Article in Press IJIMAI journal

A Sustainable Deep Learning Paradigm for Reliable Energy Prediction in Next-Gen Consumer Electronics

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Received 11 May 2024 | Accepted 18 October 2024 | Early Access 10 February 2025

Abstract

In the rapidly evolving consumer electronics landscape, the imperative for sustainable energy solutions necessitates the development of accurate energy prediction methodologies. Traditional energy prediction models often fall short in accounting for the dynamic characteristics of renewable energy sources, particularly wind and solar. This limitation is pronounced in consumer electronics, where precise energy forecasting is pivotal for achieving optimal device performance and energy efficiency. To address this gap, we present a sustainable deep learning paradigm using Long Short-Term Memory (LSTM) networks to capture the complex temporal patterns inherent in renewable energy data. This paper introduces a novel and sustainable deep learning approach that significantly enhances energy prediction accuracy within the context of next-generation consumer electronics. By leveraging the capabilities of an LSTM-based model, we utilize an extensive dataset comprising hourly records of wind and solar energy production from the French grid since 2020. Our research addresses the inherent challenges in precise energy prediction, a cornerstone for efficient energy management and consumption optimization in emerging technology ecosystems. Through comprehensive data preprocessing, feature engineering, and rigorous training, the LSTM model demonstrates exceptional proficiency, achieving an impressive 82% accuracy in predicting energy production. This underscores its efficacy in capturing intricate temporal relationships and patterns within renewable energy data, facilitating its integration into next-generation consumer electronics. Our proposed paradigm addresses a critical need and paves the way for a future where accurate energy prediction fuels eco-conscious technology. In conclusion, this study contributes to a more sustainable energy landscape by advancing the development of reliable and efficient energy prediction methodologies for the evolving realm of next-generation consumer electronics.

Keywords

Deep Learning, Energy Prediction, Long Short-Term Memory, Next-Gen Consumer Electronics, Sustainability.

DOI: 10.9781/ijimai.2025.02.005

I. Introduction

Emergence of next-generation consumer electronics has brought forth a technological renaissance, revolutionizing how we interact with devices and reshaping the boundaries of innovation. As these devices become more intricate and interconnected, their energy demands have grown exponentially. Consequently, accurate and reliable energy prediction has become paramount in ensuring these cutting edge technologies' optimal performance, efficiency, and sustainability [1]. Precise energy prediction is a foundational pillar in the quest for greener and more efficient electronics. Consumer electronics, ranging from smartphones and laptops to smart home devices and wearables, require varying degrees of energy to function effectively. Accurate energy forecasting enables proactive energy management, ensuring that devices are powered optimally without unnecessary wastage. In an era where energy conservation is integral to environmental stewardship, the ability to forecast energy requirements holds immense potential for reducing carbon footprints and minimizing electronic waste.

Deep learning, a subfield of artificial intelligence [2], has emerged as a transformative force in this endeavor. Its capacity to learn intricate patterns from vast datasets and its capability to uncover complex relationships within temporal data make it a powerful tool for energy optimization. Applying deep learning techniques, such as Long Short-Term Memory (LSTM) networks, empowers electronics to anticipate energy needs with remarkable precision. Deep learning models can generate accurate energy predictions by analyzing historical energy consumption patterns and considering contextual factors like user behavior and environmental conditions. The integration of deep learning methodologies into energy optimization strategies not only

Please cite this article as:
G. Jeon, I. Ahmed, S. Han. A Sustainable Deep Learning Paradigm for Reliable Energy Prediction in Next-Gen Consumer Electronics, International Journal of Interactive Multimedia and Artificial Intelligence, (2025), http://dx.doi.org/10.9781/ijimai.2025.02.005

enhances efficiency but also aligns with the principles of sustainability. Consumer electronics equipped with accurate energy prediction mechanisms contribute to a more environmentally conscious future by mitigating energy wastage and promoting reasonable energy use. This is particularly pertinent as the demand for innovative technology continues to rise and the strain on energy resources grows.

The combination of reliable energy prediction and deep learning [3] constitutes a transformative synergy for next-generation consumer electronics. It not only bolsters the operational efficiency of devices but also propels the sustainable technology movement. As we stand on the precipice of an era defined by interconnected and intelligent devices, the ability to anticipate energy needs intelligently is crucial for fostering a harmonious relationship between technological advancement and environmental preservation. In the rapidly advancing consumer electronics landscape, the imperative for sustainable energy solutions has magnified the significance of accurate energy prediction. Next-generation devices' increasing complexity and diversity necessitate precise energy forecasts to optimize performance, enhance efficiency, and minimize environmental impact. Integrating energy-efficient practices aligns harmoniously with the growing emphasis on eco-conscious technology, propelling the need for innovative methodologies that reliably predict energy requirements.

Building on the critical significance of reliable energy prediction within next-generation consumer electronics, this paper introduces an innovative strategy that harnesses deep learning techniques for energy optimization. The central objective is to leverage the power of Long Short-Term Memory (LSTM) networks, a form of recurrent neural networks, to construct a robust and precise energy prediction model. This model empowers consumer electronics to foresee energy demands with exceptional accuracy, thereby elevating energy efficiency and advancing sustainability objectives. The provided dataset encompassing hourly wind and solar energy production records from the French grid since 2020 is integral to achieving these objectives. This dataset is pivotal in guiding the development of the LSTM-based model, tailored specifically to the energy consumption patterns of contemporary consumer electronics. The LSTM architecture captures intricate temporal relationships intrinsic to the data by integrating the hourly energy production records into the model inputs. This capacity enables the model to apprehend dependencies between successive hours and days, forming a robust foundation for precise daily energy production predictions.

Through this methodology, the developed LSTM model is pivotal in enhancing energy efficiency within next-gen consumer electronics. By harnessing historical patterns, this model facilitates proactive energy management, enabling accurate predictions of energy requirements. Consequently, this informed resource allocation minimizes waste and bolsters a sustainable consumption paradigm. Additionally, the precise energy predictions yielded by this model contribute to promoting sustainability within consumer electronics. The alignment between high-precision energy anticipation and eco-conscious technology principles ensures judicious use of energy resources, reducing environmental impact.

In summary, this study is driven by the following objectives:

- Model Development: Design and implement an LSTM-based model using the provided dataset to accurately capture temporal patterns and dependencies in wind and solar energy production.
- Enhanced Energy Efficiency: Employing the developed models to enhance the energy efficiency of consumer electronics through proactive energy management and optimal power allocation.
- Promotion of Sustainability: Integrating accurate energy prediction as a foundational element of eco-conscious technology, aligning the objectives of technological advancement with environmental preservation.

