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RESEARCH ARTICLE

Assessing the Feasibility of Integrating Renewable Energy: Decision Tree Analysis for Parameter Evaluation and LSTM Forecasting for Solar and Wind Power Generation in a Campus Microgrid

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ABSTRACT The world has embarked on a road to sustainable energy production. As a result, countries have turned to microgrid developments. This article aims to study the feasibility of renewable sources such as solar PV and wind power for integrating a microgrid campus, taking the example of a case in East Africa, precisely the case of the University of Djibouti. We applied the weather parameters to evaluate the solar and wind potential with the Decision Tree method for analyzing and classifying the degrees of solar radiation and the consistency of wind speed. These data are spread over eight years to establish and capture seasonal changes and prove the accessibility of renewable sources in a specific site. The results were compared to Random Forest, Logistic Regression, K-Nearest Neighbors, Support Vector Machine, and Naïve Bayes classifiers, which showed that the performance of classifying the Decision tree outperformed all other methods with an accuracy of 0.99321. The second work of this article explored the forecasting of the possible powers predicted with the LSTM deep learning method by the generation of the Solar PV array and wind turbines which were simulated on PVLib and Windpowerlib. The results are favorable, and the LSTM has performed well on the different hyperparameters. With the combination of machine learning and deep learning, it was possible to theoretically conclude the integration of renewable energies since we investigated all the potential possibilities in evaluating meteorological parameters and power predictions. Finally, decision scores from the Decision Tree architecture and the LSTM features were integrated to form a hybrid Tree-LSTM fusion method. It introduces a novel architectural concept that can effectively address sequential data and harness the non-linear capabilities of decision trees. The proposed model was validated by tuning the hyperparameters. Enhancing the maximum depth of the model increases the performance at a certain point, and conversely, reducing the minimum sample split improves the model performance. These contributions will help to create sustainable energy systems and increase the transition to a clean CO2 environment.

INDEX TERMS Decision tree, LSTM, microgrids, energy integration, feasibility, decision making.

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NOMENCLATURE

AUC	Area Under the Curve.
BESS	Battery Energy Storage System.
Bi-LSTM	Hybrid Bidirectional LSTM.
CNN	Convolutional Neural Networks.

DER	Distributed energy resources.
G(h)	Global Horizontal Radiation.
Gb(n)	Global Normal Direct Radiation.
Gd(h)	Diffuse Horizontal Radiation.
GRU	Gated Recurrent Unit.
IEA	International Energy Agency.
IR(h)	Infrared Radiation.
JRC	European Commission's Joint Research Centre.
KNN	K-Nearest Neighbors.
LSTM	Long Short-Term Memory.
MCDA	Multi-Criteria Decision Analysis.
MPC	Model Predictive Control.
PVGIS	Photovoltaic Geographical Information System.
RES	Renewable Energy Sources.
RH	Relative humidity.
ROC	Receiver Operating Characteristics.
SP	Specific Pressure.
SVM	Support Vector Machine.
T2m	Temperature at 2m height.
WD10m	Wind direction at 10m.
WS10m	Wind speed at 10m

I. INTRODUCTION

Djibouti is a country abundant in RESs. It boasts a remarkable potential of 1000 MW for geothermal energy [1], with extensive windy regions [2] and a predominantly sunny climate that persists throughout the year [3]. Looking ahead to 2035, Djibouti has ambitious plans to harness RES primarily [4]. In line with this vision, the University of Djibouti has recently installed a mini-power plant that combines solar PV modules, wind turbines, and battery energy storage. This microgrid has a capacity of 19 kW for the solar panels and 6.5 kW for the wind turbine. The university aims to reduce its attachment to fossil fuels and participate in reducing Co2 emissions. In this case, it is imperative to properly integrate these technologies with the exciting electrical network [5]. Nevertheless, with the intermittent use of renewable energies, it is advisable to calculate and model the feasibility of renewable energy integration [6]. This model must serve as an example of renewable energy integration into educational institutions in the East African region that generally have the same climate and potential for renewable energy. In recent years, the integration of RESs in microgrids has increased considerably due to their capacity to provide a sustainable energy landscape [7], [8], [9]. Microgrids are localized energy systems that offer increased energy efficiency, reduced transmission losses, and improved reliability [10]. Djibouti, a country characterized by its warm climate, has long grappled with significant electricity challenges throughout its history [11]. However, there is an opportunity to profit from the application of this technology. With its favorable geographical location, the government of Djibouti is actively investing in harnessing solar and wind-based microgrids [12]. Several sources affirmed that Djibouti is a prime candidate for implementing renewable energy projects [3], [5], [11]. These studies [3], [13], [14], [15], [16], [17], [18], and [19] have demonstrated the energy potential of Djibouti through different marches and methods based on critical climatic data such as solar radiation and wind speed. Conducting feasibility studies is essential when transitioning from intermittent RES. Reference [20] proposed an energy forecasting model using a GRU to predict solar and wind energy fluctuations and decide on renewable integration in tested scenarios. Conversely, solar and wind penetration levels could be studied so far in the literature. Reference [21] tried an MPC with the help of the LSTM. LSTM models are used analogously to detect the high penetration levels of RES [22]. The correlation and dependencies between RES are studied in [23] by forecasting the power generation of different sources with CNN, Attention-based Long Short-Term Memory (A-LSTM), and Auto-Regression model. Reference [24] added an analysis based on the PV power network by investigating the high impedance caused by the RES volatility. In almost every energy assessment, climate meteorological data are the key to determining potential risks in solar or wind sources. Reference [25] suggested applying different machine learning methods to the long-term mean monthly wind speed prediction by finding geographical information such as longitude and latitude. Reference [26] suggested a BiLSTM, which proved high accuracy compared to the other machine learning methods. Furthermore, the forecasting of PV output power is pivotal as a parameter, given the significant penetration of PV systems [27] The University of Djibouti's Balbala campus is located to the southeast of Djibouti City in an arid place with a particular climate from the other regions. Starting with the general approximate models, it would be difficult to quickly judge the feasibility of integrating the RESs into the grid. Reference [28] contested the wind speed evaluation on the wind energy produced in a site near the border with Ethiopia with a different climate from the University of Djibouti Balbala. This research presents plausible climate parameters for possible energy generation, such as solar radiation, temperature, humidity, and wind speed, as presented in this research [29]. Thus, the meteorological data of this site will be analyzed by a decision tree machine learning algorithm to assess the feasibility of renewable energy integration. By studying with decision trees the solar radiation, temperature, humidity, and wind speed, we will be able to see and identify the correlations that confirm the reliability of the project. Then, in a second work, we will make predictions of the power produced by the solar PV array and the wind turbine of the microgrid with the LSTM deep learning algorithm method. Although the concept of RES integration in microgrids has often been reached in the literature, the specific context of Djibouti's Balbala site and its unique geography and climatic conditions, as well as the feasibility of integrating renewable energy sources into the university microgrid, remains a research gap. The site presents a unique geography and climatic conditions with distinctive energy consumption of the university campus. Prior research in this area needs to be improved in Djibouti.

The significant contribution of this research paper is to investigate the feasibility and potential of integrating renewable energy sources into the university microgrid at the Djibouti Balbala Site. The possible contributions of the research paper proposed in this paper are: (i) Study of RES integration into campus microgrid with the unique geography, climatic conditions, and energy consumption of Djibouti's Balbala site. (ii) Classifying meteorological parameters using Decision Tree machine learning. (iii) Predicting solar and wind power generation from the microgrid by applying LSTM deep learning. (iv) Addressing the Djibouti microgrid context by contributing to the research of RES integration. (v) Proposing a new hybrid Tree-LSTM Fusion Model for learning climatic parameters. (vi) Building an example study for the East African region microgrid solar PV and wind-based with similar climate and energy potential. The introduction will present the general concept of the paper and previous research and give the upcoming works. The proposed model's methods and outliers are described in the proposed model. The research method presents the mathematical modeling of the Decision tree and LSTM components. In the results and discussion, the findings and results analysis are depicted. Finally, the study is concluded with a conclusion that resumes the paper.

