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Seasonality-Aware Time Series Modeling for Monthly Solar PV Power Forecasting: A Comparative Study

Ecem Nur Sener[1], Ebru Idman[2], Osman Yildirim[3]

[1] MSc Student, Department of Electrical and Electronic Engineering, Istanbul Aydin University
[2] Assistant Professor, Department of Electrical and Electronic Engineering, Istanbul Aydin University
[3] Professor, Department of Electrical and Electronic Engineering, Istanbul Aydin University

Abstract

Accurate monthly forecasting of solar photovoltaic (PV) energy production is essential for medium-term energy planning, grid integration, and operational decision-making. Although monthly photovoltaic (PV) forecasting is still difficult to perform because it has large seasonal variability and there are few sources of high resolution weather data, this paper presents an objective comparison of three models of time series forecasting; Double Exponential Smoothing (DES); Holt-Winters Triple Exponential Smoothing (TES); and Seasonal Autoregressive Integrated Moving Average (SARIMA). Each model was tested on operational data from a grid connected solar PV power station over the period 2022 – 2025 and demonstrated a very distinct annual seasonality pattern. Using standard error measurements such as root mean square error (RMSE), mean absolute error (MAE), and bias each model's ability to forecast the power output accurately was evaluated. The results indicated that although DES did not take into consideration any seasonal patterns, it had large systematic errors and therefore poor forecasting performance. TES improved upon the forecasting accuracy of DES by incorporating multiplicative seasonal patterns, however, TES also failed to capture rapid changes in power output at times when the PV power plant was producing at its maximum capacity. Conversely, SARIMA provided the best forecasting accuracy and the least amount of bias, thus allowing for accurate modeling of trends and annual seasonal cycles. These results demonstrate the need for explicit inclusion of seasonal patterns in monthly PV forecasting, and confirm SARIMA as being a robust and reliable method for use with seasonal uncertainty.

Keywords: Solar Photovoltaic Power Forecasting, Monthly Energy Prediction, Seasonal Time Series Analysis, SARIMA, Holt-Winters Exponential Smoothing, Double Exponential Smoothing, Seasonal Uncertainty

1. Introduction

Solar energy has been at the leading edge of all renewable energy resources that are expanding around the world due to its low carbon footprint, sustainability goals, and contributions to the global energy supply security. With the increasing integration of photovoltaic (PV) systems into the electricity grid, accurate and reliable energy production forecasting has become a critical requirement for grid operation, maintenance planning, and medium-term energy management [1, 2]. A clear comparison of seasonality-aware statistical models for monthly PV forecasting under real operational conditions is provided, contributing to the applied renewable energy literature.

A significant portion of the studies in the literature on solar energy production forecasting focusses on short-term (hourly or daily) predictions [3,4,5]. In contrast, although monthly PV production forecasts are of great importance for energy planning, economic feasibility analysis, and maintenance-investment decisions, they have been addressed in a relatively limited number of studies [6]. In monthly time scale predictions, seasonal variations in solar radiation and meteorological uncertainties make the modelling process more complex.

Time series-based statistical methods are widely used in PV production forecasting. Specifically, Exponential Smoothing and Seasonal Autoregressive Integrated Moving Average (SARIMA) models offer effective tools for capturing trends and patterns in historical production data [7,8,9]. While the Double Exponential Smoothing (DES) method considers the trend component, the Holt-Winters Triple Exponential Smoothing (TES) model includes both trend and seasonality components. SARIMA models, on the other hand, can represent annual cycles more flexibly thanks to seasonal differencing and seasonal lagged terms [10].

However, the number of studies in the literature that comparatively evaluate seasonality-sensitive models for monthly solar PV production is limited. Additionally, some studies have reported that results obtained without adequately modelling seasonality lead to serious prediction errors, especially during the summer and winter months [11]. This situation highlights the necessity of explicitly modelling seasonality in monthly PV production series.

The DES, TES, and SARIMA models are compared for predicting monthly solar PV energy production in this study. The predictive performance of the models was evaluated using operational data from a grid-connected PV power plant, based on RMSE, MAE, and bias metrics. The main contribution of the study is to quantitatively demonstrate that approaches explicitly modelling seasonality significantly improve the accuracy of monthly PV forecasts.

