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Grid Integration and Pathways to Market for Renewable Energy: Leveraging AI and Machine Learning

AGENDA

INTRODUCTION

Artificial Intelligence holds the key to unlocking the full potential of renewable energy, enabling smarter grids, optimizing energy use, and accelerating the global transition to a sustainable future.

- **Global Shift Towards Renewable Energy**
  - Rapid adoption of wind and solar power worldwide
  - Commitments to reduce carbon emissions and combat climate change
- **Challenges in Renewable Energy Integration**
  - Intermittent and unpredictable nature of renewable sources
  - Technical and operational issues affecting grid stability and reliability
- **Objective of the Presentation**
  - Explore how advanced control algorithms and Artificial Intelligence (AI) can enhance the integration of renewable energy into power grids
  - Focus on increasing grid stability, reliability, and market access for renewable energy

Challenges in Renewable Energy Integration

Source

- **Technical Challenges**
  - **Variability and Intermittency:** Renewable energy sources like wind and solar are inherently variable, leading to fluctuations in power generation.
  - **Grid Stability:** Maintaining consistent voltage and frequency levels becomes challenging with the integration of intermittent energy sources.
- **Operational Challenges**
  - **Real-Time Supply and Demand Balancing:** The unpredictability of renewable energy generation complicates the matching of supply with consumer demand.
  - **Energy Storage Limitations:** Current storage technologies may not adequately compensate for periods of low renewable energy generation.

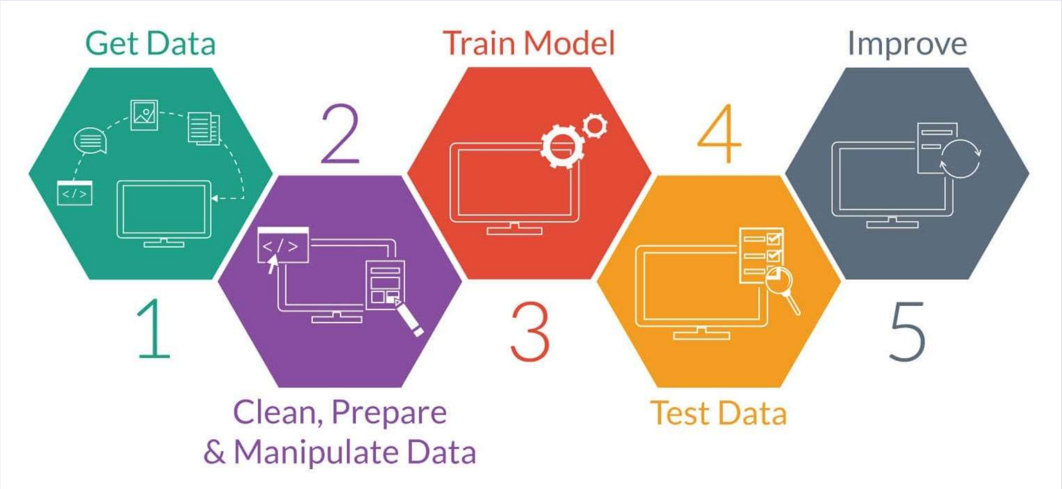
Advanced Control Algorithms and AI Applications

- **Enhancing Grid Stability and Reliability**
  - **Real-Time Monitoring and Control:** Implementing AI-driven systems for continuous observation and immediate response to grid fluctuations.
  - **Predictive Maintenance:** Utilizing machine learning models to anticipate equipment failures, thereby reducing downtime and maintenance costs.
- **Optimizing Energy Distribution**
  - **Dynamic Load Balancing:** Employing AI algorithms to adjust energy distribution in response to real-time demand and supply variations.
  - **Minimizing Transmission Losses:** Applying advanced control strategies to enhance the efficiency of energy transmission across the grid.

Source

Machine Learning Models for Generation Forecasting

- Utilizing Historical and Real-Time Data
  - **Data Sources**: Incorporation of weather patterns, wind speeds, solar irradiance, and historical generation data.
  - **Data Processing**: Cleaning, normalization, and feature extraction to prepare data for model training.
- Improving Forecast Accuracy
  - **Machine Learning Techniques**: Deployment of algorithms such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and ensemble methods.
  - **Model Training**: Utilizing supervised learning approaches to train models on labeled datasets.
  - **Validation and Testing**: Implementing cross-validation techniques to assess model performance and prevent overfitting.



