NTU Journal for Renewable Energy (2026) Vol. 10 (1): 1-10
DOI: https://doi.org/10.56286/zczemr04

IRAQI
Academic Scientific Journals

ISSN: 2788-9912 (print); 2788-9920 (online)
NTU Journal for Renewable Energy
Available online at:
https://journals.ntu.edu.iq/index.php/NTU-JRE

Modeling and Optimization of Solar Panel Cooling using Machine Learning and Deep Learning Techniques

Mohammed F. Alsarraj[1] Yaareb E. Ahmed[2] Sarah B. Ezzat[3]
Jagadeesh Pasupuleti[4]

[1*]Technical Engineering College for Computer and AI–Mosul, Northern Technical University, Mosul, 41001, Iraq.

[2,3]Department of Mechanical Technical, Polyphonic college Al-Hawija, Northern Technical University, Kirkuk, 36007, Iraq.

[4]Institute of Sustainable Energy, Universiti Tenaga Nasional, Kajang 43000, Selangor, Malaysia.

Article Informations

Received: 12 - 11 - 2025
Accepted: 12 - 28 - 2025
Published: 01 - 09 - 2026

Corresponding Author:
Mohammed F. ALSARRAJ

Email:
mohammed_alsarraj@ntu.edu.iq

Key words:
Solar Panels, Cooling Optimization, Deep Learning, Neural Networks, Reinforcement Learning, Photovoltaic Efficiency, CNN, Intelligent Energy Management.

ABSTRACT

Photovoltaic (PV) modules experience a marked efficiency drop when the cell temperature exceeds the nominal operating range. This study proposes an AI-driven cooling control framework that couples short-term temperature forecasting with adaptive decision-making to maximize the net energy yield under tropical operating conditions. This study used a six-month, 1-minute-resolution dataset collected near Kuala Lumpur, Malaysia, integrating IoT field measurements (PV rear-surface temperature, on-site irradiance, ambient temperature, relative humidity, wind speed, and inverter energy output) with meteorological/irradiance archives (MetMalaysia and the NREL Solar Radiation Database), resulting in approximately 2.6×10^5 time-stamped samples. After preprocessing (1.8% missing data handled via interpolation and KNN imputation; z-score standardization), a convolutional neural network (CNN) predicted the near-future PV surface temperature, and a reinforcement learning (RL) agent selected the cooling mode (passive, low-power fan, high-power fan, or water spraying) to balance thermal mitigation against auxiliary energy consumption. CNN achieved an RMSE, MAE, and R^2 of 1.38°C, 1.04°C, and 0.95, respectively, enabling anticipatory control that reduced unnecessary switching.

Introduction

Solar energy is the most conservative source of renewable energy, and photovoltaic (PV) panels are the most widespread method of transforming sunlight into electricity. Nonetheless, the PV efficiency declines with the panel temperatures; the average rise is at 0.4-0.5 percent/°C beyond 25°C. Proper thermal control is necessary to achieve a high energy output. Other traditional cooling systems, such as passive heat sinks, forced air, and spraying of water, cannot dynamically respond to changing environmental conditions and absorb unnecessary energy or cool incompetently. Smart cooling devices can be actively implemented in real time owing to the development of deep learning (DL) and artificial neural networks (ANNs) to predict the panel temperature and take corrective measures [1], [2].

This study constructed and experimented on a deep learning-based solar panel cooling optimization system that maximizes the utilization of the available cooling power system to obtain peak efficiency with minimum auxiliary power. The suggested framework applies instantaneous environmental data, equations of metrics of panel performance, and cooling system parameters to estimate the most effective cooling plan. The sources of environmental information in this study included real-time and historical information acquired through various channels. In particular, sensors based on the IoT were installed on-site to measure the temperature of the PV rear surface (thermocouples), solar irradiance (pyranometers), ambient temperature, relative humidity (environmental sensors), and wind speed (anemometers). To make these measurements more robust and consistent, meteorological and irradiance data were obtained from the Malaysia Meteorological Department (MetMalaysia) and the National Renewable Energy Laboratory (NREL) Solar Radiation Database to guarantee continuity and consistency of the data.

The proposed framework relies on instantaneous sources of environmental information, equations for measuring panel performance, and cooling system parameters to estimate the best cooling strategy. The DL model can be adjusted to changes in season and long-term degradation factors using historical data and lifelong learning. Simulation and field testing of an existing Indian pilot system using a solar plant will determine the efficacy of the system by comparing the energy and level of cooling execution of the system with conventional methods [3], [4].

