SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V10I7P107

Volume 10 Issue 7, 63-73, July 2023

Original Article

Sensor-Assisted Machine Learning Models Approach to Equipoise Renewable Energy using Microgrids

Shreenidhi H S[1], Narayana Swamy Ramaiah[2]

[1,2]Faculty of Engineering and Technology, JAIN (Deemed to be University), Banglore, Karnataka, India.

[1]Corresponding Author : shreenidhihs.14@gmail.com

Received: 29 April 2023 Revised: 26 June 2023 Accepted: 16 July 2023 Published: 31 July 2023

Abstract *- Sensor-assisted machine learning framework for renewable energy balancing in microgrids (MG). Integrating renewable energy sources into microgrid systems brings the challenge of managing renewable energy generation's intermittent and variable nature. The proposed framework leverages sensor technology to collect real-time data on energy generation, consumption, and grid conditions. Machine learning algorithms are then applied to analyze this data and optimize energy flow within the microgrid. The proposed machine learning models can use historical data to forecast renewable energy generation and demand, enabling proactive energy management (PEM). The framework also incorporates optimization techniques to allocate energy efficiently, considering storage capacity, load demand, and grid stability factors. The sensor-assisted machine learning algorithm enhances microgrid systems' reliability, precision, fi-score, recall, and support by dynamically adapting energy generation and consumption based on real-time conditions. This framework represents a significant step towards achieving sustainable and resilient microgrid operations by maximizing the utilization of renewable energy resources. The optimized results by sensing the physical quantity achieved an accuracy of 70%.*

Keywords *- Sensor, Machine learning, Proactive energy management, Microgrids, Renewable energy.*

1. Introduction

Integrating renewable energy sources into microgrid systems has gained significant attention due to its potential for sustainable and resilient power supply. However, the intermittent nature of renewable energy generation poses challenges in maintaining a balance between energy supply and demand within microgrids[1]. A sensor-assisted machine learning framework for renewable energy balancing in microgrids is proposed to address this challenge[2]. This framework leverages sensor technology and machine learning algorithms to optimize energy flow and enhance the efficiency and stability of microgrid operations. The increasing deployment of renewable energy sources, such as solar photovoltaic (PV) and wind turbines, has led to a decentralized energy generation landscape. Microgrids, localized energy systems that can operate independently or in connection with the primary grid, offer a promising solution for integrating renewable energy sources. However, renewable energy's intermittent and variable nature challenges maintaining a stable and reliable power supply within microgrids. Challenges in Renewable Energy Balancing: Balancing the supply and demand of renewable energy in microgrids is essential to ensure efficient utilization of available resources and grid stability. Key challenges include the unpredictability of renewable energy generation, varying load demands, and the need for real-time decision-making. Traditional approaches, such as rule-based control and centralized management, often fail to adapt to the dynamic nature of renewable energy systems. Role of Sensors in Renewable Energy Balancing sensors enables real-time monitoring of energy generation, consumption, and grid conditions. They provide valuable data on solar irradiance, wind speed, temperature, and load demand. This real-time data allows for a better understanding and prediction of energy generation patterns, load profiles, and system performance. Machine Learning for Energy Balancing Machine learning algorithms can analyse vast sensor data, detect patterns, and forecast accurately. Using prior data, machine learning predicts renewable energy generation and demand for proactive energy management.

These models optimise energy flow in real-time utilising sensor data for energy balance and machine learning algorithm Random forest; the framework aims to improve the reliability, precision, fi-score, recall of renewable energy generation and demand forecasting. Optimize energy flow in real-time based on predicted and observed data. Enable proactive decision-making for load management, energy storage, and grid stability. Maximize the utilization of available renewable energy resources and minimize reliance on the primary grid. The following machine learning algorithms are used in th proposed framework.

1.1. Random Forest Algorithm

The Random Forest Algorithm[3] combines numerous decision trees for a more accurate classification or regression model. This is how the algorithm operates:

Step 1 : we will randomly choose some samples from the training data.
Step 2 : Construct a decision tree whereby a random subset of characteristics is considered at each node, using the specified subset.
Step 3 : A number of decision trees may be generated by repeating steps 1 and 2.
Step 4 : Aggregate the predictions of all the decision trees to arrive at the predicted class label or value (through voting for classification or average for regression, respectively).

To avoid overfitting, Random Forest combines numerous decision trees that were trained independently. The ensemble model's Diversity and precision are boosted by randomization in feature selection and data sampling.

1.2. AdaBoost Classification

AdaBoost [4] (Adaptive Boosting) is a repeated ensemble learning method that uses weak classifiers to make a robust classifier. Here is how the method works:

Step 1 : Give each training example the same amount of weight.
Step 2 : Use the weighted training data to teach a weak algorithm what to do and determine how wrong it is.
Step 3 : Raise the weights of the misclassified examples to make them more likely to be picked in the next round.
Step 4 : Repeat steps 2 and 3 for a set number of times or until you get the level of accuracy you want.
Step 5 : Put together the weak categories by giving those with better results more weight.
Step 6 : Make predictions by adding up all the weak classifiers' guesses and weighting them by how well they did.

AdaBoost focuses on the most complex cases in each cycle, improving the ensemble model's performance evaluation. A robust classifier can be constructed that accurately predicts the target variable by iteratively adjusting the weights and combining weak classifiers.

