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Artificial Intelligence for Smart Renewable Energy Asset Management in Jordan: A Comparative Case Study Analysis Based on Asset Management Standards Using MATLAB [1]

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Abstract

The variability of solar generation presents challenges to the management of PV projects, and there is no benchmark for the forecasting of solar irradiance in Jordan, despite the country's renewable energy programme. To overcome the challenges of solar generation variability, machine learning models are proposed in this paper to estimate solar irradiance in Ma'an, using satellite data from NASA POWER in MATLAB. The compact ANN model produces the best results for irradiance estimation (R^2 = 0.986, MAE = 23.5 Wh/m²). Furthermore, by using the irradiance estimations to schedule maintenance for the Shams Ma'an plant, costs due to plant outages were reduced by 56%, saving the plant 625 MWh per year. Results of this study establish the first benchmark for solar irradiance forecasting in Ma'an.

Keywords: *Solar irradiance forecasting; Machine learning; Renewable energy management; Asset management; NASA POWER; Maintenance scheduling; Jordan.*

1. Introduction

Due to its reliance upon imported energy sources, Jordan implemented the Renewable Energy and Energy Efficiency Law of 2012, leading to the growth of the nation's solar and wind power capacity[1]. The southern regions of the Kingdom are thought to receive some of the best solar resources within the region, receiving energy at the rate of 5 to 7 kWh/m² of solar direct radiation per day, and experiencing around 310 sunny days per year[2]. Furthermore, these regions include development zones dedicated to large scale industrial projects, such as the Ma'an Development Area[2]. Additionally, the Kingdom also has developed large scale wind farms, such as the 117 MW Tafila wind farm[3]. Due to the growth of these renewable energy sources to represent around

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half of Jordan's total power generation, the country is facing challenges in managing these power plants. AI systems, implemented into the smart grids that supply power to the Kingdom, have been identified as the technology that can best manage the variable output of these power plants[4].

There are three main reasons for performing the study that is presented in this paper. The first of these reasons is based upon the fact that existing research on the use of AI in the management and operation of power plants is mainly conceptual in nature; while there are some publications of the use of AI in various aspects of the power plants, there are few examples of the actual implementation of those AI systems into the power plants, and none that discuss the potential monetary value of implementing such AI systems into those power plants to assist in their management decisions [5, 6]. Second, there are numerous technical publications of the use of ML methods to forecast solar irradiance with accuracies of over 95% [7, 8]; however, the majority of these technical publications do not provide a complete view of the accuracy of the models that were published in those journals; they report different metrics of the accuracy of those models, they publish only single results for the accuracy of those models without implementing alternative, non-AI methods for comparing accuracy, and they do not publish information regarding the effort required to develop those models to forecast solar irradiance [9-11]. Finally, there are numerous technical publications of the use of satellite data to model solar irradiance within countries like Egypt and Algeria [12, 13]; however, there are no existing models for the use of ML methods to forecast solar irradiance within the nation of Jordan, and specifically within the area of Ma'an. Table 1 provides an overview of each of these existing studies on the use of AI in the management of power plants, and the relationship of the present study to each of those existing research efforts.

Table 1. Recent arid-region ML irradiance-forecasting studies and the position of the present work.

Study	**Location / data**	**Best model(s)**	**Reported R^2**	**Non-AI baseline?**
Taha et al. [12]	Zafarana, Egypt; NASA POWER	RF; gradient boosting	≈0.99 / 0.97	No
Ladjal et al. [13]	Ghardaia, Algeria; ground DNI	CNN–LSTM hybrid	High (DNI)	No
Islam & Ustun [9]	Long-term met. dataset	GBR; RNN (13 tested)	High	Partial
This study	**Ma'an, Jordan; NASA POWER**	**ANN; bagged trees; SVR**	**0.986 (ANN)**	**Yes (2)**

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This paper makes three contributions to the literature. First, it establishes the first documented machine learning (ML) estimation benchmark for Ma'an by evaluating the models' ability to accurately forecast unseen future data over time, while also comparing those results to two different non-AI methods for meeting the same goal. The data used was collected from the same time periods as the training data for the ML models, meaning that the evaluations were performed for a very short time horizon for the models rather than over several hours of future data. Second, the proposed method for evaluating ML models based upon the accuracy of the models' forecasts relative to the efforts required to implement those models within the power plant is provided. The efforts for each of the models were calculated by employing the typical hyperparameters for each of the ML models as published in the existing literature. Third, the accuracy of the ML models is translated into management currency through the performance of a maintenance scheduling experiment at the power plant, as well as through validation of the forecasts performed within a Simulink model of the components of the power plant. The remainder of this paper is organised as follows: Section 2 describes the data and methods that were used in this paper; Section 3 presents the results of the experiments and simulations performed in this paper; Section 4 discusses the decision experiment, its validation, and its implications; and Section 5 contains the conclusions and recommendations from this paper.

