

Integrated performance analysis of solar-powered atmospheric water generators using machine learning

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Article Info

Article history:

Received Nov 3, 2025

Revised Aug 20, 2026

Accepted Aug 27, 2026

Keywords:

Atmospheric water generator

Photovoltaic

Random forest regression

Thermal management

Water production rate

ABSTRACT

The integration of sustainable energy into atmospheric water harvesting offers a promising solution for supplementary water supply in off-grid and dry regions. This study investigates the performance of a hybrid photovoltaic-atmospheric water generator (PV-AWG) system and evaluates machine learning (ML) models for predicting water production rate (WPR). Experimental results showed that the Peltier module reached a stable temperature of approximately 17 °C before the PV system achieved peak power output, indicating effective thermoelectric cooling. A critical operating threshold of approximately 61 W was identified, above which increased electrical power caused a gradual rise in Peltier temperature, indicating thermal saturation and reduced cooling effectiveness. For WPR prediction, random forest regression (RFR) achieved strong agreement with experimental data, with a root mean square error (RMSE) of 0.077 and an R^2 of 0.966. Comparison with decision tree (DT) and support vector machine (SVM) models confirmed the superior predictive performance of RFR. These findings provide practical guidance for optimizing power management in PV-AWG systems and demonstrate the potential of ML to support adaptive monitoring and energy management in autonomous atmospheric water harvesting systems.

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1. INTRODUCTION

Climate change is exerting increasingly significant pressure on the global availability of safe and clean water [1], [2], resource exploitation, and continuous population growth [3]. In Indonesia, approximately 64% of regions experience meteorological drought annually, particularly in the eastern areas [4]. Conventional water supply technologies, such as deep bore wells and large-scale desalination, remain limited by high operational costs and dependency on conventional power grids [5]. This situation necessitates the search for renewable and decentralized water solutions. In this context, the atmospheric water generator (AWG) technology offers a promising approach by extracting water vapor directly from the ambient air through a cooling cycle [6]-[9]. AWGs are highly relevant for autonomous water supply in remote communities or areas lacking access to conventional water infrastructure [10], [11].

To ensure the sustainable operation of AWGs in off-grid locations, integration with renewable energy sources, specifically solar power plants or photovoltaic (PV) systems, is essential [12], [13]. However, this PV-AWG hybrid system faces unique operational complexity. The water production rate (WPR) is simultaneously influenced by two interacting groups of variables: environmental factors (ambient

temperature and relative humidity (RH)) [14], [15] and energy factors (solar irradiance, voltage, current, and solar power plants output power) [16]. This multi-variable dependency results in a highly non-linear relationship that hinders accurate performance estimation necessary for effective system design and control [17].

Most prior research concerning AWG focuses on thermal design optimization or the development of simple thermodynamics-based empirical models [18], [19]. These models are frequently inadequate for predicting performance under the dynamic conditions of a real-world PV-AWG system. To address this non-linearity, advanced machine learning (ML) techniques have begun to be adopted [20]. Although artificial neural networks (ANN) have been utilized for AWG performance forecasting [21], ANN models are often characterized as black-box, making it difficult to quantitatively measure and interpret the contribution of each input variable to the total WPR—information crucial for system optimization [22], [23].

This study proposes the implementation of random forest regression (RFR), an ensemble learning method, for the integrated performance analysis of the PV-AWG system [24], [25]. RFR was adopted due to its proven capability in effectively addressing non-linear dependencies, its stability against overfitting, and its unique strength in providing an explicit metric for feature importance score. This approach allows the researchers to simultaneously achieve high-accuracy WPR prediction and identify the quantitative ranking of environmental and energy variables contributing to system performance.

Based on these research gaps, this study aims to investigate the dynamic thermal–electrical performance of a hybrid PV-AWG system while developing an interpretable ML model for accurate WPR prediction. The novelty of this work lies in the integration of experimental thermal analysis with RFR to identify the operational thermal saturation threshold of the thermoelectric subsystem and to quantify the contribution of environmental and operational variables through feature-importance analysis. Furthermore, comparative benchmarking with decision tree (DT) and support vector machine (SVM) models is conducted to evaluate the predictive capability of the proposed approach. The findings are expected to provide practical engineering insights for improving thermoelectric power management, optimizing PV-AWG system design, and supporting the future development of adaptive monitoring and energy-management strategies for autonomous water harvesting in dry-land and off-grid environments.

2. METHOD

This research adopts an integrated approach combining physical system testing with data-driven predictive modeling. The overall research workflow is schematically presented in Figure 1. The study initially focuses on the acquisition of operational data derived from a hybrid AWG system functioning under dynamic environmental conditions. Subsequently, the multivariate data is subjected to rigorous collection and pre-processing procedures to ensure its quality and consistency. This structured approach is fundamental before utilizing the cleaned and standardized data to train and validate the ML model, specifically RFR. The outcomes of this modeling include performance prediction and feature significance analysis, which form the foundation for the results and discussion section.

