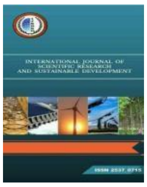

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الاتحاد العربي للتنمية المستدامة والبيئة

Leveraging Machine Learning for Sustainable Solar Power: Techniques for Enhanced Generation and Management

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Abstract

The paper in hands presents a Long Short-Term Memory (LSTM) model to forecast solar power generation and management, as it aiming to improve the reliability and efficiency of solar energy systems. LSTM, a type of recurrent neural network, is well-suited for handling time series data and capturing long-term dependencies, making it an effective tool for predicting fluctuations in solar power generation due to variable weather patterns and seasonal changes. By utilizing historical weather data, irradiance levels, and past solar output, the LSTM model predicts short-term and medium-term solar power generation, allowing for optimized energy management and improved grid integration. This model helps address challenges in balancing demand and supply, reducing reliance on fossil fuels, and enhancing the sustainability of renewable energy sources. The results indicate that the LSTM-based forecasting model achieves high accuracy, significantly reducing prediction errors compared to traditional forecasting methods, thereby supporting more efficient solar power management strategies.

إستخدام التعلم الآلي للطاقة الشمسية المستدامة: تقنيات لتعزيز التوليد والإدارة

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تقدم الورقة التي بين ايدينانموذج ذاكرة طويلة قصيرة الأجل (LSTM) للتنبؤ بتوليد وإدارة الطاقة الشمسية، بهدف تحسين موثوقية وكفاءة أنظمة الطاقة الشمسية بشكل كبير. يُعدLSTM ، وهو نوع من الشبكات العصبية المتكررة، حيث يكون مناسباً للتعامل مع بيانات السلاسل الزمنية المعقدة واستيعاب التبعيات طويلة الأجل، مما يجعله أداة فعالة للتنبؤ بتقلبات توليد الطاقة الشمسية الناتجة عن التغيرات المناخية الموسمية وتغيرات الطقس اليومية. من خلال استخدام بيانات الطقس التاريخية ومستويات الإشعاع الشمسي وبيانات الإنتاج الشمسي السابقة، يتنبأ نموذج LSTM بتوليد الطاقة الشمسية على المدى القصير والمتوسط، مما يسمح بتحسين إدارة الطاقة الشمسية وتكامل أفضل مع الشبكة الكهربائية. يساعد هذا النموذج الذكي في معالجة تحديات موازنة العرض والطلب على الطاقة، وتقليل الاعتماد على الوقود الأحفوري، وتعزيز استدامة مصادر الطاقة المتجددة. وتشير النتائج إلى أن نموذج التنبؤ المستند إلى LSTM يحقق دقة عالية، مما يقلل بشكل كبير من أخطاء التنبؤ مقارنة بالطرق التقليدية، وبالتالي يدعم استراتيجيات إدارة الطاقة الشمسية بكفاءة أعلى واستدامة أكبر.

معلومات عن البحث:

الكلمات الدالة:
تنبؤ الطاقة الشمسية، LSTM (الذاكرة الطويلة قصيرة الأجل)، توقعات الطاقة المتجددة، التعلم العميق للطاقة الشمسية

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1. INTRODUCTION

In recent years, solar power generation has gained significant attention as an es- sential contributor to sustainable energy solutions in the face of climate change, environmental degradation, and resource limitations. Advances in photovoltaic (PV) technologies, such as improved energy conversion efficiency and cost re- ductions, have made solar energy increasingly viable for large-scale deployment and decentralized applications, especially in remote or developing regions (Ho- senuzzaman et al., 2014; Soto et al., 2022). Solar energy's unique potential to alleviate electricity shortages in areas lacking traditional infrastructure has made it indispensable for critical applications, from healthcare in rural commu- nities to urban residential solutions. Despite its promise, the solar energy sector faces challenges in maximizing energy output and reliability due to factors like fluctuating solar irradiance, weather unpredictability, and infrastructure costs. Machine learning (ML) has emerged as a powerful tool to address these issues by enabling predictive maintenance, energy output forecasting, and optimizing energy management systems. Recent studies demonstrate that ML-driven models, including deep learning, have shown significant promise in enhancing solar power generation accuracy and efficiency through advanced algorithms that adapt to varying conditions and complex data (Salimi et al., 2022; Hussin et al., 2017).