The proposed structure is an integrated approach to optimizing the cooling options of solar panels owing to the inclusion of multiple databases and advanced machine learning algorithms. These are the environmental parameters that are averaged with the performance parameters of the panel, which include the power output of the panel, its efficiency, and heat distribution over the panel surface. In addition, the parameters of the cooling system (coolant flow rate, temperature, and patterns) were introduced into the framework [5]. These data are complex and are integrated to gain comprehensive insights into the dynamics of solar panel systems under different circumstances.

The deep learning (DL) model is the core of the framework for inputting these complicated data and predicting the most desirable cooling apparatuses that would boost energy production with the least amount of energy used for cooling. The model relies on previous information on seasons and weather conditions to build a complex model of the effect of environmental factors on panel performance and cooling demand [6], [7]. To prove the efficiency of this innovative method, a thorough evaluation plan should be developed. Initial testing will be carried out at the level of a simple computer simulation, which will allow a faster cycle of the model and optimize it in terms of a high number of potentially possible contingencies. Simulations are important for providing significant data on the potential usefulness of adaptive cooling systems compared to traditional and fixed cooling systems [8], [9], [10].

1. Literature Review

1.1 Passive Cooling Systems

Passive cooling technologies do not employ powered means but instead rely on the natural dissipation of heat. PCMs, finned heat sinks, and a more active convection surface that cools the PV panels. Al-Waeli et al. (2021) note that PCMs would cool a panel by 4-6°C, which allows energy production to exceed requirements under high-temperature climates. In addition, where appropriate, some studies have examined advanced surface coatings and nano-coatings that increase emissivity and thus radiative heat loss, which cools at night. While these are cheap and inexpensive means of cooling, they are not as effective in cooling, are susceptible to outside elements, and are limited in mobility needed to sustain rapid changes in the environment and thus, reduce effectiveness across varying climates [11], [12].

1.2 Active Cooling Systems

Active cooling approaches use mechanical or fluid-based interventions, such as water spraying, forced air ventilation, or hybrid air-water systems, to actively remove heat from PV panels. Bahaidarah et al. (2013) showed that water cooling through the rear surface has the potential to raise PV efficiency to 10% in places with high levels of irradiance (in other words, hot arid areas), and that air cooling through fan-forced cooling can reduce the surface heat very quickly, especially when there is great irradiance. However, they are associated with the requirement of auxiliary energy, which can nullify the benefits owing to its ineffectiveness. Multiple active hybrid systems have been found to perform much better; however, they increase the level of complexity, operational cost, and maintenance needs, and a further issue is meeting cooling perspectives and efficiency with energy costs. Hence, intelligent control strategies are necessary. [13], [14].

1.3 ML in PV Performance Prediction

The growing use of machine learning (ML) methods to forecast PV performance variables (e.g., temperature, power output, and degradation trends) based on environmental and operating data has gained momentum. Yang et al. (2020) employed Artificial Neural Networks to predict PV output with high predictive capabilities compared to those who employed Support Vector Machines (SVMs) and Gradient Boosting to estimate temperature and irradiance. Although these models may theoretically be able to capture nonlinear dependencies in PV performance, they incur large amounts of manual feature engineering, are sensitive to training data quality problems, and are not generally capable of being run in conjunction with real-time control systems to manage thermals [15], [16], [28].

1.4 DL for Renewable Energy Systems

Deep Learning (DL) models, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have progressed renewable energy analytics by automatically extracting features and modeling intricate spatial-temporal relationships in big data. Hossain et al. (2022) reported the recognition of spatial patterns with CNNs and the description of changes in sequence in the environment with LSTMs to generate more precise predictions related to solar irradiance, and power production by PV is used. Even after these developments, DL applications in PV cooling have not been widely accepted, and most of the literature on this topic has focused on predicting and not on the application of predictive models in real time in adaptive cooling control systems operating with respect to local thermodynamics [17], [18], [29], [30].

1.5 Research Gap

While significant progress has been made in PV temperature prediction and cooling technologies, existing research typically addresses these aspects in isolation without combining predictive modeling with intelligent real-time control optimization. Few studies have implemented deep learning models alongside reinforcement learning and other adaptive decision-making structures, which dynamically select the most energy-efficient cooling strategy. In addition, solutions to optimize both efficiency increase and auxiliary power requirements are absent when considering variable and extreme climatic situations [19], [20], [21]. The manner in which AI-powered cooling might fill this gap, thereby maximizing net energy production and placing the overall system on a sustainable footing, remains an open question.

