Avrupa Bilim ve Teknoloji Dergisi
Sayı 52, S. 153-160, Kasım 2023

Araştırma Makalesi

www.ejosat.com ISSN:2148-2683

European Journal of Science and Technology
No. 52, pp. 153-160, November 2023

Research Article

Modeling of Photovoltaic/Thermal System by Artificial Neural Network Based on The Experimental Study

Muhammed Musab Bayat[1*] , Ertan Buyruk[2]

[1*] Sivas Cumhuriyet University, Faculty of Engineering, Departmant of Electrical and Electronics Engineering, Sivas, Turkey, (ORCID: 0000-0002-4631-6516), muhammed@cumhuriyet.edu.tr
[2] Sivas Cumhuriyet University, Faculty of Engineering, Departmant of Mechanical Engineering, Sivas, Turkey, (ORCID: 0000-0002-6539-7614), buyruk@cumhuriyet.edu.tr

(İlk Geliş Tarihi 11 Ağustos 2023 ve Kabul Tarihi 17 Eylül 2023)

(**DOI:** 10.5281/zenodo.10259964)

ATIF/REFERENCE: Bayat, M.M., Buyruk, E. (2023). Modeling of Photovoltaic/Thermal System by Artificial Neural Network Based on The Experimental Study. *Avrupa Bilim ve Teknoloji Dergisi*, (52), 153-160.

Abstract

In this study, Artificial Neural Network model (ANN) has been used to model the temperature dependent current, voltage and output power characteristics of uncooled and cooled photovoltaic panels with phase change material (PCM). In the previous laboratory experiment, the current and voltage values produced by the photovoltaic panels in the temperature range of 20 ˚C - 65 ˚C for one hour were measured. Models have been created using the Artificial Neural Network technique with experimental data containing 60 samples for each of these three photovoltaic/thermal (PV/T), including uncooled and two different cooled models. The combinations and features of the Artificial Neural Network model that provide the lowest model error have been achieved. The performance of the Neural Network model performed well in both the uncooled photovoltaic, cooled with flat fins/PCM and cooled with perforated fins/PCM, with RMSE model errors of 1.15e-02, 6.76e-03 and 6.10e-03, respectively. Therefore, it was suggested as a potent tool for modeling current, voltage, and generated power at all temperatures reached during the hour-long experiment.

Keywords: Artificial neural network, Photovoltaic/Thermal System, PV-PCM.

Deneysel Çalışmaya Dayalı Fotovoltaik/Termal Sistemin Yapay Sinir Ağı ile Modellenmesi

Öz

Bu çalışmada soğutmasız ve faz değişim malzemesi (FDM) ile soğutmalı fotovoltaik panellerin sıcaklığa bağlı akım, gerilim ve çıkış gücü karakteristiklerini modellemek için Yapay Sinir Ağı modeli (YSA) kullanılmıştır. Bir önceki laboratuvar deneyinde fotovoltaik panellerin 20 ˚C- 65 ˚C sıcaklık aralığında bir saat boyunca ürettikleri akım ve gerilim değerleri ölçülmüştür. Soğutmasız ve iki farklı soğutmalı model olmak üzere bu üç fotovoltaik/termal (PV/T)'nin her biri için 60 örnek içeren deneysel verilerle Yapay Sinir Ağı tekniği kullanılarak modeller oluşturulmuştur. Yapay Sinir Ağı modelinin en düşük model hatasını sağlayan kombinasyonları ve özellikleri belirlenmiştir. Sinir Ağı modelinin performansı sırasıyla 1.15e-02, 6.76e-03 ve 6.10e-03 RMSE model hatalarıyla hem soğutmasız fotovoltaik, düz kanatçıklar/FDM ile soğutulan hem de delikli kanatçıklar/FDM ile soğutulan fotovoltaikte iyi performans gösterdi. Bu nedenle, bir saatlik deney sırasında ulaşılan tüm sıcaklıklarda akım, gerilim ve üretilen gücü modellemek için güçlü bir araç olarak önerildi.

Anahtar Kelimeler: Yapay sinir ağı, Fotovoltaik/Termal Sistem, PV-FDM.