1.3. Support Vector Machine Classification

A strong machine-learning technique may be used for classification as well as regression. SVM [5] seeks to discover an ideal hyperplane that splits data into various classes with the greatest margin in the context of classification. An SVM classifier's equation is expressed as follows:

The decision function is defined as,

$$f(x) = \text{sign}(w^T * x + b)$$

A data point's input characteristics are represented by x.
w is the weight vector that governs the hyperplane's orientation.
b is the bias factor that causes the hyperplane to shift.

In order to identify the optimal values for w and b, SVM works to solve a convex optimisation problem. It works towards minimising the space that separates the hyperplane and the data points that belong to each category. Support vectors are the name given to the data points on the margin; they are essential in identifying the decision boundary.

SVM is useful for dealing with complex decision boundaries, mainly when the data is not linearly separable. The kernel method may also translate the data into a higher-dimensional space, allowing for nonlinear classification.

2. Literature Review

Recent years have witnessed rapid renewable energy and electric vehicle grid penetration. Despite their environmental benefits, their stochasticity makes profile prediction difficult. This article suggests a linearized energy management methodology to lower microgrid operating costs.

This model considers microgrid components, including renewable energy, energy storage, distributed generation, combined heat and power, and electric vehicle parking. The system's stochastic factors—load demand, electricity pricing, renewable energy supply profile, and electric vehicle availability in the parking lot—are controlled using machine learning and point estimate techniques [6, 7].

Renewable power generation has grown recently and will soon be necessary to provide environmentally sustainable and eco-friendly electricity[8]. Sustainable energy sources power microgrids. Due to weather patterns and seasonal fluctuations[9-11], DER integration is expected to cause intermittent power production. End-user power usage varies by season. Energy storage device functions depend on energy supply and load forecasts.

This article discusses solar energy as a critical source and how solar irradiance varies by place and time. This article examines solar forecasting over one month. Knowing the source's availability may help load control if days of autonomy occur. Source forecasting uses Fuzzy Logic, ML, and DL. To build a dataset for a microgrid, irradiance, data, and other aspects are considered. This article summarises microgrids and source forecasting methods. This research compares the Root Mean Square Error (RMSE) levels of machine learning and deep learning methods[12, 13]. Waste management firms are major greenhouse gas emitters. Waste management companies must work with renewable energy sources to reduce this situation. Waste management organisations need plenty of energy. However, many enterprises use local power generation, making microgrid research crucial.

This project aims to maximise waste management company efficiency by efficiently processing trash and integrating it into microgrids with little user intervention. A unique machine-learning approach achieves this. In this technique, an artificial neural network (ANN) predicts how much garbage may be provided to these businesses[14, 15]. The Lagrangian Algorithm processes and optimises the waste, considering renewable energy needs. This method allows user input and preferences. A support vector machine processes user inputs into the model. Active learning incorporates user input. A Warendorf waste management firm tested this approach. Thus, user input helps control microgrid energy consumption[16].

Wind and solar energy in microgrids reduce transmission expansion costs, improve power quality and lower prices. However, their volatility makes them problematic to use in microgrids. Time series analysis finds patterns and trends in historical data to understand energy demand and supply swings.

Data can help estimate energy needs and improve microgrid operations. One-class SVMs estimate solar or wind unit capacity. Heuristic scheduling optimises electricity production. This heuristic architecture improves machine learning accuracy. Thus, the system efficiently manages renewable energy microgrids. Solar power affects voltage profiles and frequency responsiveness, while wind energy is unpredictable[17].

Modern power systems and microgrids need accurate net load forecasting (NLF) for effective operation and management. As microgrids integrate more renewable energy sources, classic statistical net load forecasting (NLF) methods fail to anticipate accurately. Machine learning (ML) models might improve statistical performance.

This research compares six machine learning models-artificial neural network, extreme gradient boosting, k-nearest neighbours, random forest, recurrent neural network, and support vector regression—for prediction. To find the best short-term net load forecasting (STNLF) model.

The University of Cyprus renewable integrated microgrid provided historical net load and weather data for the comparison investigation. All STNLF ML models have below 10% accuracy. The random forest model performed well with 4.32% normalised root mean square error. The findings show that STNLF machine-learning models can help renewable integrated microgrid operators manage and regulate their heterogeneous assets[18].

3. Methodology

This effort first creates a database to establish an accurate microgrid model to balance renewable energy sources and electricity utilisation. Creating a standard model requires a few steps.

Data Collection: Collect relevant data for training your Random Forest model. This may include historical energy generation data from renewable sources, sensor data such as weather conditions, energy demand data from the microgrid, and other relevant variables that may impact energy generation and consumption.

Data Preprocessing: The data that has been gathered should undergo a procedure of cleaning and preprocessing. This procedure involves the administration of missing values, the normalisation or scaling of features, and the encoding of categorical variables if deemed necessary. It is recommended to partition the data into distinct sets for training and testing.

Feature Engineering: Feature engineering extracts relevant features from data. Aggregating or modifying raw data may provide new features that capture crucial patterns or connections.

Model Training: Train a Random Forest model. Random Forest predicts by combining many decision trees. It handles numerical and categorical features and resists overfitting.

Model Evaluation: Assess the trained model's testing performance. Regression measures include MSE, MAE, and R-squared.

Model Optimization: Tune the parameters and hyperparameters of the model to enhance its efficacy. Cross-validation and grid search can be used to determine the optimal parameter settings.

Deployment and Monitoring[19]: Once the model's performance is satisfied, deploy it in a production environment. Monitor and evaluate its performance to ensure it adapts well to changing conditions.

