



A Multi-Stage AI Framework for Solar Energy Prediction and Smart Irrigation Scheduling with Economic and Land Optimization

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Abstract. Effective management of water and energy resources has become an important issue for contemporary agriculture, especially with regard to the emergence of renewable energy sources such as solar energy. Nevertheless, the intermittency of solar energy can affect the process of providing energy supply in order to sustain agricultural irrigation systems. This paper presents an approach for solar energy prediction and scheduling of irrigations by using an AI system that consists of multiple stages. Specifically, the system includes an LSTM model and a Random Forest model for forecasting solar energy availability in real time and predicting daily energy production, respectively. Solar energy forecasts are transformed into actual energy production taking into consideration the photovoltaic properties of panels. Moreover, the proposed framework employs a decision-making system for scheduling irrigation in accordance with the availability of energy, water needs, and time of the day without scheduling irrigation during times of high temperatures. In addition, the framework takes into consideration an advisory system for energy management and agrivoltaics land optimization analysis. Experimental findings reveal high levels of prediction accuracy where the R^2 values for both the Random Forest and LSTM models are 0.9896 and 0.819 respectively. The introduced model is efficient in enhancing energy consumption from renewable sources, lowering cost, and sustainable precision farming practices. Besides, the model is aligned with SDGs 2, 7, and 12 since it ensures efficient use of resources in agriculture.

Keywords: Solar Energy Prediction, Smart Irrigation, LSTM, Precision Agriculture, Renewable Energy.

1 Introduction

Agricultural activity requires large amounts of resources, especially water and energy. Traditional approaches to irrigation include using a fixed schedule for irrigation and monitoring manually. As a result, such a system may lead to inefficient water usage, high costs for irrigation processes, and lower productivity. For solving this

issue, recent approaches in the area of precision agriculture have introduced IoT-based techniques, artificial intelligence, and machine learning [16], [17].

On the other hand, renewable energy sources, especially solar energy sources, have been developed as environmentally friendly solutions to power the agriculture sector. Solar irrigation systems will not only help in reducing the reliance on grid electricity and fossil fuels but will also result in reduced costs and minimal environmental degradation. The solar energy production process, however, depends heavily on atmospheric conditions, causing changes in energy production [4], [18]. Predicting the available energy and solar radiation levels becomes very important in order to provide adequate power supply to irrigation systems during irrigation times.

Advances in machine learning (ML) and deep learning (DL) models have yielded positive outcomes for forecasting solar energy. LSTM models, which can take into account the dependency among sequential meteorological observations, have proven highly efficient at predicting solar irradiance in the short term [1], [5]. The integration of attention mechanism in more advanced models increases the efficiency of forecasts, allowing the identification of complicated interactions [1], [2]. Additionally, ensemble learning techniques like Random Forest can yield accurate photovoltaic power predictions by modeling environmental relations [4].

At the same time, the development of the smart irrigation systems has been driven by IoT-based sensing and control strategies for irrigation systems. Various researchers have employed environmental sensing, machine learning techniques, and MPC methods to create an effective irrigation strategy and increase water efficiency [3], [6], [13]. Despite the effectiveness that has been achieved through the implementation of these solutions, the vast majority of the currently used models treat the prediction of solar energy and optimization of irrigation schedules as two separate issues.

Land-use optimization is another critical factor when considering sustainable agriculture. There has been considerable interest in agrivoltaics systems because of their capability to enhance land use efficiency and sustainability [7], [10], [14]. It has been found that optimized agrivoltaics systems can successfully achieve a balance between energy production and agricultural productivity by proper panel placement [11], [12]. Further, economic studies have proved that irrigation using solar energy can significantly help farmers by being financially beneficial with a good return period [15]. However, there is a lack of practical application of energy forecasting, irrigation planning, economic assessment, and agrivoltaics optimization in existing literature.

To overcome such issues, the current research suggests an AI-based hierarchical approach to predict solar energy generation and schedule irrigation based on this prediction. Specifically, the suggested approach comprises the use of the LSTM model for predicting short-term solar irradiation and the Random Forests model for estimating energy generated during one day. Then, obtained data are used to estimate electrical energy based on the physical photovoltaic model taking into account panel area, efficiency, and performance ratio. The suggested framework is beneficial for sustainable precision agriculture by increasing the use of renewable sources of energy, conserving water, and saving on operating costs. It aligns with global sustainability goals, particularly SDG 2 (Zero Hunger), SDG 7 (Affordable and Clean Energy), and SDG

12 (Responsible Consumption and Production), by promoting efficient agricultural resource management and renewable energy adoption.

