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Original Paper

Estimation of power outputs of two different photovoltaic solar panels with different heuristic algorithms

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ABSTRACT

The estimation of the power values obtained from photovoltaic (PV) systems is of critical importance for the reliable and economical use of solar energy panels. This estimation affects many processes, starting from the installation phase of solar panels to guiding electricity companies, energy management, and distribution. At the same time, it is necessary to detect the adaptations of solar panels in a timely manner and reach the optimal production capacity to provide the most efficient energy production. In this context, Artificial Neural Networks (ANN) were used to estimate the power values obtained from PV panels. In this study, heuristic algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Clonal Selection Algorithm (CSA), Ant Colony Optimization, and Artificial Bee Colony (ABC) were used to estimate the power values obtained from monocrystalline and polycrystalline photovoltaic panels. In the verification of the estimation results, the most common statistical evaluation criteria, Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Variance (R^2) equations were used. The estimation values made with the PSO algorithm were the closest to the real values. 98.95% estimation was achieved in monocrystalline photovoltaic solar panels and 93.94% in polycrystalline photovoltaic solar panels.

I. INTRODUCTION

Solar energy is a renewable energy type. It is also a silent, maintenance-free energy source that does not emit harmful gases to the environment. Fossil fuels such as natural gas, coal, and oil have negative effects on the environment. The decrease of these resources over time and the meeting of energy needs with the increasing population have caused photovoltaic (PV) systems to gain importance.

For the safe and economical operation of current and modern power systems, production planning must be made in real-time, daily, weekly, monthly, and annually. Therefore, the power output values of renewable power facilities such as PV panel stations emerge as a basic process. Many studies are carried out in this area [1-7].

The efficiency (output power) of solar power stations varies according to different weather conditions. For this reason, it has been observed that studies estimating the power output values of PV panels have increased significantly recently. Today, there are two basic approaches widely used for power estimation of PV panels [1]. The first one is the calculation of active power in PV systems with the help of the estimation of environmental parameters such as solar radiation and ambient temperature, and some parameters are obtained using mathematical models. The other one is the direct estimation of active power outputs of PV systems [2].

They stated that global solar radiation (Rs) measurements, which are critical for solar energy systems, are limited due to high costs and maintenance requirements. As a solution to this problem, a hybrid machine learning model,

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PSO-ELM (Particle Swarm Optimization and Extreme Machine Learning), was developed. The model was compared with other methods in Rs estimation and achieved superior success, especially on the data from the Loess Plateau of China for the years 1961-2016. PSO-ELM determined that the north-western regions, which offer higher Rs and PV potential, are suitable for solar energy and proved their effectiveness in areas without measurements [3]. It is important to note that the performance of PV power systems may deviate from nominal values; therefore, it is difficult to estimate real power production accurately at the local level. As the use of solar energy increases, local weather conditions and atmospheric changes affect system efficiency, leading to fluctuations in energy production. In the USA, the abundance of solar radiation and meteorological data provides a significant advantage for estimating the performance of PV systems at the local level and evaluating energy production models. One of the methods that provide the best prediction results for PV systems by analysing past energy production data is the random forest repressor [4]. An LSTM-based deep learning model has been proposed to analyse trends in energy time series for photovoltaic systems. This model aims to predict whether the series will rise, fall, or remain constant rather than numerical prediction. It has shown robustness and versatility in nonlinear series in tests. In the future, its integration into more complex prediction systems is planned [5]. Considering the difficulties in PV energy prediction, the performance of neural networks and intelligent algorithms for short-term prediction has been evaluated with a comprehensive analysis. In the study conducted with data from a PV plant in England, seasonal effects were taken into account, and it was seen that the proposed hybrid model gave the highest accuracy results [8]. A hybrid model combining CNN, LSTM, and the two was developed for PV energy prediction and tested with data from DKASC. It was determined that the hybrid model had the highest accuracy, while LSTM provided the fastest training but showed low performance in terms of accuracy. It was emphasized that the estimation accuracy increased with long input sequences [9]. It was stated that the variable nature of solar energy made integration into energy systems difficult, but this problem could be overcome with accurate estimation. In the proposed LSTM-CNN hybrid model, temporal and spatial features were processed respectively, and superior estimation performance was shown when compared to other models [10]. A system was developed to analyse and predict PV performance at Qatar University. Several regression models and ANN-based estimations were made with environmental and PV data, and it was seen that ANN had the highest accuracy. It was stated that feature selection techniques (CFS and Relief F) increased the estimation success. It was emphasized that the estimations could be improved with more parameters and long-term data in the future [11]. In the studies carried out in Mersin province of Turkey, air temperature, relative humidity, wind speed, sunshine duration and cloudiness data were used to estimate solar radiation. He applied artificial neural networks, and regression analysis methods in the predictions and compared the results [12].

In the literature, many methods have been proposed for the estimation of PV panel power outputs. Many studies have been conducted comparing the solar radiation estimations obtained by using multiple linear regression methods and ANN models, which reveal the PV panel power output characteristics using weather data [13-19]. In Kou’s study, solar panel output power estimation was made by using the ANN structure trained using ANN using meteorological data [20]. Qasrawi designed a multi-layered ANN trained with ANN (Levenberg-Marquardt) using the panel outputs obtained from solar panels placed in different regions and the data obtained from satellites. Humidity, solar radiation, daylight duration, and cloudless weather conditions were given as inputs to the system. The performance of the network was verified with test data [21]. Zhu applied the wavelet transform method to the data reduction. After using a hybrid method study in the training of ANN, they subjected the data to the structuring process again with the Wavelet Decomposition Method and produced a study that required less mathematical processing compared to existing ANN studies [22]. Jency Paulin and Praynlin presented a comparative study in which they trained a GY-based ANN using the average ambient temperature, average panel temperature, average converter temperature, solar radiation, wind speed, and power output data as inputs in solar panels [23].

In this study, the power outputs of monocrystalline and polycrystalline solar panels were estimated using different heuristic methods. In the study, a comparative evaluation of the power values obtained with Particle Swarm Optimization, Genetic Algorithm, Clonal Selection Algorithm, Ant Colony Optimization and Artificial Bee Colony heuristic algorithms was made. In addition, the effectiveness of the method on the obtained results was verified by analysing the average percentage error between the measured real and estimated values. The study revealed that the highest efficiency was achieved from solar panels with high installation costs.

In the second part of the study, the general working scheme of the system is shown. The heuristic algorithms used in the study are explained. The error analysis methods used in the study are explained. The technical data and electronic circuits of the solar panels used in the system are shown. In the third part, the electrical energy produced by two different solar panels is shown daily and monthly as a result of the study. The results of five different heuristic algorithms are compared with the produced energy. Finally, the results of the heuristic algorithms are examined with error analysis methods.

