528 and 0.0221 ($I_C < 42$ A), respectively. The RMSE and MAPE of the interpolated value are 5.9161 and 0.0349 ($I_C < 42$ A), respectively. However, the BP neural network estimation and interpolation accuracy will be reduced in the real experiment because it is hard to obtain over 1000 samples. Using the Kalman filter based on BP neural network and interpolation can further stabilize the

TABLE 4: RMSE and MAPE comparisons of three predicting methods.

Method	Condition	RMSE ¹	MAPE ²
BP mean	$I_C < 42$ A	3.6528	0.0221
	$I_C > 42$ A	5.2501	0.0309
Interpolation	$I_C < 42$ A	5.9161	0.0349
	$I_C > 42$ A	5.5588	0.0335
Kalman filter	$I_C < 42$ A	2.6415	0.0166
	$I_C > 42$ A	4.8282	0.0284

¹Root mean square error. ²Mean absolute percentage error.

oscillation and reduce the error below 5°C . The RMSE and MAPE of Kalman filter prediction are 2.6415 and 0.0166 ($I_C < 42$ A), respectively. As one can see, Kalman filter prediction performs better than interpolation or BP estimation. In another condition ($I_C > 42$ A), the three predicting methods perform similarly.

The prediction of junction temperature is important for condition monitoring and degradation of the IGBT devices. Section 4.2 indicates it is feasible to estimate the junction temperature using BP neural network without modifying the standard package. Section 4.5 shows that the Kalman filter prediction accuracy in both conditions ($I_C < 42$ A and $I_C > 42$ A) is higher than the BP estimation or interpolation. In addition to increasing accuracy, it also enhances robustness. Even when outliers appear, the prediction filtered by the Kalman filter can still maintain stability.

Furthermore, there are several possibilities for improvement in this scheme. First, the updated version of the BP neural network such as PSO-BP [24], GA-BP [25], and MEA-BP [26] can be applied to increase the speed and accuracy of the convergence. Second, the use of the combined TSEPs can increase the reliability of the prediction [27, 28]. Third, other prediction models can be used instead

of interpolation, because the accuracy of interpolation could be greatly affected by the sample size.

In sum, both BP neural network and Kalman filter can work well in predicting IGBT junction temperature. The Kalman filter method further enhances accuracy and robustness. Nevertheless, compared with BP neural network, the Kalman filter based on it requires more complex processes. With the rapid development of deep learning or neural network, the accuracy of junction temperature prediction is expected to be further improved. Theoretically, the neural network can approach any complex function perfectly. What is more, the application scope of deep learning can be expanded to evaluate the aging degree or failure rate of the power device.

6. Conclusions

The Kalman filter based on BP neural network and interpolation proposed in this article has the following advantages:

- (1) There is no need to modify the standard module package.
- (2) It is simpler than the conventional TSEP method. The voltage drop between the junction and the measurement point can be neglected.
- (3) It is more accurate and stable than the BP neural network estimation.
- (4) It can be migrated to online monitoring after the entire prediction model has been built.
- (5) There is a large room for improvement.

Deep learning in power electronics devices can help monitor the operating condition and evaluate the degradation from a new perspective. It is expected to promote the development of power electronics further.

Data Availability

The data and MATLAB code used to support this research article are available from the author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this paper.