---

[*] Corresponding Author: muhammed@cumhuriyet.edu.tr

1. Introduction

Clean and renewable energy sources are increasingly sought after as environmental degradation and energy scarcity become more prevalent (Alzaabi et al.). Solar energy is gaining popularity due to its clean and environmentally friendly properties. A major solar energy technology that represents a promising prospect is photovoltaic (PV) power generation. The efficiency of most PV panels under ideal conditions is only 15-20%, despite the fact that PV systems have been commercialized and widely used (Ma T et al.). Solar cells are highly sensitive to external climate conditions (solar irradiance, wind, temperature, etc.) since they are usually located outdoors (Kazem HA et al.). Some of the temperature is absorbed by the PV panels, while some is influenced by the environment around it. This results in a reduction in open circuit voltage of the PV panel. The efficiency of PV panels decreased by 5 % with every increase of 10 °C, according to a study by Dos Santos et al. Photovoltaic/thermal (PV/T) systems have become popular in recent years as a new photoelectric system. In a photovoltaic thermal system (PVT), heat is recovered from a conventional photovoltaic module through an integrated heat recovery mechanism. In addition to increasing the electrical efficiency of the system, these systems absorb the extra heat produced by the photovoltaic cells, thereby enhancing the efficiency of the system (M. Sardarabadi et al.). Studies evaluating PCM passively integrated with photovoltaic systems generally focus on both thermal and photovoltaic measurements. Based on the weather conditions, Park et al. investigated BIPVs incorporated with PCM for their annual electrical performance. They found that incorporating a PCM with a melting point of 25 °C increased electrical efficiency by 1.0–1.5 % over an uncooled PV module. An experimental study was conducted by Hasan et al. to determine the impact of PCM on PV efficiency. In their study, it was found that the generation of PV electricity increased by 7.2 % when the PCM was integrated to the system. An integrated photovoltaic/thermal system's electrical and thermal performances containing ZnO/water nanofluid doped PCM were examined experimentally by Sardarabadi et al. An average electricity generation increase of over 13% and an almost 9% rise in thermal efficiency can be attributed to the PCM and the nanofluid. Several arrangements of internal fins were used in Huang et al's experiment to enhance energy efficiency. The authors found that by increasing the area of heat transfer and improving natural convection through internal fins, temperatures of the PV-PCM system can be effectively reduced, resulting in an increased generation of PV power. In order to achieve effective temperature control, a PV-PCM (photovoltaic phase change materials) system with different PCM containment options as well as a combination of PCMs with different melting points was tested under different solar radiation intensities, both indoors and outdoors. Over the past few years, PV systems have increasingly implemented PCM. An investigation was conducted to determine whether PCMs can maintain PV panel temperatures close to ambient temperatures. Various types of PCMs were examined, ranging from non-organic to organic. There is an organic paraffin wax that is commonly used for this application as it has a number of melting points, is relatively inexpensive, and is readily available. A PCM-based PV panel operates better under hot climate conditions than a conventional PV panel. It is because they can store a great deal of energy. PCM have low thermal conductivity, which is their primary disadvantage. Using fins in the PCM is an alternative to the traditional methods of cooling and storing them. By using this method, these materials can be made more thermally conductive. The PV-PCM technology was proven to limit temperature rise and improve PV performance, concluding that it is an effective way to limit temperature rise and increase PV performance.