II. EXPERIMENTAL METHOD

In this study, different heuristic algorithms were used to estimate the power values obtained from photovoltaic (PV) systems. For this purpose, monocrystalline and polycrystalline solar panels, each with a power of 20 Wp, were used. The current and voltage of the solar panels were measured instantly in the designed circuit. In addition, the outdoor temperature and humidity values were measured. All values produced in the study are displayed on the computer screen. All values are recorded at 10-minute intervals. With this data, Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Clonal Selection Algorithm (CSA), Ant Colony Optimization (ACO), and Artificial Bee Colony (ABC) algorithms were used among the commonly used algorithms in estimating the output power of solar panels. Each of these algorithms was used as a specialized method to estimate the output power in photovoltaic systems. The general operating principle of the system is shown in Figure 1.

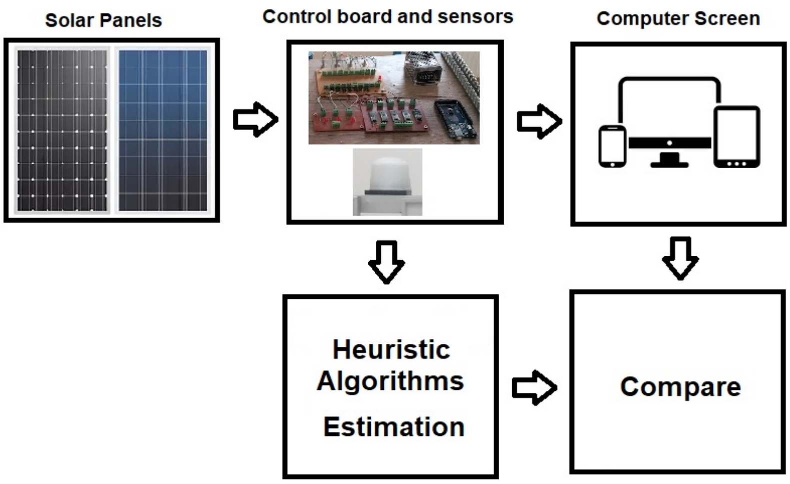


Figure 1. Materials used in the system

2.1 Artificial Neural Network

Artificial Neural Networks (ANN) are artificial intelligence algorithms with data processing and learning capacity inspired by the functioning of nerve cells in the human brain. Neural networks enable many simple processing units (neurons) to perform complex tasks by connecting them together. This network structure works similarly to the transmission of electrical signals between neurons in the biological nervous system. In artificial neural networks, data is taken from the input layer and processed through intermediate layers, and the result is obtained in the final output layer. Each neuron processes the information it receives through weights, biases, and activation functions. Thanks to this process, neural networks can model non-linear relationships and learn complex patterns in the data set. The learning process of ANN is usually carried out using an algorithm called backpropagation. In this process, the network initially starts with random weights, and then the error is calculated using the training data. The error is propagated back from the output layer, which allows the network to update its weights. This iterative process allows the network to be continuously improved so that it can make accurate predictions. Artificial neural networks are powerful tools that can work with high accuracy in many different application areas. ANN, which can achieve effective results in complex data sets such as image recognition, voice command detection, and natural language processing, is especially useful in non-linear and multivariable problems. One of the biggest advantages of ANN is its ability to learn complex relationships in data. For example, problems such as solar panel output power estimation have a non-linear structure because they are affected by environmental factors (such as solar radiation, temperature, and humidity). While traditional mathematical modelling methods may be insufficient in such problems, ANN offers a powerful solution. By analysing the data received from the solar panel, the neural network can learn the relationships between these data and accurately predict future output power. In addition, the learning ability of ANN can be improved over time with more data. During the training process, the network can be tested with data it has not seen before, which increases the accuracy of the prediction.

The success of artificial neural networks largely depends on the correct network structure and appropriate training parameters. Many parameters such as network structure, number of neurons, layer depth, learning rate and activation functions affect the performance of the network. While multi-layer structures (deep learning) are used to model more complex data, single-layer structures may be sufficient for simpler problems. In addition, correct training strategies should be applied to avoid problems such as overfitting (network over-learning) and underfitting (network under-learning). Otherwise, the network may give results that are incompatible with real-world data. It should also be taken into account that ANN requires high computational power and training times. Therefore, it is important to manage computational resources correctly when working with large data sets. Artificial neural networks are extremely powerful and flexible thanks to their capacity to learn from data. In applications such as solar panel output power estimation, ANN is effective in making accurate estimations by analysing both historical data and environmental variables. This allows for more efficient solar energy production estimations in the energy sector. Moreover, the fact that ANN enables such efficient predictions also contributes to areas such as energy management and optimized panel placement. However, the success of ANN depends on the correct configuration of the algorithm and the quality of the data set. With correct training and appropriate modelling, ANN can provide extremely successful results in energy production, time series prediction, and many other areas.

2.1.1. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is an optimization algorithm inspired by group movements observed in nature. First developed by James Kennedy and Russell Eberhart in 1995, PSO is a meta-heuristic method belonging to the family of evolutionary algorithms. This algorithm was developed by observing how flocks of birds or groups of whales coordinate their complex movements. PSO represents potential solutions in the solution space as "particles", and each particle is a point in the solution space. Each of these particles moves in the solution space by following its individual best solution (persistence) and the best solution of all particles (global best). The speed and positions of the particles are updated over time; these updates are performed by trying to find the new position of each particle. Each particle accelerates and determines its direction based on its own past best position and the best position of the entire group. This creates a dynamic search process where all particles share each other's information to reach a point closer to the solution. This process allows the algorithm to approach the global optimum without getting stuck in local minima. One of the biggest advantages of PSO is that it offers a very powerful and flexible optimization technique despite having a very simple structure. Parameter settings are minimal, and thanks to its ability to optimize many parameters simultaneously, PSO is a very effective method for complex and high-dimensional optimization problems. In addition, since the algorithm searches for a solution without using derivative information directly, it can be successfully applied to problems that do not require derivatives. PSO uses a global optimization approach, trying to find the most suitable solution in the solution space while avoiding local optima. In this way, very successful results can be obtained in large data sets, machine learning problems, engineering designs, and many different application areas. However, PSO also has some limitations and difficulties. PSO carries the risk of getting stuck in local minima and can sometimes be slow in finding the optimum solution. To overcome this situation, the performance of PSO can be improved by using various hybrid methods and parameter adjustments. Careful adjustment of learning rates, speed constraints and other parameters can significantly improve the efficiency of the algorithm. In addition, different types and variants of PSO have been developed and can provide faster and more effective solutions to special problems. Particle Swarm Optimization can be used in a wide range of applications thanks to its flexible structure, and powerful optimization features, and is an effective tool that provides solutions to large, complex and multi-dimensional optimization problems [24-26].

