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Intelligent Energy Ecosystems: A Hybrid Framework for Real-Time Prediction and Distributed Resource Allocation

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Abstract

The increasing global demand for sustainable energy solutions has accelerated the integration of renewable energy systems, such as wind, solar, and hydroelectric power, with emerging technologies. This review explores the transformative role of Artificial Intelligence (AI) and Machine Learning (ML) in optimizing the efficiency, reliability, and scalability of these renewable energy systems. It highlights AI driven algorithms for predictive maintenance, energy forecasting, and dynamic grid management, addressing key challenges like energy storage, load balancing, and resource intermittency. Furthermore, the paper examines advanced ML techniques for improving grid resilience, optimizing energy storage solutions, and enhancing smart grid operations. By analyzing recent developments, this review provides insights into the potential of AI and ML in driving the next generation of intelligent renewable energy systems, with a particular focus on operational efficiency and sustainability.

Keywords

Renewable Energy, Artificial Intelligence, Machine Learning, Smart Grids, Energy Storage, Predictive Maintenance, Energy Optimization, Wind Energy, Solar Power, Hydroelectric Systems, Grid Management.

1. INTRODUCTION

The future energy system consists of several integral components, including renewable energies such as wind, solar, and hydro. However, their variability creates peculiar challenges that are now followed by problems of reliability and grid stability. Sensitive technologies will be crucial in addressing such challenges, and Artificial Intelligence has proved to be an indispensable tool for enhancing the generation, distribution, and storage of renewable energy [1]. This way of working has built renewable energy systems to become more efficient and reliable, as it involves the use of advanced algorithms in data analysis, pattern recognition, and prediction. As an example, machine learning models help to analyze large volumes of weather data for predicting energy production, and AI can change mechanisms for storing energy at different scales that balance supply and demand in real time. Thus, AI will help overcome the challenges produced by wind and solar, intermittent renewable sources, so that there can be a stable and efficient energy grid. The introduction of AI in smart grids has changed the patterns by which electricity is distributed and consumed. It makes it possible for the smart grids to track electricity flows in real time and further calibrate such flows to conform to demand, thus improving energy storage systems [2]. This paper discusses the applications of AI in renewable energy systems, from optimization techniques to energy storage solutions, and further into smart grids. The authors also present relative performance of several AI models while opening up gaps in current research, mostly concerning data standardization and scalability issues in AI-driven solutions for energy systems.

2. LITERATURE REVIEW

With increasing urgency and criticality of needed efficient, reliable, and sustainable energy solutions, AI and ML integration into renewable energy systems has emerged as an area of vital research interest. Optimization using AI methods has been applied in various domains of renewable energy, like wind, solar, and smart grid systems for efficient production, storage, and distribution of energy. The review will synthesize the latest development status, core methodologies, and future trends of AI applications in renewable energy systems [3].

A. AI in Optimizing Wind Energy

Because of its inherent variation, wind energy is characterized as erratically behaved in nature and calls for a strong and precise forecasting along with optimization techniques. A few AI and ML methods have emerged in recent times, some of which more robust than the traditional methods, in which the output accuracy for wind energy has improved with greater predictability [4]. Deep learning models, especially LSTM networks, seem quite promising in capturing complex temporal dependencies in the wind data. To the contrary, deterministic techniques along with multi-objective optimization have been used for the unit sizing optimization of hybrid wind energy systems, focusing on maximum efficiency and lowest possible operational costs [1]. These AI-based approaches are essential to the real-time management of wind energy; they allow for sharper forecasting and adjustments within the system in ways that might reduce waste of energy and increase overall efficiency.

B. AI and Machine Learning in Solar Energy Systems

Solar energy systems particularly pose specific challenges because of the intermittency of solar resources generated due to variability in weather and seasonal alterations. To these challenges, machine learning models have been applied; they have helped in forming more accurate solar energy forecasts that have optimized the idea initially. Probabilistic models helped very much in assessing the long- term performance evaluation of solar systems and also implied reliability and sustainability of such a system. Hybrid models involve the use of several AI techniques together, which include CNN and models of neural nets. Hybrid models attain much more accurate predictive estimates than the previous older models [2].