A significant amount of research has been conducted on artificial neural networks (ANNs) in a wide range of fields, especially in the field of energy (M. Mohanraj et al.). A PV-PCM system's electrical performance can be predicted using the ANN model. There has been much research on using artificial neural networks (ANN) to predict PV and PV/T system performance. PV panel temperature and solar radiation were used as input variables, while energy generation was used as an output variable. As inputs to a concentrating PVT system, Renno et al. used ANN models to predict solar radiation. In their study, they demonstrated that the ANN models can estimate both direct normal solar irradiance and daily radiation reasonably accurately. A comparison was made between the estimated and analytical results by Celik. Based on his results, ANNs provide better predictions of current than analytical models. A photovoltaic power supply system was modeled using an Adaptive Neuro-fuzzy Inference Scheme (ANFIS) by Mellit and Kalogirou. A number of climatic conditions were encountered in the development of the model, and performance and reliability were found to be satisfactory. Their performance was superior to that of Artificial Neural Networks, under all of these conditions. Grid-connected PV power output was estimated using artificial neural networks by Huang et al. In this study, they proposed an algorithm for improving the accuracy of photovoltaic power estimations based on artificial neural networks. As a result of combining environmental information like ambient temperature, irradiance, and wind speed, Hiyama and Kitabayashi evaluated the estimation of PV maximal power using artificial neural networks (ANNs). An innovative methodology was presented by Ceylan et al. for estimating the profile of PV panel power production. This study proposes two artificial neural networks (ANNs) that can be applied to sunny and cloudy days. By using ANN-models, they were able to produce reasonable estimates of the power. Recently, Voyant et al. presented a review study explaining various types of machine learning approaches that can be used to forecast solar irradiation. In numerous studies, ANNs were found to be capable of predicting the effects of PCM and simulating their behavior. The study presents the proposed ANN model and correlations between data from laboratory experiments. Thus, this article contributes by providing a model that incorporates an artificial neural network to compare the productivity and performance of PV/T systems exposed to different cooling systems. The use of artificial neural networks and fuzzy inference systems has been used in recent years to develop predictive models for estimating parameters (Torun, Y., & Doğan, H.). Researchers found that ANNs can yield reasonably accurate estimates of output parameters, while input parameters play an important role in modeling.

PV/T analysis and evaluation of different cooling systems models is the objective of this paper. It is compared between the output of the models based on PCM and fin and the output of the model based on ANN. It can be seen from the experimental results that they are very close to the ANN results in terms of electrical efficiency, comparing the experimental and ANN results.

$$P = V \times I \tag{1}$$

2. Method and Material

2.1. Experimental Work

Experimental data were obtained from monocrystalline solar panels, the properties of which are given in Table 1, under 600 W/m^2 constant radiation under laboratory conditions (M.M. Bayat et al.). For this study, an organic PCM named RT28HC was used. In the experimental setup, there are two types of containers with aluminum-fins: with flat fins and with perforated fins. Furthermore, a photovoltaic cell was used as a reference throughout the experiment but was not cooled. For cooling, containers were placed at the backs of other solar panels. For measuring light intensity, Mastech SM206 sensors were used. Measurements of PV module surface temperatures were performed with K-type thermocouples. Measuring voltage and current values, a load resistor used that has 22-ohm values. An hour-long test was conducted with minute-by-minute data collection. The temperature and electrical data were stored on a computer using an Agilent 349070A data logger. Finally, Eq. (1). allows determining output power. The experimental setup and type of containers are shown in Figure 1.

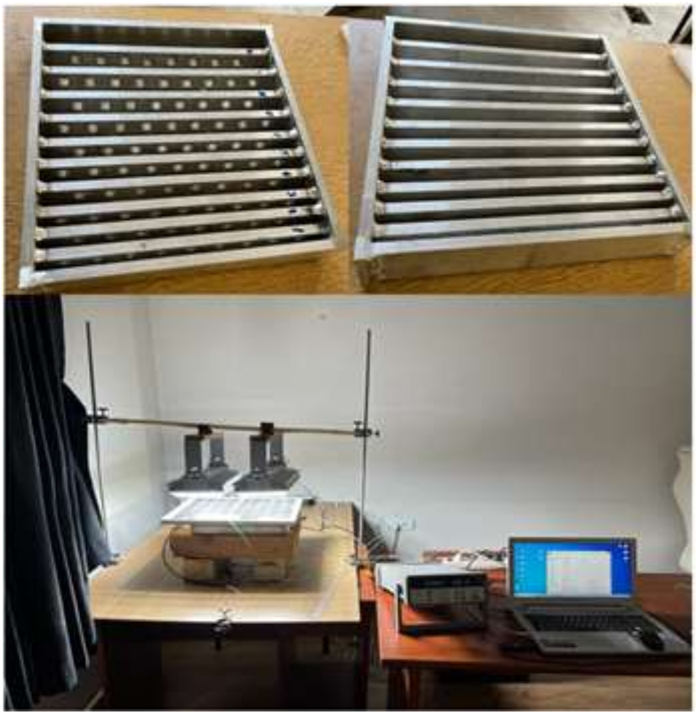

Figure 1. Containers and experimental setup (M.M. Bayat et al.)

