Solar Panel Optimization using Machine Learning

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***Abstract*—This research presents a machine learning-driven approach to optimize solar panel tilt angles, for maximizing energy generation efficiency. Using historical solar irradiance data, weather conditions, and geographic information, our model accurately predicts optimal tilt angles. A user-friendly web interface integrates the trained model, allowing real-time predictions which can be used by the users or the stakeholders. We have also mentioned alternative approaches which we can integrate in order to increase the efficiency and usefulness.**

***Index Terms*—Solar panel optimization, Tilt angle prediction, Machine learning in solar energy, Solar panel orientation**

I. Introduction

TRaditional energy sources like fossil fuels contribute to climate change and environmental degradation, while renewable energy sources like solar and wind power offer clean and abundant alternatives. Environmental conservation and preservation are increasingly important due to pollution, deforestation, climate change, and biodiversity loss. To protect ecosystems and resources for future generations, local communities and international policymakers must address the variability and intermittency of renewable energy production. Machine learning models can help optimize the generation, distribution, and storage of renewable energy by accurately forecasting production, managing grid stability, and optimizing energy storage. Accurate predictions can reduce waste and increase efficiency, while managing grid stability ensures electricity supply meets demand, preventing blackouts, and maximizing renewable energy use. Optimizing energy storage allows for more reliable and cost-effective use of renewable energy sources.

A. Problem Statement

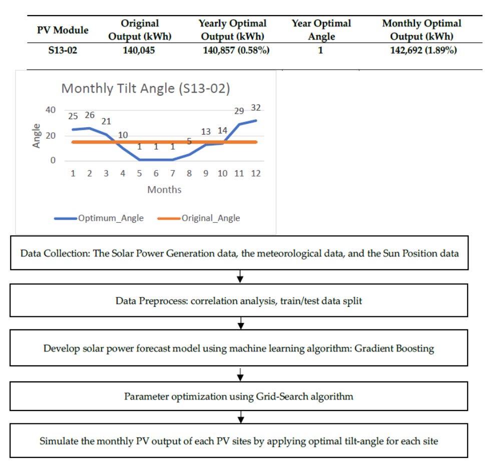
Solar panels are crucial for generating electricity in solar power systems. Getting their tilt angle and orientation right is key for making them work efficiently. But just setting them at a fixed angle might not always be the best choice because the sun moves and the weather changes.

Deciding on the perfect tilt angle and orientation for solar panels is complex. It depends on many input parameters like location, time, weather conditions, cloud cover, shade, etc. Past studies usually figured this out with manual calculations, but they often didn't think about how local weather affects things.

B. Relevant Works

A study suggests that, in India, energy production of the panel can be increased up to 30% using the optimal tilt angle [1].

A Case Study of Daegu City, South Korea [2]



PV Module	Original Output (kWh)	Yearly Optimal Output (kWh)	Year Optimal Angle	Monthly Optimal Output (kWh)
S13-02	140,045	140,857 (0.58%)	1	142,692 (1.89%)

Fig. 1: Graphical Abstract

It presents a forecasting model based on the gradient boosting algorithm to predict solar power generation by PV modules on both monthly and yearly bases. The study utilized solar power generation data, meteorological data, and sun position data. Compared to fixed angles, adjusting panel angles annually based on the model brought a slight increase (0.83%) in overall energy generation. However, when panel angles were

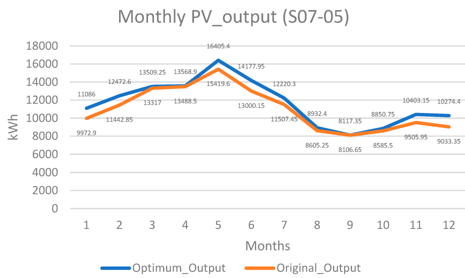


Fig. 2: Monthly tilt angles and outputs of S07-05 module

adjusted monthly, the overall energy generation increased significantly (3.32%). The economic efficiency gain of applying these changes annually was calculated to be 3302 thousand KRW for yearly optimal tilt angles and 13,483 thousand KRW for monthly optimal tilt angles.

The study acknowledges the limitation of generalizing its findings to different PV modules in various geographical conditions, as it was conducted on modules within a single city. Future studies plan to collect data from different cities to improve generalization. Additionally, the study recognizes the need to address issues such as the effect of rain or clearing dust on PV output through feature engineering or statistical techniques.