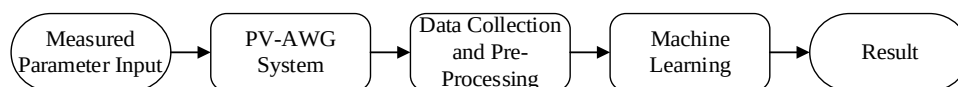


Figure 1. Research workflow

2.1. Photovoltaic–atmospheric water generator system

The prototype of the PV-AWG system developed for this investigation is presented in Figure 2. The physical structure of the system is supported by the solar panel, which is mounted at the top, functioning as the primary power source. The DC energy generated by the solar panel is regulated by the solar charge controller (SCC) (located inside the control panel box) and stored in the battery. This battery ensures a stable energy supply for the entire system operation. The core compartment is the isolated condensation chamber. Ambient air is drawn in through the air inlet fan and routed across the cooling circulation pipe coil, which is cooled to trigger condensation. The condensed water is collected in the water tank at the bottom, with drainage provided via the condensed water outlet. The system is powered by the solar energy. Power distribution also includes the air ventilation fan and the panel box fan, which are crucial for maintaining optimal operational temperatures and facilitating continuous airflow across the condensation chamber. This architecture is essential for accurately mapping the correlation between dynamic environmental/energy inputs and the resultant water production output.



Figure 2. PV-AWG prototype

The core control and data acquisition functions, as illustrated in Figure 3, are precisely managed by the Arduino Uno microcontroller. This unit integrates an array of sensors for real-time monitoring of critical parameters: the DHT22 measures RH and ambient temperature; the DS18B20 monitors the temperature within the thermal management circuit (cooling loop); and the HC-SR04 detects the collected water level for accurate WPR calculation. The specifications and measurement characteristics of the sensors used in the PV-AWG prototype are summarized in Table 1 [26]-[28]. All measured sensor data are timestamped with high precision using the real-time clock (RTC) DS3231 module and concurrently logged onto a MicroSD module (data logger), while also being displayed on the LCD 2×16. System actuators, which include the DC cooling pump (for thermal regulation) and the Peltier element, are automatically controlled via relay modules. This comprehensive and integrated control architecture ensures the autonomous monitoring, precise data logging, and stable regulation of the condensation and cooling processes critical for sustainable operation.

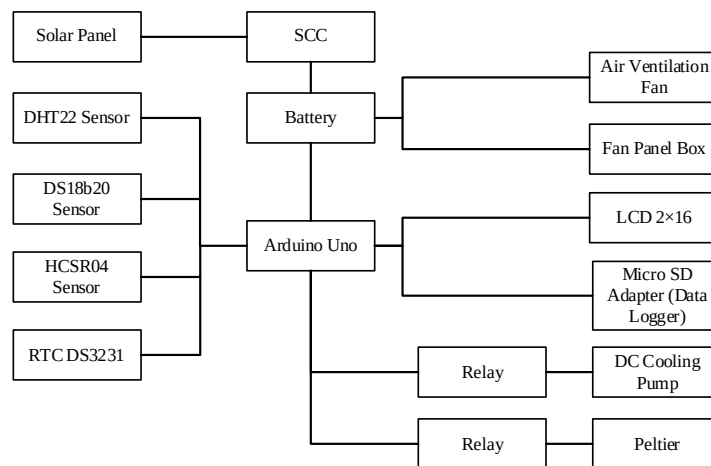


Figure 3. PV-AWG control system

Table 1. Sensor specifications used in the PV-AWG system

Sensor	Function	Measurement range	Accuracy
DHT22	Measures ambient temperature and RH	Temperature: $-40\text{ }^{\circ}\text{C}$ to $+80\text{ }^{\circ}\text{C}$ Humidity: 0–100 % RH	Temperature: $\pm 0.5\text{ }^{\circ}\text{C}$ Humidity: $\pm 2\text{--}5\text{ }%$
DS18B20	Measures the temperature of the Peltier module	$-55\text{ }^{\circ}\text{C}$ to $+125\text{ }^{\circ}\text{C}$	$\pm 0.5\text{ }^{\circ}\text{C}$
HC-SR04	Measures distance to determine water level in the storage tank	20 cm – 400 cm	$\pm 3\text{ mm}$

The mechanism for water extraction in this AWG system is achieved through the principle of thermoelectric cooling integrated with forced coolant circulation. The process is initiated when power is supplied to the Peltier element (thermoelectric cooler (TEC)) via a relay, causing a significant heat transfer and establishing a cold side on the cooling surface [29]. This cold side is thermally coupled to the cooling circulation pipe inside the condensation chamber, effectively lowering the pipe's temperature below the ambient air's dew point (which is monitored by the DHT22 sensor). Moist air, drawn in by the air inlet fan and channeled across the cold pipe, releases its latent energy and condenses into liquid water. Effective dissipation of the excess heat accumulated on the Peltier's hot side is mandatory for maintaining the overall process efficiency. This is accomplished by the DC cooling pump, which actively circulates the coolant. This effective hot-side thermal management is crucial for sustaining a high temperature differential (ΔT) across the Peltier element, thereby ensuring an optimal WPR [30]. This entire process is generally described by the following energy balance (1):

$$Q_{cond} = h_c \cdot A \cdot (T_{air} - T_{surface}) \quad (1)$$

where: Q_{cond} is convective heat transfer rate (W), h_c is convective heat transfer coefficient ($\frac{W}{m^2 \cdot K}$), A is condensation surface m^2 , T_{air} is ambient air temperature $^{\circ}C$, and $T_{surface}$ is cold surface temperature of the Peltier module $^{\circ}C$.

