# Integrative Forecasting of Solar Energy Production and Demand in Saudi Arabia using Machine Learning

**Abdulaziz Alhayd[1] & Dr. Grazia Todeschini[2]**

[1, 2], King's College, London, UK

[1]King Abdulaziz City for Science and Technology (KACST), Saudi Arabia

[1]Corresponding Author Email: K21169202@kcl.ac.uk

**Abstract**

Balancing power generation and demand is a critical challenge in large-scale renewable energy systems. This paper focuses on energy forecasting for demand and supply in Saudi Arabia, leveraging a high-resolution dataset encompassing solar energy production from the country's first large-scale solar plant and the energy demand of a nearby city. Advanced machine learning models are developed and evaluated to predict energy supply and demand patterns, addressing the inherent variability of renewable energy sources. The models effectively utilise historical and weather-related data to deliver accurate forecasts, enabling optimised planning and integration of renewable energy into the grid. This research contributes to advancing energy forecasting techniques for large-scale systems, enhancing sustainability and reliability in Saudi Arabia's renewable energy sector.

**Keywords**: Solar Energy, Demand forecasting, Machine-learning, Saudi Arabia.

## Introduction

AI and Renewable Energy in Sustainable Grid Management Power generation is divided into non-renewable and renewable sources. The non-renewable category includes fossil fuels (coal, oil, natural gas) and nuclear power, which have significant environmental impacts and are finite resources. Renewable energy encompasses hydropower, wind, and solar energy, which are more sustainable but can be variable and dependent on environmental conditions.

Global warming caused by burning fossil fuels has forced the world to think seriously about power generation techniques. Among the options, renewable energy is attracting particular attention. This matches the green policy objectives drafted in most countries in the world. Renewable energy encompasses hydropower, wind, and solar, which are sustainable but can be variable and dependent on environmental conditions. The availability of natural resources (like sunlight, wind, and water) dictates the primary energy sources for each country. For example, countries with abundant sunlight may rely heavily on solar energy, while those with strong winds might invest more in wind power. This geographic influence may lead to a hybrid policy option in countries with varied renewable sources.

The main challenge facing power-generating industries, irrespective of the generating source, is supply and demand fluctuation. Energy demand can peak during specific times (like evenings or hot & cold days), thus matching the energy production and consumption demand requires a careful selection of strategies.

Renewable energy generation is inherently intermittent, making it difficult to match supply with demand. The matching of supply and demand requires implementing policies to manage the balance. This requires a mechanism for effective ways to store energy when the generation peaks and consume it when the demand rises. Energy storage solutions, incentivise the generation and use of renewable energy, with effective demand-response programs aiming to optimise energy generation and ensure stability and reliability. Maintaining a stable grid requires careful management of energy flow, especially as the share of variable renewable energy increases. This requires a policy framework that is different for different countries and requires technological solutions.

Advances in AI, grids, and energy storage technologies are critical for improving the integration of renewable energy sources and maintaining equilibrium between generation and consumption. Addressing these challenges is essential for achieving a sustainable and reliable energy future. Historically, energy demand and consumption have been managed through various methods and technologies, reflecting changes in society, economy, and technology. In the early 20th century demand forecasting used statistical methods to predict energy demand helping the planning and generation capacity. Load management uses ‘Peak Shaving’ to manage high demands [1].

In the century advances in new technologies led to the creation of smart grids, a technology that uses real-time data to manage energy consumption more efficiently. Demand Response Programs incentivise consumers to reduce or shift their energy use during peak periods. Energy Storage Solutions such as battery storage and other technologies have improved the ability to manage supply and demand, particularly with intermittent renewable sources.

In conclusion, energy demand and consumption management have evolved from simple local solutions to complex, data-driven systems addressing global sustainability challenges. The challenges faced in maintaining energy supply and demand using renewable energy sources will benefit from applying AI /Machine learning and optimisation models to ensure a continuous and sustainable energy provision. The challenge in this context is choosing the right AI techniques and methods and using Machine Learning optimisation models [2].

This research highlights the potential for substantial improvements in solar energy systems’ efficiency, reliability, and sustainability using advanced AI /Machine learning techniques and mechanisms within the grid context.

**Research Questions**

1. What is the most appropriate AI framework for solar energy management systems?

2. What AI techniques and mechanisms are suitable for a data-driven machine-learning model?

3. Can the AI/Machine Learning and optimisation model be applied to all renewable energy resources?

4. Can the AI/Machine Learning design for forecasting and optimisation models be made adaptable to address region-specific climate?

5. How can the model be effectively validated before being adopted?

**Literature Review**

**Historic context**

In the early supply-demand energy management system, the initial framework was to match the demand by increasing the energy supply. In this concept, the primary goal was ensuring electricity generation consistently meets consumer demand [3]. This was achieved by dynamically adjusting the electricity supply from various power-generating sources. In this framework, the centralised power grid was fed through a network of main power-generating networks responding to estimated power demand in the national grid. Large plants (typically coal, nuclear, or large hydro) provided a baseline supply of electricity, operating continuously to meet average demand. The variation in demand was served by commissioning and decommissioning smaller power-generating plants (gas or oil-fired) in and out of the national grid to meet peak demands and match the energy supply and demand. The same framework is applied to hydropower generation, where small hydropower stations could be phased in and out of operation utilising a water flow management to immediate demand changes. In this context, energy demand forecasting relies on historical data and predictive models to estimate demand patterns, adjusting generation schedules accordingly. The Challenge is to ensure a stable and reliable power supply which requires constant monitoring and quick responses to demand changes. Reliance on fossil fuels for peaking plants raised concerns about emissions and environmental sustainability however, improvements in forecasting and advances in data analytics and modelling improved the accuracy of demand predictions, enhancing the efficiency of the supply-demand balance. Integration of renewable energy gained traction, the framework evolved to accommodate the variable nature of sources like wind and solar into the equation.

The core of the developed framework evolved for power management systems in the 20th century as discussed is a solid framework applicable to modern energy forecasting and management. The main point in the generation source is the adaptation of the framework to replace large plants which are typically fossil fuel-based or nuclear, providing the baseline supply of electricity, to the renewable baseline of power generation to support an apparent continuous power generation to respond not only to the average power demand but also to meet the variation in energy demand at peak periods [4].

