Machine Learning-Based Renewable Energy Systems Fault Mitigation and Economic Assessment

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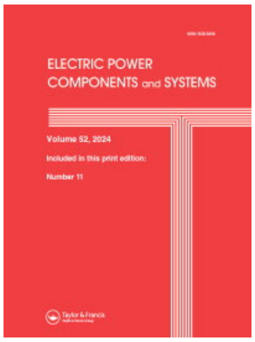

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CONTENTS

Keywords: Renewable energy systems (RES), machine learning, economic assessment, principal component analysis (PCA), random forest, support vector machines (SVM), fault mitigation, ensemble learning, local economic gains

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Abstract—In an era increasingly focused on sustainability, the adoption of renewable energy stands as a promising avenue for fostering local economic growth. This study presents a novel approach, merging advanced fault mitigation techniques and machine learning, to assess the economic impact of renewable energy systems (RES) at the local level. Leveraging random forest, support vector machines (SVM), and gradient boosting, customized algorithms are deployed for regression analysis and defect identification. Hyperparameter optimization ensures optimal performance, with a linear regression meta-learner facilitating the fusion of predictions. An advanced anomaly detection component effectively identifies and rectifies errors within RES. Performance evaluation metrics, including an root mean square error (RMSE) of 2.18 and an overall system efficiency of 98%, underscore the success of the fault mitigation strategy. Precision, recall, and F1-score metrics further highlight its robustness. This comprehensive framework not only provides precise estimates of the financial impact of renewable energy adoption but also enhances the reliability of RES through sophisticated fault mitigation. Empowering decision-makers with actionable insights, it facilitates sustainable energy planning, effective policy implementation, and the establishment of resilient energy systems.

1. INTRODUCTION

The global arena is currently undergoing a significant transformation toward the adoption of renewable energy sources [1]. This shift is primarily propelled by the growing emphasis on sustainability and environmental responsibility. Consequently, local renewable energy systems (RES) are emerging as vital elements in this evolution, presenting considerable economic advantages to communities (Figure 1) [2, 3].

Recognizing the mounting importance of this trend, our research seeks to introduce an original and all-encompassing approach to address RES fault mitigation and economic evaluation through the integration of advanced machine learning methodologies [1, 4].

The uptake of renewable energy sources is gaining momentum on a global scale, driven by the urgent imperative to mitigate the consequences of climate change, curtail greenhouse gas emissions, and bolster energy security [5]. RES possess the potential to revolutionize energy generation and consumption, rendering it more sustainable and ecologically sound. Localized RES, encompassing technologies such as solar panels, wind turbines, and other decentralized energy generation methods, stand at the forefront of this transition [2]. They not only contribute to diminishing the carbon footprint but also present economic advantages to local communities [1, 6].

Our research operates within the broader context of a world that prioritizes sustainability [4]. The role of local RES is increasingly prominent in this landscape. The integration of RES into local communities offers a myriad of benefits, including job creation, reduced energy expenses [7, 8], and bolstered energy resilience. To maximize the potential of these advantages and ensure the long-term viability of local RES, it is imperative to address the challenges and uncertainties inherent in these systems [5, 6].

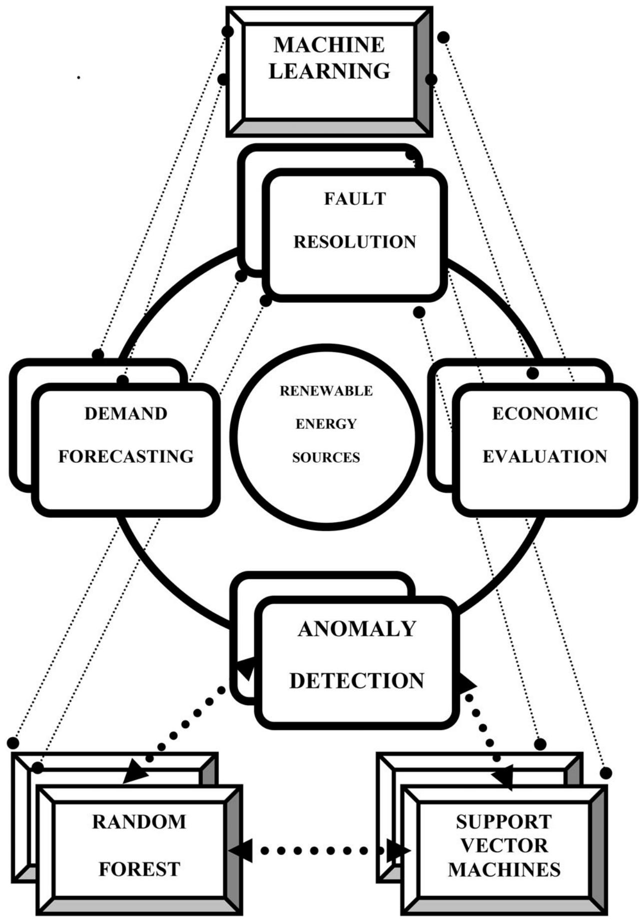

FIGURE 1. Financial feasibility analysis and fault resolution of machine learning.