Table 1. PV panel specification

Property	Value
Peak Power	25 W
Open circuit voltage (V_{oc})	24,62 V
Short circuit current (I_{sc})	1,28 A
Max. power voltage (V_{mp})	20,84 V
Max. power current (I_{mp})	1,23 A
Dimensions	360x420x20 mm
Weight	2 kg
Operating temperature	-40˚C - +85˚C

PV panel surface temperatures obtained over time are shown in Figure 2. At the end of the test, the uncooled PV panel, PV panel with flat aluminum -fins and PV panel with perforated aluminum -fins reached 59.3 °C, 47.1 °C, and 46 °C, respectively. A one-hour experiment was conducted to compare the electrical performance of PV panels with and without cooling. A comparison of the output powers for uncooled PV panel and each cooled PV panels can be found in Figure 3.

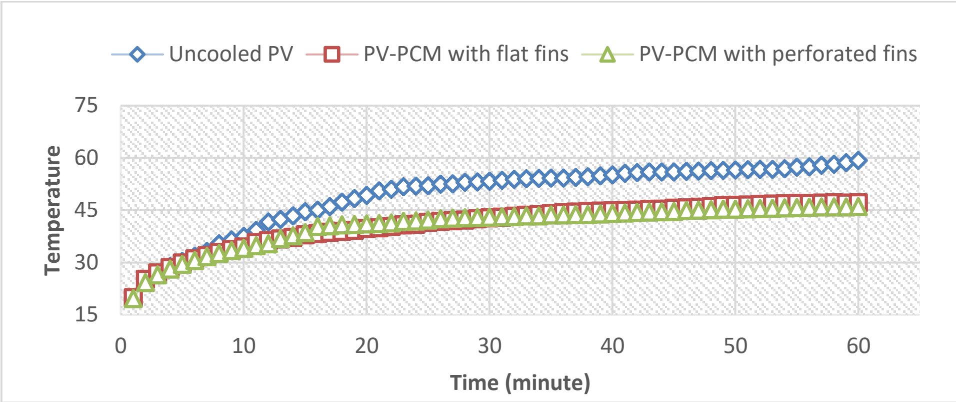

Figure 2. Surface temperatures of uncooled and cooled PV panels

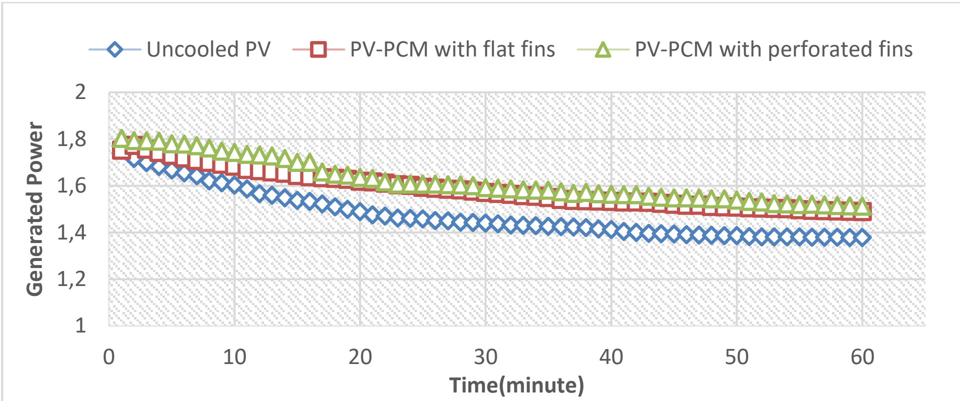

Figure 3. P_{max} of uncooled and cooled PV panels

2.2. Neural Network-based approximation of temperature and output power characteristic of PV panels

In terms of temperature changes, generated power from PV panels has a wide range of nonlinearity. By discrete sampling, current and voltage are measured to determine output power characteristics. Neural Network models aid in obtaining current and voltage values at specific temperatures within a known radiation value. Models mimic real systems, predicting output power without extra experimental measurement, based on temperature. The next subsection describes the artificial neural network tool that was used to model the output power characterization of the PV panels in the current study.