Decision Support: Utilize the trained Random Forest model to make informed decisions about balancing renewable energy sources within the microgrid. It can provide predictions or recommendations on distributing energy from different sources based on real-time sensor data and historical patterns.

In Fig 1, the proposed using sensors, microgrids, and machine learning to balance renewable energy entails gathering real-time data from sensors to enhance a microgrid's performance[20]. Machine learning algorithms analyse this data to anticipate energy production, use, and storage trends. These forecasts are used by the microgrid's control system to dynamically balance energy production and demand, maximising the usage of renewable resources and lowering costs[21,22]. With this strategy, energy efficiency is improved, non-renewable resource dependence is decreased, grid resilience is increased, and environmental sustainability is promoted.

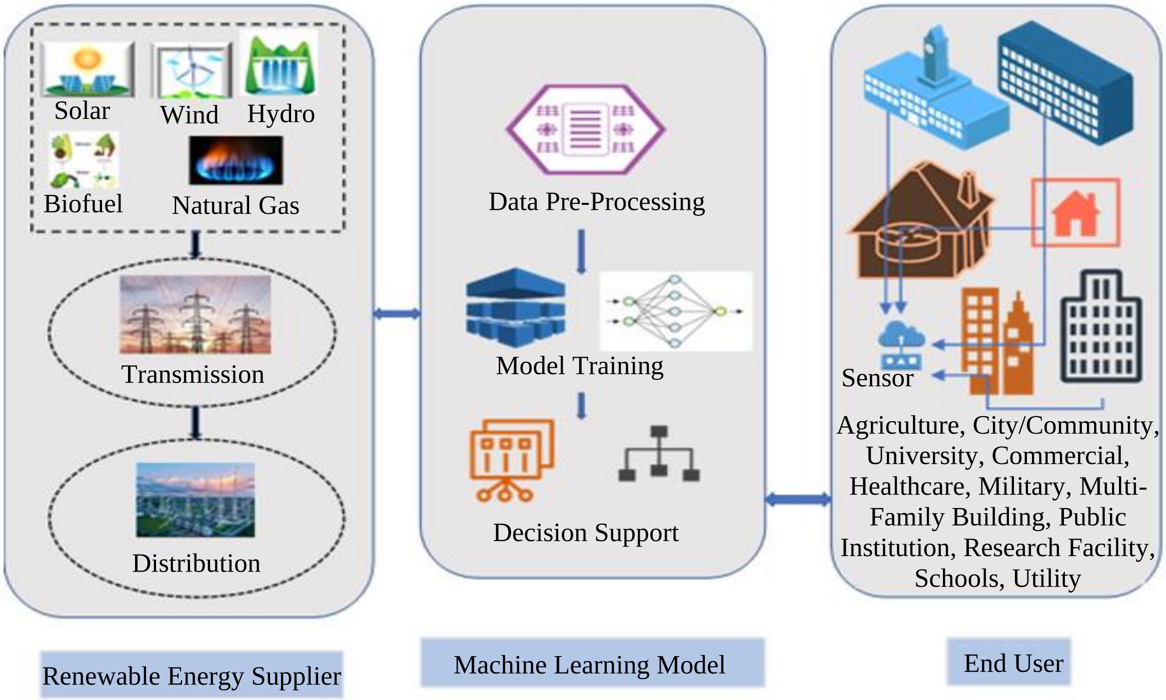

Fig. 1 Framework for the proposed methodology

4. Design and Implementation

4.1. Dataset Description and Data Preprocessing

The dataset combines several renewable energy applications categorized into Agriculture, City/Community, College/University, Commercial, Hospitals/Healthcare, Military, Multi-Family Buildings, Public Institutions, Research Facilities, Schools, and Water Treatment/Utility. The Microgrid Database is a data collection effort sponsored by the U.S. Department of Energy and maintained by ICF Inc. The database contains a comprehensive listing of microgrid installations throughout the country[23].

4.2. Datasets Distribution

In Figure 2, To comprehensively understand the dataset distribution for renewable energy applications, let us examine each category individually.

The analysis of the dataset distribution could provide helpful information into the diverse applications of renewable energy across multiple sectors, the extent of its implementation, its geographical spread, and its effects on energy consumption, carbon emissions, and cost reduction. Including these statistics would enhance comprehension of sustainable energy adoption patterns and the potential advantages they offer across various implementation domains.

Data Cleaning: During this procedure, we correct for things like missing data, extreme values, and background noise. Finding and fixing outliers, filling in missing data, and reducing noise via smoothing and filtering are all possible.

Data Integration: Integration unifies data from diverse sources and formats. This may entail fixing errors, combining duplicates, or standardising data.

4.3. Distribution of Microgrid Projects by Operational Year

Figure 3 shows the Distribution of Microgrid Projects by Operational Year. The distribution of microgrid projects by operational year varies depending on geographical location, funding availability, and project timelines. While some microgrid projects may have been operational for many years, others are still in the planning or implementation phase. The growing interest in microgrids has also led to increasing operational projects in recent years, reflecting the global shift towards decentralized and sustainable energy systems.

4.4. Total Capacity Vs Solar Capacity

The total capacity of a microgrid refers to the maximum amount of power that the microgrid can generate, store, and distribute to meet the energy needs of its local area. The solar capacity vs total capacity is shown in Figure 4. This capacity can be a combination of various energy sources, such as solar, wind, batteries, and conventional generators. Solar capacity, however, refers to the portion of the microgrid's total capacity derived from solar energy. It represents the maximum power generated by solar panels installed within the microgrid.