2. Materials and Methods

2.1 Study site and data

The data were obtained from the NASA POWER project for the location of Ma'an (30.205°N, 36.799°E) in Jordan (approximately 944 m above sea level). Five different variables were obtained from the NASA POWER project for this location: the all-sky global horizontal irradiation (the target variable to be forecasted), the direct normal irradiation, the diffuse horizontal irradiation, the air temperature at 2 meters above the ground, and the wind speed at 10 meters above the ground. Published studies indicate good agreement between the POWER project data and measurements of irradiance from ground-based sensors in other arid regions of the planet [14]. Thus, the NASA POWER project is the only available data set for Ma'an, and was the same project used to provide the most recent weather forecasts for Egypt [12]. Due to the length of time required to process the satellite-based measurements of solar irradiance, data between 27 June 2025 and 30 March 2026 (approximately 6,648 measurements of irradiance for the 277 complete days of measurements during this period) was used for analysis, and there were no missing data values within this time period.

2.2 Pre-processing and experimental design

All processing was performed in MATLAB R2023b (Statistics and Machine Learning Toolbox). The features of hour-of-day and day-of-year were encoded using sine-cosine pairs, as were two

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lag features for GHI (one hour and twenty-four hours earlier), with all night hours removed from the dataset; hence, only the 3,344 daytime samples were used to train the models, which were divided into training and test set as described below. The training and test set were divided chronologically (not randomly) into two subset with 2,675 and 669 time steps, respectively (training: 28 June 2025 to 3 February 2026, test: 3 February to 30 March 2026).

Thus, the models would be evaluated on a time period that was ahead of and unseen by the models during training. Both the training and test data were standardised using only the training set statistics. Additionally, the test data samples fall within the part of the time series that exhibits the greatest variability in weather conditions. Figure 1 summarises the methodology used to produce the results presented in this paper.

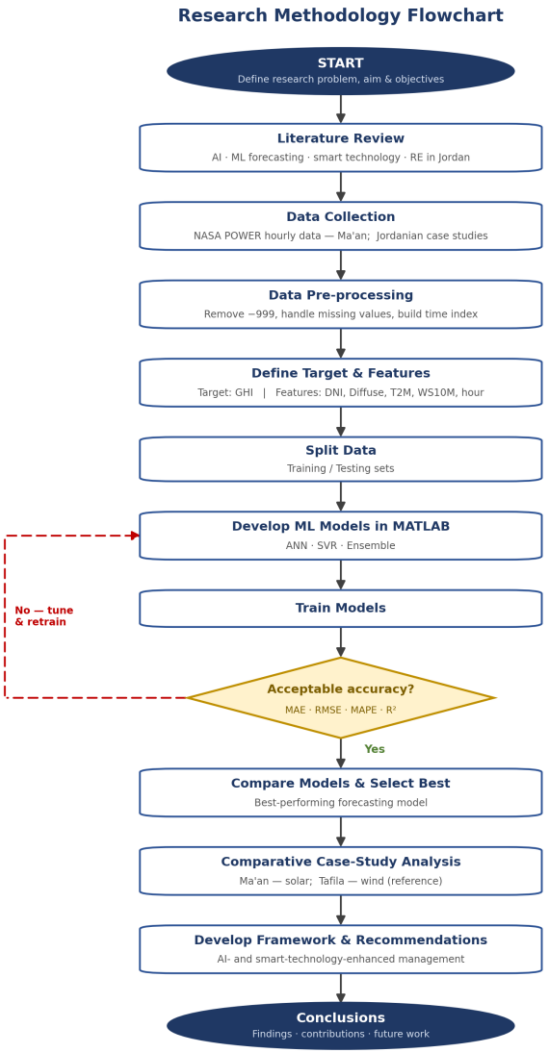


Fig. 1. Research methodology.

