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Predictions on Flexible CdTe Solar Cell Performances by Artificial Neural Networks

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ABSTRACT

CdTe solar cells on ultra-thin glass substrates are light and flexible. Flexible cells are widely preferred modules in technological fields. The flexibility of these cells enables them to cope with deformations. The efficiency of these has reached 19%. In this work, we used artificial neural network (ANN) method for the determination the performance of flexible CdTe solar cells despite bending and time. The performances of the solar cell before and after bending have been predicted. According to the results from the ANN calculations using the experimental data in the literature, MSE values of ANN estimates range from 0.06% to 0.28%.

Keywords: CdTe flexible solar cell, Solar cell efficiency, Artificial neural network.

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Introduction

Solar energy has become one of the most essential resources of the world in the last decades, due to the restriction of resource reserves and environmental problems of fossil energy. Unlike other non-renewable resources of energy, use of solar energy does not yield any harm to the environment. The silent and clean operation, little maintenance, long life, unobtrusiveness, and direct conversion of solar energy into electricity without moving parts and without producing atmospheric emissions are the main advantages of Photovoltaic (PV) energy systems [1]. Thin-film solar-cells are lightweight and flexible as compared with modules built by traditional crystalline silicon cells. Moreover, thin-film cells may be easily molded into various shapes and sizes. The rapid development of flexible PV panels in recent years makes it the main source of energy for the future. The investigation of the performances of solar cells when flexed is important for the applications of flexible devices. CdTe solar cells which are commonly used in alternative energy source studies were introduced about 50 years ago and they have been particularly studied recently. CdTe solar cells on ultra-thin glass surfaces are advantageous because they are light and flexible. These characteristics of batteries are important in applications that require high specific power, unique form factors and low manufacturing costs. Solar modules based on CdTe are due to its remarkable qualities such as having a direct energy band gap of 1.45 eV, a high absorption coefficient (> 1×104 cm-1) and excellent thermodynamic stability [2-5]. The performance of lightweight and flexible CdTe depends on flexing as well.

In recent years artificial neural network (ANN) has been used in solar energy field. Qian et al. [6] predicted the mass proportion of trichromatic colorants and acrylic substrate on the optical and thermal performance of external wall coatings by using an artificial neural network. Wang et al. [7] performed PV output prediction using artificial neural network with overlap training range. Su et al. [8] applied machine learning techniques to study the large-lattice-mismatched CdS/CdTe interface. Jaber et al. [9], predicted the performance of different pv modules using artificial neural networks. Few studies exist in the literature on the effect of flexing photovoltaic on Ultra-thin glass (see Ref. [5] and reference therein). Teloeken et al. investigated experimentally the performance of CdTe flexible solar cells due to the effect of bending and time. In their work, the photovoltaic performance was measured by current density versus voltage. The measurements were performed for planar (before and after flexing) and flexed states in a bend Radius of 32 mm [5]. In this study, we have borrowed the data from their experiments and used in our present machine learning applications. From the study from which the data was obtained, solar-cell performances are available after a bending radius and different waiting times. However, determining the performance for different bending radius and waiting times is also important in terms of increasing efficiency. An alternative simpler way to make this determination is to perform machine learning with existing data to estimate performance for the desired bending radius and waiting times. This is the main motivation of our work. Thus, we can state that the main goal of the study is whether ANN method is a suitable tool for the prediction of the performances of flexible solar cells in different conditions. According to the results obtained from the present study, seeing that the performances of the solar cells at new bending angles are accurately estimated by this method, through machine learning without the need for any extra new experiments, revealed the importance of the ANN method. Therefore, we conclude that the ANN method is highly successful in predicting the performance of flexible solar cells.

Materials and Methods

In this work, the artificial neural network (ANN) method [10] has been used for the prediction of the performance of the flexible CdTe solar cell. The data is borrowed from Teloeken et al. [4] which is available in the literature. The photovoltaic performance was measured by J-V under AM1.5G at 25 ^{0}C following a 10-minute light soak, using an ABET Technologies Sun 2000 Solar Simulator [5]. The measurements were performed when the cell was in a planar state (0F], and then when flexed to a 40 mm and subsequent 32 mm bend radius (0B). After flexion the device was relaxed and measured flat. In addition, the sample was held at a bend radius of 32 mm for 168 hours with measurement at 0, 24, 48, 120, 144 and 168 hours. Again, the sample was measured flat before (168F) and after (168B) the bending test. As a nonlinear mathematical method, ANN mimics the brain functionality and consists of several processing units which are called as neurons [11]. The neurons in different layers have connected to each other by weighted connections. Input layer neurons receive the data and the output layer neurons give the result as close as to the desired results. There is no rule for the determination of the number of hidden layers which are located between the input and output layers. In the training of the ANN, Levenberg-Marquardt algorithm and tangent hyperbolic activation function were used which give the better results [12,13].

