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An experimental study on determination of the shottky diode current-voltage characteristic depending on temperature with artificial neural network

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A R T I C L E I N F O

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Artificial neural network
Current
Voltage
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A B S T R A C T

Shottky diodes are one of the important components of electronic systems. Therefore, it is very important to determine the parameters of the diodes according to the area in which they will be used. One of the most important of these parameters is the current-voltage characteristic of the diode. In this study, firstly, current values of the Schottky diode in the voltage range of −2 V to +3 V are experimentally measured in the temperature range of 100–300 K. In order to estimate the current-voltage characteristic of Shottky diode at different temperatures, a multi-layer perceptron, a feed-forward back-propagation artificial neural network was developed using 362 experimental data obtained. In the artificial neural network where temperature (T) and voltage (V) values are selected as input variables and the hidden layer has 15 neurons, the current (I) value is obtained as output. The results obtained from the artificial neural network have been found to be in good agreement with the experimental data of the Schottky diode.

1. Introduction

Metal-semiconductor contacts have an important place in the technology of semiconductor devices. Today, they are indispensable elements of many high-tech products [1,2]. One of the important factors that determine the electrical properties of these contacts is the electronic properties of the semiconductor [3]. At this point, Silicon carbide (SiC) is an interesting material due to its electrical properties such as wide bandwidth, high thermal conductivity, and critical breakdown electric field [4–7]. On the other hand, it plays a role in making electronic materials that require high magnetic fields and can withstand high voltage or high power, high temperature, and high frequency, where many circuit elements are forced [8–10]. It is also used in applications such as laser diodes due to its low dielectric constant [11]. Apart from these, metal-oxide semiconductor diode is used in semiconductor transistor construction, field-effect transistor construction, and hydrogen sensor construction [12–14]. Many researches have been carried out to determine the electronic properties of these structures, which are used in such a wide area. In particular, some of the most important parameters of these structures, such as barrier height, ideality factor and resistance, are determined by the method of current-voltage characteristics. Therefore, in metal-semiconductor contacts, current and voltage are interconnected by a kind of correlation. To understand this correlation, artificial neural networks (ANN) have been used recently. Artifical neural networks detect the relationship between data patterns, collect their information and learn (or are trained) by experience, not by programming [15,16]. It basically consists of three basic layers. Input neurons layer gets data from input files or directly from electronic sensors in real-time applications. The output layer sends information directly to the outside world, secondary computer operation, or other devices such as a mechanical control system. The hidden layer between these two layers contains most of the neurons in various interconnected structures. The inputs and outputs of each of these hidden neurons only go to other neurons [17].

Chen et al. [18], in their study, the surface and interface properties of Pd0·9Cr0.1/SiC Schottky diode gas sensors both before and after annealing Auger electron spectroscopy (AES), scanning electron microscopy (SEM) and energy dispersion spectroscopy (EDS) they

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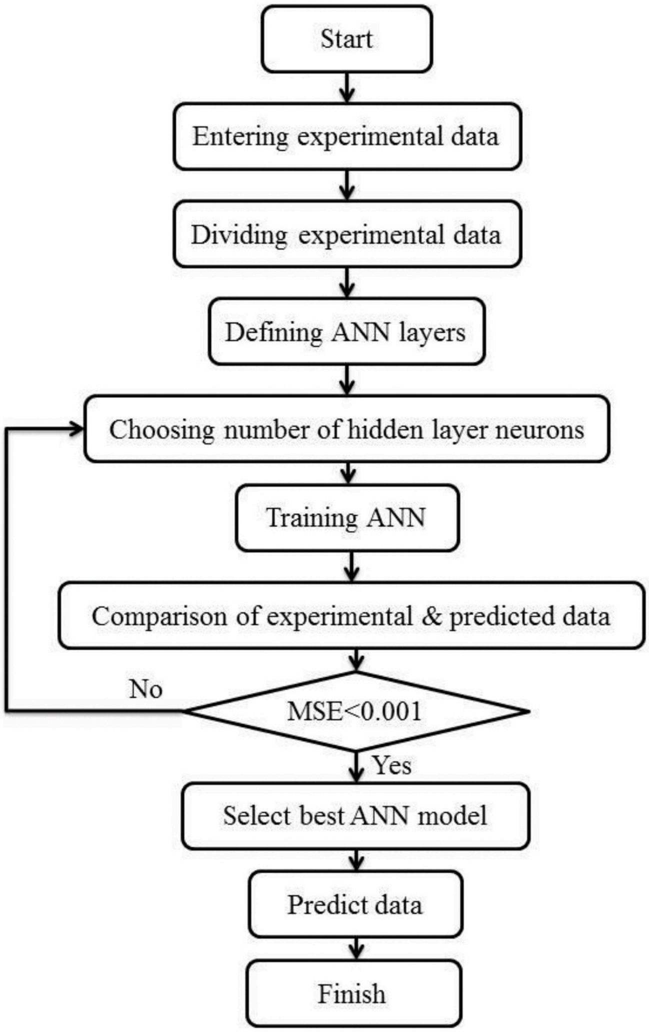


Fig. 1. A process of an ANN based model development.

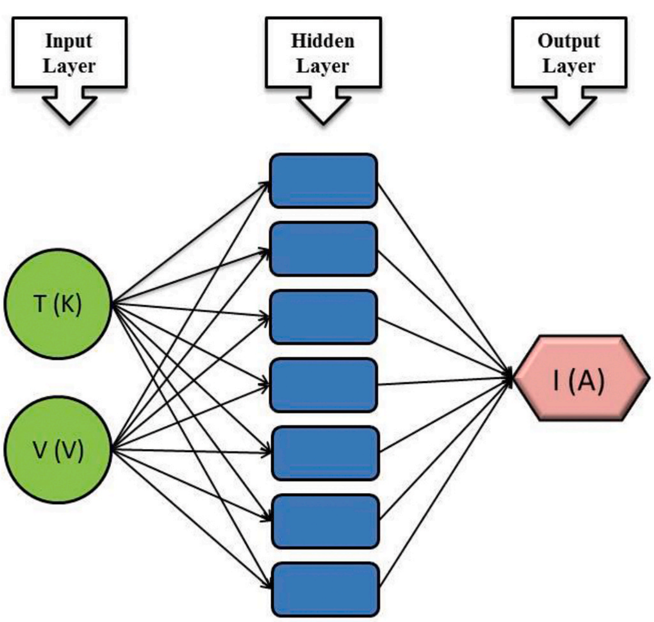


Fig. 2. The architecture of the artificial neural network.

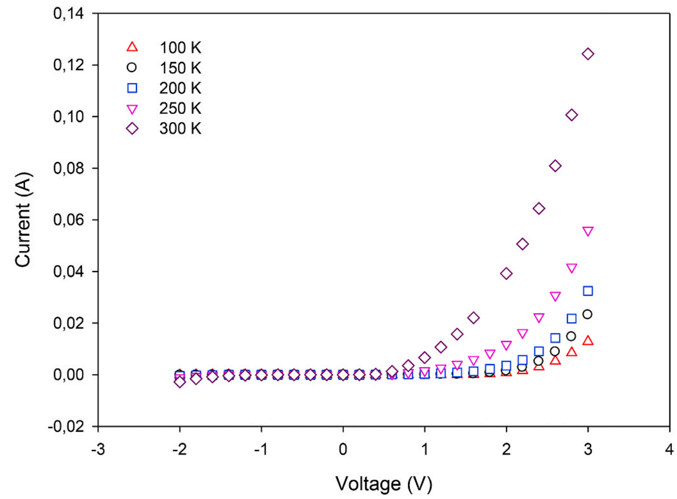


Fig. 3. Current-voltage characteristic of the Schottky diode.