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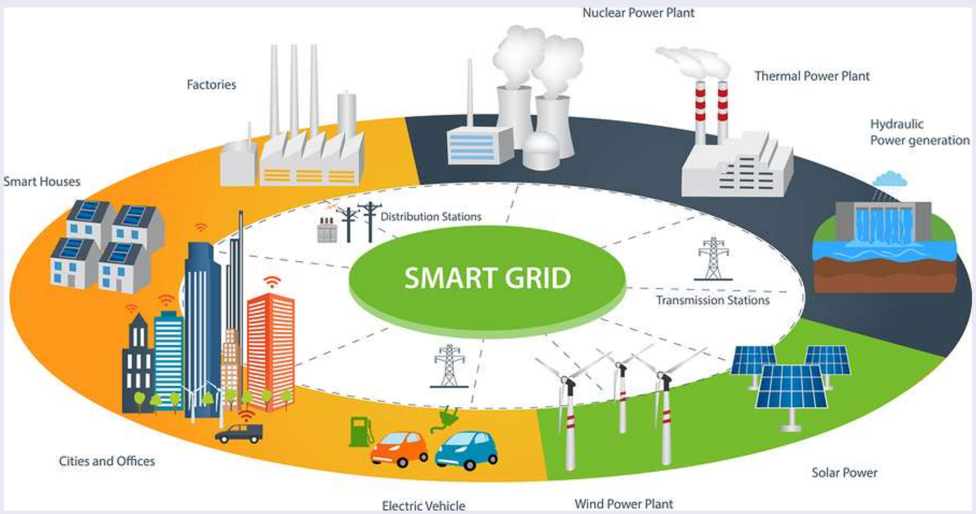
AI in Grid Optimization



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- **Enhancing Energy Flow**
  - **Dynamic Routing:** AI algorithms adjust energy pathways in real-time to minimize congestion and transmission losses.
  - **Load Forecasting:** Machine learning models predict demand patterns, enabling proactive energy distribution.
- **Integrating Distributed Energy Resources (DERs)**
  - **Seamless Integration:** AI facilitates the incorporation of DERs like solar panels and electric vehicles into the grid.
  - **Decentralized Management:** Intelligent systems manage energy flows from multiple sources, ensuring stability and efficiency.

AI-Driven Market Access Enhancement

- **Analyzing Price and Cost Dynamics**
  - **Real-Time Market Analysis:** AI algorithms process vast datasets to provide insights into current energy prices and market trends.
  - **Cost Forecasting:** Machine learning models predict future costs associated with renewable energy production and distribution.
- **Developing Real-Time Energy Markets**
  - **Dynamic Pricing Models:** AI facilitates the creation of pricing structures that reflect real-time supply and demand, promoting market efficiency.
  - **Enhanced Trading Platforms:** Intelligent systems enable more responsive and flexible energy trading, accommodating the variability of renewable sources.

Case Studies and Real-World Applications

[Source]

- **Predicting Offshore Wind Farm Power Output (European Case Study)**
  - *Study Focus*: Applied machine learning models (k-NN, Random Forest, Decision Tree, Linear Regression) to predict power output across 29 offshore wind farms in Europe.
  - *Key Findings*: Tree-based models provided the highest accuracy, aiding in grid integration and operational planning.
  - *Real-World Impact*: Supports accurate power forecasting, essential for balancing grid supply and demand.
- **Short-Term Wind Speed Forecasting (Lillgrund Offshore Wind Farm)**
  - *Study Focus*: Hybrid deep learning model (Bi-LSTM with evolutionary algorithm) for short-term wind speed prediction at Lillgrund, Baltic Sea.
  - *Key Findings*: Outperformed standard models in 10-minute and one-hour forecasting.
  - *Real-World Impact*: Enables reliable scheduling and cost-efficient operations, minimizing offshore wind variability.
- **Data Science for Offshore Wind Energy in Norway**
  - *Study Focus*: Utilized transfer learning and other ML techniques for resource assessment and decision-making in Norwegian offshore wind farms.
  - *Key Findings*: Improved resource prediction and operational efficiency.
  - *Real-World Impact*: Enhanced integration into energy markets, contributing to cost reductions and grid stability.

Publications

- A Comprehensive Review of the Current Status of Smart Grid Technologies for Renewable Energies Integration and Future Trends: The Role of Machine Learning and Energy Storage Systems
- Evaluating Solar Power Forecasting Robustness: A Comparative Analysis of XGBoost, RNN, KNN, RF, and LSTM with emphasis on Lagged Steps, Sensitivity, and Cross-Validation Techniques
- Enhancing Wind Power Forecasting Accuracy in Canada Using a Solar Data-Enhanced Hybrid Machine Learning Model: Integrating ANN, LSTM, and SVR
- EV Battery Management System for Grid Optimization
- Enhancing Fire Protection in Electric Vehicle Batteries Based on Thermal Energy Storage Systems Using Machine Learning and Feature Engineering

