Development of Weather Monitoring and Forecasting System Using Reinforcement Learning Algorithms for Enhanced Solar Power Response in PV System

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Abstract: This work deliberates the integrated approach on using reinforcement learning algorithms for photovoltaic system performance and efficiency optimization in concurrence with monitoring and forecasting weather conditions. Thus, the proposed novel architecture of continuously monitoring and predicting meteorological variables such as temperature, humidity, cloud cover, and irradiance with Reinforcement learning algorithm to adaptively control and manage the PV system operations based on real-time weather data to maximize energy output, improve system stability, and reduce the power generation costs. By using this method, the overall efficiency increased from 74% to 91%, and also the accuracy increased with response time. In this work, it is observed that the use of Reinforcement Learning in weather forecasting has shown significant improvement in efficiency and accuracy than the traditional method.

1 INTRODUCTION

Accurate weather forecasting is essential for predicting solar power generation from sunlight. In earlier times, limitations in forecasting techniques made it difficult to assess the atmospheric conditions accurately, which negatively impacted on regional development (J. Wang *et al, 2019)*. Weather can be referred as to what extent the environment is whether it is hot or cold or wet or dry, or calm or stormy or clear or foggy. Weather is the atmospheric condition of the environment based on considering some external factors like temperature, precipitation activity etc., over a certain interval of time (K. Krishnamurthi, *et al.* 2015) Solar power has been used extensively across the globe and is one of the most promising and fast-growing alternative sources of energy. Accurate forecasting of solar power is crucial to providing the reliable and cost-effective operation of power systems (P.Prem Sagar et al., 2022) As of 2016, 303 GW of PV power was installed worldwide, representing a 33.48% increase from 2015. We can enhance the power output of the solar system by making use of the weather data. This weather monitoring system specially designed for determining the solar radiance of the particular area to determine that area for efficient for power generation using PV systems (P. Ashok Baste *et al, 2021)* Compared to statistical models like Autoregressive Integrated Moving Average (ARIMA), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU), reinforcement learning approaches, such as Q-learning algorithm, demonstrate a superior performance in certain forecasting tasks (E. O. Arwa *et al., 2021)* In order to successfully incorporate solar photovoltaic systems into the current power grid, the conversion process and stabilization of the grid that manage variations in solar power need to be done effectively (Anand, R., Stallon, S.D *et al.*., 2024) Grid stability is required to sustain a balance between supply and demand during weather fluctuations. Efficient energy conversion in solar PV systems ensures the complete use of solar energy available. Proper energy conversion mechanisms and some grid stabilization techniques may cause power quality problems, resulting in more operational problems for the grid if solar PV systems are integrated (Ramasamy, M., & Thangavel, S.) The International Energy Agency (IEA) reports that solar energy contributed around 12% to the global energy mix in 2024, an increase from 8% in 2020. Forecast suggest this share could exceed 20% by 2030, fueled

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by technological innovations and policy-driven incentives worldwide.

2 RELATED WORKS

A lot of research has already been published in this regard, more than 57 research papers and articles particularly focused on this intersection of weather forecasting, reinforcement learning, and solar energy optimization. The sources of these references are peer-reviewed journals, and conferences such as IEEE Xplore and Google Scholar.

Das et al. proposed an optimized PSO-based SVR model for solar power forecasting using novel data preparation algorithms for preprocessing the weather reports. Their model was able to deliver a huge gain in accuracy up to 2.841 nRMSE. The research stated that parameter optimization along with preprocessing gives a reliable prediction of solar power (U. K. Das *et al*., 2022) Manohar et al. proposed a protection scheme for hybrid PV-wind microgrids using stochastic weather models and rotation forest-based classifiers. Wavelet-transformed data improve fault detection accuracy under diverse conditions, emphasizing resilient strategies to address the issues due to weather intermittency in renewable energy systems M. Manohar et al.2020). Liu et al. proposed a technique for home solar energy scheduling based on adaptive dynamic programming.