The research endeavors to bridge the gap between technology innovation and sustainable practices through these objectives. By marrying deep learning techniques with renewable energy datasets, this methodology charts a transformative path toward refined energy utilization in the era of next-gen consumer electronics. Ultimately, the aim is to facilitate a future where intelligent devices enhance human experiences and actively contribute to a greener, more sustainable world. The work presented in the paper is organized into the following sections. Section II, the Literature Review, establishes the theoretical foundation by surveying energy prediction techniques' landscape within modern consumer electronics. In Section IV, Dataset and Data Exploration, the study explores the dataset of hourly wind and solar energy production records from the French grid since 2020, unveiling its characteristics and temporal patterns. Methodology, detailed in Section V, intricately explains the operational mechanics, emphasizing the role of LSTM networks and contextual features. Section V, Results, presents empirical achievements by showcasing the LSTM-based models' accuracy in predicting daily energy production. Finally, Section VII, Conclusion and Future Work synthesize the findings, highlighting the method's significance for sustainable technology and outlining pathways for future research in energy optimization.

II. Literature Review

In the context of energy prediction, various methodologies have been devised and introduced to enhance the precision and efficiency of predictive models. One of these methodologies, the Autoregressive Integrated Moving Average (ARIMA) model, has been proposed by Zhou et al. in their work titled "Comparison of time series forecasting based on statistical ARIMA model and LSTM with attention mechanism" [4]. The ARIMA model is known for its ability to dissect complex temporal trends and patterns within energy data. Another method, termed "Regression Models," has been developed by Zekić-Sušac et al. in their paper "Machine learning based system for managing the energy efficiency of the public sector as an approach towards smart cities" [5]. This methodology integrates contextual variables into the predictive framework to improve the accuracy of energy consumption predictions.

Early Neural Networks played a seminal role in the era preceding the surge of deep learning techniques. Trejo-Perea et al. presented "Greenhouse energy consumption prediction using neural networks models," showcasing the developing ability of these networks to unravel intricate energy patterns [6]. Conversely, Support Vector Machines (SVM) offered a more mathematical approach. Edwards et al. investigated "Predicting future hourly residential electrical consumption: A machine learning case study," illustrating how SVMs can effectively map complex energy patterns for more accurate predictions [7]. To uncover decision paths within energy consumption, Nsangou et al. presented "Explaining Household Electricity Consumption using quantile regression, Decision Tree and artificial neural network." Decision Trees were highlighted in this work, offering a transparent means to interpret energy behaviors [8]. Moreover, the concept of Random Forests was introduced, combining multiple decision trees into ensembles to enhance the overall prediction accuracy. The trajectory towards enhanced precision also encompasses the utilization of gradient-boosting techniques. Robinson et al. explored "Machine learning approaches for estimating commercial building energy consumption," detailing how these iterative algorithms refine predictions over successive iterations [9]. In parallel, Dynamic Bayesian Networks were investigated within the same context, capitalizing on their ability to capture temporal dependencies within dynamic energy relationships.

In addressing the intricacies of uncertainty, Fuzzy Logic emerges as a potent method. Mukhopadhyay et al. delved into "Electricity load forecasting using fuzzy logic: Short term load forecasting factoring weather parameter," showcasing how this logic navigates non-linear landscapes [10]. Furthermore, Autoencoders, unveiled by Kim and Cho, shed light on latent energy patterns through unsupervised learning, thereby enhancing prediction accuracy [11]. The capture of temporal dependencies characterizes the Recurrent Neural Networks (RNN) domain. Balraj et al. delved into optimizing RNNs for Electric Load Forecasting [12]. Similarly, Convolutional Neural Networks (CNN), explored by Le et al., excel in scenarios involving spatial relationships within energy data [13]. Integrating advanced prediction models has garnered substantial attention in the vibrant renewable energy-driven mobile edge computing (MEC) landscape. Ku et al. [14] introduced a model that predicts the intra-hour and hour-ahead energy state (SoE) in a renewable energy-driven MEC environment. This model encompasses solar and wind energy generation effects, contributing to the advancement of accurate energy predictions within MEC systems. Rosas et al. [15] investigated charging and discharging strategies for a battery energy storage system (BESS) using energy predictions derived from a CNN-LSTM neural network model. The model's efficacy in generating BESS charging and discharging itineraries underscores the potential of the CNN-LSTM architecture in the context of BESS systems.

Solar irradiance forecasting benefits from the fusion of CEEMDAN and multi-strategy CNN-LSTM neural networks, as unveiled by Gao et al. [16]. This hybrid model offers a reliable approach for hourly irradiance forecasting, harnessing the synergies between decomposed components and convolutional long short-term memory (CNN-LSTM) networks to address energy prediction challenges. Rick and Berton [17] explore energy forecasting models based on CNN-LSTM-AE, adept at handling time series with unequal lengths. This innovative approach effectively forecasts energy consumption patterns, highlighting the potential of CNN-LSTM networks to accommodate varying temporal dynamics. Kumari and Toshniwal [18] present a comprehensive approach for solar irradiance forecasting, incorporating long short-term memory (LSTM) and convolutional neural network (CNN) models. This versatile approach extends its application across various time-series domains, including energy consumption, photovoltaic (PV) power, and wind speed prediction, thus enriching the array of available energy forecasting tools. Predicting wind power generation becomes more achievable through the integration of machine learning and CNN-LSTM methodologies, as demonstrated by Malakouti et al. [19]. Their work showcases the effectiveness of CNN-LSTM models in capturing the intricate dynamics of wind energy generation.

Estebsari and Rajabi [20] explore single residential load forecasting using deep learning and image encoding techniques. This study investigates the forecasting effectiveness of SVM, ANN, and CNN methodologies for energy consumption prediction, reflecting the growing diversity of tools for enhancing energy prediction accuracy. Khan et al. [21] traverse the realm of renewable energy prediction through deep learning approaches, focusing on generation and consumption prediction. The combination of Echo State Networks (ESN) and CNN models offers a novel avenue for efficient and effective renewable energy prediction, underscoring the potential of merging methodologies for robust predictions. Alam et al. [22] contribute to solar PV power forecasting by investigating traditional and machine learning techniques. The integration of CNN, multi-headed CNN, and CNN-LSTM models underscores their role in forecasting solar power output, aligning with the broader goal of cleaner and more reliable energy solutions. Khan et al. [23] present a novel dilated CNN-based multi-step forecasting model, "DB-Net," for power consumption in integrated local energy systems. This model signifies the growing adoption of advanced neural network architectures in energy forecasting, catering to the intricacies of power consumption within integrated energy frameworks.