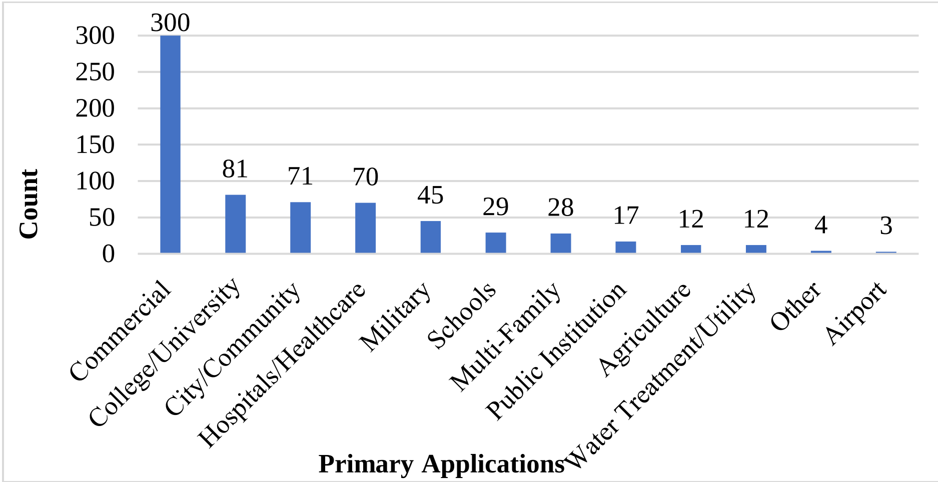

Fig. 2 Distribution of microgrid projects by primary application

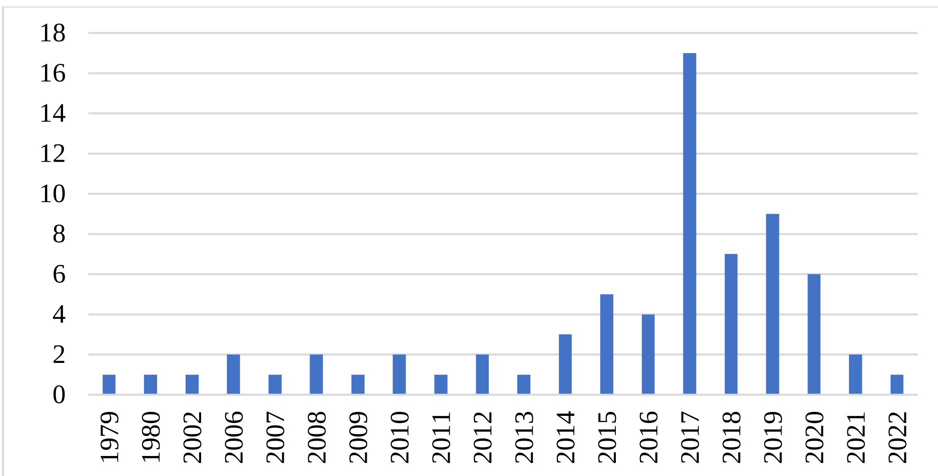

Fig. 3 Distribution of microgrid projects by operational year

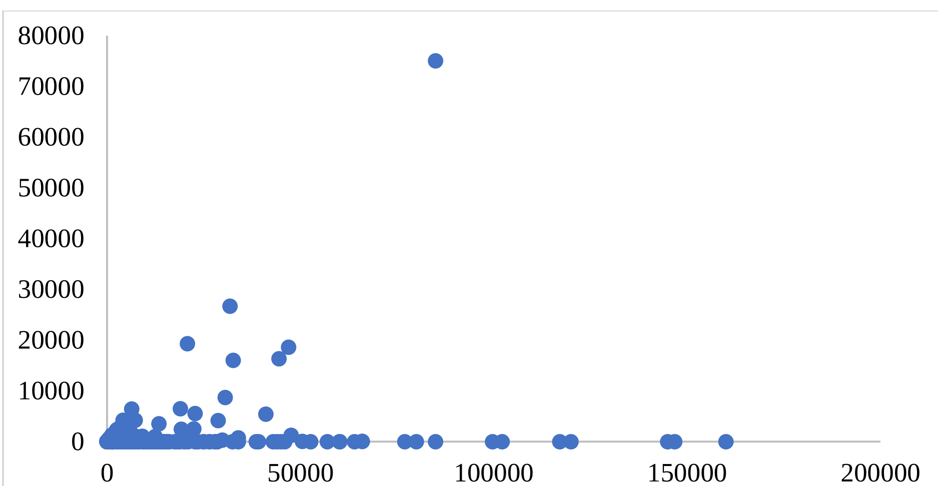

Fig. 4 Total capacity vs Solar capacity

The ratio of total capacity to solar capacity in a microgrid can vary depending on several factors, including geographical location, energy demands, available resources, and system design. In some microgrids, especially those located in regions with ample sunlight, solar capacity can be the dominant source, providing a significant portion or the majority of the total capacity. These microgrids rely heavily on solar energy to meet the energy needs of the local community. However, in other cases, where solar resources are limited or insufficient to meet the energy demands, the total capacity of the microgrid may include a larger share of other energy sources like wind, batteries, or conventional generators. Solar capacity may represent a smaller portion of the overall capacity.