Their technique reduces costs and enhances load balancing through weather pattern categorization and preferring energy sources. The self-improving neural networks prove the worth of dynamic scheduling models and further enhance system performance. (D. Liu *et al. 2018)*. Wu et al. proposed one-day-ahead PV power was subsequently forecast using weather-classification-based forecasting methods, deep AI models in XGBoost, GRU, and Transformer, and clustering methods such as K-means. The prediction accuracy of this method is high as it captures seasonal and temporal patterns. This approach also showcases how machine learning and weather classification complement each other in enhancing solar forecasting. (Y. K. Wu, *et al., 2024)*. Lyu and Eftekharnejad had addressed solar forecasting under fluctuating weather conditions through a dynamic probabilistic model. That is, their method dynamically quantifies spatio-temporal correlations by merging copula theory and machine learning that could potentially enhance accuracy to up to 60% higher than previously known in non-sunny conditions. This further supports the use of unpredictability adaptation in weather-dependent solar power generation (C. Lyu and S. Eftekharnejadet al., 2024). Feng et al. introduced a reinforcement learning-based dynamic model Selection (DMS) strategy for short-term load forecasting (STLF). Their method employed a Q-learning agent to adaptively select the most effective model from a set of machine learning algorithms. This technique resulted in a 50% improvement in the forecasting accuracy as compared to the traditional static methods (C. Feng and J. Zhang., 2019). The paper from the author Baste et al. who designed a cost-effective weather station using Arduino Mega for monitoring climatic parameters is reference for the proposed work. The system provides real-time data transmission and storage, enabling insights for optimizing solar plant efficiency and offering a lightweight, affordable alternative to commercial weather stations (P. Ashok Baste *et al*., 2021)

From the previous findings, it is concluded that it can not correlate with the real-time uptodate information. So, this is why the Reinforcement learning algorithm is used to dynamically improve the photovoltaic system based on real-time weather characteristics. The aim of the study is to enhance the efficiency and accuracy of the PV system using the RL algorithm.

3 MATERIALS AND METHODS

This work is linked to some notable studies including ARIMA, LSTM, and their combination. With relatively stable weather conditions, ARIMA was successful in forecasting temperatures in the northern part of Europe. However, it proved unsuccessful in the tropical regions of highly variable weather, such as Southeast Asia, due to the nonlinear nature of data Hyndman, R.J., & Wang, E. (2016). LSTM produced state-of-the-art accuracy in forecasting solar irradiance in California, given the availability of vast historical data. However, the inability of this model to adjust dynamically led to poor results during unexpected anomalies in weather conditions (Y. I. Febriansyah *et al*., 2024) Hybrid ARIMA-LSTM model implemented in Germany enhanced the day-ahead electricity demand forecasting by 12%. However, it needed to be retrained often, which restricted its applicability in real-time systems (Yildirim.A., Bilgili.M *et al 2023)*

This work addresses the development of a Weather Monitoring and Forecasting System integrated with reinforcement learning algorithms, which will optimize solar power generation by using real-time environmental data in advanced prediction models to ensure adaptability to variations in weather. RL integrates and enhances the decisions toward the renewable energy infrastructure while taking energy systems as operational elements in operations. Its outcome opens way toward smarter renewable infrastructure. Figure 1. describes our model's outer structure, including its six-layer setup, beginning with an input layer and leading all the way up to the output layer, as discussed therein.

From the figure.1, shows the sequence of actions involved in collecting data, training and applying the reinforcement learning (RL) model, forecasting weather, optimizing solar power output, and deploying the system in real-time. The system first gathers environmental data using various sensors such as temperature, humidity, irradiance, pressure, and wind speed. These sensors transmit real-time data to a processing unit.

