

# **AI-Driven Comparative Forecasting of Solar Irradiance and Temperature for Sustainable Energy Planning in Saudi Arabia**

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## **Abstract**

Saudi Arabia's rapid solar expansion under Vision 2030 increases the need for reliable long-term monthly forecasts of global horizontal irradiance (GHI) and ambient temperature to support siting, procurement, and capacity planning. In this study, we apply and compare a suite of traditional and AI-driven forecasting approaches, Holt-Winters, SARIMA, Random Forest, Support Vector Regression, Prophet, and Bayesian Linear Regression, using monthly data from Dhahran (training: 2018–2022, test: 2023). The integration of machine learning (Random Forest, SVR) and probabilistic AI models (Prophet, BLR) enables nonlinear pattern recognition and uncertainty-aware

forecasting critical for sustainable energy planning. After standardized preprocessing and back testing, Random Forest achieves the lowest GHI error (MAPE 4.34%), while Prophet and BLR yield the most accurate temperature forecasts (MAPE 1.61% and 2.67%) with interpretable trends and predictive intervals. AI-based models demonstrate superior adaptability and transparency, underscoring their value for data-driven solar energy planning under Vision 2030.

## **Keywords**

Long-term forecasting, Solar irradiance, Ambient temperature, Machine learning, Probabilistic models, Renewable energy planning

## **1. Introduction**

Accurate long-term forecasting of solar irradiance and ambient temperature is crucial for solar energy planning and grid integration. To achieve this, a wide range of methods is employed, from classical statistical models to advanced machine learning algorithms (Leo et al., 2025). These approaches are typically grouped into numerical/mathematical models, probabilistic frameworks, and machine learning techniques.

As classical time-series approaches, Holt–Winters exponential smoothing and seasonal ARIMA (SARIMA) rely on historical patterns to capture trends and periodicity (Leo et al., 2025; Almazrouee et al., 2020). Such methods have been widely applied to long-term solar forecasting, often providing strong baseline accuracy. Probabilistic models such as Bayesian linear regression and semi-parametric approaches like Facebook’s Prophet provide prediction intervals that capture uncertainty, thereby improving forecast robustness across variable conditions. Meanwhile, modern artificial intelligence (AI) and machine learning (ML) models, such as Random Forest ensembles (Leo et al., 2025) and Support Vector Regression (SVR), excel at capturing complex, nonlinear dependencies between meteorological variables and solar energy outputs. Recent advancements in hybrid architectures that integrate statistical foundations with AI-driven learning mechanisms have further enhanced forecast precision and robustness. In this study, we leverage AI and ML alongside traditional statistical and probabilistic models to establish a comparative framework for long-term forecasting of solar irradiance and temperature. This integration not only quantifies the performance of AI-based methods in energy planning but also demonstrates their practical potential for improving accuracy, interpretability, and uncertainty management in sustainable solar development.

## **2. Literature Review**

### **2.1. Traditional Forecasting Methods**

Traditional statistical techniques such as ARIMA, ARMA, and SARIMA have been foundational in energy forecasting due to their simplicity, interpretability, and low computational demands. The ARIMA effectively captures trends and autocorrelation, while the Grey Model (GM) is favored for sparse data environments (Xu et al., 2024). However, these methods assume linearity and static structures, limiting their effectiveness in handling non-linear, dynamic data such as solar irradiance or temperature changes (Zhou et al., 2024). VAR models handle multivariate data but become computationally expensive as the number of dimensions increases. Their inability to capture non-stationary and nonlinear behavior has made statistical models less effective in modern forecasting applications. Despite these limitations, traditional models remain useful as baselines for their transparency and historical significance (Xu et al., 2024; Zhou et al., 2024).