The adaptation of the framework encompasses the integration of grids, storage technologies and AI/ Machine Learning.

This AI framework in which Machine learning models forecasting electricity demand and generation underpins the apparent continuous and sustainable solar power generation serving modern green energy systems which are the focus of this research.

**Power Generation and Demand Predictions**

The baseline energy supply for a country irrespective of its generating source is to support a daily average energy requirement however, rapid hourly fluctuation in energy demand needs an accurate prediction forecast where machine learning models can play a pivotal role [5] In the case of renewable energy, the baseline energy demand for power generation is also subject to fluctuations and therefore, strategies that handle this type of energy as a source need to predict the rapid hourly fluctuation in energy generation and demand for a large-scale power generation system [6] The large-scale renewable energy powerplant needs to ensure high operational efficiency which needs accurate power generation and demand pre- dictions to enable a seamless match of demand and consumption with high accuracy [7]. Continuous power generation in a large-scale renewable power plant is critically important due to the intermittency of the sources where the need to accommodate the instantaneous variation of power generation and demand is of paramount importance [8]. In such systems, accurate predictions are critically important to the proactive commissioning and decommissioning of power sources to sustain uninterrupted operations that meet demand fluctuations [9]. Interruption to power generation of any sort has grave economic impacts on the domestic and commercial sectors of a country [10]. Initially, in the early 20th century increasing the power generation capability was the policy, but over the years, various approaches have been employed to predict power demand, each with its own set of advantages and limitations [11]. This section reviews some of the key methodologies used historically and their inherent challenges.

Accurate power generation and demand predictions are essential for optimising the performance of large-scale renewable energy power plants. These systems must manage the inherent variability of renewable sources, such as solar and wind, while simultaneously addressing fluctuating energy demands throughout the day [12] The baseline energy supply must support daily average requirements, but energy demand can vary rapidly on an hourly basis. This necessitates the use of machine learning models to forecast these fluctuations effectively [13]. Accurate predictions enable power plants to match energy generation with consumption, thereby enhancing operational efficiency. In renewable energy systems, the unpredictability of energy production requires advanced strategies to predict both generation and demand [14]. These strategies are crucial for continuous power generation and maintaining a steady supply of energy despite the intermittent nature of renewable sources. Accurate forecasts allow for proactive management of energy re- sources to avoid disruptions [15]. Efficient operations rely on the ability to anticipate demand and adjust generation accordingly. This minimises waste and maximises the utilisation of renewable resources. To sustain uninterrupted operations, large-scale renewable power plants need accurate demand predictions to allow for the timely activation or shutdown of power sources, ensuring that energy generation meets real-time consumption needs. Interruptions in power generation can lead to significant economic consequences for domestic and commercial sectors. These disruptions can be minimised by improving prediction accuracy, protecting the economy and maintaining stability. Integrating machine learning models for predicting power generation and demand is essential for large-scale renewable energy systems. By addressing the challenges of fluctuating energy demand and generation, these models can enhance operational efficiency and support the sustainable growth of renewable energy infrastructures. The continuous advancement in predictive analytics will play a pivotal role in shaping the future of energy management [16].

**Overview of Machine Learning Models for Energy Demand Prediction**

Machine learning models are used in every field. The choice is based on their learning style and application. In this context, the learning categories are Supervised Learning [17], Unsupervised Learning [18], Semi-Supervised Learning [19], Reinforcement Learning [20], Deep Learning [21], and Ensemble Methods [22]. The AI technique chosen for this research is supervised learning with mechanisms from a choice of Linear regression, Logistic regression, Decision trees, Support Vector Machines (SVM) and Neural networks. Ensemble methods combine multiple models to form a hybrid model to improve performance could help the prediction. Bagging reduces variance with random forest being an example model based on majority rule and boosting with reducing bias with AdaBoost and XGBoost as a model.

Early approaches to energy demand prediction relied on statistical methods, including linear regression, logistic regression, and time-series analysis. These methods aimed to identify correlations between energy demand and generation considering various variables, such as hot and cold weather conditions, and seasonal day and night duration

[23] Linear regression models attempt to predict energy demand by fitting a linear relationship between the dependent variable (hot and cold weather, day and night duration) and one or more independent variables (predictors). While simple and easy to interpret, linear regression models assume a linear relationship between variables, which is often not the case in complex systems. This limitation reduces their predictive accuracy [24].

Logistic regression is used for binary classification problems. This method is useful for handling categorical outcomes but still assumes a linear relationship between the predictors and the log odds of the outcome, which may not adequately capture the complexities of energy demand and generation [25].

Time-series models, such as ARIMA (Autoregressive Integrated Moving Average), are designed to handle temporal dependencies in data. These models can capture trends and seasonality of energy demand but struggle with the non-linear interactions between multiple variables. Additionally, time-series models require large amounts of historical data and may not perform well with sudden and/or instantaneous changes in underlying patterns [26].

The introduction of machine learning (ML) in the late 20th and early 21st centuries as a technique marked a significant shift in energy demand and prediction methodologies. ML algorithms can handle large datasets, learn from data, and capture complex, non-linear relationships between variables as a dominant feature in predicting power generation and consumption [27].

Decision trees partition the data into subsets based on feature values, creating a tree-like structure of decisions that may suffer from overfitting and underfitting. Random forests improve decision trees by constructing multiple trees and aggregating their predictions to address the underfitting and overfitting issues. Random forest is a powerful method but can become overly complex, particularly with high-dimensional data [28].

Bidirectional Long Short-Term Memory (BiLSTM) networks enhance the basic LSTM model by processing data in both forward and backward directions. Although LSTMs are proficient in handling long-range dependencies, they typically process sequences in only one direction—from beginning to end (forward). While this approach works well for many tasks, it can be beneficial in certain applications, such as energy demand forecasting, to consider both past and future context [29]. Despite BILSTM potential, the model requires large amounts of data and significant computational resources for training and deployment [30].

Hybrid models, such as LSTM-CNN, combine the strengths of various techniques. LSTM-CNN models in- integrate the temporal sequence modelling capabilities of Long Short-Term Memory (LSTM) networks with the spatial feature extraction abilities of Convolutional Neural Networks (CNN). This combination enables a more comprehensive analysis and enhances prediction accuracy.