The studies summarised above show that time series methods are widely used in predicting solar PV energy production; however, there are limited studies in the literature that explicitly and comparatively address seasonality in monthly time scale predictions. A significant portion of existing research either focusses on short-term forecasts or does not quantitatively examine the impact of seasonal components on model performance. In this context, the error structures caused by models that ignore or indirectly address seasonality in monthly PV production series have not been sufficiently clarified. The main objective of this study is to systematically compare the DES, TES, and SARIMA models in terms of their sensitivity to seasonality in predicting monthly solar PV energy production and to reveal the impact of seasonal components on prediction accuracy. The main contributions of this study are: (i) a comprehensive evaluation of monthly prediction performance using data from a real grid-connected PV power plant, (ii) a quantitative demonstration of the superiority of approaches that explicitly model seasonality in terms of error metrics, and (iii) the provision of practical and actionable insights for model selection in monthly PV forecasting.

2. Literature

Estimating solar energy production has become a critical research area, especially in the process of integrating renewable energy sources into the grid. The majority of studies in the literature on PV power generation forecasting have focused on short-term (hourly-daily) predictions, and these studies are mostly centred around methods that model cloud cover, irradiance variability, and atmospheric uncertainties [3,4,5]. However, on a monthly timescale, the modelling process becomes more complex due to both data limitations and strong seasonal cycles, and this scale has been relatively little studied in the literature [6].

Among traditional statistical methods, Exponential Smoothing and ARIMA-based models offer significant advantages in capturing the trend and seasonal components of time series. For example, the Holt-Winters TES model is widely used in cyclical structures such as PV production because it can model both trend and seasonality components simultaneously [7]. However, the assumption of fixed seasonality in TES can limit its performance in scenarios with unexpected monthly fluctuations [9].

On the other hand, SARIMA models can naturally represent annual cycles thanks to seasonal lagged terms and seasonal differencing structures, and they perform strongly, especially in series with distinct seasonality, such as energy consumption or renewable energy production [8,9,10]. However, the number of studies in the literature that compare methods such as SARIMA and TES on monthly PV production is limited, and most research focusses only on the performance of a single method [11]. This situation increases the need for comprehensive comparative analyses where seasonality is explicitly modelled.

Due to the non-linear nature of PV production, machine learning-based approaches are also increasingly being used, and studies using LSTM, CNN-LSTM, and hybrid models are known to offer high accuracy, especially in short-term predictions [12,13]. However, the performance of these models on a monthly time scale has been less studied compared to statistical models due to high data requirements and overfitting risks.

In this context, studies that directly reveal the performance differences in monthly PV forecasting of seasonality-sensitive statistical models are quite limited. This gap in the literature highlights the critical importance of model selection for monthly PV production forecasts, and strengthens the scientific contribution of the comparative approach presented in this study.

3. Methodology

In this section, three basic time series models used for estimating monthly solar PV energy production-Double Exponential Smoothing (DES), Holt-Winters Triple Exponential Smoothing (TES), and Seasonal ARIMA (SARIMA)-are presented along with their mathematical structures and application steps. All models generate future predictions by representing the trend and seasonality components in past data in different forms.

3.1. Double Exponential Smoothing (DES)

The DES model assumes that only level and trend components are present in the time series. Therefore, DES is used in situations where seasonality is not pronounced or is not directly represented by the model. The DES equation set is as follows:

Level update:

$$L_t = \alpha Y_t + (1-\alpha)\,(L_{t-1} + T_{t-1}) \quad (1)$$

Trend update:

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \quad (2)$$

h-step forward prediction:

$$\hat{Y}_{t+h} = L_t + hT_t \quad (3)$$

Here, Yt represents the actual values, while α and β are correction coefficients within the range of 0-1. The logical flow of DES is as follows: (i) updating the level at each step, (ii) renewing the trend based on the new level, and (iii) calculating future values based on these two components.

3.2. Holt-Winters Triple Exponential Smoothing (TES)

For time series with strong seasonal structures, like PV generation, the TES model is frequently utilized because it includes a seasonal component in addition to DES. A multiplicative seasonality structure is used in this study in accordance with the features of monthly data.