2.2.1. Artificial neural network (ANN)

An ANN is an artificial neural network, which is a powerful nonlinear approximation tool that resembles the human mind (K. Hornik et al.). Three layers are involved in the construction of ANNs: input, hidden, and output. For function approximation tasks, input data instants flow from input to output neurons in a single direction, whereas in the training phase, approximation error is backpropagated in the opposite direction as output to the input layer in order to reduce approximation error. In Fig. 4, an ANN architecture is suggested for modeling the PV panel's temperature-dependent output power characteristic. For each connection, finding the optimal weights between neurons is the goal of training an artificial neural network (ANN). The ANN model in the current study was trained using Levenberg-Marquardt. Utilizing the "Mean Square Error" function, training is carried out in accordance with the network performance measurement.

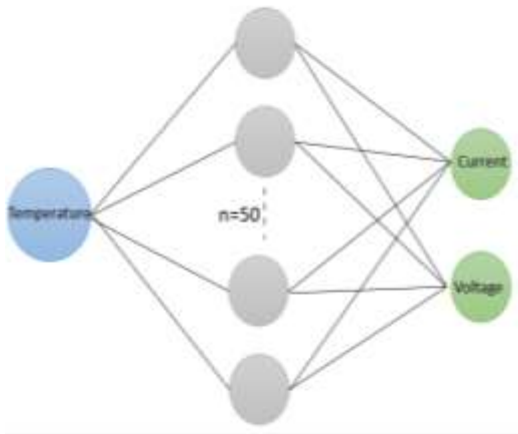

Figure 4. Modeling PV panel characteristics with an ANN architecture

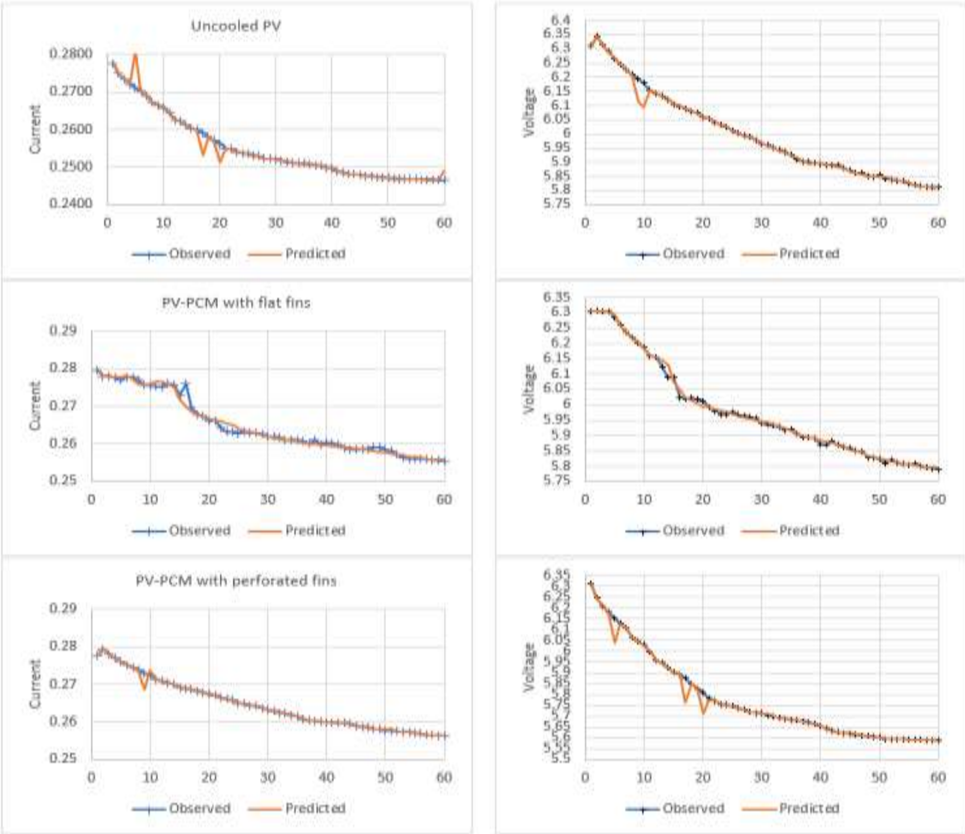

Figure. 5. Comparing PV current and voltage measurements with predicted values through ANN