Ensemble methods, including random forests and gradient boosting machines, combine the predictions of multiple models to improve robustness and accuracy. By leveraging the strengths of individual models, these techniques help reduce the risk of overfitting and enhance generalisation [31].

**Challenges and Future Directions in Predictive Modelling for Renewable Energy**

Despite the advances in predictive modelling techniques, the accuracy of predictive models depends heavily on the quality and availability of data. Incomplete, inaccurate, or inconsistent data can significantly impact model performance. Moreover, obtaining real-time data for dynamic prediction remains a challenge [32]. Advanced machine learning and deep learning models, while powerful, are computationally intensive. Training these models requires substantial computational resources and time, which can be a barrier to their widespread adoption in operational settings [33]. Complex models, such as deep learning architectures, often operate as ”black boxes,” making it difficult to interpret their predictions. This lack of transparency can hinder trust and acceptance among stakeholders [34]. Many predictive models can be developed and validated using data from specific countries or regions. This can limit their generalisability where different environmental conditions could impact the prediction however, to prove the concept a generalisability issue may not be the main concern. In general, integrating predictive models with existing renewable power plants is challenging. Ensuring seamless interaction between predictive models and real-time decision-making processes is critical [35] [36]. This literature review highlights the advancements in energy generation and demand prediction models using Machine learning and deep learning techniques as discussed in this text. It addresses various models, including...SVMs, ANNs, LSTMs, CNNs, and possible hybrid models. The review also examines the broader application of AI in the power generation industry, emphasising its impact on predictive energy management of renewable energy generation and consumption. Despite significant progress, gaps remain in the existing research. Many studies have focused on individual renewable energy sources or specific datasets, limiting the generalisability of the models. The integration of unstructured data sources is also in its early stages. This research aims to develop a predictive AI/Machine Learning and optimisation model that is robust and adaptable for solar energy generation and consumption. The model uses a high-dimensional real raw dataset from Saudi Arabia’s First Solar Plant and City Demand. The dataset will partly be used to train the data and partly to validate the AI model. The design is to apply and test the models discussed in this review to solar energy generation and consumption and compare

and analyse parameters such as R-squared ($R^2$), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), which are relevant to the prediction models. The out-come of the research proposes a model unique to solar energy that will be based on a hybrid AI/Machine Learning model to process the dataset, with high predictive accuracy and reliability.

**Knowledge Gaps**

The primary knowledge gap in this research is the lack of an integrated AI/Machine learning framework that predicts hourly energy demand and balances solar power generation while optimising the supply and demand in large-scale systems.

Despite significant advancements in energy forecasting and optimisation techniques, crucial gaps re- main in applying AI/Machine learning technology to large-scale energy systems that lack integrated AI-driven forecasting-optimisation frameworks in regions with unique climatic challenges.

The AI-driven forecasting-optimisation framework requires high-resolution datasets (hourly measurements) to capture rapid fluctuations and the dynamic nature of energy consumption and generation.

A high-resolution dataset is crucial for accurately modelling an AI/Machine learning model.

Most forecasting and optimisation models are developed for small-scale applications and are not adaptable to region-specific climates. These models do not support large-scale energy systems.

**Methodology**

This section outlines the methodology adopted for forecasting energy demand and photovoltaic (PV) supply using advanced machine learning models. It details the dataset utilised, feature engineering techniques, model architectures, training and validation strategies, and evaluation metrics.

**Model Selection**

Time-series forecasting in energy systems necessitates models capable of capturing temporal dependencies, handling multivariate input, and performing well under varying seasonal conditions. The following models were selected based on their suitability for such tasks and documented effectiveness in similar studies [37], [38].

**Table 1: Comparison of Machine Learning Models Used in the Study**

| **Model** | **Strengths** | **Limitations** |
|---|---|---|
| Long Short-Term Memory (LSTM) | Effective at learning sequences with extensive temporal depths [38]. | High computational burden and sensitivity to hyperparameter settings [39]. |
| Bidirectional LSTM (BLSTM) | Superior at understanding contextual relationships in data sequences [39]. | Increased computational demand [39]. |
| Gated Recurrent Unit (GRU) | Requires less computational power, making it faster to train [37]. | Potentially less effective at capturing very complex dependencies [39]. |

| | | |
|---|---|---|
| Temporal Convolutional Network (TCN) | Exceptional scalability and reduced training times [40]. | The fixed receptive field may not be ideal for all time-series applications [41]. |

**Dataset Description and Preprocessing**

The dataset comprises hourly solar power output, energy demand, and weather-related variables collected over one year. Key variables include:

Historical Variables: Hourly solar energy production from the first large-scale solar plant and corresponding city electrical demand (in megawatt-hours) [37].

Lagged Variables: Values from 1 and 24 hours prior (Lag 1H, Lag 24H) [44].

Preprocessing steps ensure data quality and facilitate model training.

Data Cleaning: Missing and erroneous values were handled via linear interpolation [37].

Scaling: Features were normalised to a [0,1] range using MinMaxScaler, reducing the influence of features with larger ranges [38].

Windowing: Sliding windows of 24 hours were applied to structure the data for sequential input into models [40]. Figure 1 illustrates the data split strategy for model training and validation, showing how the data is allocated over time.