ANN includes two main stages: training and test. The whole data belonging to the problem is separated into two different parts. One part (%75) is for the training of ANN and the second part (%25) is for the test. In the training stage, the weights between neurons are modified correctly to construct ANN for the true solution of the given problem. If weights are modified well, constructed ANN works for all similar type data that is never seen in the training stage. Training stage continues until the acceptable error level between desired and obtained outputs. The error is calculated by the mean square error (MSE) formula as given below in Eq.(1).

$$MSE_{=}\frac{1}{n}\sum_{i=1}^{n}(Y_i-\hat{Y}_i)^2 \quad (1)$$

Our study consisted of three different stages performed with ANN. In the first stage, we considered the wavelength (λ) of the light on the flexible CdTe solar cells as the input of the ANN. The outputs of the ANN were before 0F, 0B, 168F and 168B external quantum efficiencies of the solar cell. After the calculations for the number of hidden layer neurons 4, 7 and 10, the results were presented for each calculation. In Fig.1, 1-7-4 ANN topology has been presented. The total number of adjustable weights was 20, 35 and 50 for 4, 7 and 10 hidden neuron numbers.

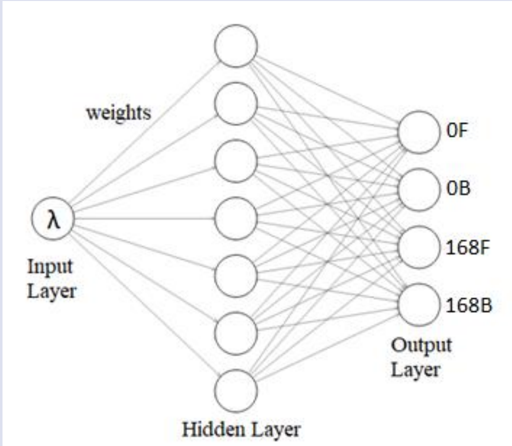

Figure 1. ANN structure (1-7-4) for the prediction of the solar cell performance.

In the second stage of the work, the inputs were the wavelength (λ) of the light on the flexible CdTe solar cells and external quantum efficiencies of 0F. The output was external quantum efficiencies of 0B. After the trials with low (h=4), medium (h=7) and high (h=10) neuron numbers, it was seen that the number of neurons giving the best results was 10. At this stage, we examined the effect of the bending flexible solar cells on performance. The total number of adjustable weights was 12, 21 and 30 for 4, 7 and 10 hidden neuron numbers in this stage. In Fig.2, we have shown the 2-7-1 ANN topology as an illustration

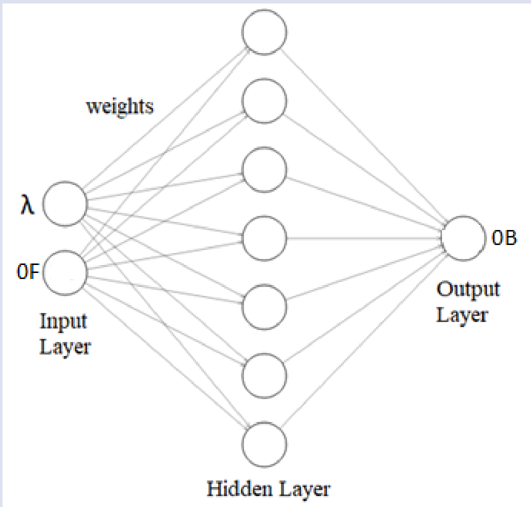

Figure 2. ANN structure (2-7-1) for the prediction of the solar cell performance by bending.

In the last stage of the work, the inputs were the wavelength (λ) of the light on the flexible CdTe solar cells and external quantum efficiencies of 0F. The output was external quantum efficiencies of 168B. Again, the hidden neuron numbers were taken as 4, 7 and 10, separately. InFig.3, 2-7-1 ANN structure has been given with the total number of adjustable weights of 21. For the 4 and 10 hidden neuron numbers, the weights numbers were 12 and 30, respectively. In the study we carried out at this stage, we examined the effect of time on the performance of solar cells.