2.3. Modeling Environment

The Matlab Toolbox (Matlab R2019a) was used to create the Neural Network model. A desktop computer with an i7 processor from the fourth generation and 16 GB of RAM has been used to run the model codes. The experimental data have divided up randomly for training and testing. As a result, training covers 70 % of the data, and testing covers the remaining 30 %. Three performance indices have been determined. The Root Mean Square Error (RMSE) was calculated as follows:

$$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}\left|I_i - \hat{I}_i\right|^2\right]^{\frac{1}{2}} \quad (2)$$

Mean absolute error (MAE) was calculated as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|I_i - \hat{I}_i\right| \quad (3)$$

Mean square error (MSE) was calculated as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(I_i - \hat{I}_i\right)^2 \quad (4)$$

where I_i is current (I)'s experiment value that was acquired; $\hat{I}_i$ is the anticipated value of the current state for the ith instant out of all the instants.

3. Results and Discussion

For computing and analyzing, this work uses an artificial neural network (ANN) based on the backpropagation algorithm. The input for ANN is surface temperature while the output is voltage and current. In ANN, network performance is affected by the number of neurons in the hidden layer. Both the training and testing phases, a high number of neurons is responsible for overfitting and long consumption times, whereas a low number of neurons increases RMSE. The assessment of number of neurons on performance, the size of neurons was varied from 10 to 100 neurons in steps of 10. A Levenberg-Marquardt learning algorithm in ANN has been used to achieve the best MSE with 50 neurons in the hidden layer. In the beginning of the training stage, the system's behavior under testing conditions is determined without any prior knowledge of the input matrix' covariance. Due to this, ANNs are trained using random values of weights, which results in some oscillations in the network output from the first few iterations.

Table 2. Performance indices for predicted current

	Uncooled PV	PV-PCM with flat fins	PV-PCM with perforated fins
(R^2)	0.9834	0.9910	0.9820
RMSE	1.649e-03	6.189e-04	1.034e-03
MAE	4.536e-04	1.442e-04	5.962e-04
MSE	1.844e-05	4.924e-05	7.590e-05

Table 3. Performance indices for predicted voltage

	Uncooled PV	PV-PCM with flat fins	PV-PCM with perforated fins
(R^2)	0.9933	0.9898	0.9968
RMSE	2.400e-02	1.521e-02	8.870e-03
MAE	6.507e-03	3.787e-03	5.461e-03
MSE	5.468e-03	3.012e-03	1.298e-03

The purpose of this paper is to compare the performance of different cooling systems models for analyzing and evaluating PV/T. The output from the actual models based on PCM and fin is compared to the outcome of the ANN model. When the experimental results are compared to the ANN results, the curves are very close, especially in terms of electrical efficiency.

For uncooled and cooled models, the predicted and actual value of PV panel current and voltage have been shown in Fig. 5. Similarly, the estimated and actual value of the generated power calculated from the PV panel current and voltage values are shown in Fig. 6. Data in the training dataset makes up 70% of the total data, while data in the test dataset makes up 30% of the total data. The training dataset consists of 42 samples, and the test dataset contains 18 samples.

For all three models, Fig. 5 shows the results of the experiment and the ANN output. In comparison with the other models, the PV-PCM with perforated fins model achieved the highest electric current production and all three models predict the output with a high level of accuracy as shown in Fig. 5. A table with the RMSE, MSE, MAE, and R^2 values is also provided in Table 2 for an improved understanding of the models. Moreover, both observed and ANN results indicate that the voltage rate of the perforated model obtained the highest results in comparison with the other models. A low MSE and MAE are also shown in Table 3. An analysis of the generated electrical power between PV/T and PV systems is presented in Fig. 3. A greater degree of cooling resulted in a higher electrical efficiency, which is claimed to have been achieved by the PV-PCM with the perforated system. ANN models are also more similar to experimental results. Based on Table 4, the MSE and MAE of the ANN model are low, which indicates better accuracy of the model.