C. AI in Smart Grid Integration

The concept of the smart grid brought in change in renewable sources integration in the energy systems. Energy producing, consuming, and storages nicely manage the variability of renewables sources such as wind and solar. AI provides a significantly critical role in optimizing decisions regarding the operation of smart grid in optimizing the collected analytics in real-time as well as predictive modelling [5]. For instance, distributed control systems are employed through AI in improving advanced infrastructure with meters for efficient balancing in real time between supply and demand to ultimately improve the stability and reliability of the grids. To obtain an evolutionary algorithm for smart grids, it maximized the configuration of multi-renewable energy systems, increased energy generation, reduced the costs, and improved the reliability in the system [6]. AI solutions are very much in need as they are of high importance because of the reason that they grow with their evolution and scalability [7].

D. Challenges and Research Gaps

It is incredible how much can be progressed in the field of AI- driven renewable energy optimization yet, at the same time, quite a number of problems are still surfaced. An example for this illustration includes the quality of data that needs to be trained in AI models. Low or noisy quality of such data may severely impede model performance. Though the results are promising for most AI techniques relative to controlled environments, deployment in real cases is restricted due to the complexity of extant infrastructures as well as integration problems. Lastly, a significant research gap still prevails for developing countries where renewable energy systems have the potential to greatly work but technically and infrastructurally would face a challenge. Moreover, another area that is under researched is the long-term socio-economic impact of AI adoption in renewable energy systems that should be further researched to understand the actual and beneficial implications that come with it.

E. Emerging Trends and Future Directions

Among the other emerging trends on the radar for AI-driven optimization of renewable energy include the multimodal usage of source data sources such as satellite imagery and IoT data, thereby raising the precision in the predictions made. Probabilistic models and even reinforcement learning algorithms, where the uncertainties in forecasts could be quantified, are also under much attention these days to improve the decision-making aspects associated with grid management. That is forward-looking, creating new and more streamlined and robust interdisciplinary collaborations that will assume the complexity of integrating AI in renewable energy systems. Innovative data management techniques and policy implications will very be essential in leading AI advancement so as to align it with the objectives of sustainability worldwide. Hybrid renewable energy systems and smart grids by optimizing AI present opportunities for the future of innovation and large-scale deployments [5].

F. Enhancing Energy Storage Systems through AI

Energy storage systems, such as batteries, play a critical role in balancing supply and demand, especially when integrating intermittent renewable energy sources like wind and solar. AI algorithms have significantly advanced energy storage optimization by improving charge-discharge cycles, predicting battery degradation, and integrating storage with renewable energy systems. Predictive models using AI enable better estimation of storage needs based on fluctuating renewable energy generation and grid demand. For instance, reinforcement learning algorithms have been used to optimize battery management systems (BMS), enhancing storage capacity and extending battery lifespan [8][10][13]. Moreover, the integration of AI with thermal energy storage and other innovative storage technologies ensures reliable energy availability even under fluctuating generation conditions [10][12].

G. AI for Predictive Maintenance and Fault Detection

AI-driven predictive maintenance has become a cornerstone of renewable energy systems, ensured system reliability and minimized downtime. Machine learning algorithms analyse historical and real-time sensor data to detect anomalies and predict equipment failures. This is particularly impactful for wind turbines and solar panels, where mechanical or electrical issues can disrupt energy production. Techniques such as convolutional neural networks (CNNs) and support vector machines (SVMs) are increasingly applied to image-based fault detection, enabling early intervention and reducing maintenance costs [8][11][13]. Furthermore, AI-driven diagnostics streamline maintenance schedules, ensuring efficiency and cost-effectiveness in renewable energy systems [12][16].

H. AI-Driven Policy and Energy Market Analysis

In addition to technical advancements, AI is revolutionizing energy market analysis and policy development. Energy markets, often influenced by fluctuating renewable energy contributions, benefit from AI models that predict price volatility, optimize energy trading strategies, and identify the most cost-effective integration points for renewables. For instance, AI tools help policymakers simulate scenarios, assess economic impacts, and develop incentives for renewable energy adoption. These models support the creation of energy policies that balance environmental sustainability with economic viability, paving the way for widespread renewable energy deployment [5][14][15].

