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Original Article

Forecasting the Power Output of Photovoltaic Systems Using Ant Colony Optimization and Determining the Optimal Time Interval for Agricultural Use

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ABSTRACT

The rapid increase in global energy demand, driven by industrialization, population growth, and technological advances, has emphasized the importance of the transition to renewable energy sources. In addition, renewable energy, especially photovoltaic (PV) systems, has become a widespread energy source in agricultural applications to meet the energy needs in agricultural irrigation. However, the efficiency of PV systems varies depending on meteorological and environmental factors such as solar radiation and temperature. Therefore, predictability of energy production is a critical requirement for the effective operation of irrigation systems. In this study, the Ant Colony Optimization (ACO) algorithm is implemented to estimate the power output of PV systems using historical solar radiation, temperature, and actual power production data. Inspired by the foraging behavior of ants, the ACO algorithm optimizes the estimation process by iteratively refining the solutions based on pheromone trails and adaptive learning. The proposed method is evaluated using a case study on a solar power plant located in the Central Anatolian region of Türkiye. The accuracy of the model is evaluated by comparing the predicted values with the actual measurements at various time periods including hourly, daily, weekly, monthly and seasonal forecasts. The results show that the ACO based forecast model provides high accuracy in predicting the PV power output, with the Mean Absolute Percentage Error (MAPE) values improving as the forecast period increases. The findings of this study suggest that ACO is a robust and efficient optimization technique to improve PV power forecasting. The proposed model provides strategic information that can be used in energy planning of agricultural irrigation systems with high accuracy.

Key words: Photovoltaic Systems, Power Prediction, Ant Colony Optimization, Renewable Energy, Solar Radiation.

Karınca Kolonisi Optimizasyonu ile Fotovoltaik Sistemlerin Güç Çıkışının Tahmini ve Tarımsal Kullanım İçin En Uygun Zaman Aralığının Belirlenmesi

ÖZ

Küresel enerji talebindeki hızlı artış, sanayileşme, nüfus artışı, teknolojik ilerlemeler tarafından yönlendirilen, yenilenebilir enerji kaynaklarına geçişin önemini vurgulamıştır. Bunun yanında, tarımsal sulamada enerji ihtiyacını karşılamak için yenilenebilir enerji, özelliklede fotovoltaik (PV) sistemler aracılığıyla tarımsal uygulamalarda yaygınlaşan bir enerji kaynağı haline gelmiştir. Ancak, PV sistemlerinin verimi, solar ışınımı ve sıcaklık gibi meteorolojik ve çevresel faktörlere bağlı olarak değişkenlik göstermektedir. Bu nedenle, sulama sistemlerinin etkin çalışması için enerji üretiminin öngörülebilir olması kritik bir gerekliliktir. Bu çalışmada, PV sistemlerinin güç çıktısını tahmin etmek için Karınca Kolonisi Optimizasyonu (KKO) algoritması, geçmiş solar ışınımı, sıcaklık ve gerçek güç üretim verileri kullanılarak uygulanmıştır. KKO algoritması, karıncaların yiyecek arama davranışından esinlenerek, feromon izleri ve adaptif öğrenme temelinde çözümleri yinelemeli olarak rafine ederek tahmin sürecini optimize eder. Önerilen yöntem, Türkiye'nin Orta Anadolu bölgesinde bulunan bir güneş enerjisi santrali üzerine yapılan bir vaka çalışması kullanılarak değerlendirilmektedir. Modelin doğruluğu, saatlik, günlük, haftalık, aylık ve mevsimsel tahminler dahil olmak üzere çeşitli zaman dilimlerinde tahmin edilen değerlerin gerçek ölçümlerle karşılaştırılmasıyla değerlendirilir. Sonuçlar, KKO tabanlı tahmin modelinin PV güç çıktısını tahmin etmede yüksek doğruluk sağladığını, Ortalama Mutlak Yüzde Hatası (OMYH) değerlerinin tahmin süresi uzadıkça iyileştiğini göstermektedir. Bu çalışmanın bulguları, KKO'nun PV güç tahminini geliştirmek için sağlam ve verimli bir optimizasyon tekniği olduğunu önermektedir. Önerilen model, tarımsal sulama sistemlerinin enerji planlamasında yüksek doğrulukla kullanılabilecek stratejik bilgiler sunmaktadır.

Anahtar kelimeler: Fotovoltaik Sistemler, Güç Tahmini, Karınca Kolonisi Optimizasyonu, Yenilenebilir Enerji, Solar Işınım.

INTRODUCTION

Energy demand is rapidly increasing due to technical developments, industrial operations and the continuous increase in the global population. As a result, electrical energy has emerged as a vital element of contemporary life with an increasing demand. Turkey, similar to the global trend, receives a significant portion of its energy requirements from fossil fuels. The harmful effects and ecological consequences of fossil fuels on sustainability lead to significant environmental problems such as global climate change, increasing temperatures and glacial melting.

Agricultural irrigation plays a vital role in the sustainability of productivity in agricultural production, and the energy requirement of irrigation systems constitutes a significant operational cost item for farmers. Especially in arid and semi-arid climate zones, the effective operation of irrigation systems is largely dependent on energy. At this point, solar energy, which stands out among renewable energy sources, both ensures environmental sustainability and reduces the problem of access to energy in rural areas. However, the performance of PV systems varies depending on meteorological parameters such as sunshine duration, radiation intensity and ambient temperature. Therefore, it is critical to be able to accurately predict solar energy production in order to optimize the timing and capacity planning of agricultural irrigation systems.

Greenhouse gases emitted especially as a result of burning fossil fuels contribute significantly to critical environmental problems such as global warming and climate change. This scenario disrupts the balance of ecosystems by affecting natural habitats, sea levels and air quality. As a result, it is imperative to switch to renewable energy sources to ensure a reliable, environmentally friendly and sustainable energy future. Renewable sources such as wind, solar and hydroelectric energy hold significant promise for environmental sustainability and serve as an alternative to limited fossil fuel resources.