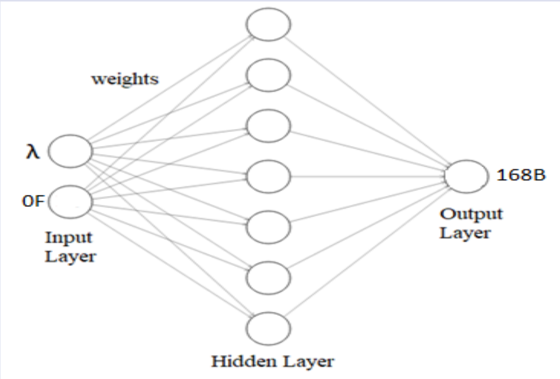

Figure 3. ANN structure (2-7-1) for the prediction of the solar cell performance by time.

Results and Discussion

For all three stages, the results of the calculations in which the number of hidden neurons is used as seven are presented in detail with their graphics. However, the statistical values of the calculations in which the number of hidden layer neurons are four and ten are also given in Table 1 in tabular form. The results obtained from the artificial neural networks (ANN) calculations carried out in the first stage of the study are shown separately on the training and test data. In Fig. 4, the results of the predictions of the ANN over the training data are presented. As can be seen from these results of calculations in which 0F, 0B, 168F and 168B values are estimated against wavelength, the difference between the experimental data of external quantum efficiency (%) values and the result of the ANN shows a maximum range of +4 to -4 for h=4 and h=7, +1 to -1 for h=10. However, it is seen that the distribution is concentrated in zero-line for h=10 ANN structure. It is clear from the graph that the variation is larger around the wavelength of around 400 and 800 nm for h=4 and h=7 and around 600 nm for h=10. For h=10, the RMSE values of the estimations of all wavelengths on the training data were obtained as 0.32, 0.35, 0.33 and 0.35 for 0F, 0B, 168F and 168B, respectively. The maximum absolute deviation of the ANN results from experimental values are 1.34, 0.80, 1.12 and 1.11 for 0F, 0B, 168F and 168B. For the other hidden neuron numbers, the statistical values on the results were presented in Table 1.

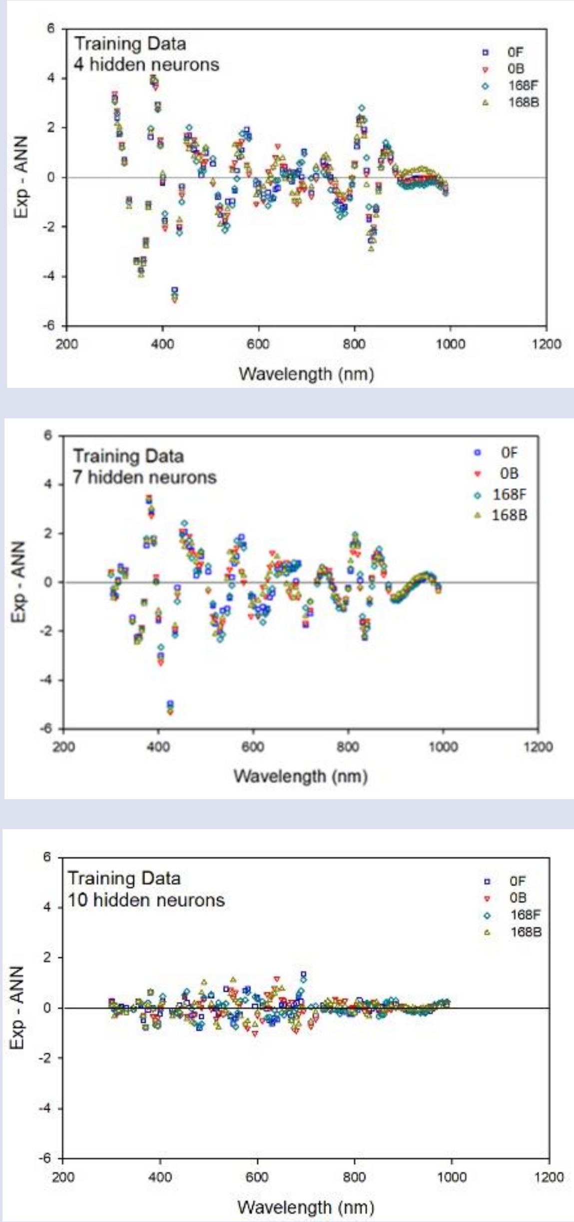

Figure 4. Difference between the experimental and ANN prediction values for external quantum efficiencies of the solar cells on training data for hidden neuron numbers 4 (top), 7 (middle) and 10 (bottom).