II. RELATED WORK

Integrating renewable energy sources has shown a fruitful area for exploring sustainable energy solutions. This section will compare the key and relevant studies to our research. In recent years, methods have been proposed to study the integration of renewable energies in the microgrid. The assessment of microgrid integration in rural areas of Sub-Saharan Africa is studied in this review [30]. Their study showed that sustainable energy solutions are not limited to urban centers but can be extended to resource-constrained regions, aligning closely with our focus on the University of Djibouti campus in East Africa. The application of machine learning techniques is explored in this paper [31] for long-term wind power forecasting. The study used five traditional machine learning algorithms based on daily wind speed data across diverse geographical locations. The authors employed algorithms such as Random Forest and Support Vector Machine to predict energy generation from renewable sources. This work relates to our study as we compared various classification methods, but they differ as they produce regression predictions. Furthermore, the authors of this reference [32] proposed LSTM neural networks for short-term power forecasting in wind farms. Their research performed accurately the prediction of wind power generation. Therefore, we extended this approach to predict power generation from solar PV arrays and wind turbines. Reference [33] proposed a review that assembles the MCDA concept for inquiring about energy systems' sustainability. Their approach is based on the technical aspects and environmental factors for evaluating energy solutions. The IEA [34] emphasizes the importance of developing sustainable energy solutions yearly. Thus positioning our research within the context of striving for global scarce energy. In this reference [35], the objective was to investigate integrating renewable energy sources into smart grids. Their study advanced some new control strategies for optimizing the grid. The papers of this review [36] explored methods for designing and optimizing hybrid solar and wind combinations. Their contributions are beneficial for the energy mix microgrid Djibouti case. Reference [37] proposed an evaluation of different storage systems. Their study considered the impact of batteries and supercapacitors on energy source integration. Reference [38] has further explored community microgrids fostering resilience to generate renewable energy. Reference [39] presented microgrid development's policy and regulatory aspects by investigating the policies that can yield microgrid developments in the United States, the European Union, and China to understand the regulatory landscape of long-term sustainability. The authors of reference [40] examined the demand side energy management efficiency for microgrids. Their research is valuable for energy consumption and distribution within microgrid systems. Reference [23] also focused on energy forecasting by utilizing machine learning and meteorological data for accurately predicting solar and wind power generation. The review of this reference [41] proposed a deep examination of the resilience of microgrids against the natural disasters caused by global warming and climate change for maintaining power supply. These strategies can be beneficial when analyzing renewable sources' integration into the electrical grid. The reference [42] proposes an economic case analysis, which considers the costs and the long-term benefits. This study targets the financial viability of microgrid decision-making. The paper [43] suggested an analysis of the possibility of integrating renewable sources in academic campuses. This study bases the educational and research opportunities on incorporating natural sources into campus infrastructure. These references highlighted [44], [45], [46] the grid resilience for effectively providing strategies and operations for proposed an ameliorated grid. Moreover, the reference [47] addressed a comprehensive survey paper on MGs and ESS integration to control challenges. DER control with the advancement of microgrid systems is the future of an efficient smart grid [48]. Microgrids are generally isolated or grid-connected and connected to energy sources or neither. These different operation modes signify the improvement of the DERs control systems [49]. A novel approach for determining the reliability uncertainties capacity of the microgrid is proposed in this paper [50]. This study analyzed both supply and demand risk uncertainty. The results were convenient as they were tested on an islanded hotel microgrid. Microgrid economics are fundamental in building the microgrid and investing in sustainable energy. This paper [51] assessed a business case for evaluating natural gas technologies. The main results were structured around controlling the carbon emissions from these plants. In addition to the microgrid energy market, cybersecurity importance has been highlighted in recent years with the developments of technology. The reference [52] addressed the roles of the cybersecurity utility in distributed electric power systems. The integration of renewable energy sources in microgrids is simulated through various tools in the literature [53], [54], [55]. This paper presented a plan for demand response integration in the microgrid. The study proposed to shift from bottom-up microgrid planning to reshape traditional power system planning approaches [56]. This study emphasized the architecture's communications functions when integrating DER into the grid and compared the current centralized, unidirectional grid structure [57]. Techno-economics consists of a crucial step in maximizing DER usage. This paper [58] focused on the solar-based microgrid to study the economic and efficiency sustainability. This reference [59] offered an examination of the various challenges present in the photovoltaic power industries for reducing emissions and costs. This related work sums up the related studies on renewable integration in microgrids. It groups energy solutions and machine learning. We draw from these studies the landscape of microgrid development.

III. PROPOSED MODEL

Figure 1 visually depicts the method flow, illustrating the sequential steps in exploring energy integration within the model. For a comprehensive understanding, please refer to the subsequent subsections for a detailed explanation:

Step 1: We began collecting weather data for each of the parameters in the study.

Step 2: We prepared and processed the collected data for analysis in a suitable format.

Step 3: We employed a Decision Tree Classifier to classify whether the climatic data parameters are within the desired range. This step consists of training the Decision Tree for feasibility prediction purposes.

Step 4: We analyzed the results of the Decision Tree classification. We interpreted the feasibility of each parameter and understood which ones were within the desired range. We then identified important relations from the classification results.

Step 5: We introduced a step to model energy consumption and microgrid modeling characterization based on climatic data.

Step 6: We introduced PVLib and Windpowerlib. We modeled the PV and wind power that will be predicted with the LSTM model. This step is primordial for integrating PVLib and Windpowerlib with the existing workflow.

Step 7: We transitioned to predicting power production using the LSTM deep learning method.

Step 8: We trained using the required evaluation metrics and predicted the LSTM model using the historical PV and wind power data simulated in PVLib and Windpowerlib.

Step 9: We proposed a Tree-LSTM Fusion Model in this step. This model will learn climatic parameters by utilizing the decision scores of the Decision Tree and the LSTM features from the LSTM sequential data model to create a fusion layer.

Step 10: We then summarized the findings from the Decision Tree classification, LSTM power prediction, and power modeling with PVLib and Windpowerlib.

In this part, we expose the proposed model to reach the feasibility process of renewable energy resources. It consists of four major processes: Data preparation, Parameter evaluation using the Decision Tree classification method, the power prediction from the LSTM deep learning method, and the Tree-LSTM fusion method.

A. DATA PREPARATION

In the first step of the research methodology, data processing is performed to prepare the dataset for further analysis. The dataset is sudden to transformations and adjustments to ensure the data is consistent for machine learning exploration. A series of operations exist before applying the data to the Decision tree and LSTM methods. The time frame was initially changed to a DateTime format to provide temporary interpretations. Next, we divided the data into numerical and DateTime features. The Min-Max operation scaled the normalization of the numerical features. The data will be ready to examine and arrive at results by defining these operations.

B. PARAMETER EVALUATION USING DECISION TREE ANALYSIS

In our study, we used the decision tree classifier to classify whether the parameters of the climatic data are in the desired range. This interval relates to the maximum operating condition of the power generation. The model yields rules that identify the right situation for the integration into the microgrid of renewable energy sources that combine climatic conditions and energy production.

C. POWER GENERATION FORECASTING USING LSTM

After having classified the feasibility of the different parameters of the climatic data and having interpreted the feasibility of all the parameters included in the interval, we also tried to predict the power produced by the machine learning LSTM model. This model is based on the history of the energy produced by wind and solar power. By analyzing them, the LSTM can give a model capable of predicting the power produced by the microgrid. This prediction provides a plus to the planning and optimization of the integration of renewable energies in the microgrid.

D. COMBINING THE DECISION TREE AND THE LSTM METHODS

Next, we proposed to combine the Decision Tree and the LSTM methods. To test their complementary strengths, we tested the Decision Tree and LSTM fusion in this part.

TABLE 1. Summary of research studies in renewable energy integration into microgrids.

Reference	Focus Area	Methodologies	Key Findings
[30]	Microgrid Integration	Solar and Wind Assessment	Feasibility in Sub-Saharan Africa.
[31]	Machine Learning	Prediction Models	Assessing renewable potential.
[32]	Power Forecasting	LSTM for Wind	Accurate wind power prediction.
[33]	Sustainability	Multi-Criteria Analysis	Holistic energy sustainability.
[34]	Global Transition	Policy Analysis	Worldwide clean energy trends.
[35]	Smart Grids	Advanced Control	Efficient energy management.
[36]	Hybrid Systems	Design Optimization	Maximizing energy output.
[37]	Energy Storage	Technology Evaluation	Enhanced microgrid stability.
[38]	Community Microgrids	Local Generation	Empowered communities.
[39]	Policy Frameworks	Regulatory Analysis	Facilitated microgrid deployment.
[40]	Efficiency	Operational Strategies	Optimized energy consumption.
[23]	Forecasting	Machine Learning	Improved solar and wind prediction.
[41]	Microgrid Resilience	Disaster Preparedness	Resilient microgrid design.
[42]	Economic Analysis	Cost Evaluation	Financial viability insights.
[43]	Campus Integration	Sustainability in Education	Renewable energy in academia.
[44]–[46]	Grid Resilience	Resilience Strategies	Enhanced grid resilience.
[47]	Energy Storage	Battery Integration	Optimized energy storage.
[48]	Control	Control Algorithms	Efficient microgrid control.
[49]	Distributed Resources	DER Integration	Evaluated distributed resources.
[50]	Reliability Assessment	Reliability Modeling	Quantified microgrid reliability.
[51]	Market	Business Models	Assessed microgrid market models.
[52]	Cybersecurity	Security Measures	Enhanced microgrid cybersecurity.
[53]–[55]	Modeling	Simulation Tools	Modeled microgrid performance.
[56]	Demand Response	Demand Management	Integrated demand-side management.
[57]	Communication	Network Infrastructure	Reliable microgrid communication.
[58]	Techno-Economic Analysis	Cost-Effectiveness	Economic evaluation of microgrids.
[59]	Industrial Integration	Industrial Microgrids	Addressed industrial energy needs.

IV. RESEARCH METHOD

We referred in this part to the methods and frameworks employed in the results section. This section contains the choice of methods that shape the study. The decision Tree method is introduced, followed by the LSTM method, the fusion of the proposed Tree-LSTM method, and therefore the energy system modeling tools are explained.