The Global Status Report (Members, 2023) shows that recent global public opinion polls reveal an increasing interest in renewable energy sources. In recent years, solar energy has received the most attention and has the largest capacity expansion among renewable energy sources. The increasing interest is due to the numerous benefits provided by solar energy. Solar energy is an abundant and inexhaustible source that does not create air pollution. Its transportation costs are very low, which distinguishes it from alternative energy sources (Members, 2023). In recent years, solar energy has become the fastest growing renewable energy source in Türkiye (Figure 1).

In light of sustainability goals and increasing environmental problems, environmentally friendly energy production is very important today. As a result, solar energy is emerging as a more ecologically sustainable approach to electricity generation. The sun acts as a source of heat and light, generating energy by emitting equal amounts of light in all directions. These features make solar energy a clean, silent, inexhaustible and reliable alternative to other energy sources.

The high cost and low efficiency of photovoltaic panels are the main reasons why solar energy is not yet a major energy source. However, current research and technology developments have led to a significant decrease in solar module prices. This has made solar energy more accessible. In particular, since 2020, photovoltaic module costs have decreased by more than 40% (Irena, 2020). This decrease and its continuation are expected to make solar energy more economically viable and expand its applications.

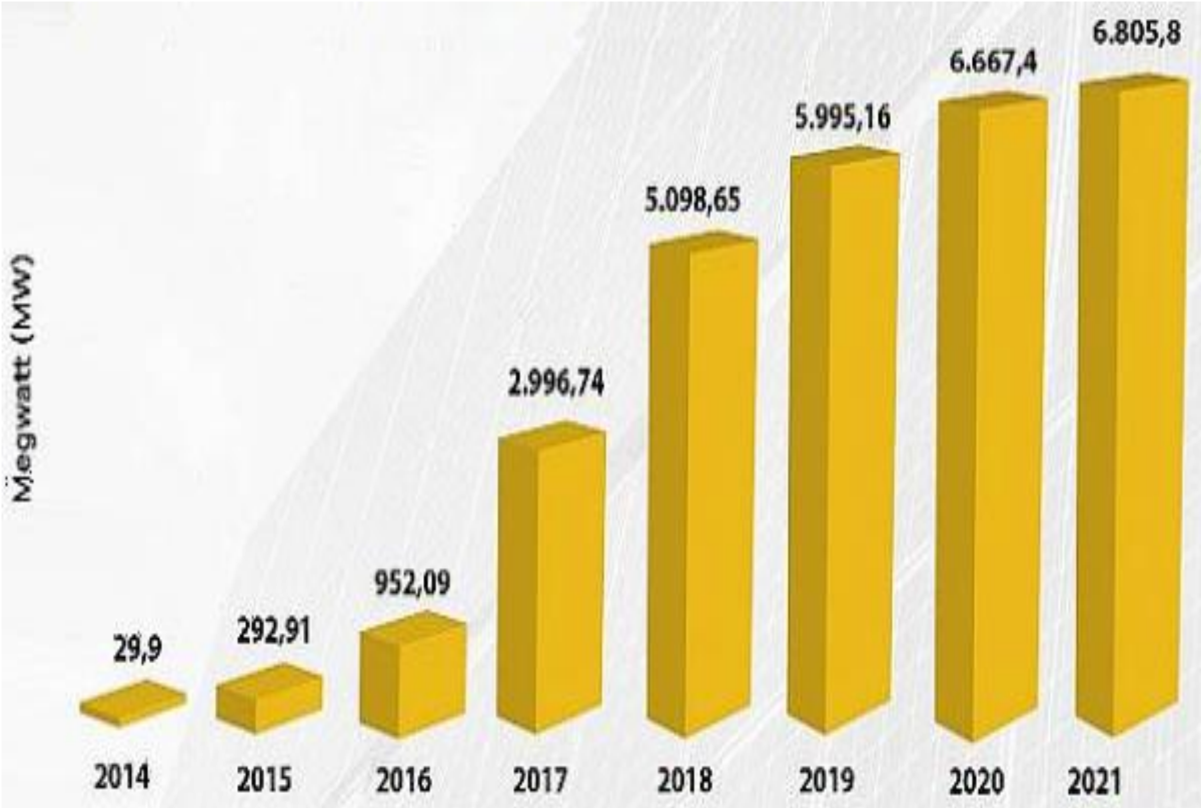

Figure 1. Total installed capacity of solar energy in Türkiye by years.

Solar radiation continuously serves as the main energy source for photovoltaic systems; therefore, accurate assessment of solar radiation is essential for the operation of power grids and photovoltaic systems. A review of similar studies in the literature reveals various methodologies and strategies used in photovoltaic power assessment. Mandal et al. proposed a hybrid artificial intelligence (AI) and wavelet transform (WT) method to estimate PV output power. Wind turbulence greatly affects the time series data of photovoltaic generation, but AI solutions reduce photovoltaic variations (Mandal et al., 2012). Zhang et al. collected data using panel temperature, average temperature, relative humidity, and solar radiation. The genetic algorithm-based backpropagation ANN prediction model produced RMSE at 0.11 MW and MAPE at 3.31 MW in daily predictions, as well as the proposed k-means result (Zhang et al., 2021). Netsanet et al. determined the MAPE values as 22.31 MW and RMSE values as 0.71 MW for the long-short-term memory-based neural network model. In hourly photovoltaic power prediction, the 2NN model based on variational mode decomposition and ant colony optimization outperformed the ANN models based on genetic algorithm and ant colony optimization (Netsanet et al., 2022). Visser et al. studied multiple machine learning models for photovoltaic power prediction using historical photovoltaic power data and meteorological projections (Visser et al., 2019). Daily precipitation, relative humidity, air temperature, wind direction, active energy, and global and scattered horizontal solar radiation data were used for a temporal convolutional network model developed by Zhang et al. (Zhang et al., 2021). Liang et al. discovered that weather uncertainty and error rates increase as the forecast period increases and proposed a combination of decision trees, an improved whale bat optimization algorithm, and least squares support vector regression (Liang et al., 2023). Huang et al. presented a weather forecast-based PV power forecast using K-means clustering to categorize historical production data and a long-short memory neural network with attention mechanism to improve power forecasting (Huang et al., 2019).

