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# Solar Intelligence Predictive Models for Power Generation and Radiation using Machine Learning

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**ABSTRACT**: This study presents a Machine Learning-based Solar Intelligence Predictive Model for forecasting solar radiation and power generation using historical and real-time meteorological data. The model incorporates key atmospheric factors such as GHI, DNI, temperature, humidity, cloud cover, and seasonal variations to enhance prediction accuracy. It employs a hybrid approach combining Random Forest, ARD Regression, Ridge Regression, and Decision Tree Regression, ensuring robustness, flexibility, and interpretability. Designed for real-world applications, the system offers timely, accurate insights with an intuitive interface. Experimental results show R<sup>2</sup> scores of 90–95%, outperforming traditional methods (75–85%).

**KEYWORDS:** Solar Energy Forecasting, Machine Learning, Meteorological Data, Hybrid Model, Prediction Accuracy.

#### I. INTRODUCTION

Cognitive Radio (CR) ad-hoc networks are designed to improve spectrum efficiency by allowing unlicensed (secondary) users to opportunistically access underutilized licensed channels without interfering with primary users. These networks enable mobile nodes to exploit temporarily available spectrum and intermittent connectivity for end-toend communication. CR is a foundational technology for Dynamic Spectrum Access (DSA), allowing nodes to adaptively adjust their transmission parameters based on spectrum availability. However, CR networks face key challenges such as unpredictable network partitioning due to varying node mobility and spectrum conditions. These partitions often lack stable end-to-end paths, making traditional routing ineffective. To address this, Spectrum-Aware Flooding (SAF) is used, where messages are forwarded through selected path nodes over available channels. While broad message replication minimizes delay, it can lead to high energy consumption and interference. This paper proposes two optimization schemes to enhance communication efficiency the Node Selection Scheme (NSS) and the Channel Selection Scheme (CSS). NSS enables each node to evaluate its potential benefit in forwarding a message versus the energy cost, ensuring minimal energy usage without increasing delay. CSS allows nodes to dynamically choose licensed channels that offer the best spectrum availability with minimal interference to primary users, thus improving overall spectrum utilization. Furthermore, the paper addresses security concerns in spectrum sensing by introducing a Trust-Worthy algorithm, which enhances the reliability of sensing data and ensures that only trustworthy nodes participate in the communication process. This combination of efficient resource selection and secure sensing improves the performance and reliability of CR ad-hoc networks in dynamic environments.

#### **II. SYSTEM MODEL AND ASSUMPTIONS**

The proposed system is designed to forecast solar power generation and radiation using machine learning models. It begins with the collection of both historical and real-time meteorological data, including solar irradiance, temperature, and humidity, from sources like Kaggle and real-time sensors. This data is then preprocessed using Python libraries such as Pandas and NumPy to remove missing or duplicate values and normalize features for consistency. Visual tools like Matplotlib and Seaborn are used for data visualization to detect trends and anomalies. Once cleaned and prepared, the data is used to train various machine learning models including Random Forest, ARD Regression, Ridge Regression, and Decision Tree Regression. These models are evaluated using performance metrics like RMSE, MSE, and R<sup>2</sup> score to select the most accurate one for deployment.

It is assumed that the collected data is reliable and representative of actual solar conditions. The models are expected to generalize well to unseen data, assuming consistent weather patterns and valid sensor readings. The system is





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integrated into a user-friendly web application built with Django, allowing real-time interaction for users to input current weather parameters and receive forecasts. It uses SQLite3 for database management and can be deployed on cloud platforms like AWS or PythonAnywhere for accessibility. It is also assumed that users have internet access and that the system operates in environments with minimal data transmission delays. These assumptions ensure efficient forecasting, improved energy management, and timely solar power predictions.