References

- [1] A. Stippich, "Key components of modular propulsion systems for next generation electric vehicles," *CPSS Transactions on Power Electronics and Applications*, vol. 2, no. 4, pp. 249–258, 2017.
- [2] A. Asadi and F. Pourfatah, "Effects of constructal theory on thermal management of a power electronic system," *Science Reports*, vol. 10, p. 21436, 2020.
- [3] Electronics Prognostics 2020, <https://ti.arc.nasa.gov/tech/dash/groups/pcoe/electronics-prognostics/>.
- [4] H. Wang, M. Liserre, and F. Blaabjerg, "Toward reliable power electronics: challenges, design tools, and opportunities," *IEEE Industrial Electronics Magazine*, vol. 7, no. 2, pp. 17–26, 2013.
- [5] M. H. M. Sathik and S. Prasanth, "Comparison of IGBT junction temperature measurement and estimation methods—a review," *Asian Conference on Energy, Power and Transportation Electrification (ACEPT)*, vol. 1–8, 2017.
- [6] Y. Avenas, L. Dupont, and Z. Khatir, "Temperature measurement of power semiconductor devices by thermo-sensitive electrical parameters—a review," *IEEE Transactions on Power Electronics*, vol. 27, no. 6, pp. 3081–3092, 2012.
- [7] L. Dupont, Y. Avenas, and P.-O. Jeannin, "Comparison of junction temperature evaluations in a power IGBT module using an IR camera and three thermosensitive electrical parameters," *IEEE Transactions on Industry Applications*, vol. 49, no. 4, pp. 1599–1608, 2013.
- [8] J. Zarebski and K. Gorecki, "The electrothermal large-signal model of power MOS transistors for SPICE," *IEEE Transactions on Power Electronics*, vol. 25, no. 5, pp. 1265–1274, 2010.
- [9] L. M. Hillkirk, "Dynamic surface temperature measurements in SiC epitaxial power diodes performed under single-pulse self-heating conditions," *Solid-State Electronics*, vol. 48, no. 12, pp. 2181–2189, 2004.
- [10] X. Perpiñà, J. F. Serviere, J. Saiz, D. Barlini, M. Mermet-Guyennet, and J. Millán, "Temperature measurement on series resistance and devices in power packs based on on-state voltage drop monitoring at high current," *Microelectronics Reliability*, vol. 46, no. 9–11, pp. 1834–1839, 2006.
- [11] W. Brekel, "Time resolved in situ T_{vj} measurements of 6.5 kV IGBTs during inverter operation," in *Proceedings PCIM Europe*, pp. 808–813, Nuremberg, Germany, May 2009.
- [12] Z. Hu, W. Zhang, and J. Wu, "An improved electro-thermal model to estimate the junction temperature of IGBT module," *Electronics*, vol. 8, no. 10, p. 1066, 2019.
- [13] I. Bahun, V. Sunde, and Z. Jakopovic, "Estimation of insulated-gate bipolar transistor operating temperature: simulation and experiment," *Journal of Power Electronics*, vol. 13, no. 4, pp. 729–736, 2013.
- [14] U. M. Choi, F. Blaabjerg, F. Iannuzzo, and S. Jørgensen, "Junction temperature estimation method for a 600 V, 30A IGBT module during converter operation," *Microelectronics Reliability*, vol. 55, no. 9–10, pp. 2022–2026, 2015.
- [15] Z. Xu, F. Xu, and F. Wang, "Junction temperature measurement of IGBTs using short circuit current as a temperature sensitive electrical parameter for converter prototype evaluation," *IEEE Trans. Ind. Electron.*, vol. 62, pp. 3419–3429, 2014.
- [16] N. Baker, S. Munk-Nielsen, F. Iannuzzo, and M. Liserre, "IGBT junction temperature measurement via peak gate current," *IEEE Transactions on Power Electronics*, vol. 31, no. 5, pp. 3784–3793, 2016.
- [17] A. Amoiridis, A. Anurag, P. Ghimire, S. Munk-Nielsen, and N. Baker, "Vce-based chip temperature methods for high power IGBT modules during power cycling—a comparison," in *Proceedings of the 2015 17th European Conference on Power Electronics and Applications*, pp. 1–9, EPE'15 ECCE-Europe), Geneva, Switzerland, September 2015.
- [18] C. Dong and P. Mao, "The junction temperature measurement of insulated gate bipolar transistor based on multi-layer feed-forward neural network is presented," in *Proceedings of the 2020 IEEE International Conference on Mechatronics and Automation (ICMA)*, pp. 136–140, Beijing, China, August 2020.
- [19] P. M. Granitto, P. F. Verdes, and H. A. Ceccatto, "Neural network ensembles: evaluation of aggregation algorithms," *Artificial Intelligence*, vol. 163, no. 2, pp. 139–162, 2005.

- [20] A. Suliman and Y. Zhang, "A review on back-propagation neural networks in the application of remote sensing image classification," *Journal of Earth Science and Engineering*, vol. 5, pp. 52–65, 2015.
- [21] X. Glorot and Y. Bengio, "Understanding the difficulty of training deep feedforward neural networks," in *Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics*, pp. 249–256, Sardinia, Italy, May 2010.
- [22] C. Campestrini, T. Heil, S. Kosch, and A. Jossen, "A comparative study and review of different Kalman filters by applying an enhanced validation method," *Journal of Energy Storage*, vol. 8, pp. 142–159, 2016.
- [23] Y. Duan and X. Chen, "Benchmarking deep reinforcement learning for continuous control," 2016, <https://arxiv.org/abs/1604.06778>.
- [24] J. Huang and L. He, "Application of improved PSO - BP neural network in customer churn warning," *Procedia Computer Science*, vol. 131, pp. 1238–1246, 2018.
- [25] Y. H. Yang, L. Peng, X. B. Chen, and X. Z. Liu, "A GA-BP neural network model for predicting the temperature of slabs in the reheating furnace," *Applied Mechanics and Materials*, vol. 58–60, pp. 1371–1377, 2011.
- [26] J. L. Gai, "Modeling of photovoltaic cell based on BP neural networks improved by MEA," *Applied Mechanics and Materials*, vol. 219, pp. 809–814, 2012.
- [27] L. Shao, Y. Hu, and G. Xu, "A high precision on-line detection method for IGBT junction temperature based on stepwise regression algorithm," *IEEE Access*, vol. 8, pp. 186172–186180, 2020.
- [28] D. Herwig, T. Brockhage, and A. Mertens, "Combining multiple temperature-sensitive electrical parameters using artificial neural networks," in *Proceedings of the 2020 22nd European Conference on Power Electronics and Applications (EPE'20 ECCE Europe)*, Paris, France, September 2020.