Enhancing Fire Protection in Electric Vehicle Batteries Based on Thermal Energy Storage Systems Using Machine Learning and Feature Engineering

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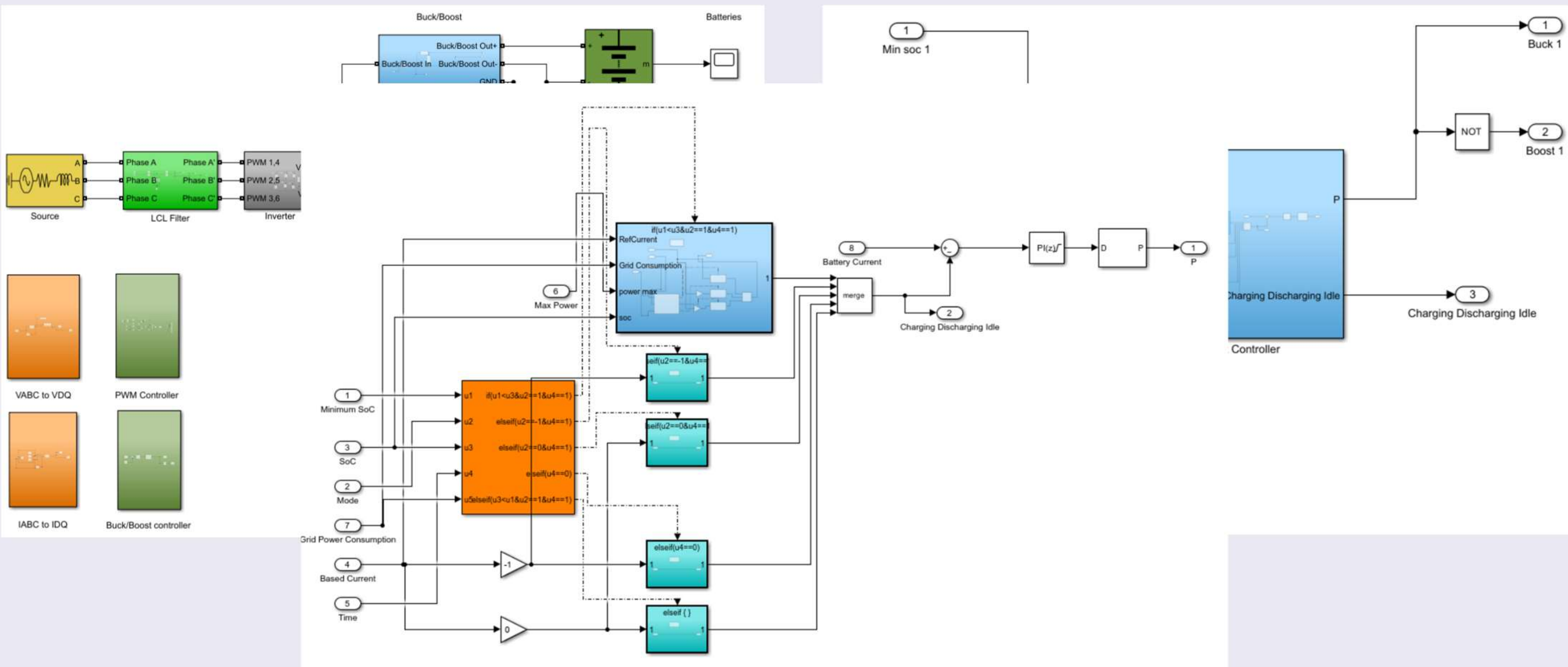
(This article belongs to the Special Issue Advances in Thermal Energy Storage in Fire Prevention and Control)