3. PROPOSED METHODOLOGY

1. Data Collection and Pre-processing

The core dataset for this research work is the London Smart Meters Dataset, which was collected and compiled by Low Carbon Company, that is an energy company in London. This dataset can be downloaded from Kaggle, which has a list of the daily energy usage of all of London's localities. Also used a data set mapping the localities of London to coordinates. Lastly also had utilized the Boundaries of London's Statistical GIS dataset available from the official UK Government web sites for analysis that consisted of the exact Shape file of London. It begins with loading the data of daily energy consumption. There will be no rows having Null. Assigned an alphabet code to each Locality so that they are easily categorized. Converted the Date column into proper Date Time format, then extract Day, Month, Year, and Day of Week. There choosed four values; Month and Year are the ones used to be on top of population trend whereas Day and Day of the Week are ones used in capturing different kinds of patterns of energy use during different days of the week. For instance, a residential area would consume more energy during the weekend, whereas a commercial area consumes more energy during a weekday.

The central dataset used for this research was the daily_dataset of the London Smart Meters Dataset. The dataset contains the statistics of the energy usage of the different areas of London for more than two years. This time series dataset was used to train the model. It contains various statistics relating to energy usage of that locality. These features were used to make the model more accurate. Even though only the energy_mean was the feature to be predicted, the addition of these other measures meant that the model didn't underfit. For instance, a single extreme value in a dataset can skew it mean. The mean of the data set sounds more reasonable in such situations.

	A	B	C	D	E	F	G	H	I
1	LCLid	day	energy_median	energy_mean	energy_max	energy_count	energy_std	energy_sum	energy_min
2	MAC000131	15-12-2011	0.485	0.432045455	0.868	22	0.239145797	9.505	0.072
3	MAC000131	16-12-2011	0.1415	0.296166669	1.1160001	48	0.281471318	14.2160001	0.031
4	MAC000131	17-12-2011	0.1015	0.1898125	0.685	48	0.188404686	9.111	0.064
5	MAC000131	18-12-2011	0.114	0.218979167	0.676	48	0.202919279	10.511	0.065
6	MAC000131	19-12-2011	0.191	0.325979167	0.788	48	0.259204962	15.647	0.066
7	MAC000131	20-12-2011	0.218	0.3575	1.077	48	0.28759657	17.16	0.066
8	MAC000131	21-12-2011	0.1305	0.235083333	0.705	48	0.222069649	11.284	0.066
9	MAC000131	22-12-2011	0.089	0.221354167	1.094	48	0.267238875	10.625	0.062
10	MAC000131	23-12-2011	0.1605	0.291125	0.749	48	0.249076048	13.974	0.065
11	MAC000131	24-12-2011	0.107	0.169	0.613	47	0.150684669	7.943	0.065
12	MAC000131	25-12-2011	0.2175	0.3391875	0.866	48	0.263101199	16.281	0.069
13	MAC000131	26-12-2011	0.1495	0.261708333	0.838	48	0.244792744	12.562	0.066
14	MAC000131	27-12-2011	0.143	0.274	0.778	48	0.252127458	13.152	0.068
15	MAC000131	28-12-2011	0.1455	0.300520833	1.207	48	0.298680288	14.425	0.066
16	MAC000131	29-12-2011	0.152	0.307041667	0.888	48	0.264454634	14.738	0.066
17	MAC000131	30-12-2011	0.135	0.276854167	0.782	48	0.261185757	13.289	0.064
18	MAC000131	31-12-2011	0.1515	0.325729167	1.252	48	0.309888294	15.635	0.066
19	MAC000131	01-01-2012	0.151	0.256020833	0.812	48	0.225249412	12.289	0.068
20	MAC000131	02-01-2012	0.134	0.252083333	0.851	48	0.23721297	12.1	0.068
21	MAC000131	03-01-2012	0.1475	0.2355	0.674	48	0.209995339	11.304	0.068
22	MAC000131	04-01-2012	0.101	0.216270833	0.731	48	0.215205764	10.381	0.065
23	MAC000131	05-01-2012	0.146	0.331020833	0.786	48	0.27337337	15.889	0.063
24	MAC000131	06-01-2012	0.1025	0.223645833	0.765	48	0.241187002	10.735	0.064
25	MAC000131	07-01-2012	0.0995	0.137395833	0.572	48	0.094495466	6.595	0.065
26	MAC000131	08-01-2012	0.137	0.2305	0.857	48	0.221244449	11.064	0.068
27	MAC000131	09-01-2012	0.1345	0.260354167	0.771	48	0.243380491	12.497	0.065
28	MAC000131	10-01-2012	0.1435	0.201291667	0.694	48	0.16980514	9.662	0.068