The power generation of photovoltaic systems may vary depending on environmental conditions. The performance of photovoltaic systems is subject to daily and seasonal fluctuations due to environmental factors such as solar radiation, seasonal changes, and weather conditions. These differences pose a significant obstacle, especially for the planning and installation of large-scale photovoltaic systems. Changes in power generation affect the decision-making processes of large-scale systems, and strategic planning should be made considering these changes. Therefore, it is very important to estimate the power production in advance so that the systems can be installed in suitable areas and capacities.

This study aims to estimate the power production to be obtained from PV systems with a model based on the ACO algorithm. The performance of the model at hourly, daily, weekly, monthly and seasonal levels was evaluated and error rates were calculated. In addition, it is aimed to provide strategic information in planning the most appropriate irrigation scheduling in agricultural irrigation with the power output estimation of PV systems.

MATERIALS AND METHODS

PV Model

PV systems are semiconductor devices used to convert solar energy directly into electrical energy. PV systems are becoming increasingly important among renewable energy sources, especially in today's world where energy demand is increasing and dependence on fossil fuels must be reduced, by offering environmentally friendly, sustainable and economical solutions. Photovoltaic panels, which usually consist of silicon-based cells, use the photovoltaic effect to convert solar radiation into electrical energy.

The physical and environmental conditions that affect the panel's electricity production can be modeled with mathematical expressions for PV models. A photovoltaic cell produces electricity based on solar radiation (Hossain & Mahmood, 2020). Sunlight intensity, module efficiency, temperature, and the orientation and tilt of the panel are among the many factors that affect the performance of photovoltaic systems. Maximum power point (MPP) tracking technologies, inverters and control systems ensure that the system always reaches its optimum performance level. This maximizes energy production and increases the efficiency of the system.

Advantages:

• Renewable Energy Source: Solar energy is an unlimited source.
• Environmentally Friendly: Generates electricity without carbon emissions.
• Low Operating Costs: Systems are generally long-lasting and have low maintenance costs.

Disadvantages:

• High Initial Cost: Installation and initial investment costs can be high.
• Weather Dependent: Production may decrease on cloudy or rainy days.
• Area Requirement: High power production requires a large area.

PV output power can be affected by many factors. Panel structure, natural events and panel location are among the many factors that can affect output power and efficiency. The most important factors affecting PV output power, such as solar radiation, temperature, number of panels and efficiency, are explained below.

Solar Radiation (W/m2): Solar radiation measured in W/m2 directly affects the energy output of photovoltaic panels. Under standard test conditions (STC), solar radiation is expected to be 1000 W/m². However, daily variations, cloud cover and geographical location can affect actual radiation values (HassanzadehFard et al., 2020).

Temperature (T): The efficiency of solar panels depends on temperature. Environmental variables such as temperature and radiation significantly affect the output power of the photovoltaic module. Rising temperatures can reduce the voltage of solar cells and thus reduce the overall output. Panels reach optimum power at 25°C; however, efficiency decreases with increasing temperatures. The temperature coefficient (%β) affects this phenomenon. This varies between -0.3% and -0.5% per degree for the majority of panels (Singh et al., 2020).

Number of Panels (N): The number of panels used in the system affects the overall power output. Various calculations are made using series or parallel configurations. Series-connected panels increase the voltage while maintaining a constant current. Parallel-connected panels increase both current and voltage. Equation 1 is used to determine the output power of the photovoltaic module (Sultan et al., 2021):

$$P_{PV} = \eta \times A \times G \tag{1}$$

In this context, η represents the overall efficiency of the photovoltaic panel, A denotes the area of the photovoltaic panel, and G signifies the solar radiation.

Efficiency (η): In photovoltaic systems, energy losses occur due to factors such as inverters, wiring, thermal losses and pollution. The overall efficiency of photovoltaic panels is determined using Equation 2 (Sultan et al., 2018):

$$\eta = \eta_r \times \eta_t \times \left[1 - \beta_T \times (T_c - 25) - \beta_T \times I_r \times \left(\frac{T_{nom} - 20}{800}\right) \times (1 - \eta_r \times \eta_t)\right] \tag{2}$$

In this context, η_r denotes the reference efficiency, while η_t represents the highest power point efficiency. β_T denotes the temperature coefficient. T_c denotes the cell temperature, while T_{nom} signifies the nominal cell temperature.

The output power of photovoltaic systems is directly affected by environmental conditions and system components. In fact, shadow, pollution, and maintenance conditions can reduce efficiency. As a result, temperature effects and losses should be taken into account during system design. To achieve maximum power, efficient panels should be selected, optimum panel positioning should be provided, and high-efficiency inverters should be used.

Ant Colony Algorithm (ACO)

ACO is a metaheuristic optimization technique derived from the behavior of ant colonies in nature in finding food and returning to their nests. This approach determines the optimal solution by a collection of virtual "ants" that randomly traverse the solution space. Ants determine their routes within the solution space using chemical agents known as "pheromones". The density of pheromones fluctuates according to the quality of these routes, and over time, the evaporation of these trails reduces the influence of less preferred channels (Dorigo & Stützle, 2019).

After this procedure is completed, routes with higher pheromone concentrations represent superior solutions, which leads to a preference for these routes among other ants. The cooperative action of ants facilitates the discovery of superior and more efficient solutions within the solution space (Blum, 2005).

Utilization of Ant Colony Optimization for Estimating Photovoltaic Power Output

Ant Colony Algorithm is an effective technique especially for complex and multivariate optimization challenges. This paper describes the application of ACO in predicting the power output of photovoltaic systems (Xia et al., 2024).

Solution Space: The output of photovoltaic power depends on various factors such as solar radiation, temperature, humidity, wind speed and panel efficiency. These parameters are related to the solution space that each ant moves in the ACO algorithm. The ants try to optimize these variables and determine the parameters that will give the most accurate power estimate (Titri et al., 2017).