Table 1
Performance data of the ANN.

Data Set	MSE	MoD (%)	R	Number of Data
Training	5.670E-07	−0.29	0,99995	254
Validation	8.656E-07	−0.36	0,99989	72
Test	8.651E-07	0.035	0,99992	36
All	7,659E-07	−0.27	0,99992	362

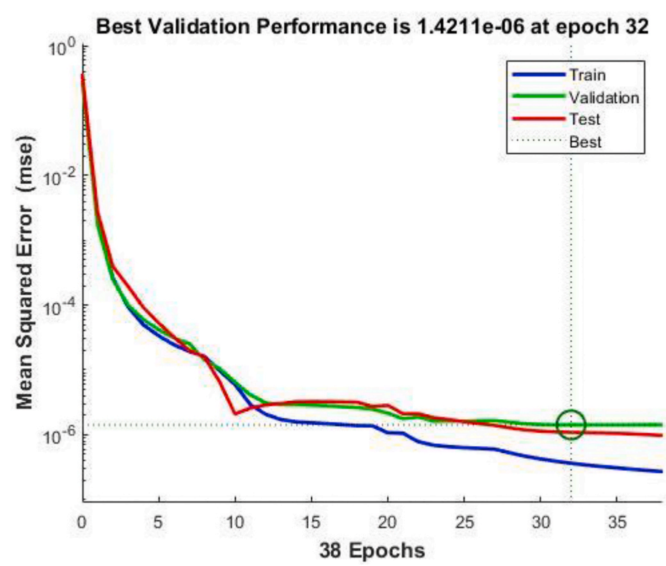


Fig. 4. Variations of MSE vs epoch.

examined using. As a result of the study, it was observed that the Schottky contact surface has much less silicon and carbon impurities than the surface of an annealed Pd/SiC structure. Caddemi et al. [19] investigated extensively the effects of temperature on DC behavior, small signal and noise performance at microwave frequencies of Pseudomorphic HEMTs. The experimental data obtained were then used to extract temperature dependent models by means of several extraction techniques. The results obtained as a result of the study showed that the most important electrical parameters such as output current, threshold voltage, transient conductivity, forward transmission coefficient and

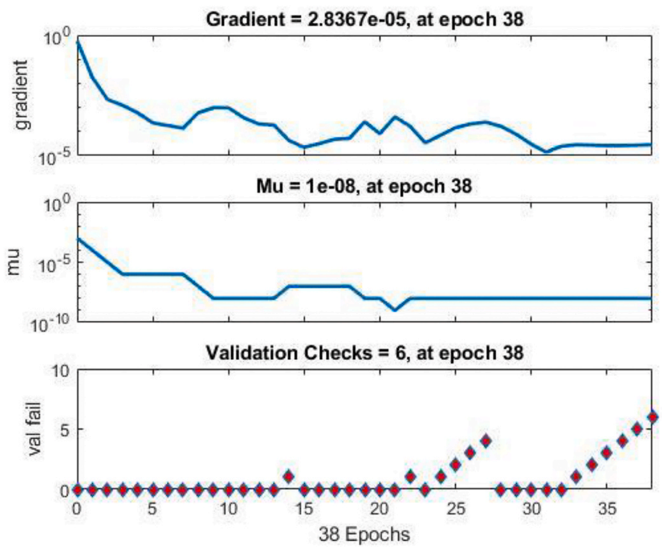


Fig. 5. Training state of the ANN.

noise shape are reasonably affected by thermal events. In their study, Alade et al. [20] estimated the change of breakdown voltage of N-GaN Schottky diodes over the temperature range (300–900 K) using online backpropagation nerve analysis based on existing Sze and Monemar models. The results obtained showed that the Breaking Voltage of n-GaN Schottky diodes does not decrease rapidly with temperature increase, in line with previous studies in the literature. Marinković et al. [21] presented a neural approximation model to derive a multi-bias model of a gallium nitride high electron mobility transistor in their study to investigate the high power and high temperature applications of gallium nitride high electron mobility transistors (GaN HEMTs). The accuracy of the model developed in the study was verified by comparing it with experimental measurements. In the study of Michael Olusope Alade [22], he used the neural network method to calculate the electrical parameters of GaN Schottky diodes at high temperatures. In the study, the potential energy barrier height, depletion layer thickness and junction capacitance properties of a GaN Schottky diode as a microwave frequency sensor have been predicted at 300–950 K temperature range by computational method. He compared the outputs of this system with the theoretical outputs. He reported that the results obtained were in good agreement with the theoretical results. Milošević et al. [23] modeled the S-parameters of the SMS 7630 zerobias Schottky diode using ANN. The frequency band of measurements made using a vector network analyzer is in the range 0.5–5 GHz and the input power is between −25 dBm and 5 dBm. The results obtained by testing the learning and generalization abilities of the developed ANN were compared with experimental measurements. Jarndal [24] presented an effective ANN electrothermal modeling approach applied to GaN devices in his study. It is interconnected by physics-related equivalent circuits to accurately simulate the transistor. Genetic algorithm (GA) based training procedure was applied to find the most suitable values for the weights of ANN models. The simulation results obtained from ANN matched very well with the measurements and confirmed the validity of the technique developed for dynamic electrothermal modeling of active devices.

In this study, an artificial neural network was developed to determine the current-voltage characteristic of a Schottky diode based on temperature, using the data of an experimental study [25] that had been previously published. The results obtained from the artificial neural network were compared with the experimental data and simulations were made for different temperatures. In the literature, there is no study on determining the temperature-related current-voltage characteristics of Schottky diodes with artificial neural networks. This study is a valuable study aimed at filling this gap in the literature.

2. Experimental

In this study, a (001) oriented n-type/6H–SiC semiconductor wafer with a thickness of 280 μm and a 2-inch radius at a donor concentration

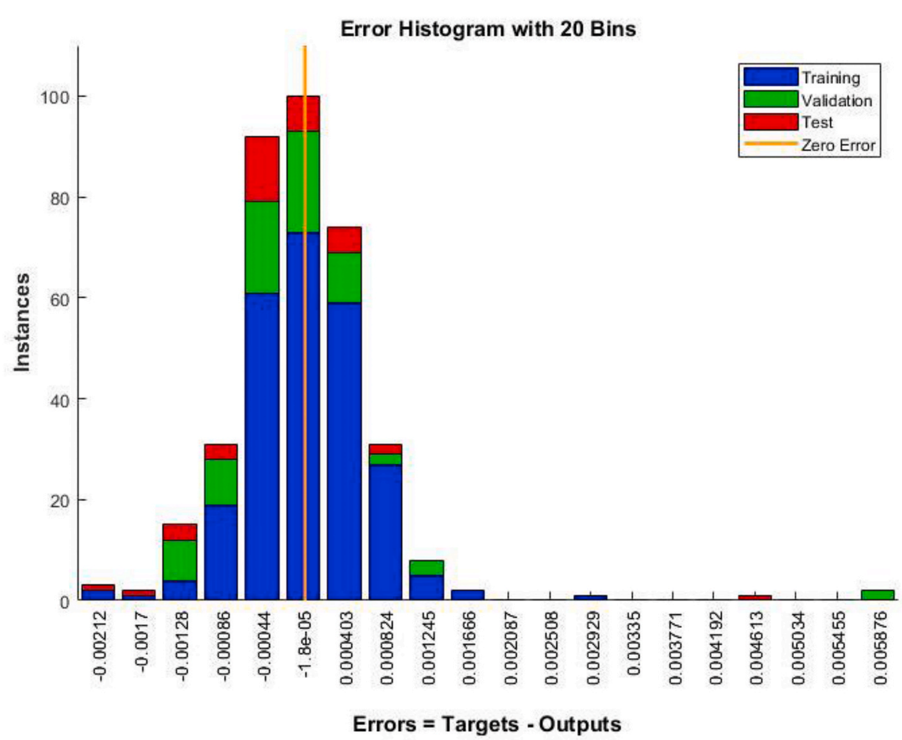


Fig. 6. Error histogram.