The results of the ANN predictions on the test data are shown in Fig. 5 for h=4, h=7 and h=10 ANN structures. In the graph where the ANN estimates against the experimental data are drawn, it is seen that the data points are concentrated on the diagonal line, especially for h=10. This indicates that the ANN structure with 10 hidden layer neurons is more successful in estimating external quantum efficiency values. For h=10, the RMSE values of the estimations of all wavelengths on the test data were obtained as 0.45, 0.42, 0.43 and 0.36 for 0F, 0B, 168F and 168B. The maximum absolute deviation of the ANN results from experimental values are 0.90, 1.00, 0.90 and 1.00 for 0F, 0B, 168F and 168B, respectively. For h=4 and h=7, the statistical indicators were presented in Table 1.

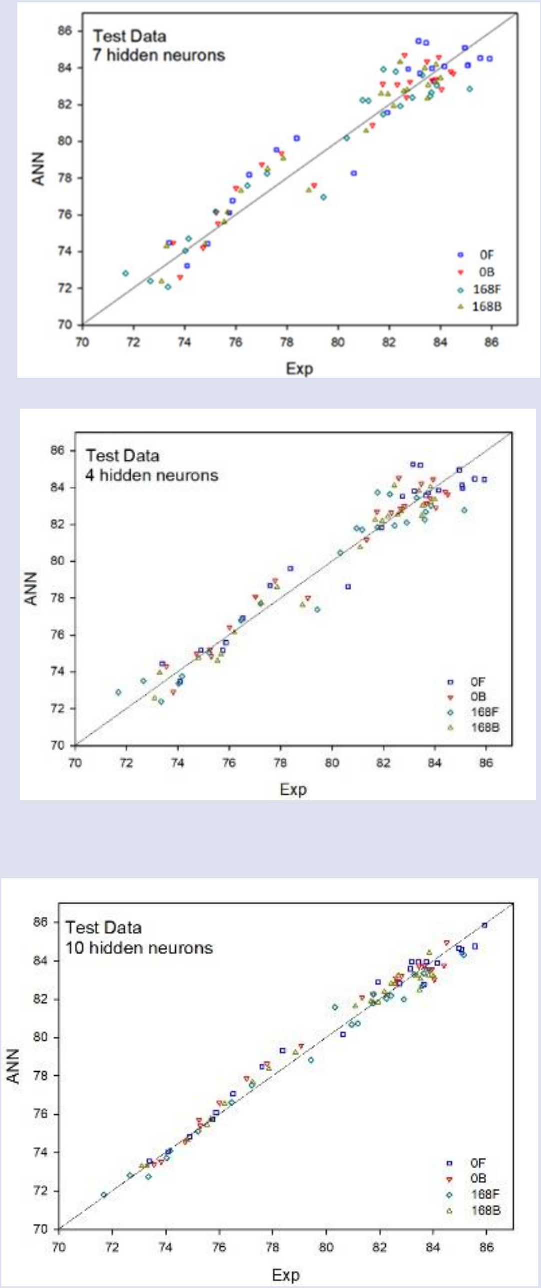

Figure 5. The experimental versus ANN prediction values for external quantum efficiencies of the solar cells on test dataset for hidden neuron numbers 4 (top), 7 (middle and 10 (bottom).

In the second stage of our study, the wavelength and 0F external quantum efficiency values were accepted as the input values of the ANN, and the 0B values were estimated. As can be seen from Fig. 6, the results of the ANN predictions are also in good agreement with the experimental data in this study. In other words, it has been seen that ANN can be used as an alternative to experimental studies in examining the effects of bending on solar cell performances. According to the ANN results, it is seen that the highest efficiency is in the range of about 500 to 800 nm. For the training stage, the RMSE and maximum absolute deviation values were obtained as 0.59 and 1.42 for hidden neuron number 10. For the other hidden neuron numbers, the statistical values were given in Table 1. These results indicate that the ANN trained for the current bending radii of the experimental data can successfully yield results for other radii. In addition, for wavelengths that are not used experimentally, if we have the external quantum efficiency information in the flat state, the bending value might be estimated by ANN. The usefulness of the method is evident from Fig. 7, where the ANN results on the test dataset are compared with the experimental data. In the graph where the results of the ANN against the experimental data are presented, it is seen that the data points are concentrated on the diagonal line. The RMSE and maximum absolute deviation values of the predictions on the test data were obtained as 0.53 and 1.34, respectively, for h=10. For h=4 and h=7 ANN structure, the statistical values can be seen in Table 1.