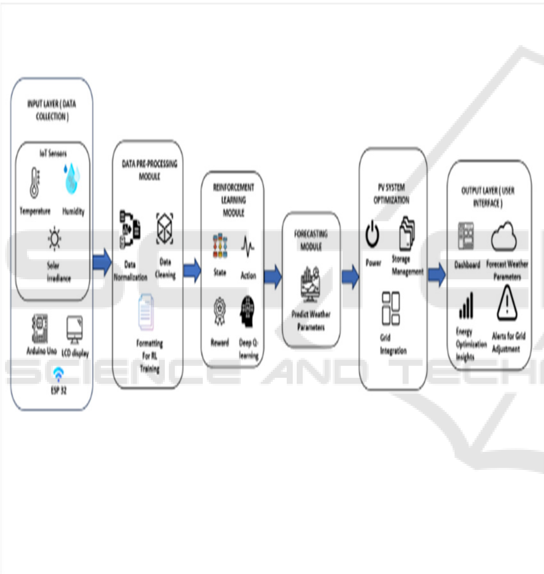

Figure 1: Flow chart of the model.

That processing unit performs filtering and normalization by using the raw sensor data. Then these data will be stored in the database for long-term pattern analysis. After that, the processed data goes to the training model [RL model]. The RL model is trained by using the real-time data and historical weather data. This model will learn the best actions to optimize the solar power generation under varying weather conditions. It provides forecasts of temperature, solar irradiance, cloud cover and humidity. That predicted result is used to optimize energy management in the PV systems. This improves the system PV efficiency and enhances energy utilization.

4 CALCULATION

For calculating the output voltage is shown in equation (1)

$$V_{out} = Sensor\ Reading \times \frac{V_{ref}}{1024} \quad (1)$$

Here V_{ref} is the reference voltage (typically 5V for Arduino) and the value 1024 is the ADC resolution for a 10-bit ADC. Calculating the temperature sensor reading depends on the type of sensor used and its output characteristics and the related formula for the Temperature (in °C) calculation is shown in equation (2),

$$T_c = \frac{V_{out}}{10mV/°C} \quad (2)$$

Relative Humidity (RH): The sensor typically provides RH directly as a percentage and calculates the actual RH using the equation (3). Use the sensor's datasheet formula, if necessary.

$$RH_{actual} = RH_{measured} \times \frac{1.0546 - 0.00216 \times T}{1024} \quad (3)$$

Solar irradiance $\left(\frac{W}{m^2}\right)$:

The solar irradiance can be calculated using equation (4)

$$I_{solar} = \frac{V_{out}}{Sensitivity \times A} \quad (4)$$

Where the V_{out} is the sensor output voltage, Sensitivity is typically measured in $mV\left(\frac{W}{m^2}\right)$, and A is the sensor's active area $(in\ m^2)$.

Pressure $(in\ hpa)$: The sensor typically outputs the pressure directly. We can use the conversion from the datasheet with the help of equation (5).

$$p = Raw\ Sensor\ Output \times Conversion\ Facto \quad (5)$$

Altitude (in meters):

Altitude can be measured using equation (6)

$$h = \frac{T}{0.0065}\left(1 - \left(\frac{P}{P_0}\right)^{\frac{1}{5.257}}\right) \quad (6)$$

Where T is the temperature in Kelvin, P is the current pressure in hPa and Po is the sea-level standard atmospheric pressure (1013.25 hPa).

DERIVED CALCULATIONS FOR FORECASTING

Dew Point (°C):

Dew point can be calculated using the equation (7) with temperature and RH parameters.

$$T_{dew} = T - \frac{(100 - RH)}{5} \quad (7)$$

Where T is the temperature in °C and RH is relative humidity in %.

Heat Index (°C):

The calculation for the heat index is measured using the equation (8) with known parameters such as Temperature, Relative humidity.

$$HI = -8.7847 + 1.6114T + 2.3385RH - 0.1461T \times RH + 0.0123T^2 + 0.0164RH^2 - 0.0003T^2 \times RH \quad (8)$$

5 RESULTS AND DISCUSSIONS

A series of testing had been conducted using the developed model for weather forecasting and with the data obtained, the graphical data represents variations in temperature, humidity, light level, and solar voltage recorded from 28th of February, 2025 to 5th of March, 2025 at various intervals. The data gives insight into environmental conditions during the testing hours. Temperature and irradiance would tend to be monotonic decreasing as the daylight hours disappear, but the humidity would be enhanced because of cooling in the night air. Interpretation of the variables would offer insights into dynamics in the environment and in terms of optimizing renewable systems, such as tuning photovoltaic responses or predicting performance toward an overall optimization of efficiency over evening periods.