Pheromone System and Fitness Function: Ants use pheromones to indicate the path they follow in the solution space; this depends on the degree of error between the estimated and actual power outputs. The fitness function is represented by error, such as Mean Absolute Error (MAE) or MAPE. Ants prefer paths that produce minimum error values.

Iterations and Optimization: Iterations and Optimization: ACO continues until an optimal solution is determined by an iterative procedure. Over time, pheromones start to attract paths closer to the optimal solution. As a result, an optimized model is created that calculates the power output of the photovoltaic system, taking into account solar radiation, temperature, and other environmental variables. The process flow of ACO is shown in Figure 2.

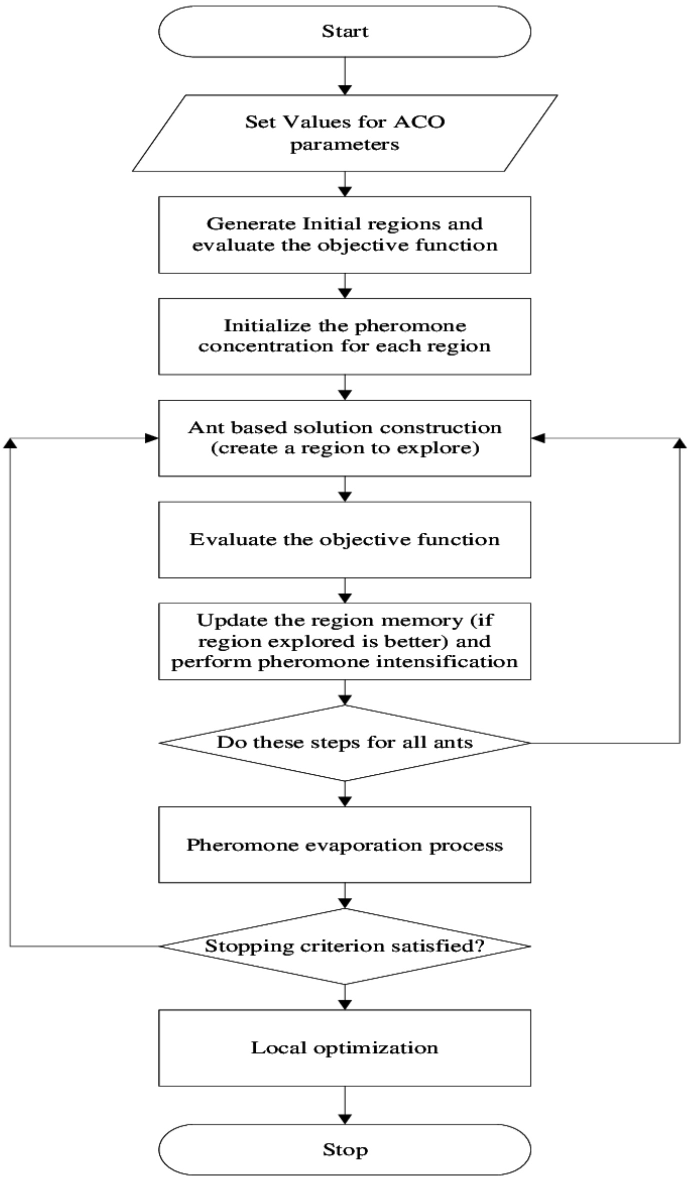

Figure 2. Ant Colony Algorithm (Nandihal et al., 2022).

RESULTS AND DISCUSSION

In this study, an ACO model is used to estimate the power generation of PV systems using a case study of a solar power plant located in the Central Anatolia Region of Türkiye. In order to evaluate the effectiveness of the model, the actual measured data and predicted power values of the PV system are evaluated. The effect of the output power on solar radiation and temperature is analyzed and the predicted results are compared with the actual values of the photovoltaic system. According to the power output estimates of the PV systems, it is aimed to provide preliminary information on the most effective and efficient planning of irrigation in which hours, days, months and seasons to meet the energy needs in agricultural irrigation. The analyses are conducted in multiple time intervals and the correlation between the produced results and the actual results is evaluated using graphical representations. In order to verify the precision of the estimates, the MAPE values are calculated and shown in a comparable manner. The MAPE equation is shown in Equation 3.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{P_{Real}-P_{Prediction}}{P_{Real}}\right| * 100 \quad (3)$$