Effective condensation occurs when $T_{surface} \leq T_{dew}$, where T_{dew} is the dew point temperature calculated using the Magnus-Tetens equation.

2.2. Environmental input data

Environmental input data constitutes a crucial stage in the system analysis. These data are employed as key independent variables controlling the thermodynamics of the condensation process and the rate at which moisture is harvested from the atmosphere. The parameters measured reflect the atmospheric conditions surrounding the AWG unit [18]. The following main parameters were utilized:

- Time and date (timestamp): records the precise acquisition time for each dataset, serving as the basis for temporal (time series) analysis.
- Light intensity (lux): indicates the illumination level received, influencing the PV module's performance and electrical output.
- Solar irradiance (W/m^2): quantifies the solar radiation energy per unit area received by the solar panel.
- PV voltage (V) and PV current (A): represents the electrical performance produced by the solar panel at a specific time.
- PV power (W): calculated PV voltage and current ($P = V \times I$), indicating the actual electrical power output of the PV system.
- AWG voltage (V) and AWG current (A): represents the electrical power supplied from the solar panel to the AWG system.
- AWG power (W): serving as a primary indicator of the energy consumption for the thermoelectric cooling (Peltier) system, calculated using (2):

$$P_{AWG} = V_{AWG} \times I_{AWG} \quad (2)$$

- Ambient temperature ($^{\circ}C$): indicates the surrounding air temperature, which significantly influences the condensation process.
- RH, %: represents the atmospheric water vapor content, which is the primary source material for the condensation process.
- Dew point temperature (T_{dew} , $^{\circ}C$): represents the temperature at which the air reaches saturation and vapor begins to condense. It is calculated using the Magnus-Tetens as (3) and (4):

$$T_{dew} = \frac{c\gamma(T, RH)}{b - \gamma(T, RH)} \quad (3)$$

where,

$$\gamma(T, RH) = \ln\left(\frac{RH}{100}\right) + \frac{bT}{c+T} \quad (4)$$

with $b = 17.27$, $c = 237.7^{\circ}C$, T is the ambient temperature, and RH is the relative humidity.

- Peltier temperature ($^{\circ}C$): the temperature of the cold side of the thermoelectric module, which functions to condense water vapor.

- ΔT (°C): the difference between the ambient air and the cold surface temperature, which plays a critical role in the efficiency of the condensation process, calculated using (5):

$$\Delta T = T_{air} - T_{surface} \quad (5)$$

- WPR , mL/min: indicates the volume of water produced per minute.
- Total water volume (mL): the accumulated volume of condensed water collected during the observation period.

2.3. Data collection and pre-processing

Data acquisition was performed using an integrated sensor system connected to a microcontroller (Arduino Uno), recording all physical parameters at a fixed interval of 1 minute. All recorded data were transmitted to a computer via serial communication and stored in .csv format for subsequent analysis. Data preprocessing is a crucial stage to ensure that the data used for modeling are reliable, consistent, and representative for ML analysis. This stage involves the following sequential steps:

- Data cleaning focuses on improving the reliability of the dataset:
 - Handling missing values: identifying and addressing any gaps in the recorded data (missing values).
 - Outlier detection: managing extreme data points (outliers) based on statistical methods such as the Z-score and interquartile range (IQR).
 - Unit standardization: adjusting measurement units to ensure consistency across all variables.
- Data transformation prepares the data for model ingestion:
 - Temporal conversion: transforming the time column into a continuous numerical variable (ranging from minute 0 to minute 1439).
 - Feature engineering: creating derived features such as the dew point temperature (T_{dew}) and the temperature differential (ΔT) between ambient air and the cold surface.
- Normalization, all numerical features were normalized using the min-max scaling method within the range of [0, 1] to ensure the stability of the learning algorithm and prevent features with larger magnitudes from dominating the regression process. The normalization (6) used is:

$$X^i = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (6)$$

- Feature selection was performed using Pearson correlation and the feature importance score derived from the RF model to quantitatively determine the most influential parameters contributing to the predicted output.
- Data splitting: the processed dataset was partitioned into a training set (75%) and a testing set (25%) for model validation and assessment of regression performance.

2.4. Machine learning modelling

RFR was adopted for its high performance with non-linear, multi-variate datasets and its intrinsic resistance to overfitting property. The method generates a stable average prediction value by operating on the principle of ensemble learning: constructing multiple DTS from random data partitions and aggregating their predictions [31]. Mathematically, the RFR model can be expressed as (7):

$$\hat{y} = \frac{1}{N} \sum_{i=1}^N f_i(x) \quad (7)$$

where: $\hat{y}$ is average predicted value (WPR), N is total number of DTS, $f_i(x)$ is prediction result from the i -th DTS, and X is vector of environmental and operational feature.