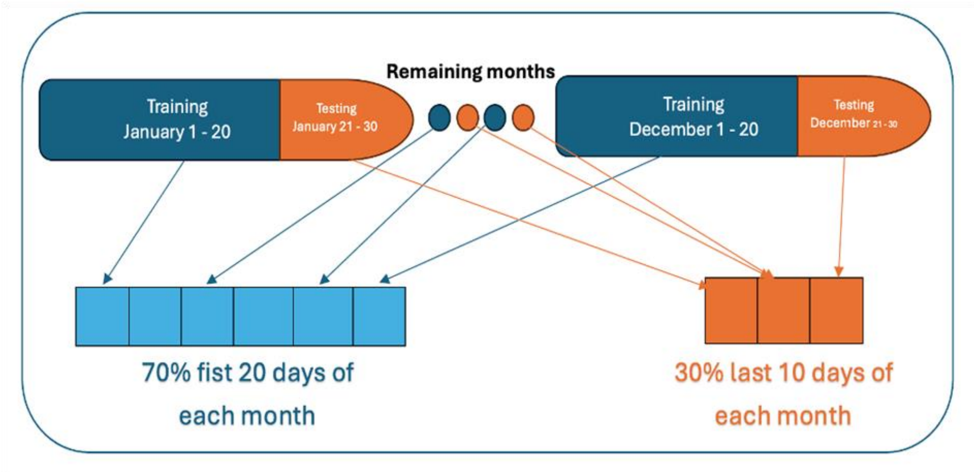


**Figure 1: Data split strategy for model training and validation, illustrating the allocation of data over time.**

**Feature Engineering**

Feature engineering was performed to enhance the dataset's predictive power by incorporating both raw and derived features:

Temporal Features: Time-based attributes such as hour of the day, day of the week, and weekend indicators were extracted to capture seasonal and cyclic patterns [43].

Lagged Features: Lag variables for solar power and energy demand were created (Lag 1H and Lag 24H) to capture autoregressive patterns [44].

Weather Interactions: Interaction features (e.g., Temperature × Humidity) were derived to account for the combined effects of meteorological factors [41].

## Model Architecture and Training

The architectures of the machine learning models were meticulously designed to address the specific challenges of time-series forecasting in the context of energy demand and solar supply data [39], [40].

**Training Procedures**

The models were trained to optimise performance metrics, utilising a comprehensive set of training details that ensured robustness and generalisability:

Input Representation: Each model processed multivariate input sequences with a window size of 24 hours, designed to capture daily cycles and trends [44].

Loss Function: Mean Squared Error (MSE) was employed as the primary criterion for training loss, supporting the minimisation of prediction errors.

Optimiser: The Adam optimiser was chosen for its effectiveness in managing sparse gradients and its adaptability, with a learning rate of 10−3 [39].

Training Configuration: Each model underwent a training regime spanning 50 epochs, with a batch size of 32. A validation split of 20% was used to monitor overfitting and validate model accuracy periodically [41].

Data Split: To test the models' efficacy on unseen data while preserving the integrity of temporal data sequences, a 70/30 split was employed, allocating 70% of data to training and 30% to validation, segmented monthly [41].

**Evaluation Metrics and Strategy**

The models were evaluated using standard regression metrics:

– Mean Squared Error (MSE): Commonly used in energy forecasting studies [37].

– Mean Absolute Error (MAE): Useful for measuring absolute errors [39].

– Root Mean Squared Error (RMSE): Often applied in solar forecasting [38].

– Coefficient of Determination (R2): Helps in quantifying model fit [41].

Metrics were computed for each month to capture seasonal variability, and the results were averaged to identify the best-performing models and feature sets [40].

**Results and Discussion**

**Data Acquisition and Analysis of Large-Scale Solar Supply and Urban Demand**

The analysis is based on a unique, raw dataset collected from a major solar power plant in Saudi Arabia, comprising hourly data on solar energy production and urban energy demand for the entire year. This high-resolution dataset provides detailed insights into the temporal and seasonal dynamics of large-scale solar energy supply and its interaction with urban demand.

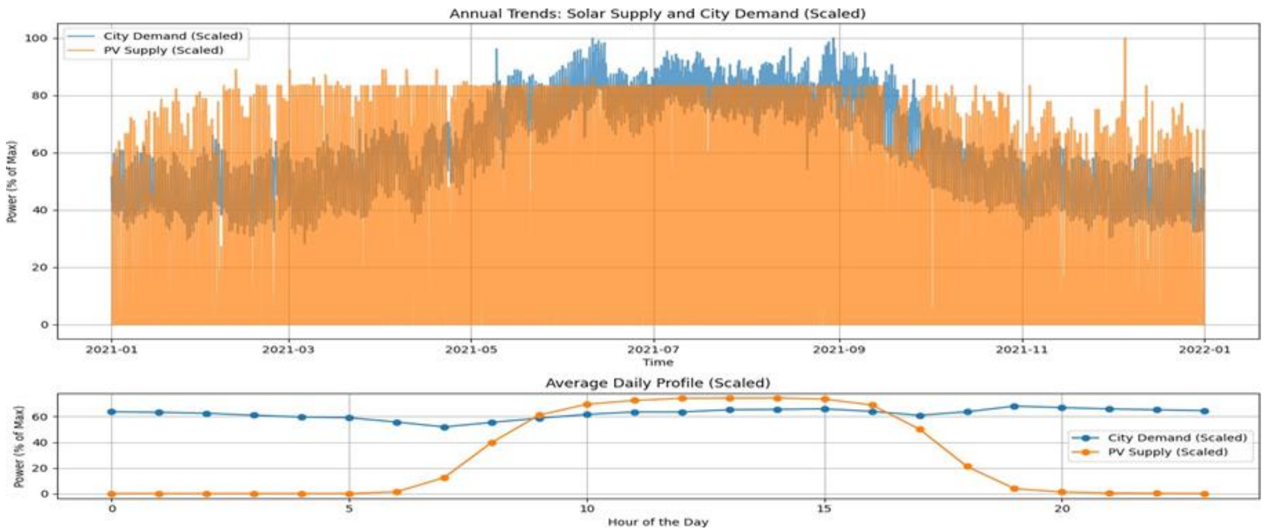


**Figure 2: Annual and daily patterns of solar energy supply (PV) and city demand (scaled).**

The figure highlights the temporal misalignment between midday peaks in solar energy production and evening peaks in urban demand, as well as seasonal variations throughout the year.

**Key Insights**

– Temporal Misalignment: The data highlights a clear mismatch between peak solar production and peak urban energy demand, emphasising the need for advanced storage solutions and grid management strategies to mitigate this imbalance.

– Seasonal Variability: Both solar supply and city demand exhibit significant seasonal fluctuations, which are critical for effective long-term energy system planning and optimisation.

– Relevance and Implications: The unique nature of this raw dataset makes it invaluable for energy research, particularly in developing models to predict and manage energy supply and demand in large-scale systems. By leveraging this data, it is possible to propose innovative strategies for energy storage, grid stability, and demand response that address the inherent variability in solar energy generation and urban consumption patterns.