Abstract

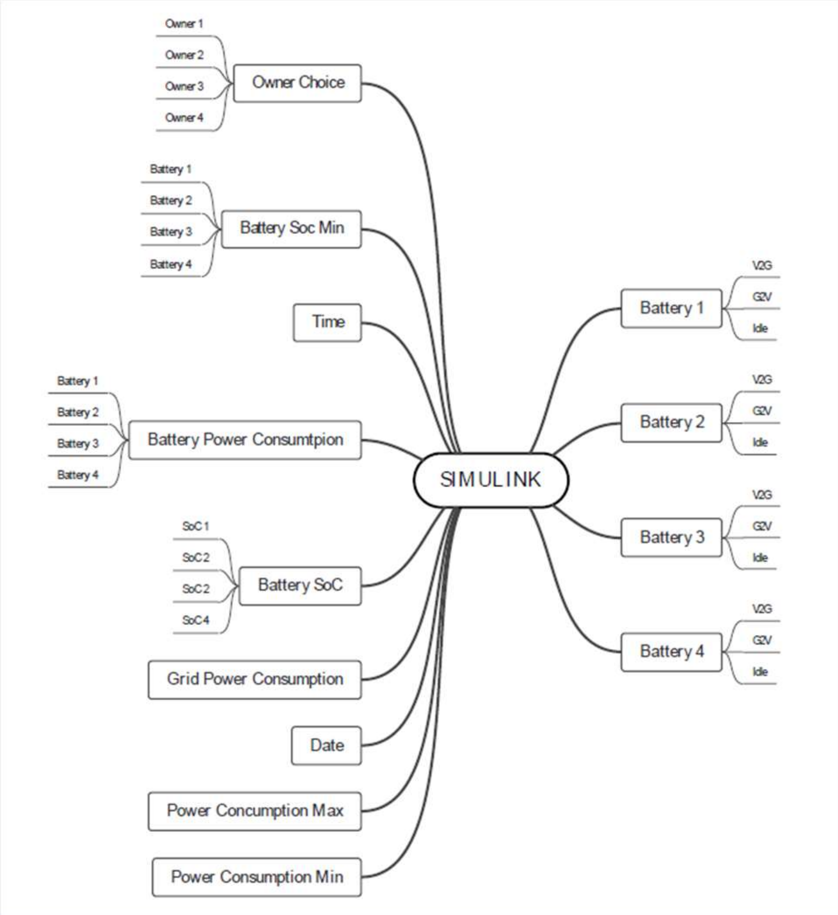
Thermal Energy Storage (TES) plays a pivotal role in the fire protection of Li-ion batteries, especially for the high-voltage (HV) battery systems in Electrical Vehicles (EVs). This study covers the application of TES in mitigating thermal runaway risks during different battery charging/discharging conditions known as Vehicle-to-grid (V2G) and Grid-to-vehicle (G2V). Through controlled simulations in Simulink, this research models real-world scenarios to analyze the effectiveness of TES in controlling battery conditions under various environmental conditions. This study also integrates Machine Learning (ML) techniques to utilize the produced data by the simulation model and to predict any probable thermal spikes and enhance the system reliability, focusing on crucial factors like battery temperature, current, or State of charge (SoC). Feature engineering is also employed to identify the key parameters among all features that are considered for this study. For a broad comparison among different models, three different ML techniques, logistic regression, support vector machine (SVM), and Naive Bayes, have been used alongside their hybrid combination to determine the most accurate one for the related topic. This study concludes that SoC is the most significant factor affecting thermal management while grid power consumption has the least impact. Additionally, the findings demonstrate that logistic regression outperforms other methods, with the improving feature to be used in the hybrid models as it can increase their efficiency due to its linearity capture capability.

Keywords: thermal energy storage; fire protection; Li-ion batteries; electrical vehicles; vehicle-to-grid; machine learning; simulink simulation; feature engineering

A proposed controller for real-time management of electrical vehicle battery fleet with MATLAB/SIMULINK



A proposed controller for real-time management of electrical vehicle battery fleet with MATLAB/SIMULINK



A proposed controller for real-time management of electrical vehicle battery fleet with MATLAB/SIMULINK (talk about the charging type)

- **Reduced Power Fluctuations:** The controller smooths out power consumption, leading to a more consistent load on the grid.
- **Efficient Energy Management:** By coordinating the battery operations based on factors like SoC and power demand, the controller improves the overall energy efficiency of the system.
- **Grid Stability:** A stable power profile reduces stress on the grid infrastructure, which is especially beneficial in systems with high renewable energy penetration.
- **Cost Savings:** The optimized charging and discharging cycles can reduce electricity costs, benefiting both the grid operator and the end-users.
- **Upcoming paper:** A Hybrid Machine Learning Framework for One-Hour Ahead Prediction of Electric Vehicle State of Charge: Integrating Feature Engineering and Explainable AI