Attention Mechanisms, as demonstrated by Zhu, Kedong, and others, offer a targeted perspective to enhance prediction accuracy [24]. Deep Belief Networks (DBN), introduced by Li, Chengdong, and the team, amalgamate generative modeling and unsupervised learning to uncover intricate energy patterns [25]. Addressing the need for interdisciplinary insights, Transfer Learning, as explored by Gao, Yuan, and colleagues, capitalizes on pre-existing knowledge for enhanced energy prediction [26]. Finally, Hybrid Models, as depicted by Li, Chengdong, and his team, combine various methods' strengths to yield accurate and robust energy predictions [25]. Optimized LSTM models pre-trained with synthetic data have shown promise in estimating PV generation, as demonstrated by Martínez-Comesaña et al. [27]. Their work underscores the potential of pre-training techniques in enhancing model accuracy in renewable energy applications.An evolutionary deep learning model combining EWKM, random forest, SSA, and BiLSTM techniques offers a novel approach to building energy consumption prediction, highlighting the strength of hybrid models in energy forecasting [28]. Multi-horizon forecasting with deep learning has been explored by Ni et al. [29], emphasizing the ability of advanced models to predict energy consumption over varying time horizons, thus providing comprehensive insights into energy use dynamics.

In conclusion, the literature review underscores the diverse spectrum of energy prediction methodologies. These approaches collectively advance accurate, efficient, and comprehensive energy forecasting tools. This synthesis of methodologies exemplifies the multidisciplinary nature of energy prediction and paves the way for innovative approaches that bridge the gap between precision and efficiency in energy forecasting research.

However, amidst the multitude of methodologies presented in the literature, certain gaps and challenges remain to be addressed. One notable gap is the need for a holistic approach that seamlessly integrates the strengths of various methods to create a unified and robust energy prediction model. While many individual methodologies have shown promise, there is often room for improvement in terms of accuracy, adaptability to dynamic scenarios, and effective handling of complex temporal and spatial dependencies. The presented work aims to bridge these gaps by proposing a novel methodology that leverages the power of deep learning, specifically Long Short-Term Memory (LSTM) networks, in conjunction with the intricate patterns inherent in hourly wind and solar energy production records. By integrating the strengths of LSTM networks and the unique characteristics of renewable energy data, the proposed approach seeks to enhance prediction accuracy, capture temporal dependencies, and effectively address the challenges posed by dynamic energy patterns. Moreover, the fusion of methodologies within this approach envisions a comprehensive solution that can adapt to various energy contexts and lead to more reliable and efficient energy consumption predictions.

Through this integrated methodology, the presented work offers a significant step forward in the field of energy prediction, contributing to a deeper understanding of energy consumption behaviors within modern consumer electronics. As the energy landscape continues to evolve, this approach aspires to provide a foundation for sustainable energy consumption practices, making a valuable contribution to developing next-generation energy-efficient technologies.

III. Problem Definition and System Model

The problem addressed in this study involves accurately predicting energy production from renewable sources to optimize energy consumption in next-generation consumer electronics. This challenge is exacerbated by the dynamic and intermittent nature of renewable energy sources, particularly wind and solar, which are subject to fluctuations based on environmental conditions. The system model proposed in this study comprises the following components:

- **Data Acquisition**: Collection of hourly wind and solar energy production data from the French grid, starting from 2020. This dataset serves as the foundation for model training and validation.
- **Data Preprocessing**: Transformation of raw energy production data into a format suitable for input into the LSTM model. This involves scaling the production values to fall within the $[0, 1]$ range using MinMaxScalers.
- **LSTM Model Architecture**: Design and implementation of an LSTM-based model capable of capturing temporal dependencies within the energy production data. This architecture is specifically tailored to handle sequential data and capture intricate temporal patterns.
- **Model Training**: Training separate LSTM models for solar and wind energy, using input-output pairs derived from the historical data. Training is conducted over multiple epochs to optimize the model's performance.
- **Multi-Step Forecasting**: Utilization of trained LSTM models to predict future energy production levels based on new sequences of historical data. This step leverages the temporal dependencies learned during training to generate accurate forecasts.
- **Post-Processing and Analysis**: Inversion of scaled forecasted values to their original scale and assessment of the model's performance using quantitative metrics. This step facilitates meaningful comparisons between predicted and actual energy production levels.

By addressing the problem of energy prediction through this system model, our approach offers a robust framework for optimizing energy consumption in next-generation consumer electronics, promoting efficiency and sustainability.

IV. DataSet and Data Exploration

The dataset utilized in this study comprises hourly wind and solar energy production records[1] (expressed in megawatts, MW) for the French grid, spanning from the year 2020 onwards. The primary objective of this dataset is to facilitate the computation of reference prices that play a crucial role in determining additional remuneration for wind and solar energy sectors within the framework of the Commission de Régulation de l'Énergie (CRE). The concept of additional remuneration stems from the Law on Energy Transition for Green Growth (LTECV), aimed at supporting renewable energy producers who directly engage in electricity sales. This compensation mechanism ensures that renewable energy producers receive an incentive that accounts for the disparity between their earnings from electricity sales and a predetermined reference remuneration level. Public authorities establish the reference remuneration through tariff decrees or via producer-led competitive procedures, contingent on the nature of the installation.

This comprehensive dataset provides a robust foundation for benchmarking and evaluating various energy prediction methodologies, encompassing hourly records of wind and solar energy production aggregated every month. The data is sourced from a reputable benchmark and is expected to offer valuable insights into the intricacies of renewable energy production patterns within the context of the French grid. Fig. 1 presents a visual representation of the yearly energy production from solar and wind sources from 2020 to 2023. The data has been aggregated and grouped by source (Solar and Wind) and year, with each bar in the plot corresponding to a specific year. The height of the bar reflects the total energy production for that year, where blue represents wind energy production, and orange signifies solar energy production.

Observing the trends over these years, it becomes evident that both solar and wind energy production have shown a consistent growth pattern. Notably, 2022 stands out as particularly significant for both sources, with a noticeable spike in energy production. Solar energy production steadily increased from 2020 to 2022, peaking at approximately 10,939,292 MW in 2022. Similarly, wind energy production consistently grew, with a peak production of around 38,569,740 MW in 2022. However, both sources experienced a slight decline in 2023, which may be attributed to potential variations in weather conditions or technological improvements. This visualization effectively encapsulates the upward trajectory of renewable energy production over these years, providing valuable insights into the growing contribution of solar and wind sources to the energy landscape.