It is important to note that microgrid configurations can vary greatly, and the optimal mix of energy sources, including solar capacity, will depend on each microgrid project's specific requirements and constraints[24]. Factors such as cost, reliability, environmental considerations, and local regulations also play a role in determining the balance between total capacity and solar capacity in a microgrid.

It is important to note that the specific capacity distribution in microgrids can vary significantly based on local conditions, available resources, energy demand patterns, and project objectives. Therefore, the distribution of total capacity by primary application in microgrids can differ from one project to another.

Sensor data: Install sensors throughout the microgrid to capture real-time data on solar radiation, wind speed, temperature, energy usage, and battery levels.

Data Monitoring and Analysis: Monitor and analyze the sensor data to understand the microgrid's energy production and consumption patterns. Identify periods of high renewable energy generation and peak demand.

Load Management: Based on the analysis, implement load management strategies to balance the energy supply and demand. This can involve adjusting the operation schedules of energy-intensive processes or implementing demand response programs to incentivize energy usage during high renewable energy availability periods.

Energy Storage and Distribution: Utilize batteries or pumped hydro storage to store extra renewable energy during high production. Stored energy may be sent during low renewable energy output or high demand to sustain supply.

Predictive Analytics: Utilize advanced analytics techniques to forecast renewable energy generation, demand patterns, and storage requirements. This enables proactive planning and optimization of the microgrid operation.

Feedback and Control: Continuously monitor the microgrid's performance and use feedback loops to adjust system parameters and improve energy balancing. This feedback and control mechanism ensures that the microgrid operates optimally and efficiently.

Evaluate machine learning model: The evaluation measures include accuracy, precision, recall, F1-score, and AUC. Cross-validation and train-test splits may also evaluate model performance on unseen data to prevent overfitting or underfitting.