daily_dataset

Figure 1. Central database snapshot

Tomorrow.io Weather API provides real-time, hyperlocal weather data customized to the solar and wind energy forecast. The data are all of the critical parameters - the solar irradiance, the wind speed, the wind direction, the temperature, the cloud cover. For the generation of photovoltaic energy, it offers the sun intensity and atmospheric conditions. It provides the advanced wind profile and optimizes the efficiency of turbines and predicts power production. This API applies sophisticated meteorological models with machine learning for higher accuracy and global coverage. Integration of this tool would help renewable energy systems to make their operation, planning, and resource utilization process more efficient in tackling the challenges presented by the variability of resources. The Tomorrow.io Weather API is indispensable for building solutions toward sustainable energy, empowering organizations with data-driven insights toward dependable renewable energy production as required by the increasingly rising need for reliable sources.

2. Training the Model:

This integrates energy usage prediction with weather-based solar and wind energy production forecasting to optimize energy source recommendations. The model first predicts the energy usage of a locality using independent variables such as Locality ID, Day, Month, Year, and Day of the Week. Energy Usage is the dependent variable. The data is divided 80:20. The high-performance choice for this regression task was XGBoost, specifically XGBRegressor. Hyperparameters such as n_estimators and learning_rate are tuned, and the model is evaluated using metrics such as MAE, MSE, RMSE, R- squared, and EVS. In the second part, weather data from an API is used to estimate daily solar and wind energy production by considering factors like Solar Global Horizontal Irradiance (GHI) and Wind Speed. These predictions are aggregated to estimate yearly energy production. The two energy sources are then compared, and the more efficient source is recommended based on the predicted yearly output. To further refine the predictions, an XGBoost model is trained using historical weather data to improve the accuracy of future energy production forecasts. In this integrated approach, it enables optimized energy decisions by recommending the most efficient energy source based on weather conditions and Historical Data.

3. Designing and Integrating GUI:

It can be used for predicting the energy demand in any areas and has a Date Picker so that the user could easily choose any day by putting in the desired day by which the energy demand should be predicted. Below that Date Picker, a button has been given such that after it has been clicked, the procedure for calculating the energy demand of that selected date would start. This section helps in determining the energy needs for certain dates, thus making it useful for energy suppliers to plan resources effectively. It therefore means that the other GUI part presents to localities the distribution of total produced energy proportional to their estimation of expected demand. It includes a text box where the amount of energy generated is typed in and another Date Picker for the date selection of energy generation. When the total energy and date are introduced, there is a bottom button of the textbox so that the user could send the energy appropriately. The section relates the amount of energy generated to the demand forecasted, giving ways for users to efficiently make a way about resource management. Together, the two sections give an intuitive interface for energy providers to predict and allocate energy efficiently, thus acquiring better management and distribution of renewable energy resources.

4. Predicting Energy:

The system relies on a predictive model, namely XGBoost to forecast energy demand on a certain date from the historic dataset. It provides a prediction for energy demand for each locality so that energy distribution would be even more efficient. Heatmap: The energy demands are depicted in the geographical map with localities and colors based on predicted demand for energy. The darker the color on the map, the more energy that will be required. Thus, with such a tool, the users can easily identify where the energy is going to be needed in larger quantities. The GUI also shows the total energy demand for the chosen date together with the minimum amount of energy the power plant should produce. Furthermore, one can download the prediction data in an Excel file for further analysis. The Projection Solar Power factors are used to predict the daily output of the solar are the available roof area that can be dedicated to mounting the solar panels in square meters, the measured value for the Global Horizontal Irradiance of solar in kWh/m²/day, and the mounted panel angle. Assuming that the efficiency value is 60% and the panel efficiency level is 20%, then the applied formulae for daily predicting the production of solar is:

$$\text{Daily Energy} = \text{Usable Area} \times \text{Solar GHI} \times \text{Efficiency} \quad (1)$$