### **2.2. Rise of AI and Machine Learning**

Artificial intelligence (AI) and machine learning (ML) approaches have advanced solar forecasting by overcoming the linear and stationary assumptions of classical models. Neural networks (ANNs), along with ELMs and SVMs, enable nonlinear mapping and improved accuracy (Xu et al., 2024; Zhou et al., 2024). SVMs, especially when hybridized with PSO or GA, show resilience to noise and sparse functions. Recurrent models like LSTM and GRU effectively capture long-term dependencies in time series data (Sauter et al., 2023; Wang et al., 2024) (Saadati & Barutcu, 2025). Deep learning and ensemble methods (e.g., Echo State Networks, GANs) further enhance forecasting in chaotic environments (Cui et al., 2024). Tools like Facebook Prophet and IoT-integrated systems demonstrate the trend toward interpretable, real-time forecasting solutions.

### **2.3. Transition and Hybridization**

(Hanif & Mi, 2024) The evolution from statistical to ML approaches has led to hybrid models that integrate both strengths. ARIMA layers, for instance, often support trend extraction within neural networks. Combining both physical and ML models enhances accuracy in data-scarce conditions (Michael et al., 2022). Attention mechanisms and probabilistic learning now support uncertainty-aware forecasting, a vital component of renewable energy integration. Hybrid architectures (e.g., LSTM with convolutional layers or random forests) yield top-tier results. Feature selection methods like Bayesian optimization and dual encoders further improve

performance. Yet, challenges like high computation cost and limited scalability remain. Despite this, AI/ML, especially when informed by domain knowledge, is widely seen as the future of solar forecasting (Zhou et al., 2024).

### 3. Contribution

**AI-Enhanced Comparative Benchmark for Saudi Arabia**

This study establishes a localized benchmark for long-term (monthly) solar irradiance and temperature forecasting in Saudi Arabia by comparing six representative models, Holt-Winters, SARIMA, Random Forest, SVR, Prophet, and Bayesian Linear Regression, under a unified evaluation protocol (RMSE, MAE, MAPE). The inclusion of AI-driven models (Random Forest, SVR) enables the assessment of nonlinear and data-adaptive forecasting capabilities alongside classical approaches.

**Uncertainty-Aware Forecasting for Energy Planning**

By integrating probabilistic AI models such as Prophet and Bayesian Linear Regression, the study provides uncertainty quantification and interpretable prediction intervals, key for robust decision-making in energy planning and policy development under Vision 2030.

**Decision-Oriented Model Selection Framework**

The results are translated into practical guidance: Random Forest for accuracy-focused solar assessments, and Prophet/BLR for transparency and risk-aware applications requiring interpretable uncertainty bounds.

**Cross-Paradigm AI Framework for Future Hybrid Models**

The models are categorized into three paradigms: statistical, probabilistic, and AI/ML-based, establishing a cross-paradigm foundation that supports the design of next-generation hybrid forecasting systems for renewable energy applications.

### 4. Methodology

This study investigates a diverse set of forecasting models for analysing solar energy data, incorporating both classical time-series techniques and modern machine learning methods. The objective is to capture nonlinear trends and seasonal patterns to enhance predictive accuracy.

The forecasting methods are organized into three main categories: (1) Numerical/Mathematical, (2) Probabilistic, and (3) Machine Learning. Each category reflects distinct modelling paradigms based on historical data, underlying assumptions, and computational strategies. Representative models from each group are briefly introduced, along with their core mathematical formulations and key applications in solar energy forecasting.

#### 4.1. Statistical Methods (classical-time series)

##### 4.1.1. Holt-Winters Method

The Holt-Winters is a classical time-series model that decomposes data into level  $l_t$ , trend  $b_t$ , and seasonal  $s_t$  (seasonality  $m=12$ ) components. Eqs. (1)–(4) define additive formulation:

$$\text{Level: } l_t = \alpha(y_t - s_{t-m}) + (1 - \alpha)(l_{t-1} + b_{t-1}) \quad (1)$$

$$\text{Trend: } b_t = \beta(l_t - l_{t-1}) + (1 - \beta)b_{t-1} \quad (2)$$

$$\text{Seasonal: } s_t = \gamma(y_t - l_t) + (1 - \gamma)s_{t-m} \quad (3)$$

$$\text{Forecast: } \widehat{y}_{t+h} = l_t + hb_t + s_{t+h-m(k+1)} \quad (4)$$

where  $l_t$  is the deseasonalized level at month  $t$ ;  $b_t$  is the month-to-month trend;  $s_t$  is the month-of-year seasonal effect;  $\alpha$ ,  $\beta$ , and  $\gamma$  control how quickly the components adapt.