This paper, titled "Leveraging Machine Learning for Sustainable Solar Power: Techniques for Enhanced Generation and Management," explores the intersection of ML and solar power systems, focusing on innovative ML methodologies designed to improve solar energy generation, forecast demand, and manage energy resources more efficiently. By synthesizing recent developments in machine learning and solar power, this study aims to address the technical and economic challenges that hinder the full potential of solar power, particularly in highpotential regions like the Middle East and North Africa (MENA) where solar resources are abundant but often underutilized due to infrastructural and eco- nomic barriers (Bayomi & Fern´andez, 2019; Abu-Rumman et al., 2020). This approach aims to contribute to the development of scalable, sustainable energy solutions capable of meeting global energy demands while supporting environmental conservation.

The remainder of this paper is organized as follows: Section 2 highlights the already conducted studies in the field. Section 3 explains the employed methodology of the LSTM architecture. section 4 discusses the conducted experiments and explains thoroughly the obtained results. Section 5 cites the faced challenges during the implantation and the use of solar power generators. Section 5 concludes the paper.

2. RELATED WORKS

In recent years, solar power generation has gained prominence in addressing climate change and environmental issues, especially in developing regions.

Advances in photovoltaic (PV) technology, such as higher efficiency and cost- effectiveness, have been noted (Hosenuzzaman et al., 2014 ; Hussin et al., 2017 ; Soto et al., 2022). Solar energy's role is particularly crucial in re- mote areas where traditional electrification is challenging, with applications like healthcare facilities relying on it for reliable power (Soto et al., 2022).

Arab countries, notably the Gulf Cooperation Council (GCC) region, have significant solar potential, with high solar intensity and favorable climates. The United Arab Emirates, with an average potential of 1826 kWh/kWp, leads in solar initiatives (Salimi et al., 2022; Abugoukh, 2019). Other GCC nations like Saudi Arabia and Oman also benefit from substantial solar resources (Farahat, 2024).

However, challenges persist, such as fossil fuel dependency, high capital costs, and technical barriers in integrating solar energy into existing grids (Bayomi & Fern´andez, 2019; Abu-Rumman et al., 2020). In Lebanon and Jordan, solar installations are increasing, reflecting a move toward enhanced energy security (Tarnini et al., 2023; Abu-Rumman et al., 2020).

Beyond electricity, solar energy supports water desalination and hydrogen production, contributing to sustainable development, especially in arid regions (Rashid et al., 2023; Abdel-Aal, 2014).

3. METHODOLOGY

The methodology of the Solar Forecasting LSTM model involves the following key steps:

a. Data Preprocessing: Load and clean the data, normalizing solar power and weather-related features for consistent scaling.
b. Data Windowing: Organize data into time series sequences, allowing the model to learn from past observations.
c. Model Architecture: Use an LSTM network to capture temporal dependencies in the data.
d. Training: Train the model using Mean Squared Error (MSE) as the loss function.
e. Evaluation: Assess the model on test data, comparing actual and predicted values.