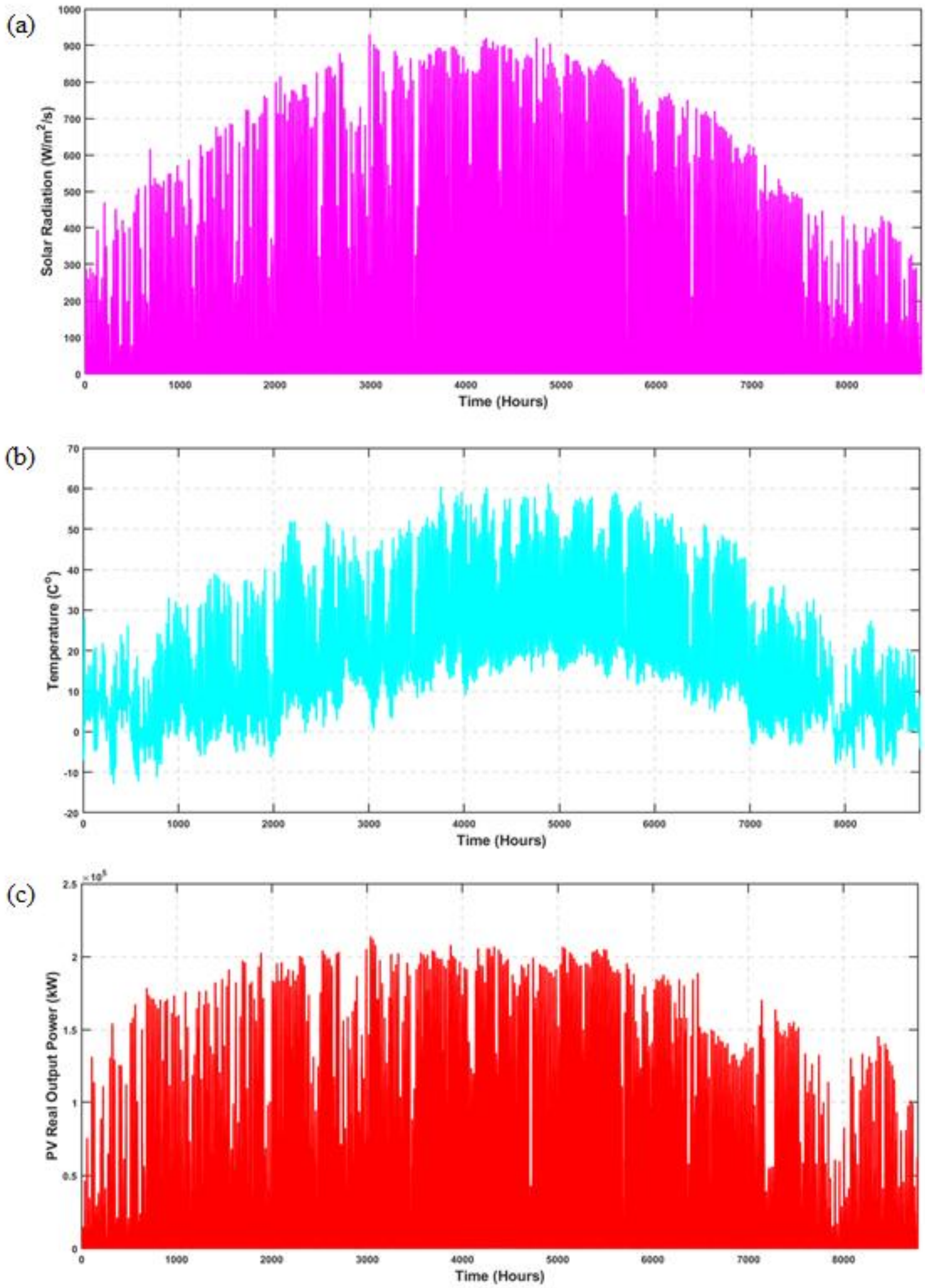

Figure 3. One year data (a) Solar radiation (b) Temperature (c) Real power output

Five hundred watt photovoltaic panels were used in the study. The efficiency of the panels was 22%. Annual solar radiation, temperature and real power production variables were used to evaluate the power of the photovoltaic panels.

Figure 3 shows the daily solar radiation, temperature and real power values for panels (a), (b) and (c) during a year, respectively. Figure 3(a) shows the daily variation in solar radiation. Temporal variations in solar radiation directly affect the energy production capacity of photovoltaic panels.

Figure 3(b) shows the daily temperature fluctuations. Temperature significantly affects the efficiency of photovoltaic panels. An increase in temperature usually results in a decrease in panel efficiency.

Figure 3(c) shows the daily real power output of photovoltaic panels. The change in power production with solar radiation and temperature can be easily seen here. In order to evaluate the efficiency of the forecast model, the forecast power levels were juxtaposed with the real measured values over several periods. The analyses were carried out daily, weekly, monthly and seasonally over a year. In addition, July, the sunniest month with the highest power output of the year, was compared with July 7, the month with the highest production intensity in July. Energy production increases on days with high solar radiation, allowing irrigation systems to operate for longer and more powerfully. However, the efficiency of PV panels decreases as the temperature increases. This situation reveals the need to pay attention to energy efficiency, especially in summer months, in irrigation processes.

Figure 4 shows the graph between the real power measured hourly and the predicted power over a year. The hourly analysis for one year shows that there is a significant consistency between the estimated and actual power outputs. In the instantaneous temperature and solar radiation change values, there are small differences between the ACO algorithm and the actual values. The MAPE value was determined to be 16.433% per day. The error margin of the model in hourly estimates is higher than other time periods. This is due to the fact that sudden weather changes (cloudiness, temperature increase, etc.) during the day directly affect energy production. Energy insufficiency may occur especially in periods when there is little sunlight, such as early morning or late afternoon.