**Machine Learning Model Selection for Prediction**

This study evaluated several advanced deep-learning architectures to determine the most effective model for forecasting city energy demand and photovoltaic (PV) supply loads. Based on findings from the literature, the selected models included Long Short-Term Memory (LSTM), Bidirectional LSTM (BLSTM), Gated Recurrent Unit (GRU), and Temporal Convolutional Network (TCN). Each model was carefully designed to capture the temporal dependencies inherent in the data. The methodology, preprocessing steps, and evaluation results are detailed below.

The datasets for city demand and PV supply were collected at hourly intervals. Missing load values were filled using linear interpolation to ensure data continuity. The data was then scaled to the range [0, 1] using MinMaxScaler to standardise inputs and improve training efficiency. To facilitate time-series forecasting, a sliding 24-hour window was applied, using the previous 24 hours as features to predict the load for the next hour. This window size was chosen for its ability to capture short-term temporal dependencies effectively.

Model Architectures and Parameters: Table 2 provides a summary of the architectures and hyperparameters for each model. These include the number and type of layers, units per layer, activation functions, and the optimiser used. All models employed the Adam optimiser for its ability to handle sparse gradients efficiently, while ReLU activation was used in the dense layers to enhance stability in predictions. These configurations were specifically tailored to balance complexity and performance, optimising the models for the forecasting tasks.

**Table 2: Model architectures for supply and demand forecasting**

| Model | Layers | Units per Layer | Activation | Optimiser |
|---|---|---|---|---|
| LSTM | 2 LSTM layers, 1 Dense layer | 50 | ReLU (Dense) | Adam |
| BLSTM | 2 Bidirectional LSTM layers, 1 Dense layer | 50 | ReLU (Dense) | Adam |
| GRU | 2 GRU layers, 1 Dense layer | 50 | ReLU (Dense) | Adam |
| TCN | 2 Conv1D layers, 2 Max-Pooling layers, Flatten, 1 Dense layer | 64 (Conv1D) | ReLU | Adam |

Model performance was evaluated using Mean Squared Error (MSE) and Mean Absolute Error (MAE). MSE was selected for its sensitivity to large prediction errors, providing a measure of overall accuracy, while MAE offered an interpretable assessment of average error magnitude. The results, as illustrated in Figure 3, show the comparative performance of the models across both forecasting tasks.

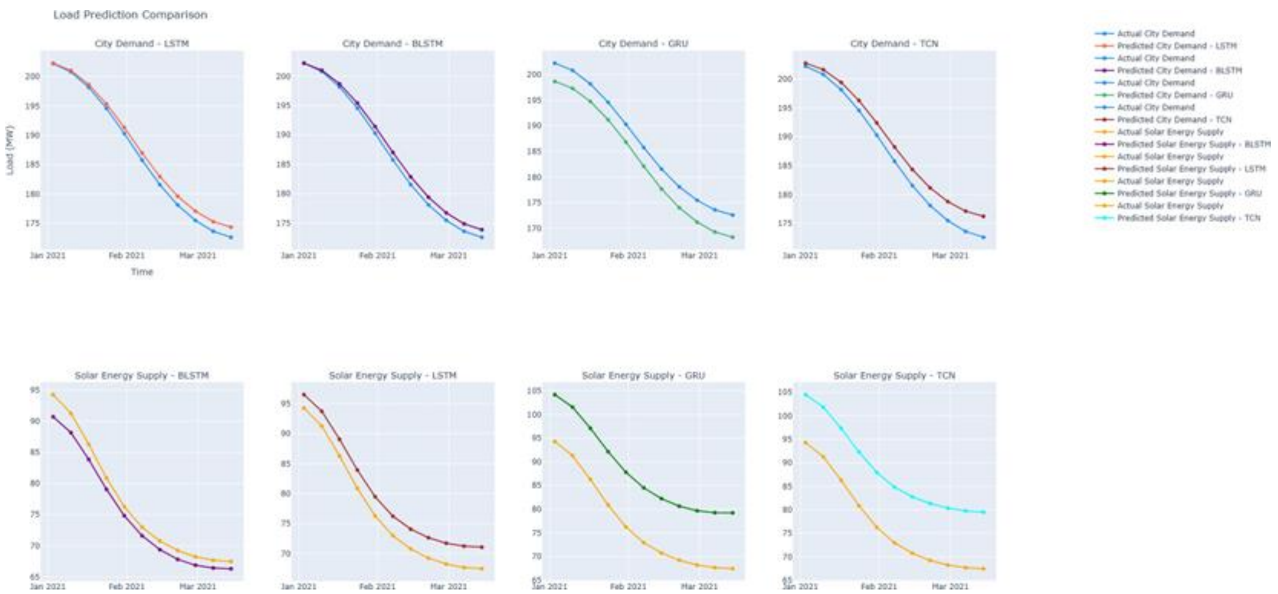


**Figure 3: Machine Learning Model Selection and Evaluation**

For city demand forecasting, the BLSTM model consistently achieved the lowest MSE and MAE values, outperforming other models. Its bidirectional structure, which processes sequences both forwards and backward, allowed it to capture complex temporal patterns, particularly during high-demand periods, better than unidirectional models such as LSTM and GRU.

In PV supply forecasting, both LSTM and BLSTM performed well due to their ability to retain long-term dependencies, a critical factor for modelling the variability of solar energy. However, the BLSTM model had a slight edge, leveraging its bidirectional structure to better capture broader temporal patterns, especially during rapid transitions in supply. By contrast, GRU and TCN models struggled with larger deviations, particularly in predicting peak and trough values.

Overall, BLSTM was selected as the primary model for both tasks due to its consistently superior performance. As shown in Figure 3, its predictions closely tracked actual trends with minimal deviations, while its bidirectional architecture allowed it to make use of both past and future contextual information. These attributes make BLSTM particularly well-suited for renewable-integrated energy systems, where data irregularities and complex patterns are common.