Summing up the daily energy prediction over the year will approximate the total yearly solar energy production. This will allow the user to make an assessment about the energy that could have been generated by the solar panels on the rooftops all through the year considering the prevailing weather conditions. It will predict the wind energy. The amount of wind energy produced is estimated by taking wind speed and rotor diameter as predictors of the daily energy from a wind turbine. Considering the parameters, it will use air density at 1.225 kg/m³, compute the rotor swept area in terms of rotor diameter and wind speed in m/s, and use turbine efficiency set at 35%. The formula to calculate daily power output from the wind turbine is:

$$\text{Daily Power}=0.5\times\text{Air Density}\times\text{Swept Area}\times(\text{Wind Speed } 3)\times\text{Efficiency}\times\text{Hours per Day} \quad (2)$$

It will, however take into account the wind's kinetic energy while making its way over the turbine-rotor. The number of energy units computed happens in kilowatt hours; a sum of the sums for every day is accumulated in a year to gauge how much energy could potentially be produced from the same amount of wind.

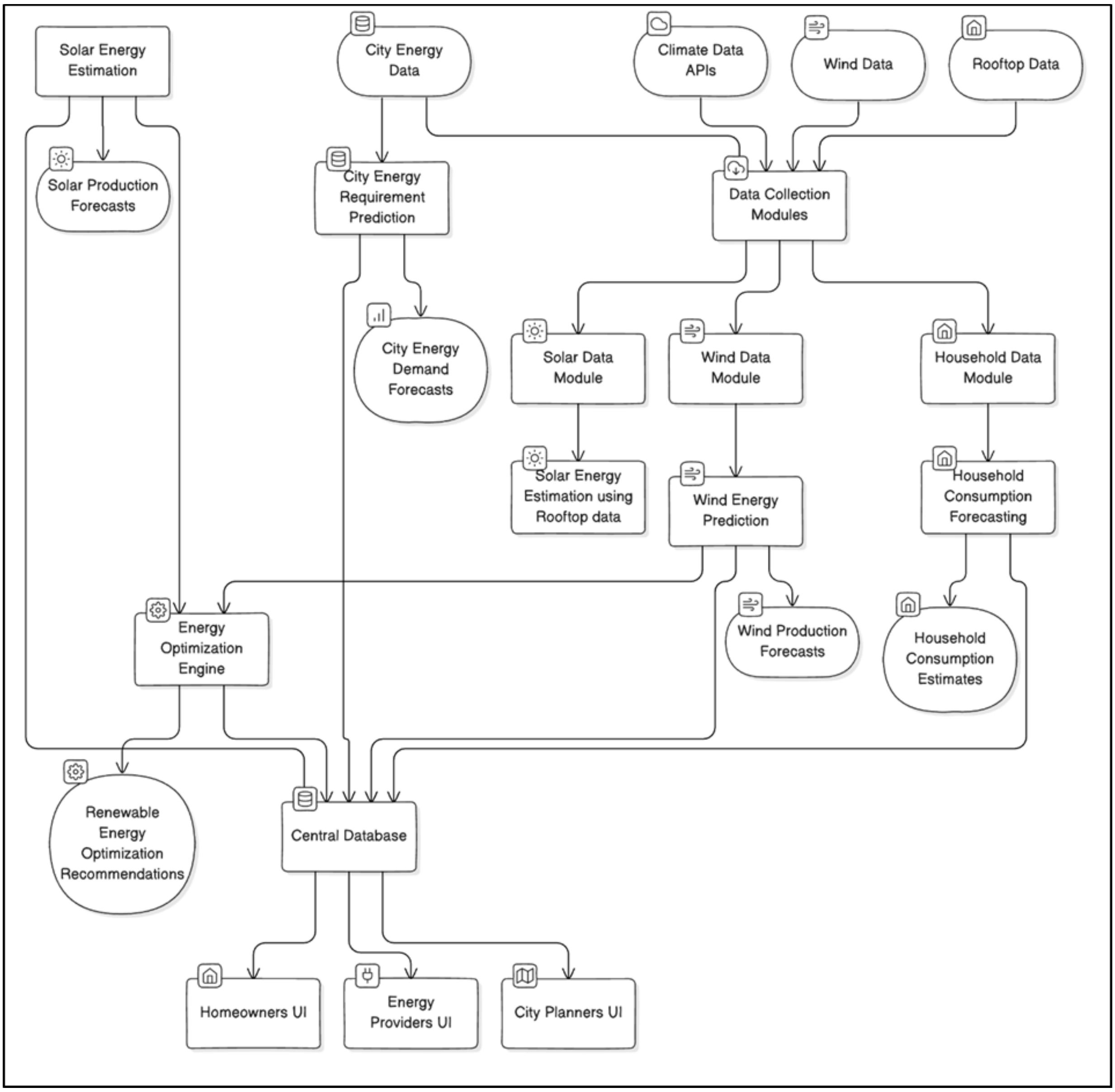

Figure 2. The monitoring system of energy distribution

The Distribution of Energy is PuLP library, through LP techniques, addresses the job of energy distribution. Optimization has to be carried over all the energy that was dispatched to every locality. Here in this work, previously established prediction models were taken regarding demand at every locality while passing the total energy which got generated on that specified date to the system. Then, PuLP solves the LP problem with two key constraints: The total