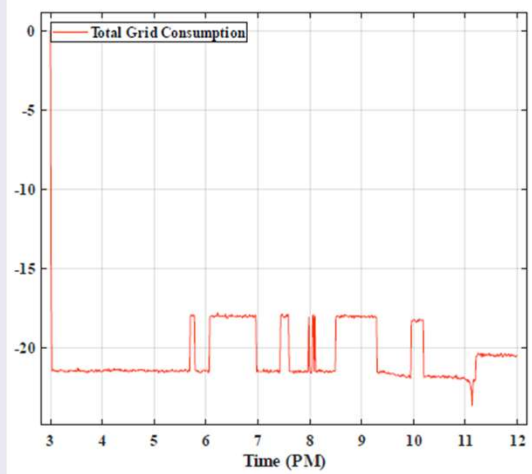


Figure 23 Total grid power consumption with controller

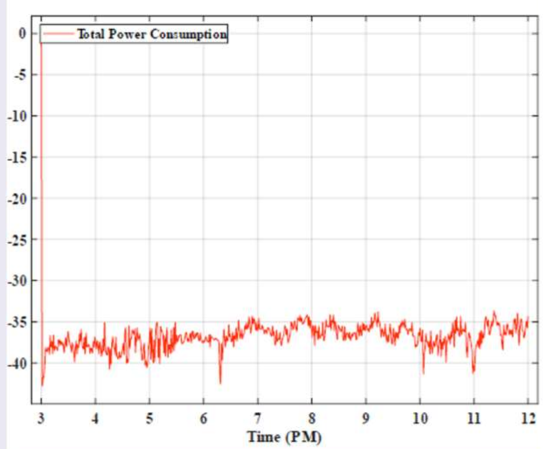


Figure 24 Total grid power consumption without controller

Evaluating Solar Power Forecasting Robustness: A Comparative Analysis of XGBoost, RNN, KNN, RF, and LSTM with emphasis on Lagged Steps, Sensitivity, and Cross-Validation Techniques

ANI KANNAL · UPDATED 4 YEARS AGO

911 | New Notebook | Download (2 MB)

Solar Power Generation Data

Solar power generation and sensor data for two power plants.

Data Card | Code (258) | Discussion (21) | Suggestions (0)

About Dataset

This data has been gathered at two solar power plants in India over a 34 day period. It has two pairs of files - each pair has one power generation dataset and one sensor readings dataset. The power generation datasets are gathered at the inverter level - each inverter has multiple lines of solar panels attached to it. The sensor data is gathered at a plant level - single array of sensors optimally placed at the plant.

There are a few areas of concern at the solar power plant -

1. Can we predict the power generation for next couple of days? - this allows for better grid management
2. Can we identify the need for panel cleaning/maintenance?
3. Can we identify faulty or suboptimally performing equipment?

Usability
10.00

License
Data files © Original Authors

Expected update frequency
Never

Tags
Renewable Energy

Evaluating Solar Power Forecasting Robustness: A Comparative Analysis of XGBoost, RNN, KNN, RF, and LSTM with emphasis on Lagged Steps, Sensitivity, and Cross-Validation Techniques

1 XGBoost

- Powerful ensemble learning method
- High efficiency, accuracy, and scalability
- Utilizes decision trees to correct errors iteratively

2 RNN

- Captures sequential dependencies in data
- Ideal for time series forecasting
- Uses internal loops to maintain memory of previous inputs

3 LSTM

- Captures long-term dependencies in sequential data
- Mitigates the vanishing gradient problem in RNNs
- Flexible with varying input and output sequence lengths