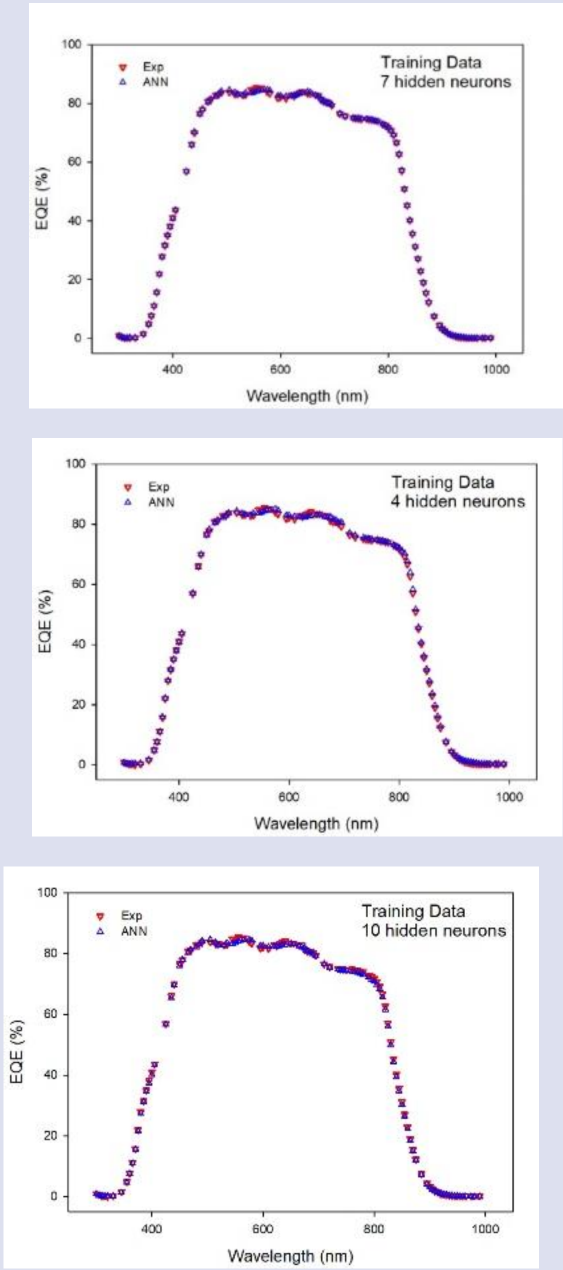

Figure 6. The experimental and ANN prediction values for 0B external quantum efficiencies of the solar cells on training data for hidden neuron numbers 4 (top), 7 (middle) and 10 (bottom).