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2.3 Models and evaluation

Three model families, each representing one of the main approaches to the problem described in the literature, were implemented using hyperparameters set to values typical of textbook examples: an artificial neural network that contains two hidden layers with 32 and 16 ReLU neurons, respectively; support-vector regression with a Gaussian kernel with parameters C = 10 and ε = 5 Wh/m²; and an ensemble of 200 bagged regression trees with a minimum leaf size of 5. Each model was trained using a random seed to ensure that the results were reproducible. Finally, two additional models that do not employ any form of artificial intelligence were also evaluated on the same data set: a model that represents the rule that the operator employs to perform 24 hour persistence, and a model that is based on multiple linear regression with the same ten features of the data. The accuracy of each of these models was evaluated using four different metrics: the mean absolute error (MAE), the root mean squared error (RMSE), the mean absolute percentage error (MAPE) calculated only for the daytime hours of the data, and the coefficient of determination (R^2). Each of these metrics was calculated to avoid the problem of inconsistent evaluation of the accuracy of the models. Fig. 1 represents a diagram of the overall research methodology that was employed, and Table 2 contains a description of the design of each of the models that were implemented. It should be made explicit that because the variables used as predictors (DNI, DIF, temperature and wind speed) are drawn from the same time step as the variable to be predicted (GHI), the problem is actually better characterised as an irradiance estimation and nowcasting problem rather than a multi-hour-ahead forecasting problem. The lagged variables for GHI (respectively, one and twenty-four hours) are the only variables that contain the information necessary to appropriately predict GHI, and the model is developed as a result to ensure compactness, interpretability, and reproducibility of the model. Extending the time horizon for which the model is used would necessitate either replacing the contemporaneous variables with their own forecasts or using weather prediction model outputs, which is the focus of the future work that is presented in this paper.

Table 2. Summary of experimental design.

Element	**Decision**
Data	NASA POWER hourly; 27 Jun 2025 – 30 Mar 2026; 6,648 h; 277 days
Target / features	GHI (daytime); DNI, DIF, T2M, WS10M, 4 cyclical encodings, 2 GHI lags
Split	Chronological 80/20: train 2,675 h; test 669 h (unseen future)
Models	ANN (32–16 ReLU); SVR (Gaussian, C=10, ε=5); bagged trees (200)

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Baselines	Persistence-24; multiple linear regression
Metrics	MAE, RMSE (primary), MAPE, R^2

3. Results

3.1 Exploratory characteristics

The average daytime GHI at Ma'an is 452 Wh/m² with clear sky values of 1,068 Wh/m² and ambient temperatures ranging from −1.8°C to 44.0°C. The mean daily seasonal values of GHI (Fig. 2) indicate that summer averages are approximately 950 Wh/m² as compared to the averages of approximately 550 Wh/m² during the winter months; the majority of the deviation between these average seasonal values occur during the winter months - the period that covers the test window. GHI correlates with its constituent variables of DNI (r = 0.93), DIF (r = 0.83), with less correlation to ambient temperature (r = 0.56) and wind speed (r = 0.11). Each of these variables were, therefore, included within the model to account for these correlations between the variables.

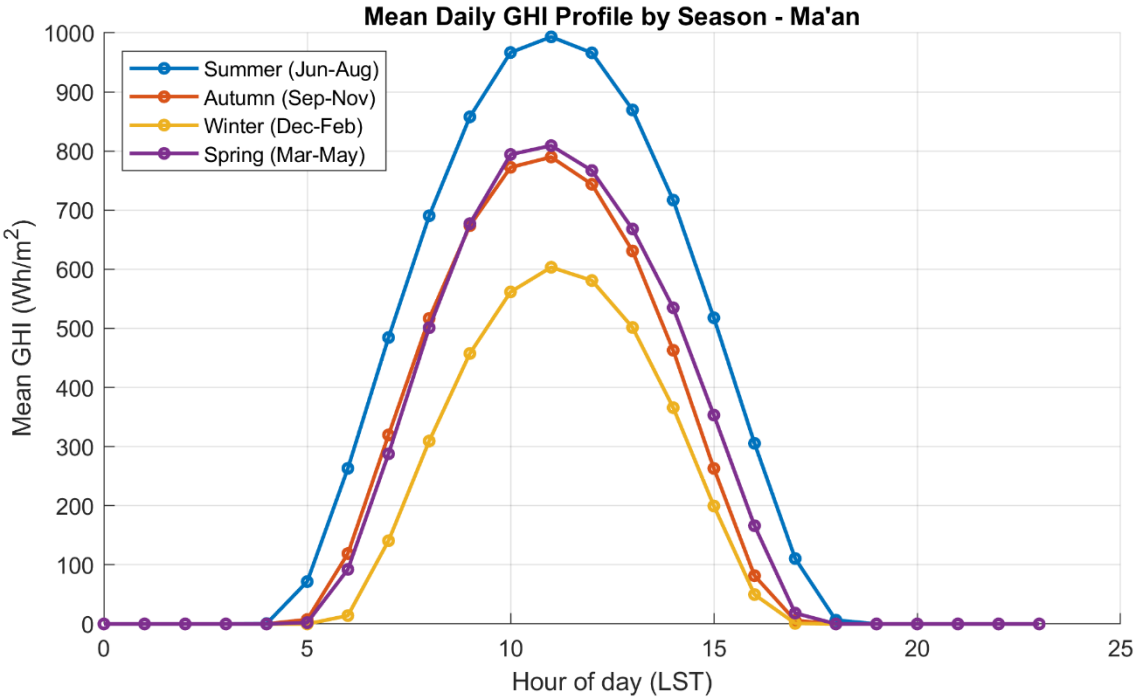


Fig. 2. Mean daily GHI profile by season, Ma'an.