A. DECISION TREE

The decision tree was applied successfully in several applications, such as finance, healthcare, and engineering. The decision tree method is a supervised machine learning that can construct a decision tree [60]. This tree model is performed in classification, regression problems, and anomaly detection. The decision tree consists of nodes, branches, and leaf nodes. The nodes of the tree permit to

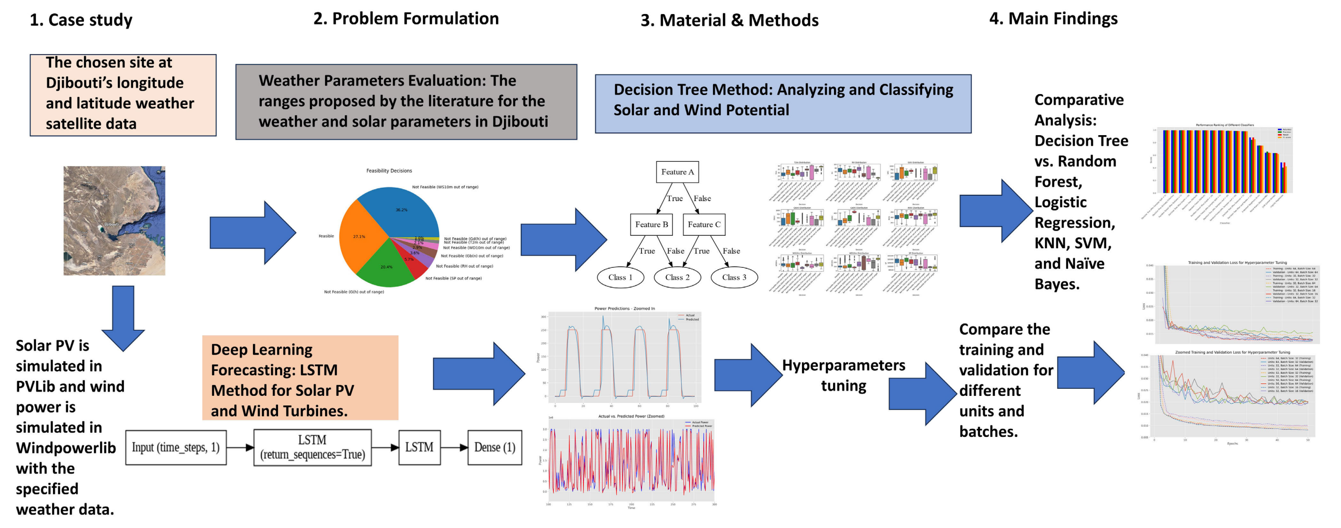

FIGURE 1. Feasibility of renewable microgrid: solar PV and wind power integration at the university of djibouti.

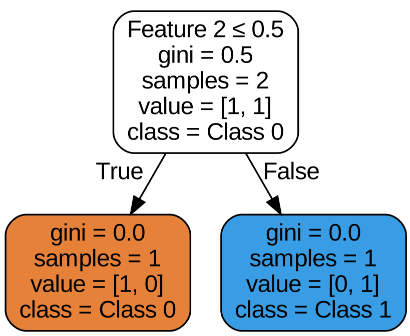

FIGURE 2. Decision tree architecture.

denote the feature, and the branch states the decision based on that feature. Then, leaf nodes give the class label or the result.

1) NODES

The internal node is prominent in decisions and training the data. Features require characteristics of the node. Based on the information received at the node level, the data is split, and this will determine how to split the data with a value of tolerance, knowing that each node corresponds to a feature [61]. This selection is essential because it induces data division from hereditary nodes. Figure 2 shows an example of a decision tree. The nodes signify that they split the criteria given by the input data of the feature. They are separated to show the associated decisions, the features, and the threshold value.

2) BRANCHES

Branches are made to interconnect nodes that represent different decisions [60], [61]. This generates the condition of the features. These conditions are evaluated in the given samples. Thus, the decision follows from left to right or from right to left. The branches are simply the possible results of each node. The branches make it easier to understand the data by multiplying the analysis directions. This notion allows us to analyze and conclude the decision tree decision-making process in all possible scenarios.

3) LEAF NODES

The leaf node is the node sought or desired to reach the final decision of the model [60], [61]. When the possibility leads to this node, the decision points of the method are finished. The class label and regression values represent leaf nodes. Leaf nodes resume the final prediction offered by the decision tree model prediction.

4) DECISION TREE EVALUATION ACCURACY

The predictive performance of this decision tree method is measured at the leaf node level [62]. Because the latter has an essential influence on the effectiveness of the prediction, suppose that the information leaves at a point of node i and has a feature f_i and a tolerance value θ_i of the data separation. Assume also that a training dataset D has samples and class labels. As stated before, the decision tree method chooses to split the data according to the varying conditions of the features. Therefore, it is judicious to determine the choice of the best feature and the best threshold value. The Gini impurity measures the rate of impurity level in the dataset, and it is expressed as:

$$Gini(D) = 1 - \sum^{k} (p^k)^2 \tag{1}$$

where p^k is the proportion of samples in class k. Entropy is also proposed to rate the impurity, and it is expressed as:

$$Entropy(D) = -\sum^{k} p^k \log_2(p^k) \tag{2}$$

TABLE 2. Evaluation metrics and formulas.

Evaluation metric	Measurement	Formulas
Accuracy	The correctness of the model	Accuracy = NCP / TNP
Precision	The positive true proportion	Precision = NTP / (NTP + NFP)
Recall	Sensitivity rate of the true positive in the data	Recall = (NTP) / (NTP + NFN)
F1 score	The balance between Precision and Recall	F1 score = 2 * ((Precision * Recall) / (Precision + Recall))

These evaluations will help to detect the impurity of the data, in other words, the data quality during the splitting. These impurities were also subject to reductions during data splitting. This operation is measured and evaluated by the information gain parameter, and it is expressed as:

$$\text{Information Gain}(D, f) = \text{Impurity}(D) - \sum^{k} \left(\frac{|D^k|}{|D|} \right) \times \text{Impurity}(D^k) \tag{3}$$

where D^k represents the subset of D that satisfies the split condition. After evaluating these metrics, the decision tree algorithm should choose the most significant gain in each node. Apart from these metrics, the performance of the classification prediction is evaluated by the specialized classification metrics. These are Accuracy, F1 score, Precision, and Recall [63]. Table 2 gives their definition and formulas where NCP is the number of correct predictions, TNP is the total number of forecasts, NTP is the number of true positives, NFP is the number of false positives, and NFN is the number of false negatives.

B. LSTM

LSTM is widely used in applications such as language translation, time series data, etc. LSTM is a variant of recurrent neural networks.

1) LSTM MODEL

This method has the advantage of the presence of memory to store information that can be deposited over periods such as short-term. The design objective concept of the LSTM is the same as the GRU, and it is to tackle the problem of the vanishing gradient problem. The LSTM architecture consists of an input gate, a forget gate, a cell state, and an output gate. These mechanisms have different roles. For instance, the gates are made for the stability of the transmission of information, and the cell is the constituent that allows it to have a memory generating to store information in the short term. The input and forget gates comprise sigmoid activation functions σ to perform their gate role [64]. The input gates are denoted by $i(t)$, and the forget gates are represented by $f(t)$. The formulas of the gates are expressed as:

$$i(t) = \sigma(W_i * [h(t-1), x(t)] + b_i) \tag{4}$$

$$f(t) = \sigma(W_f * [h(t-1), x(t)] + b_f) \tag{5}$$

The state of the cell $C(t)$ is gotten by using the previous cell information $\hat{C}(t)$. In contrast to the gates, the cell uses the hyperbolic function *tanh* to activate [64]. Their formulas are given as follows:

$$\hat{C}(t) = \tanh(W_c * [h(t-1), x(t)] + b_c) \tag{6}$$

$$C(t) = f(t) \cdot C(t-1) + i(t) \cdot \hat{C}(t) \tag{7}$$

Finally, the output gate also uses the sigmoid function σ to activate, and its formula is as follows [64]:

$$o(t) = \sigma(W_o * [h(t-1), x(t)] + b_o) \tag{8}$$

The W_i, W_f, W_c, and W_o represent the model weights. The model's biases are the b_i, b_f, b_c, and b_o. Furthermore, the LSTM setup process uses backpropagation. In this concept, the gradients are computed to update the parameters, allowing learning in the temporal space [64].

2) LSTM EVALUATION METRICS

The evaluation metrics are the measure of LSTM effectiveness predictions. From the existing literature, four widespread evaluation metrics are used to assess the accuracy of the LSTM models [65]. These metrics are generally Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Average Percentage Error(MAPE). Their formulas are expressed as follows:

$$MSE = \frac{1}{n} \sum (y - \hat{y})^2 \tag{9}$$

$$MAE = \frac{1}{n} \sum |y - \hat{y}| \tag{10}$$

$$RMSE = \sqrt{MSE} \tag{11}$$

$$MAPE = \frac{1}{n} \sum \left(\frac{|y - \hat{y}|}{|y|} \times 100 \right) \tag{12}$$

C. HYBRID TREE-LSTM FUSION APPROACH

This section proposes a machine-learning pipeline that combines the LSTM and Decision tree classifier functionalities. Figure 3 displays the system architecture of the model. This new methodology contains a Decision tree classification decision score, LSTM features from the LSTM sequential data model, and a fusion layer. This fusion offers several advantages, such as combining the ability to target sequential data with the non-linear capability of the decision tree. Moreover, the fusion will shorten the overfitting risks. Thus, it will adapt to every problem and dataset.

D. ENERGY SYSTEM MODELING

This part is dedicated to modeling a representative of energy generation forecasting in the integration feasibility assessment. Software tools like MATLAB, EnergyPlus, or HOMER Pro are mainly employed as simulation platforms

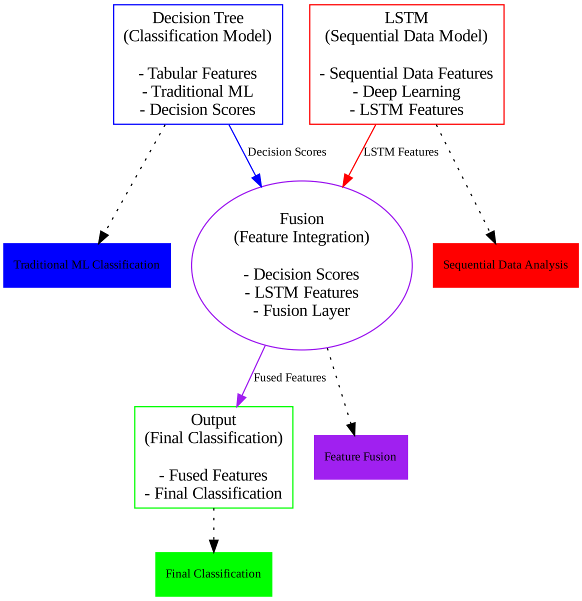

FIGURE 3. Hybrid Tree-LSTM fusion approach.