Predictions of Surface Solar Radiation on Tilted Solar Panels using Machine Learning Models [3]
This paper focuses on enhancing the capability of photovoltaic systems by constructing forecasting models to estimate surface solar radiation and solar irradiance received by solar panels at different tilt angles. The study was conducted in Tainan, Taiwan, known for its abundant sunlight due to its location at a latitude of approximately 23°. Four forecasting models were developed using the multilayer perceptron (MLP), random forests (RF), k-nearest neighbors (kNN), and linear regression (LR) algorithms. These models aimed to predict solar irradiance on an hourly basis, with a forecast horizon ranging from 1 to 12 hours. The findings revealed that a combination of ground weather data and solar position data effectively estimated solar irradiance. RF and kNN performed better than MLP, and LR showed the worst predictive performance due to its linear nature in predicting nonlinear problems.

The study also determined the optimal tilt angle for solar panels in Tainan to be 20–22°, based on the analysis of solar irradiance received at different tilt angles. The total annual global irradiance was highest at this angle, indicating that it maximizes energy generation efficiency. Overall, the research contributes to improving the reliability and efficiency of photovoltaic systems through accurate solar irradiance forecasting and optimal tilt angle determination.

C. Our Contributions

The optimal tilt angle for solar panels is a complex task influenced by factors such as sun position variability, weather conditions, location-specific factors, energy generation models, and trade-offs. The sun's angle changes throughout the day and season, making it difficult to predict in real-time. Weather conditions, such as cloud cover and atmospheric conditions, also impact the amount of sunlight reaching the panels. Geographical location also affects the optimal tilt angle. Developing accurate models based on tilt angle requires sophisticated mathematical and computational techniques. Balancing energy generation with other factors like installation cost and appearance adds complexity to the decision-making process. India has done little on optimizing tilt angles due to a focus on other aspects of solar energy generation, limited research resources, or lack of awareness. A proposed approach for optimizing solar panel tilt using machine learning is innovative and comprehensive, utilizing dynamic adjustment, advanced algorithms, continuous refinement, real-time monitoring, visualization, a user-friendly interface, and scalability.

D. Organization

The new method introduced includes an algorithm to streamline complex procedures, with the goal of boosting productivity and precision, as well as encouraging the use of sustainable energy practices and economical solutions. Through in-depth discussions, the strengths and limitations of the methodology are pinpointed, offering insights for potential improvements. Numerical results highlight the algorithm's effectiveness, showing considerable enhancements compared to current methods. In conclusion, this strategy presents a hopeful resolution with real-world implications for sustainable energy and cost-efficiency, as well as avenues for future exploration and advancement.

II. Proposed Approach

In PV system, optimal tilt angle is very crucial to get the maximum output. In traditional approach, the tilt angle is optimised only based on the sun's position on the sky. But this is not optimal, since the tilt angle is also dependent on the weather conditions of that location [4]. So, to find out the complex relationship between the tilt angle of PV system and weather conditions of the location, we have used various machine learning algorithms.

By using our algorithm, we can find out hourly, daily and monthly optimal angle for a PV system based on that location. In this paper, we have shown the results of Ahmedabad City at latitude 23.03 and longitude 72.59.

To optimise the tilt angle, we have used several machine learning algorithms like Linear Regression, Random Forest, Decision Tree, XGboost and LSTM [5].

Objective:
The aim is to increase the effectiveness of PV system by applying machine learning algorithms for solar panel tilt angle prediction and optimization dynamically, where this optimization will include many other environmental and system factors to ensure maximum energy production through solar panels.

A. Data

For any machine learning technique, data is essential. With the help of previously observed data, machine learning

algorithm can help predict the tilt angle for future case.
In our algorithm, we have gathered the data for Ahmedabad City from NASA Powers [6], which provides wide range of data for different use cases. It contains features as described below.

TABLE I: Data Input Features

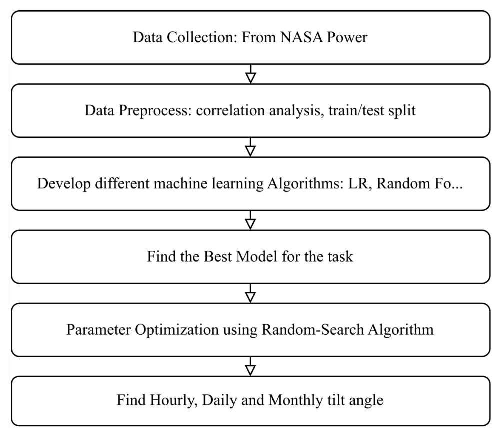
Feature	Unit
Date-time	-
Surface Shortwave Downward Irradiance	W/m^2
Clear-sky Surface Shortwave Downward Irradiance	W/m^2
All-Sky Insolation Clearness Index	-
All-sky surface albedo	-
Wind speed	m/s
Temperature	$^{\circ}C$
Humidity	g/kg