4. EXPERIMENTS and DISCUSSIONS

We conducted a set of experiments on the Solar Power generation dataset obtained from Kaggle. Understanding the correlations between the data-set variables helps enhance the model's ability to predict solar power based on influential weather-related parameters as shown in 1

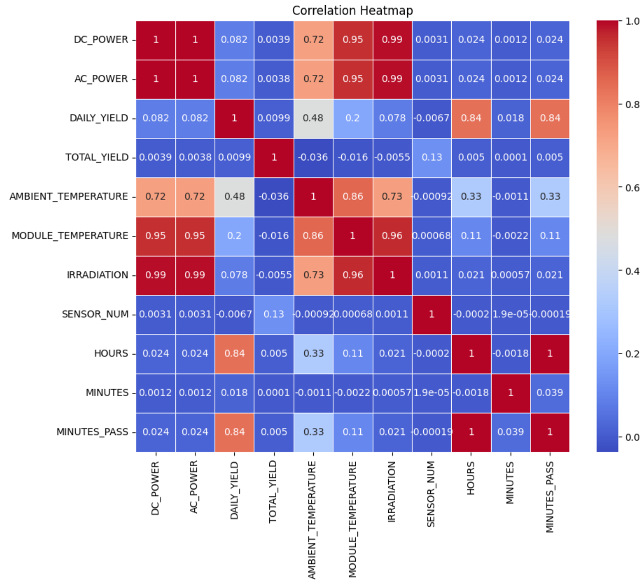

Figure 1: A sample figure illustrating solar power output over time

The analysis reveals key correlations in solar plant performance, such as strong links between DC/AC power and temperature, daily yield and ambient temperature, and power with irradiation, emphasizing the influence of environ- mental factors on energy output. Outliers point to potential equipment issues, including inverter faults and faulty photovoltaic cells. Performance differences among equipment groups suggest installation timing as a factor. Data quality concerns, such as unexpected drops in daily yield, highlight issues in data processing. Recommended actions include setting up alerts, auditing data pipelines, and evaluating yield by installation date to enhance reliability.

As shown in figure 2 inverters 1BY6WEcLGh8j5v7 and bvBOhCH3iADSZry show lower performance than the others, indicating potential maintenance or replacement needs. However, before addressing these specific units, it’s important to investigate any broader issues affecting the entire plant by reviewing DC power generation during daylight hours over the 34-day period. Likely due to a technical issue, even a minor drop in ambient temperature can significantly affect module temperature, potentially explaining the lower performance. By examining instances where module temperatures exceed 50 degrees, we can gain insights into whether an overload is impacting inverter functionality.

After a thorough analysis, we obtained 68 records with faulty operation!

These types of failures and anomalies, dictate the use of LSTM to learn how the yield changes over time and make predictions for future time intervals.

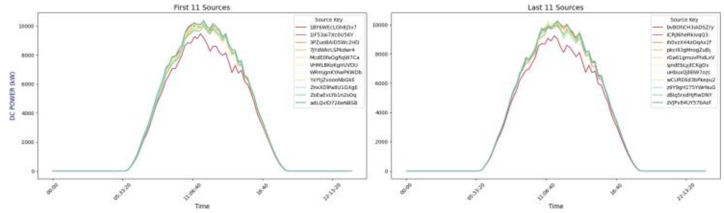

Figure 2: Faulty Inverter Identification

The LSTM architecture is detailed in table 1. The architecture consists of four layers:

- LSTM Layer: Outputs 32 features and has 4,352 parameters, designed to capture temporal dependencies in sequential data.
- Dense Layer: Produces 8 features with 264 parameters, transforming the output from the LSTM.
- Dropout Layer: Maintains the output shape of 8 but has no parameters, serving as a regularization technique to prevent overfitting.
- Dense Layer 1: Outputs a single value with 9 parameters, likely for re gression or binary classification tasks.

Overall, this model effectively processes sequential data and includes mechanisms to enhance learning and generalization.

Table 1: Model Layer Details

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 32)	4,352
dense (Dense)	(None, 8)	264
dropout (Dropout)	(None, 8)	0
dense 1 (Dense)	(None, 1)	9

This plot shows 3 a comparison between the train predictions (blue dots) and the actual values (green line with ”x” markers) for a variable called ”Daily Yield” over a series of time steps (sample indices). Actual Values: The actual values (green line) increase gradually until they plateau around a yield of 140, then maintain that level for a period. A sharp drop occurs around the 90th time step, after which the yield settles near zero. Train Predictions: The train predictions remain constant at approximately 40 for most of the time steps, failing to capture the trend or changes in the actual values. Near the end (around the 90th time step), there is a slight dip in predictions, possibly attempting to follow the drop in actual values, but it does not match the magnitude or pattern of the change.