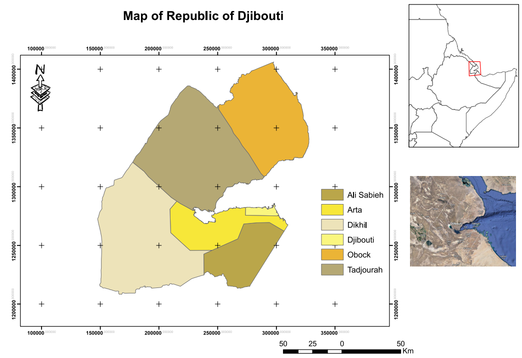

FIGURE 4. Study area map.

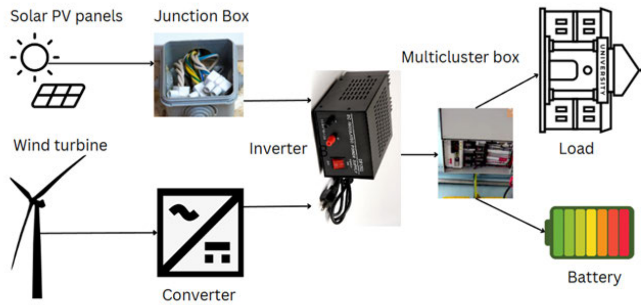

FIGURE 5. Synoptic diagram of the microgrid installation.

in energy feasibility studies. Nowadays, Python has stood out for its ease in programming mathematical concepts and reproducing them with extravagant models. This model will consist of meteorological data from the chosen site. With the help of the history of these data, which are solar radiation, wind speed, and temperature, the energies that the microgrid will potentially generate will be determined. The modeling in Python is mainly ensured by PVLib, which is a platform to simulate the performance of PV systems [66] for solar energy generation, and the Windpowerlib library for estimating the wind power output [67]. To identify the feasibility of this microgrid project, this study will exploit the microgrid's performance by observing the stability of the usage of wind and solar to integrate them into the grid and by planning their reliability. Moreover, the energy demand should be analyzed to logically represent this microgrid's potential load to assess whether a balance between production and consumption would be possible.

V. RESULTS AND DISCUSSION

In this part of the research, we applied the described methods to the university microgrid campus to test the proposed model. Figure 4 shows the localization of the University of Djibouti in the Republic of Djibouti on the map.

A. MICROGRID CHARACTERIZATION

The university microgrid is a critical component of this research study. Thus, its characteristics are vital for assessing the feasibility of renewable energy integration. Then, the energy generation capacity, load profile, and energy consumption patterns are determined. This campus microgrid has 19 kW solar photovoltaic systems, a 6.5 kW wind turbine, and a new, not yet installed battery energy storage system. Figure 5 shows the installed microgrid of the Balbala site campus in Djibouti, which comprises a solar PV array connected to a junction box, which is further connected to inverters. A wind turbine is also connected to a converter connected to the inverters. The inverters are subsequently linked to a multicluster box, facilitating two connections: one with loads and another with a BESS. The microgrid is designed to supply the electrical faculty building of the university, which consists of 20 classrooms. The load profile analysis for the regular electric grid supplying the university's electrical faculty building revealed a more fixed approximately 300 kW energy consumption. Generally, peak demand occurs when the building is occupied, driven by lighting, air conditioning, and equipment usage, and off-peak hours of power demand are shown when lower occupancy.

Figure 6 and Figure 7 show the load profile of the electrical faculty building for over 1-year. The x-axis is given time in days, and the y-axis is the energy consumption in Watts. We can conclude how to manage the microgrid's resources by analyzing the graph.

B. DATA PROCESSING

In this research study, meteorological data collection is the heart of assessing the feasibility of renewable energy integration in the Djibouti Balbala Site. PVGIS is used to download meteorological data from 2006 to 2016 from the specified latitude and longitude of the microgrid site. JRC

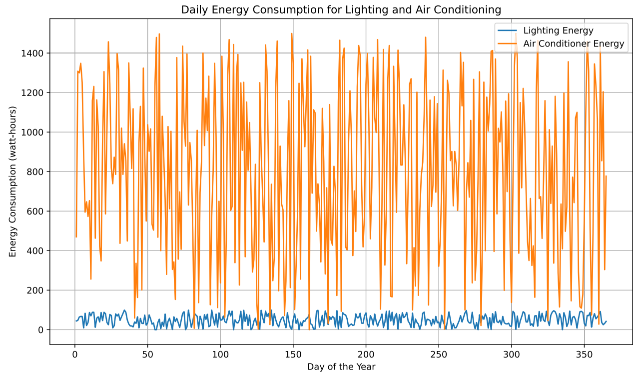

FIGURE 6. Daily energy consumption for lighting and air conditioning.

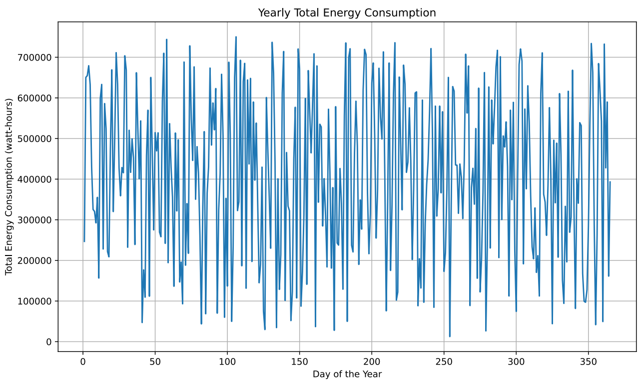

FIGURE 7. Yearly total energy consumption.

TABLE 3. Parameter statistics.

Parameter	Count	Mean	Std	Min	25%	50%	75%	Max
T2m	8760	29.04	4.45	19.12	25.59	28.58	31.92	41.52
RH	8760	64.88	17.84	15.55	52.65	67.75	79.70	97.10
G(h)	8760	254.59	342.58	0.00	0.00	0.00	540.00	1089.00
Gb(n)	8760	222.68	304.77	0.00	0.00	0.00	495.54	1004.84
Gd(h)	8760	93.39	121.08	0.00	0.00	0.00	182.00	496.00
IR(h)	8760	405.71	26.54	324.47	388.40	409.81	425.65	466.65
WS10m	8760	3.52	1.79	0.00	2.08	3.31	4.76	11.52
WD10m	8760	137.90	83.77	0.00	78.00	108.00	199.00	360.00
SP	8760	100514.13	493.71	99385.00	100072.00	100570.00	100948.00	101506.00

developed PVGIS, and it is an available online platform. We performed fundamental data analysis to gain initial thoughts into the dataset. Figure 8 shows the T2m, RH, and WS10m variations over time in UTC. Figure 9 shows the solar radiation components G(h), Gb(n), Gd(h), and IR(h) parameters over time in UTC. Table 3 refers to the statistics of each meteorological parameter.

C. SIMULATION RESULTS

1) DECISION TREE RESULTS ANALYSIS

Upon aggregating the ranges of climate parameter data, we assessed them in terms of their auspiciousness or suitability for energy development, as informed by the comprehensive literature research conducted in Djibouti [68], [69], [70], [71], [72], [73], [74], [75], [76], [77], [78], [79]. The pie chart in Figure 10 shows the distribution of diverse feasibility decisions through the dataset. Looking at this figure, each fragment represents a decision made

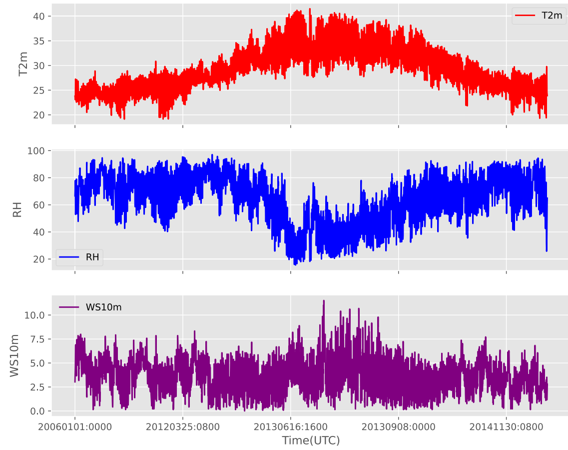

FIGURE 8. Environmental parameters and wind speed over time.

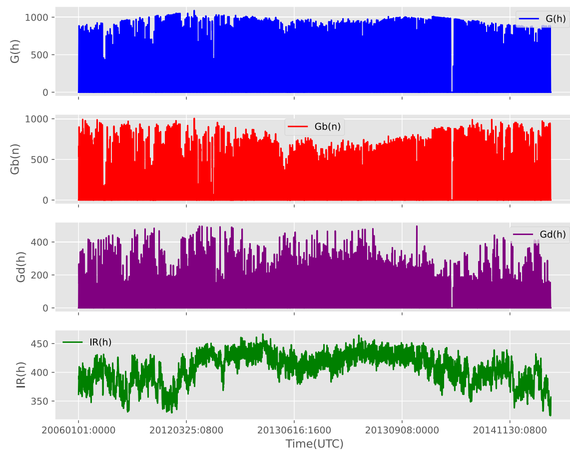

FIGURE 9. Solar parameters over time.