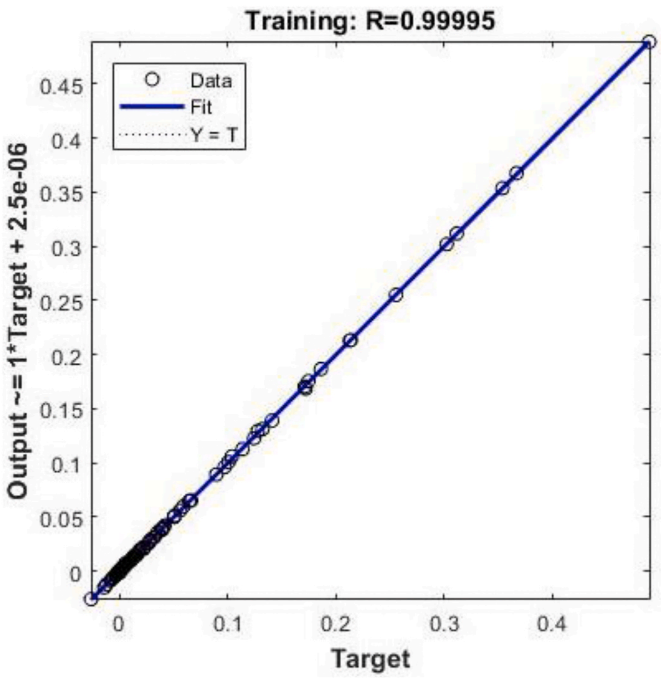


Fig. 7. Training status of the ANN.

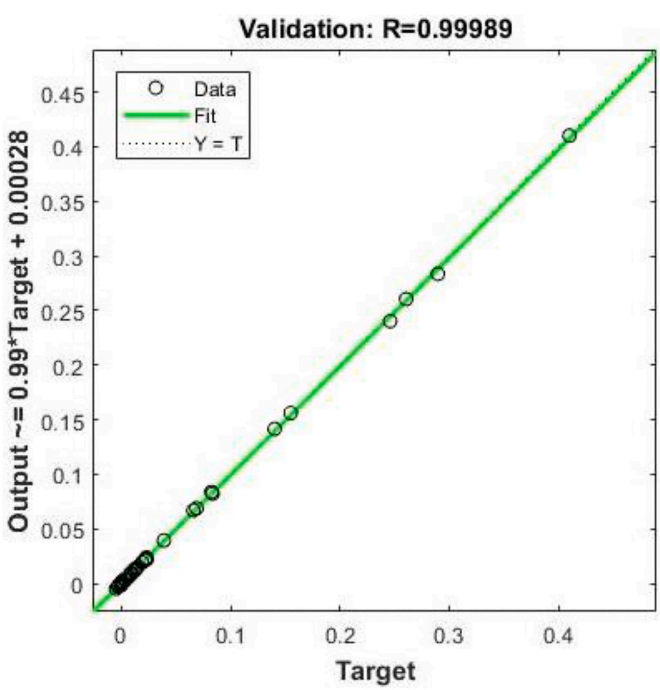


Fig. 8. Validation status of the ANN.

doped of 2.6×10^{17} cm^{-3} was used to compose the Schottky barrier. Before starting diode production, the semiconductor material was washed with trichloroethylene, acetone, and methanol along 5 min and then rinsed with deionized water (DIW). After this procedure, a hydrofluoric acid solution (HF/H20, 1: 20) was placed in the solution to remove the oxide layer formed on it. Pure gold (99.99%) was sputtered under a pressure atmosphere of 10^{-6} mbar to form a 150 nm thick

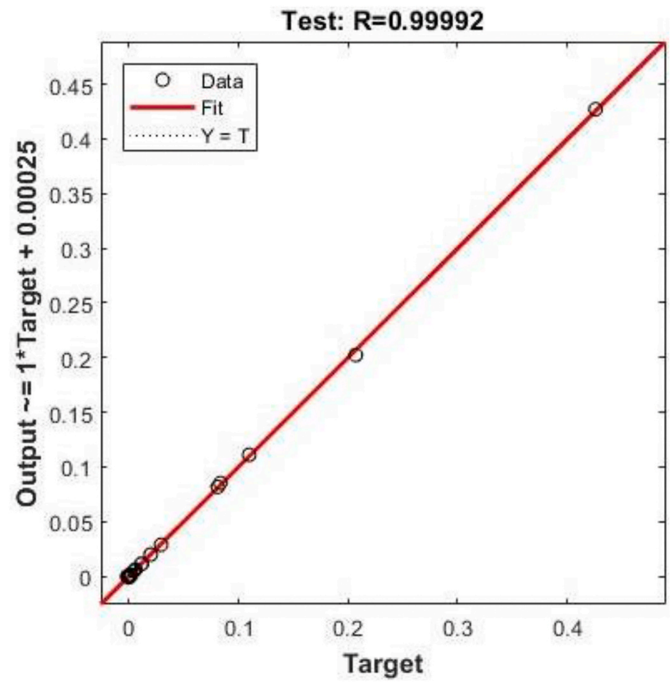


Fig. 9. Test status of the ANN.

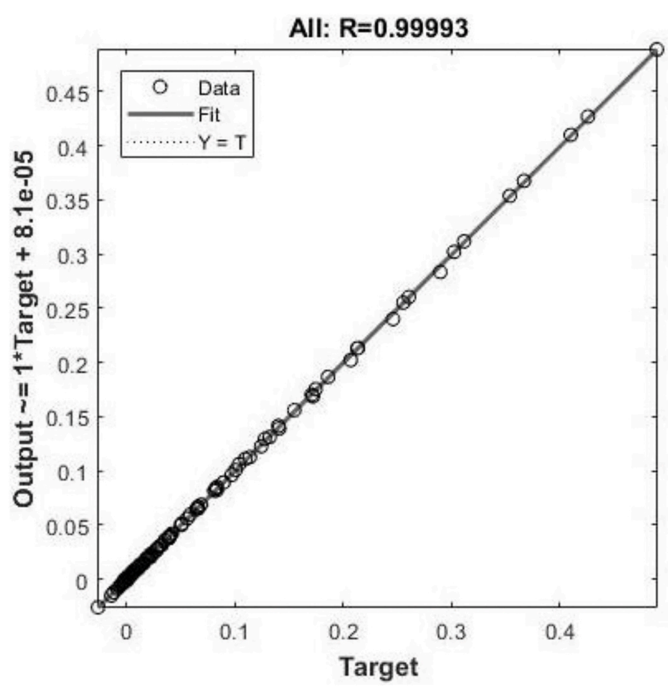


Fig. 10. All data for the ANN.

contact on the n-type/6H–SiC semiconductors matte surface. It was then annealed at 950 °C for 5 min in N_2 atmosphere to create good quality ohmic contact. Next, 150 nm thick pure gold was sputtered onto the polished side of the semiconductor to form the Schottky contact. These Schottky contacts were created with a diameter of 2 mm. For this, a porous stainless steel mask with circles of 2 mm diameter was used during the formation of Schottky contacts. Afterwards, Keithly 2400