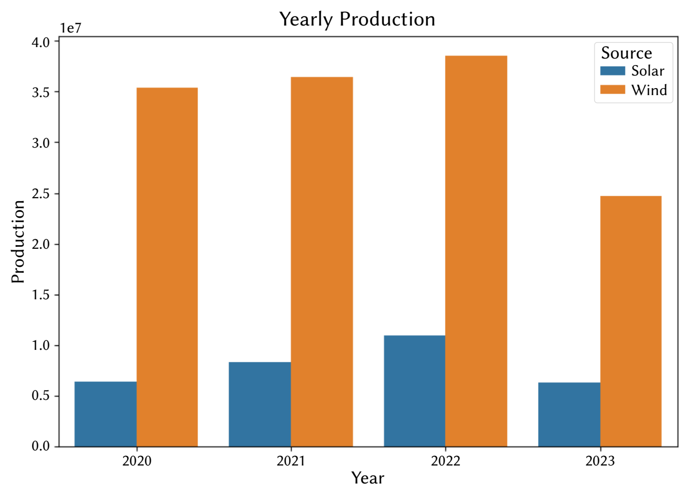

Fig. 1. Yearly Energy Production: This bar chart illustrates the yearly energy production from solar and wind sources on the French grid since 2020. The y-axis represents the total energy production (in MW), while the x-axis denotes the years. The distinct bars for each source are color-coded for easy differentiation, providing a visual representation of how solar and wind energy production have evolved annually.

Fig. 2 offer an insightful view into the monthly energy production trends for solar and wind sources across multiple years. Each subplot in the arrangement corresponds to a specific year, capturing the distribution of energy production across the months. The pie charts provide a visual breakdown of how energy production is distributed among the months of the year for both solar and wind sources, highlighting recurring patterns.

Analyzing the figures, it's clear that there have been recurring patterns in energy production for both solar and wind sources over the years. For solar energy, the distribution of energy production tends to peak during the sunnier months, with a higher percentage of production in the summer and spring months. Conversely, wind energy production exhibits variations across the months, with some months witnessing higher contributions than others. This suggests a certain level of seasonality in producing solar and wind energy.

Furthermore, comparing the energy production between solar and wind sources within each year, it is evident that the seasonal variations affect them differently. While solar energy production tends to be more consistent throughout the months within a year, wind energy production experiences more fluctuations, indicating the influence of varying wind patterns and weather conditions. These visualizations effectively highlight the dynamic nature of renewable energy production, emphasizing the interplay between natural factors, such

[1] https://www.kaggle.com/datasets/henriupton/wind-solar-electricity-production?datasetId=3570391&sortBy=voteCount

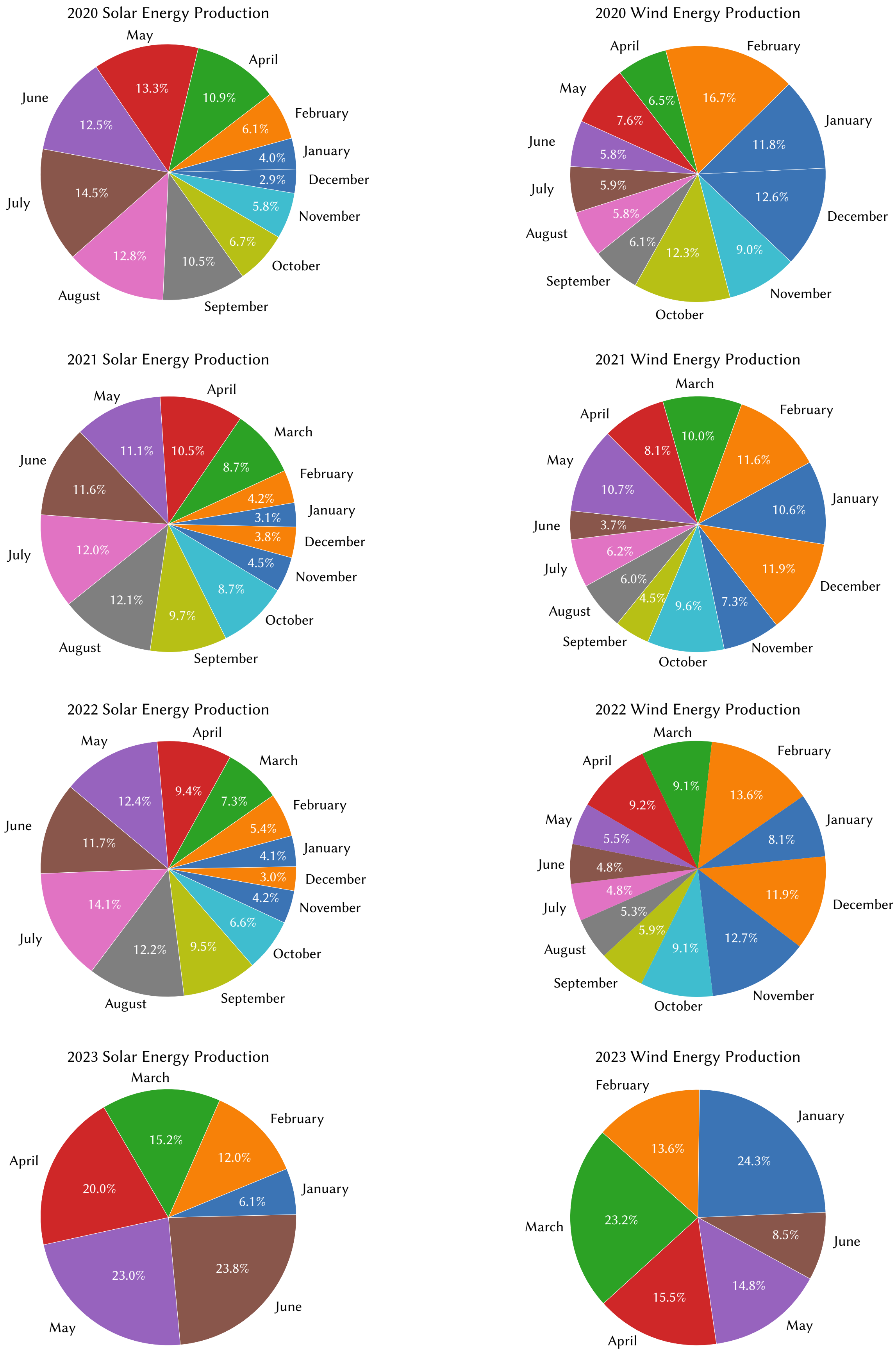

Fig. 2. Monthly Energy Production in Every Year: A series of pie charts showcased energy production distribution from solar and wind sources across different months and years. Each pair of pie charts corresponds to a specific year, with the left chart depicting solar energy distribution and the right chart representing wind energy distribution. The pie slices are labeled with the respective months and the percentage contribution of energy production. These pie charts reveal the seasonal variations in energy generation, emphasizing the dominance of solar energy during sunnier months and wind energy during colder periods.