This model is suitable for data with stable seasonal effects. The multiplicative form is used when seasonality scales with the level.

##### 4.1.2. SARIMA Model

SARIMA captures both seasonal and non-seasonal dependencies using the backshift operator  $B$ , autoregressive polynomials, and moving-average polynomials. It models a value as a mix of its own past values (AR), past shocks (MA), and seasonal differences. The model is expressed in Eq. (5):

$$\Phi_p(B^m)\phi(B)(1 - B)^d(1 - B^m)^p y_t = \Theta_q(B^m)\theta(B)\varepsilon_t \quad (5)$$

where  $B$  is the backshift operator,  $\phi$  are autoregressive polynomials, and  $\theta$  are moving average polynomials.

This model is great at capturing repeating yearly structure and short-term autocorrelation.

## 4.2. Machine Learning (non-linear, data-driven)

### 4.2.1. Random Forest

Random Forest builds an ensemble of decision trees using features such as lags and month indicators. The output forecast is defined in Eq. (6):

$$\hat{y}_{t+1} = \frac{1}{T} \sum_{i=1}^T f_i(x_t) \quad (6)$$

where  $f_i$  is the prediction from the  $i^{th}$  tree, and  $x_t$  is the feature vector. Each  $f_i$  is a decision tree trained on a bootstrap sample and random feature subsets.

### 4.2.2. Support Vector Regression

SVR minimizes an  $\varepsilon$ -insensitive loss function. The optimization objective is given in Eq. (7):

$$\min \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n (\xi_i + \xi_i^*) \quad (7)$$

Subject to the constraints defined in Eqs. (8) and (9):

$$y_i - w^T \phi(x_i) - b \leq \varepsilon + \xi_i \quad (8)$$

$$w^T \phi(x_i) + b - y_i \leq \varepsilon + \xi_i^* \quad (9)$$

$$\xi_i, \xi_i^* \geq 0 \quad (10)$$

where  $\phi(x)$  is a kernel mapping function,  $C$  is a regularization constant,  $\varepsilon$  is the error tube, and  $\xi_i, \xi_i^*$  are slack variables.

## 4.3. Probabilistic Methods (uncertainty aware)

### 4.3.1. Prophet Model

Prophet models time series as an additive combination of trend, seasonality, and holiday effects. It yields prediction intervals via its posterior predictive distribution. The complete structure is shown in Eq. (10):

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t \quad (11)$$

The trend component  $y(t)$  is defined using a piecewise linear (or logistic) trend:

$$g(t) = (k + a(t)^T \delta)t + (m + a(t)^T \gamma) \quad (12)$$

Yearly seasonality  $s(t)$  is modeled using a Fourier series with period 12 months:

$$s(t) = \sum_{n=1}^N \left[ a_n \cos\left(\frac{2\pi n t}{P}\right) + b_n \sin\left(\frac{2\pi n t}{P}\right) \right] \quad (13)$$

where  $h(t)$  is the holiday or event effects.

### 4.3.2. Bayesian Linear Regression

BLR models probabilistic relationships with posterior inference, using Eqs. (13)–(17) to define its formulation. It fits a linear relationship between engineered time features and the target, producing a full predictive distribution for uncertainty-aware forecasts.

$$y = X\beta + \varepsilon, \quad \varepsilon \sim \mathcal{N}(0, \sigma^2 I) \quad (14)$$