**Supply Predictions**

The dataset used in this research consists of hourly measurements of photovoltaic power output and meteorological conditions throughout 2021, collected from Saudi Arabia. The preprocessing phase involved several key steps to ensure the dataset's integrity and its suitability for time-series analysis. First, data cleaning was performed to remove 150 records with erroneous power output readings, caused mainly by sensor malfunctions and data transmission errors. These anomalies, including abrupt drops to zero uncorrelated with weather conditions, were excluded to maintain data reliability. For continuous variables like irradiance and temperature, sporadic missing values were filled using linear interpolation to preserve the continuity essential for time-series forecasting. The data was then restructured into a chronological time-series format, with a date-time index based on hourly timestamps, ensuring accurate sequencing for prediction.

Feature Engineering was implemented to explore the predictive power of different inputs and encapsulate dynamics affecting energy output. The features included:

– Historical Data: Past power output measurements to enable the model to learn temporal patterns.

– Weather Variables: Key meteorological factors such as temperature, humidity, atmospheric pressure, wind speed and direction, solar irradiance, and UV index are all hypothesised to impact photovoltaic power generation.

– Derived Features: These included the clearness index, lagged features, and time-of-day adjustments to account for daily variations.

The predictive model utilised a Bidirectional Long Short-Term Memory (BLSTM) network, chosen for its capability to learn dependencies in sequential data by processing information in both forward and reverse directions. The model architecture comprised a BLSTM layer with 50 units and a dense output layer that produced the final power generation forecast. The model was compiled using the Adam optimiser with Mean Squared Error (MSE) as the loss function.

For training and validation, the data was split monthly with a 70/30 division; 70% of the data was allocated for training, and 30% for validation. Transfer learning was employed, with model weights reinitialised at the start of each new month based on data from the previous month. This approach enabled the model to adapt to emerging trends while retaining historical insights. Model Evaluation Results showed robust performance across various feature combinations. As shown in Table 3, the results highlight the impact of feature selection on model accuracy.

**Table 3: Model performance across various feature sets.**

| **Supply Feature Set** | **MSE** | **MAE** | **RMSE** | **$R^2$** |
|---|---|---|---|---|
| Baseline 1_(Historical) | 0.0133 | 0.0653 | 0.1134 | 0.9152 |
| Baseline 2_ (Historical & Weather) | 0.0129 | 0.0685 | 0.1115 | 0.9192 |
| Full Feature Set | 0.0282 | 0.0957 | 0.1468 | 0.8404 |
| Historical & Clearness | 0.0133 | 0.0644 | 0.1134 | 0.9153 |
| Historical & Humidity | 0.0149 | 0.0695 | 0.1193 | 0.9049 |
| Historical & Irradiance | **0.0110** | **0.0617** | **0.1032** | **0.9311** |
| Historical & Pressure | 0.0139 | 0.0694 | 0.1158 | 0.9115 |
| Historical & Temperature | 0.0137 | 0.0680 | 0.1155 | 0.9126 |
| Historical & UV INDEX | **0.0111** | **0.0593** **0.1039** | **0.9291** | |
| Historical & Windspeed | 0.0138 | 0.0661 | 0.1155 | 0.9123 |
| Lag Features | 0.0125 | 0.0649 | 0.1100 | 0.9200 |
| Time of Day + Lag Features | 0.0119 | 0.0600 | 0.1069 | 0.9247 |

The baseline model, which included only historical data, achieved an $R^2$ of 0.9152. Adding basic weather information slightly improved this to an $R^2$ of 0.9192. The Historical & Irradiance model exhibited the best performance, achieving an MSE of 0.0110, MAE of 0.0617, RMSE of 0.1032, and $R^2$ of 0.9311. Similarly, the Historical & UV INDEX model showed high accuracy with an MSE of 0.0111, MAE of 0.0593, RMSE of 0.1039, and $R^2$ of 0.9291. Models incorporating lagged and temporal features consistently demonstrated high performance.

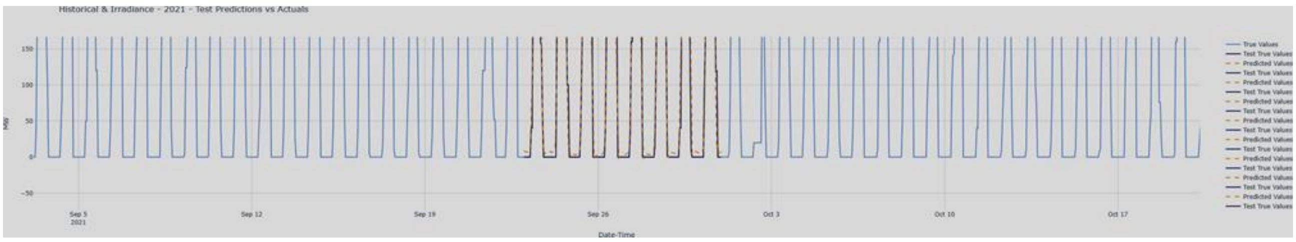


**Figure 4: Historical & Irradiance - Test Predictions vs Actuals**

As illustrated in Figure 4, the Historical & Irradiance model closely tracks actual power generation trends with minimal deviations. The model effectively captures variations caused by weather conditions, showcasing its robustness in forecasting photovoltaic power output.

**Demand Predictions**

The dataset used in this demand forecasting analysis comprises hourly energy demand measurements and meteorological data throughout 2021, sourced from Saudi Arabia. Data preprocessing was essential to prepare the dataset for accurate time-series analysis. First, erroneous entries were identified and removed, ensuring the reliability of the dataset by addressing issues likely stemming from sensor errors or data transmission faults. Missing values, particularly in weather variables, were filled using linear interpolation, preserving the continuity crucial for time-series forecasting. The data was then organised into a structured, chronological format with a datetime index based on hourly timestamps, preserving the sequential integrity required for forecasting. Feature Engineering played a central role in enhancing model predictiveness, encapsulating various factors influencing energy demand. Key features included:

– Historical Data: Previous energy demand values enabled the model to capture autoregressive patterns within the time series.

– Weather Variables: Essential meteorological factors, such as temperature, humidity, atmospheric pressure, wind speed, wind direction, solar irradiance, and UV index, were included due to their anticipated impact on energy consumption patterns.

– Derived Features: The clearness index (representing solar radiation effectiveness), lagged demand values, and time-of-day adjustments were incorporated to improve the model's understanding of consumption patterns.