Level update:

$$L_t = \alpha \frac{Y_t}{S_{t-m}} + (1-\alpha)(L_{t-1} + T_{t-1}) \quad (4)$$

Trend update:

$$T_t = \beta(L_t + L_{t-1}) + (1-\beta)\,T_{t-1} \quad (5)$$

Seasonal component update:

$$S_t = \gamma \frac{Y_t}{L_t} + (1-\gamma)S_{t-m} \quad (6)$$

h-step prediction:

$$\hat{Y}_{t+h} = (L_t + hT_t)\,S_{t+h-m} \quad (7)$$

Here, m represents the annual seasonal period (m=12 for monthly series). The level, trend and seasonality update process is carried out in parallel using the TES flow logic, as each new input will be processed through all three areas to produce a single output.

3.3. Seasonal ARIMA (SARIMA)

Seasonal ARIMA models provide a parametric representation of the temporal relationship of a time-series data set by modeling short term interdependencies while also accounting for an annual periodic cycle of seasonality. The SARIMA(p,d,q)(P,D,Q)m model has the following general form:

$$\Phi_P(B^m)\Phi_P(B)(1-B)^d(1-B^m)^D Y_t = \Theta_Q(B^m)\theta_q(\mathrm{B})\varepsilon_t \qquad (8)$$

Where:

• p, d, q: autoregressive (AR), differencing, and moving average (MA) terms,

• P, D, Q: seasonal AR, seasonal differencing, and seasonal MA terms,

• m = 12: annual seasonal period (monthly data),

• B: lag operator,

• ε_t: white noise error term.

4. Findings

The results indicate that while the DES method is successful in identifying short-term trends, it exhibits limited performance in PV production series with strong seasonality. A significant portion of the rapid increase, especially during the 2025 test period, has not been modelled. The difference between the DES forecast and the actual values confirms the need for more advanced seasonal time series models (SARIMA, Holt-Winters, LSTM). Therefore, DES can only be used as a baseline model; it is insufficient for seasonal PV production series.

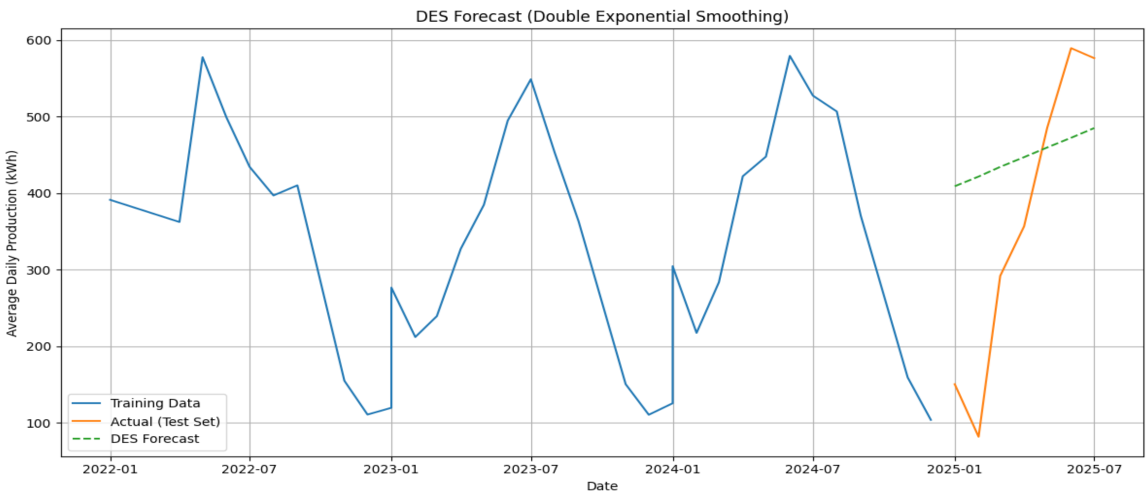

Figure 1. Estimated Energy Production with DES (Double Exponential Smoothing)

Figure 1 shows the forecasting performance of the Double Exponential Smoothing (DES) method on solar energy production data for the period January 2022 - July 2025. The graph includes three main data groups:

•Training Data (Blue Line):

- The training data includes the average monthly production values of the facility from January 2022 through December 2024. It is evident from this data that the seasonal cycle exists:
  • The production increases to a range of 500-580 kWh during the Summer Months.
  • The production decreases to a range of 100-150 kWh during the Winter Months.

- There were three distinct seasonal cycles exhibited within the 2022-2024 data, indicating that the data exhibit a high degree of trend and seasonality behavior.