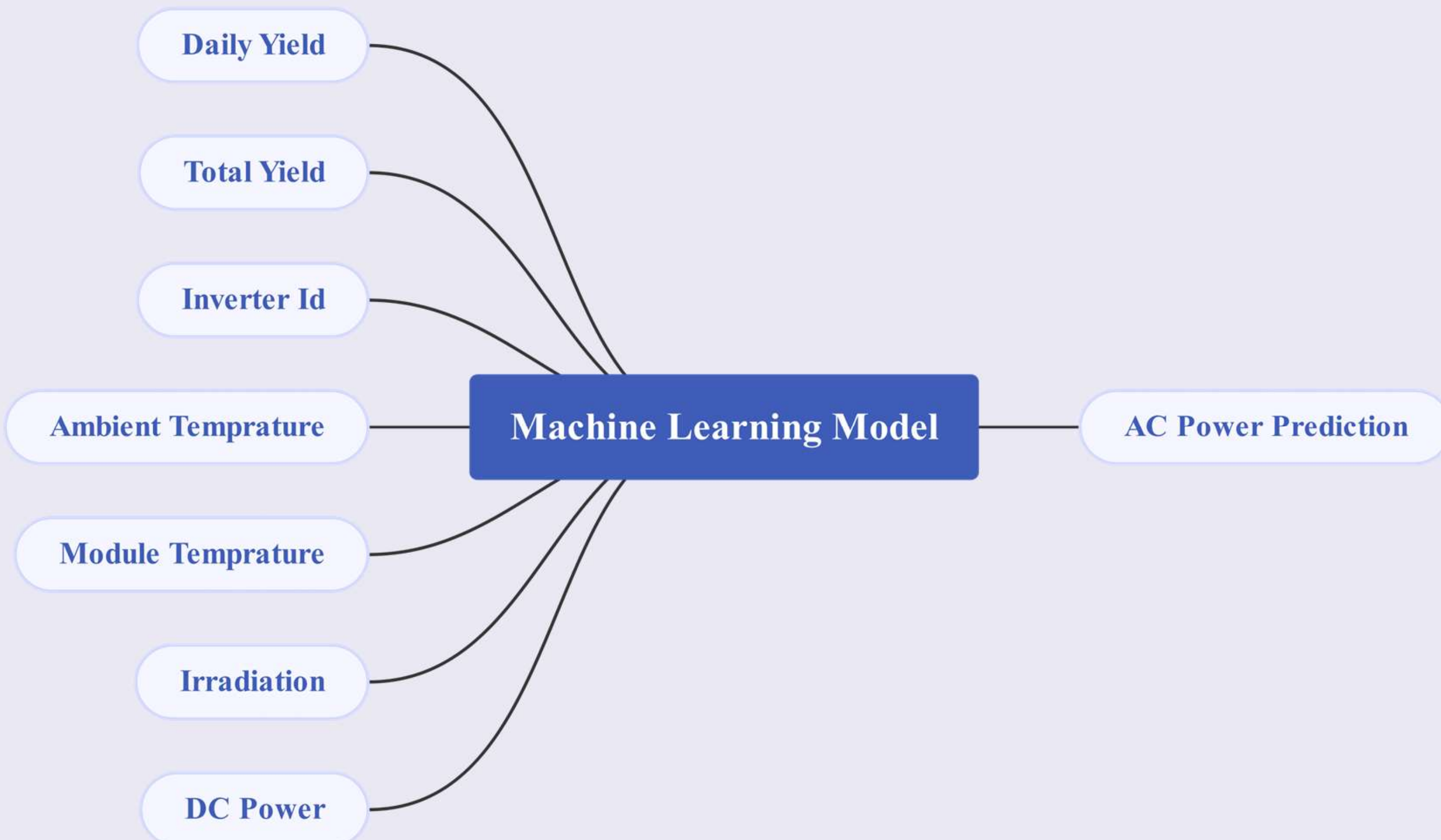
4 KNN

- Simple and effective for regression tasks
- Predicts values based on 'k' nearest data points
- Performance influenced by choice of 'k' and distance metric

5 RF

- Ensemble of multiple decision trees
- Outputs mean prediction for regression problems
- Robust against overfitting, handles large datasets with high dimensionality

Evaluating Solar Power Forecasting Robustness: A Comparative Analysis of XGBoost, RNN, KNN, RF, and LSTM with emphasis on Lagged Steps, Sensitivity, and Cross-Validation Techniques



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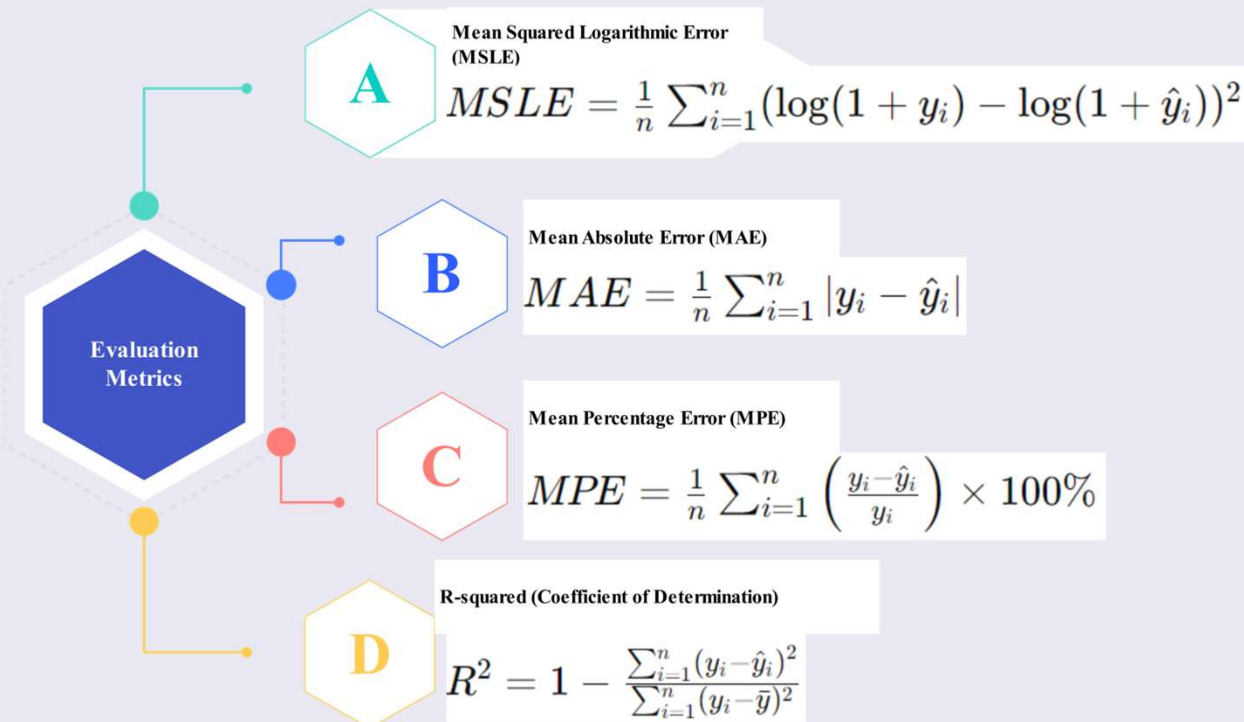