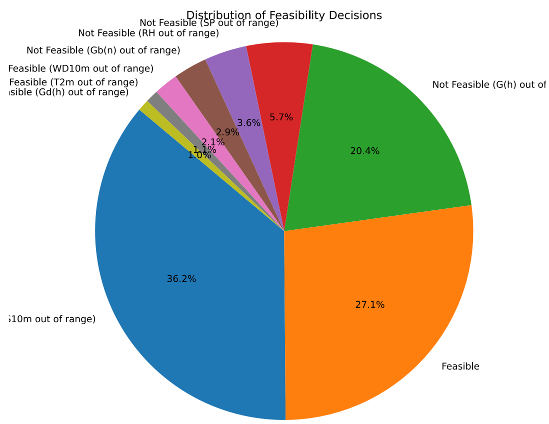

FIGURE 10. Distribution of diverse feasibility decisions.

on a parameter. The amplitude of the distribution depends on the repetitive occurrence of the decision. The decision tree method uses this labeling to perform an in-depth classification to manage optimal decisions better when integrating renewable energies.

The model will use training data to predict the labels made for the tested data. Figure 11 shows the decision tree classifier visual exploration constructed in Python, especially by the sci-kit-learn library. The outcomes of each parameter are then classified per the influence of individual features to understand the predictive modeling of the Decision tree. Figure 14 shows the feature importance for feasibility prediction. Within the decision tree classifier, we computed the Gini score, entropy, and information gain for each node in the decision tree.

The Gini score value near 0 indicates a pure node and a value near 1 tells an impure node. A lower entropy indicates better splits. Moreover, information gain measures effectiveness in splitting the training data. From the analysis in the Figure and appendix, we understood that the model effectively splits and minimizes impurity to maximize the information gain. At node 0, the Gini score indicates 0.748, meaning a high presence of impurity. Then, the impurity is reduced to 0, indicated by the zero Gini score and entropy values at node 3 and node 4, showing pure nodes that show no gain in information. These are leaf nodes that reveal the presence of a specific class. We can see from Figure 12 that the Gini scores, entropy, and information gain of the last nodes (96, 97, 98) are zero.

Therefore, decision-making processes are quickly resolved within this classification. Furthermore, this can be backed by the confusion matrix shown in Figure 13 to assess the classification performance. Within the matrix, the classifier predictions are compared to the actual values. A heatmap represents the confusion matrix to observe the model's true positives, true negatives, false positives, and false negatives. The correct predictions are in the diagonal of the confusion matrix. In Figure 13, all the elements except the diagonal are zero, demonstrating a solid identification of the class instances.

More importantly, it is knowledgeable that the model performed well from that information. It is also possible to compute the accuracy, precision, recall, and F1-score metrics from the confusion matrix, which are generally used to evaluate the decision tree model. The model data training and testing results showed that accuracy found a value of 0.993721. An accuracy of nearly 100% corresponds to a correct classification of the test instances. Additionally, the precision score of the decision tree model is settled to 0.993895, which is a sign that the resulting optimistic predictions were accurate with no false positives. The recall with a value of 0.993721 is an added justification that the model correctly identified all the positive instances. Summarized by the F1 score with a Value of 0.993748, the sum of recall and precision marks a balance between these two metrics. Even if these performance metrics point out the model's performance, validating these results with comparisons of other methods is crucial. The decision tree is analyzed by implementing different splitting and hyperparameter settings. We evaluated the decision tree by creating scenarios. The evaluation metrics are based on accuracy, precision, recall, and the F1 score. The default decision tree model has already been previously studied.

TABLE 4. Classifier performance metrics.

Classifier	Accuracy	Precision	Recall	F1-score
Decision Tree (Default)	0.993721	0.993895	0.993721	0.993748
Decision Tree (Max Depth = 10)	0.994292	0.994401	0.994292	0.994307
Decision Tree (Min Samples Split = 5)	0.996005	0.996043	0.996005	0.995997
Decision Tree (Min Samples Leaf = 10)	0.986872	0.988466	0.986872	0.98723
Decision Tree (Entropy Criterion)	0.995434	0.995517	0.995434	0.995435
Decision Tree (Max Leaf Nodes = 10)	0.880708	0.842842	0.880708	0.852653
Decision Tree (Max Features = 5)	0.978881	0.979032	0.978881	0.978866
Random Forest (Default)	0.993151	0.993356	0.993151	0.993145
Random Forest (Max Depth = 10)	0.99258	0.992759	0.99258	0.992552
Random Forest (Min Samples Split = 5)	0.992009	0.992203	0.992009	0.991991
Random Forest (Min Samples Leaf = 10)	0.983447	0.983662	0.983447	0.982684
Random Forest (Max Features = 5)	0.994863	0.994948	0.994863	0.994847
Logistic Regression	0.484018	0.403567	0.484018	0.424628
K-Nearest Neighbors (K=5)	0.752283	0.754761	0.752283	0.752376
Naive Bayes (GaussianNB)	0.638699	0.655814	0.638699	0.636977
SVM (Linear Kernel)	0.633562	0.635254	0.633562	0.61738

In this part, we evaluated and compared the performance of Decision Tree, Random Forest, Logistic Regression, KNN, Naive Bayes (GaussianNB), and SVM with a linear kernel using the split and the hyperparameters tuning. Unfortunately, Random Forest and the Decision Tree are the only two that can tune and split into different scenarios. The other classifiers should then only have the default settings. Table 4 shows the results comparisons of the several scenarios. Overall, the decision tree scenarios, assigning the Min samples Split to value five and the entropy criterion setting, perform best in all the metrics.

In contrast to these two scenarios, assigning the Max Leaf Nodes to 10 and the Max Features to 5 had lower performance results. The default Random Forest classifier showed promised results with an accuracy of 0.993151 and became the second-best performer classifier behind the

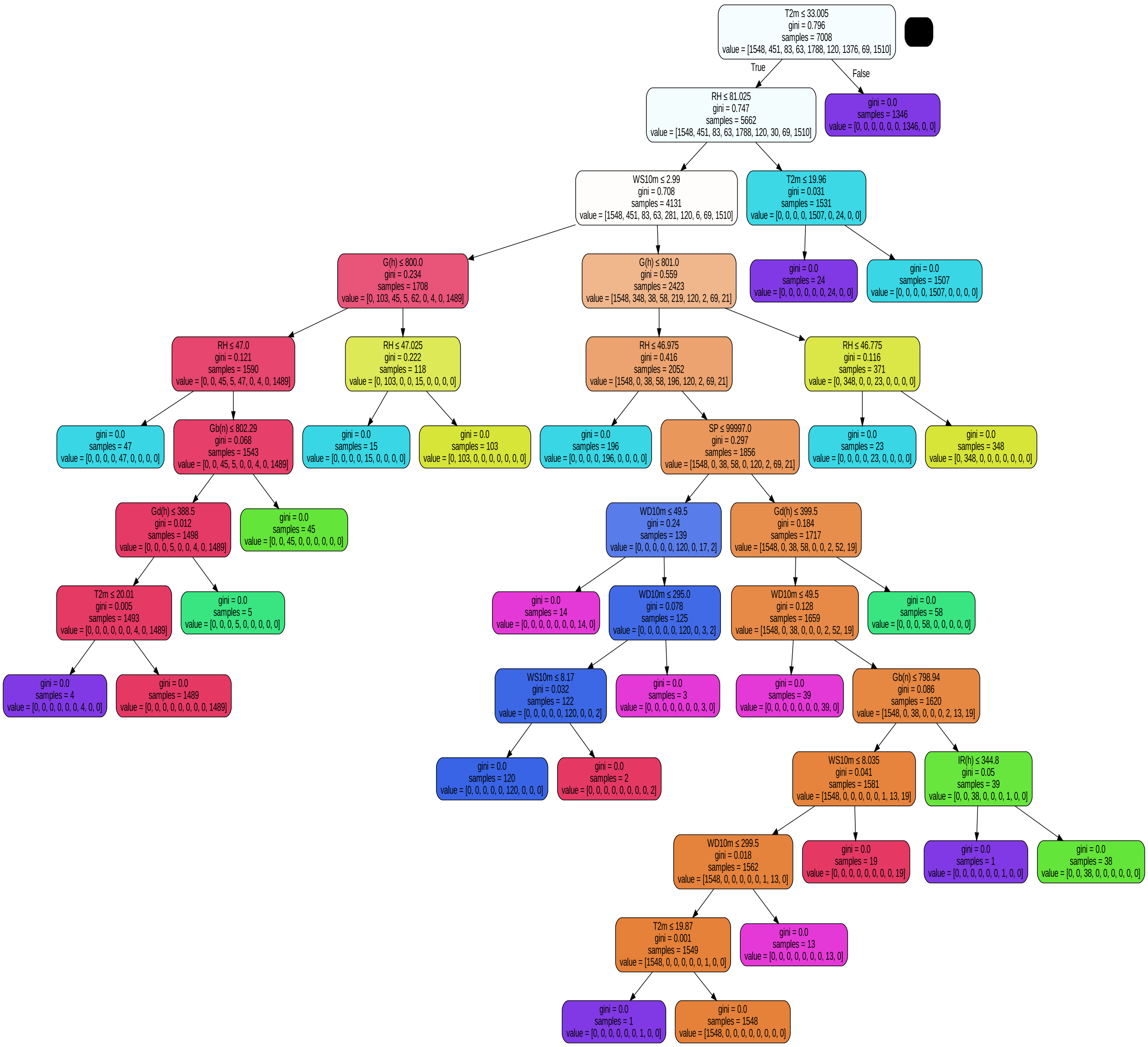

FIGURE 11. **Decision tree for feasibility prediction.**

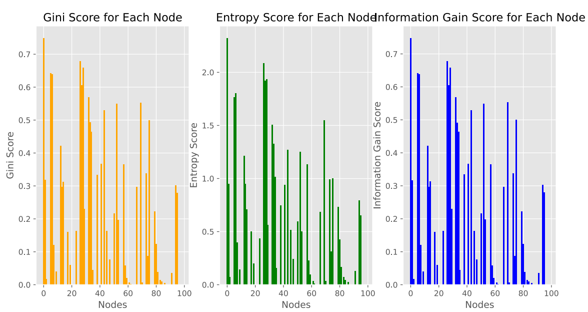

FIGURE 12. **Gini, entropy, and information gain scores for each node.**

decision tree in this study. However, classifiers behaved at lower performance in specific scenarios for the Decision Tree and Random Forest, but the accuracy scores are still good at approximately 0.98. Logistic regression showed lower performance in all the evaluated metrics, especially with an 0.484, which is very bad. For the matter of information in Table 4, KNN(K = 5), Naive Bayes (GaussianNB), and SVM (Linear Kernel) showed better results than the Logistic regression. Notably, these classifiers had an accuracy of 0.752283, 0.638699, and 0.633562, respectively, which is moderate compared to the high accuracy of the Decision Tree and Random Forest classifiers and the low accuracy of the Logistic Regression.