2 Literature Review

With an increase in demand for sustainable agriculture practices, the use of smart irrigation systems and renewable energy has become widespread in current agricultural practices. Conventional irrigation techniques typically follow predetermined timings and are manually operated, which tend to cause overuse of water, energy inefficiencies, and higher costs associated with their application. The use of IoT, AI, and ML technologies has made irrigation processes more effective through automation and real-time monitoring [16], [17]. Such irrigation systems have proven to be more efficient in water use compared to traditional irrigation systems.

Solar energy is considered a suitable alternative among renewable energy sources to power agriculture owing to its availability and ecological advantages. But the irregularity in solar irradiance makes it difficult to ensure a continuous energy supply to irrigate crops. Hence, it is important to forecast solar irradiance accurately. It has been observed that deep learning models, especially Long Short-Term Memory (LSTM), exhibit excellent performance in modeling the temporal correlation between data values of solar radiation and hence are extensively utilized for solar irradiance prediction problems [1], [5]. The application of hybrid models, with the inclusion of spatio-temporal attention models, has yielded high accuracy due to the incorporation of both temporal and spatial information about the atmosphere [1].

Apart from the deep learning methods discussed above, ensemble learning methodologies like Random Forest have been used effectively in PV power estimation owing to their capability of handling non-linearities and modeling intricate meteorological variables [4]. Such models have proven highly efficient when estimating energy levels for aggregated/daily forecasts. Besides, IoT-based environmental monitoring systems enhance predictive precision through continuous environmental measurements and real-time data collection [3].

There are recent studies that investigate the concept of intelligent irrigation scheduling through the implementation of predictive and optimization methods. In particular, Ghazouani and Azzouazi [5] proposed an irrigation prediction model for greenhouses based on LSTM architecture that is able to adjust irrigation strategies depending on the environmental factors. At the same time, Agyeman et al. [6] applied machine learning techniques along with the Model Predictive Control algorithm for optimizing irrigation strategies.

Another growing field of sustainable agriculture includes the use of agrivoltaics, which involves the simultaneous use of farmland for growing crops and generating electricity using photovoltaics. The integration of sustainable energy generation from solar panels with farming practices can increase the efficiency of land use while ensuring its sustainability [10], [14]. According to Willockx et al. [7] and Miljkovic et al. [8], it is crucial to optimize designs and utilize geographical information when designing such agrivoltaics structures. Likewise, research conducted on the use of

semi-transparent and bifacial solar cells showed how their use could enhance the sustainability of crop production and energy generation processes [11], [12].

Feasibility from an economic perspective is another key issue that determines the implementation of solar irrigation systems. Several techno-economic studies have demonstrated that irrigation systems utilizing renewable energy sources can significantly decrease operation costs, offering advantageous payback periods, especially for small- to medium-scale agricultural producers [15]. Moreover, AI-enabled optimization methodologies have been suggested for optimizing energy consumption in photovoltaic-driven irrigation systems [18].

While there have been great advancements in areas such as solar forecasting, irrigation optimization, and agrivoltaics, there are still some critical areas that require additional research to be done. The majority of the available studies only consider one component of the whole process at a time, such as the process of solar irradiance forecasting, irrigation planning, or photovoltaic optimization. Moreover, there is a lack of consideration for incorporating short-term solar forecasting, energy generation planning, irrigation planning, economic feasibility planning, and land allocation for agrivoltaics purposes.

Moreover, despite the outstanding performance of more complex algorithms like LSTM and Random Forest, relatively few attempts have been made to apply multi-level forecasting strategies simultaneously for real-time and next-day decisions. Existing models pay insufficient attention to decision support based on farmer perspectives, including the assessment of cost reductions and renewable energy application. To counteract the weaknesses mentioned above, the suggested solution introduces an AI-based multiple-step approach that combines LSTM-based forecasting of short-term solar irradiance, daily energy calculation through the use of random forest, physical conversion of PV energy into electricity, smart irrigation scheduling, and agrivoltaics-based cost and land optimization.