Each tree is constructed based on a random selection of feature subsets (feature bagging) and data samples (bootstrap sampling). Consequently, the model is capable of capturing complex relationships between variables without sacrificing generalization ability. In addition to its predictive capability, RF was selected because the present study requires both accurate estimation and model interpretability. Unlike single-tree models, the ensemble-learning strategy reduces variance and improves generalization, while feature importance enables quantitative interpretation of environmental and operational variables influencing WPR.

2.5. Performance evaluation

The predictive performance of the model was evaluated using the following statistical metrics: root mean square error (RMSE). The RMSE measures the average magnitude of the errors between the predicted values and the actual values [32], calculated using (8):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (8)$$

Coefficient of determination (R^2 Score) the R^2 score represents the proportion of the variance in the dependent variable that is predictable from the independent variables, indicating the goodness-of-fit of the model shows in (9):

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \quad (9)$$

A lower RMSE indicates smaller prediction errors, whereas an R^2 value approaching unity indicates that the model explains a larger proportion of the observed variation in WPR. These metrics were jointly employed to evaluate the predictive capability of the proposed model.

3. RESULT AND DISCUSSION

This section details the findings derived from the operational testing of the PV-AWG system and the subsequent validation of the developed ML model. The analysis is structured into two principal components: first, the evaluation of the thermal and electrical performance of the physical prototype, and second, the assessment of the RFR model's accuracy and reliability in predicting the WPR.

3.1. Dynamic thermal-electrical performance of the photovoltaic-atmospheric water generator system

The analysis of time-dependent performance reveals that the energy input critically dictates the core thermal response through a strong negative relationship. Figure 4 illustrates the overall power distribution of the system. Figure 4(a) shows the PV output power during peak hours, while Figure 4(b) depicts the corresponding energy consumption of the AWG unit. The PV power output (Figure 4(a)) follows a characteristic bell-shaped curve, peaking at approximately ≈ 108 W around midday, which subsequently triggers a rapid cooling response in the AWG subsystem. The cold-side Peltier temperature (Figure 4(b)) exhibits a sharp thermal decay shortly after the PV power is engaged, reaching and sustaining a stable steady-state condition at ≈ 17.5 °C from approximately 07:00 onwards. The system reached thermal stability before peak PV power. This indicates effective control and hot-side thermal management (DC cooling pump). The consistent maintenance of the Peltier temperature below the ambient dew point demonstrates that the stability of the cold surface temperature is the primary factor governing water production, rather than the magnitude of the maximum PV power available.

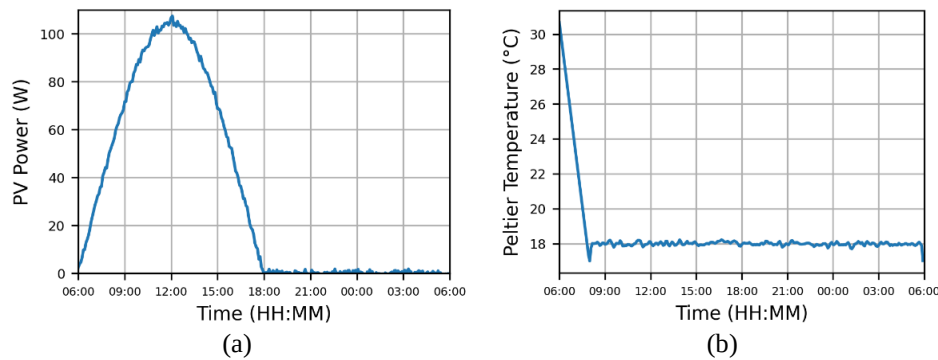


Figure 4. Dynamic thermal-electrical performance of the PV-AWG system; (a) PV power output (W) versus time and (b) Peltier temperature °C versus time

3.2. Correlation of atmospheric water generator power and Peltier temperature

The scatter plot (Figure 5) reveals two distinct operational thermal regimes, crucial for assessing system efficiency. In Regime I (≈ 54 W to ≈ 61 W), the Peltier temperature is sustained at its lowest stable point, ≈ 17 °C. This stability validates that the power input within this range is sufficient and optimal to achieve and maintain the temperature below the ambient dew point. However, when the power exceeds a critical threshold of ≈ 61 W (Regime II), a counter-intuitive thermal behavior is observed: the Peltier temperature increases linearly with the rising AWG power. This temperature escalation indicates thermal saturation of the hot-side cooling system, leading to the saturation of cooling efficiency (thermal runaway). The transition point at ≈ 61 W establishes a critical limit, signifying that power supplied beyond this threshold merely augments energy consumption without contributing to effective cooling, thereby diminishing the overall condensation efficiency of the system.