2) PERFORMANCE EVALUATION OF RENEWABLE ENERGY INTEGRATION IN THE MICROGRID

Evaluating the performance of the energy production of wind and solar sources is a crucial step in assessing the long-term use of these energies on this site. In our study, after simulating

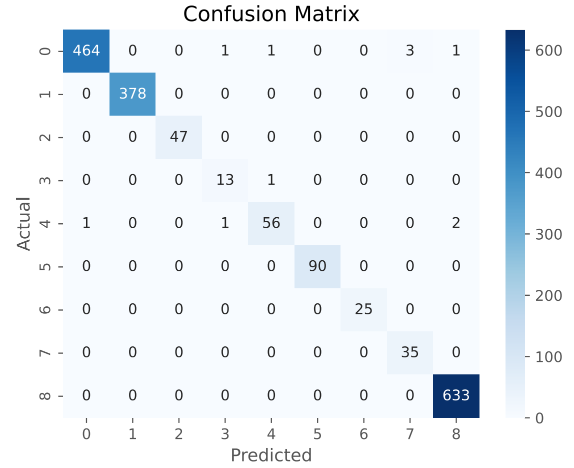

FIGURE 13. Confusion matrix of the decision tree classification.

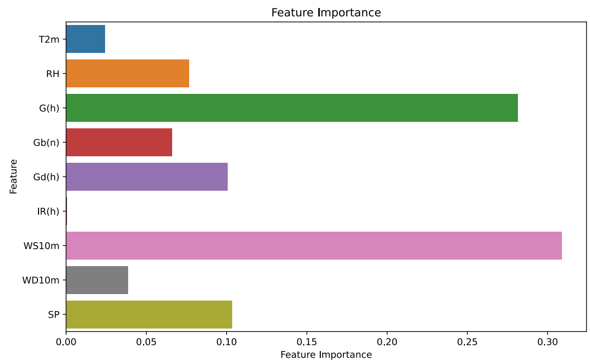

FIGURE 14. Feature importance for feasibility prediction.

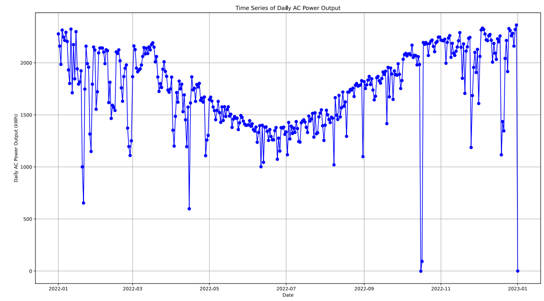

FIGURE 15. PV time series of daily AC power output.

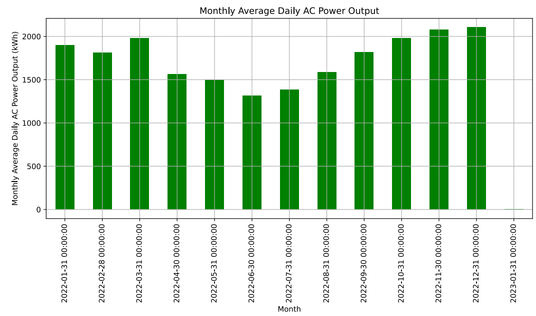

FIGURE 16. Monthly average daily AC power PV output.

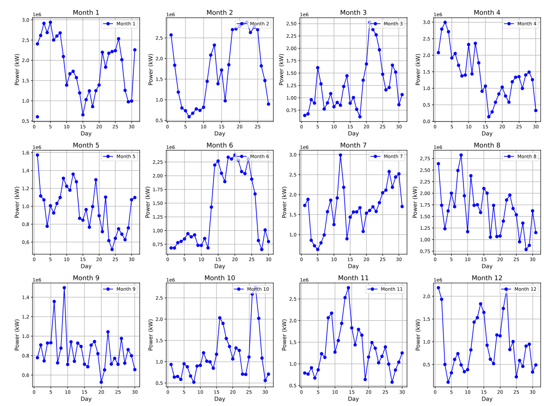

FIGURE 17. Monthly wind power output.

an entire year of power generated by these sources in this specific location with longitude and latitude in PVLib and Windpowerlib, which are Python packages, we analyzed the stability and variability of these energies with the help of predictions from deep learning methods, in particular LSTM which is specially used for time series data. Figures 15 and 16 are the daily solar PV production and the monthly solar PV production, respectively. Figure 17 shows the wind monthly power distribution. Figures 24 and 18 present the loss training and validation of solar and wind power prediction by tuning different hyperparameter scenarios of units and batches sizes (64, 64), (32, 32), (32, 64), (32, 16), and (64, 32) in the LSTM model to identify the optimal combination of units and batches for the best performance respectively. In this analysis, the loss curves are represented by the MSE. For each prediction, training and validation losses are zoomed in. For instance, the PV tuning loss is zoomed between 0.005 to 0.04, and the wind power is zoomed from 0.010 to 0.04 to obtain a clear view of the model behavior. In the case of wind power, the combination (32, 16) resulted in the lowest training loss of 0.011923, and generally, the smaller batch sizes, the more the fit is better. However, it is vital to measure the balance to avoid overfitting. In contrast, the validation loss is lower with the larger batch sizes in the model generalization, with the (32, 64) couple having the lowest loss validation, 0.01274. Similarly, the lowest PV power prediction training and validation loss combine (64, 32). Figures 19 and 25 display the performance of wind and solar hyperparameter tuning using the negative RMSE metric, which induces higher negative RMSE and loss, thus, lower performance, respectively. Figures 20 and 22 are the predicted wind power and solar PV power for the entire dataset, respectively. Figures 21 and 23 highlight the details of a specific region of actual and predicted wind power and solar PV, respectively.

3) ENHANCING BINARY CLASSIFICATION WITH FUSION OF LSTM AND DECISION TREE MODELS RESULTS

LSTM sequential data is trained with Keras and dense layers with appropriate loss and optimization functions around the training data. After this process, LSTM predictions are

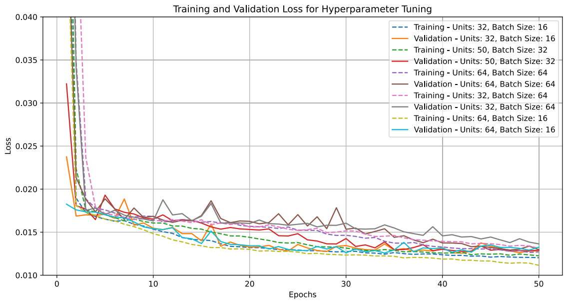

FIGURE 18. Wind power hyperparameter tuning loss.

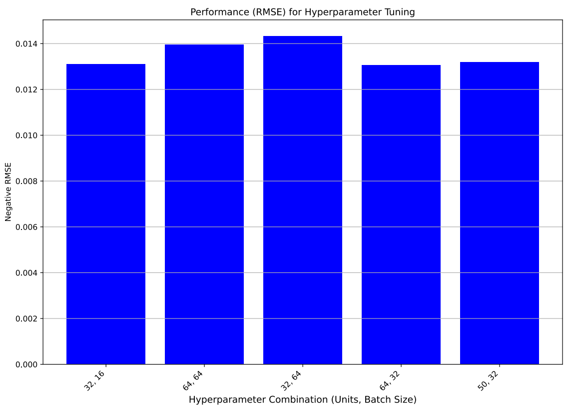

FIGURE 19. Wind power hyperparameter tuning rmse.

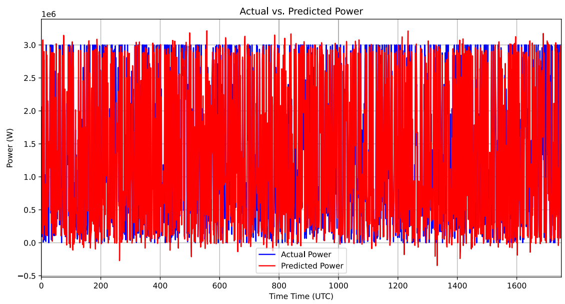

FIGURE 20. Wind power actual vs. predicted power plot.