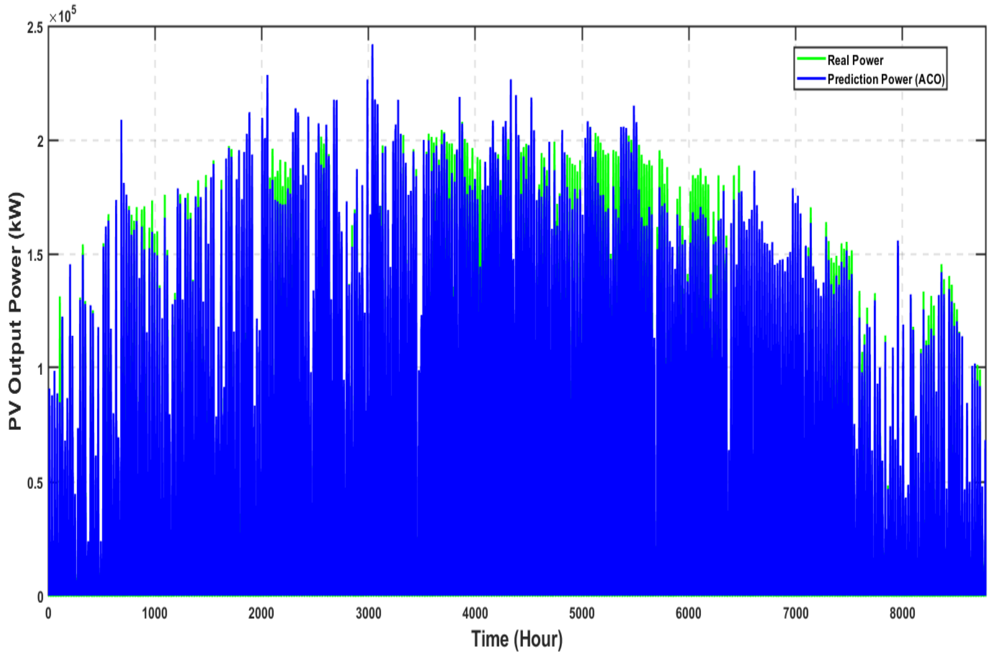

Figure 4. Graph of actual power and predicted output power in hours over a year

Figure 5 shows the correlation between daily actual power and estimated power over one year of data. The daily study shows that there is a significant consistency between the estimated and actual power outputs. However, the model was not able to adequately predict certain sudden short-term fluctuations. The MAPE value was determined to be 11.472% per day. Although daily forecast accuracy has been improved, short-term sudden changes can negatively affect model performance at this level. It is possible to benefit from this data in the daily scheduling of irrigation systems; for example, it can be said that the energy needs of water pumps can be met on days when sunlight is more intense, and battery support can be planned against energy shortage on cloudy days.

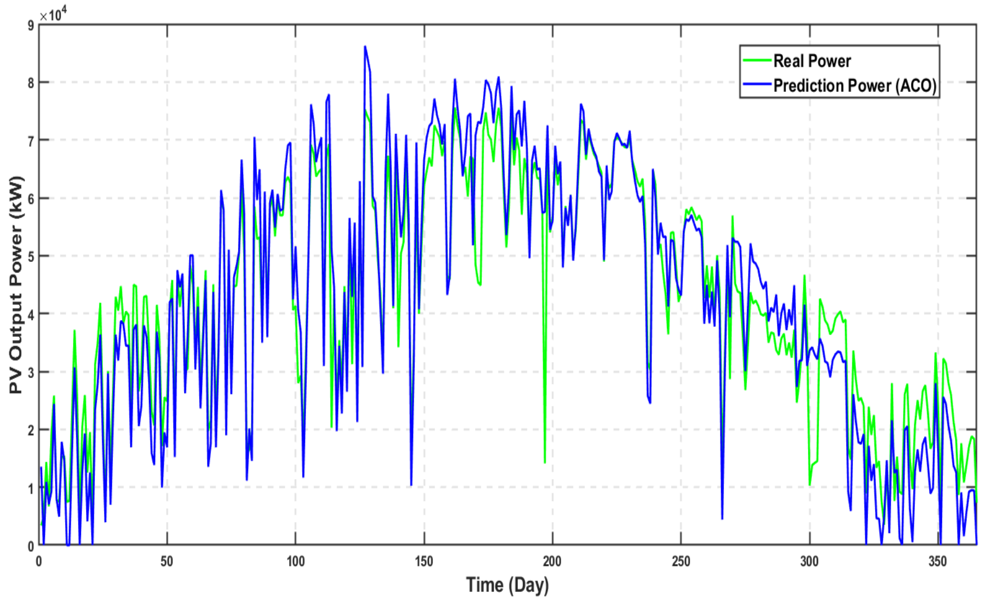

Figure 5. Graph of actual power and predicted output power by day of a year

Figure 6 shows the weekly changes in the real power value and the estimated power. The weekly analysis shows that the daily changes are more stable. The model has effectively determined the general trend and the error rate is reduced compared to the daily analysis. The MAPE value of the weekly estimates is determined as 9.705%. The weekly estimates provide a more stable view and show that the general trends in energy production are correctly captured. This level of accuracy can be very useful for farmers who create weekly irrigation schedules. For example, synchronizing the irrigation activities to be carried out on certain days of the week with energy production can increase the system efficiency.

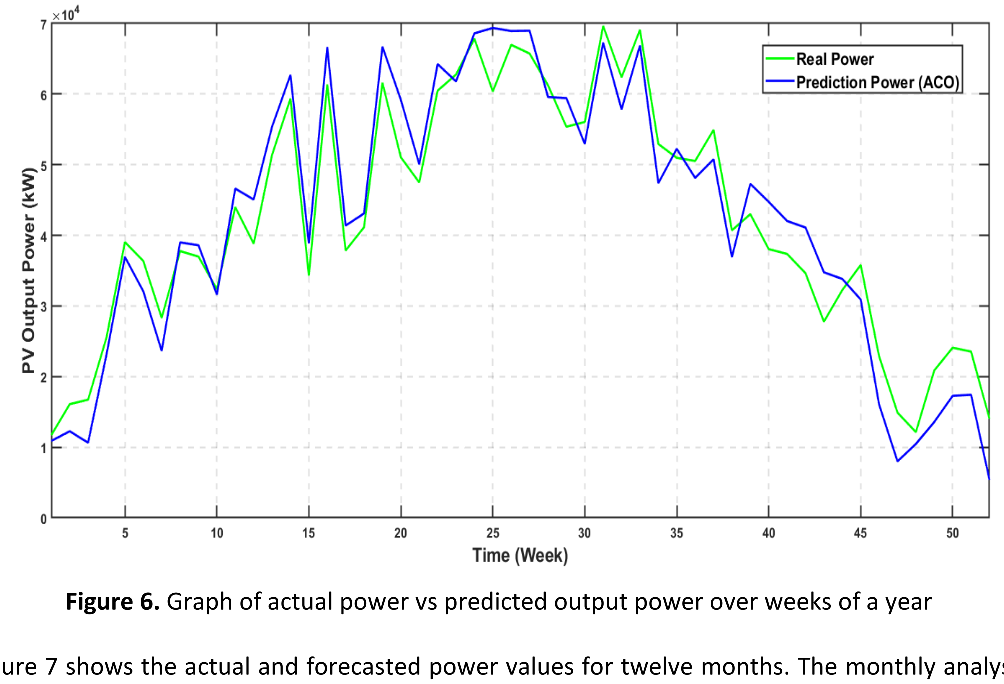

Figure 6. Graph of actual power vs predicted output power over weeks of a year

Figure 7 shows the actual and forecasted power values for twelve months. The monthly analysis shows that the model can predict power production with exceptional accuracy. Errors due to temporary fluctuations are less pronounced in this context, and the MAPE value is calculated as 7.414%. The lower margin of error in monthly forecasts allows the creation of long-term strategies in energy planning. Large-scale agricultural enterprises can more effectively manage irrigation frequency, system capacity and water consumption based on monthly energy production forecasts. In addition, energy storage solutions integrated into irrigation systems can be optimized with such forecasts.