2.1.2. Clonal Selection Optimization

Clonal Selection Optimization (CSA) is an optimization technique inspired by the immune system and is among the evolutionary computational methods. CSA is inspired by the natural defence mechanisms developed by the immune system against antigens and aims to obtain effective results in the solution search process by applying these principles to mathematical optimization problems. The algorithm imitates the process of selecting, multiplying, and producing better antibodies through the evolutionary process of antibodies produced against antigens in the natural immune system. Clonal Selection Optimization is designed to be used in solving complex and high-dimensional problems, and it has been successfully tested in real-world applications. The basic principles of Clonal Selection Optimization include the multiplication of B cells that produce body-specific antibodies when an antigen is encountered in the immune system and the selection of the better-performing of these antibodies. In CSA, each individual in the solution space is considered an antibody. Each antibody is a representative of the solution, and the quality of these solutions is measured by the "affinity" (binding ability) of the antibodies. The affinity of a solution determines how compatible it is with the solution of the problem. A high-affinity value indicates that the solution is optimal or close to the optimal solution, while a low-affinity value indicates that the solution is further away. The algorithm's working process works as follows: In the first step, the initial population is randomly created. This population contains antibodies represented by different solutions. Then, the affinity value of each antibody is calculated. This value determines how close each individual is to the target function. Antibodies with high affinity values are replicated more. This replica focuses on producing good solutions and helps explore a larger part of the solution space. In the replica process, antibodies with low affinity values are replicated less or sometimes eliminated completely. The replicated antibodies are subjected to processes such as mutation, i.e., small random changes are added. This helps the algorithm maintain the balance between exploration and exploitation. Mutation aims to discover new solutions and increase the diversity of the population [27].

One of the strengths of Clonal Selection Optimization is its capacity to find high-quality solutions quickly. Because CSA imitates the selection and reproduction principles of the natural immune system, it continuously selects and improves the best solutions. In addition, the algorithm offers a wide search space to avoid local optima, because mutation and reproduction operations allow for a wider search by focusing on different points of the solution space. However, while the algorithm focuses on finding better solutions in each generation, it reaches the result by rapidly narrowing the solution space [28].

There are also some limitations of Clonal Selection Optimization. First of all, CSA generally requires correct parameter settings. In particular, parameters such as mutation rate, population size and selection strategies need to be determined carefully. In addition, the algorithm may require more computational power, and time to increase the accuracy of the solution in complex problems. Despite this, the advantages of CSA become evident especially when it comes to complex, multi-dimensional, and non-linear optimization problems. CSA can be used effectively in engineering design, artificial intelligence, machine learning, and many other areas. Clonal Selection Optimization is a powerful and flexible application of evolutionary computational methods. Inspired by the immune system, this algorithm, designed to provide innovative and effective solutions to problems, has been successfully used to solve many optimization problems. CSA allows problems to be solved faster and more effectively thanks to the simulation of natural processes and can be further developed with future research. It can be made more efficient with different variations and hybrid methods, especially to avoid local minima and reach global optima [29].

2.1.3. Genetic Algorithm

Genetic Algorithm (GA) is an optimization technique inspired by natural evolutionary processes and is a method belonging to the evolutionary computation family. This algorithm was developed by adapting the processes of biological evolution, such as natural selection, genetic crossover, and mutation, to the solution of mathematical problems. First developed by John Holland in the 1970s, the genetic algorithm treats the possible solutions in the solution space as "individuals" and creates a population of these individuals. Each individual represents a point in the solution space or a representative of the solution, and the quality of the individuals is generally evaluated by a metric known as the fitness function. This fitness function determines how good a solution is and measures how close the solution is to the targeted result. Genetic algorithms aim to ensure that these individuals find the best solution through evolutionary processes. The genetic algorithm consists of four main components: selection, crossover, mutation, and natural selection. These processes allow the population to evolve according to the quality of the individuals. First, an initial population is randomly created. This population consists of individuals representing possible solutions in the solution space. Each individual is represented by a "genome" that contains a part of the solution (genetic material). This genome is expressed with various coding techniques (binary coding or real values) to represent the problem on which the genetic algorithm works. Then, each individual is evaluated with a fitness function, and a success rating is assigned according to the contributions of the individuals to the solution. A high fitness value means a better solution. Selection is used in the first step of the genetic algorithm to select the best individuals. The selection process improves the population by ensuring that the best individuals pass to the next generation. During selection, individuals with higher fitness are selected with a higher probability, but various methods are applied so that individuals with lower fitness also have a chance. One of these methods is roulette wheel selection; here, the fitness value of each individual is converted into a "selection probability" and individuals with higher fitness values are more likely to be selected. However, different methods such as tournament selection can also be used [30].

Crossover is another important component of the genetic algorithm in the evolutionary process. Crossover produces new individuals by combining the genetic information of two individuals. This process simulates the "genetic mixing" process in natural evolution and creates new solutions. During crossover, a certain portion of the genetic material is taken from the two parent individuals to create a new offspring individual. This new individual carries the characteristics of both parents and increases genetic diversity in order to create better solutions. The crossover rate is usually kept high because this process provides faster evolutionary development.

Mutation is the third component of the genetic algorithm and is used to provide genetic diversity. Mutation allows new characteristics to emerge by making small random changes in the genetic structure of individuals. This allows local optima to be avoided and a wider search to be made in the solution space. Mutation mimics the genetic changes that occur in nature and allows the algorithm to search for more solutions. However, when the mutation rate is too high, the algorithm can become random and difficult to optimize. Therefore, careful adjustment of the mutation rate is necessary. The process of natural selection is one of the most important steps in the evolutionary algorithm. Natural selection ensures that only the fittest individuals survive and pass on to the next generation in each generation. This process accelerates evolutionary adaptation and directs the population to produce better solutions. Individuals with high fitness values are selected with greater probability, which leads to a greater prevalence of their traits in the next generation [31].

Genetic algorithms are quite effective in providing the balance between exploration and exploitation. Exploration means exploring new solution spaces, while exploitation means exploring existing good solutions in more depth. Crossover and mutation provide a balance between exploration and exploitation, allowing genetic algorithms to produce high-quality solutions. However, the effectiveness of genetic algorithms largely depends on the parameter settings. Correctly determining parameters such as population size, crossover rate, mutation rate, and selection strategies directly affect the success of the algorithm. Incorrectly set parameters can cause the genetic algorithm to get stuck in local minima or to over compute. Genetic algorithms are widely used in solving many complex problems such as solar panel output power estimation, machine learning, robotic systems, and renewable energy systems. Especially in nonlinear systems where many parameters need to be optimized, genetic algorithms can provide effective and efficient solutions. In addition, the parallel working ability of genetic algorithms makes them ideal for application to large-scale problems. Genetic algorithms are a very powerful optimization tool, especially in solving multi-dimensional, complex and non-linear problems. Inspired by evolutionary processes, this method can be used to produce low-cost, and effective solutions in many different areas. However, making the right parameter settings and determining the appropriate solution strategies are critical for the successful application of genetic algorithms [32].

2.1.4 Ant Colony Optimization

Ant Colony Optimization (ACO) is a meta-heuristic algorithm inspired by the food-seeking behaviour of ants in nature and is often used to solve complex optimization problems. In the natural world, ants leave a chemical trail called pheromone on their paths when they reach food sources. This trail acts as a guide for other ants and encourages them to follow the same path. While shorter and more efficient paths are preferred by more ants due to the pheromone density on them, less efficient paths are abandoned over time. This behaviour allows ants to find the shortest and most suitable paths with their collective intelligence without individual knowledge. ACO transforms this natural mechanism into a mathematical algorithm and makes it applicable to various optimization problems. The basic principle of ACO is to model the problem in a graph structure and allow ants to explore paths on this graph. Ants start from a random starting point and choose their next steps based on a probability function. This probability is determined by factors such as the amount of pheromone on the path and the attractiveness of the path (e.g., shortness of distance). In each iteration, ants explore potential solutions and mark better paths with pheromone updates. While the pheromone density is increased on shorter paths, the pheromone on longer or low-quality paths evaporates and loses its effect. In this way, the system evolves from random searches to focused optimization. Pheromone evaporation also prevents the algorithm from getting stuck in local minima and allows it to explore a larger part of the overall solution space [33].