•Actual Test Data (Orange Line):

- These are the actual production values for the first six months of 2025.

  After the lowest level of production was observed in late 2024, a very rapid increase occurred (100 kWh, 580 kWh Range). The rapid increase may indicate that the weather conditions of 2025 included increased amounts of solar irradiation, or improved operational conditions of the facility (i.e. panel cleanliness, inverter efficiency, troubleshooting, etc.)

• DES Forecast (green dashed line): The DES model generated a forecast for the 2025 test period. The forecast line shows an increasing trend, approximately in the range of 400-480 kWh. Although the DES captures the trend component, it fails to capture the seasonal component, and therefore cannot follow the sharp increase in actual values. This situation highlights the structural limitation of DES:

- DES only processes level + trend components,
- and performs poorly on series with strong seasonal patterns, such as monthly solar energy production.

When examining the training data, it is observed that solar energy production significantly increases during the summer months and decreases during the winter months. This strong and recurring seasonal pattern is successfully captured by the Holt-Winters Triple Exponential Smoothing (TES) model, which incorporates an additive trend and multiplicative seasonality.

Unlike DES, the TES forecast follows the exact timing and magnitude of the seasonal cycle, which reflects the variable output of the sun's irradiance throughout the year. From an examination of the training data, the analysis shows that there is a substantial increase in solar production during the summer months and a decrease in the winter months (See Figure 2).

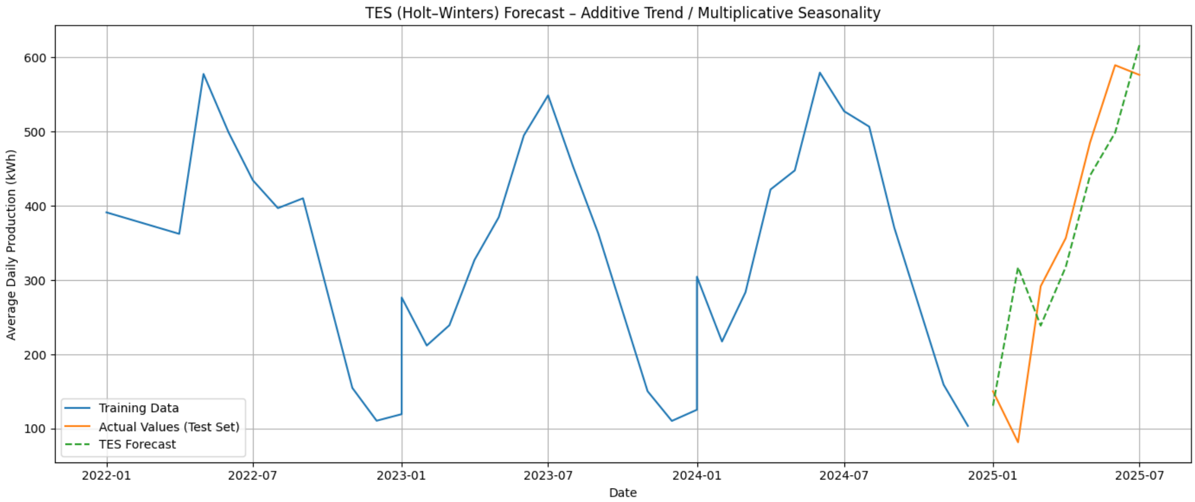

Figure 2- Estimated Energy Production with TES

During the 2025 testing time frame, the actual production values rose rapidly from their winter low to their summer high. The TES model was better at approximating this upward trend than the non-seasonal smoothing models used. The green dashed forecasted curve tracks the seasonal pattern in the actual historical data and does capture the upward trend of early 2025; however, the TES forecast still has some minor deviation in its tracking because of the common large month-to-month fluctuation characteristics in actual PV generation data. Overall, the TES provided a much better predictive performance for forecasting monthly solar energy production when the environment has a strong seasonal component.

The Table 1 compares the actual monthly solar energy production values for 2025 to the estimated monthly values based on the Holt-Winters TES method. The error term for each month is defined as (real-estimated), where a positive value represents an underestimation and a negative value represents an overestimation.