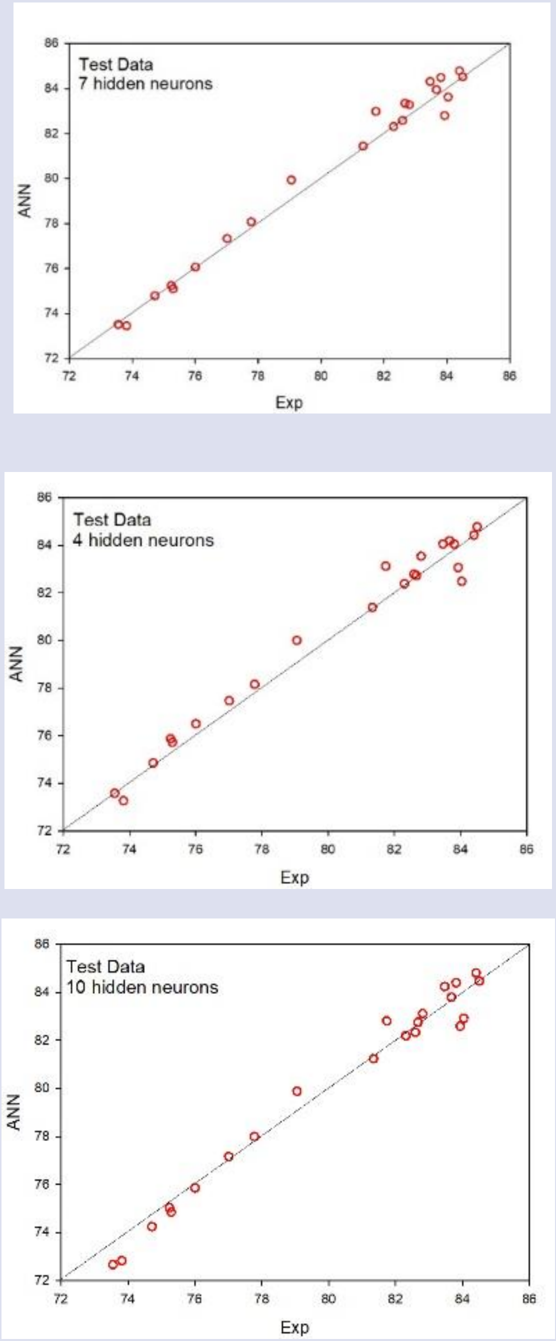

Figure 7. The experimental versus ANN prediction values for 0B external quantum efficiencies of the solar cells on test dataset for hidden neuron numbers 4 (top), 7 (middle) and 10 (bottom).

In the last stage of the study, the wavelength and 0F external quantum efficiency values were taken as inputs of the ANN and the 168B value was tried to be estimated. Thus, it is planned to investigate the effects of both bending and elapsed time on external quantum efficiency. In Fig. 8, the ANN predictions on the training data are presented together with the experimental data. As can be clearly seen from the figure, the ANN results are in good agreement with the experimental data. It is seen that the highest efficiency is obtained in the range of about 500 to 800 nm. For h=10, the RMSE and maximum absolute deviation values of the estimations on the training data were calculated as 0.18 and 0.55. For the other ANN structures with h=4 and h=7, the results can be seen in Table 1. In Fig. 9, the results of the studies at this stage on the test data are presented. The RMSE and maximum absolute deviation values belonging to the results are 0.45 and 0.69, respectively, for hidden neuron number 10. For the other hidden neuron numbers, statistical values were presented in Table 1. It is seen that the ANN estimates against the experimental data are almost on the diagonal line in the graph. This indicates that the method is quite useful for this purpose. Knowing the external quantum efficiency value of the solar cell in its flat state at the beginning and revealing how the external quantum efficiency value will change after time and bending point out how powerful a tool the ANN is.

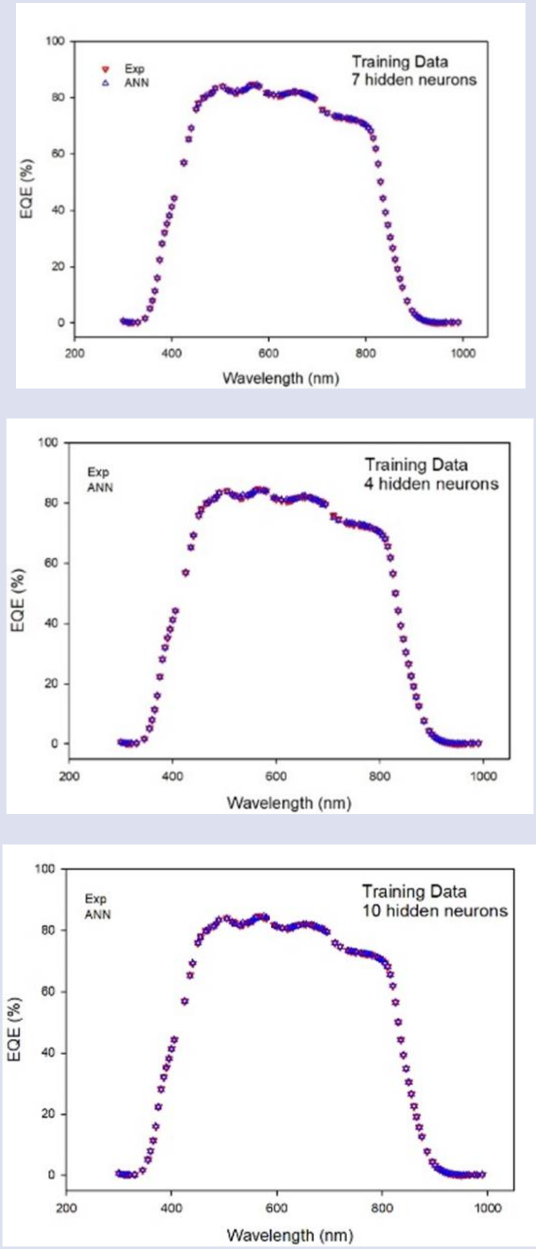

Figure 8. The experimental and ANN prediction values for 168B external quantum efficiencies of the solar cells on training data for hidden neuron numbers 4 (top), 7 (middle) and 10 (bottom).