2. Study Area and Dataset Analysis

2.1 Study Area

This study is concerned with the performance and cooling optimization of photovoltaic (PV) systems in hot and humid climates, specifically in conditions close to Kuala Lumpur, Malaysia. The average daily temperatures in this area are 27°C to 34°C, with the highest solar radiation around 800 W/m and 1000 W/m at noon. High humidity (70-90%) and strong solar energy also affect PV modules and may be good examples for the consideration of cooling strategies. Moreover, the change in cloud cover and occasional rain make it possible to evaluate the flexibility of intelligent cooling control systems under rapidly changing environmental conditions.

Table 1: Data Source Summary

Data Type	Source	Resolution	Units	Period Covered
PV Surface Temperature	IoT-based thermocouples (mounted at rear surface)	1 min	°C	6 months
Solar Irradiance	NREL Solar Radiation Database + On-site pyranometers	1 min	W/m²	6 months
Ambient Temperature	IoT environmental sensors + Malaysia Meteorological	1 min	°C	6 months

	Department (MetMalaysia)			
Relative Humidity	IoT environmental sensors	1 min	%	6 months
Wind Speed	IoT ultrasonic anemometers	1 min	m/s	6 months
Energy Output	PV inverter log data	1 min	kWh	6 months

2.2 Data Description and Preprocessing

The dataset comprises six months of continuous monitoring data collected from IoT-based field sensors and public meteorological archives. The features obtained were PV surface temperature, ambient parameters (temperature, humidity, and wind speed), and operating parameters (irradiance and energy output). Field sensor data were collocated with weather station data so that the data were aligned in time [22], [23], [24].

2.2.2 Missing Data Handling

Missing data points were sometimes caused by sensor failure, network and transmission errors, and maintenance. The percentage of records with missing values was approximately 1.8%. Gaps in short intervals (less than 5 min) were interpolated with linear regression, whereas gaps in long intervals (more than 5 min) were imputed with a K-nearest neighbors imputation algorithm (k=5) based on the features of space and time (i.e., irradiance and ambient temperature) correlated across space and time [25].

2.2.3 Data Transformation and Encoding

Prior to feeding the dataset to the deep learning models, various transformation and encoding processes were applied to enhance the learning effectiveness and compatibility of the data to fit the neural network structures. The continuous variables of irradiance, temperature, humidity, wind speed, and energy output were standardized using the Z-score to give their distributions a mean of zero and unit variance.

$$Z = \frac{X - \mu}{\sigma} \qquad (1)$$

This standardization was preferred to min-max scaling to make the method more resistant to outliers and seasonal changes in environmental variables. Variables with high skewness, such as energy output, were log-transformed to decrease the variance and increase the symmetry of the distributions.

Additionally, categorical features, such as cooling mode labels at the supervised training stages, were encoded to one-hot representation to avoid creating relationship annotations with omnipresent ordinality.

This process of normalization, transformation, and encoding not only scaled the dataset uniformly but also preserved the temporal patterns and provided semantic consistency between features, allowing the deep learning models to achieve convergence faster and thus improve generalization to novel environmental conditions.

3. Proposed Methodology

3.1 System Architecture

This section presents the AI-based photovoltaic cooling optimization system that works through the integration of outside conditions in real time, temperature prediction, and reinforcement learning–based real-time adjustments to maintain photovoltaic function at optimal levels with minimal supplemental cooling energy consumption.

The system architecture operates on four functional layers, ensuring a structured and modular approach from data acquisition to smart cooling actuation. The four functional layers are (i) Data Acquisition, (ii) Data Processing and Storage, (iii) Prediction and Optimization, and (iv) Control and Actuation. A feedback control loop from the final layer to the storage element ensures a cumulative learning performance.

.

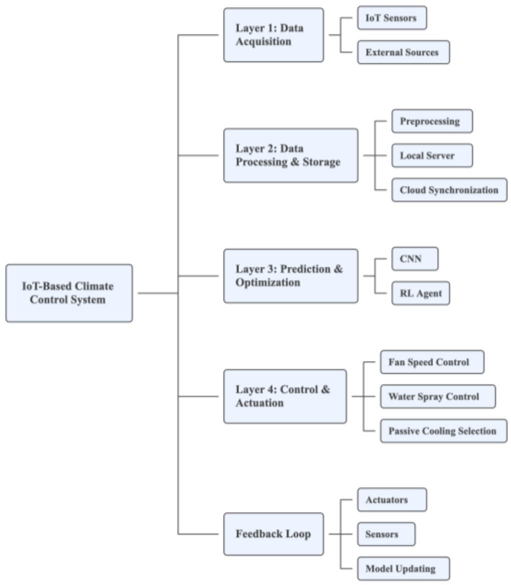

Figure (1): Architecture of the proposed CNN–RL-based photovoltaic cooling control system.