3.2 Forecasting performance and non-AI benchmark

Table 3 reports on the methods applied to the same 669-hour test set. The results of the ANN are the best in this table with an R^2 of 0.986 and an MAE of 23.5 Wh/m² (about 5% of the mean of

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the daytime irradiance levels). The irradiance levels predicted by the ANN match the actual irradiance levels very well, whether on clear days or cloudy days, including the irradiance peak of 6 February (Fig. 3). The bagged ensemble model has an R^2 of 0.926 with the smallest MAPE of 14.4% which indicates that it performs slightly better with lower irradiance levels. The untuned SVR model, however, produces irradiance levels of only around 500-600 Wh/m² with an R^2 of 0.578 and seems to under-predict the irradiance peaks on days with high levels of solar irradiance (Fig. 4). Thus, the SVR model appears to be more sensitive to configuration settings than the other models tested [10].

To confirm that this result is not an artefact of the train-test split that was used in evaluating the model's performance, the ANN was evaluated using five-fold rolling-origin cross-validation. In this method, the training data is divided into five folds, each of which contains only the data that was recorded prior to the fold itself, and the model is evaluated using the fold immediately following that in the time series. The ANN achieved MAE = 24.3 ± 15.1 Wh/m², RMSE = 33.6 ± 19.9 Wh/m², MAPE = 21.1 ± 10.7%, and R^2 = 0.983 ± 0.016 over the five folds, all of which is similar to the results achieved by the model when evaluated on the dataset that was used to calculate the results presented above in Table 3. Furthermore, since these five folds collectively represent the entire year's worth of data (as opposed to only the winter fold that was used in calculating the results of the model's accuracy), these cross-validation results help to additionally indicate that the model maintains its accuracy throughout the year, not just during the period for which Table 3 reports its accuracy.

A further, informative finding emerges from the same cross-validation experiment: the untuned SVR exhibited marked instability in its predictions (R^2 = −0.23 ± 0.37). To provide a fair comparison between the tuned and untuned SVR classifiers, the hyperparameters of the SVR model were optimised via grid search. Grid search was used to find an optimal value of the box constraint (C) and epsilon (ε) parameters by evaluating the model using rolling-origin validation on the training set alone. The resulting values of C = 100 and ε = 1 led to poor generalisation to the test set (R^2 = 0.224). Repeating this search using built-in Bayesian optimisation to find optimal values for the box constraint, kernel scale and epsilon parameters over 30 evaluations using five-fold cross-validation on the training set led to the following parameters: C = 983.8, kernel scale = 3.24 and ε = 2.05. These parameters led to a model with MAE = 30.5 Wh/m², RMSE = 44.7 Wh/m², MAPE = 35.8% and R^2 = 0.975 on the test set (Table 3). These results are almost as good as the ANN. Thus, the relative weakness of SVR is due to the effort that was invested in deploying the algorithm, not the intrinsic properties of the algorithm itself.

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Table 3. Performance on the identical held-out test set (669 h, Feb–Mar 2026).

Method	MAE (Wh/m²)	RMSE (Wh/m²)	MAPE (%)	R^2
Persistence-24 (no AI)	82.0	138.9	26.2	0.760
Linear regression (no AI)	42.4	66.3	33.0	0.945
SVR (untuned)	147.7	184.1	252.6	0.578
SVR (tuned, Bayesian optimisation)	30.5	44.7	35.8	0.975
Ensemble (bagged trees)	46.4	76.9	14.4	0.926
ANN (this study)	**23.5**	**33.2**	**16.6**	**0.986**