A Bidirectional Long Short-Term Memory (BLSTM) network was employed for forecasting, chosen for its ability to learn dependencies in sequential data by processing inputs bidirectionally. The model architecture comprised a BLSTM layer with 50 units, designed to capture both past and future context within the time series, and a dense output layer to generate final demand forecasts. The model was compiled using the Adam optimiser and Mean Squared Error (MSE) as the loss function.

For training and validation, the data was split monthly, with 70% designated for training and 30% for validation on the most recent data. This chronological split preserved time dependency, essential for maintaining forecasting accuracy. A transfer learning strategy was adopted, where model weights were reinitialised, each month using the previous month's data, allowing the model to adapt to changing trends while retaining historical patterns.

**Table 4: Model performance across various feature sets for demand forecasting.**

| **Load Feature Set** | **MSE** | **MAE** | **RMSE** | **$R^2$** |
|---|---|---|---|---|
| Baseline 1 (Historical) | 0.0064 | 0.0621 | 0.0793 | 0.7991 |
| Baseline 2 (Historical & Weather) | 0.0086 | 0.0637 | 0.0851 | 0.7231 |
| Full Feature Set | 0.0063 | 0.0609 | 0.0774 | 0.8013 |
| Historical & Clearness | **0.0041** | **0.0459** | **0.0627** | **0.8764** |
| Historical & Humidity | 0.0106 | 0.0700 | 0.0910 | 0.6806 |
| Historical & Irradiance | 0.0054 | 0.0569 | 0.0725 | 0.8339 |
| Historical & Pressure | 0.0061 | 0.0571 | 0.0760 | 0.8039 |
| Historical & Temperature | 0.0057 | 0.0576 | 0.0748 | 0.8255 |
| Historical & UV INDEX | **0.0049** | **0.0526** | **0.0695** | **0.8462** |
| Historical & Windspeed | 0.0069 | 0.0619 | 0.0812 | 0.7843 |
| Lag Features | 0.0040 | 0.0456 | 0.0616 | 0.8811 |
| Time of Day + Lag Features | **0.0039** | **0.0448** | **0.0594** | **0.8867** |

Model Evaluation Results demonstrated strong predictive performance across different feature sets. As shown in Table 4, the results reveal the impact of feature selection on model accuracy: The baseline model, using only historical demand data, achieved an $R^2$ of 0.7991, while adding basic weather information (Baseline 2) slightly reduced accuracy to an $R^2$ of 0.7231, indicating that weather data alone may not necessarily improve model performance linearly. The Historical & Clearness configuration achieved an MSE of 0.0041, MAE of 0.0459, RMSE of 0.0627, and an $R^2$ of 0.8764, leveraging the clearness index to capture solar irradiance effects. The Historical & UV INDEX model also performed well, achieving an MSE of 0.0049, MAE of 0.0526, RMSE of 0.0695, and an $R^2$ of 0.8462. Models with advanced temporal features, particularly the Time of Day + Lag Features model, demonstrated the highest accuracy with an MSE of 0.0039, MAE of 0.0448, RMSE of 0.0594, and an $R^2$ of 0.8867.


**Figure 5: Historical & Time of Day + Lag Features vs Actuals (Short-Term)**

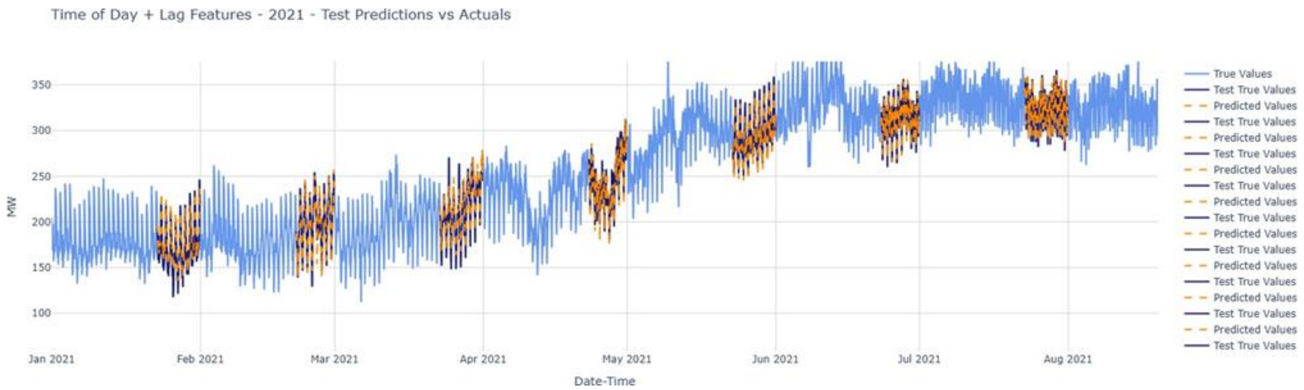


**Figure 6: Historical & Time of Day + Lag Features - Test Predictions vs Actuals (Full Year)**

As illustrated in Figure 5, the Time of Day + Lag Features configuration closely tracks actual short-term demand trends, achieving minimal deviations even during peak periods. Over a full year, as shown in Figure 6, the model demonstrates robust long-term predictive capabilities, effectively aligning with observed demand patterns. These results highlight the importance of incorporating temporal features and derived metrics in improving forecast accuracy.

**Conclusion**

This research has demonstrated the efficacy of advanced machine learning models in forecasting and managing the balance between energy demand and photovoltaic (PV) supply, specifically within Saudi Arabia's first large-scale solar farm. The Bidirectional LSTM (BLSTM) model, in particular, has shown superior performance, effectively capturing complex temporal patterns due to its ability to process data from both past and future contexts. This capability makes it an excellent candidate for integration into smart grid technologies, where accurate and reliable predictions are crucial for maintaining energy stability and optimising grid operations.

The findings underscore the importance of sophisticated feature engineering and the strategic selection of machine learning models tailored to the specific characteristics of the energy dataset. By incorporating both historical and meteorological data, the models were able to achieve a high level of accuracy, demonstrating their potential to significantly contribute to the advancement of renewable energy integration within the region.