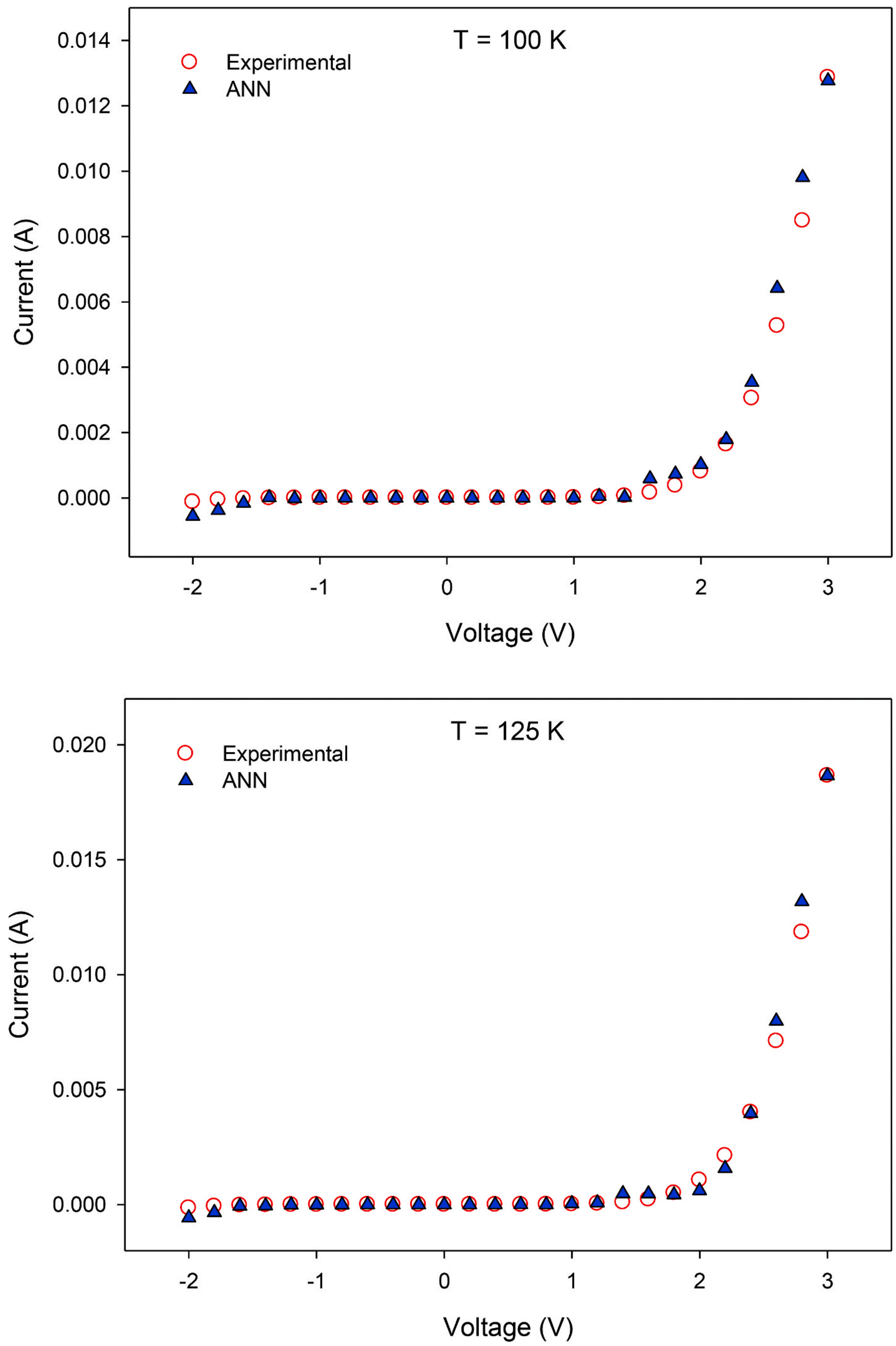


Fig. 11. Comparison of the experimental results and artificial neural network outputs.

Sourcemeter was used for I–V measurements of the sample after testing measurement was made from the produced contacts. The measurements of the diode were made in the voltage range of −2 to +3 V and the temperature range of 80–300 K in 25 K increments.

3. Selection of artificial neural network model

In the analysis of nonlinear, complex functions, artificial neural networks are one of the frequently used methods due to their advantages such as high sensitivity, short results, and low costs [26]. Artificial neural networks, inspired by the biological system of the human brain, are a whole process that can control complex relationships between input variables and outputs [27]. The flow diagram of an ideal artificial neural network is given in Fig. 1.

In a typical artificial neural network architecture, there are input layer, hidden layer and output layer. In this study, a multi-layer perceptron (MLP), feed-forward back-propagation (FF-BP) artificial neural network was designed. In the artificial neural network, the Levenberg-