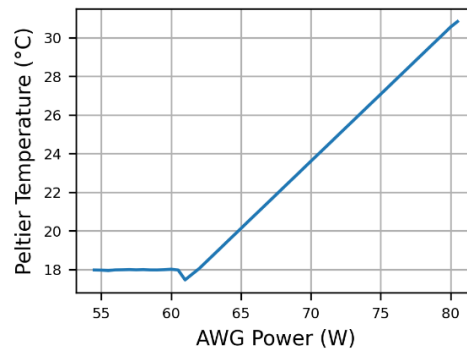


Figure 5. Correlation between AWG power (W) and Peltier temperature (°C)

The identification of the 61 W threshold has significant engineering implications. Beyond this point, additional electrical power no longer contributes to effective cooling because the heat rejected from the hot side of the thermoelectric module exceeds the capacity of the cooling system. Consequently, the coefficient of performance (COP) of the Peltier module decreases, resulting in higher energy consumption without proportional gains in water production. From a practical perspective, this finding indicates that AWG operation should be regulated below the thermal saturation threshold to maximize energy efficiency. Implementing a power management strategy that dynamically limits AWG power according to environmental conditions may significantly reduce unnecessary energy losses while maintaining stable water production. This threshold also provides useful design guidance for selecting appropriate cooling capacity, heat sink dimensions, coolant circulation rate, and PV sizing in future PV-AWG systems.

3.3. Validation of random forest predictive model for water production rate

The predictive capabilities of the RFR model are validated through a comparison of the forecasted WPR with the actual WPR data derived from the testing set (Figure 6). The predicted values closely match the actual data in both trend and magnitude between the prediction curve (green) and the actual curve (blue), proving the RFR's capability to accurately capture the high non-linearity and volatility characteristic of the hybrid PV-AWG system's output. The model successfully replicates the highly dynamic and oscillatory nature of the WPR while precisely predicting macro-scale daily trends, including periods of ramping up and ramping down. The minimal deviation observed, particularly at peak and trough values, indicates that the model is well-generalized and represents an effective predictive model mapping the complex multi-variate relationship between environmental/energy inputs and the resultant water production output in off-grid applications.

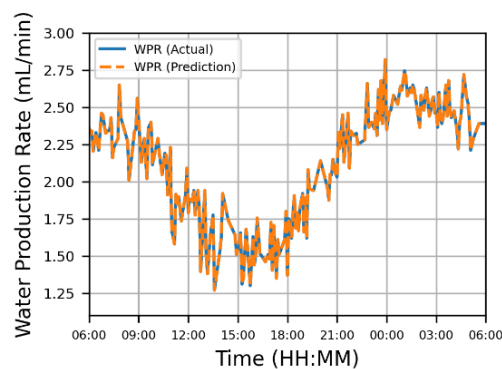


Figure 6. Comparison of RF model predictive performance for WPR against actual data

3.4. Evaluation of model performance

Standard statistical metrics, specifically the root mean squared error (RMSE) and the absolute error, were employed to evaluate and quantify the predictive performance of the RFR model, as shown in Figure 7. The model's evaluation yielded an RMSE value of 0.077 (± 0.000), an absolute error of 0.061 (± 0.047), and square correlation of 0.966. The low RMSE value confirms that the average magnitude of the prediction error between the actual WPR values and the model's predictions is minimal. This result indicates that the model

performs reliably for estimating water output within the context of mL/minute. Furthermore, the small absolute error demonstrates high predictive accuracy and minimal bias. The consistently low error values demonstrate the predictive capability of the RF model in mapping the complex nonlinear and multivariate relationships of the PV-AWG system under the tested operational conditions. However, because alternative ML models were not experimentally benchmarked in this study, these results should be interpreted as evidence of strong predictive performance rather than superiority over other modelling approaches.

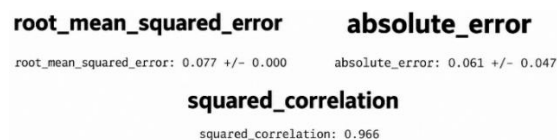


Figure 7. RMSE, absolute error, and square correlation of the RFR performances

3.5. Feature importance ranking

As proposed in the conceptual framework, the RFR model allows for an interpretability analysis through feature importance ranking. Figure 8 presents the contribution of each input variable to the WPR prediction. The analysis reveals that RH is the most dominant factor, contributing 68% to the model's predictive power. Therefore, the deployment of PV-AWG systems should prioritize locations where relatively high atmospheric humidity coincides with adequate solar irradiance, since solar energy alone is insufficient to ensure high water productivity.

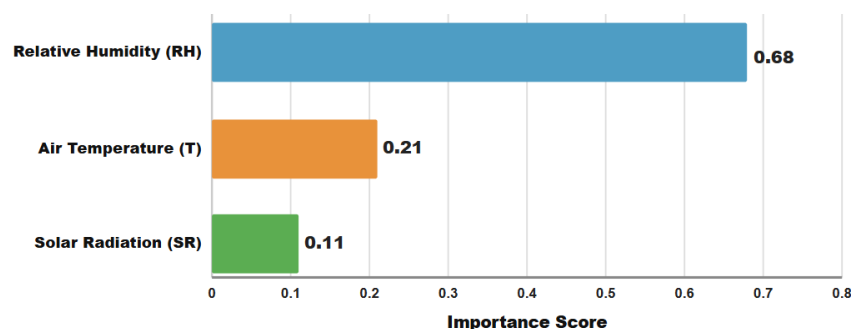


Figure 8. Feature importance ranking of the RFR model

Despite the significant predictive accuracy and physical validation achieved in this study, several limitations must be acknowledged to contextualize the findings. First, the dataset was collected exclusively within a tropical region (Makassar, Indonesia), which implies that the system's performance metrics might vary when deployed in arid or temperate climates with different atmospheric profiles. Furthermore, the study represents a specific seasonal cycle; thus, long-term longitudinal data are still required to fully evaluate the durability of the Peltier modules and the potential degradation of PV panel efficiency over extended operational periods. Recognizing these constraints provides a more balanced interpretation of the RFR model's generalizability and sets the stage for future cross-climatic validations.