- **Input Features:**
  - ***Date and Time*** is the date and time for the observed parameters. We have used hourly data for each day from 5:00 am to 6:00 pm, because time of sunlight usually lies between that period in Ahmedabad, We have taken data from 1^{st} January 2021, to help predict the model better.
  - ***All-sky Surface Shortwave Downward Irradiance*** is the total amount of shortwave solar radiation (sunlight) that reaches the Earth's surface from the entire sky dome. It includes direct sunlight and diffuse sky radiation.
  - ***Clear-sky Surface Shortwave Downward Irradiance*** is the solar energy reaching the surface from sun under clear sky conditions i.e. when there are no clouds or important atmospheric obstructions. It is an important parameter because it provides information about the greatest possible amount of solar energy that can be received at a given place under ideal conditions.
  - ***All-Sky Insolation Clearness Index*** is a dimensionless parameter used in studies related to solar energy which quantifies how much light is coming through a cloudy sky in comparison with that reaching an Earth surface under clear sky conditions. The Clearness Index gives a measure of cloudiness or clarity of sky compared with ideal clear-sky conditions
  - ***All-sky surface albedo*** is a term that refers to the portion of sunlight that bounces off the entire sky hemisphere (including both sky and ground) in all directions. This involves direct sunshine as well as scattered skylight. The absorption of solar radiations or it reflects them back into space relies on the surface albedo.
  - ***Temperature*** refers to the temperature of Ahmedabad in given date and time. Solar panel efficiency varies with temperature variations. The high temperatures reduce the performance of solar panels due to an increase in electrical circuit resistance, resulting in less conversion photoelectricity.
  - ***Wind speed*** refers to the wind speed in Ahmedabad at given date and time.
  - ***Humidity*** refers to the humidity in Ahmedabad at given date and time. Humidity is also vital in optimal PV panel output.
- **Output:**

Our machine learning considers all the abovementioned features and finds the optimal angle for Ahmedabad City at a particular date and time. With the help of our model, we can get the best output of the PV panel.

B. Method Procedure

In order to receive the best results using machine learning techniques, we have used some set of procedures.



Performance Evaluation:

To ensure the accuracy and reliability of the software model, we are utilizing these methodologies for performance analysis which include validation against unseen data sets and evaluation using Mean Absolute Error (MAE) or Root Mean Square Error (RMSE).

Mean Absolute Error is a metric that is used to measure how good a regression model can predict. It gives the average magnitude of errors between the predicted values and the actual ones.

On the other hand, Root Mean Square Error can be another measure used in evaluating regressions' goodness-of-fit [7]. It works the same as MAE but with more emphasis on large errors due to squaring differences between predictions and real values.

III. Algorithms

There are several machine learning algorithms used in our project. We have used Linear Regression, Random Forest, Decision Tree and LSTM.

A. Linear Regression

A linear regression model is a statistical method used to understand the relationship between a dependent variable and one or more independent variables.

The model assumes that the relationship between the dependent variable and the independent variables is linear, meaning that the change in the dependent variable is proportional to the change in the independent variables [8]. Here, we have given the equation for linear regression of y on the dependent variables $x_1, x_2, \ldots x_n$.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \epsilon$$

B. Decision Tree

Decision Tree is a non-parametric supervised learning method used for classification and regression tasks. It creates a model that predicts the value of a target variable based on several input variables.

In decision tree, the model is represented as a tree where each internal node represents a ”test” on an attribute (e.g., whether a customer is older than 50) and each leaf node represents a class label (for classification) or a continuous value (for regression) [9].

The tree is built by splitting the dataset into subsets based on the values of the input variables. The splits are chosen to maximize the homogeneity (e.g., purity or information gain) of the target variable within the subsets.

C. Random Forest

The tree is built by splitting the dataset into subsets based on the values of the input variables. The splits are chosen to maximize the homogeneity (e.g., purity or information gain) of the target variable within the subsets. [10]

Random Forest builds multiple decision trees using a subset of the training data and a random subset of the features. Each tree is trained independently. Each tree is trained on a bootstrap sample (random sample with replacement) from the original training data. At each split in the tree, only a random subset of features is considered for splitting.

D. XGBoost

XGBoost (Extreme Gradient Boosting) is an optimized distributed gradient boosting model designed to be highly efficient, flexible, and portable. It is widely used for supervised learning tasks. XGBoost is based on the gradient boosting framework [11]. It also provides regularization features such as L1 and L2. XGBoost uses tree pruning to get better and more efficient results.