#### **III. EFFICIENT COMMUNICATION**

The proposed system combines advanced machine learning and dynamic spectrum management to enable accurate solar power forecasting and efficient communication in Cognitive Radio (CR) Networks. It begins by collecting historical and real-time meteorological data—such as solar irradiance, temperature, and humidity—which is preprocessed and visualized using Python libraries like Pandas, NumPy, Matplotlib, and Seaborn. Machine learning models including Random Forest, ARD Regression, Ridge Regression, and Decision Tree Regression are trained and evaluated using metrics like RMSE, MSE, and R<sup>2</sup> Score to select the most accurate model. This model is then deployed via a Django-based web application integrated with a cloud database for real-time predictions. In parallel, efficient communication in CR networks is ensured using Spectrum-Aware Flooding (SAF) and enhanced by two selection schemes: Node Selection Scheme (NSS) and Channel Selection Scheme (CSS). NSS minimizes energy use by evaluating message forwarding benefits, while CSS optimizes channel selection to reduce interference with primary users. A Trust-Worthy algorithm further strengthens spectrum sensing security. These integrated solutions ensure accurate forecasting, secure spectrum utilization, and energy-efficient, low-latency communication in real-world smart energy environments.

#### **IV. SECURITY**

Security is a vital aspect of the proposed Cognitive Radio (CR) network system due to the dynamic and open nature of spectrum access. To maintain trust and reliability, the system employs a **Trust-Worthy algorithm** that evaluates the accuracy and honesty of spectrum sensing reports from participating nodes. This helps to identify and isolate malicious or faulty nodes that may provide false data, protecting primary users from harmful interference. Beyond trust management, the system incorporates secure authentication and encryption protocols to safeguard communication channels from eavesdropping, spoofing, and unauthorized access. Additionally, intrusion detection mechanisms continuously monitor network traffic and node behavior to detect anomalies or attacks such as denial-of-service or spectrum sensing data falsification. These layered security approaches not only preserve the integrity of spectrum sharing but also enhance the resilience and robustness of CR networks in practical deployments, especially in critical infrastructure like smart grids and renewable energy systems.

- **Trust-Worthy Algorithm:** Continuously assesses the reliability of nodes by analyzing historical sensing accuracy and behavior patterns to prevent false spectrum data submissions.
- Malicious Node Detection and Isolation: Identifies nodes exhibiting abnormal or suspicious activity, isolating or excluding them to protect network integrity.
- Secure Authentication Mechanisms: Uses cryptographic protocols (e.g., digital signatures, certificates) to verify the identity of nodes before granting access to the network or spectrum resources.
- End-to-End Encryption: Ensures all data communications between nodes are encrypted to prevent interception, tampering, or replay attacks by unauthorized parties.
- Intrusion Detection and Prevention Systems (IDPS): Employs real-time monitoring tools to detect anomalies such as unusual traffic patterns or repeated failed access attempts, triggering alerts or automated mitigation.
- Spectrum Sensing Data Validation: Cross-verifies sensing reports from multiple nodes to filter out inconsistent or misleading information, enhancing decision accuracy.





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#### V. RESULT AND DISCUSSION

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Figure 1: Solar Prediction Input Form

This is the Solar Prediction user input interface. It allows users to input key weather and environmental data using weather api (e.g., radiation, temperature, humidity) to predict solar power output. This form integrates user data into the solar prediction model.



Figure 2: Solar Power Prediction Analysis

This figure displays the **Solar Power Prediction Analysis**. The predicted solar power output is **869.00**, indicating a **high generation potential**. The graph represents how different features (e.g., temperature, pressure, humidity) contribute to the prediction. The sharp peaks suggest some features have a strong influence on the model's outcome.





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Figure 3: Radiation Prediction Input Form

This figure shows the Radiation Prediction interface, where users enter weather parameters like temperature, pressure, humidity, wind direction, and speed. The system then processes this data to predict solar radiation, which can later be used in the solar power model.



Figure 4: Radiation Prediction Analysis

This figure shows the Radiation Prediction result, which is approximately 755.18. The plotted line graph visualizes how various environmental parameters—such as radiation, temperature, pressure, humidity, wind direction, and speed—affect the radiation prediction used to estimate solar generation.

#### VI. CONCLUSION

The Solar Intelligence Predictive Models for Power Generation and Radiation Using Machine Learning project leverages machine learning algorithms to forecast solar power generation and radiation levels with high accuracy. By utilizing diverse datasets, including weather conditions, geographical factors, and solar panel performance, machine learning techniques such as regression models, time-series forecasting, and deep learning methods can predict solar energy output under various conditions. These predictive models can optimize solar energy production, improve efficiency, and assist in better decision- making for energy storage and consumption. Ultimately, this project has the potential to enhance the reliability of solar energy systems, promote sustainability, and support the transition towards renewable energy by providing more precise and real-time predictions of solar radiation and power generation.





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