Layer 1 Data Acquisition: The data acquisition layer consists of real-time and historical data necessary for temperature prediction and cooling management. IoT-based sensors are installed on-site to obtain relevant environmental data in real time, collecting PV rear-surface temperature (thermocouples), solar irradiance (pyranometers), ambient temperature and relative humidity (environmental sensors), and wind speed (anemometers). All features were evaluated at a fine temporal resolution (1 min) to appropriately capture immediate changes in the environment.

In addition, further meteorological and irradiance data (off-site) were collected and integrated from trustworthy sources, such as the Malaysia Meteorological Department (MetMalaysia) and the National Renewable Energy Laboratory (NREL) Solar Radiation Database. These two databases have large-scale networks of gauge stations that complement localized IoT sensors. Such integration increases robustness, maintains data consistency in the case of sensor failures, and ultimately provides better learnable generalizability.

Layer 2 Data Processing: The second layer consists of processed, aligned, and stored acquisition data. This increases the integrity through the optimal correction of sensor results, where feasible. First, readings are aligned to be noise-free through outlier rejection. Subsequently, dropout issues from faulted sensors or communication failure are mitigated by hybridizing short-term gaps between similar values that are interpolated, while larger gaps are compensated for by K-nearest neighbors' imputation.

Second, all features were normalized through z-score standardization to ensure numeric stability for model training. Thereafter, the processed data are stored on a local server for time-sensitive prediction/control modules and redundantly backed up to the cloud for periodic synchronization. Long-term storage is required to support offline analysis and long-term archiving/retraining of deep learning and reinforcement learning models.

Layer 3 Prediction and Optimization: The prediction and optimization layer is the central intelligent part of the proposed solution for deep learning-based temperature prediction and reinforcement learning-based decision-making, which can provide anticipatory and energy-conscious cooling-management.

For example, in a convolutional neural network (CNN), systematic short-term prediction is made based on prior environmental states and operational conditions. By predicting thermal phenomena in the near future, CNN control can be implemented before a problem occurs, instead of responding after.

Thus, the predicted temperature value with the concurrent system state (current environmental data, PV operational conditions, and cooling status) was input into the reinforcement learning (RL) agent. The RL agent applies a state/action perspective to cooling management, which is transformed into a sequential decision-making problem. An action refers to a specific cooling mode (i.e., passive cooling, low-speed fan, high-speed fan, or water spraying). This means that every positive 1 maximizes the net energy gain by increasing the PV efficiency and compensating for the auxiliary cooling energy costs.

Layer 4 Control and Actuation: The control and actuation layer necessitates action based on the RL agent-optimized results. Depending on the cooling strategy executed, the actuators will be instructed to use variable-speed fans, solenoid valves for water spraying, or passive cooling if active cooling is not warranted.

This means that cooling will occur in real time with low latency; no cooling will be overly aggressive if cooled sufficiently, and no auxiliary energy will be wasted. Fan speeds can be reduced, and the speed and duty cycles of water spraying can be reduced, allowing this to run as seamlessly as possible to maintain the PV temperature within optimal ranges for performance.

3.2 Feedback Loop and Continuous Learning

The feedback loop between the control and actuation layer and the data processing and storing layer is shown in Figure 1. At the end of each control action, additional measurements of the thermal and electrical response of the PV system are taken by the necessary sensors for acquisition and storage.

Thus, the system not only runs according to pre-trained deep learning models, but it also sustains performance over time as users can monitor effectiveness and reschedule and retrain the CNN and RL models periodically. Thus, the design is responsive to seasons, long-term PV system degradation, and evolving environmental conditions over time, ensuring performance when deployed in the field for extended periods.

4. Experimental Setup

An experimental system was used to confirm the functionality of the proposed deep-learning cooling framework in a realistic operational and environmental setup. The test procedures included model training with historical data offline and testing with real-time experimentation via IoT-based monitoring systems to assess adaptability and robustness.

4.1 Dataset

The study area, comprising six months of high-resolution data on the location of the IoT sensors (Kuala Lumpur, Malaysia), along with historical weather data (NREL Solar Radiation Database), were merged to create the dataset used in developing the model. The measured parameters were PV surface temperature, solar irradiance, ambient temperature, relative humidity, wind speed, and energy production at 1 min intervals. To consider seasonal variability, clear-sky and cloudy-day conditions, as well as rainy-day conditions that are characteristic of tropical climates, were included in the dataset [26], [27].