E. LSTM

LSTM is a type of recurrent neural network (RNN) architecture designed to capture long-term dependencies in sequential data. It is particularly effective in tasks such as speech recognition, language modeling, and time series prediction [12].

Instead of a recurrent neural network (RNN), each layer in the LSTM can be realised in four steps, which are the forget gate, the input gate, the update gate, and the cell output gate, as described below.

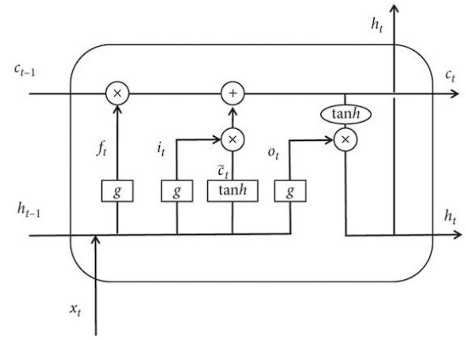


Fig. 3: LSTM diagram

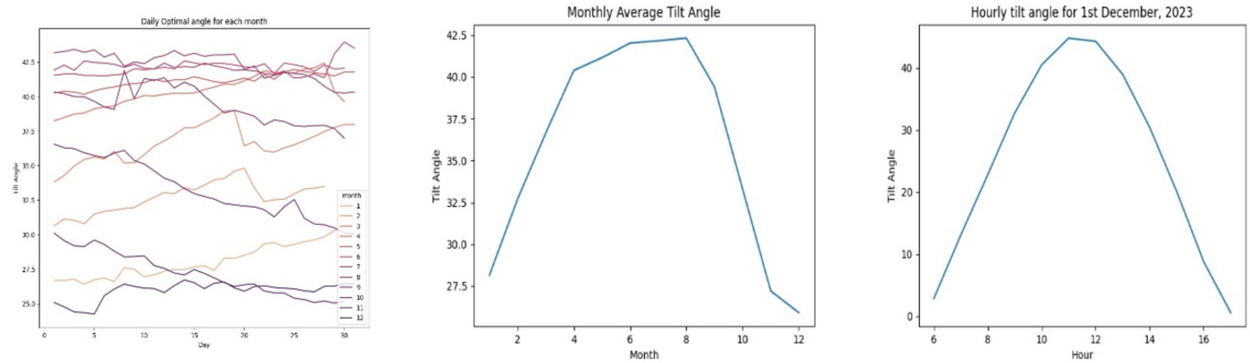
IV. Discussion and Remarks

Traditional solar panels are installed in fixed positions, which means they cannot adapt to changing environments such as the amount of clouds or the obstruction coming in between. Our project aims to address this limitation by using the technology that allows solar panels to dynamically adjust their tilt angles by taking into account the changes in sunlight intensity and other environmental factors.

Initially, we explored the use of standard machine learning algorithms that relied on historical weather data and predefined rules to predict the optimal tilt angles for solar panels. However, there are limitations with this approach, particularly in its ability to adapt to rapidly changing weather conditions leading to not so optimal performance in optimizing solar panel orientation.

Here are some ideas which we can integrate into our machine learning algorithm. Though it becomes very costly integrating these elements, it provides us with increased efficiency:

- ***1. Weather Forecast Integration:*** To overcome the limitations of these standard algorithms, we propose integrating real-time weather forecasts into our system. By requesting up-to-date weather predictions from meteorological agencies, we can dynamically adjust the tilt angles based on probable changes in weather conditions. This approach enables our system to respond to forecasted changes in sunlight intensity, cloud cover, or other environmental factors, and optimizes energy capture.
- ***2. Use of Sensors and Actuators:*** Another approach involves the use of sensors and actuators, which utilize them to continuously monitor the position of the sun throughout the day. These sensors track the sun's movement across the sky and dynamically adjust the tilt angles of solar panels to ensure they are always oriented towards the sun so that it can get maximum sunlight exposure. By these sensors, we can achieve accurate and real-time adjustments to optimize energy generation and enhance overall efficiency.
- ***3. Using Open Source Community:*** Pooling data from various solar installations within a community is crucial. By combining information from individual panels, weather stations, and energy metrics, advanced techniques



Daily optimal angle for each month | Monthly average tilt angle | Hourly tilt angle

Fig. 4: Numerical Results

like machine learning can spot trends and improve system performance. This collaborative approach among solar stakeholders fosters knowledge exchange and boosts energy production efficiency across the community.