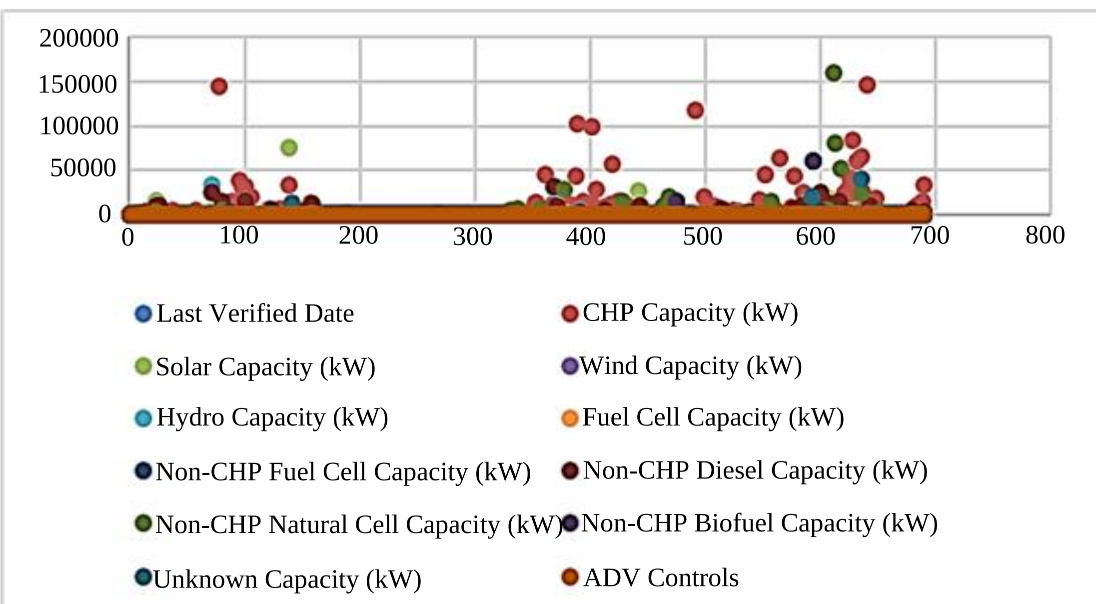

Fig. 5 Total capacity distribution by primary application

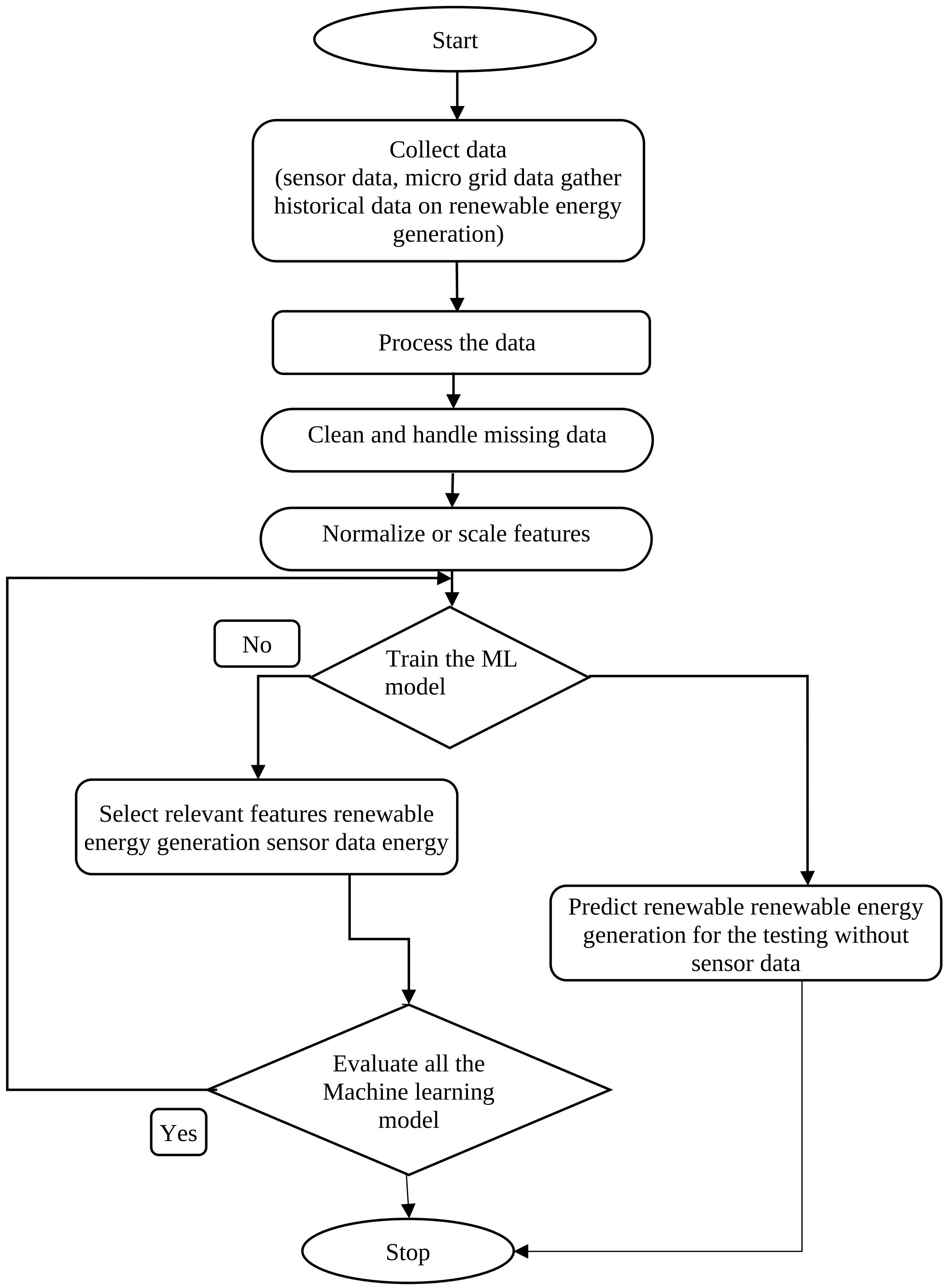

Fig. 6 Flow chart of the machine learning models working

5. Result and Discussion

Before discussing the findings, we discuss several fundamental techniques for evaluating ML models' performance during training and testing. We calculate several metrics and produce a confusion matrix to evaluate the models' ability to classify data. The model parameters and the experiments' results are shown below. To classify data, the multiclass classification uses True Positive (TP), False Positive (FP), and False Negative (FN) categories. Positive photos are classified as true positives. Misclassifying some samples as belonging to the group under examination is called a false positive, whereas misclassifying some samples from the current class as belonging to another class is called a false negative. These characteristics are measured through a variety of performance tests. The effectiveness of the approaches is assessed using the following criteria:

Precision: Precision is the proportion of accurately predicted positive samples out of all anticipated class samples. In rare incidents or circumstances with serious repercussions, it reduces false positives.

Higher precision means fewer false positives and greater model confidence in optimistic predictions. Precision evaluates a model's positive prediction accuracy. Divide the number of true positive (TP) forecasts by the total of TP and FP predictions. Precision formula:

Precision = TP/(TP+FP).

Recall: It indicates the proportion of positive results correctly discovered. Recall=TP/(TP+FN)

F1-Score/F1-Measure: The maximum F1 score is 1. The harmonic mean of accuracy and recall ensures that each measure contributes equally to the outcome. The F1 score is particularly useful for imbalanced datasets when each class has a different number of samples. It analyses a model's ability to make accurate positive predictions and minimise false positives and negatives.

F−score=(2×Precision×Recall)/(Precision+ Recall)

Table 1. Precision, recall, f1-score accuracy of SVM classifier

Support Vector Machine Classification				
	Precision	Recall	F1-score	Support
Agriculture	0.00	0.00	0.00	2
Airport	0.00	0.00	0.00	1
City/Community	0.50	0.14	0.22	
College/University	1.00	0.29	0.45	17
Commercial	0.59	1.00	0.74	69
Hospitals/Healthcare	0.27	0.23	0.25	13
Military	0.00	0.00	0.00	6
Multi-Family	0.00	0.00	0.00	3
Public Institution	0.00	0.00	0.00	1
Research Facility	0.00	0.00	0.00	4
Schools	0.00	0.00	0.00	6
Water Treatment/Utility	0.00	0.00	0.00	2

Table 2. Precision, recall, f1-score accuracy of random forest classification

Random Forest Classification 70%				
	Precision	Recall	F1-score	Support
Agriculture	1.00	0.50	0.67	2
Airport	0.00	0.00	0.00	1
City/Community	0.40	0.43	0.41	14
College/University	0.58	0.41	0.48	17
Commercial	0.79	0.93	0.85	69
Hospitals/Healthcare	0.50	0.54	0.52	13
Military	0.86	1.00	0.92	6
Multi-Family	0.67	0.67	0.67	3
Public Institution	0.00	0.00	0.00	1
Research Facility	0.00	0.00	0.00	4
Schools	0.67	0.33	0.44	6
Water Treatment/Utility	1.00	0.50	0.67	2
Accuracy			0.70	138
Macro Avg	0.54	0.44	0.47	138
Weighted Avg	0.66	0.70	0.67	138

Accuracy: The maximum F1 score is 1. The harmonic mean of accuracy and recall ensures that each measure contributes equally to the outcome. The F1 score is particularly useful for imbalanced datasets when each class has a different number of samples. It analyses a model's ability to make accurate optimistic predictions and minimise false positives and negatives.