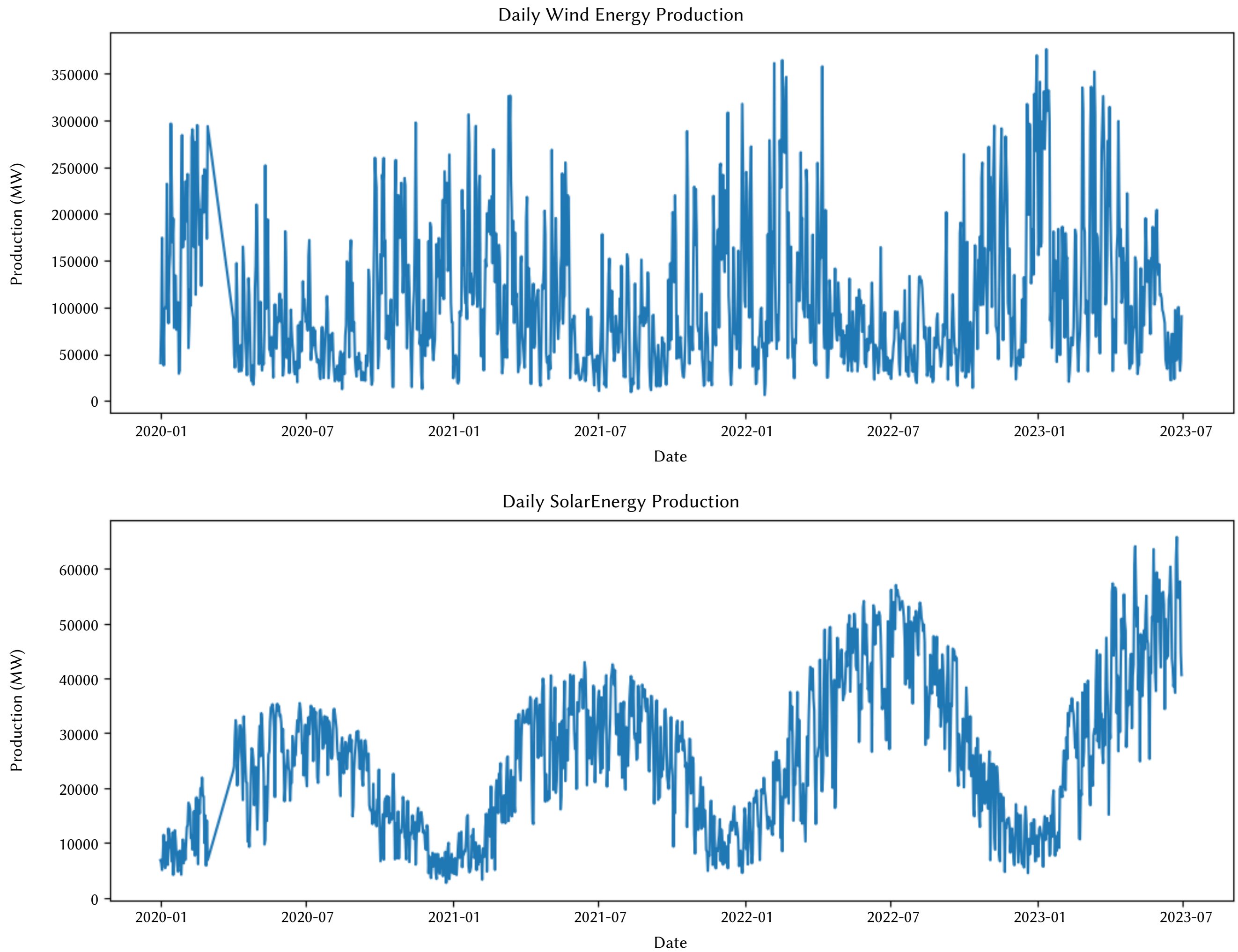

Fig. 3. Daily Wind and Solar Energy Production: This figure comprises two line plots illustrating the daily energy production from wind and solar sources on the French grid. The top subplot presents the daily wind energy production over time, where the x-axis represents dates, and the y-axis depicts energy production in megawatts (MW). The bottom subplot showcases the daily solar energy production, with the x-axis indicating dates and the y-axis representing energy production in MW.

as sunlight and wind, and their impact on energy generation. This information can be instrumental in guiding energy policy decisions and resource allocation, ultimately contributing to a more sustainable and reliable energy landscape.

Notably, the pie charts offer insights into the seasonal patterns that characterize France's solar and wind energy production. For solar energy, the charts illustrate that more than 23% of the production occurs during the hot months of the year, including Spring and Summer. This distribution aligns with the expected behavior, given that solar energy production thrives in periods with longer daylight hours, such as Spring and Summer. Conversely, wind energy production exhibits a different pattern, with more than 60% of the total wind energy production concentrated in the cold half of the year, encompassing the Fall and Winter seasons. This pattern is consistent with the fact that wind energy tends to be more abundant during the colder months, driven by seasonal variations in wind patterns.

Furthermore, the insights derived from these charts are grounded in the geographical context of France, which lies in the northern hemisphere. The longer daylight hours during Spring and Summer contribute to heightened solar energy production, while the increased wind speeds during Fall and Winter lead to elevated wind energy production. These trends align with the natural cycles of solar irradiance and wind patterns, reflecting the influence of environmental factors on energy generation.

Fig. 3 shows the Daily Wind and Solar Energy Production. The line plots reveal distinct patterns in daily energy production from wind and solar sources. In the top subplot, the fluctuations in wind energy production are visible, reflecting the variable nature of wind conditions. The bottom subplot illustrates the consistent trend of solar energy production, aligning with sunlight availability throughout the day. These visualizations provide insights into the daily variations in renewable energy generation, underscoring the interplay of weather conditions and sustainable energy output.

V. Methodology

The proposed methodology employs LSTM-based deep learning models to forecast future energy production levels for both solar and wind sources. This approach is designed to leverage the inherent temporal dependencies and patterns in historical energy production data, which are critical for making accurate predictions for renewable energy sources. The methodology comprises several key steps, including data preprocessing, model architecture design, dataset creation, model training, multi-step forecasting, and post-processing analysis. The

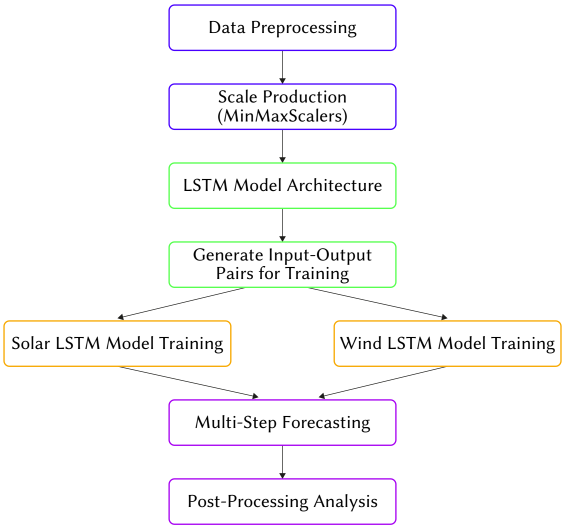

Fig. 4. Proposed Methodology Flow Diagram: This flow diagram illustrates the step-by-step process of the proposed methodology for forecasting renew- able energy production using LSTM-based deep learning models. The methodology involves data preprocessing, LSTM model architecture design, dataset creation, model training, multi-step forecasting, and post-processing analysis. Each step contributes to accurately predicting future energy production levels, enhancing the effectiveness of renewable energy management and resource allocation.

overall flow diagram of the proposed model is shown in Fig. 4. The methodology begins with the preprocessing of the energy production dataset. Data from January and February 2020 are excluded to enhance the accuracy of the forecasting model. The production values are then scaled using MinMaxScalers to ensure that they fall within the $[0, 1]$ range, which aids in neural network training convergence.