Ant Colony Optimization is especially used in combinatorial optimization problems. One of the most well-known application areas is the traveling salesman problem (TSP), where a salesman aims to find the shortest route while visiting all cities. In addition, it is effectively applied in many areas such as vehicle routing, job scheduling, network routing, and logistics planning. ACO is used not only in technical problems, but also in disciplines such as bioinformatics, data mining, and telecommunications. One of the biggest advantages of the algorithm is that it is suitable for parallel operation. Many ants can work simultaneously to discover different solutions, which can increase the computational speed. In addition, thanks to the flexible structure of ACO, it is possible to easily adapt it to different types of problems. However, the algorithm also has some disadvantages. Parameters such as pheromone evaporation rate, number of ants, and number of iterations must be set correctly; otherwise, the algorithm may not produce efficient results. In addition, computational costs may increase in large problem sizes, which can slow down the implementation process. As a result, Ant Colony Optimization, as an algorithm inspired by nature, offers a powerful method for solving complex problems. This approach, developed with inspiration from natural systems, provides optimized solutions using the power of collective intelligence. ACO is not only an optimization tool, but also a successful example of how effective it can be to transform biological processes into mathematical models [34,35].

2.1.5. Artificial Bee Colony

Artificial Bee Colony (ABC) is a meta-heuristic optimization algorithm inspired by the natural foraging behaviour of honeybees. First introduced by Karaboğa in 2005, this algorithm is used as an effective method for solving complex optimization problems. The food source search processes of honeybees include an information-sharing mechanism. Bees scan the environment to find food sources and share this information with other members of the colony. Inspired by this natural process, the Artificial Bee Colony algorithm models optimization processes with a simulation in which bees take part. In the ABC algorithm, bees are divided into three groups: worker bees, observer bees, and scout bees. Worker bees search for available food sources and share the information they obtain. Observer bees select the best sources using the information provided by worker bees. Scout bees represent the exploration ability of the colony and search for new sources instead of abandoned or decreasing productive sources. This distribution of roles allows the algorithm to balance both local and global search capabilities. Thus, both existing solutions are improved, and new solutions are discovered [36,37].

The basic working steps of the ABC algorithm start with generating random solutions at the beginning. Worker bees search within a certain area to improve these solutions. Then, observer bees evaluate these solutions and focus on the best resources. If a resource cannot be improved for a long time, scout bees' step in and discover a new solution area. This process continues until a certain stopping criterion is met. The stopping criterion is usually defined as reaching a certain number of iterations or the solution not being improved any further.

Among the advantages of the Artificial Bee Colony algorithm, the ease of its applicability and the simplicity of its parametric settings stand out. In addition, it provides successful results in a wide range of optimization problems thanks to its fast convergence ability and global search capacity. However, it also has some disadvantages. For example, in complex or high-dimensional problems, the parameters must be adjusted appropriately, and the solution process may require more computational power. However, the adaptive structure of the algorithm allows the user to flexibly implement it according to the type of problem. The ABC algorithm is used in a wide variety of fields such as engineering design, machine learning, data mining, route optimization, neural network training, and bioinformatics. It is effectively applied to issues such as finding the shortest and cheapest route in logistics problems, bandwidth optimization in telecommunication networks, or efficient resource allocation in energy systems. The Artificial Bee Colony is an important example of the success of nature-based algorithms, as a method inspired by the collective intelligence of bee colonies in nature. Transforming the organizational structure and cooperation principles of bees into an optimized system offers an innovative and effective approach to solving complex problems [38,39].

2.2. Evaluation Criteria

In this study, a set of widely used statistical metrics are used to evaluate the accuracy of the output power predictions of photovoltaic systems. These criteria are selected to objectively measure the prediction performance of the model. The main evaluation criteria used consist of three basic metrics: Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Variance (R^2). Each criterion evaluates the model's performance from different perspectives and helps us understand how reliable the predictions are.

2.2.1. Mean Absolute Percent Error (MAPE)

MAPE is an evaluation criterion that calculates the average of the percentage differences between the predicted values and the actual values. This metric is a very widely used method to express the accuracy of the model and is often preferred, especially in the business world and engineering applications. MAPE allows the absolute difference between the predicted value and the actual value to be expressed as a percentage, which allows us to understand the errors of the model more easily. MAPE is calculated with the following formula:

$$MAPE \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\tilde{Y}_{i\,real}-Y_{i\,estimate}}{Y_{i\,estimate}}\right| * 100 \tag{1}$$

A low value of MAPE indicates that the model is making a high-prediction prediction. MAPE typically ranges from 0% to 100%, with lower values indicating greater predictive power. However, there are cases where MAPE can be misleading, particularly when the true values are close to zero, which can inflate the error rate.

2.2.2. Root Mean Square Error (RMSE)

RMSE is calculated by taking the square root of the mean square of the difference between the predicted values and the true values. RMSE is another important criterion used to evaluate the predictive performance of the model and is generally preferred in regression analysis and nonlinear problems. RMSE is a direct measure of the error magnitude of the model, because larger errors create a larger squared difference, which increases the RMSE value. RMSE is calculated as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\tilde{Y}_{i\,real} - Y_{i\,estimate}\right)^2} \tag{2}$$

A small RMSE indicates that the model's predictions are close to the true data. RMSE emphasizes the magnitude of the error more, because large errors contribute much more than small errors. Therefore, RMSE may be a more appropriate evaluation criterion in cases where larger errors are important. Another important feature of RMSE is that the error unit is the same as the original data unit, which allows RMSE to provide a concrete metric for understanding the model's error magnitude.

2.2.3. Variance (R^2)

Variance (R^2) is another important statistical metric used to measure the accuracy of the model's predictions in regression analysis, indicating how well the model's independent variables (inputs) explain the dependent variable (output power). The R^2 value indicates how well the model fits and whether it explains the overall variance of the data. The R² value ranges from 0 to 1, where 1 indicates that the model perfectly explains all the variance, while 0 indicates that the model has no explanatory power. The R² value is calculated with the following formula:

$$R^2 = 1 - \frac{\sum_{i=i}^{n} (\tilde{Y}_{i\,real} - Y_{i\,estimate})^2}{\sum_{i=i}^{n} (\tilde{Y}_{i\,real} - Y_{i\,estimate})^2} \tag{3}$$

A high R² value indicates that the model provides a strong fit with the data and is successful in its predictions. When the R² value is close to 0, the model's fit to the data decreases and the predictions are less accurate. R² is usually used to understand the overall success of the model, but sometimes a high R² value can also indicate that the model may have over fitted, so considering only this criterion can be misleading.