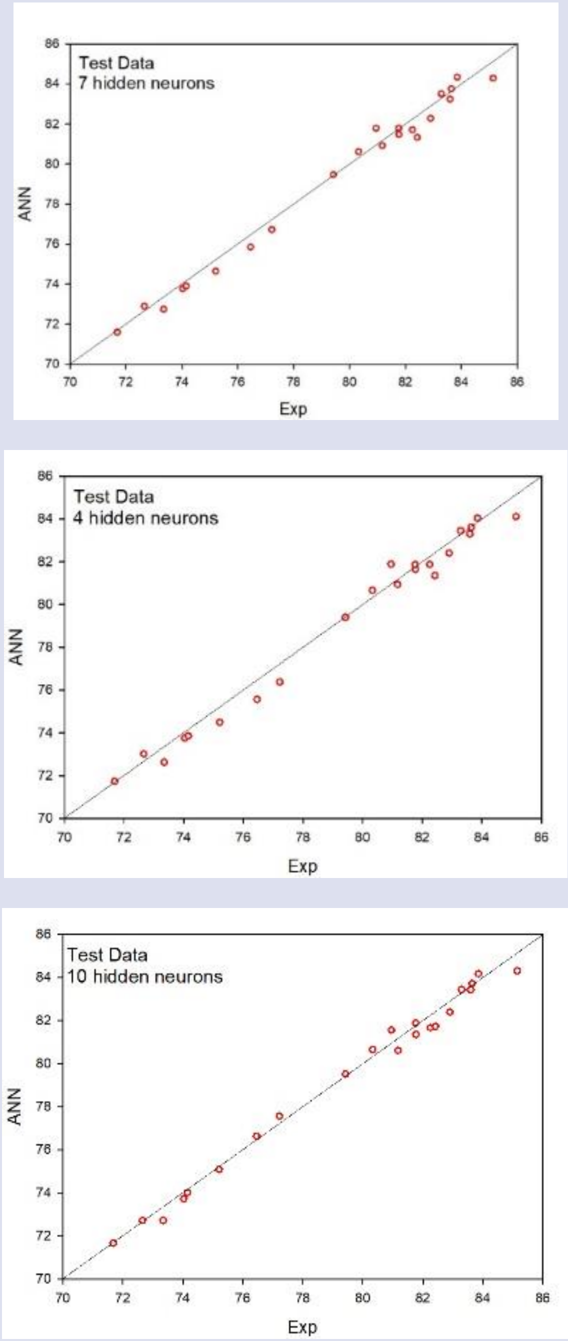

Figure 9. The experimental versus ANN prediction values for 168B external quantum efficiencies of the solar cells on test dataset for hidden neuron numbers 4 (top), 7 (middle) and 10 (bottom).

Table 1. Statistical indicators of the ANN results for hidden neuron numbers 4, 7 and 10 (RMSE: root-mean square error, MAXE: maximum absolute error).

		Training Data (h=4)		**Training Data (h=7)**		**Training Data (h=10)**	
		MAXE	RMSE	MAXE	RMSE	MAXE	RMSE
1	0F	3.87	1.43	4.97	1.24	1.34	0.32
	0B	4.07	1.43	5.32	1.23	0.80	0.35
	168F	3.97	1.49	5.09	1.27	1.12	0.33
	168B	3.94	1.46	5.28	1.22	1.11	0.35
2	0B	1.50	0.56	1.31	0.36	1.42	0.59
3	168B	0.78	0.25	0.85	0.20	0.55	0.18
		Test Data (h=4)		Test Data (h=7)		Test Data (h=10)	
		MAXE	RMSE	MAXE	RMSE	MAXE	RMSE
1	0F	4.98	1.80	5.66	1.94	0.90	0.45
	0B	5.51	1.81	6.12	1.94	1.00	0.42
	168F	5.17	1.87	5.75	1.94	0.90	0.43
	168B	5.50	1.81	6.19	1.98	1.00	0.36
2	0B	1.56	0.51	1.23	0.44	1.34	0.53
3	168B	1.06	0.45	1.09	0.41	0.69	0.34