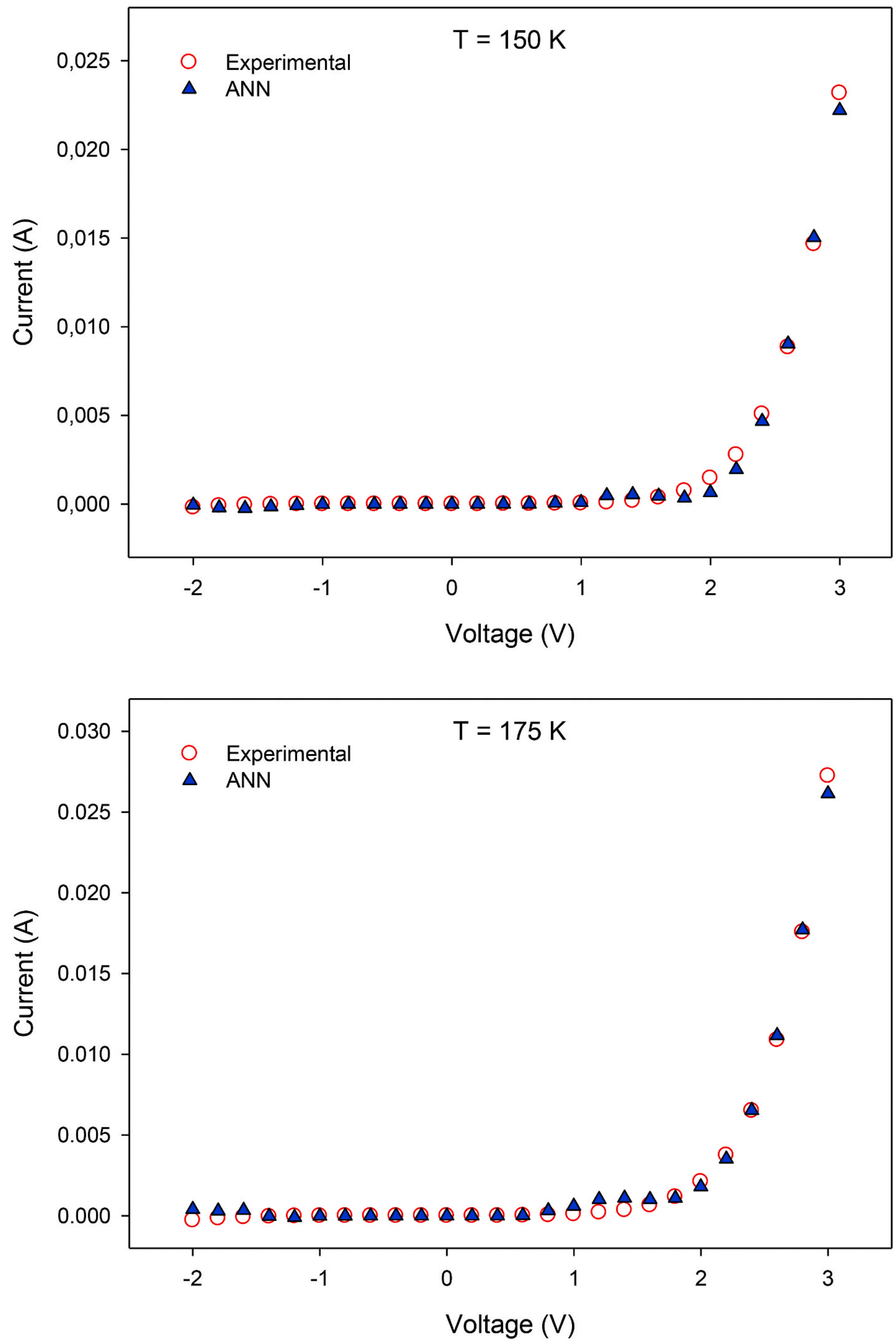


Fig. 11. (*continued*).

Marquardt algorithm, which is frequently used in the literature, was preferred for the training algorithm [28]. For the hidden layer of the artificial neural network, the Tan-Sig transfer function given in equation (1) and the Purelin function given in equation (2) were selected for the output layer:

$$f(x) = \frac{1}{1 + \exp(-x)} \tag{1}$$

$$Purelin(X) = X \tag{2}$$

In the study, temperature (T) and voltage (V) were selected as input variables, and current (I) values are obtained as output parameters. Optimizing data in artificial neural networks is one of the parameters that directly affect estimation performance. A total of 362 experimental data were used to develop the artificial neural network with 15 neurons in its hidden layer. 70% of this data set was reserved for training, 15% for validation, and 10% for test phases. The architecture of the artificial neural network developed is given in Fig. 2.

In order to evaluate the performance of the artificial neural network, the mean square error (MSE) given in equation (3) and R value given in

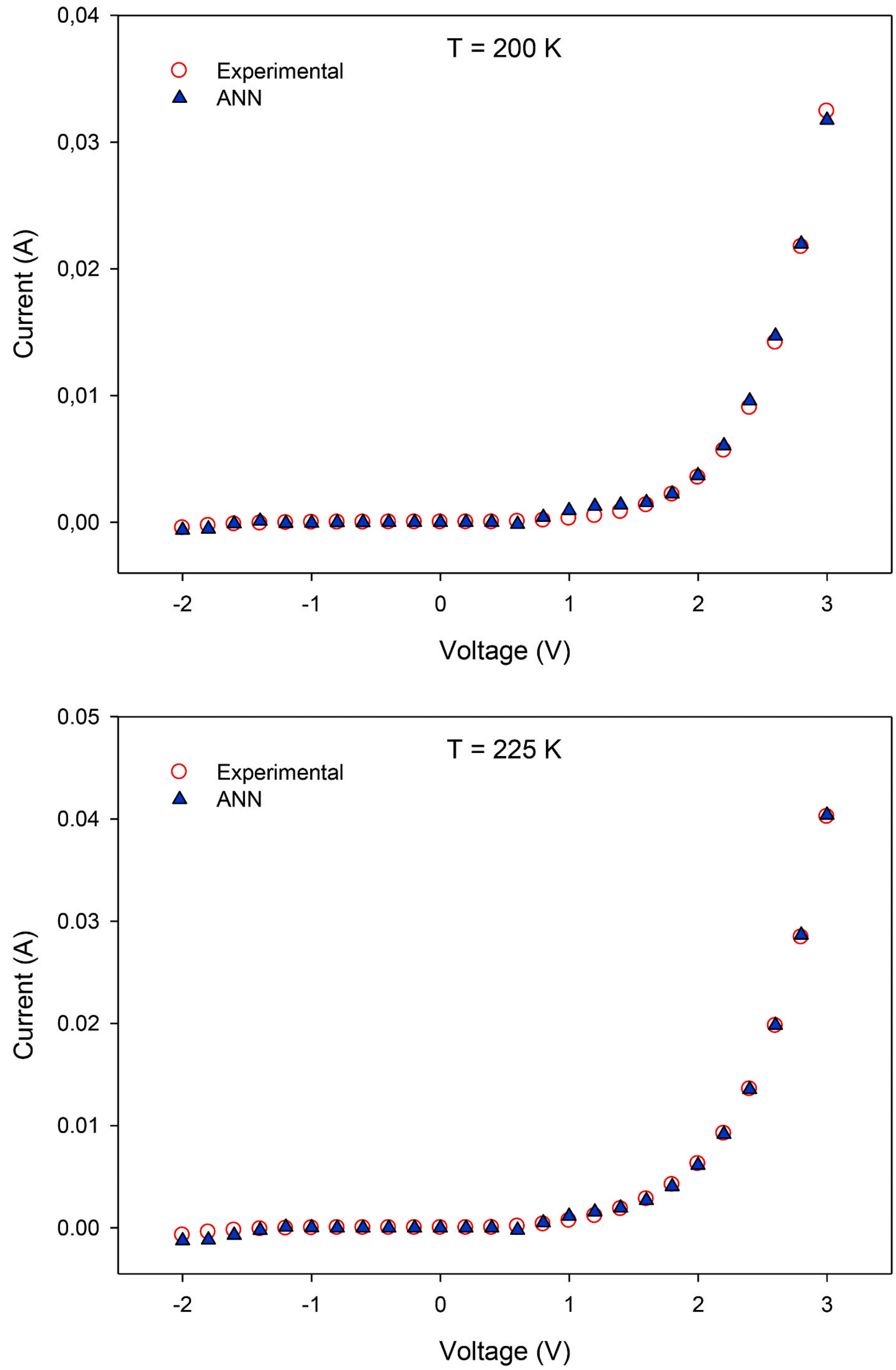


Fig. 11. (*continued*).

equation (4) was used [29]:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(I_{exp(i)} - I_{ANN(i)}\right)^2 \tag{3}$$

$$R = \sqrt{1 - \frac{\sum_{i=1}^{N}\left(I_{exp(i)} - I_{ANN(i)}\right)^2}{\sum_{i=1}^{N}\left(I_{exp(i)}\right)^2}} \tag{4}$$

where, N is the number of data points and exp and ANN subscripts represent experimental and artificial neural network outputs, respectively.