4.2 Evaluation Metrics

The effectiveness of the intended system was validated based on the prediction accuracy and performance for cooling optimization. For CNN-based prediction, performance will be validated based on the Root Mean Square Error (RMSE) of the numerical result through which the exact PV temperature differs from the predicted PV temperatures; Mean Absolute Error (MAE) the prediction performance in general; the coefficient of determination (R^2) the percentage of variance explained by the method; for reinforcement learning–based cooling optimization, performance will be validated based on the expected control effectiveness gains (PV electrical efficiency improvement percentage based on kWh/HW produced in comparison to the same conditions without cooling), cooling energy savings (how much auxiliary energy consumption has been reduced compared to active cooling that was fixed), or net energy gain (kWh) how many usable KWh output increases.

4.3 Baseline Models

To establish a comparative benchmark, the proposed CNN+RL framework was evaluated against several baseline approaches:

- Passive Only Kooling: Natural convection with a finned heat sink and no active elements.
- Fixed Active Cooling - Fans run at full speed all the time, irrespective of weather conditions.
- Machine Learning Prediction + Manual Control ANN-based temperature prediction using fixed cooling rules.
- Reinforcement Learning Without CNN Forecasting RL-based control is based on the current readings alone and not on future projections.
- They also enable tangible comparisons of the benefits of integrating predictive modeling and adaptive decision-making on a single platform.

Figure 2 is a chart in which the performance of the proposed CNN+RL framework is compared with that of the state-of-the-art models, with the parameter of Efficiency Gain (%) on the primary axis and the parameter of Cooling Energy Reduction (%) on the secondary axis. The findings indicate that passive cooling or fixed active cooling have moderate performance in terms of efficiency gains but are either not flexible or consume a lot of energy. All alternative combinations never reached the efficiency improvement rates of CNN+RL (12.6%) and saved cooling energy use of 18 percent.

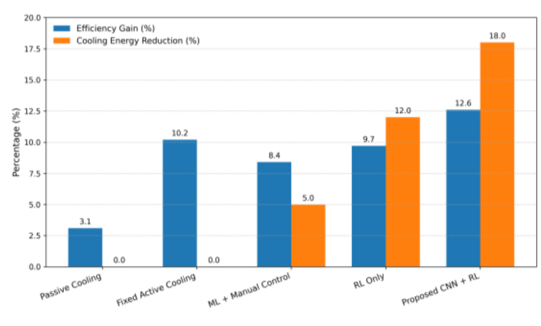

Figure (2): Performance Comparison of Models

5. Results and Discussion

5.1 Prediction Performance

The CNN model performed excellently on PV surface temperature prediction because it produced much lower errors than the ANN and SVM base models. Short-term predictive temperature enabled the RL controller to make active cooling choices in advance, which prevented excessive switching of the active cooling system.

Table 2: Temperature Prediction Performance

Model	RMSE (°C)	MAE (°C)	R^2 Score
ANN	2.48	1.96	0.89
SVM	2.74	2.12	0.87
CNN (Proposed)	**1.38**	**1.04**	**0.95**

5.2 Cooling Efficiency and Energy Savings

By combining CNN-based predictive control with RL-based control, the dynamic adaptation of cooling strategies was implemented based on the predicted thermal conditions. This provided the greatest efficiency improvement and the greatest decrease in auxiliary cooling energy consumption of all methods tested.

Table 3: Cooling Performance Comparison

Method	Avg. Efficiency Gain (%)	Cooling Energy Reduction (%)	Net Energy Gain (kWh)
Passive Cooling	3.1	N/A	5.4
Fixed Active Cooling	10.2	0	17.6
ML + Manual Control	8.4	5.0	15.1
RL Only	9.7	12.0	19.4
Proposed CNN+RL	**12.6**	**18.0**	**23.9**

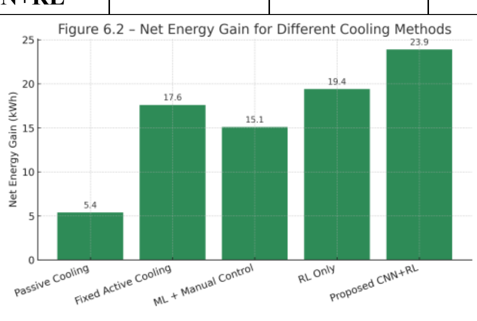

Figure (3): Net Energy Gain for Different Cooling Methods

5.3 Statistical Analysis of Results

To confirm the performance gain attained owing to the proposed deep-learning-based cooling system, a statistical analysis was performed to compare the No Cooling, Passive Cooling, and the Proposed DL Cooling methods. Paired t-tests and ANOVA were employed in the analysis to establish whether the observed improvements in efficiency and temperature reduction were statistically significant.