V. Numerical Results

We have used forementioned machine learning models to get the most optimal tilt angle for the PV panel. In this section, we are providing different results obtained from our machine learning techniques.

A. Models evaluation

We have used evaluation metrics such as Mean Absolute Error and Mean Squared Error to evaluate our models and find the best model for optimised tilt angle prediction.

TABLE II: Test data errors for the machine learning models

Model	MAE	RMSE
Linear Regression	3.01	16.15
Decision Tree	0.71	2.75
Random Forest	0.52	1.37
XGBoost	0.633	1.08
LSTM	0.004	0.01

As we can see above, the LSTM model outperforms the other models in the test dataset. So, for further results, we have used the LSTM model to predict the tilt angle.

B. Optimal Tilt Angle For Ahmedabad

We have found out the hourly, daily and monthly optimal angle for Ahmedabad city using LSTM model. We have shown this result in Figure 4. As we can see from the image, the optimal angle is very different for each hour in a day. Also, from the image, we can also see that, the daily optimal angle is very different in different months. So, we can say that, instead of using a single tilt throughout the year, the optimal tilt angle can help achieve better solar output for a PV panel.

VI. Future scopes

A. Future Hardware Scope - Automatic Solar Panel Positioning

While our current approach focuses on providing recommendations for manually adjusting solar panel tilt angles, there exists a significant opportunity to integrate our machine learning technology into hardware systems for automatic panel positioning, particularly in scenarios where manual adjustments are impractical or inconvenient.

Solar panels generate maximum power when sun rays are incident at a right angle to the panel. Almost of the solar panels are stationary models, they fail to use the sun's intensity. Although sunlight with high intensity is available during most times of the day, the stationary panels are unable to utilize it to its potential due to their fixed position reducing productivity.

- ***A. System Design*** A single-axis rotating solar panel would be designed that rotates horizontally from east to west and keeps the panel perpendicular to the sun-rays, thus maximising the productivity of the solar panel.The positioning system would consist of sensors to detect sunlight intensity and direction, actuators to adjust panel tilt angles, and a control unit to process data and make real-time adjustments. The control unit would utilize our machine learning model to determine the optimal tilt angle based on current environmental conditions, ensuring maximum energy yield throughout the day [13].
  Components required:-
  Microcontroller(Arduino, RasberryPI, etc), LDR (Light Dependent Resistor) sensors, Potentiometer, Servo motors, Battery

- ***B. Methodology***
  Rechargeable battery connected to the charge controller of the solar panel is stores the power generated by the panel and helps in powering the stepper motor through the motor driver. The stepper motor helps in rotating the panel. The rotation of the motor can be controlled by the microcontroller, which decides the rotation of the stepper motor according to the input given by the LDRs.

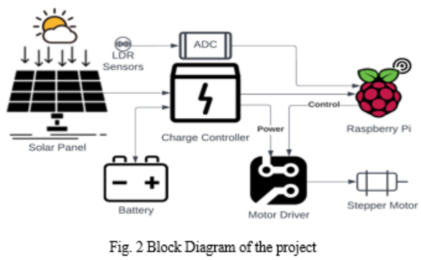


Fig. 5: Overall schematic of the system

B. Future Software Scope

- **Advanced Tracking Algorithms:** Continued refinement of tracking algorithms will enable more precise and dynamic adjustment of solar panel orientation to optimize energy capture,Exploring the use of advanced ML models like deeplearning for even more accurate predictions.

- **Remote monitoring and control:**Enhanced remote monitoring and control functionalities will enable solar panel operators to manage and optimize their installations from anywhere with an internet connection. Real-time monitoring of performance metrics, combined with remote control capabilities, will streamline maintenance activities and ensure optimal operation of the solar tracking system.

- **Integration with Building Information Modeling (BIM):** Integration with BIM software can facilitate the design and implementation of solar tracking systems within architectural and construction projects. BIM models can be used to simulate the performance of rotating solar panels in various environmental conditions, optimizing placement and orientation for maximum energy efficiency.

- **Open-Source Collaboration:** Collaborative development initiatives within the open-source community can drive innovation and standardization in the software.

VII. Conclusion

In conclusion, our research shows that using technology like machine learning, can help us find out the best angle for solar panels to capture the most sunlight. Our model, along with an easy-to-use website, makes it simple for anyone in the solar energy world to predict these angles accurately. Our model and website can also be used by the general users and the stakeholders which can help them significantly in this field. This work moves us closer to making solar energy more efficient and accessible, which is very important for a sustainable future.

Appendix A
Experiments

The code for this project and its results can be found at here.

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