The margin of deviation between experimental data and the artificial neural network outputs was calculated using equation (5):

$$\text{Margin of Deviation}(\%) = \left[\frac{I_{exp} - I_{ANN}}{I_{exp}}\right] x100 \tag{5}$$

4. Results and discussion

Fig. 3 shows the current-voltage characteristic of the Schottky diode in the temperature range of 100–300 K. Considering the graph given in Fig. 3, it has seen that the low voltage part of the semi-logarithmic I–V graph is linear and deviation from linearity occurs with the voltage increase. The most important reason for this deviation is the series

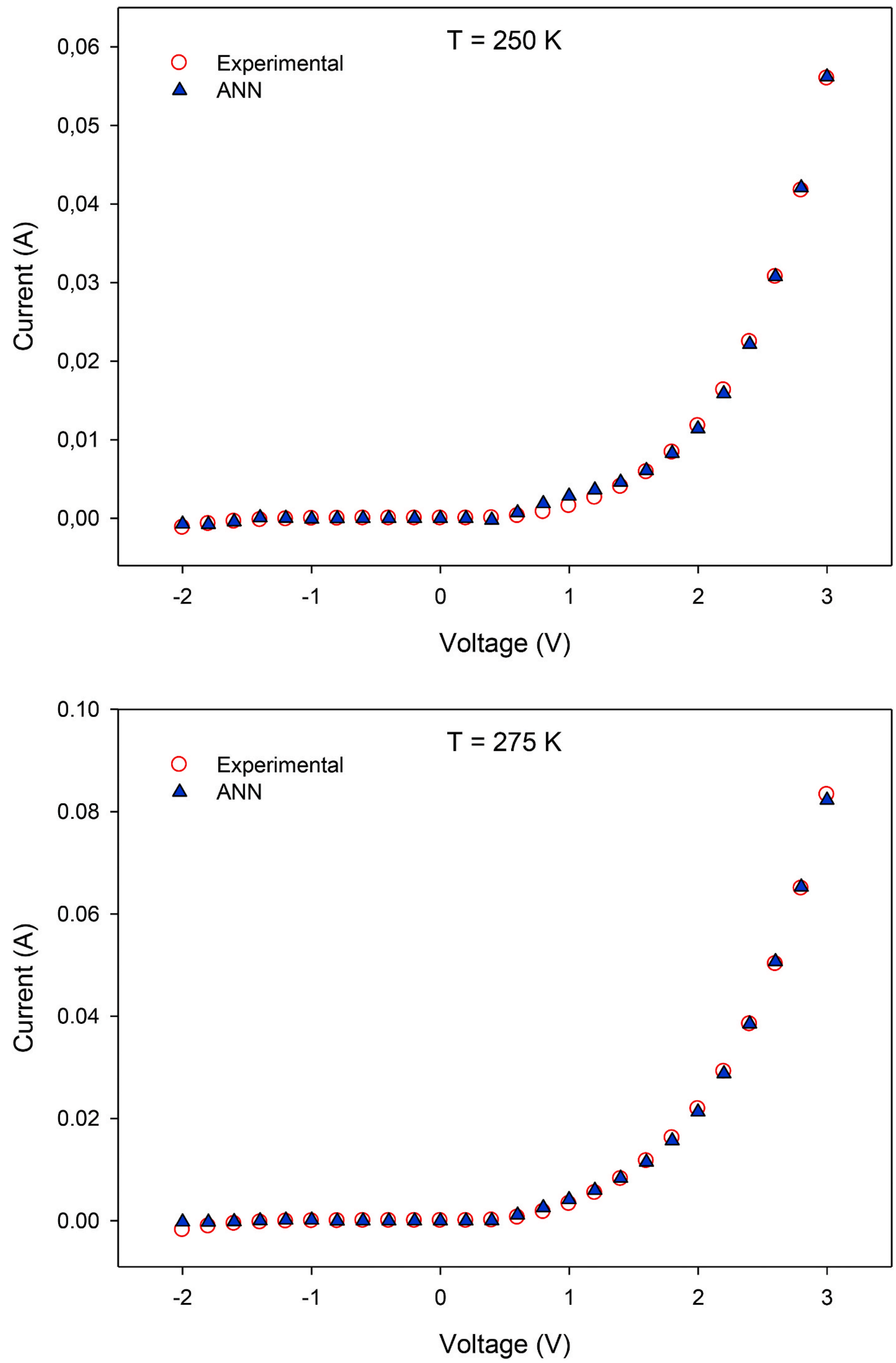


Fig. 11. (*continued*).

resistance (R) effect. Series resistance effect, which is a very important parameter, also affects the current transmission mechanism.

The data set used in the artificial neural network, designed using 362 experimental data, was divided into three sections. 254 of these data for neural network training, 72 for verification, and 36 for testing were used. Performance data of the developed neural network are given in Table 1.

Fig. 4 shows the variation between the experimentally measured current values of the diode and the ANN outputs in terms of the epoch vs MSE. As can be seen in Fig. 4, the MSE value, which was initially high, decreases in the following periods. The fact that the decrease in MSE value reached the best result with a minimum of 1.4211E-06 after 32

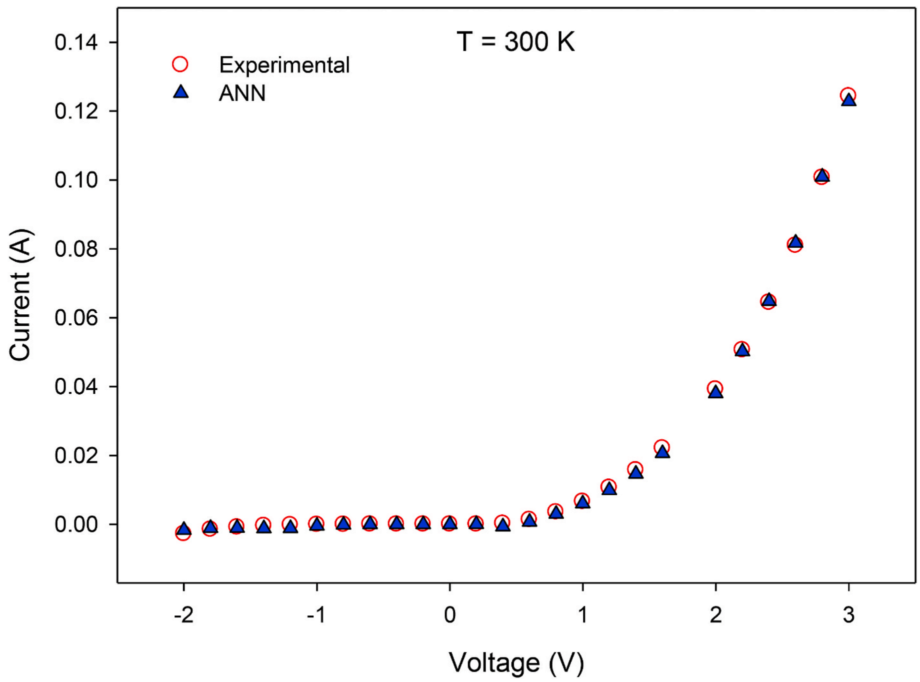


Fig. 11. (*continued*).

iterations is an indication that the training process of the ANN model is ideally designed. The training state of the artificial neural network developed is shown in Fig. 5. As can be seen from the graph, the validation error value was the same 6 times and the training procedure was stopped in the 38th epoch. In the training and testing phase of ANNs, it is important to reach the lowest gradient coefficient value. As can be seen from Fig. 5, gradient value goes on decreasing with increase in number of epochs.