3 Methodology

The proposed intelligent framework is an approach that combines several stages involving machine learning, energy calculations based on the laws of physics, and decision-making processes for managing solar irrigation operations. For this purpose, meteorological and solar radiation data can be obtained from the National Solar Radiation Database (NSRDB) for Pune, India. The dataset includes meteorological and environmental parameters such as Global Horizontal Irradiance (GHI), temperature, relative humidity, wind speed, type of cloud cover, solar zenith angle, Direct Normal Irradiance (DNI), Diffuse Horizontal Irradiance (DHI), aerosol optical depth, precipitable water, pressure, and dew point.

In the first place, the gathered data will be preprocessed to enhance its quality and suitability for modeling purposes. During the cleaning stage, missing values and inconsistencies in the dataset will be addressed, after which normalization will be done to minimize differences in scales between variables. The temporality aspect in the

data will be retained through transforming the dataset into a time series that can be used in deep learning models.

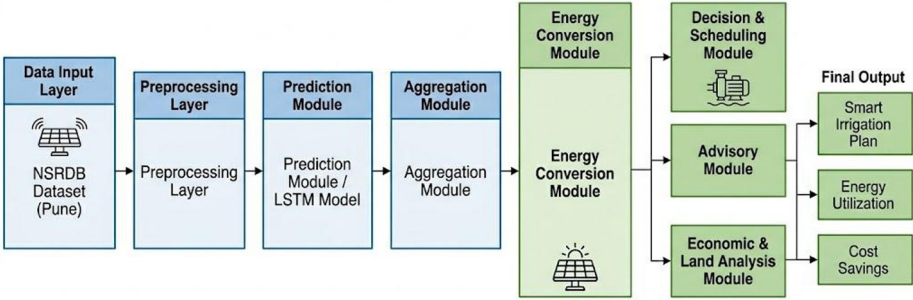


Fig. 1. Multi-stage framework for solar energy prediction and intelligent irrigation scheduling.

The entire process flowchart of the developed framework has been described through Fig. 1. Firstly, the weather data has to be preprocessed and prepared for being used as input for prediction models. Next, the processed time series have to be introduced to the LSTM model to forecast the solar irradiation in the short term. Afterward, these predictions will be aggregated to estimate the daily energy generation, which has to be converted to energy in terms of electricity with physical equations.

NSRDB data set was chosen owing to its high temporal resolution and detailed meteorological information. Preprocessing involved data cleansing, deletion of inconsistencies, conversion to date-time format, and sorting of temporal data. Time series modeling was used to take into consideration the dependencies in the atmosphere because of the nature of data collection that involved environmental parameters collected at various times. Splitting the data involved 80:20 split of training and testing sets respectively.

The initial phase of the proposed methodology includes short-term prediction of solar radiation using an LSTM-based machine learning algorithm. LSTM models have been chosen due to their capability to account for dependencies and non-linear connections in sequential data, such as the one that represents weather conditions at various time intervals. In this model, historical records of meteorological parameters were inputted to the system sequentially, and it outputted GHI values corresponding to the next hour. As weather conditions cause some deviations in forecasts, several hourly predictions were made and averaged. The LSTM model was built based on historical sequential meteorological data with a time interval of 48 minutes. It included two LSTM layers and one dense layer for prediction of solar irradiation. Model training lasted 20 iterations, with batch size being set to 32 and the optimizer being Adam; Mean Squared Error was selected as the loss function. Evaluation of model performance was done via RMSE, MAE, R^2 , NSE, and GPI coefficients.

The irradiance values are then combined to estimate the daily amount of solar energy. Rather than depending only on the instantaneous forecast, the averaging process gives a reliable measure of daily energy that can be used for irrigation planning purposes. The estimated irradiance is then transformed into electrical energy using a theoretical model of energy conversion by photovoltaics given in Equation (1):

$$E = GHI \cdot A \cdot \eta \cdot PR$$

(1)

where (E) represents the electrical energy generated, (A) denotes the effective solar panel area, (η) is the panel efficiency, and (PR) is the performance ratio that considers the system losses. Effective panel area is determined through estimating the total area of farmlands available, wherein it is assumed that roughly 20% of the total agricultural land will be set aside for solar panel installation according to the agrivoltaics concept.