Prior coefficients:

$$\beta \sim \mathcal{N}(\mu_0, \Sigma_0) \quad (15)$$

Posterior distribution:

$$\beta|X, y \sim \mathcal{N}(\mu_n, \Sigma_n) \quad (16)$$

$$\Sigma_n = \left( \Sigma_0^{-1} + \frac{1}{\sigma^2} X^T X \right)^{-1}, \quad \mu_n = \Sigma_n \left( \Sigma_0^{-1} \mu_0 + \frac{1}{\sigma^2} X^T y \right) \quad (17)$$

Predictive distribution:

$$p(y_*|x_*, X, y) = \mathcal{N}(x_*^T \mu_n, x_*^T \Sigma_n x_* + \sigma^2) \quad (18)$$

## 5. Results and Analysis

The forecasting models were trained on monthly solar irradiance (GHI) and temperature data from Dhahran, Saudi Arabia (2018–2022), and tested on 2023 data. Table 1 compares model performance using RMSE, MAE, and MAPE, with Random Forest excelling in GHI prediction, and Prophet and BLR performing best for temperature. Key results for each model are illustrated in Figures 1 to Figure 6.

Table 1. Model Performance Summary

Model	GHI RMSE	GHI MAE	GHI MAPE (%)	Temp RMSE (°C)	Temp MAE (°C)
Holt-Winters	13.80	7.70	5.47	0.49	0.43
SARIMA	13.80	10.73	7.27	0.51	0.39
Random Forest	9.80	7.59	4.34	1.42	0.93
SVR	12.04	9.96	6.28	1.12	0.88
Prophet	12.25	9.19	6.47	0.50	0.40
BLR	14.69	11.18	8.14	0.79	0.62

### 5.1 Statistical Models

Figure 1 (a) shows that the Holt-Winters model accurately captures seasonal GHI trends, with minimal error in June (0.08 kWh/m<sup>2</sup>), but significantly overestimates winter values, particularly in January (error = 30.48 kWh/m<sup>2</sup>), resulting in a MAPE of 5.47%. Figure 1 (b) illustrates the temperature forecast, which closely follows the annual sinusoidal pattern, achieving high accuracy in summer (July error = 0.02 °C) and maintaining a low MAPE of 1.70%. While seasonally robust, the model's reduced winter accuracy suggests potential benefit from hybrid or probabilistic enhancements.

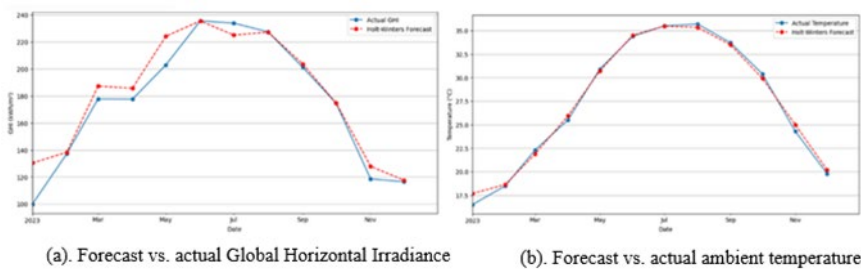


Figure 1. Holt-Winters model performance.

SARIMA captured mid-year GHI patterns with high accuracy (June error = 2.09 kWh/m<sup>2</sup>), though it overestimated winter values, leading to a MAPE of 7.27%, as shown in Figure 2 (a). Temperature forecasts closely followed seasonal trends, achieving peak accuracy in July (0.03 °C error) and an MAPE of 1.76%, as illustrated in Figure 2 (b).

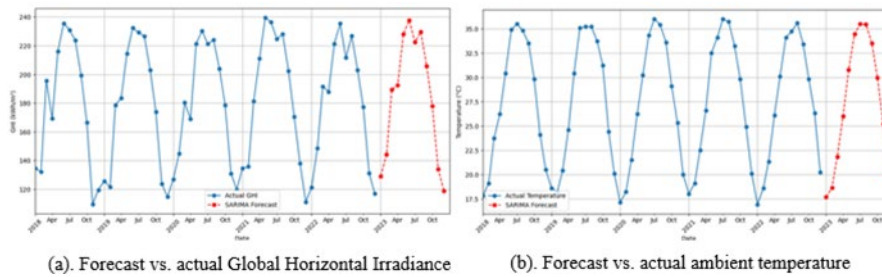


Figure 2. SARIMA model performance.