Table 4. Performance indices for predicted generated power

	Uncooled PV	PV-PCM with flat fins	PV-PCM with perforated fins
(R^2)	0.9942	0.9928	0.9952
RMSE	1.153e-02	6.764e-03	6.100e-03
MAE	3.309e-03	1.552e-03	3.779e-03
MSE	1.286e-03	1.124e-03	9.261e-05

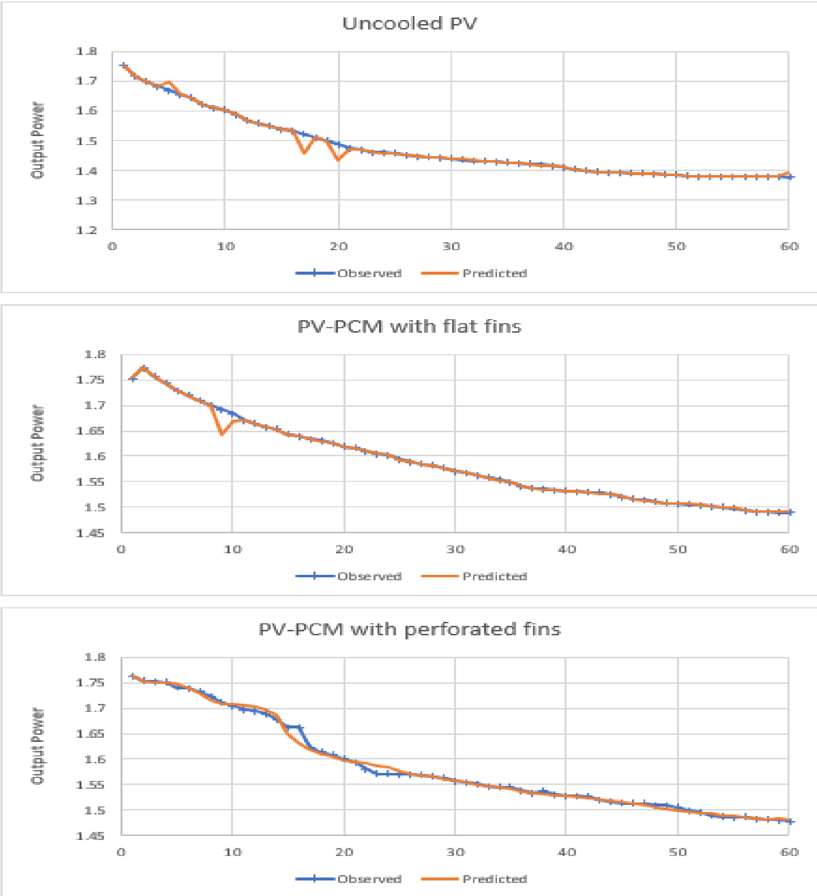

Figure 6. Comparing PV generated power measurements with predicted values through ANN

4. Conclusions and Recommendations

In order to mimic the behavior of the PV/T model, the ANN models aim to reproduce and predict it as accurately as possible. ANN models also provide accurate predictions of future outcomes wherever solar power is available. An ANN is used in this paper to compare conventional PV and PCM-based PV/T systems under the same conditions. The results of practical experiments and ANN models almost matched. Through the development of a simulation model, researchers are able to optimize design for PVT systems.

For the purpose of determining the effect of refrigerant on PV/T output power, two PV/T systems were designed and implemented. Testing was conducted in a laboratory environment to determine the electrical behavior of PV/T cooling strategies. Artificial Neural Networks (ANNs) were used to confirm the exploratory results. Among the two tested systems, PCM with perforated fins provided the greatest cooling effect, achieving a 9.46 % electrical efficiency as opposed to 7.43 % for PCM with flat fins.

5. Acknowledge

This study was supported by Sivas Cumhuriyet University Scientific Research Projects (CUBAP) with project number M-2022-829.