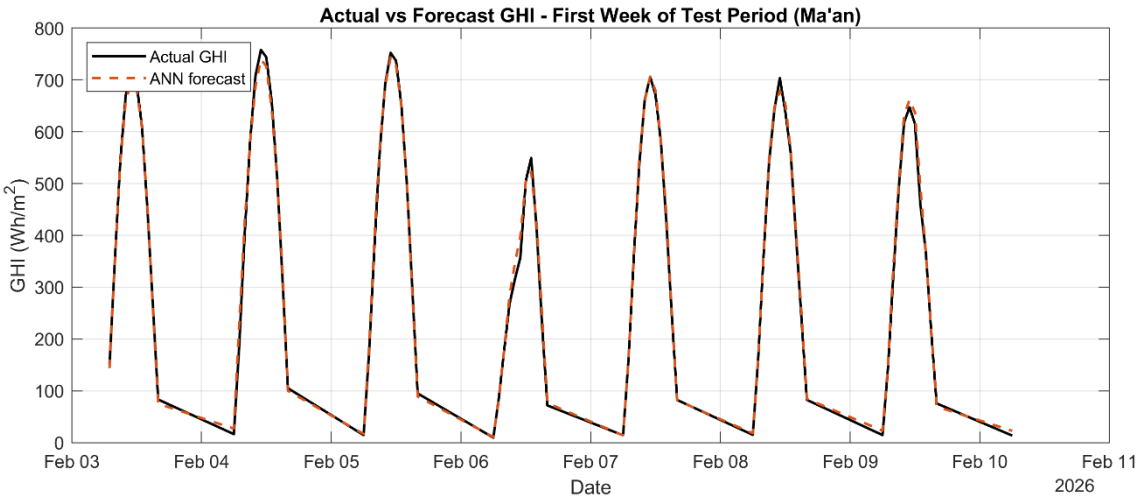


Fig. 3. Actual versus ANN-forecast GHI, first test week.

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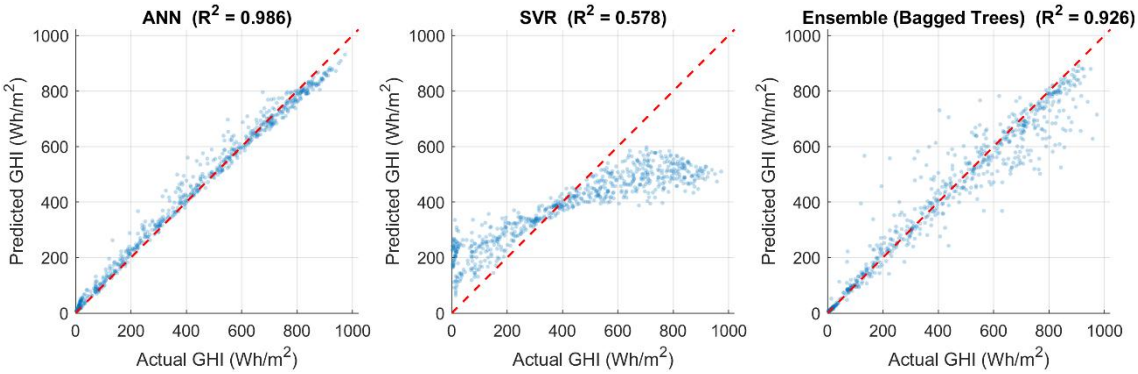


Fig. 4. Predicted versus actual GHI for the three ML models.

The gradient of the benchmark is steep (Fig. 5). The traditional rule yields an R^2 value of 0.76, but both linear regression and the artificial neural network model halve the error of the persistence rule - reducing the RMSE by 76% relative to the operator rule calculated over the same dataset. Thus, the difference in performance between the rule-based method and the machine learning methods indicates that the improvement is due to the application of machine learning methods, and that the relationship between the features and the target variable is not linear in nature. The importance weights of each feature within the artificial neural network are slightly less precise than the coefficients for the linear regression model, but reveal the same general results (Fig. 6). The most important feature within the model is the 24-hour lag variable, followed by DNI, the one-hour lag variable, and finally the wind speed feature, which is close to zero in importance - once again confirming the results of both the correlation analysis and the solar-focused analyses performed above of the importance of each feature.

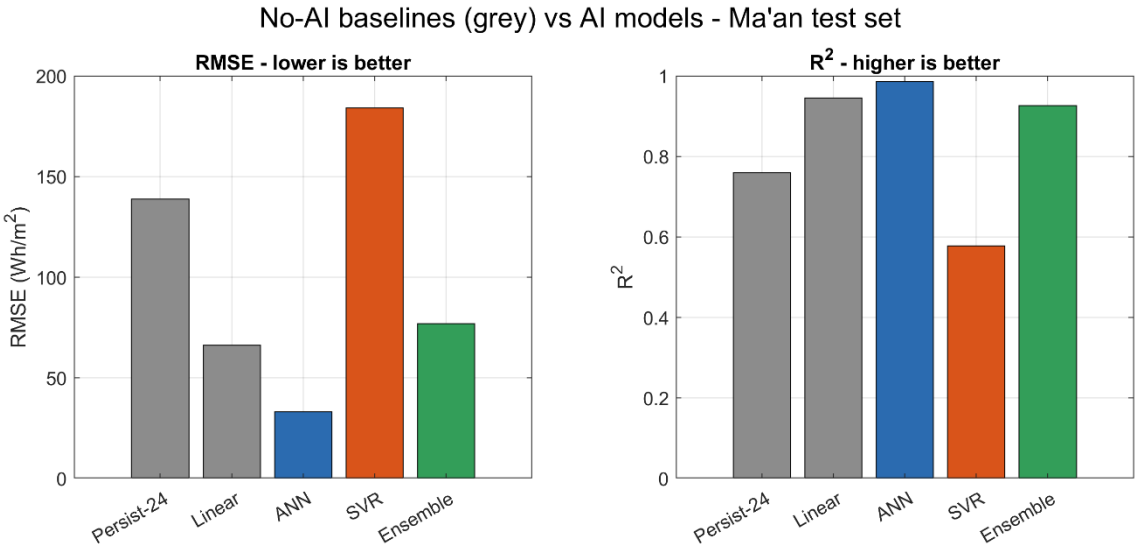


Fig. 5. No-AI baselines versus AI models: RMSE and R^2.