## 5.2 Machine Learning Models

Random Forest demonstrated strong seasonal adaptability, achieving MAPEs of 4.34% for GHI and 3.09% for temperature. It captured peak irradiance and thermal cycles accurately, with minimal error in December for GHI (1.15 kWh/m<sup>2</sup>) and in September for temperature (0.03 °C), as illustrated in Figure 3 (a) and Figure 3 (b), confirming its robustness for long-term energy forecasting.

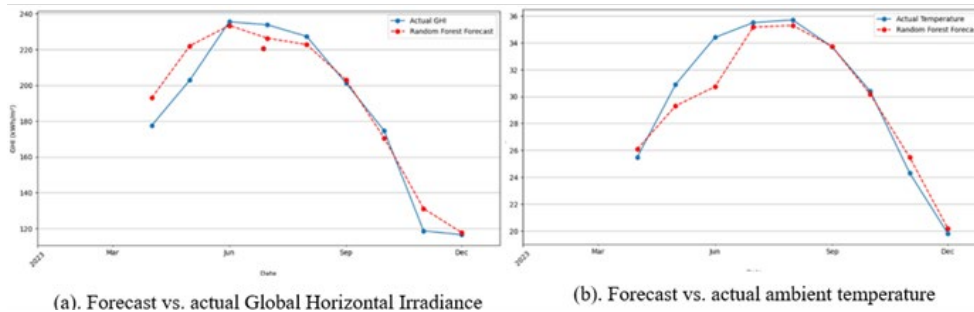


Figure 3. Random Forest model performance.

The SVR model produced seasonally smooth forecasts but struggled with abrupt variability, particularly in GHI (MAPE = 6.28%), with November showing the most significant error (22.78 kWh/m<sup>2</sup>), as seen in Figure 4 (a). Temperature forecasts were more stable (MAPE = 3.13%), though November again marked the peak error (2.30 °C) in Figure 4 (b), highlighting sensitivity during transitional periods.

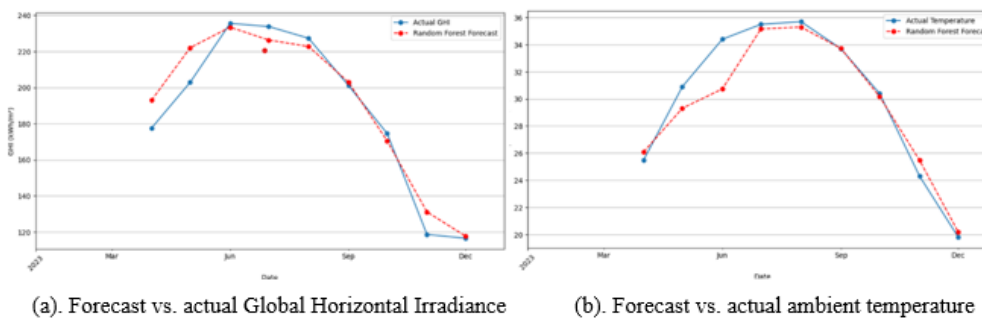


Figure 4. SVR model performance.

## 5.3 Probabilistic and Hybrid Models

Seasonal patterns were well captured by the Prophet model, with GHI forecasts showing reasonable overall accuracy (MAPE = 6.47%) but notable winter overestimation, particularly in January Figure 5 (a). Temperature predictions were more consistent, achieving high precision during stable months and a low MAPE of 1.61%, as illustrated in Figure 5 (b).