Conclusion

In this study, it was investigated whether external quantum efficiency values can be predicted by the artificial neural networks (ANN) method using the data of a previous experimental study on CdTe flexible solar cells. Efficiency values in the flat state, 32 mm bent state, and after bending were estimated for different wavelengths of light. In the first stage of the study, the external quantum efficiency values in all cases were produced against the wavelength values. According to the results obtained, the RMSE value was obtained as approximately 0.40. In the second step, the effect of bending was estimated by ANN by using the untwisted efficiency value. When the results obtained at this stage were examined, it was seen that the RMSE value was around 0.50. In the last stage of the study, the efficiencies of the bent solar cell after 168 h of time were estimated from the measured efficiency value in the initial flat state. According to the results obtained, the RMSE value is around 0.45 for this stage. When the results are evaluated as a whole, it is concluded that the ANN method is an alternative powerful tool for estimating the external quantum efficiency of flexible CdTe solar cells.

The results of the study in which bending tests were carried out showed the results of using CdTe solar cells, where it is beneficial to store them in a flexible state before use, or producing curved modules without compromising performance. It has been supported in this study that CdTe solar cells do not show a significant deterioration in performance when exposed to a small bending radius. We also examined the effect of the number of hidden layer neurons in predicting the performance of flexible solar cells, it is seen that RMSE values generally decrease from h=4 to h=7 and then to h=10 for the training data set. After h=10, it increases again. However, examinations on the test data set showed that RMSE increased from h=4 to h=7, and then decreased at h=10. It has been observed that the optimum number of hidden layer neurons for the ANN structure may be around 7.

Conflict of interests

The authors state that did not have conflict of interests.

References

[1] Romeo A., Artegiani E., Cdte-based thin film solar cells: Past, present and future, *Energies*, 14 (2021) 1684.

[2] Fang, Z., Wang X.C., Wu H.C., Zhao, C.Z., Achievements and challenges of CdS/CdTe solar cells, *International Journal of Photoenergy*, (2011) 297350.

[3] Mathew X., Thompson G.W., Singh V.P., McClure J.C., Velumani S., Mathews N.R., Sebastian P.J., Development of CdTe thin films on flexible substrates—a review, *Solar Energy Materials and Solar Cells*, 76 (2003) 293.

[4] Kranz L., Buecheler S., Tiwari A.N., Technological status of CdTe photovoltaics, *Solar Energy Materials and Solar Cells*, 119 (2013) 278.

[5] Teloeken A.C., Lamb D.A., Dunlop T.O., Irvine S.J.C., Effect of bending test on the performance of CdTe solar cells on flexible ultra-thin glass produced by MOCVD, *Solar Energy Materials and Solar Cells*, 211 (2020) 110552.

[6] Qian S., Deng Y., Li X., Jin, Z., Long E., Prediction and influence of the mass proportion of trichromatic colourants and acrylic substrate on the optical and thermal performance of external wall coatings: An artificial neural network approach, *Solar Energy Materials and Solar Cells*, 236 (2022) 111551.

[7] Wang S., Zhanga Y., Hao P.,Lu H., An improved method for PV output prediction using artificial neural network with overlap training range, *Journal of Renewable and Sustainable Energy*, 13 (2021) 063502.

[8] Su M., Yang Ji-H., Liu, Zhi-P., Gong Xin-G., Exploring Large-Lattice-Mismatched Interfaces with Neural Network Potentials: The Case of the CdS/CdTe Heterostructure, *J. Phys. Chem. C* 126 (2022) 13366.

[9] Jaber M., Abd Hamid A.S., Sopian K., Fazliza, A., Ibrahim A., Prediction Model for the Performance of Different PV Modules Using Artificial Neural Networks, *Appl. Sci*. 12 (2022) 3349.

[10] Haykin S., "Neural Networks: a Comprehensive Foundation" Englewood Cliffs, Prentice-Hall, New Jersey, pp.842 (1999).

[11] Hornik K., Stinchcombe M. and White H., Neural Networks, 2 (1989) 359.

[12] Levenberg K., Amethodforthesolutionofcertainnon-linearproblems inleastsquares, *Q. Appl. Math*., 2 (1944) 164.

[13] Marquardt D., An algorithm for least-squares estimation of nonlinear parameters, *SIAM J. Appl. Math*., 11 (1963) 431.