When these three evaluation criteria (MAPE, RMSE and R²) are used together, it is possible to comprehensively evaluate the accuracy of a prediction model. While MAPE shows the overall prediction error of the model as a percentage, RMSE concretely expresses the error magnitude and R² shows the level of fit of the model to the data. Each metric helps to determine the strengths and weaknesses of the model and to identify areas for improvement.

Especially in complex and nonlinear systems such as photovoltaic output power prediction, using these criteria together allows a more accurate analysis of the model's prediction accuracy. These evaluation methods help us understand which parameters and algorithms are most suitable to improve the accuracy of the model.

2.3. Dataset and Solar Panel Types

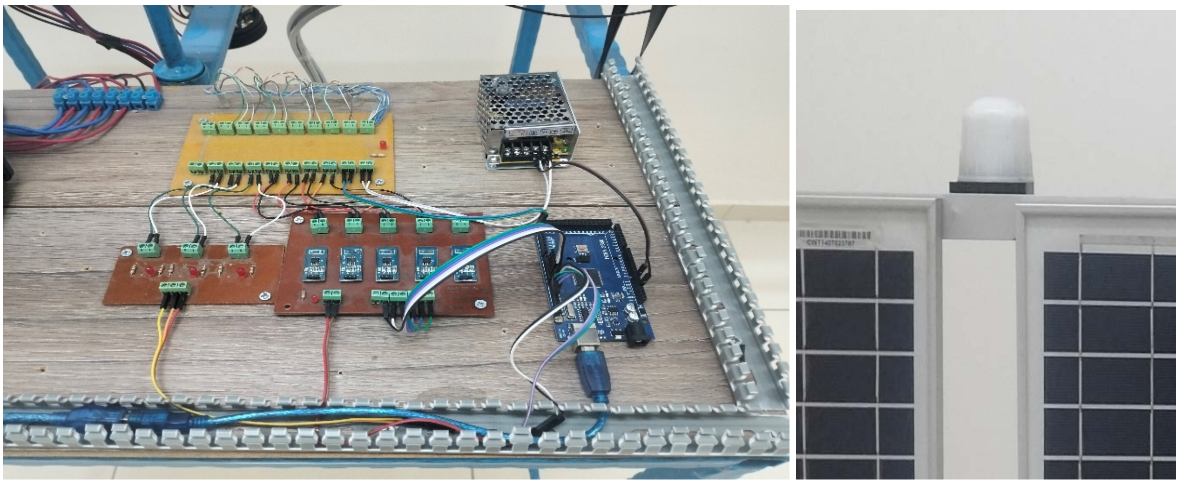
The data used in this study was obtained using monocrystalline and polycrystalline photovoltaic panels. Monocrystalline and polycrystalline solar panels are the two most used technologies in photovoltaic systems, and each offers certain advantages and disadvantages. Monocrystalline panels are produced from a single crystal structure, making them more efficient. During the production process, silicon crystals are grown in a special way, which achieves high efficiency. These panels generally have a longer lifespan because the single crystal structure produces electricity homogeneously, and there is less energy loss. In addition, monocrystalline panels are preferred in places with limited space, as they have the capacity to produce more energy while taking up less space. However, this efficiency makes the production process more complex and expensive, which increases initial costs. Polycrystalline panels are formed by combining multiple silicon crystals. This production process is simpler, and therefore, the costs of polycrystalline panels are lower than those of monocrystalline ones. However, the efficiency of polycrystalline panels is lower than monocrystalline panels because silicon crystals have a more heterogeneous structure, which means more losses in electricity production. Therefore, polycrystalline panels are generally preferred in projects that require energy production in large areas or with a lower budget. The efficiency of polycrystalline panels may vary depending on environmental factors, but the low production costs of these panels allow them to reach larger audiences. The choice between monocrystalline and polycrystalline solar panels is determined by the size of the area where the system will be placed, the budget, and the desired energy efficiency. Both panel types provide environmentally friendly energy production, allowing the full potential of solar energy to be utilized. Figure 2 shows the monocrystalline and polycrystalline solar panels used in the study. Table 1 shows the technical specifications of the monocrystalline and polycrystalline solar panels used in the study.

Figure 2. Monocrystalline and polycrystalline solar panels used in the study

Table 1. Technical specifications of monocrystalline, and polycrystalline solar panels

Electrical / Mechanical Properties	Monocrystalline	Polycrystalline
Maximum panel power (Pm)	20 Wp	20 Wp
Open Circuit Voltage (Voc)	21,5 V	21,9 V
Short Circuit Current (Isc)	1,24 A	1,19 A
Maximum Power Voltage (Vmp)	17,2 V	18,0 V
Maximum Power Current (Imp)	1,15A	1,11 A

In the study, ACS712 was used for the current sensor. Thanks to these current sensors, the currents produced by each solar panel were measured separately. Two resistors were used in series as voltage sensors. DHT22 sensor was used to measure temperature and humidity values. Arduino MEGA 2560 microcontroller was used to process the data coming from the sensors. The data coming from the sensors is processed thanks to Arduino microcontroller. In addition, all data is sent to the computer via USB port. All data produced in the study were recorded on the computer at 10-minute intervals. Figure 3a shows the current, voltage sensors and microcontroller used in the study, and 3b shows the temperature and humidity sensors.



a) b)

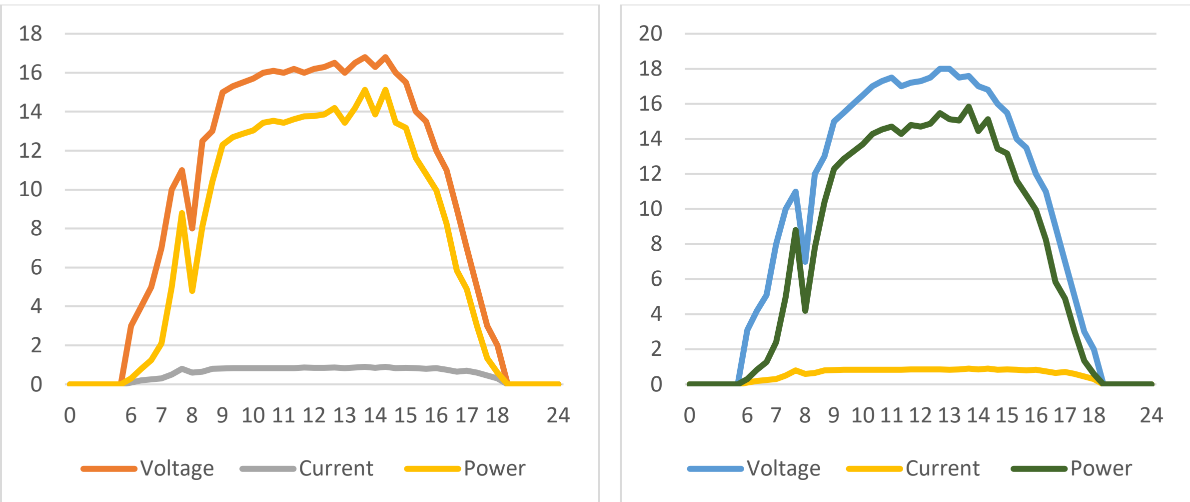
Figure 3a. Current, voltage sensors and microcontroller used in the study, **3b.** Temperature and humidity sensor

In this study, two monocrystalline and polycrystalline solar panels were used. It was used as a backup solar panel against possible failures in one solar panel. At the same time, the current and voltage of both solar panels were measured. Average values were taken after the measurement. Figure 4 shows the system prepared for this study.