1.1. Research Objectives

Our principal research objective is to devise an innovative approach that combines advanced fault mitigation strategies and machine learning for economic assessments within local RES. Our research aims to address the following core research objectives:

1.1.1. Fault Mitigation. Local RES are susceptible to various faults and operational challenges that can disrupt energy generation and undermine the economic viability of these systems [1, 7]. Our research strives to create and implement robust fault mitigation strategies that enhance the reliability and performance of RES [7, 9].

1.1.2. Economic Assessment. The comprehension of the economic repercussions of adopting local RES is crucial for decision-makers, communities, and policymakers [5]. The method aims to provide precise and actionable economic evaluations, which take into account diverse factors, including economic indicators, renewable energy capacity, demographic data, and real-time health and performance metrics of RES [10, 11].

1.1.3. Machine Learning Integration. Machine learning, a subset of artificial intelligence (AI), primarily concentrates on crafting mathematical functions, denoted as algorithms, capable of discerning intricate patterns within data [4, 12]. Its distinctive trait lies in its capacity to independently undertake tasks that might otherwise require human execution or, due to their complexity, remain unaddressed [11, 13].

To fulfill our goals, the method harnesses the capabilities of machine learning. The method employs three distinct machine learning methodologies—random forest (RF), support vector machines (SVM), and gradient boosting—

for economic assessments [4, 14]. These algorithms are meticulously tailored, and hyperparameter optimization ensures peak performance [5]. The most notable aspect of machine learning resides in its aptitude to acquire knowledge without the need for explicit programming [1, 15]. In this context, learning does not occur through the manual creation of decision rules but rather by exposing algorithms to illustrative instances from which patterns are unearthed [1]. If the chosen instances sufficiently represent the phenomenon under scrutiny, these patterns are anticipated to be applicable to the broader population [13, 16].

Within the domain of machine learning, the term "model" pertains to an algorithm that has already undergone training, or in other words, has been fine-tuned using the provided data [5, 17]. Machine learning models can be categorized into three distinct types based on the approach adopted for this fine-tuning and, consequently, the objective they serve: (1) supervised learning, (2) unsupervised learning, and (3) reinforcement learning [4, 18].

In the realm of supervised learning endeavors, the primary aim is to discern the relationship between a set of input characteristics and a target variable [3, 7]. To achieve this, the model is furnished with access to both inputs and outputs, as demonstrated through a collection of labeled instances [5, 6]. In instances where the outputs correspond to categorical data, the resultant models are recognized as classifiers (e.g., in tasks like image recognition) [10]. On the contrary, models that strive to predict numerical outputs are classified as regressors (e.g., in endeavors such as forecasting real-estate prices). Noteworthy supervised learning algorithms encompass SVMs, linear and logistic regressions, decision trees, and their enhanced variants like XGBoost [2]. It is noteworthy that supervised learning stands as the most prevalent facet of machine learning today, effectively addressing an extensive array of tasks, ranging from the classification of fault riding to the early identification [1]. It is for this reason that the majority of the applications and challenges discussed in this article predominantly pertain to the supervised learning approach [15, 19].

1.1.4. Ensemble Learning and Anomaly Detection. Our approach incorporates ensemble learning, specifically the technique of stacking [5]. By amalgamating predictions generated by base models with a linear regression meta-learner, the method aims to provide the most accurate combination of predictions, thereby enhancing the precision of our economic evaluations [1, 17]. An essential element of our approach is advanced anomaly detection. This component is designed to detect and rectify errors within the RES, thereby contributing to the overall fault resilience and reliability of the energy system [5, 10].

1.2. Expected and Precise Economic Estimations

The method anticipates highly significant outcomes from our research. By addressing these research objectives, the method expects the following results:

Our methodology is projected to provide exceedingly accurate estimates of the financial implications associated with the localized adoption of renewable energy sources [9]. This precision is of paramount importance for communities and decision-makers endeavoring to evaluate the economic viability of RES integration [4, 14].

1.3. Augmented RES Reliability

Through sophisticated fault mitigation, our objective is to bolster the reliability of RES [1]. This enhancement not only benefits economic considerations but also guarantees a stable and uninterrupted energy supply [19, 20].