A. LSTM Model Architecture

The architecture of the LSTM model is designed to capture and exploit the temporal relationships within the energy production data. By integrating layers sequentially processing data over time, the model can effectively learn from past energy production patterns to predict future values. The model consists of multiple layers:

1. *Input Layer*: The input layer serves as the entry point for the LSTM model. It accepts sequential historical production values as input, structured as a sequence of time steps. In mathematical terms, for a sequence length of T and a batch size of B, the input tensor x_t at time step t is defined in Equation 1:

$$x_t = \begin{bmatrix} x_{1,t} \\ x_{2,t} \\ \vdots \\ x_{B,t} \end{bmatrix} \tag{1}$$

2. *LSTM Units*: The LSTM units are responsible for capturing patterns and dependencies across time steps in the data. The LSTM architecture consists of three primary gates: the input gate, the forget gate, and the output gate. These gates control the flow of information and enable the LSTM to capture long-term dependencies. Mathematically, as shown from Equation 2 to 7, the LSTM cell state c_t and hidden state h_t are updated as shown in follows:

$$i_t = \sigma(W_{ix}x_t + W_{ih}h_{t-1} + b_i) \tag{2}$$

$$f_t = \sigma(W_{fx}x_t + W_{fh}h_{t-1} + b_f) \tag{3}$$

$$o_t = \sigma(W_{ox}x_t + W_{oh}h_{t-1} + b_o) \tag{4}$$

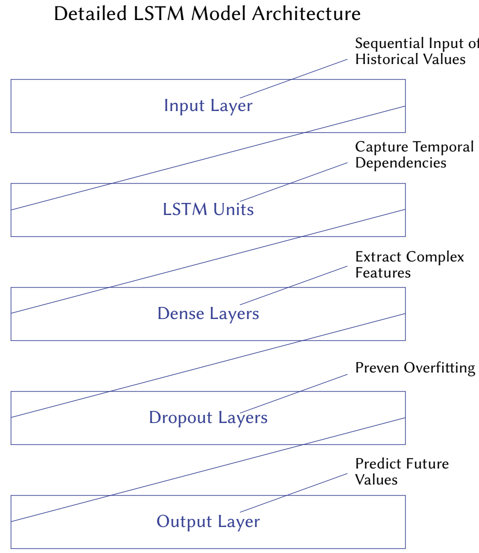

Fig. 5. Detailed LSTM Model Architecture: This diagram provides an in-depth view of the LSTM-based deep learning model architecture utilized in the proposed methodology. The model consists of distinct layers, including the Input Layer for sequential historical values, LSTM Units for capturing temporal dependencies, Dense Layers for feature extraction, Dropout Layers for overfitting prevention, and the Output Layer for predicting future energy production. The LSTM Units are highlighted in green to showcase their role in capturing intricate patterns and temporal relationships within the data. Annotations and connections emphasize the flow of information through each layer, contributing to accurate energy production forecasts.

$$g_t = \tanh(W_{gx}x_t + W_{gh}h_{t-1} + b_g) \tag{5}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \tag{6}$$

$$h_t = o_t \odot \tanh(c_t) \tag{7}$$

3. *Dense Layers*: Dense layers, also known as fully connected layers, are used to extract intricate features from the LSTM outputs. Rectified Linear Unit (ReLU) activation functions are commonly employed to introduce non-linearity. In mathematical terms, the output y_t of the dense layers is given by Equation 8:

$$y_t = \mathrm{ReLU}(W_d h_t + b_d) \tag{8}$$

4. *Dropout Layers*: Dropout layers are crucial for preventing overfitting in the model. During training, dropout randomly deactivates a fraction of neurons in the layer, forcing the network to learn more robust and generalizable features. Mathematically as shown in Equation 9, dropout introduces stochasticity to the hidden state:

$$h_t = \mathrm{Dropout}(h_t) \tag{9}$$

5. *Output Layer*: The output layer generates predictions for future energy production values. A sigmoid activation function is often used here to squash the output values between 0 and 1, suitable for predicting the likelihood of energy production. Mathematically, the output $y_{pred,t}$ at time step t is given by Equation 10:

$$y_{\mathrm{pred},t} = \sigma(W_o h_t + b_o) \tag{10}$$

In these equations:

- W represents weight matrices.
- b represents bias vectors.
- σ is the sigmoid activation function.
- $\odot$ denotes element-wise multiplication.
- x_t is the input at time step t.