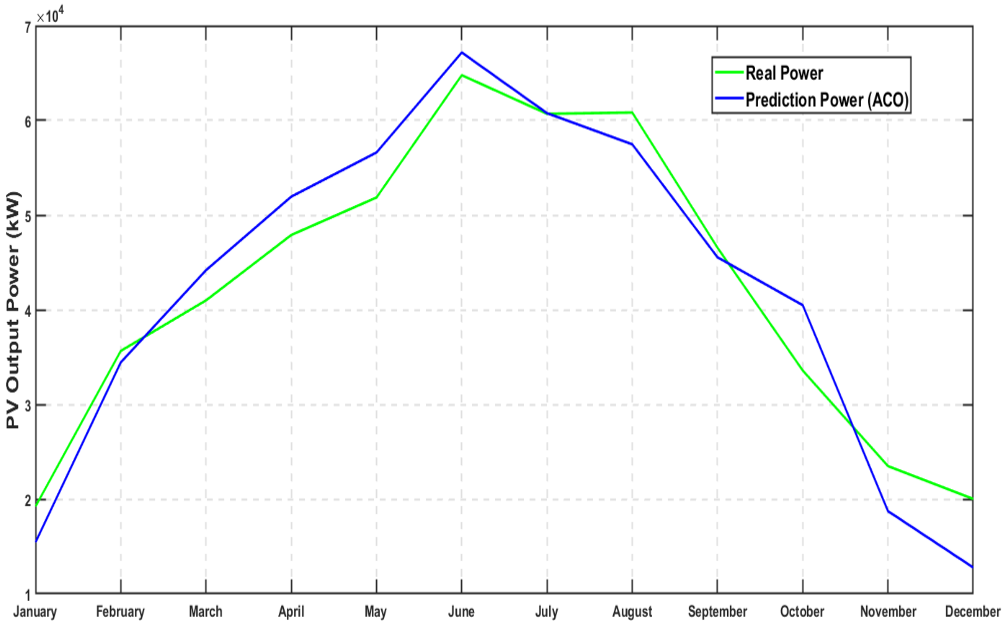

Figure 7. Twelve-month actual power vs. projected output power graph

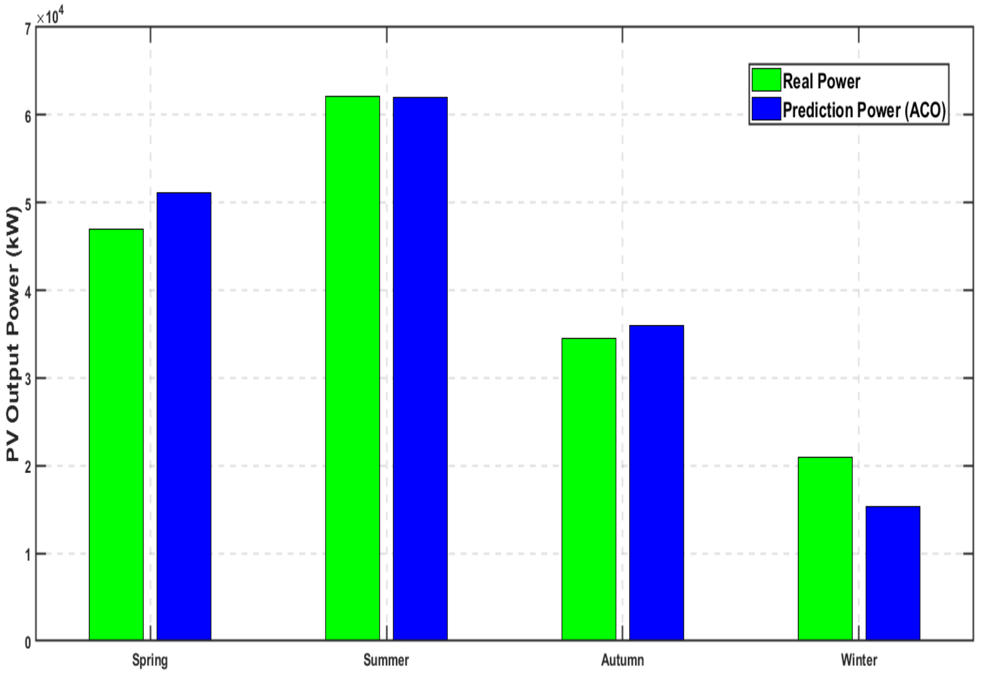

Figure 8. Graph of actual power and predicted power output for a one-year season

Figure 8 presents the graph of electricity production and forecast figures categorized by season. Seasonal analysis shows that the model captures long-term trends well. The power production output of the photovoltaic system reached its peak in the summer month when solar radiation is at its maximum intensity. Significant production differences between summer and winter seasons were evaluated. The MAPE value calculated on a seasonal basis is 5.045%. The observation of the lowest error rate in seasonal analyses shows that irrigation strategies can be structured on a seasonal basis. The increase in both energy production and water demand in summer months can be evaluated as the most efficient period for PV-supported irrigation systems. In this context, it is recommended that the installation of PV systems should be planned by taking into account the high performance especially in summer months.