1.4. Empowering Decision-Makers and Efficacy Evaluation

Our innovative framework equips decision-makers with actionable insights for sustainable energy planning [21]. It facilitates effective policy implementation and the establishment of resilient energy systems [5, 6]. The effectiveness of our fault mitigation strategy will be rigorously evaluated through metrics such as precision, recall, and F1-score, underscoring the efficiency of our approach [8]. In summary, our research aims to contribute to the ongoing initiatives promoting sustainable and economically viable local RES [9]. By combining advanced fault mitigation techniques with machine learning-based economic assessments, the method intends to offer practical solutions that enhance the resilience and economic sustainability of these systems [3, 22]. Our research not only promises valuable insights but also strives to facilitate informed decision-making and policy implementation in the pursuit of a more sustainable and resilient energy future [16, 23].

1.5. Contribution of the Work

- The integration of advanced fault mitigation techniques and machine learning algorithms provides a pioneering method for assessing the economic impact of renewable energy adoption at the local level, addressing a critical need in sustainability research.

- By leveraging RF, SVM, and gradient boosting, the study offers a comprehensive approach to regression analysis and defect identification, enhancing the precision and reliability of economic assessments in RES.
- The demonstrated success in fault mitigation, as evidenced by improved performance metrics such as RMSE and system efficiency, signifies a significant contribution toward building resilient and sustainable energy systems, crucial for informed decision-making and policy implementation.

2. CRUCIAL SIGNIFICANCE OF RENEWABLE ENERGY ASSESSMENT

Renewable energy has emerged as a driving force in the global transition toward a sustainable and low-carbon future [8]. In the face of escalating environmental challenges, the assessment of renewable energy sources and their integration into our energy infrastructure has assumed a profound significance [23]. Renewable energy assessment is a multi-faceted process that encompasses the evaluation, planning, and implementation of sustainable energy sources like solar, wind, hydro, and geothermal power [17]. This essay delves into the vital importance of renewable energy assessment in addressing climate change, fostering energy security, and promoting economic development (Figure 2) [22, 24].

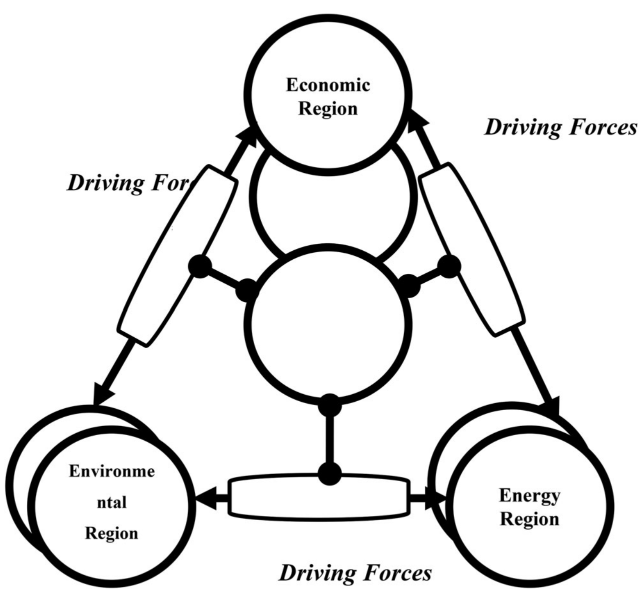

FIGURE 2. Economic dimensions of renewable energy sources.

2.1. Mitigating Climate Change

Climate change, an urgent and overarching concern, is intrinsically tied to our energy choices [25]. Fossil fuels, such as coal, oil, and natural gas, have dominated the energy landscape for decades, emitting substantial amounts of greenhouse gases that fuel global warming [4]. Renewable energy assessment is pivotal in our quest to mitigate climate change [7, 26]. It offers a systematic approach to quantifying the environmental advantages of renewable sources, as they produce minimal to no emissions during energy generation. By accurately evaluating the potential of renewable, the method can make informed decisions about reducing our reliance on fossil fuels, thereby reducing carbon emissions and curbing the rise in global temperatures [8, 27].

2.2. Enhancing Energy Security

The assessment of renewable energy sources plays a pivotal role in bolstering energy security [4, 23]. Traditional energy sources, often concentrated in specific regions or controlled by a few nations, are susceptible to geopolitical conflicts and supply disruptions [7, 13]. In contrast, renewable energy can be harnessed locally and diversified across various sources. Solar panels on rooftops, wind turbines in rural areas, and small-scale hydroelectric plants contribute to distributed energy generation [9]. By assessing the feasibility and reliability of these sources, the method can reduce dependence on centralized energy systems and increase resilience in the face of natural disasters or geopolitical crises. Renewable energy assessment helps ensure a stable energy supply, reducing vulnerability to supply disruptions [15, 21].