Support: When talking about a dataset's "support," we refer to the number of examples that fall under each class. It is essential for social groups' inequalities since it clarifies how such groups are distributed. The dataset is kept constant for the following investigation while the models and classifiers change.

5.1. Tools and Programming Language Used for CNN Model Training

Anaconda with Visual Studio Code simplifies data science development. Data scientists and machine learning practitioners love it because it simplifies Python environment setup and maintenance, has excellent code editing, and allows interactive data analysis using Jupyter Notebooks.

The Tables 1-3 describes the analysis of microgrid dataset analysis concerning sensor data. Random Forest, Support Vector Machine (SVM) Classification, and AdaBoost Classification are crucial for accurate and efficient decision-making. Each model achieved 70%, 57% and 54%, respectively, as shown in Fig 7.

Table 3. Precision, recall, f1-score accuracy of random adaboost classification

AdaBoost Classification				
	Precision	Recall	F1-score	Support
Agriculture	0.00	0.00	0.00	2
Airport	0.00	0.00	0.00	1
City/Community	0.00	0.00	0.00	14
College/University	0.00	0.00	0.00	17
Commercial	0.53	1.00	0.70	69
Hospitals/Healthcare	0.00	0.00	0.00	13
Military	0.86	1.00	0.92	6
Multi-Family	0.00	0.0	0.00	3
Public Institution	0.00	0.00	0.00	1
Research Facility	0.00	0.00	0.00	4
Schools	0.00	0.00	0.00	6
Water Treatment/Utility	0.00	0.00	0.00	2
Accuracy			0.54	138
Macro Avg	0.12	0.17	0.14	138
Weighted Avg	0.30	0.54	0.39	138

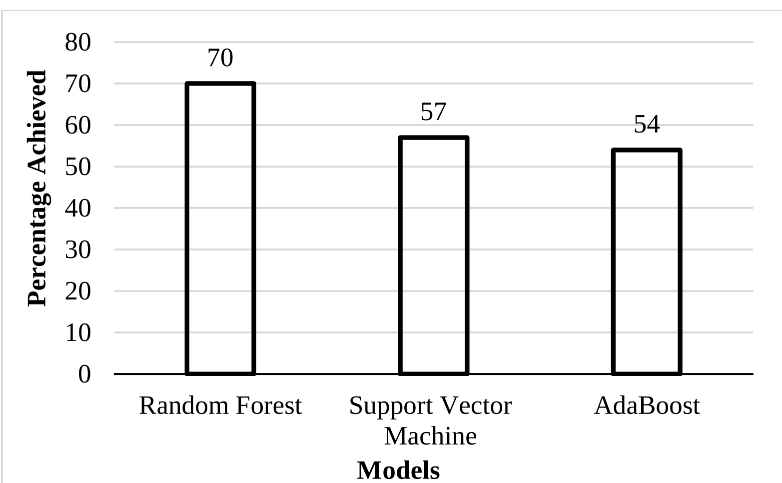

Fig. 7 Accuracy machine learning models comparision

6. Conclusion

Random Forest is an ensemble learning method that combines multiple decision trees to make predictions. It excels at handling large datasets with high-dimensional features and provides robustness against overfitting. SVM Classification, on the other hand, is decisive in dealing with both linear and non-linear data by creating optimal decision boundaries. It works well with small to medium-sized datasets but might suffer from scalability issues.AdaBoost Classification is an ensemble technique that iteratively improves the model's performance by emphasizing misclassified data points. It is efficient and versatile for various datasets, including those with imbalanced classes. However, it can be sensitive to noisy data. The accuracy of each model in microgrid sensor data analysis depends on Rigorous model evaluation and hyperparameter tuning are essential to identify the most suitable model for a given microgrid scenario is random Support Vector Machine achieved 70% accuracy compared to Random Forest and AdaBoost Classification. An ensemble of these models or a combination of their outputs can often yield even better results by leveraging their strengths and compensating for their weaknesses.

Data Availability

The Data used to support the findings of this study will be shared upon request.

Acknowledgment

Authors are grateful to the management and Directors Faculty of Engineering and Technology, Jain (Deemed-to-be University).