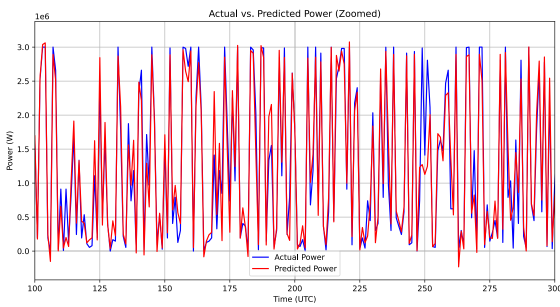

FIGURE 21. Wind power actual vs. predicted power plot (zoomed version).

trained to learn the data. The model is up to generate similar predictions for testing data. The method is based on integrating the LSTM predictions with the original features. The fusion takes place with the derivatives of LSTM and the original attributes. Therefore, the roles of the classification are enriched by this merger. Consequently, the Decision tree evaluates the combined feature sets. This methodical approach forms a hybrid approach that combines deep learning (LSTM) and traditional machine learning (Decision Tree). To measure the proposed model's accuracy and performance, we simulated a hyperparameter tuning to tune and find the best-performing architecture for the combined LSTM and Decision tree. Hyperparameter tuning is the search for the most optimal configuration of hyper-parameters. This process constitutes an important concept in machine learning because the choice of hyperparameters profoundly impacts a model's performance. The objective

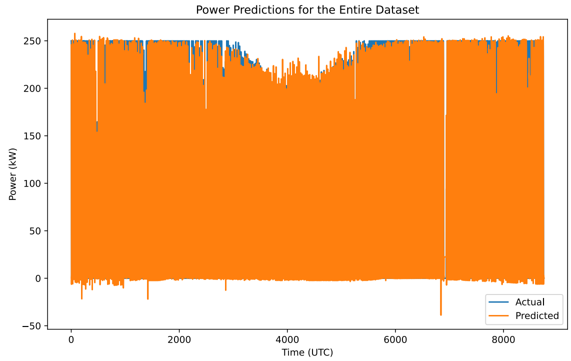

FIGURE 22. Solar PV power actual vs. predicted power plot.

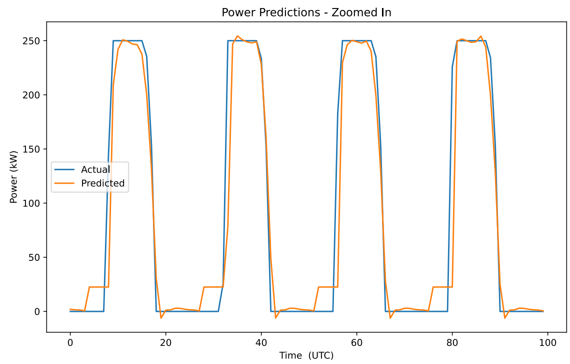

FIGURE 23. Solar PV power actual vs. predicted power plot (zoomed version).

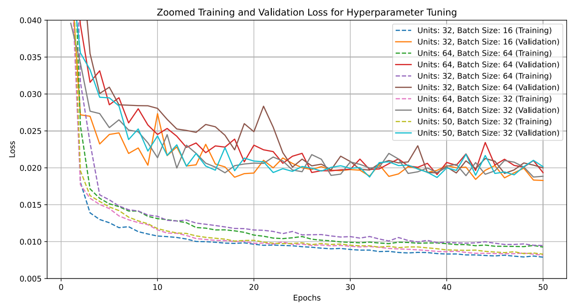

FIGURE 24. Solar PV power hyperparameter tuning loss.

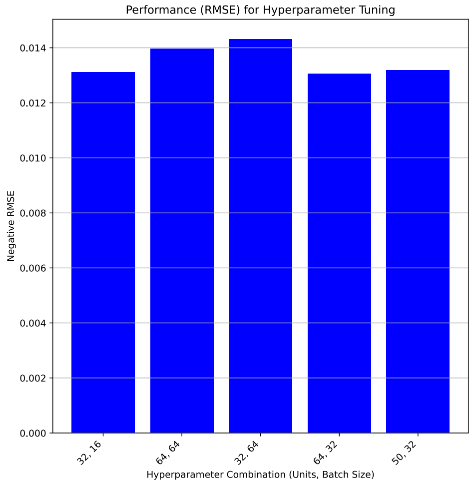

FIGURE 25. Solar PV power hyperparameter tuning rmse.

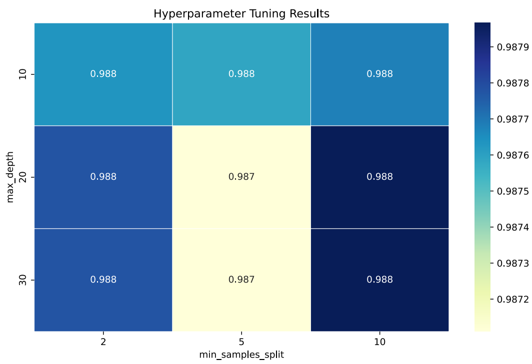

FIGURE 26. Hyperparameter tuning results.

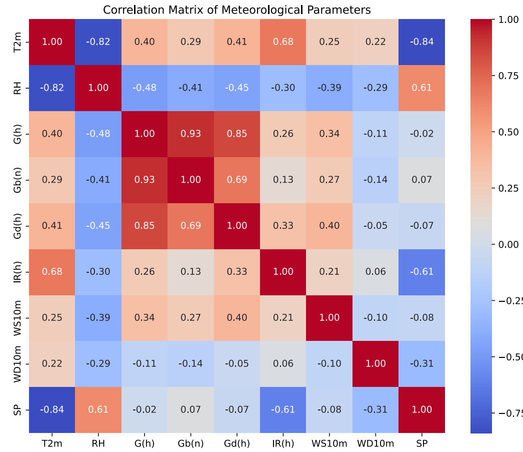

FIGURE 27. Correlation matrix of meteorological parameters.

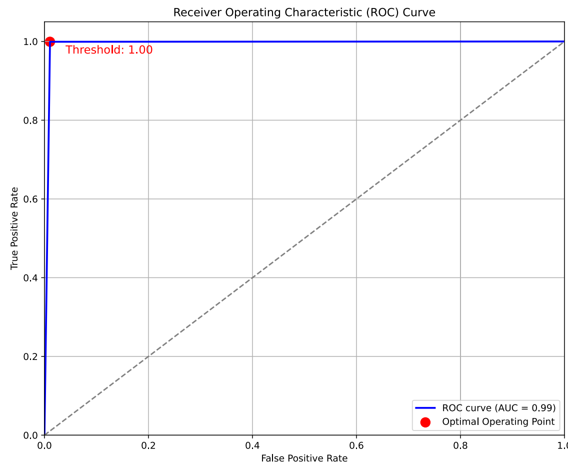

FIGURE 28. Receiver operating characteristic (ROC) curve for the feasibility classifier.

is to identify the hyperparameters that result in the highest model performance. Likewise, hyperparameter tuning is among the components of model validation. The training model is validated with hyperparameter tuning. Figure 26 displays the results of the model hyperparameter tuning. It shows the mean test scores for different combinations of hyperparameters (max depth and min samples split). We identified the best combination of hyperparameters to train the final Decision Tree Classifier. The accuracy of the best model is shown in percentage. The Figure 26 heatmap indicates that increasing max depth improves the model performance up to a certain point. Still, in contrast, a lower min sample split is associated with better performance. The highest mean test score highlights the best hyperparameters. After tuning the hyperparameters, the accuracy associated with the best model is displayed in the heatmap. With the help of this result, we assisted with informed decisions regarding model selection and deployment.

D. ANALYSIS OF METEOROLOGICAL DATA AND FEASIBILITY ASSESSMENT

In this section, we present a discussion of the obtained results. Figure 27 shows the correlation analysis of the meteorological parameters. T2m and IR(h) show the closest correlation with 0.68, inducing that a temperature rise is followed by an increase of IR(h). Furthermore, T2m and RH are correlated with -0.82, which induces an inverse dependency. Similarly, T2m and Gb(n) are correlated with -0.45, which explains the decrease in radiation when T2m increases.

Figure 29 displays the feasibility possibility of the nine meteorological parameters. The distribution is described by the whiskers of the box plot between the median of both feasible and non-feasible cases. This comparative analysis highlighted the relationship between feasibility and meteorological parameters. For illustration, the T2m median is higher in the feasible case than the non-feasible one.

The literature proposes that T2m and G(h) are fundamentals of solar generation [80], [81]. Thus, we presented a decision boundary visualization in Figure 30a of the Decision tree classifier. The blue areas are the feasible regions, and the red ones are the non-feasible solar generation. We can determine the solar feasibility with these two meteorological parameters' feasible overlapping areas. Literature also