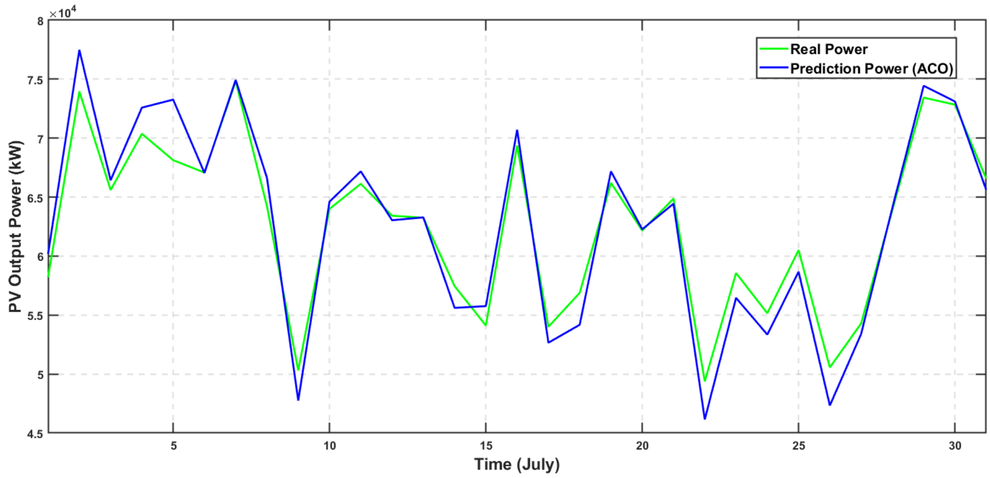

Figure 9. July actual power and projected output power chart.

Figure 9 shows the production and forecast graph for the July season, which is characterized by peak solar radiation. July was studied because it is the month with the highest solar radiation. The model predicted the power output for this month with exceptional accuracy. The MAPE value for July was determined as only 9.517%. July stands out as the period with the highest solar radiation. This is also the period when the irrigation demand is at its maximum. The high accuracy of the model during this period shows that the system can reliably meet the energy demand during the peak irrigation periods.

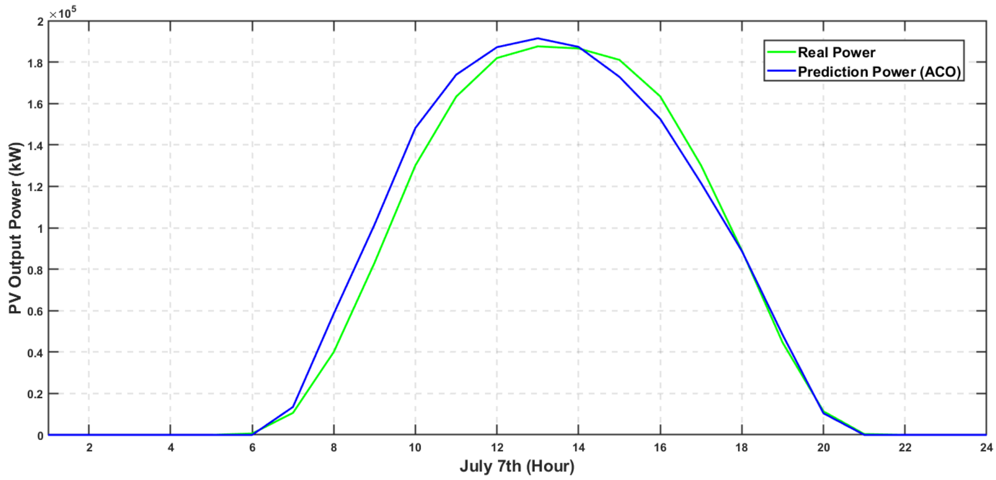

Figure 10. July 7, actual power and predicted output power chart.

Figure 10 presents the analytical results for the highest production day of the year, July 7th. The model for the highest production day is important for assessing short-term forecast accuracy. The expected power production on this particular day was remarkably consistent with the actual data. The analysis conducted for July 7th shows that the model can be used effectively in planning specific days.

Table 1. MAPE values according to different time intervals

Time Range	MAPE (%)
Hour	16.433
Day	11.472
Week	9.705
Month	7.414
July	9.517
July 7th	9.246
Season	5.045

Table 1 summarizes the MAPE values calculated for various periods. The accuracy rate of the model increases with the extension of the period. Although the error rate is high in daily forecasts, the model shows more efficiency in long-term forecasts. From the perspective of agricultural irrigation, weekly and monthly models have higher field applicability. Seasonal forecasts can play a leading role in strategic energy management and infrastructure planning.

CONCLUSION

The increasing dependence on renewable energy sources necessitates the development of accurate and efficient forecast models to optimize energy production and distribution. In this study, an ACO based approach was used to forecast the power output of PV systems by analyzing the relationships between solar radiation, temperature and historical energy production data. The results show that the ACO algorithm is quite effective in forecasting PV power output, especially for long-term forecasts. The ACO based model provided reliable forecasts and the MAPE values improved over long time intervals. While short-term (hourly and daily) forecasts showed slight deviations due to sudden weather fluctuations, weekly, monthly and seasonal forecasts showed significantly lower error rates. The lowest MAPE value (5.045%) was recorded for seasonal forecasts, demonstrating the algorithm's ability to capture long-term energy production patterns. The model is highly sensitive to environmental factors such as solar radiation and temperature changes. It was determined that increasing temperatures in summer reduce the PV panel efficiency, but energy production still reaches its peak thanks to the intensity of solar radiation. This shows that seasonal analysis is of great importance in planning energy-dependent agricultural applications such as irrigation. The comparison between the actual energy production and model predictions revealed a strong correlation confirming the reliability of the ACO-based prediction approach. Moreover, the scalability of the model allows its integration into large-scale solar farms, enhancing its utility for regional and national energy strategies. The algorithm effectively adapts to different time intervals, highlighting its potential for real-world applications in energy management and grid stability. The findings show that ACO is a robust and efficient technique to improve PV power output prediction. This approach can contribute to better energy planning, grid integration, and load management of solar energy systems. Overall, it is concluded that the model developed with the ACO algorithm provides a reliable, flexible, and effective prediction mechanism for PV systems, and can also be used as a decision support system in applications requiring energy management such as agricultural irrigation systems. Incorporating additional meteorological variables such as humidity and wind speed in future iterations could further refine the model's precision. Future research can explore hybrid optimization techniques and deep learning methods to further increase the prediction accuracy.

Declaration of interests

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

Author Contributions

The authors declare that they have contributed equally to the article.

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