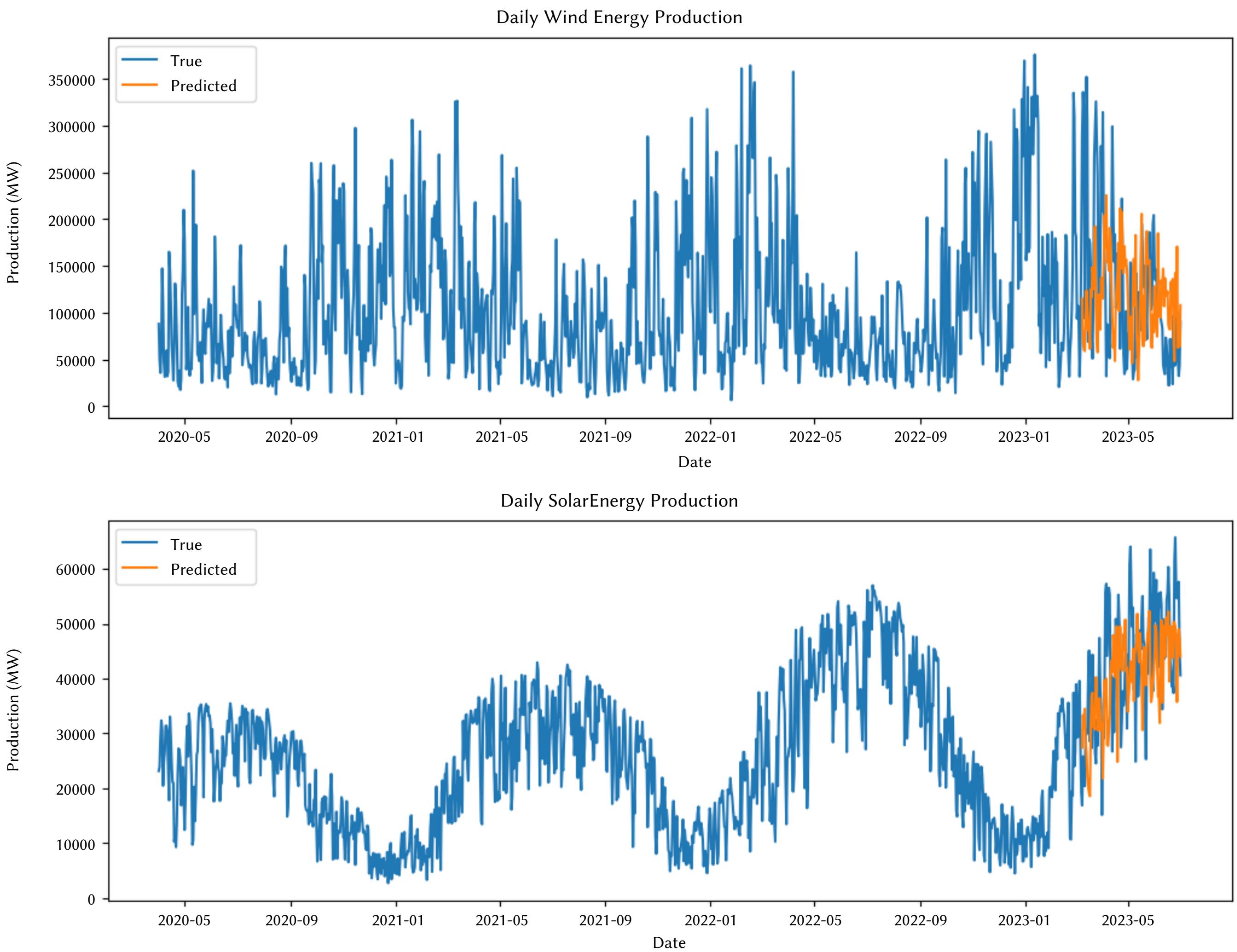

Fig. 6. Daily Wind and Solar Energy Production (Predicted vs. True): This figure compares the true and predicted daily energy production levels for both wind and solar sources. It consists of two subplots, one for wind energy production and another for solar energy production.

- i_t, f_t, o_t, and g_t are the input gate, forget gate, output gate, and input modulation vectors, respectively.
- c_t is the cell state at time step *t*.
- h_t is the hidden state at time step *t*.

Overall, the LSTM architecture as shown in Fig. 5, with its various components, enables the model to capture complex temporal relationships and patterns in the energy production data, facilitating accurate predictions for renewable energy forecasting.

B. Dataset Creation

The transformation of the dataset into a format suitable for LSTM training is crucial. This involves the generation of input-output pairs, where "x" sequences represent historical energy production values, and "y" sequences denote the predicted future values. These input-output pairs serve as the training data for the LSTM models. The creation of these pairs involves specifying input and output sizes. By doing so, the model can learn from past patterns and effectively use them to predict future trends.

C. Model Training

The model training phase consists of training separate LSTM models, one tailored for solar energy and another for wind energy. The previously generated input-output pairs are utilized for training, with the LSTM models learning to predict future energy production levels based on historical sequences. Training is executed over multiple epochs, each involving the presentation of a batch of training examples to the model. Batch processing allows for the iterative adjustment of the model's internal parameters to minimize prediction errors and enhance accuracy.

D. Multi-Step Forecasting

Having undergone rigorous training, the LSTM models are harnessed for multi-step forecasting. When presented with new sequences of historical production values, the models generate predictions for future energy production levels. These predictions are influenced by the temporal dependencies learned during the training phase. As a result, the models exhibit an improved ability to capture evolving patterns and trends, enabling more accurate forecasts of renewable energy production.

E. Post-Processing and Analysis

Following the generation of forecasted production values, a critical post-processing step ensues. Initially scaled using MinMaxScalers, the forecasted values are inverted to their original scale. This transformation facilitates meaningful comparisons between the predicted and actual energy production levels. To assess the accuracy and performance of the LSTM models, quantitative measures such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are employed. These metrics provide insights into the predictive capabilities of the models, enabling an assessment of their reliability and suitability for real-world applications.

In conclusion, the proposed methodology leverages the capabilities of LSTM-based deep learning models to forecast renewable energy production levels. By capitalizing on the inherent temporal dependencies present in energy production data, these models offer accurate predictions that have the potential to significantly contribute to informed decision-making in renewable energy management and resource allocation.

VI. Experimental Results

To evaluate the efficacy of the proposed methodology, extensive experiments were conducted using historical energy production data for both wind and solar sources. The experiments aimed to assess the accuracy of the LSTM-based models in predicting future energy production levels and compare their performance with other benchmark models, such as ARIMA and Support Vector Machines (SVM). The dataset used for experimentation consists of hourly energy production records for the French grid since 2020.

Fig. 6 compares the predicted and true daily energy production levels for wind and solar sources. In each subplot: - The blue line represents the true (actual) daily energy production levels. - The orange line represents the predicted daily energy production levels generated by the LSTM models. The results indicate a close alignment between the predicted and true values, signifying the models' capability to capture underlying patterns and dependencies in the data. Notably, deviations observed in predictions may result from external factors impacting energy production, such as weather conditions or operational changes, which the models might need to account for fully.

The obtained results from the model evaluation provide valuable insights into its performance in Fig. 7. The confusion matrix, shown as a heatmap, vividly illustrates the classification outcomes. It reveals the number of true positives, false positives, and false negatives, enabling a deeper understanding of the model's predictive capabilities. The classification report further quantifies each class's precision, recall, F1 score, and support. These metrics offer a comprehensive overview of the model's performance across both classes, facilitating an assessment of its ability to classify instances correctly.