energy distributed across all localities cannot exceed the total energy generated and, given an LP problem, each locality gets at least its predicted energy demand. The goal here is to distribute the energy so that every locality gets exactly the amount it needs according to the demand. The results of the distributions are presented in a form of heatmap, where more energy supplied to each place is marked by color intensity in which the darker the area then the more energy it allocates. Users can even download their energy distribution in the Excel file for further analyzing purposes. The system also checks whether the energy grid can meet the demand and alerts the user if any locality is assigned less energy than its projected demand.

4. RESULTS

The comparison table below shows that XGBoost is the best model for predicting energy usage in smart grids. For MAE, MSE and RMSE, the lower the value, the better it is. On the other hand, for R-squared and EVS, the higher the value, the better it is. With a mean absolute error (MAE) of 0.097657, a mean squared error (MSE) of 0.027027, and a root mean squared error (RMSE) of 0.164398, it attained excellent metrics. Its Explained Variance Score (EVS) and R-squared were also 0.060278. LSTM was unable to outperform XGBoost while displaying respectable results with an MAE of 0.103389 and an RMSE of 0.171382. With a high MAE of 126.107720 and low R-squared and EVS values, ARIMA, on the other hand, dramatically underperformed, demonstrating the efficacy of XGBoost for precise energy forecasting in smart grids.

TABLE II.Model Details

Model	MAE	MSE	RMSE	R-squared	EVS
XGBoost	0.09766	0.027027	0.164398	0.60278	0.06028
LSTM	0.10339	0.027027	0.170382	0.019213	0.020209
ARIMA	26.1077	21821.704	147.7217	-1.462597	-0.001475