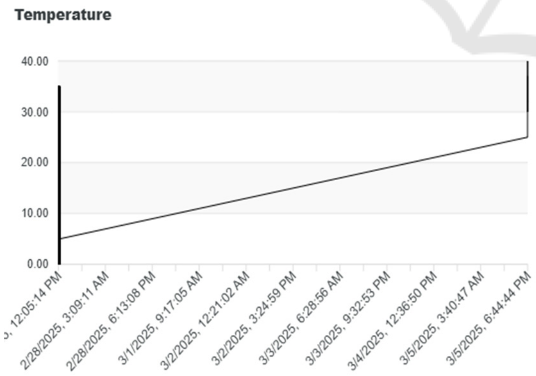

Figure: 2 Temperature data during the testing period.

From figure 2, during the testing hours the temperature is gradually increasing in Linear manner from 6°C to 25°C of temperature. Since the testing was conducted in various hours, the temperature is measured in the Morning, Noon, Evening period. During the morning hours the temperature is reached below 10°C and during the evening and noon hours it reached to 25°C. This shows that the climatic condition is most favorable during the noon and evening period in the month of February and March month.

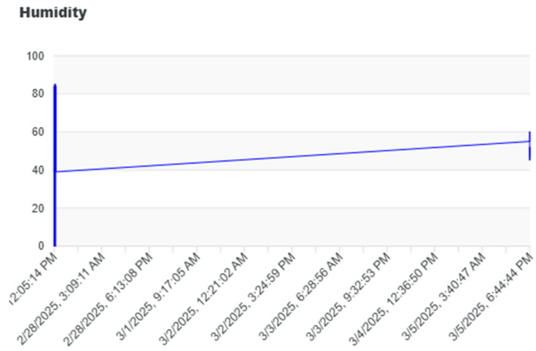

Figure: 3 Humidity data during the testing period.

while comparing with humidity of that same environment with the figure 3., that temperature is directly related to the humidity. Here the humidity rises from 40% in the evening of 28th of February to 58% in the evening of 5th march which is proportionate with the temperature.

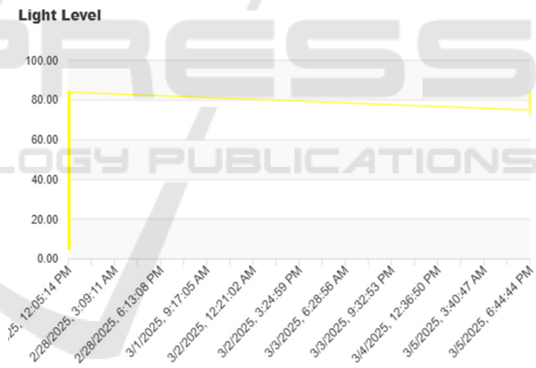

Figure: 4 Light level data during the testing period.

When looking at the light level during the testing hours from the figure 4, the peak value is registered on the Feb 28th, 2025 of about 83%. During the 5th Mar, 2025, the value is down of about 72%, this significant decrease is due to the change in climatic factors such as cloud cover. This may be one of the significant reasons for decrease in light level during the testing.

From figure 5, the power generation levels during the testing hours keep varying due to the change in climatic conditions. During the testing hours, the peak value of voltage is reached around 5.10V and keeps changing its value. The detailed review from the report is tabulated in table 1, from which the numerical relationship between each parameter can be defined.