The estimated energy values are used within a constrained decision-making scheme for the purpose of optimizing irrigation schedules. This takes into account the amount of available solar energy and other agricultural parameters such as water requirement and time of day. Irrigations are performed during early mornings or late evenings when the possibility of evaporation is reduced to allow the crops to recover without being exposed to excessive heat during irrigation. When there is enough renewable energy, all irrigation work will be powered by solar energy. Otherwise, when there is not enough energy, the recommended action to take would be to delay operations or supplement energy usage.

Moreover, apart from irrigation planning, the proposed model comprises an advising tool related to energy consumption and economic assessment. Electrical energy is linked to the practical use cases of power required for irrigation, lighting, and other agricultural machinery. Economic assessment is carried out based on conversion of electrical energy into estimated money savings, utilizing local electricity rates. Also, land assessment is conducted to estimate the potential area available for installing solar panels along with the economic versus renewable energy production ratio according to agrivoltaics concepts.

Table 1. Comparative analysis of Existing Approaches with Proposed Methodology

Study	Solar Prediction	Irrigation Scheduling	Energy Estimation	Agrivoltaics	Integrated Framework
Ref [1]	Yes (LSTM)	No	Partial	No	No
Ref [2]	Yes (Hybrid ML)	No	No	No	No
Ref [4]	Yes (AI-based)	No	Yes	No	No
Ref [5]	Yes (LSTM)	Yes	No	No	No
Ref [6]	No	Yes (MPC)	No	No	No
[18]	Yes	Yes	Yes	No	No
Proposed System	Yes (LSTM + Aggregation)	Yes (Con-straint-aware)	Yes (Physics-based)	Yes	Yes

4 **Results and Discussion**

The developed framework was first assessed for predicting short-term solar irradiance through the LSTM approach, which yielded RMSE of 0.1046 and MAE of 0.0744 on the normalized dataset. The values of R^2 and NSE of 0.819 show that the model managed to account for around 82% of variations in the pattern of solar irradiance, while a

GPI value of 0.723 highlights the stability of the model during varied atmospheric conditions. On the other hand, the Random Forest model used for predicting daily energy exhibited significantly greater levels of accuracy with respect to RMSE and MAE values of 193.99 and 133.51, respectively. In this context, large values for absolute error can be expected since the scale of the predictions is higher. On the whole, the Random Forest model has been shown to have R^2 and NSE values of 0.9896 and a GPI value of 0.969.

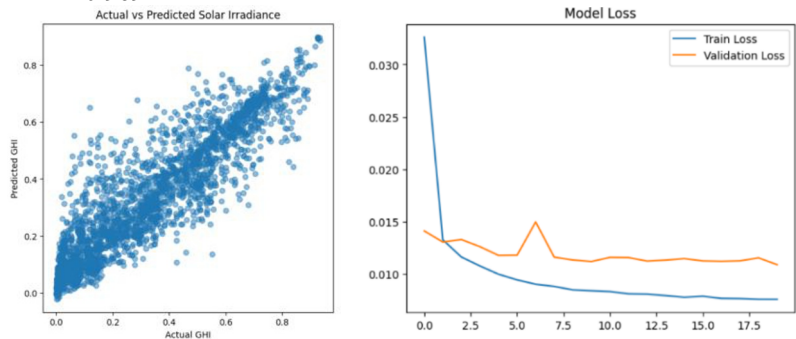


Fig. 2. Actual vs Predicted GHI Scatter Plot and Training–Validation Loss Curve

Fig 2 shows the prediction performance and convergence of the LSTM-based model. The compact distribution of predicted values relative to the regression line and the steady convergence of loss values in the training and validation datasets reflect efficient temporal learning with no signs of overfitting.

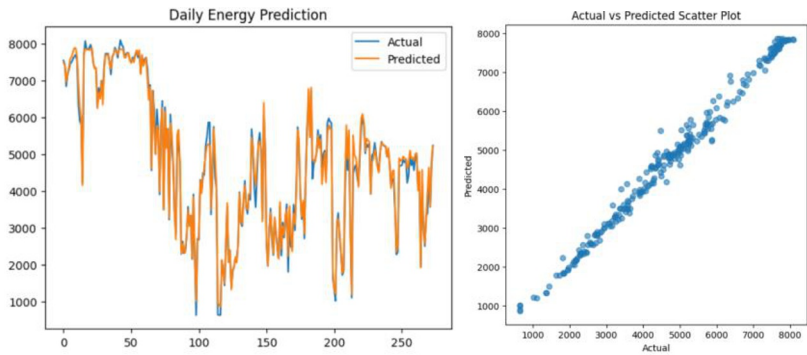


Fig. 3. Actual v/s Predicted Daily GHI curve and scatter plot

Fig 3 confirms that the proposed model is effective in estimating daily irradiance values through outputs closely aligned with the actual measurements. In order to verify the proposed model framework, linear and decision tree regressors were considered for comparison purposes. This comparison shows that the LSTM model performed better than the traditional regression models because of its capability to identify temporal relationships within the sequence of meteorological data. Even though Linear