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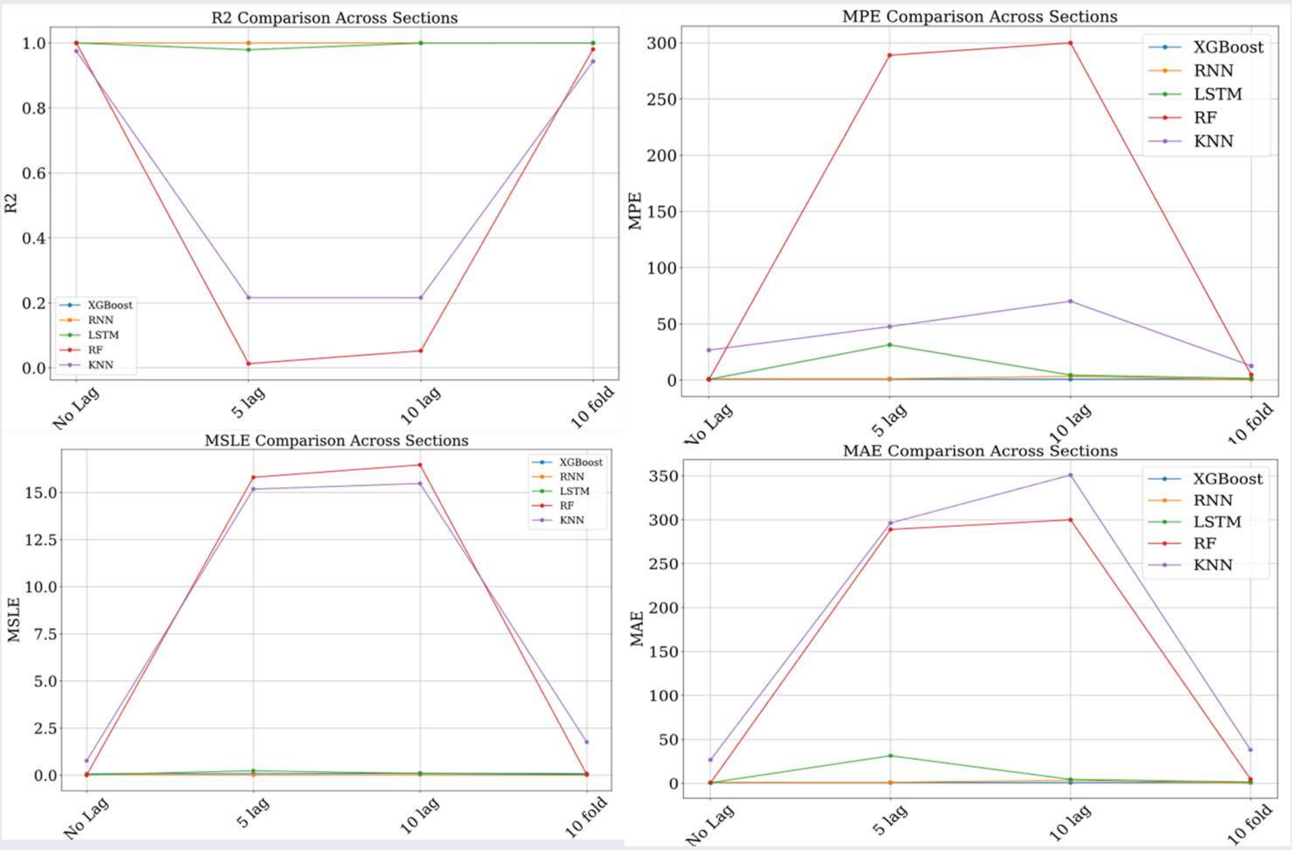


Results Summary:

1.XGBoost:

1. Shows stable performance with high R^2 and low errors (MPE, MSLE, MAE).
2. Consistently outperforms others, especially in no-lag and minimal-lag sections.