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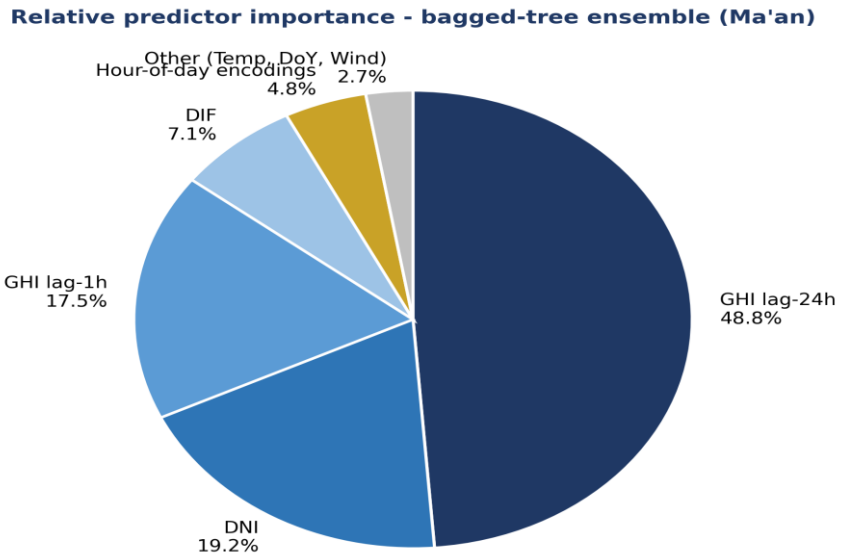


Fig. 6. Relative predictor importance (bagged-tree ensemble).

4. Discussion

4.1 From accuracy to management value: a decision experiment

The hourly values of GHI were converted to AC power for a 1 MW reference plant using the PVWatts model with NOCT cell temperature correction. The total energy forecast for the week differed from the actual energy delivered by only about 1%. The decision of during which four hour period of daylight an activity that would reduce the plant's power output should be scheduled can be answered with a simple calculation. If scheduled without regard to the solar power forecast, such an activity would result in the loss of about 1,764 kWh of power per MW of installed capacity. By scheduling the activity during the cloudy morning of February 6, according to the solar power forecast, the reduction in energy output was 56% less than the best four hour period that could have been selected with perfect knowledge of the solar power output for the week (Table 4; Fig. 7). The result for energy is therefore tariff independent. Expressed in monetary terms for illustration, and scaling to the 52.5 MW Shams Ma'an plant [15], this saving of the order of 625 MWh per year results in savings of roughly USD 31,000 per year at a utility-scale PV tariff of about USD 0.05/kWh [16]. Again, this is only an order-of-magnitude calculation - it simply scales one decision variable by the number of times that it is expected to occur. Nevertheless, it indicates that the majority of the value of this application will be during the winter months, when irradiance variability is the highest.

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Table 4. Four-hour maintenance outage: energy and revenue lost per MW installed.

Strategy	Energy lost (kWh/MW)	Cost (USD)
Blind (expected)	1,764	265
Worst case	2,480	372
AI-informed (chosen on forecast)	**772**	**116**
Oracle (perfect foresight)	772	116