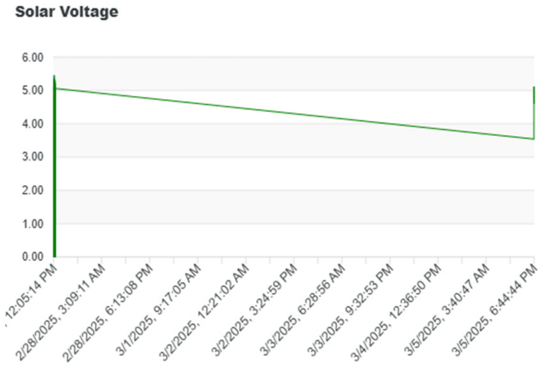

Figure: 5 Light level data during the testing period.

During the testing from 28th of February, 2025 to 5th of March, 2025. The detailed variations of various parameters such as temperature, humidity, pressure, light intensity. And the relation between climatic factors can be correlated.

Table 1: The sensor readings of several parameters.

Time Period	Parameters			
	Temperature (°C)	Humidity (%)	Light Level	Solar voltage
28th Feb	6	41	83	4.8
1st Mar	10	43	80	4.5
2nd Mar	12	45	78	4.2
3rd Mar	17	49	75	4.0
4th Mar	21	53	74	3.9
5th Mar	25	57	72	3.7

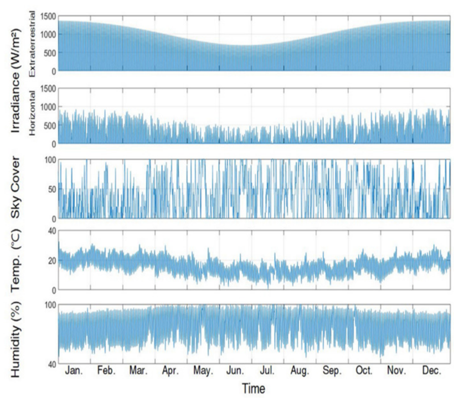

Figure: 6. Annual weather characteristics.

From figure 6, explains the annual weather characteristics throughout the year. Here the x-axis represents the month from January to December,2024 and the y-axis represents the Irradiance(W/m²) (Horizontal and Extraterrestrial), Sky cover, Temperature(°C), Humidity (%) respectively. From the graph, we can conclude that during the middle of the year, the production of irradiance is low when compared with the other months. The irradiance values vary in the range from 750 W/m² to 1400 W/m². During in the month of June, the irradiance value goes as low as 750 W/m² to 800 W/m². The peak value is reached during the month January and December as 1400 W/m².

The reference solar irradiance from the historical data is compared with proposed solar irradiance values for every month from January to December in the year 2024.

Table 2: Predictive performance of target models.

Month	RMSE (W/ m²)		
	Reference	Ref. (Sequence)	Proposed
January	43.2	34.8	26.1
February	44.1	36.5	25.4
March	58.1	42.1	26.8
April	65.6	41.3	25.4
May	58.1	40.2	30.6
June	55.2	32.3	30.6
July	55.4	26.5	35.8
August	61.4	36.5	37.2
September	61.6	55.3	36.6
October	63.2	44.2	41.5
November	60.4	47.1	31.1
December	51.3	41.4	24.3
Average	56.4	39.8	32.7
CVRMSE	12.8%	9.2%	7.0%

We conducted tests every month to measure the solar irradiance values for varying climatic conditions. The collected data was systematically recorded and organized into a table, enabling detailed analysis and comparison of monthly irradiance patterns for use in the development and validation of the forecasting system. From the table 2, we can understand that from the month of the January to April 2024, the values increasing from 44.3 W/m² to 66.7 W/m². since during that time the sunlight time is higher than other seasons. After that period, it is gradually decreasing from the April to July 2024 (66.7 W/m² to 56.3 W/m²) and then it keeps an undulating pattern, rising and falling periodically till the month of December. During the period of testing, in the month of April where the readings reached its peak value about 66.7 W/m².