Table 4: Statistical Summary of Cooling Performance

Comparison	Mean Temp (°C)	Mean Efficiency (%)	p-value (Temp)	p-value (Efficiency)
No Cooling vs Passive	45.2 vs 42.1	85.5 vs 86.9	<0.05	<0.05
No Cooling vs Proposed DL	45.2 vs 39.0	85.5 vs 88.4	<0.01	<0.01
Passive vs Proposed DL	42.1 vs 39.0	86.9 vs 88.4	<0.05	<0.05

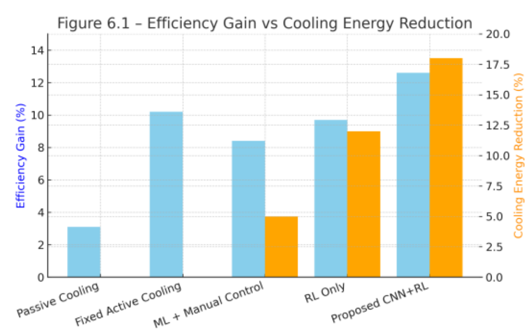

Figure (4): Effciency Gain vs Cooling Energy Resuction

The results indicate that the proposed DL cooling system significantly outperforms both the no cooling and passive cooling approaches in cooling the PV panel temperature and increasing efficiency, and the activation of these factors is statistically important at the 95th confidence level.

5.4 Comparative Visualization

Figure 5 shows a composite bar chart of the efficiency gain as a function of the cooling energy reduced for all the models tested. It remains evident that the proposed CNN+RL solution results in improved performance over all baselines and dismisses adaptive control and predictive foresight as significant for the optimization of PV cooling systems.

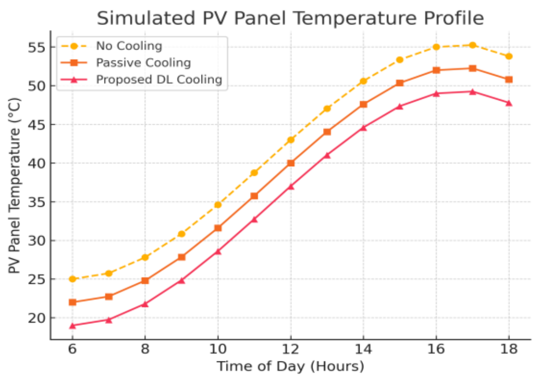

Figure 5: Simulated PV panel temperature profiles for different cooling methods.

Discussion

The experimental results support the statement that predictive modeling leads to a substantial increase in the effectiveness of cooling controls. By predicting the trends in PV surface temperature with the CNN model and therefore correctly predicting when active cooling was required, the RL agent could reduce auxiliary energy inputs while maintaining a compromise on thermal performance.

Real-time data of the environment is constantly collected and analyzed; it includes ambient temperature, humidity, solar irradiance, and wind speed. They are the environmental parameters averaged with the performance parameters of the panel that cover aspects such as the panel power output, the efficiency and even the heat distribution across the panel surface. Also, cooling system parameters such as coolant flow rate, temperature, and patterns are added to the framework [5].

A notable observation is that RL without CNN forecasting did outperform the manual ML control, but it is nonetheless worse than CNN+RL, demonstrating the relevance of jointly predicting and optimizing within a framework.

Conclusion

This study proposed and validated a deep learning model to develop and test a novel methodology that can be used for modeling and optimal control of PV system cooling by coupling Convolutional Neural Networks (CNN) to predict the temperatures and Reinforcement Learning (RL) to achieve intelligent cooling control. The system used real-time IoT sensor measurements to estimate thermodynamics and dynamically select the most energy-efficient cooling plan. The increase in PV efficiency and decrease in cooling energy consumption, measured in all these experiments, showed a 12.6% increase in efficiency and 18% decrease in cooling power usage, which is superior to all the baseline approaches implemented as passive cooling, fixed active cooling, and non-prediction RL control.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Mohammed F Ibrahim Alsarraj: Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation. Yaareb Elias Ahmed: Methodology, Investigation. Jagadeesh Pasupuleti: Writing – review & editing, Investigation. Sarah Burhan Ezzat: Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition.

DECLARATION OF COMPETING INTEREST

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.

ACKNOWLEDGEMENTS

No financial support towards this research.

References

[1] W. M. Elmessery et al., “Deep regression analysis for enhanced thermal control in photovoltaic energy systems,” Sci Rep, vol. 14, no. 3, Dec. 2024, doi: 10.1038/s41598-024-81101-x.