Table 1 - Interpretation of TES Forecast Errors for 2025

Month (2025)	**Real (kWh)**	**TES Estimated (kWh)**	**Error (Real-Estimated)**
January	150.44	130.89	+19.55
February	81.64	317.40	-235.76
March	291.88	238.78	+53.10
April	356.70	317.99	+38.71
May	485.45	440.95	+44.50
June	589.62	498.66	+90.96
July	576.54	616.47	-39.93

Overall the TES model performs reasonably well in capturing the increase in generation from Winter to Summer; however, it has significant month-to-month variation as it attempts to capture the abrupt short-term changes in solar irradiance.

Winter Period (January-February):
In January, the TES model underestimates the amount generated during this period by approximately 19.55 kWh, and therefore represents an acceptable error in a forecast. However, in February, the TES model severely overestimates the amount of electricity produced during this time frame (-235.76 kWh). The February value represents the greatest difference among those listed in the table. It appears there was a significant drop in actual electricity generated during the time frame in question that the TES model did not account for through its multiplicative seasonal component.

Spring Period (March-May):
There are three months of relatively mild underestimates in the TES model. These values represent the degree by which the TES model underestimates the amount of electricity generated during each month. The underestimates range from +38.71 kWh to +53.10 kWh for the months of March, April and May respectively. The degree of underestimation suggests that the actual electricity generated during these months was increasing at a greater rate than indicated by the TES models historical estimate of the seasonal trend. Favorable climate conditions were present in the early spring months of 2019 and may have contributed to the rapid growth of electricity generation during these periods.

Summer Period (June-July):
The TES model exhibits a large underestimation in the month of June of 90.96 kWh, suggesting that the model does not adequately capture the full magnitude of the peak in electricity generation experienced in the summer. An underestimation of -39.93 kWh is exhibited in the month of July, although it still represents one of the highest levels of electricity generation throughout the year.
The results presented in Table 1 indicate that while the TES model can adequately capture the general seasonal trends in electricity generation, it is unable to accurately predict the months when the actual electricity generation differs substantially from the historical patterns. As such, the TES model provides a good basis for making forecasts on a medium-term monthly basis, however it is less accurate when attempting to make predictions concerning anomalies.

Table 2 provides a comparative evaluation of SARIMA, Holt-Winters TES, and DES models applied to monthly solar PV production forecasting for the 2025 test period. The comparison includes trend and seasonality assumptions, as well as key performance metrics such as RMSE, MAE, and Bias.

Table 2 - Interpretation of Model Performance on the Test Set

Model	Trend	Seasonality	RMSE	MAE	Bias	Explanation
SARIMA (2,1,1)(1,1,0)	Yes	Yes (12 months)	69.77	52.48	+6.12	Strong seasonal structure; model with the lowest RMSE
TES (Holt-Winters Add/Mul)	Yes	Yes (Multiplicative)	101.51	83.45	-12.64	Seasonal structure is partially captured, weaker than SARIMA
DES (Double Exponential Smoothing)	Yes	No	182.77	148.53	+27.11	Trend component is learnt, no seasonality; weak performance

DES performs the worst among all models. This is expected, as DES does not model seasonal components, which are dominant in solar PV production data. As a result, DES fails to track the annual production cycles and shows large deviations from the actual values. Its strong positive bias indicates systematic overestimation, confirming that DES is unsuitable for forecasting strongly seasonal PV time series.

The comparison clearly shows that capturing annual seasonality is critical for accurate monthly PV power forecasting. SARIMA, which models both trend and seasonality explicitly, yields the best predictive accuracy. TES provides moderate performance but tends to underestimate in high-production months. DES is inadequate due to its inability to incorporate seasonal structure.

5. Discussion

The results of the present study confirm that the performance of time series models employed in predicting monthly solar PV energy production is strongly affected by how the models handle seasonal components. Models that fail to account for seasonality (i.e., DES) exhibit significantly reduced accuracy, especially in PV time series where annual production cycles dominate. The DES model was identified as being unsuitable for time series exhibiting strong seasonality (such as monthly PV production) in addition to level and trend components, with the DES model displaying large error values and a systematic overestimation bias. Such findings are consistent with those documented in the literature, indicating that DES should only be viewed as a suitable baseline model for short-term trend analyses or when the degree of seasonality is weak. The findings are also particularly important for medium-term energy planning in areas where there is a strong seasonal variability in solar radiation.