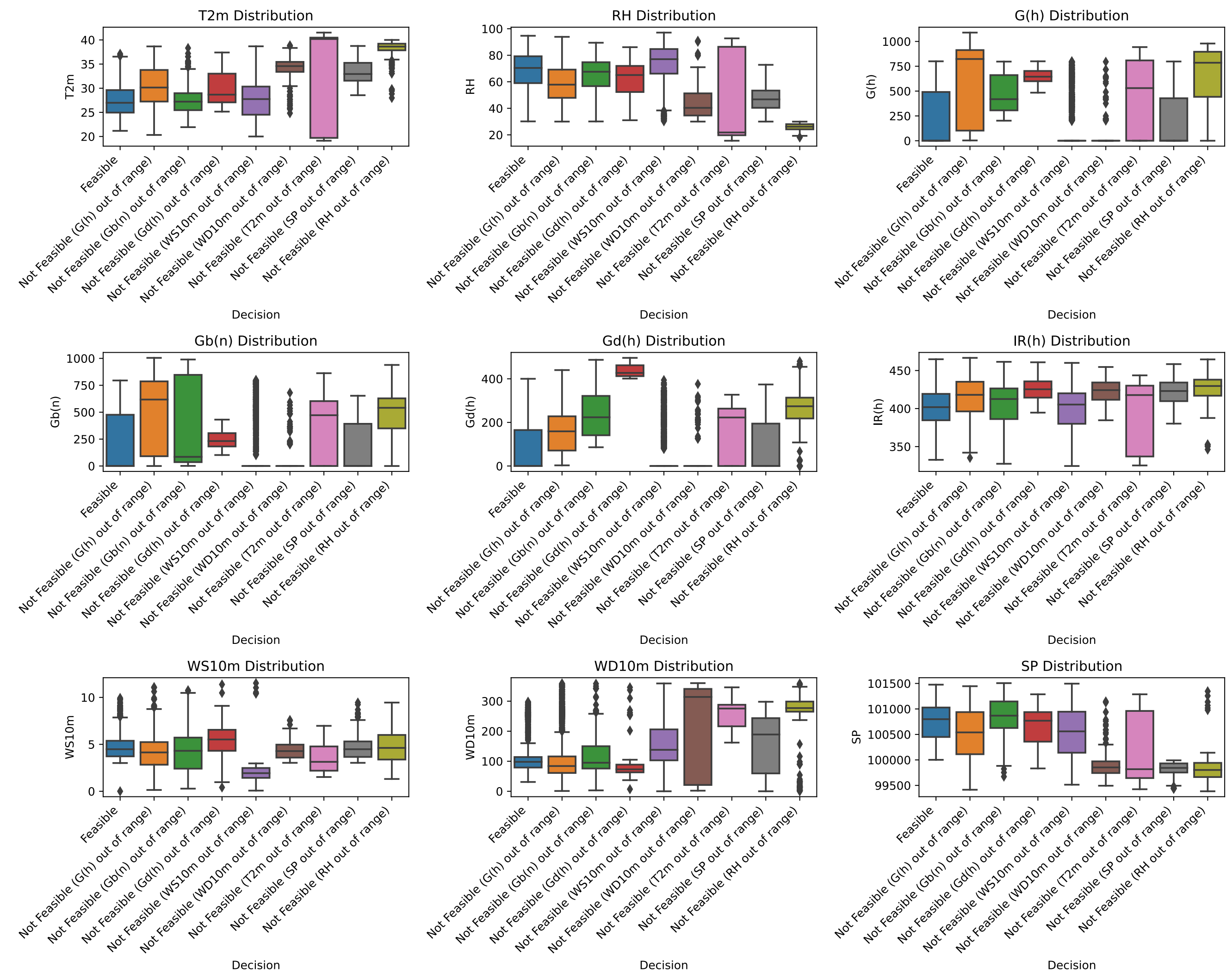

FIGURE 29. Distribution of meteorological parameters for feasible and non-feasible solar and wind energy generation.

approves that WD10m and WS10m are the most determined parameters for wind generation feasibility [82], [83]. The decision boundary of Figure 30b proposes the regions where the classifier predicts the overlapping areas to assess the wind generation. Figure 28 presents the ROC curve with the AUC score to yield the classifier's performance. This figure presents the optimal operating point calculated by Youden's J statistic. This model has 0.99 AUC, which approves that the feasible and non-regions were ideally classified. The optimal operating point where the threshold indicates a 0.99 good True positive and a low 0.01 False Positive Rate.

E. POLICY IMPLICATIONS AND REGULATORY FRAMEWORKS

The paper aims to develop a model of the sets of Decision trees and LSTM. The Decision tree classified the weather input parameters for optimizing the microgrid decisions regarding meteorological decisions for integrating renewable energy into the grid. Furthermore, the LSTM deep learning method was used to predict the performance of the microgrid energy production of wind and solar sources. Classification and prediction results establish solutions and strategies for global efforts to transition to sustainable energy sources [84]. The feasibility and potential benefits of renewable energy integration form the core of the paper's findings. The study region has recently been subject to considerable studies to implement renewable geothermal, wind, and solar energy technologies because of the ongoing challenges of urban development and climate change [85], [86]. The developed methodology can be applied to regions with the same meteorological behaviors as in the case study region [87]. Similarly, the research flow is possible to expand for worldwide microgrid development. The research practice is implemented with stakeholder collaborations, researchers, and the development of suitable infrastructure [88].

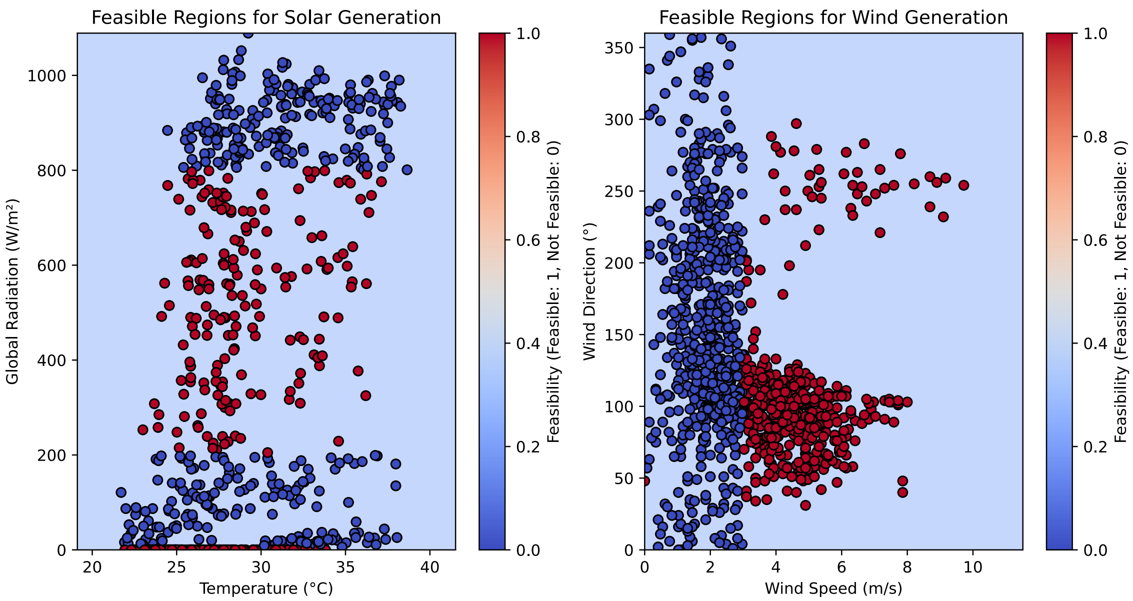

FIGURE 30. Feasibility of decision boundary solar and wind power generation visualization.

F. FUTURE DIRECTIONS AND RESEARCH OPPORTUNITIES

Research into microgrids will be advanced shortly. Industries are pressing to control and automate the systems of the microgrids. Energy consumption, renewable energy generation, and transmission are among the developments of these systems [89]. Microgrids are competent with smart grids interconnected and reliant on digital technologies [90]. These new frameworks are critical to cyber threats [90]. Additionally, DER integration to the grid and energy storage still currently presents opportunities for making newly innovative research [91], [92], [93]. Market interactions further empower consumers for decentralized energy systems [94]. It is then logical that researchers explore the feasibility of these models. By far, buildings are in the utmost place for optimized energy usage [95]. Integrating electrical grids and buildings is guided by the study of energy efficiency. The regions and context are different for each study, thus highlighting the need to follow policies and regulatory frameworks [96]. With global warming becoming more severe year after year, it is paramount to prioritize resilient systems. Future research should focus on studies on ways of accessing microgrid technology and renewable energy.

VI. CONCLUSION

The importance of the power system in today's world is perceived as the main concern for all endeavors. Hospitals, universities, and rural areas benefit from reliable microgrid energy. Mainly, in Africa and the third world, where industrial development is still rudimentary, the successful feasibility of energy integration will significantly help prepare against the variability of renewable energies. First, this paper's idea was based on evaluating the meteorological parameters by classifying them with decision boundaries produced by the Decision tree classifier, which divided the parameters into feasible and non-feasible regions. Thus, these regions overlap between solar and wind energy integration generation feasible intervals. The accuracy of this decision tree is 0.993721, outperforming the Random Forest, Logistic Regression, KNN, Naive Bayes, and SVM in the classification tasks. The various scenarios presented in the paper demonstrated that tuning the decision tree's hyperparameters can increase the classification process's efficiency. When increasing the max depth to 10, the accuracy rises to 0.994292. When assigning min-samples split to 5, the accuracy increases to 0.996005. The metrics have shown additionally that by assigning the min sample leaf to 10, or max-leaf nodes to 10, and or the max feature to 5, the accuracy underperforms slightly. Solar and wind power predictions with LSTM deep learning algorithms backed the classification task. PVLib and Windpowerlib python packages were explored to model the microgrid's solar and wind power generation for specific latitudes and longitudes. This task's objective is a year of solar and wind power forecasting. The MSE training loss for solar and wind power showed excellent results with 0.01025 and 0.011923 loss values. In combination with the decision tree classification, LSTM forecasting offers a more precise step in the magnitude of the power yielded by renewable energies. The paper's model assembles a framework based on the technical part of energy integration. We identified the optimal conditions for integrating renewable energy by analyzing the Decision Tree. With LSTM, we evaluated the energy production of the microgrid, which copes with the fluctuations of renewable energy to adapt to consumption needs. Decision scores from Decision Tree and LSTM feature integration were finally tested. The accuracy of this combination was validated by a hyperparameter tuning that showed an accuracy of 0.98. Even though the accuracy is lesser than 0.1 from the single Decision Tree. This method sets apart a new architectural concept with the ability to target sequential data and the non-linear capability of the decision tree. This combination helps decision-makers identify areas that need improvements for a resilient microgrid. Future research may be based on a similar analysis to this paper to offer responses for energy storage, load management, and scheduling energy integration.

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