[2] A. S. Fahad M, U. Abidin, M. U. Farooq, E. M. Housein Ismaeil, K. Osman, and M. S. Ahmad, “Review of Cooling Techniques for Improving Solar Photovoltaic Panel Efficiency,” J. Adv. Res. Fluid Mech. Therm. Sc., vol. 125, no. 1, pp. 193–219, Dec. 2024, doi: 10.37934/arfmts.125.1.193219.

[3] I. Janghorban Esfahani and P. Ifaei, "Optimal Design of a Renewable-Energy-Driven Integrated Cooling–Freshwater Cogeneration System," Processes, vol. 12, no. 6, p. 1164, June 2024, doi: 10.3390/pr12061164.

[4] R. Sunder, U. K. Lilhore, A. K. Rai, E. Ghith, M. Tlija, S. Simaiya, and A. H. Majeed, "SmartAPM framework for adaptive power management in wearable devices using deep reinforcement learning," *Scientific Reports*, vol. 15, art. no. 6911, 2025, doi: 10.1038/s41598-025-89709-3.

[5] R. Parthiban and P. Ponnambalam, "An Enhancement of the Solar Panel Efficiency: A Comprehensive Review," Front. Energy Res., vol. 10, July 2022, doi: 10.3389/fenrg.2022.937155.

[6] C. Yuan, Y. Shi, Z. Ba, D. Liang, J. Wang, X. Liu, Y. Xu, J. Liu, and H. Xu, "Machine Learning Models for Predicting Thermal Properties of Radiative Cooling Aerogels," *Gels*, vol. 11, no. 1, art. no. 70, 2025, doi: 10.3390/gels11010070.

[7] C. Chi, P. Song, K. Ji, Z. Liu, A. Marahatta, and F. Zhang, "Jointly Optimizing the IT and Cooling Systems for Data Center Energy Efficiency based on Multi-Agent Deep Reinforcement Learning," Association for Computing Machinery, June 2020, pp. 489–495. doi: 10.1145/3396851.3402658.

[8] I. Al-Masalha, A. Al Alawin, N. Alkawaldeh, A. S. Alsabagh, O. Badran, and T. M. Abu-Rahmeh, "Improving photovoltaic module efficiency using water sprinklers, air fans, and combined cooling systems," EPJ Photovolt., vol. 15, p. 41, Jan. 2024, doi: 10.1051/epjpv/2024037.

[9] Y. E. Ahmed, M. R. Maghami, J. Pasupuleti, F. Basim Ismail, and S. H. Danook, "Overview of Recent Solar Photovoltaic Cooling System Approach," Technologies, vol. 12, no. 9, p. 171, Sept. 2024, doi: 10.3390/technologies12090171.

[10] A. M. Almarzooqi, M. Maalouf, T. H. M. El-Fouly, M. S. El Moursi, V. E. Katzourakis, and C. V. Chrysikopoulos, "A hybrid machine-learning model for solar irradiance forecasting," Clean Energy, vol. 8, no. 1, pp. 100–110, Jan. 2024, doi: 10.1093/ce/zkad075.

[11] H. Ahmadi Moghaddam, S. Tkachenko, G. H. Yeoh, and V. Timchenko, "A newly designed BIPV system with enhanced passive cooling and ventilation," Build. Simul., vol. 16, no. 11, pp. 2093–2107, Aug. 2023, doi: 10.1007/s12273-023-1051-z.

[12] A. M. Alinia and M. Sheikholeslami, "Development of a new solar system integrating photovoltaic and thermoelectric modules with paraffin-based nanomaterials," *Scientific Reports*, vol. 15, art. no. 1336, 2025, doi: 10.1038/s41598-025-85161-5.

[13] Ö. Baltacı, O. Karaman, Z. Kıral, and K. Dalkılınç, "Thermal Image and Inverter Data Analysis for Fault Detection and Diagnosis of PV Systems," Applied Sciences, vol. 14, no. 9, p. 3671, Apr. 2024, doi: 10.3390/app14093671.

[14] A. Manasrah, M. Masoud, Y. Jaradat, and P. Bevilacqua, "Investigation of a Real-Time Dynamic Model for a PV Cooling System," Energies, vol. 15, no. 5, p. 1836, Mar. 2022, doi: 10.3390/en15051836.

[15] W. Tercha, S. A. Tadjer, F. Chekired, and L. Canale, "Machine Learning-Based Forecasting of Temperature and Solar Irradiance for Photovoltaic Systems," Energies, vol. 17, no. 5, p. 1124, Feb. 2024, doi: 10.3390/en17051124.