Future research should focus on expanding the dataset to include multi-regional data, which would help in understanding the models' effectiveness across different geographical and climatic conditions. Additionally, exploring hybrid models that combine the strengths of various architectures could further enhance prediction accuracy and reliability.

Ultimately, this research contributes to the growing body of knowledge that supports the transition towards more sustainable and resilient energy systems. By leveraging AI and machine learning, stakeholders in the energy sector can anticipate demand fluctuations more accurately and harness renewable energy sources more efficiently, paving the way for smarter energy management and a sustainable future in Saudi Arabia and beyond.

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**Appendix**

**Supply Prediction Studies**

**Table 5: Comparative Analysis of Machine Learning Models for Solar Energy Forecasting.**

| | **ML Model Used** | **Variables** | **Data Resolution** | **Review** |
|---|---|---|---|---|
| [45] | Multilayer Perceptron (MLP) with entity embedding. | Weather variables and solar energy production metrics. | Hourly over 2 years | Discusses ML models like SVM, ANN, hybrid learning models, and ensemble learning, highlighting gaps in their application for solar forecasting. |
| [46] | Hierarchical Temporal Convolutional Neural Networks (HTCNNs). | Historical PV generation, weather data. | Hourly with an 18-hour forecasting horizon | Compares with models like LSTM and CNN for regional PV forecasting and proposes hierarchical time-series approaches. |
| [47] | CNN and LSTM hybrid. | Solar radiation, temperature, sunshine duration, and other weather parameters. | Hourly | Addresses traditional ML methods' limitations and compares the hybrid CNN-LSTM model with other DL techniques. |
| [48] | Ensemble of 13 ML techniques, including ANN, SVM, RF, etc. | Temperature, humidity, wind speed, solar radiation. | Hourly | Compares the performance of various models like SVM, and ANN, showing SVM's superior predictive capabilities. |
| [13] | Random Forest(RF), ANN, and DNN. | Weather data recorded PV power output. | Hourly | Highlights limitations of simpler statistical models, positioning RF as effective for short-term horizons. |
| [49] | LSTM, SVM, Graph Spatial-Temporal Attention Neural Network (GSTANN). | Historical solar power data. | Hourly | Examines the effectiveness of LSTM and SVM, finding SVM most reliable. |
| [50] | CNN-LSTM without max pooling. | Solar irradiance, meteorological data. | Hourly | Validates CNN-LSTM's capability against typical pooling methods, showing improved accuracy. |
| [51] | LSTM and RF. | Temperature, humidity, solar radiation, pollution. | Hourly | Compares LSTM and RF in handling large datasets, concluding LSTM's superior performance. |
| [52] | Decision Tree, SVM, and Ensemble. | Electricity generation, demand, pricing, weather data. | Hourly (2015-2018) | Reviews ML models for grid reliability and pricing, underscoring Ensemble's high accuracy. |
| [13] | Bidirectional Long Short-Term Memory (BLSTM), Random Forest (RF), | Temperature, humidity, solar radiation, wind speed, wind direction, | Hourly averaged data collected at | Evaluate BLSTM for solar power forecasting, finding improved accuracy (up to 37%) across short-term horizons (1 to 4 |

| | ML Model Used | Variables | Data Resolution | Review |
|---|---|---|---|---|
| | Artificial Neural Networks (ANN), and Deep Neural Networks (DNN). | time of day and PV output (solar power generation data). | 15-minute intervals. | hours ahead) and seasons. Highlights BLSTM's effectiveness in modelling nonlinearity and seasonality in data. |

**Demand Prediction Studies**

**Table 6: Comparative analysis of machine learning models for electricity and energy demand prediction.**

| | ML Model Used | Variables | Data Resolution | Results |
|---|---|---|---|---|
| [53] | A hybrid model combining ANN, Encoder-Decoder Long Short-Term Memory (EDLSTM), and Im- proved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (ICMD). | Electricity demand, lagged time series data, and seasonal trends. | Daily electricity demand data. | The ICMD-ANN-EDLSTM hybrid model achieved a 2.82% Relative Mean Absolute Error, outperforming individual models. |
| [54] | Long Short-Term Memory (LSTM) with a multi-input, multi-output window-based architecture. | Electricity demand, seasonal, daily, and interval data. | Hourly and daily for different seasons and intervals. | LSTM model showed improved accuracy over traditional models such as Support Vector Regression (SVR). |
| [55] | Extreme Learning Machine (ELM) optimised by Jaya algorithm. | Electricity consumption, online search trends, temperature, and other economic in- indicators. | Monthly residential electricity consumption. | The model achieved significant improvements in forecasting accuracy, with a MAPE reduction between 43.03%-53.92%. |
| [56] | XGBoost for prediction and K-means for clustering DR profiles. | Building characteristics, historical demand response data, and DR profiles. | Hourly during demand response events. | The model estimated a demand shaving capacity of approximately 4.5 MWh annually across NYC. |
| [23] | Various models, including Neural Networks and Least Squares Support Vector Machines (LS-SVM). | Hourly energy consumption, temperature, and time of day. | Hourly residential energy consumption. | LS-SVM achieved the best accuracy among tested models. |
| [57] | Artificial Neural Networks (ANN), Multivariate Adaptive Regression Splines (MARS), and Hybrid ANN. | Electricity demand, climate variables from SILO and ECMWF datasets. | 6-hour and daily pre-dictions. | Hybrid ANN achieved a Relative Root Mean Square Error (RRMSE) of 3.85% for 6-hour predictions. |
| [58] | Hybrid Prophet-Gated Recurrent Unit (GRU) model. | Hourly historical consumption data for water and electricity; auxiliary variables derived from | Hourly, with data collected from six households. | The combined model achieved improved pre-diction accuracy with $R^2$ gains of 29.2% for water and 48.5% for electricity over single-resource models. |

| | ML Model Used | Variables | Data Resolution | Results |
|---|---|---|---|---|
| | | consumption patterns. | | |
| [59] | Decision Trees, Support Vector Machines (SVM), and Artificial Neural Networks (ANN). | Outdoor temperature, solar radiation, time of day, non-working hours, weekend indicators. | Short-term (hours to days), using 10-minute interval data. | ML models (especially Decision Trees) outperformed traditional linear regressions, showing potential for deployment in predictive control applications. |