2.LSTM:

1. Performs well but suffers when lag increases, impacting R^2 and MAE.

3.RNN and KNN:

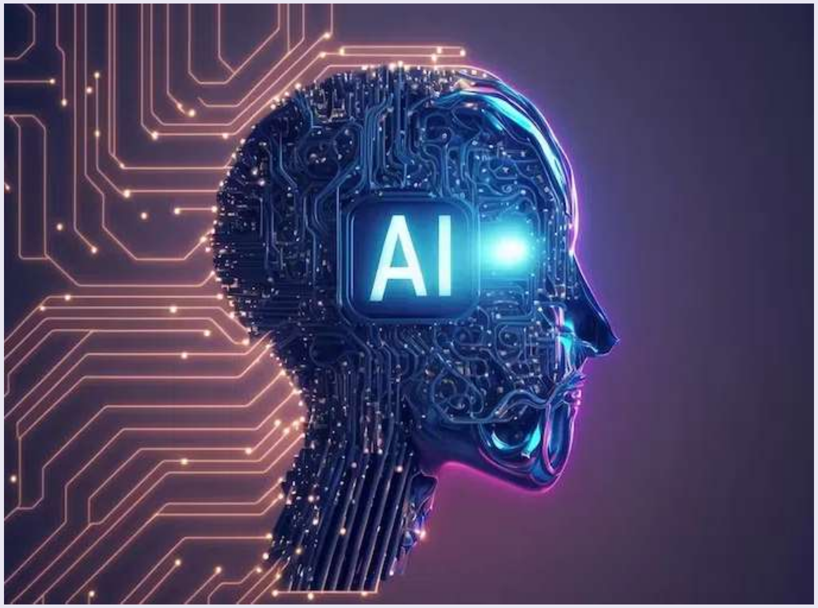
1. Show inconsistent results; higher errors in multiple metrics.

4.Random Forest (RF):

1. Provides moderate accuracy but less effective compared to XGBoost, especially with larger lag.

Benefits of AI and ML Integration

- **Technical Advantages**
  - **Enhanced Grid Resilience:** AI-driven predictive maintenance and real-time monitoring improve grid stability and reduce downtime.
  - **Optimized Energy Distribution:** Machine learning algorithms enable efficient load balancing and minimize transmission losses.
  - **Improved Forecast Accuracy:** Advanced models provide precise predictions of energy generation and consumption, facilitating better planning.
- **Economic and Market Benefits**
  - **Cost Reduction:** Automation and optimization lead to lower operational costs and reduced reliance on backup power sources.
  - **Increased Market Access:** AI facilitates dynamic pricing and real-time trading, enhancing the competitiveness of renewable energy in the market.
  - **Investment Promotion:** Demonstrated efficiency and reliability attract investments in renewable energy technologies.



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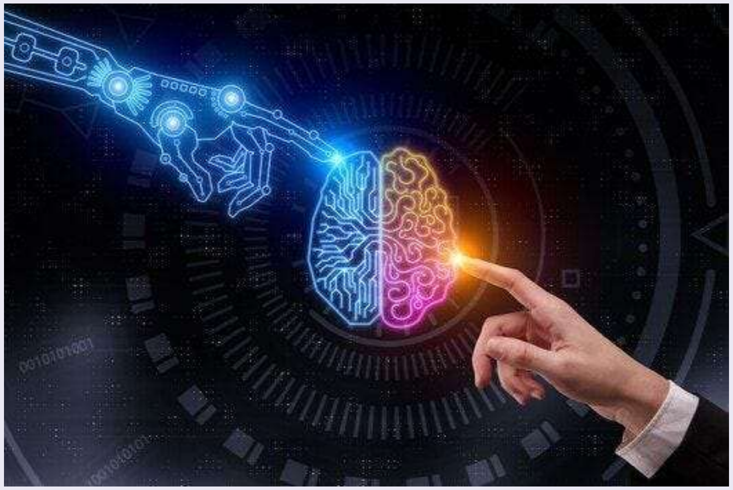
Conclusion



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- **Key Takeaways**
  - **Integration Challenges**: Renewable energy sources present variability and unpredictability, posing challenges to grid stability and reliability.
  - **AI and ML Solutions**: Advanced control algorithms and machine learning models enhance forecasting accuracy, optimize energy distribution, and improve market access.
  - **Benefits**: Implementing AI and ML leads to increased grid resilience, cost reductions, and greater investment in renewable technologies.
- **Outlook**
  - **Technological Advancements**: Continued development in AI and ML will further enhance renewable energy integration and grid management.
  - **Policy and Collaboration**: Supportive policies and collaboration among stakeholders are essential to maximize the benefits of AI in the energy sector.
  - **Sustainable Growth**: Leveraging AI and ML will facilitate a more sustainable and efficient energy future, aligning with global environmental goals.

THANK YOU

FOR YOUR ATTENTION