The TES model captured production cycles generally well owing to its multiplicative seasonality component and displayed a statistically significant increase in performance relative to DES. Nonetheless, large forecast errors were recorded during certain months for TES, highlighting its limitations stemming from its rigid assumption of a fixed seasonal structure. Unforeseen meteorological conditions or changes in operation are examples of factors limiting TES's flexibility. Overall, these findings suggest that while TES can be a viable option for applications requiring moderate accuracy, it may not provide adequate performance alone for applications requiring high levels of precision in forecasting, such as energy planning.

Finally, the superior performance of the SARIMA model substantiates the critical need to explicitly model seasonality in order to achieve accurate predictions of monthly PV production. Both seasonal differences and seasonal lagged terms enabled SARIMA to effectively represent annual production cycles and ultimately display the lowest error metrics among all models tested. These findings reinforce the SARIMA's excellent performance documented in the literature and provide evidence that SARIMA is an effective and reliable approach for modeling series characterized by regular seasonal structures, such as monthly PV production.

In summary, the sensitivity to seasonality in a model is a critical consideration for selecting appropriate models. Therefore, models that do not consider seasonality (e.g., DES) are typically insufficient for accurately predicting monthly solar PV production. Conversely, models that specifically include representation of seasonal variations (e.g., TES and SARIMA) typically provide improved performance and greater stability in their forecasts than models that do not incorporate seasonal considerations. As such, these findings provide substantial implications for selecting models in various applications including, but not limited to, medium-term energy planning, maintenance scheduling, and grid integration.

6. Conclusion

The results of the current study clearly illustrate the importance of seasonality sensitivity in predicting monthly solar PV energy production. A comparative evaluation of the DES, TES, and SARIMA models demonstrates that the omission of seasonality reduces significantly the accuracy of the forecasts. DES yielded the largest error values since it did not have the capability to represent the strong seasonal cycles in PV data; TES, despite the inclusion of both trend and seasonality, was unable to adjust to abrupt changes in production; in contrast, SARIMA exhibited the smallest RMSE, MAE, and bias values, therefore providing the best performance in predicting PV production, due to the capability to dynamically represent both trends and seasonal structures of annual duration.

Therefore, the results of the study indicate that representing seasonal components explicitly enhances the usability of monthly PV production forecasts for operational processes like energy planning, maintenance scheduling, and grid management. Consequently, the study provides a methodological framework for model selection and will serve as a reference for future studies. Nevertheless, studies employing larger-scale datasets geographically, incorporating weather variables, and/or utilizing machine learning-based hybrid models have the potential to improve the accuracy of PV production forecasts further. Future studies may utilize meteorological variables and/or hybrid models to further enhance the accuracy of PV production forecasts.

Data Availability

The data used in this study were collected from a grid-connected solar photovoltaic power plant and include operational information that cannot be made publicly available due to confidentiality constraints. However, the processed datasets and methodological details used to support the findings of this study are available from the corresponding author at the request of interested parties.

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Authors' Biography

Ecem Nur Sener is a master's student in the Department of Electrical and Electronic Engineering at Istanbul Aydın University. He completed his undergraduate studies in the fundamental areas of electrical and electronics engineering and developed a special interest in signal processing, energy systems, and digital technologies. As part of my master's studies, I am focussing on smart energy systems, renewable energy integration, and engineering applications based on digital transformation. Data analysis, modelling, and generating innovative solutions to engineering problems play an active role in research processes.

Dr. Ebru Idman holds a PhD degree in Electrical and Electronics Engineering. She completed her undergraduate education in the English-taught Computer Engineering program and earned her master's degree with a thesis in the field of Occupational Health and Safety. In her doctoral dissertation, she investigated the effects of additive methods in polymers on electrical conductivity. She continues her academic career at Istanbul Aydın University. Her research interests include organic electronic materials, polymer-based conductivity, time series analysis, and the modeling of renewable energy data.

Prof. Dr. Osman Yildirim is a faculty member in the Department of Electrical and Electronics Engineering at Istanbul Aydın University. His academic work focusses on renewable energy systems, smart grids, energy management systems, digital and green transformation, sustainable engineering applications, and artificial intelligence-supported energy forecasting models. Embracing an interdisciplinary approach, Osman YILDIRIM conducts value-added studies in the fields of university-industry collaborations, sustainable development goals, and digital transformation in engineering.