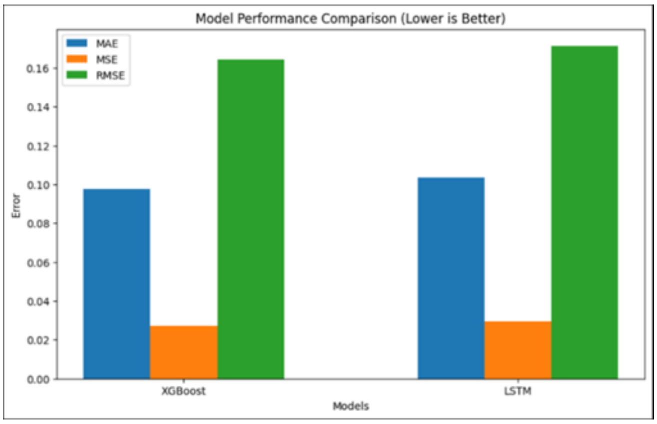

Fig. 5. Model Performance Comparison

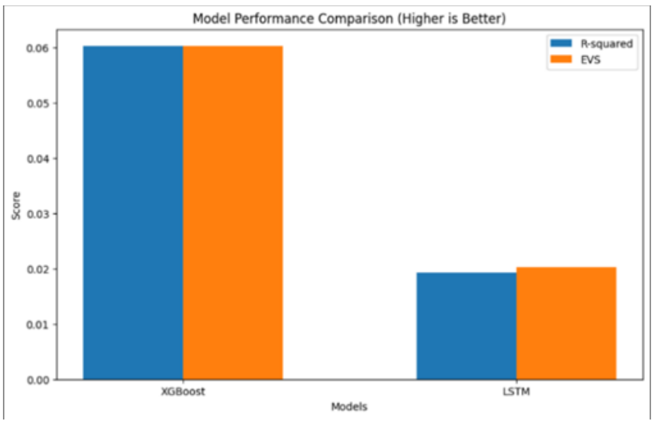

Fig. 6. Model Performance Comparison

Table II shows the result of the Hyperparameter tuning that the study performed. The XGBoost model was tested with varying values to two Hyperparameters, n_estimators and learning_rate. The metrics used to test the performance were MAE, MSE, RMSE, R-squared and EVS. MAE, MSE and RMSE are the error rates of the

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model, and these should be as small as possible. R-squared and EVS is how good the model is in terms of variance. These two numbers go between -1 and 1 where 1 is the best and -1 is the worst. Out of all the permutations I had tested, 150 n_estimators and a learning_rate of 0.2 results in the most accurate model.

Table III shows the same results as Table II, but it shows ranks instead of values, making it easier to read.

TABLE III. Error rate and accuracy with varying hypermeters

n_estimators	learning_rate	MAE	MSE	RMSE
50	0.01	0.99301	0.028186	0.1678
50	0.1	0.097921	0.027273	0.1651
50	0.2	0.097683	0.027027	0.1643
100	0.01	0.09886	0.027027	0.1671
100	0.1	0.097657	0.027027	0.1643
100	0.2	0.09759	0.026865	0.1639
150	0.01	0.09866	0.027805	0.1667
150	0.1	0.097585	0.026925	0.1640
150	0.2	0.097635	0.026833	0.1638

TABLE III. Error rate and accuracy with varying hypermeters – Ranked

n_estimators	learning_rate	MAE Rank	MSE Rank	RMSE Rank	R-Squared Rank
50	0.01	9	9	9	9
50	0.1	6	6	6	6
50	0.2	5	5	5	5
100	0.01	8	8	8	8
100	0.1	4	4	4	4
100	0.2	2	2	2	2
150	0.01	7	7	7	7
150	0.1	1	3	3	3
150	0.2	3	1	1	1

The following figures show the UI of the software created during the study. It sports a simple design for ease of use.