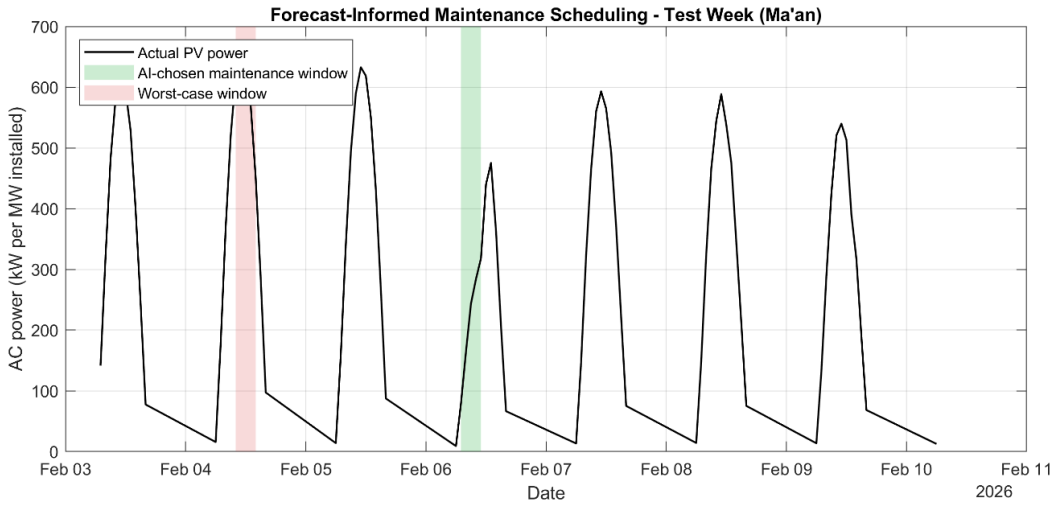


Fig. 7. Forecast-informed maintenance scheduling: AI-chosen versus worst-case window.

4.2 Physics-based validation

Further validation of the model was performed by simulating the cloudy test day through a switching-level PV/MPPT model implemented within Simulink. The PV array and boost converter were implemented by the author, and the perturb-and-observe algorithm of Motahhir et al. [17] was employed. Table 5 lists the parameters of the simulated PV array, boost converter, and MPPT controller. The configuration of the PV array that was simulated was replaced with the measured solar irradiance profile, which was applied to each of the three parallel boost converters. Simulations of the cloudy day with the actual and ANN-forecasted solar irradiances resulted in power curves similar to each other (Fig. 8). The rms difference in the power values from each simulation was 8.70 W, and the mean absolute difference was 4.48 W, in each case less than 3% of the peak power (355 W) of the simulated PV system.

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Table 5. Simulink PV/MPPT model specifications.

Parameter	Value
PV module (user-defined): maximum power, cells per module	213.15 W, 60 cells
Open-circuit voltage / short-circuit current (Voc / Isc)	36.3 V / 7.84 A
Voltage / current at maximum power point (Vmp / Imp)	29.0 V / 7.35 A
Temperature coefficient of Voc	−0.361 %/°C
Diode model: IL, I0, ideality factor, Rsh	7.865 A, 2.93×10^{-10} A, 0.981, 313 Ω
Boost converter: inductance / capacitance	7.445 mH / 419 µF
MPPT algorithm	Perturb & Observe [17]
Switching frequency / duty-cycle limits	10 kHz / 0.08–0.80

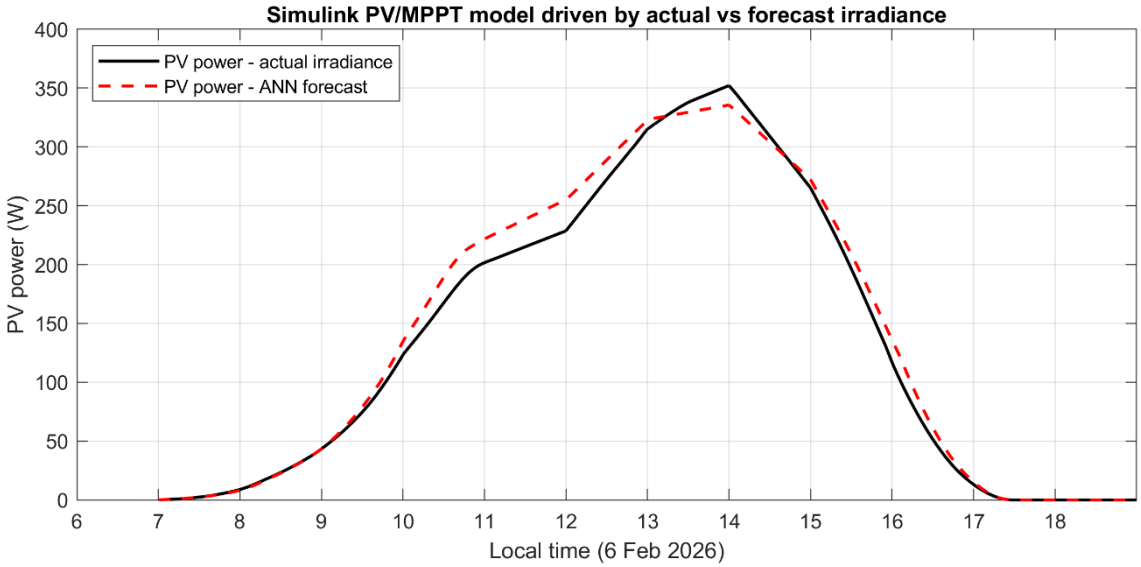


Fig. 8. Simulink PV/MPPT simulation driven by actual versus forecast irradiance (6 Feb 2026).