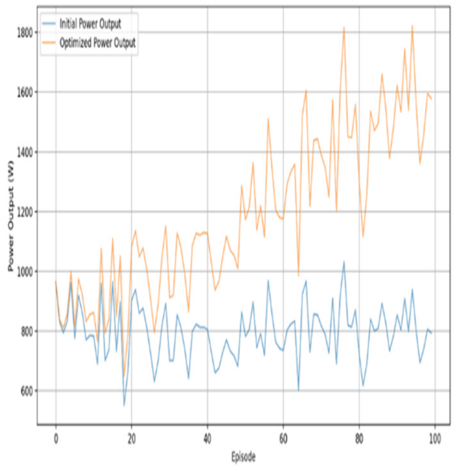

Figure: 7 RL-based PV system optimization.

The comparison of the traditional method with the RL method in the figure 8., shows the significant increase in the power production. Here, the gain of enhanced power output using the RL is compared with the traditional power output generated. The improvement is seen from the graph clearly and the power output has reached its peak value of about 1800W but in the normal method it has reached only 1000W. The is a difference of 800W between them.

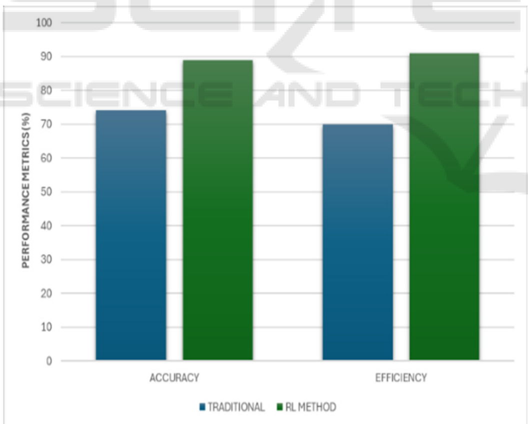

Figure: 8 Performance comparison between the traditional approach and RL approach.

From the figure 8., We can understand the improvement in the proposed system by comparing the parameters like efficiency, accuracy, response time with the traditional data. The data from hardware using the RL algorithm is compared with the traditional method. Here, the x- axis refers to the accuracy and efficiency of the model while the y-axis refers to the performance metrics. The efficiency increased from 70% to 91% while the accuracy increased from 74% to 89%. There is a significant increase in efficiency of about 21%.

The reinforcement Learning model used in the system is significantly better than the existing method. The efficiency of the system has increased from 70 to 91%. The power generation reached the peak of 1800W which is 800W more than the traditional power generation. Due to better energy optimization and reduced losses, the overall cost per unit of solar power has been reduced by 15 - 20% compared to traditional methods.

By using the IoT technology for establishing an environment suitable for monitoring the real-time tracking of climatic factors and analysing the condition. Implementing IoT-Based solutions can pay the way for more responsive and adaptive energy management systems (Bharathy.S et al. 2022). To forecast solar irradiance, certain systems developed a system based on deep learning that is mainly concerned with flexibility and resilience. It is a model based on Convolutional Long Short-Term Memory layers and supports easy addition or exclusion of sensors as well as sensor failure with higher accuracy and robustness in large-scale systems. (I. Prado-Rujas., 2021). By incorporating numerical weather prediction models (NWP) to provide detailed meteorological data, this will improve the accuracy of the forecast and studies have shown that combining multiple NWP will enhance the forecast reliability and performance (B. Saad et al., 2020).

The limitation of this system is that RL models primarily rely on past data and struggle to adapt instantly to unexpected weather conditions such as thunderstorm, heavy cloud cover. Also, the RL model cannot react instantly to sudden irradiance drop.

6 CONCLUSIONS

This work contributes immensely to optimizing renewable energy by promoting the use of more reliable, sustainable energy systems. When weather data are combined with predictions based on the RL paradigm, the result is improved forecasting accuracy; this improves strategies for maximum generation of solar power and its efficient storage and distribution. Finally, we can conclude that the overall efficiency increases from 70% to 91% and its accuracy also increases.

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