Figure 4. The system prepared for this study

III. RESULTS AND DISCUSSIONS

In the study, 20 Wp monocrystalline and polycrystalline solar panels installed at Afyon Kocatepe University Dazkırı Vocational School were used. The energy production of the solar panels was measured instantly. Solar panels vary in their energy production according to seasons and weather conditions. Figure 5 shows the daily current, voltage, and power data of the monocrystalline and polycrystalline solar panels used in the study on 23/05/2023.



a) b)

Figure 5a. Monocrystalline solar panel, 5b. Voltage, current, and power data of polycrystalline solar panel

The study covers a one-year period between 01/01/2023 and 31/12/2023. Data was obtained from solar panels during this period. Figure 6 shows the one-year power data of monocrystalline and polycrystalline solar panels.

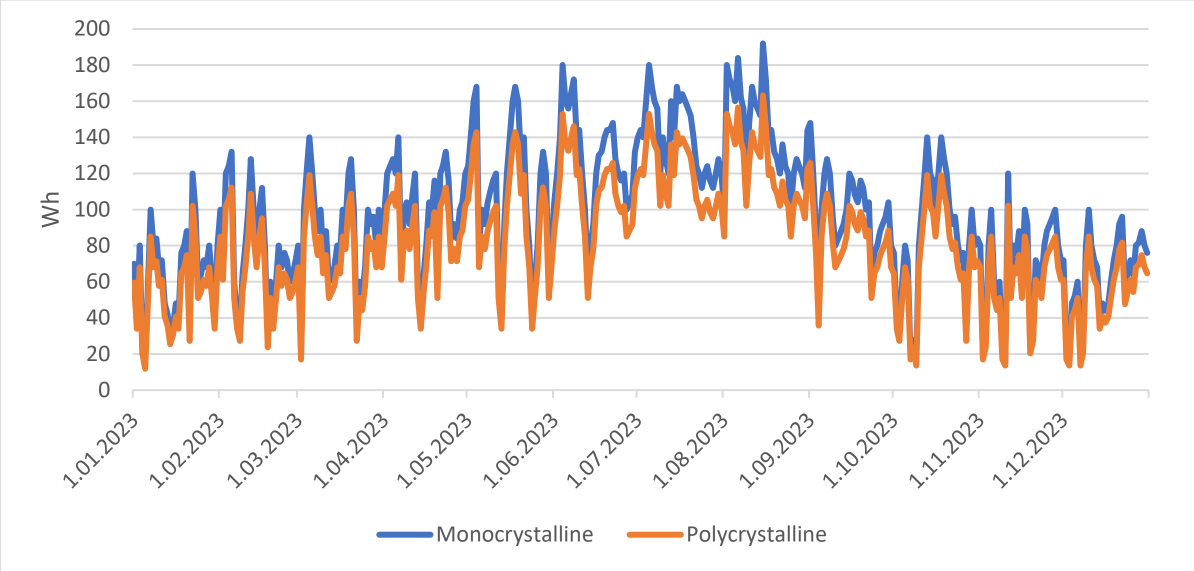


Figure 6. Annual energy production of monocrystalline and polycrystalline solar panels

The energy production of solar panels does not show changes throughout the year. While energy production decreases in winter months, it increases in summer months. The biggest reason for this is the increase in sunshine duration in summer months. When the weather is rainy and cloudy, the energy production of solar panels is very low. In the study, five different heuristic algorithms were used to estimate the energy production of solar panels. Separate studies were conducted for each solar panel. Figure 7 shows the energy production estimates of monocrystalline solar panels with different heuristic algorithms.

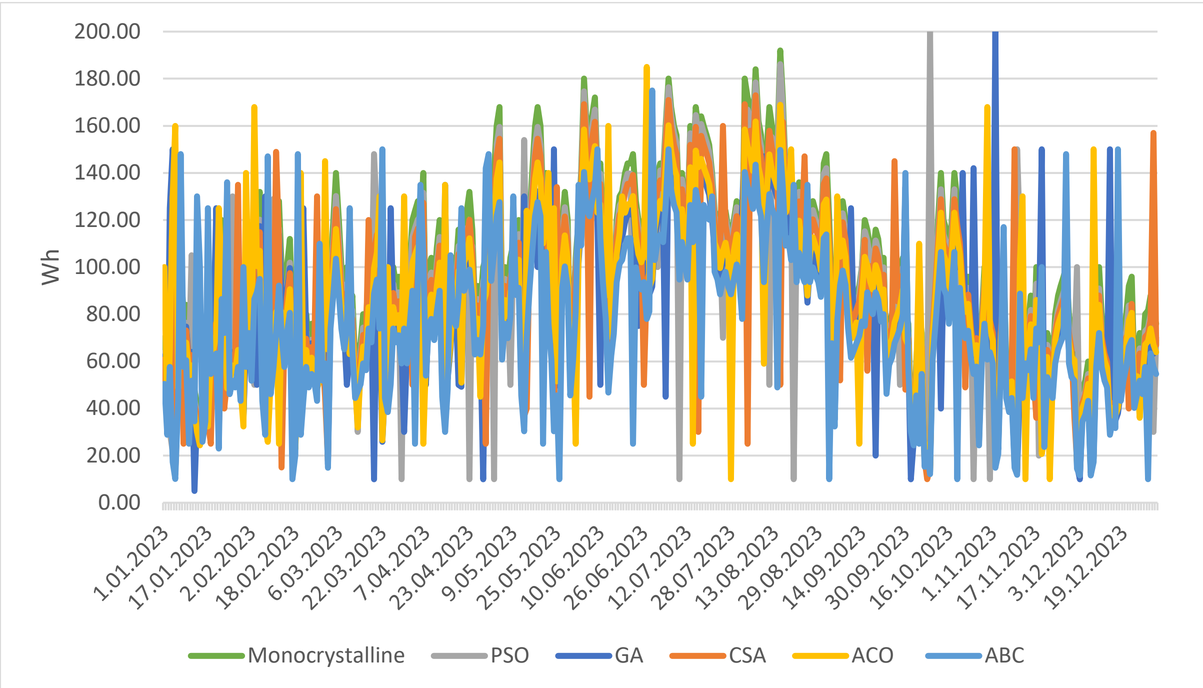


Figure 7. Five different heuristic algorithms for energy production estimates of monocrystalline solar panels

When Figure 3 is examined, it is seen that five different heuristic algorithms take very different values. Some days, very close results are seen for energy production. However, some days, very bad results are seen in the estimates. Figure 8 shows the energy production estimates of five different heuristic algorithms on a monthly basis.