Regression performed comparably, the LSTM model showed consistency in predicting results despite changes in the atmosphere.

Table 2. Comparative Performance of Prediction Models

Model	RMSE	MAE	R ²
Linear Regression	0.1103	0.0801	0.799
Decision Tree	0.1395	0.0935	0.679
LSTM	0.1046	0.0769	0.819
Random Forest	193.99	133.51	0.9896

The estimated irradiance values were used to derive the available power through the developed physics-based model for the photovoltaics. For normal operation, the system was able to generate 4.5 kWh to 7.2 kWh of energy daily for an acre farm setup with about 20% of land area dedicated to the PV panels.

Table 3. Representative Energy and Irrigation Analysis

Scenario	Estimated Energy (kWh)	Irrigation Requirement (kWh)	Status
High Irradiance	7.2	5.0	Sufficient
Moderate Irradiance	5.8	5.0	Sufficient
Low Irradiance	4.5	5.0	Insufficient

It has been observed that the energy generated from solar power can fulfill the irrigation needs in almost any environment setting. In cases where there is less radiation, the scheduling framework adjusts itself by proposing delays in irrigating plants or additional energy sources. Apart from that, the irrigation scheduling framework takes into account agronomic issues as well, such as not performing the irrigation activity during the high temperature period in the afternoon, which increases the chances of evaporation and damages the crop.

Moreover, the proposed model has evaluated the feasibility of solar power irrigation economically, as energy produced is quantified in terms of monetary savings with respect to electricity tariffs prevailing locally. Results show that savings are approximately ₹40 to ₹60 per day, resulting in about ₹1200 to ₹1800 per month and ₹14,000 to ₹21,000 per year. Analysis related to land use shows that using around 20% of farmland for the installation of solar panels achieves a reasonable compromise between agriculture and energy production through agrivoltaics. Increased land area leads to enhanced energy generation and monetary savings; nevertheless, overusing land may lead to a decline in crop productivity due to less sunlight availability.

Sensitivity analysis conducted based on changes in environmental conditions has shown that the suggested model is flexible enough to adjust irrigation schedules even during cloudy weather because of changing energy conditions. In sum, integrating solar energy prediction, intelligent scheduling, and agrivoltaics systems offers immense opportunities for sustainable precision agriculture applications.

5 Conclusion

Water and energy management have continued to pose a challenge in contemporary agriculture owing to the use of renewable energy like solar. However, the intermittent nature of solar energy makes synchronization between irrigation operations and energy production a challenging issue. As a result, inefficiency is experienced when managing the two resources. In this context, this research work proposed a multi-stage AI-enabled framework that will solve the issues of energy and irrigation operations synchronization. The solution consists of using a combination of LSTM neural network for short-term prediction and a random forest for daily predictions. Using these models, decisions could be made on whether irrigation should be done within the day or not. This system also employs physics-based modeling techniques for energy conversion from the solar irradiance to electrical energy. Such a system takes into account several system parameters, including the energy conversion rate, efficiency of panels used, and the panel area. Results of experimental evaluation indicate high accuracy with LSTM and Random Forest models providing prediction scores of 0.819 and 0.9896. The results further confirm that the proposed system not only predicts energy requirements with high accuracy but also enables more efficient use of renewable energy sources, reliable irrigation planning, and reduced costs due to energy management. From an economic perspective, farmers would be able to save on their expenses, while agrivoltaics-based land usage would confirm its applicability. It addresses global goals of SDG 2, SDG 7, and SDG 12. However, despite its advantages, the current solution requires generalized irrigation limitations and simplifications in the process of energy calculation. Further research should incorporate irrigation requirements specific to particular crops, real-time measurement of soil moisture, learning algorithms, and energy storage.

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