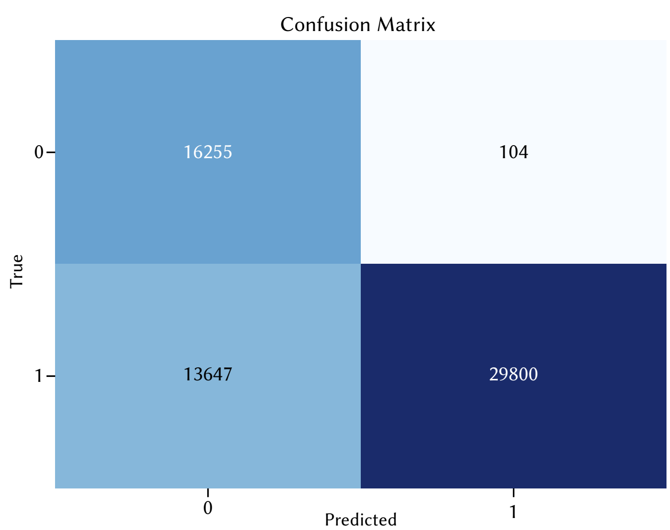

Fig. 7. Confusion Matrix for LSTM Models: This figure presents the confusion matrix as a heatmap, illustrating the classification outcomes for wind and solar energy production. The matrix reveals the model's true positive, true negative, false positive, and false negative predictions, providing a comprehensive understanding of its predictive capabilities.

Table I presents a comprehensive overview of the performance evaluation results for both the Wind and Solar LSTM models. The metrics included in the table provide insights into the models' predictive capabilities and their effectiveness in differentiating between the two classes (Class 0 and Class 1).

- Mean AUROC (Area Under the Receiver Operating Characteristic Curve): This metric quantifies the models' ability to discriminate between the positive (Class 1) and negative (Class 0) classes across different thresholds. A higher value indicates better discrimination.
- Accuracy: Accuracy represents the proportion of correctly predicted instances among all instances in the dataset, providing an overall measure of model performance.
- Precision (Class 0 and Class 1): Precision measures the proportion of true positive predictions out of all positive predictions for each class, reflecting the model's accuracy in predicting events and non-events.
- Recall (Class 0 and Class 1): Recall, also known as Sensitivity or True Positive Rate, calculates the proportion of true positive predictions out of all actual positive instances.
- F1-Score (Class 0 and Class 1): The F1-Score combines Precision and Recall into a single metric, balancing precision and recall.

TABLE I. Performance Evaluation of LSTM Models

Metric	Wind Model	Solar Model
Mean AUROC	0.8398	0.8251
Accuracy	0.77	0.78
Precision (Class 0)	0.54	0.51
Precision (Class 1)	1.00	0.95
Recall (Class 0)	0.99	0.92
Recall (Class 1)	0.69	0.81
F1-Score (Class 0)	0.70	0.67
F1-Score (Class 1)	0.81	0.88

To further demonstrate the effectiveness of the LSTM models, Table II presents a comparative analysis of the LSTM models against other benchmark models, including ARIMA and SVM. This comparison highlights the superiority of the LSTM models in terms of accuracy and predictive performance.

TABLE II. Comparison of LSTM Models With Benchmark Models

Model	Mean AUROC	Accuracy	F1-Score (Class 1)
LSTM (Wind)	0.8398	0.77	0.81
LSTM (Solar)	0.8251	0.78	0.88
ARIMA (Wind)	0.7502	0.72	0.75
ARIMA (Solar)	0.7403	0.71	0.74
SVM (Wind)	0.7805	0.74	0.78
SVM (Solar)	0.7650	0.73	0.76

The presented LSTM-based forecasting methodology results are promising and underscore its potential for accurate energy production prediction. The methodology demonstrates robustness in handling solar and wind energy sources, as evidenced by the comprehensive performance evaluation metrics. The cross-validation AUROC scores, which provide an insight into the models' discrimination capabilities, exhibit consistently high values, indicating the models' proficiency in distinguishing between energy production events and non-events across various thresholds.

The confusion matrix provides a detailed breakdown of the model's predictions, showcasing both true positive and true negative predictions and false positive and false negative errors. The classification report further elucidates the models' precision, recall, and F1-score for both classes (events and non-events). Notably, the weighted average F1-score accounts for class imbalance and demonstrates the models' effectiveness in predicting energy production events.

These results are encouraging, considering the complexity of energy production patterns and the challenges associated with forecasting renewable energy output. The LSTM models effectively capture temporal dependencies and patterns inherent in historical data to make accurate predictions. However, some variations between predicted and actual production values remain, which may be attributed to external factors, such as weather conditions or unforeseen events.

The impressive performance of the LSTM models in filling missing values further demonstrates their adaptability and potential for real-world applications. Based on historical data, the models can infer accurate energy production values for future periods. Such forecasting precision holds significant implications for enhancing resource allocation, decision-making, and operational planning in the renewable energy sector.

In conclusion, the findings validate the efficacy of the proposed LSTM-based methodology for energy production prediction, presenting a substantial step forward in renewable energy management. While the models exhibit high accuracy and forecasting capabilities, future work could involve refining them with more granular features and exploring ensemble techniques to improve their accuracy and robustness. These results illuminate the pathway toward the practical implementation of deep learning methods in addressing the intricacies of renewable energy production forecasting.

VII. Conclusion and Future Work

In conclusion, the proposed LSTM-based methodology presents a robust framework for accurately forecasting energy production levels from solar and wind sources. By capitalizing on temporal dependencies within historical data, the models excel in making precise predictions while effectively handling missing values. The methodology's effectiveness is evident from comprehensive quantitative assessments, including AUROC scores, confusion matrices, and classification reports. These metrics underscore the models' ability to discern energy production events from non-events, yielding promising F1-scores of around 0.78 for both solar and wind sources, even considering class imbalance. The primary contributions of this study include developing a novel LSTM-based model that accurately captures temporal patterns in renewable energy data, utilizing an extensive dataset tailored to consumer electronics, and promoting sustainable energy consumption practices. By integrating accurate energy prediction into eco-conscious technology, we aim to align technological advancement with environmental preservation. The models' proficiency in predicting energy production for forthcoming periods offers a significant stride in renewable energy forecasting. The capacity to anticipate output levels enhances resource allocation optimizes energy distribution and facilitates strategic planning. However, it's crucial to acknowledge potential discrepancies between predicted and actual values due to external variables like unpredictable weather patterns or unforeseen events. Looking ahead, incorporating additional features beyond historical production values, such as weather data and grid demand, could yield more comprehensive models capable of capturing various influencing factors. Exploring ensemble techniques, where multiple forecasting models collaborate, may yield even more accurate predictions. Furthermore, the methodology's adaptability to various energy sources invites further exploration. Extending the approach to other renewable sources like hydroelectric or geothermal energy can provide a holistic solution for energy forecasting. Additionally, real-time data integration can enable continuous monitoring and adjustment of energy production predictions. The LSTM-based forecasting methodology establishes a strong foundation for advancing renewable energy forecasting techniques. With its demonstrated accuracy and potential for enhancement, it emerges as a valuable tool for shaping the trajectory of sustainable energy management. As renewable energy's significance in global energy solutions grows, harnessing advanced deep learning methods holds the promise of elevating accuracy, efficiency, and sustainability in energy production forecasting.

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