In addition to its predictive capability, RF was selected because the present study requires both accurate estimation and model interpretability. Unlike a single DT, the ensemble-learning strategy reduces prediction variance and improves generalization by aggregating the outputs of multiple DTs. Furthermore, RF provides feature-importance analysis, enabling quantitative interpretation of the relative contribution of environmental and operational variables influencing WPR. As demonstrated later in the benchmarking analysis, RF also achieved better predictive performance than DT and SVM for the evaluated dataset, supporting its suitability for the proposed PV-AWG application.

3.6. Comparison with alternative machine learning models

To provide a more comprehensive assessment of the predictive capability of the proposed approach, the RFR model was benchmarked against two widely used ML algorithms, namely DT and SVM, using the identical training and testing datasets, as shown in Table 2. The benchmarking results demonstrate that RFR achieved the best predictive performance, yielding the lowest RMSE=0.077 and (mean absolute error (MAE)=0.047), together with the highest coefficient of determination ($R^2=0.966$). In comparison, the DT

model produced higher prediction errors (RMSE=0.117, MAE=0.094, and $R^2=0.909$), whereas the SVM model exhibited considerably lower predictive capability (RMSE=0.351, MAE=0.295, and $R^2=0.326$). These results indicate that the ensemble-learning mechanism employed by RFR is more effective in capturing the complex nonlinear relationships among environmental conditions, PV power generation, and thermoelectric operating characteristics than the single-tree DT model and the SVM model under the investigated operating conditions. Moreover, unlike the comparison models, RFR provides feature-importance analysis that enables interpretation of the relative contribution of each environmental and operational variable, making it particularly suitable for engineering analysis and adaptive control of PV-AWG systems.

Table 2. Performance comparison of ML models for WPR prediction

Model	RMSE	MAE	R^2
RF	0.077	0.047	0.966
DT	0.117	0.094	0.909
SVM	0.351	0.295	0.326

4. CONCLUSION

This study demonstrates the feasibility of integrating a PV-powered AWG with an interpretable data-driven approach for estimating water production under tropical conditions, particularly as a supplementary technology for supporting water availability in dry-land areas during periods of limited conventional water supply. The experimental findings show that effective PV-AWG operation depends not merely on maximizing electrical input, but on maintaining an appropriate balance between thermoelectric power and hot-side heat rejection; in the present prototype, the thermal transition observed at approximately 61 W indicates that power supplied beyond the effective cooling range may increase thermal loading and energy consumption without producing a corresponding cooling benefit. RFR demonstrated strong predictive capability within the evaluated dataset while providing interpretable information on the relative contribution of environmental variables, with RH identified as the dominant predictor, confirming that atmospheric moisture availability must be considered together with solar-energy availability and thermal operating conditions. These findings provide practical engineering guidance for the future development of adaptive energy and thermal management strategies, while the identified threshold should be regarded as specific to the tested prototype rather than a universal operating limit or evidence of superiority over other ML models. Since the study was conducted using a one-season dataset under tropical conditions, broader application will require multi-season and cross-climatic validation, robustness testing against sensor noise and power fluctuations, long-term evaluation of PV and Peltier performance, comparative benchmarking with alternative ML models using the same dataset, and assessment of the scalability of the proposed monitoring and control framework for larger-capacity atmospheric water-harvesting systems.

ACKNOWLEDGMENTS

The authors express our sincere gratitude to the Ministry of Higher Education, Science, and Technology of the Republic of Indonesia for the financial support that made this research possible. Furthermore, we wish to acknowledge the crucial institutional support received from Politeknik Negeri Ujung Pandang, particularly the Department of Electrical Engineering, and its centers of excellence (CAEES, CEISRI, and CATTAR), for the access to valuable facilities and resources essential for this work. The authors also gratefully acknowledge the support of the *Direktorat Jenderal Riset dan Pengembangan, Kementerian Pendidikan Tinggi, Sains, dan Teknologi Republik Indonesia*, through the 2026 Workshop Inclusive Publication Camp (In-Camp). The authors also sincerely thank Isa Anshori (Institut Teknologi Bandung) for his valuable guidance and constructive feedback, which contributed to improving this manuscript.

FUNDING INFORMATION

Funding for this study was provided by the Ministry of Higher Education, Science, and Technology of the Republic of Indonesia. This support was channeled through the Fundamental Research scheme (Contract No. 29/12/AL.04/2025).

AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualizationM : **M**ethodologySo : **S**oftwareVa : **V**alidationFo : **F**ormal analysisI : **I**nterpretationR : **R**esourcesD : **D**ata CurationO : Writing - **O**riginal DraftE : Writing - Review & **E**ditngVi : **V**isualizationSu : **S**upervisionP : **P**roject administrationFu : **F**unding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [MI], upon reasonable request.

REFERENCES

- [1] A. Dixit, S. Madhav, R. Mishra, A. L. Srivastav, and P. Garg, "Impact of climate change on water resources, challenges and mitigation strategies to achieve sustainable development goals," *Arabian Journal of Geosciences*, vol. 15, no. 14, p. 1296, Jul. 2022, doi: 10.1007/s12517-022-10590-9.
- [2] G. Venkatesan, G. V C, A. S, and D. D, "Solar Energized Atmospheric Water Generator Using Peltier Device," in *2024 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS)*, IEEE, Oct. 2024, pp. 1–4, doi: 10.1109/ICPECTS62210.2024.10780099.
- [3] J. Wang and W. Azam, "Natural resource scarcity, fossil fuel energy consumption, and total greenhouse gas emissions in top emitting countries," *Geoscience Frontiers*, vol. 15, no. 2, p. 101757, Mar. 2024, doi: 10.1016/j.gsf.2023.101757.
- [4] B. D. Primadita, Levina, and R. D. Ahmad, "Projecting and managing hydrological drought in Indonesia," in *The 5th International Conference on Climate Change 2020*, vol. 724, no. 1, p. 012087, Apr. 2021, doi: 10.1088/1755-1315/724/1/012087.
- [5] C. Dang et al., "System integration for solar-driven interfacial desalination," *Device*, vol. 2, no. 5, p. 100361, May 2024, doi: 10.1016/j.device.2024.100361.
- [6] M. A. Siddiqui, M. A. Azam, M. M. Khan, S. Iqbal, M. U. Khan, and Y. Raffat, "Current trends on extraction of water from air: an alternative solution to water supply," *International Journal of Environmental Science and Technology*, vol. 20, no. 1, pp. 1053–1080, Jan. 2023, doi: 10.1007/s13762-022-03965-8.
- [7] N. Pokorny, V. Shemelin, and J. Novotny, "Experimental study and performance analysis of a mobile autonomous atmospheric water generator designed for arid climatic conditions," *Energy*, vol. 250, p. 123813, Jul. 2022, doi: 10.1016/j.energy.2022.123813.
- [8] A. H. Shourideh, W. B. Ajram, J. Al Lami, S. Haggag, and A. Mansouri, "A comprehensive study of an atmospheric water generator using Peltier effect," *Thermal Science and Engineering Progress*, vol. 6, pp. 14–26, Jun. 2018, doi: 10.1016/j.tsep.2018.02.015.
- [9] M. T. Imran, A. N. Barshan, S. M. Shams, R. Tajwar, L. Zahin, and A. A. M. Azad, "Extracting Atmospheric Water using Peltier Effect Powered by Solar Energy with Contribution from Piezo-Materials," in *2022 IEEE International Systems Conference (SysCon)*, IEEE, Apr. 2022, pp. 1–7, doi: 10.1109/SysCon53536.2022.9773876.
- [10] E. B. Agyekum, F. Odoi-Yorke, W. F. Mbasso, R. O. Darko, O. R. Adegboye, and A. A. Abbey, "Towards a comprehensive understanding of atmospheric water harvesting technologies – a systematic and bibliometric review," *Energy Reports*, vol. 12, pp. 3795–3811, Dec. 2024, doi: 10.1016/j.egy.2024.09.059.
- [11] A. K. Dubey, V. Gupta, S. N. Gupta, and R. Dev, "Sustainable Drinking Water System for Rural Areas Powered by Non-Conventional Energy Sources," in *2023 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES)*, IEEE, Apr. 2023, pp. 1052–1057, doi: 10.1109/CISES58720.2023.10183472.
- [12] M. H. Rostami, G. Najafi, S. Minaei, and M. H. Khoshtaghaza, "Design, optimization and performance evaluation of water-energy nexus of an atmospheric water harvesting system (AWHS) based on subsurface cooling and solar power," *Case Studies in Thermal Engineering*, vol. 72, p. 106378, Aug. 2025, doi: 10.1016/j.csite.2025.106378.
- [13] P. K. Kushwaha, A. Kumar, and R. Choudhary, "Solar-powered water generation from atmospheric air using desiccant wheel: Theoretical and experimental investigation," *Solar Energy Materials and Solar Cells*, vol. 274, p. 112969, Aug. 2024, doi: 10.1016/j.solmat.2024.112969.
- [14] L. M. Nhut and D. T. T. Linh, "Effects of the Relative Humidity on the Performance of Thermoelectric Freshwater Generator using Solar Power Source," in *2020 5th International Conference on Green Technology and Sustainable Development (GTSD)*, IEEE, Nov. 2020, pp. 232–235, doi: 10.1109/GTSD50082.2020.9303119.
- [15] M. K. Varun and R. Jayabarathi, "Prototype implementation of Atmospheric Water Generation by Peltier Device," in *2021 International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON)*, IEEE, Oct. 2021, pp. 1–4, doi: 10.1109/SMARTGENCON51891.2021.9645838.