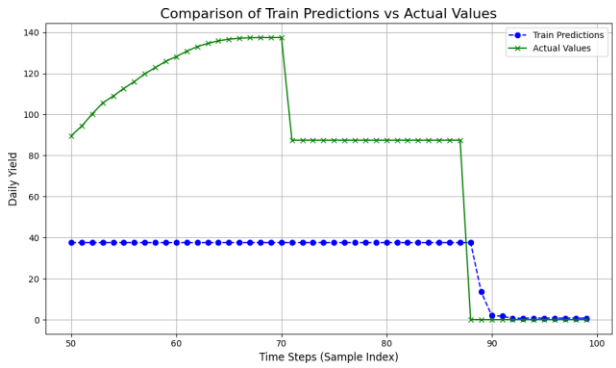

Figure 3: train predictions and the actual values

The blue line represents the actual values in 4, which follow a cyclical pattern, with sharp increases to a peak and sudden drops back to zero. The orange line shows the model's predictions, which remain relatively constant around 40 across most of the cycle. The model fails to capture the cyclical nature and magnitude of the actual values, indicating a significant underfitting issue. It cannot adapt to changes or predict the peaks and valleys observed in the actual data.

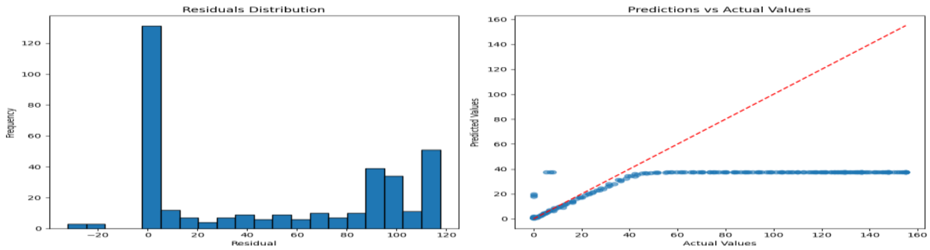

Figure 4: Residuals Distribution and Predictions vs. Actual Values

This histogram in 5 shows the distribution of residuals (the difference between actual and predicted values). A large spike around 0 indicates many predictions with low error, but there is a broad spread of residuals, with some as high as 120, reflecting significant discrepancies. This distribution suggests the model consistently underpredicts higher values in the actual data, as shown by the right-skewed residuals. Right Plot (Predictions vs. Actual Values Scatter Plot):

The dashed red line represents the ideal case where predictions perfectly match the actual values. The model's predictions (blue dots) mostly fall below the line, especially as actual values increase, indicating consistent underprediction.

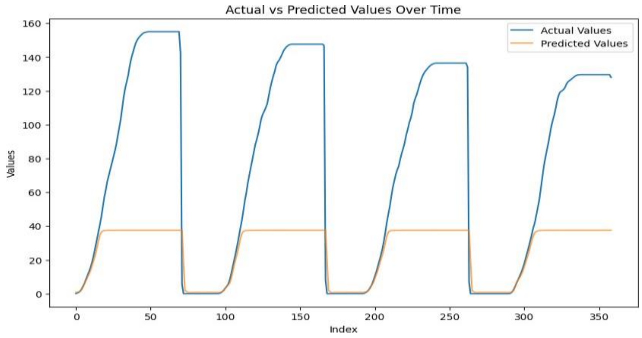

Figure 5: Train predictions and the actual values

The training output of 50 epochs shows that the model has a high training loss (144.5409) and Root Mean Squared Error (RMSE) of 12.9132, but a significantly lower validation loss (18.0209) and RMSE (5.1256), suggesting it performs better on validation data than on the training data, while the low learning rate (0.00002) could be slowing convergence. Adjusting the model complexity or learning rate might improve training performance.