4.3 Comparison with prior work and limitations

While the headline accuracy of these models is credibly below the $R^2 \approx 0.99$ reported for Zafarana using the same data source [12], which is due to the less-tuned nature of these models, the relative performance of these model families is consistent with reports for other tabular data sources in the literature [9, 12]. A few limitations to this study should be mentioned. First, the satellite-based (reanalysis) data is smoothed in both space and time, which means that the accuracy of these models is calculated only for weather conditions that are favourable to the operation of the plant; the accuracy of these models, therefore, only establishes a baseline for the performance of the Ma'an plant, not determines whether it is ready to operate; direct measurements of the irradiance

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at the plant would be required to determine such readiness. Furthermore, these tests were performed at only a single site during only a single year in the winter months, when the levels of atmospheric dust are low; the accuracy of the models may differ at other times of the year or at other sites. Additionally, all hyperparameters for these models were set before the tests were performed, so the accuracy values represent the floor for each model rather than the accuracy that could be achieved with more-tuned hyperparameters. Finally, and most importantly, these accuracy rates were calculated for an estimation and very-short-horizon-ahead model, as opposed to a model that could estimate irradiance several hours in the future. The model uses irradiance components that were simultaneously measured at the satellite sensors to calculate its estimates of irradiance at the plant at the same time step, which means that its estimates are only valid a few hours into the future. This topic will be examined more closely in the following discussion.

5. Conclusions and Recommendations

A benchmark of solar resource forecasting using machine learning methods has been established for Ma'an, Jordan. The ANN model achieved $R^2 = 0.986$ with a MAE of 23.5 Wh/m² on future data that had not been seen by the model during its training; this represents a 76% reduction in RMSE compared to the traditional method of persisting the most recent hourly measurement of GHI. The bagged-tree ensemble model achieved similar accuracy at little or no cost compared to the ANN model. The performance of the untuned SVR model, while initially weak, indicates the importance of proper model tuning when using a particular model family; once properly tuned, the SVR model achieved an R^2 of 0.975 (Section 3.2).

A forecast-informed maintenance-scheduling experiment translated this accuracy into management value: scheduling a routine four-hour outage using the ANN's forecasts reduced simulated lost energy by 56% relative to uninformed scheduling, matching the outcome achievable with perfect hindsight. Finally, a Simulink simulation of the plant, incorporating the perturb-and-observe MPPT algorithm, confirmed that power output driven by the forecast closely matches power output driven by the actual irradiance (RMSE = 8.70 W).

Based on these results, five recommendations emerge. First, solar operators should establish in-house capabilities for forecasting based on satellite data. Second, the management of solar plants should take ownership of the models. This includes the selection of models and the decision of when to retrain those models. Using both the ANN and the bagged-tree ensemble model will provide valuable information to solar operators for inexpensive early-warning signals. Third, the regulator and the Ma'an Development Area authority should invest in ground sensors to validate the satellite data. Fourth, the approach should be rolled out to solar assets first, with the deployment of the same approach to wind assets once data on hub-height winds are available. Future work will implement this methodology in the following ways: extending the satellite data collection to additional solar plants over multiple years, including summers with high levels of

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dust; optimising the hyperparameters for the ANN and the bagged-tree models to determine their potential performance; reconfiguring the ANN to enable multi-hour-ahead forecasts using lagged meteorological measurements; and implementing this methodology with another solar operator in Jordan.

Declarations

Use of AI Technology

During the preparation of this manuscript, the authors used an AI language model (Anthropic Claude) in a supportive capacity. This included assistance with language editing, restructuring text for clarity, verification and correction of methodological descriptions, and formatting of tables, figures and references. The AI tool did not design the study, collect or generate the underlying data, or determine the scientific conclusions. All research design, data analysis, interpretation of results and conclusions are the authors' own, and the authors have reviewed and take full responsibility for the content of this manuscript.

Conflicts of Interest Declaration

All authors declare that they have no conflicts of interest.

Informed Consent Declaration

This research did not involve human participants; it uses publicly available satellite-derived meteorological data (NASA POWER). No informed consent declaration is therefore required.

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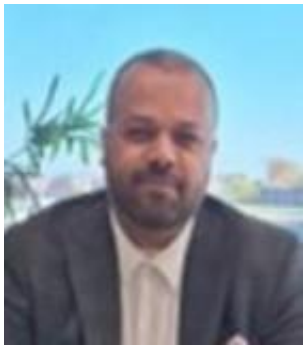
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Yousef Isleem is an MSc Engineering Management student at the University of Sunderland, UK. He holds a BSc in Mechanical Engineering from the Jordan University of Science and Technology, where his graduation project was on the simulation of photovoltaic systems and maximum power point tracking. Currently, his research focuses on utilising machine learning to enhance solar irradiance forecasting accuracy in Jordan, and on translating that accuracy into practical value for the management of renewable-energy projects.



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