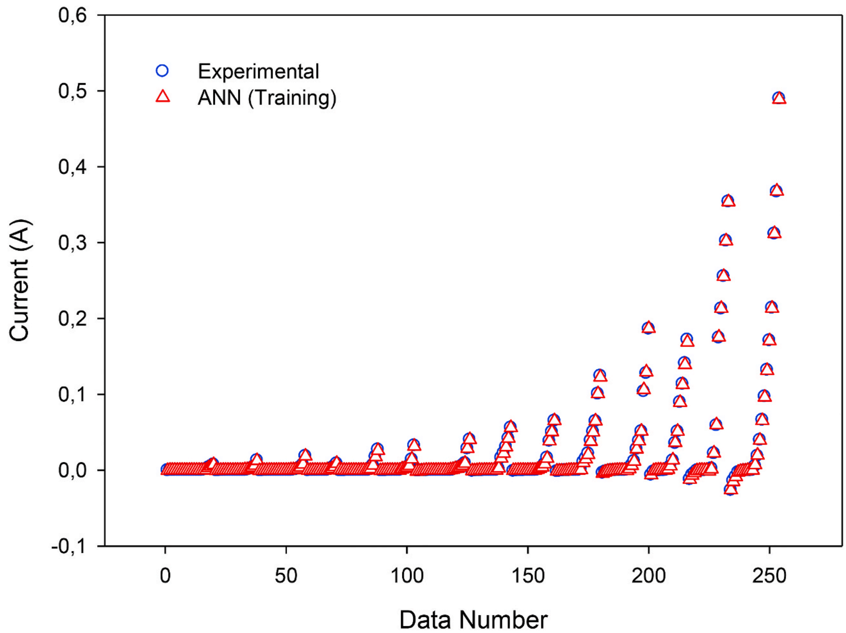
When analysing the performance of the artificial neural network, it is important to evaluate the error histogram graph. Fig. 6 shows the error histogram of the artificial neural network designed. All data obtained during the training, testing, and validation stages of the artificial neural network are shown in the error histogram graph. As can be seen in Fig. 6, training, test, and validation data were collected around the zero error line. This distribution shows that the developed artificial neural network model has an acceptable prediction error rate. The results of the training phase carried out with 254 data reserved for the training of the artificial neural network are shown in Fig. 7. The fact that the data points are positioned around the equality line, shown in blue, is an indication that the training process of the artificial neural network is ideally performed. MSE value in the training phase was obtained as 5.67046E-07 and R-value as 0.99995. Fig. 8 shows the results of the validation process of the artificial neural network. The fact that the data obtained as a result of the validation process performed with 72 experimental data is located close to the equality line shown in green, MSE value is obtained as 8.65618E-07 and R value is 0.99989, which gives an idea about the accuracy of the validation process.

One of the parameters to be evaluated is the test data to analyse whether the artificial neural network is properly designed or not. The results of the test phase of the designed artificial neural network with 36 experimental data are shown in Fig. 9. The test data found near the equality line, shown in red, together with the MSE value is 8.65054E-07 and R value is 0.99992 an indication that the artificial neural network is ideally modeled. The performance graph of the artificial neural network, which was designed with a total of 254 experimental data, is shown in Fig. 10. The fact that all the data points obtained are located very close to the equality line is one of the indicators that the artificial neural network is ideally designed. The fact that the MSE value obtained for all values is 7.65906E-07 and the R value is 0.99992 is a proof that the artificial neural network model can predict the current values of the diode at the ideal accuracy rate.

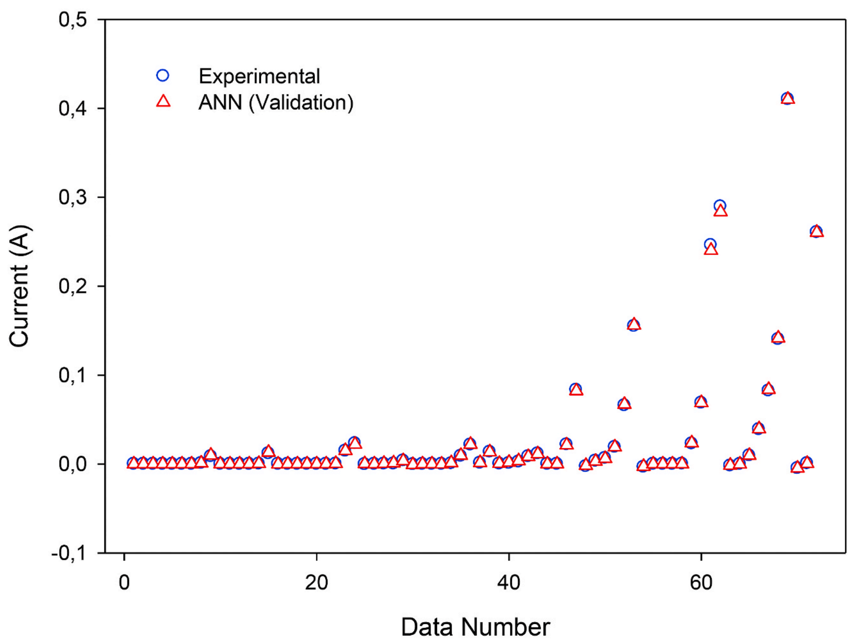
After the artificial neural network was ideally designed and confirmed by the analysis and evaluations, the current values obtained from the artificial neural network were compared with the experimentally measured current values. Experimental measurements made in the voltage range of -2 and $+3$ V and in the temperature range of 100–300 K were compared with developed artificial neural network simulation results in the same range. In Fig. 11, a comparison of the experimental results and artificial neural network outputs made in 100 and 300 K temperature intervals with 25 K intervals is given. It has been observed that the outputs obtained from the developed neural network are compatible with experimental data. The artificial neural network was able to estimate the current values of the diode with an error margin of 5.43%–5.73%.

The comparison of the outputs obtained from the artificial neural network with the current values measured experimentally is shown in Fig. 12, depending on the number of data. Comparisons were made for data aimed at the training, validation, and testing phases of the artificial neural network and then for all data. For each data set of artificial neural network, it is seen in the graph that experimental current values and artificial neural network outputs are very close to each other. It is an indication that the artificial neural network is ideally designed and all three stages are completed with optimum accuracy.

In Fig. 13, error rates of current values obtained from artificial neural network are shown according to all data sets and total data amount. The developed artificial neural network was able to predict the current



a)



b)

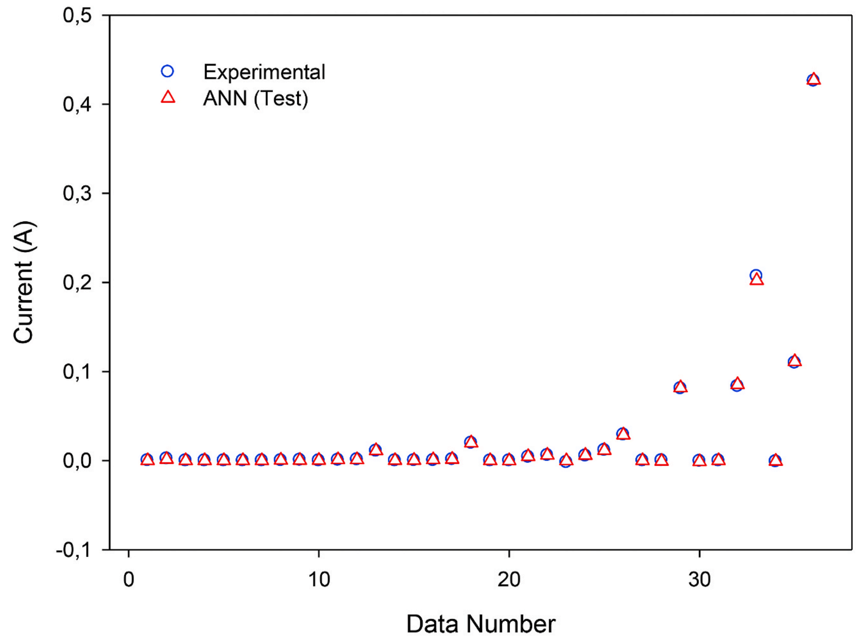
Fig. 12. The comparison of the outputs obtained from the ANN with the current values measured experimentally a) Training b) Validation c) Test d) All data.

values of the diode in the range of −5.43%–5.73%, with an average error of −0.27%. This error rate confirms that the artificial neural network is designed to give very close results with an acceptable error margin.