- [16] H. H. Jo, J. Kim, and S. Kim, "Enhancing the power generation performance of photovoltaic system: Impact of environmental and system factors," *Applied Thermal Engineering*, vol. 240, p. 122221, Mar. 2024, doi: 10.1016/j.applthermaleng.2023.122221.
- [17] W. Salameh, C. Castelain, J. Faraj, R. Murr, H. El Hage, and M. Khaled, "Improving the efficiency of photovoltaic panels using air exhausted from HVAC systems: Thermal modelling and parametric analysis," *Case Studies in Thermal Engineering*, vol. 25, p. 100940, Jun. 2021, doi: 10.1016/j.csite.2021.100940.
- [18] A. M. Ashour *et al.*, "Performance evaluation of atmospheric water generation in different climates using thermoelectric cooling," *Desalination and Water Treatment*, vol. 322, p. 101179, Apr. 2025, doi: 10.1016/j.dwt.2025.101179.
- [19] F. Salek, A. N. Moghaddam, and M. M. Naserian, "Thermodynamic analysis and improvement of a novel solar driven atmospheric water generator," *Energy Conversion and Management*, vol. 161, pp. 104–111, Apr. 2018, doi: 10.1016/j.enconman.2018.01.066.
- [20] S. Aslam, P. P. Aung, A. S. Rafsanjani, and A. P. P. A. Majeed, "Machine learning applications in energy systems: current trends, challenges, and research directions," *Energy Informatics*, vol. 8, no. 1, p. 62, May 2025, doi: 10.1186/s42162-025-00524-6.
- [21] E. S. Ravajiri, M. Hasanloo, A. Jalali, and E. Houshfar, "Techno-economic analysis and tri-objective optimization of a novel HDH desalination with PVT and vapor-compression chiller for sustainable water supply in remote areas," *Sustainable Cities and Society*, vol. 101, p. 105211, Feb. 2024, doi: 10.1016/j.scs.2024.105211.
- [22] A. Khan and C. R. Bradshaw, "A novel characterization methodology for vapor-injected compressors: A comparative analysis with existing black-box models," *International Journal of Refrigeration*, vol. 169, pp. 254–266, Jan. 2025, doi: 10.1016/j.ijrefrig.2024.10.036.
- [23] M. Najar and H. Wang, "From black box to glass box: Explainable AI for enhancing operator decision making in reactor accident scenarios," *Progress in Nuclear Energy*, vol. 190, p. 106009, Jan. 2026, doi: 10.1016/j.pnucene.2025.106009.
- [24] L. Zheng, Q. Han, and Z. Junhu, "A Combination Method of Resampling and Random Forest for Imbalanced Data Classification," in *2022 4th International Conference on Advances in Computer Technology, Information Science and Communications (CTISC)*, IEEE, Apr. 2022, pp. 1–5, doi: 10.1109/CTISC54888.2022.9849803.
- [25] N. S. Thomas and S. Kaliraj, "An Improved and Optimized Random Forest Based Approach to Predict the Software Faults," *SN Computer Science*, vol. 5, no. 5, p. 530, May 2024, doi: 10.1007/s42979-024-02764-x.
- [26] T. Liu, "Digital-output relative humidity & temperature sensor/module DHT22 (DHT22 also named as AM2302) Capacitive-type humidity and temperature module/sensor." [Online]. Available: <https://www.alldatasheet.com/datasheet-pdf/download/1132459/ETC2/DHT22.html>. (Accessed: Sep. 10, 2026).
- [27] P. By ALLDATASHEETCOM, "DS18B20 DALLAS | Alldatasheet." [Online]. Available: www.dalsemi.com
- [28] Elecfreaks, "Ultrasonic Ranging Module HC - SR04," Shenzhen, 2020. [Online]. Available: <https://cdn.sparkfun.com/datasheets/Sensors/Proximity/HCSR04.pdf>.
- [29] M. Song, L. Wang, J. Yuan, Z. Wang, X. Li, and K. Liang, "Proposal and parametric study of solar absorption/dual compression hybrid refrigeration system for temperature and humidity independent control application," *Energy Conversion and Management*, vol. 220, p. 113107, 2020, doi: 10.1016/j.enconman.2020.113107.
- [30] M. N. A. Ameer, I. S. Kareem, and A. A. Ismaeel, "Performance of Peltier-Based Thermal Management System: Impact of Multiple Modules on Cooling Efficiency and Energy Consumption," *International Journal of Engineering (IJE)*, vol. 39, no. 08, pp. 1843–1854, 2026.
- [31] Y. Liu and Y. Du, "A Deep Learning – Random Forest Hybrid Model for Predicting Historical Temperature Variations Driven by Air Pollution: Methodological Insights from Wuhan," *Atmosphere*, vol. 16, no. 9, 2025, doi: 10.3390/atmos16091056.
- [32] T. O. Hodson, "Root-mean-square error (RMSE) or mean absolute error (MAE): when to use them or not," *Geoscientific Model Development*, vol. 15, no. 14, pp. 5481–5487, 2022, doi: 10.5194/gmd-15-5481-2022.

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