Figure 7. Output Image 1

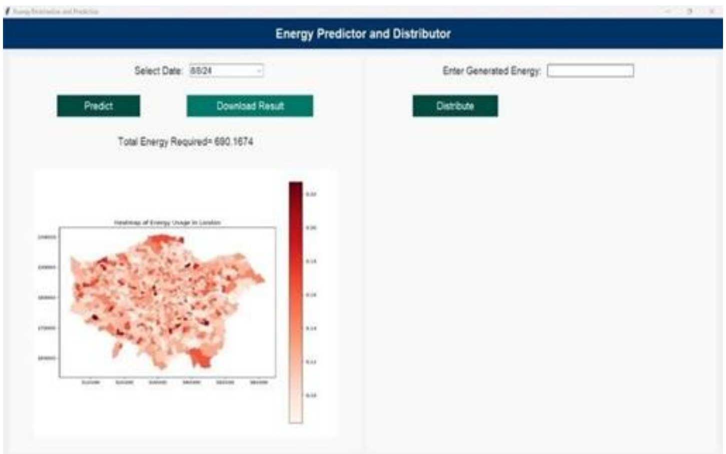

Figure 7. Output Image 2

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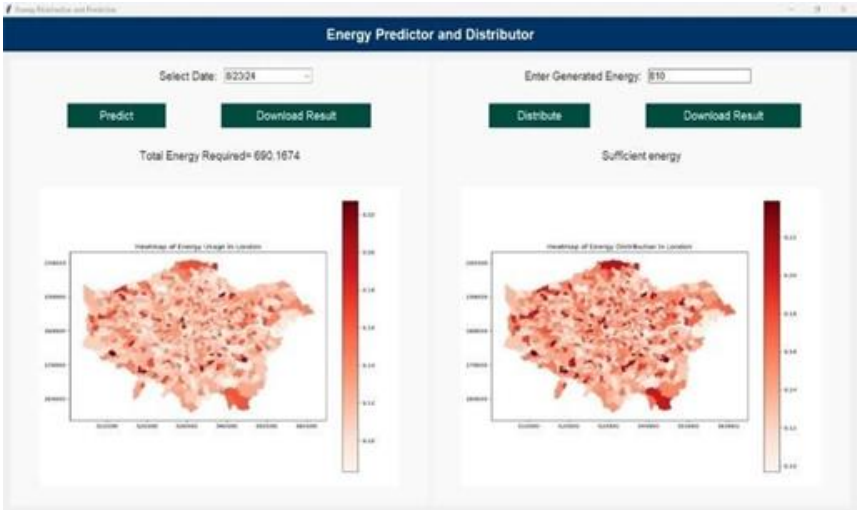

Figure 7. Output Image 3

UI for Predicting Solar and Wind Energy:

Figure. 10 Output Image 1

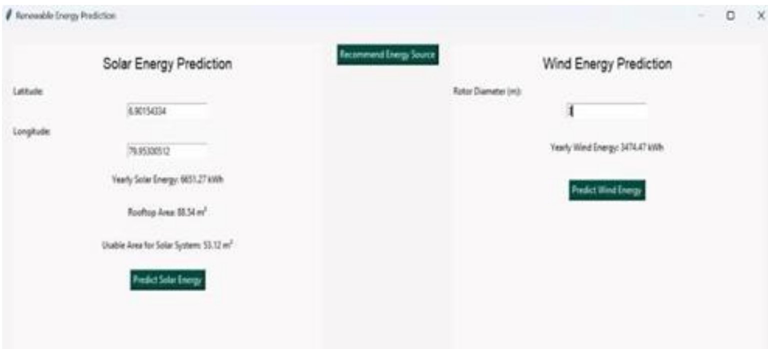

Figure. 11 Output Image 2

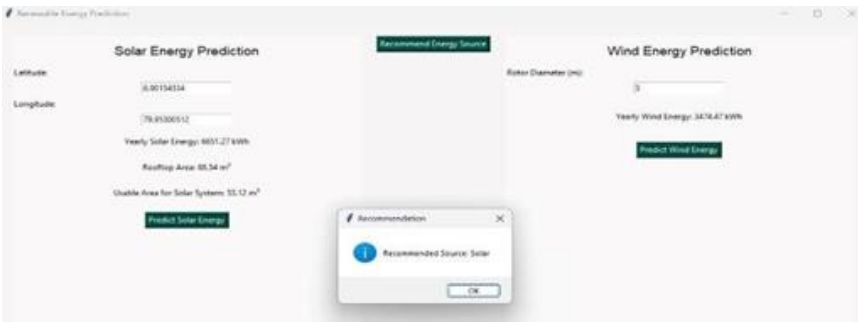

Figure. 12 Output Image 3

5. CONCLUSION

This paper proposed a hybrid framework for renewable energy prediction and distribution using machine learning and optimization techniques. The system integrates historical energy data, weather information, and XGBoost-based prediction to forecast energy demand and recommend optimal renewable energy sources. The results demonstrate that XGBoost provides superior accuracy compared to other models. Additionally, linear programming optimization ensures efficient energy distribution, while the developed GUI improves usability through visualization and analysis features. Overall, the proposed framework enhances renewable energy utilization, grid stability, and decision-making. Future work includes incorporating additional data sources, expanding to multiple regions, and integrating real-time IoT-based monitoring for improved performance and scalability.

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