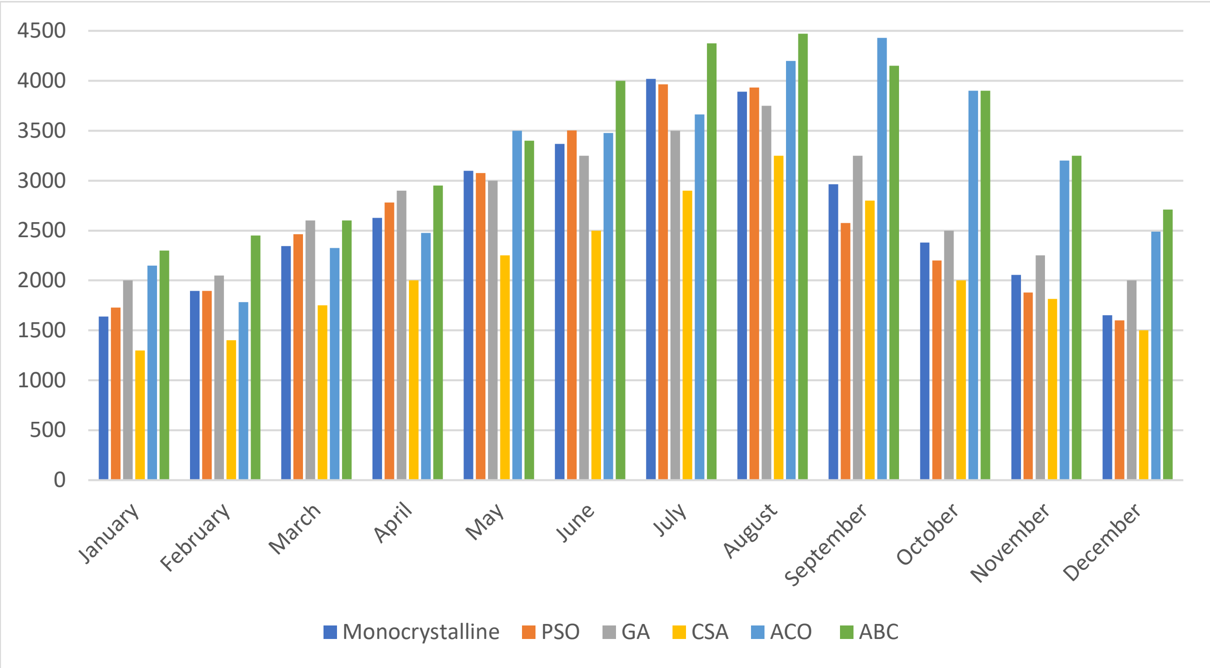


Figure 8. Monthly energy production forecast results of five different algorithms

When the energy production estimation results of heuristic algorithms are examined, it is seen that particle swarm optimization gives the best result, with 98.95%. The worst result is realized in ABC algorithm with 127%. The results in other algorithms are realized as 103.51% in GA algorithm, 117.23% in ACO algorithm, and 79.75% in CSA algorithm. Table 2 shows the evaluation results of the R^2, MAPE, and RMSE verification criteria of the measurement results of particle swarm optimization.

Table 2. Evaluation results of PSO, GA and, ACO measurement results with R^2, MAPE, and RMSE validation criteria

Months	R^2			MAPE			RMSE		
	PSO	GA	ACO	PSO	GA	ACO	PSO	GA	ACO
January	0.9996	0.9842	0.9715	0.3495	0.3506	0.3718	0.3523	0.3529	0.3681
February	0.9958	0.9831	0.9932	0.3115	0.3007	0.3349	0.3133	0.3127	0.3323
March	0.9947	0.9824	0.9981	0.4325	0.4421	0.2247	0.4725	0.4403	0.2215
April	0.9915	0.9958	0.9784	0.3548	0.3326	0.2340	0.3869	0.3297	0.2327
May	0.9958	0.9835	0.9865	0.2218	0.3007	0.2864	0.2389	0.3024	0.2830
June	0.9913	0.9803	0.9726	0.2896	0.3105	0.3009	0.2112	0.3057	0.2982
July	0.9957	0.9844	0.9738	0.2558	0.2339	0.2117	0.2047	0.2291	0.2083
August	0.9936	0.9953	0.9768	0.2317	0.2114	0.2063	0.2901	0.2082	0.2048
September	0.9948	0.9912	0.9837	0.2559	0.2947	0.2142	0.2052	0.2903	0.2130
October	0.9928	0.9974	0.9903	0.3734	0.3562	0.3375	0.3351	0.3517	0.3344
November	0.9984	0.9805	0.9915	0.4469	0.4320	0.4128	0.4286	0.4291	0.4103
December	0.9972	0.9914	0.9729	0.3167	0.2997	0.2495	0.3094	0.2924	0.2477

The best estimate for energy production of monocrystalline photovoltaic solar panels was achieved with the PSO algorithm. Validation criteria were applied to the results of the PSO algorithm. An R^2 value close to 1 indicates that the model provides a strong fit with the data and is successful in its predictions. When the R^2 results are examined in Table 1, values very close to 1 are seen. It is determined that the estimation results made with the PSO algorithm are very consistent. Figure 9 shows the energy production estimates of the polycrystalline solar panel with five different heuristic algorithms.

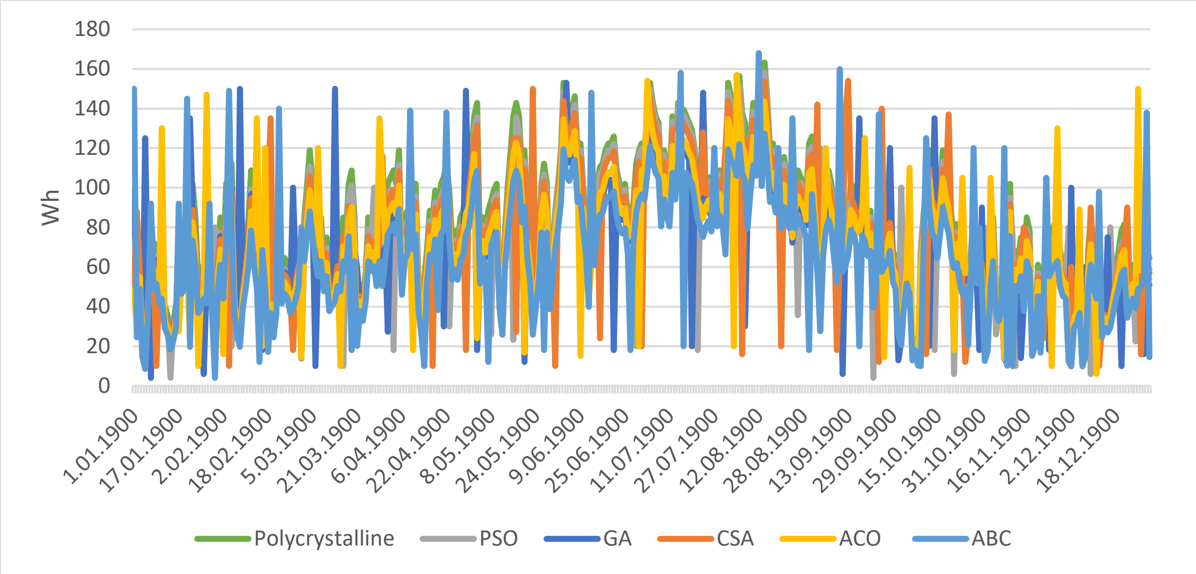


Figure 9. Five different heuristic algorithms for energy production predictions of polycrystalline solar panels

Polycrystalline solar panels produce lower levels of power than monocrystalline solar panels. When Figure 1 is examined, it is seen that the estimates change a lot in the winter months. Results are closer to energy production in the summer months. The reason for this is the weather events that occur in the winter months. Rain, snow, and closed weather conditions make it difficult to estimate energy production, which is very little or not at all. Figure 10 shows the energy production estimates of five different heuristic algorithms on a monthly basis.