References

[1] Lijun He et al., “A Day-Ahead Scheduling Optimization Model of Multi-Microgrid Considering Interactive Power Control,” *2019 4th International Conference on Intelligent Green Building and Smart Grid (IGBSG)*, Hubei, China, pp. 666-669, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[2] Esmat Samad, Ali Badri, and Reza Ebrahimpour, “Decentralized Multi-Agent Based Energy Management of Microgrid using Reinforcement Learning,” *International Journal of Electrical Power & Energy Systems*, vol. 122, p. 106211, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[3] Puli Dilliswar Reddy, and L. Rama Parvathy, “Prediction Analysis using Random Forest Algorithms to Forecast the Air Pollution Level in a Particular Location,” *2022 3rd International Conference on Smart Electronics and Communication (ICOSEC)*, Trichy, India, pp. 1585-1589, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[4] Meijin Lin, and Haoyuan Luo, “Log AdaBoost: Optimizing Polylog Loss Function to Improve the Generalization Performance of AdaBoost,” *2022 37th Youth Academic Annual Conference of Chinese Association of Automation (YAC)*, Beijing, China, pp. 958-961, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[5] Yue Wu et al., “Use of Radiomic Features and Support Vector Machine to Discriminate Subjective Cognitive Decline and Healthy Controls,” *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, Montreal, QC, Canada, pp. 1762-1765, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[6] Xiaodong Liang, and Chowdhury Andalib-Bin-Karim, “Harmonics and Mitigation Techniques through Advanced Control in Grid-Connected Renewable Energy Sources: A Review,” *IEEE Transactions on Industry Applications*, vol. 54, no. 4, pp. 3100-3111, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[7] Payman Rezaei et al., “A Novel Energy Management Scheme for a Microgrid with Renewable Energy Sources Considering Uncertainties and Demand Response,” *2022 12th Smart Grid Conference (SGC)*, Kerman, Iran, pp. 1-5, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[8] M. F. Roslan et al., “Microgrid Control Methods Toward Achieving Sustainable Energy Management,” *Applied Energy*, vol. 240, pp. 583-607, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[9] Jennifer Cronin, Gabrial Anandarajah, and Olivier Dessens, “Climate Change Impacts on the Energy System: A Revie of Trends and Gaps,” *Climatic Change*, vol. 151, no. 2, pp. 79-93, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[10] H. C. Bloomfield et al., “Quantifying the Sensitivity of European Power Systems to Energy Scenarios and Climate Change Projections,” *Renewable Energy*, vol. 164, pp. 1062-1075, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[11] Ali Q. Al-Shetwi et al., “Grid-Connected Renewable Energy Sources: Review of the Recent Integration Requirements and Control Methods,” *Journal of Cleaner Production*, vol. 253, p. 119831, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[12] Siva Prasad Chowdary Machina, Sriranga Suprabhath Koduru, and Sreedhar Madichetty, “Solar Energy Forecasting using Deep Learning Techniques,” *2022 2nd International Conference on Power Electronics & IoT Applications in Renewable Energy and Its Control (PARC)*, Mathura, India, pp. 1-6, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[13] Sunil M P, and Hariprasad S A, “Facial Emotion Recognition using a Modified Deep Convolutional Neural Network Based on the Concatenation of XCEPTION and RESNET50 V2,” *SSRG International Journal of Electrical and Electronics Engineering*, vol. 10, no. 6, pp. 94-105, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[14] Fermín Rodríguez et al., "Very Short-Term Wind Power Density Forecasting through Artificial Neural Networks for Microgrid Control," *Renewable Energy*, vol. 145, pp. 1517-1527, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[15] L. Maria Anthony Kumar, S. Murugan, and A. Therasa Alphonsa, "Robust Human Activity Recognition using Equilibrium Optimizer with Deep Extreme Learning Machine Model," *SSRG International Journal of Electrical and Electronics Engineering*, vol. 10, no. 5, pp. 1-13, 2023. [CrossRef] [Publisher Link]

[16] Vaibhav Aggarwal et al., "Integration of Waste Management Companies in Micro Grids through Machine Learning," *2021 Second International Conference on Electronics and Sustainable Communication Systems (ICESC)*, Coimbatore, India, pp. 1881-1886, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[17] Beh Xiao Yan et al., "Development of a Self-Adaptive Based Renewable Energy Management in Smart Micro Grid," *2021 IEEE 15th Malaysia International Conference on Communication (MICC)*, Malaysia, pp. 54-59, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[18] Ramya Ravibarathi, and Tamilarasu Viswanathan, "Assimilation of Gesture using 9 Axis Acclerometer Sensor," *SSRG International Journal of Electrical and Electronics Engineering*, vol. 5, no. 2, pp. 1-4, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[19] Jaiganesh P M, and B. Meenakshi Sundaram, "IoT Based Power Monitoring System," *SSRG International Journal of Computer Science and Engineering*, vol. 8, no. 4, pp. 4-7, 2021. [CrossRef] [Publisher Link]

[20] Georgios Tziolis et al., "Comparative Analysis of Machine Learning Models for Short-Term Net Load Forecasting in Renewable Integrated Microgrids," *2022 2nd International Conference on Energy Transition in the Mediterranean Area (SyNERGY MED)*, Thessaloniki, Greece, pp. 1-5, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[21] Nachat Nasser, and Meghdad Fazeli, "Buffered-Microgrid Structure for Future Power Networks; A Seamless Microgrid Control," *IEEE Transactions on Smart Grid*, vol. 12, no. 1, pp. 131-140, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[22] Guishuo Wang, Xiaoli Wang, and Xiang Gao, "Improved Seamless Switching Control Strategy for AC/DC Hybrid Microgrid," *IEEE Access*, vol. 9, pp. 55790-55801, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[23] U. S. Department of Energy Combined Heat & Power and Microgrid Installation Databases, [Online]. Available: https://doe.icfwebservices.com/downloads/microgrid

[24] Bogdan Marinescu et al., "Dynamic Virtual Power Plant: A New Concept for Grid Integration of Renewable Energy Sources," *IEEE Access*, vol. 10, pp. 104980-104995, 2022. [CrossRef] [Google Scholar] [Publisher Link]