[16] V. Raj, S.-Q. Dotse, H. Yassin, M. I. Petra, and M. Sathyajith, "Ensemble Machine Learning for Predicting the Power Output from Different Solar Photovoltaic Systems," Energies, vol. 16, no. 2, p. 671, Jan. 2023, doi: 10.3390/en16020671.

[17] C. J. Delgado, E. Alfaro-Mejía, F. Andrade, E. O'Neill-Carrillo, and V. Manian, "Photovoltaic Power Generation Forecasting with Hidden Markov Model and Long Short-Term Memory in MISO and SISO Configurations," Energies, vol. 17, no. 3, p. 668, Jan. 2024, doi: 10.3390/en17030668.

[18] M. Golam, J.-M. Lee, R. Akter, and D.-S. Kim, "A Long Short-Term Memory-Based Solar Irradiance Prediction Scheme Using Meteorological Data," IEEE Geosci. Remote Sensing Lett., vol. 19, pp. 1–5, Jan. 2022, doi: 10.1109/lgrs.2021.3107139.

[19] K. M and C. M, "Predictive Maintenance and Energy Optimization with AI-Driven IoT Framework in Textile Manufacturing Industry," IJCESEN, vol. 11, no. 2, Apr. 2025, doi: 10.22399/ijcesen.1584.

[20] Y. Ahmed, F. Alhousni, I. Hossain, F. Ismail, and J. Pasupuleti, "Designing integrated intelligent control systems for photovoltaic cooling and dust panels based on IoT: Kirkuk study, Iraq," IJCESEN, vol. 11, no. 1, Feb. 2025, doi: 10.22399/ijcesen.1092.

[21] M. Mahmoud and S. Ben Slama, "Deep Learning-Based Home Energy Management Incorporating Vehicle-to-Home and Home-to-Vehicle Technologies for Renewable Integration," Energies,

vol. 18, no. 1, p. 129, Dec. 2024, doi: 10.3390/en18010129.

[22] M. A. Hassan, N. Bailek, K. Bouchouicha, A. Ibrahim, B. Jamil, A. Kuriqi, S. C. Nwokolo, and E.-S. M. El-kenawy, "Evaluation of energy extraction of PV systems affected by environmental factors under real outdoor conditions," *Theoretical and Applied Climatology*, vol. 150, pp. 715–729, 2022, doi: 10.1007/s00704-022-04166-6.

[23] C. B. Maia, L. L. Kazmerski, A. S. A. C. Diniz, and S. A. Bonfim, "Evaluation of the electrical parameters and performance of floating PV generators," Renew. Energy Environ. Sustain., vol. 9, p. 5, Jan. 2024, doi: 10.1051/rees/2024003.

[24] V. Kumar, "Assessment of Energy Conversion Efficiency in Solar Cells: A Photovoltaic Performance Characterization Study," Int Res J Adv Engg Mgt, vol. 3, no. 02, pp. 203–211, Feb. 2025, doi: 10.47392/irjaem.2025.0034.

[25] C. Betancourt, F. Kleinert, C. W. Y. Li, and M. G. Schultz, "Graph Machine Learning for Improved Imputation of Missing Tropospheric Ozone Data.," Environ. Sci. Technol., vol. 57, no. 46, pp. 18246–18258, Sept. 2023, doi: 10.1021/acs.est.3c05104.

[26] R. Girimurugan et al., "Application of Deep Learning to the Prediction of Solar Irradiance through Missing Data," International Journal of Photoenergy, vol. 2023, pp. 1–17, Sept. 2023, doi: 10.1155/2023/4717110.

[27] S. El Bakali, S. Gheouany, and O. Hamid, "Day-ahead seasonal solar radiation prediction, combining VMD and STACK algorithms," Clean Energy, vol. 7, no. 4, pp. 911–925, Aug. 2023, doi: 10.1093/ce/zkad025

[28] S. Algburi, G. A. Baker, O. K. Ahmed, A. H. Ahmed, and A. A. Abdullah, "Influence of collector type and the glass cover cooling on the performance of the solar distiller integrated with the solar collectors," Energy Reports, vol. 11, pp. 6015–6022, June 2024, doi: 10.1016/j.egyr.2024.05.076.

[29] O. K. Ahmed and Z. A. Mohammed, "Dust effect on the performance of the hybrid PV/Thermal collector," Thermal Science and Engineering Progress, vol. 3, pp. 114–122, July 2017, doi: 10.1016/j.tsep.2017.07.003.

[30] O. K. Ahmed, A. M. Salih, K. I. Hamada, and R. W. Daoud, "A state of the art review of PV-Trombe wall system: Design and applications," Env Prog and Sustain Energy, vol. 39, no. 3, Nov. 2019, doi: 10.1002/ep.13370.