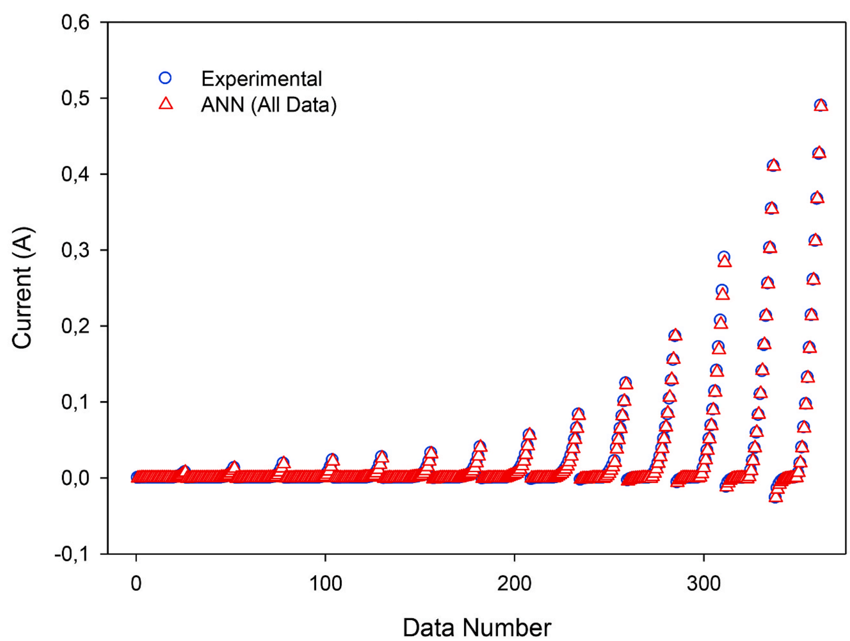
The comparison of the current values obtained from the artificial neural network and the experimentally measured current values are shown in Fig. 14. The fact that the data points are located near the equality line drawn in red indicates that the margin of error is as low and acceptable as possible.

5. Conclusion

In this study, in order to determine the current-voltage characteristic



c)



d)

Fig. 12. (*continued*).

of a Schottky diode based on temperature, a multi-layer perceptron feed-forward back propagation artificial neural network is designed. 362 experimental data were used in the artificial neural network of these data, 254 (75%) for the training, 72 (20%) for validation, and 36 (10%) for the testing of the artificial neural network were used. Artificial neural network outputs were compared primarily with experimental results. The results showed that the artificial neural network could predict the current-voltage characteristic of the Schottky diode in the range of −5.43%–5.73%, with an acceptable error margin of −0.27% on average. In addition, calculating the MSE value of the developed artificial neural network as 7.65906E-07 and R-value as 0.99992 is a clear indication that the artificial neural network is ideally designed. The results obtained from the artificial neural network were found to be in good agreement with the experimental data of the Schottky diode. These results show that the artificial neural network is an ideal model for determining the current-voltage characteristic of the Schottky diode depending on the temperature and can be used in future studies.

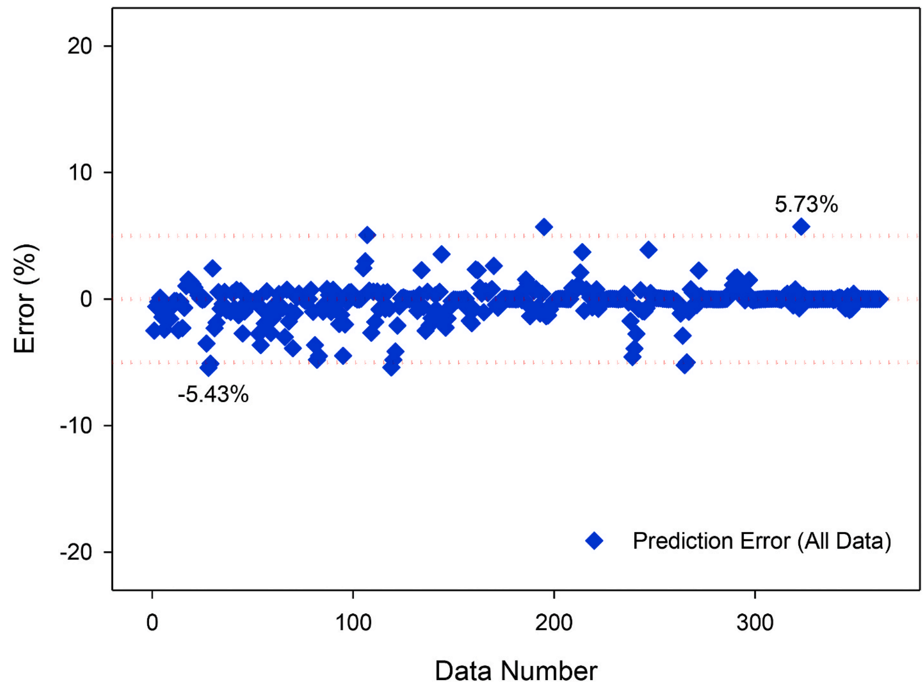


Fig. 13. Error rates of the ANN.

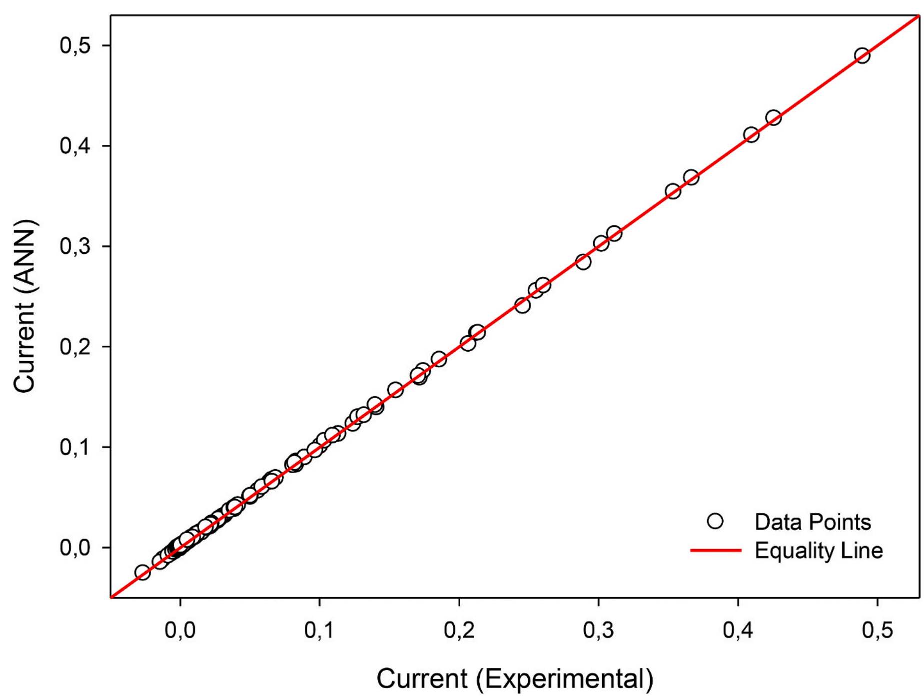


Fig. 14. The comparison of the current values obtained from the ANN and the experimentally measured current values.

Author contribution

Andaç Batur Çolak: Conceptualization, Writing – original draft, Writing – review & editing. Tamer Güzel: Investigation, Methodology & editing. Oğuzhan Yıldız: Review, Supervision. Metin Özer: Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Nomenclature

ANN	Artificial Neural Network
CPU	Central Processing Unit
DIW	Deionized Water
FF-BP	Feed-forward back-propagation
I	Current (Amper)
MLP	Multi-layer perceptron

MSE Mean Square Error
GaN Gallium Nitride
SiC Silicon carbide
T Temperature (K)
V Voltage (Volt)

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