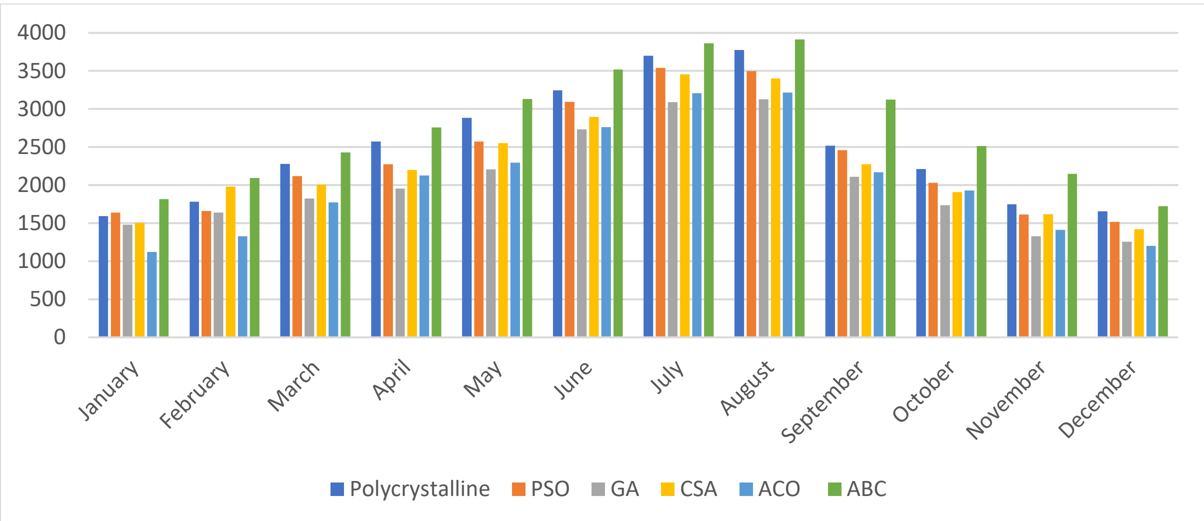


Figure 10. The energy production estimates of five different heuristic algorithms on a monthly basis

The best result in energy production of polycrystalline solar panels was 93.94% in particle swarm optimization. The worst result was 134% in ABC algorithm. The results in other algorithms were 90.13% in ACO algorithm, 111.17% in CSA algorithm and 87.38% in GA algorithm. Table 3 shows the R^2, MAPE, and RMSE verification criteria evaluation results of particle swarm optimization measurement results.

Table 3. Evaluation results of the measurement results of PSO, ACO and CSA of polycrystalline solar panel using R^2, MAPE, and RMSE validation criteria

Months	R^2			MAPE			RMSE		
	PSO	ACO	CSA	PSO	ACO	CSA	PSO	ACO	CSA
January	0.9891	0.9771	0.9239	0.4383	0.4112	0.4952	0.5382	0.4328	0.5107
February	0.9747	0.9218	0.9007	0.4092	0.4268	0.4737	0.5093	0.4218	0.4713
March	0.9843	0.9392	0.9561	0.6187	0.5194	0.5561	0.4507	0.5348	0.5595
April	0.9807	0.9948	0.9746	0.5398	0.5567	0.5937	0.4611	0.5349	0.6004
May	0.9849	0.9736	0.9852	0.4057	0.4318	0.5007	0.5090	0.4501	0.4861
June	0.9801	0.9945	0.9781	0.4759	0.4961	0.4073	0.5057	0.4719	0.4362
July	0.9835	0.9804	0.9883	0.4430	0.4178	0.4346	0.4903	0.4264	0.4591
August	0.9818	0.9732	0.9844	0.4104	0.3993	0.4073	0.5618	0.4107	0.4327
September	0.9839	0.9895	0.9368	0.4299	0.4057	0.4429	0.5933	0.4139	0.4406
October	0.9812	0.9867	0.9557	0.4516	0.4243	0.4738	0.5130	0.4231	0.4797
November	0.9871	0.9553	0.9719	0.4123	0.3985	0.4007	0.5083	0.4034	0.4232
December	0.9869	0.9731	0.9640	0.4015	0.4419	0.4535	0.4955	0.4478	0.4458

The best estimation in polycrystalline photovoltaic solar panel energy production was achieved using the PSO algorithm. Validation criteria were applied to the results of the PSO algorithm. Three different MAPE, R^2, and RMSE validation criteria were applied in the study. When examining the consistency of the study, it is necessary to examine the three criteria together. The fact that the variance result is close to 1 proves that the results are very consistent. Sometimes high variance values may be due to over-learning. For this, it is necessary to examine the MAPE and RMSE values. When Table 3 is examined, it is understood that the R^2 values are not very close to 1. When the estimation results are examined, it is a parallel value with a correct rate of 93%. It is understood that the other MAPE and RMSE values are parallel to the estimation result.

IV. CONCLUSIONS

In this study, the energy production of monocrystalline and polycrystalline solar panels was estimated using different heuristic algorithms. In the study, a comparative evaluation of the real power values and the power values obtained with Particle Swarm Optimization, Genetic Algorithm, Clonal Selection Algorithm, Ant Colony Optimization and Artificial Bee Colony heuristic algorithms was also made.

A data set was prepared for use in the study. An experimental set was created in Afyo Kocatepe University Dazkırı Vocational School to create the data set. 20Wp monocrystalline and polycrystalline solar panels were used in this set. The voltage, current, power, outdoor temperature, and humidity values produced by the solar panels were measured instantly. All data are viewed instantly on the computer screen. At the same time, all data are recorded at 10-minute intervals. One year of data was collected and used in five different heuristic algorithms.

The energy production estimates of the monocrystalline photovoltaic solar panel as a result of five different heuristic algorithms were realized as PSO 98.95%, GA 103.51%, ACO 117.23%, CSA 79.75%, and ABC 127%. The energy production estimates of the polycrystalline photovoltaic solar panel as a result of five different heuristic algorithms were realized as PSO 93.94%, ACO 90.15%, CSA 111.17%, GA 87.38%, and ABC 134%. The best result from both different photovoltaic solar panel types was realized in the PSO algorithm. In the study, MAPE, RMSE and R^2 statistical criteria were used in the verification of the estimation results with real power values. When the verification results obtained from all three criteria were examined, it was seen that the PSO algorithm was successful. In the next stage, increasing the number of inputs to be given to the network and measuring additional input parameters such as solar radiation data will affect the estimation performance.

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