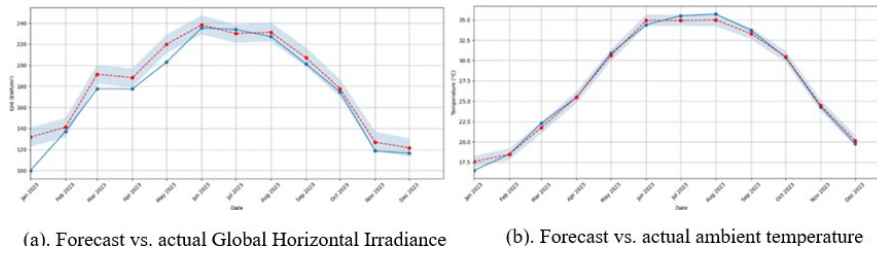


Figure 5. Prophet model performance

BLR delivered interpretable forecasts with reasonable accuracy, though GHI predictions showed notable early-year deviations (MAPE = 8.14%), as shown in Figure 6 (a). Temperature forecasts performed more consistently, especially between April and October, yielding a MAPE of 2.67% Figure 6 (b).

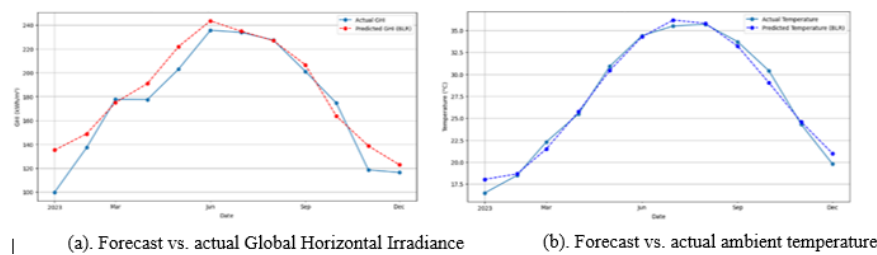


Figure 6. Bayesian Linear Regression (BLR) model performance.

## 6. Conclusion

This study compared six forecasting models: Holt-Winters, SARIMA, Random Forest, SVR, Prophet, and BLR for long-term monthly Global Horizontal Irradiance (GHI) and ambient temperature in Dhahran, Saudi Arabia, with a view toward long-term energy planning. The results indicate that Random Forest emerged as the most accurate model, especially for GHI, while Prophet and Bayesian Linear Regression (BLR) provide the most accurate temperature forecasts, with added benefits of interpretability and uncertainty estimation. Traditional models like SARIMA and Holt-Winters captured seasonality but had higher errors in transitional (low-irradiance) months, and SVR lacked precision under variable conditions. From a planning perspective, these findings are central to the development of the Energy Industry and translate into actionable guidance. The study recommends Random Forest for GHI and accuracy-focused applications and Prophet/BLR for scenarios prioritizing transparency and uncertainty. Notably, the systematic winter bias observed in classical models cautions against relying on them for procurement and adequacy decisions in December-February without additional safeguards. Because this analysis is based on a single site (Dhahran), the conclusions should be interpreted as a localized benchmark and validated across additional Saudi climatic zones before national-scale deployment. Overall, the comparative evidence supports model choice by planning objective: Random Forest to minimize point forecast error in irradiance-driven assessments, and Prophet/BLR to communicate uncertainty and seasonal risk at grid- and portfolio-level planning. In practice, this model-selection guidance can be embedded into decision-support workflows—such as PV siting and resource assessment pipelines, procurement-timing and capacity expansion studies, and policy dashboards that require uncertainty bands to stress-test adequacy under seasonal risk—supporting Saudi Arabia’s Vision 2030 solar expansion.

## 7. Limitations And Future Work

This study is constrained to a single site (Dhahran), which limits spatial generalization across Saudi Arabia’s diverse climatic regions; it also operates at a monthly resolution, smoothing sub-monthly variability relevant to grid operations and maintenance. The models are primarily univariate, and we did not formally assess probabilistic calibration. Future work will extend to multiple datasets across KSA and develop probabilistic pipelines with calibrated outputs. The forecast distributions can be linked to planning KPIs and to economics, perform structured robustness and ablation studies on futures and lags, and explore temporal downscaling to weekly/daily profiles to bridge long-term planning with operational decisions aligned to Vision 2030.

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