5. CHALLENGES of SUSTAINABLE SOLAR POWERS

Sustainable solar power management involves producing and managing solar energy in ways that minimize environmental impact, are economically viable, and support long-term energy needs. Solar power, as a renewable energy source, harnesses sunlight to generate electricity through photovoltaic (PV) panels or solar thermal systems. Effective management of this energy, including storage, grid integration, and maintenance, ensures consistent and reliable access to clean energy. In developing or ”third-world” countries, sustainable solar power can have transformative impacts:

- Access to Clean Energy: Many rural areas in third-world countries lack reliable electricity access. Solar power offers a decentralized, renewable source that can reach off-grid communities, providing a stable energy supply for lighting, cooking, healthcare, and education.
- Economic Benefits: Solar energy reduces dependency on costly imported fuels and minimizes electricity costs over time. It creates jobs in manufacturing, installation, and maintenance, stimulating local economies. For instance, small-scale solar installations can support local businesses by powering essential tools and machinery.
- Environmental and Health Benefits: By reducing reliance on fossil fuels, solar power lowers carbon emissions and air pollution. In many third- world countries, households rely on wood, kerosene, or coal for cooking and heating, contributing to indoor pollution and health problems. Solar solutions, such as solar cookers or clean lighting, reduce these risks, leading to better health

outcomes.

- Resilience and Energy Security: Solar power is a sustainable and resilient energy source in regions with abundant sunlight. It provides energy independence, making communities less vulnerable to energy price fluctuations and supply chain issues tied to fossil fuels.

On the other hand, arab countries face several challenges in implementing solar power management, despite the region’s abundant sunlight. Key challenges include:

- High Initial Investment Costs: The upfront costs for solar infrastruc- ture—like photovoltaic panels, storage systems, and grid upgrades—are high. Limited financial resources and economic instability in some Arab countries make funding large-scale solar projects difficult.
- Limited Technological Infrastructure and Expertise: The region lacks suffi- cient local expertise in solar technology, which can hinder the deployment, maintenance, and advancement of solar energy projects. Many countries rely on foreign expertise, increasing costs and reducing local ownership.
- Political and Regulatory Barriers: In some Arab countries, inconsistent energy policies, regulatory uncertainties, and political instability discourage private investments and delay renewable energy projects. Dependence on traditional fossil fuels and vested interests in oil and gas industries further slow the shift to renewable energy.
- Water Scarcity for Solar Thermal Systems: Solar thermal systems, which generate electricity by heating water, face limitations due to the region’s water scarcity. These systems require significant water for cooling, which is a challenge in the arid climates of many Arab countries.
- Grid Limitations: In several Arab countries, the electrical grid infrastructure is outdated and not equipped to handle intermittent renewable energy sources like solar. Without grid modernization, integrating large amounts of solar power is challenging.
- Public Awareness and Social Acceptance: In some areas, a lack of public awareness about the benefits of solar energy affects acceptance and support for renewable energy projects. Cultural preferences for traditional energy sources, especially in oil-rich regions, may also affect the adoption rate.

6. CONCLUSION

The implementation of an LSTM model for forecasting solar power generation and management demonstrates substantial improvements in prediction accuracy, contributing to more reliable and efficient use of solar energy. The model’s ability to handle complex time-series data allows it to adapt to variations in solar output caused by changing weather conditions, enabling better energy resource planning and storage management. This research highlights the potential of deep learning models like

LSTM in addressing the inherent variability in solar power, making it easier for grid operators and energy managers to plan for fluctuations in power generation. Furthermore, by improving solar power forecasting accuracy, this model supports the sustainable integration of solar energy into the power grid, fostering energy independence and reducing carbon emissions. Future work will focus on integrating additional data sources, such as real-time sensor data and advanced climate models, to further enhance the model's forecasting capabilities and adaptability.

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