References

Alzaabi Aa, Badawiyeh Nk, Hantoush Ho, Hamid Ak. Electrical/thermal performance of hybrid PV/T system in Sharjah, UAE. Int J Smart Grid Clean Energy 2014.

A.N. Celik, Artificial neural network modelling and experimental verification of the operating current of mono-crystalline photovoltaic modules, Sol. Energy 85 (2011) 2507–2517.

C. Renno, F. Petito, A. Gatto, Artificial neural network models for predicting the solar radiation as input of a concentrating photovoltaic system, Energy Convers. Manage. 106 (2015) 999–1012.

Ceylan, İlhan, et al. "The prediction of photovoltaic module temperature with artificial neural networks." *Case Studies in Thermal Engineering* 3 (2014): 11-20.

dos Santos Carstens DD, da Cunha SK. Challenges and opportunities for the growth of solar photovoltaic energy in Brazil. Energy Policy 2019;125:396–404.

Hasan, Ahmad, Hamza Alnoman, and Yasir Rashid. "Impact of integrated photovoltaic-phase change material system on building energy efficiency in hot climate." *Energy and Buildings* 130 (2016): 495-505.

Hiyama, Takashi, and Ken Kitabayashi. "Neural network based estimation of maximum power generation from PV module using environmental information." *IEEE Transactions on Energy Conversion* 12.3 (1997): 241-247.

Huang, Chao, et al. "Improvement in artificial neural network-based estimation of grid connected photovoltaic power output." *Renewable Energy* 97 (2016): 838-848.

Huang, M. J., et al. "Natural convection in an internally finned phase change material heat sink for the thermal management of photovoltaics." *Solar Energy Materials and Solar Cells* 95.7 (2011): 1598-1603.

K. Hornik, M. Stinchcombe, H. White, Multilayer feedforward networks are universal approximators, Neural Network. 2 (1989) 359–366, https://doi.org/10.1016/0893-6080(89)90020-8.

Kazem HA, Chaichan MT. Effect of humidity on photovoltaic performance based on experimental study. Int J Appl Eng Res (IJAER) 2015;10(23):43572–7.

M.M. Bayat, E. Buyruk, A. Can, “Use of PCM wıth aluminum fins to improve solar panel performance” 26th International Conference on Heating, Cooling and Air-conditioning (2023).

M. Mohanraj, S. Jayaraj, C. Muraleedharan, Applications of artificial neural networks for refrigeration, air-conditioning and heat pump systems, a review, Renew. Sustain. Energy Rev. 16 (2012) 1340–1358.

M. Sardarabadi, M. Passandideh-Fard, S. Zeinali Heris, Experimental investigation of the effects of silica/water nanofluid on PV/T (photovoltaic thermal units), Energy 66 (2014) 264–272.

Ma T, Yang H, Zhang Y, Lu L, Wang X. Using phase change materials in photovoltaic ystems for thermal regulation and electrical efficiency improvement: A review and outlook. Renew Sustain Energy Rev 2015; 43:1273–84DIN 1946-4, ‘’VAC Systems in Buildings and Rooms Used in The Health Care Sector’’, 2008

Mellit, Adel, and Soteris A. Kalogirou. "ANFIS-based modelling for photovoltaic power supply system: A case study." *Renewable energy* 36.1 (2011): 250-258.

Park, Jungwoo, Taeyeon Kim, and Seung-Bok Leigh. "Application of a phase-change material to improve the electrical performance of vertical-building-added photovoltaics considering the annual weather conditions." *Solar Energy* 105 (2014): 561-574.

Sardarabadi, Mohammad, et al. "Experimental study of using both ZnO/water nanofluid and phase change material (PCM) in photovoltaic thermal systems." *Solar Energy Materials and Solar Cells* 161 (2017): 62-69.

Torun, Y., & Doğan, H. (2021). Modeling of Schottky diode characteristic by machine learning techniques based on experimental data with wide temperature range. Superlattices and Microstructures, 160, 107062.

Voyant, Cyril, et al. "Machine learning methods for solar radiation forecasting: A review." *Renewable energy* 105 (2017): 569-582.