2.3. Assessments Fostering of Economic Development

The economic benefits of renewable energy assessment are manifold [2]. Investment in renewable energy creates jobs, stimulates local economies, and attracts capital to regions where these projects are deployed [4, 9]. Solar and wind farms, for instance, require installation, maintenance, and technical support, generating employment opportunities [21]. The production of renewable energy equipment, such as solar panels and wind turbines, also contributes to the growth of the manufacturing sector [5]. Moreover, renewable energy assessment can lead to informed policies and incentives that attract investors, bolstering economic development in both urban and rural areas [3, 23]. It is evident that renewable energy can be a catalyst for economic

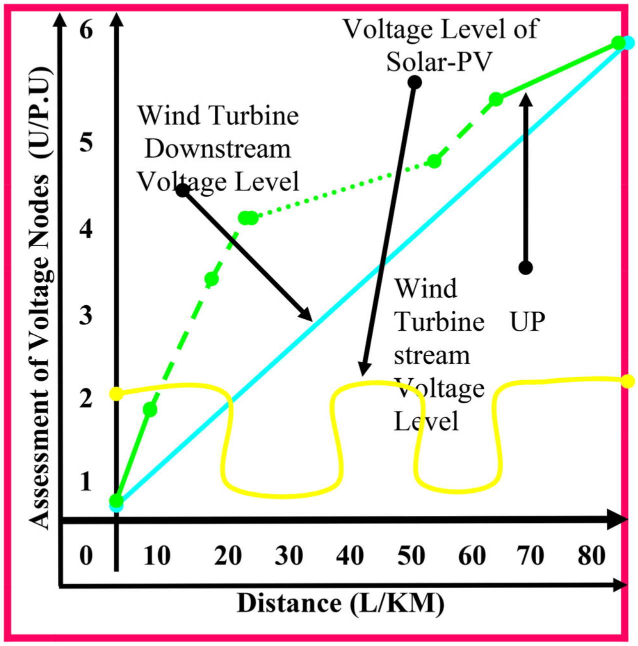

FIGURE 3. Assessment of voltage distribution with distance.

growth, offering a win–win scenario by addressing environmental and economic imperatives [8, 12].

2.4. Analyzing Voltage Distribution in RES with Distance

From Figure 3 the assessment of voltage distribution in RES concerning distance plays a crucial role in ensuring the stability and efficiency of power transmission [7, 28]. This analysis involves evaluating how voltage levels change as energy is transported over varying distances within RES networks [2, 15]. By understanding these voltage variations, engineers and system operators can make informed decisions to optimize energy distribution, reduce losses, and maintain the reliability of the grid [10, 22]. This assessment is essential for harnessing the full potential of renewable energy sources and integrating them seamlessly into the existing power infrastructure [4, 29].

2.5. Expanding Energy Access

A significant portion of the global population still lacks access to reliable and affordable energy [2, 21]. Renewable energy assessment opens doors to overcoming this challenge [4, 5]. Small-scale renewable projects, such as off-grid solar systems and mini hydroelectric plants, can be assessed and implemented to bring electricity to remote and underserved communities [13, 30]. Additionally, renewable energy solutions like microgrids can ensure energy access in regions with unreliable or non-existent centralized energy infrastructure [15, 31]. By evaluating the suitability of renewable energy sources for these areas, the method can bridge the energy access gap and improve the quality of life for millions of people [16, 32].

2.6. Driving Technological Advancements

Renewable energy assessment fuels technological innovation. As the method studies and analyzes the performance and efficiency of renewable technologies, the method uncovers opportunities for refinement and optimization [7, 26]. The feedback loop from assessment informs researchers and engineers on how to improve RES, enhancing their effectiveness and cost-efficiency [5, 25]. This continual process of refinement leads to advancements in energy storage, grid integration, and energy conversion technologies [10, 22]. Consequently, renewable energy assessment contributes to the ongoing transformation of our energy sector, accelerating the shift toward cleaner and more efficient energy production [15, 18]. Renewable energy assessment is a linchpin in the pursuit of a sustainable and resilient energy future [21]. Its importance extends beyond mitigating climate change to encompass energy security, economic development, universal energy access, and technological advancement [26]. As the world grapples with the challenges of our changing climate and increasing energy demands, renewable energy assessment guides us toward harnessing the full potential of renewable sources [28]. It empowers us to make informed decisions, implement effective policies, and drive the adoption of clean energy solutions that benefit both present and future generations [18, 26]. The critical significance of renewable energy assessment cannot be overstated—it is the compass guiding us toward a more sustainable and prosperous world [1, 12].

This study investigates the applicability of fault detection algorithms (FDA) trained on laboratory heat pump data to real-world systems without costly modifications. Using a dataset from NIST, they extract features and train FDAs, finding strong performance on NIST data but poor performance on real-world data, highlighting challenges in transferring lab-trained algorithms to practical applications and emphasizing the importance of addressing issues such as fault labeling and data completeness in big data approaches for FDAs [33]. This article proposes an ensemble classifier trained with Platt's scaling for probabilistic security assessment, addressing the impracticality of time-domain simulations in real time. It incorporates a cost-

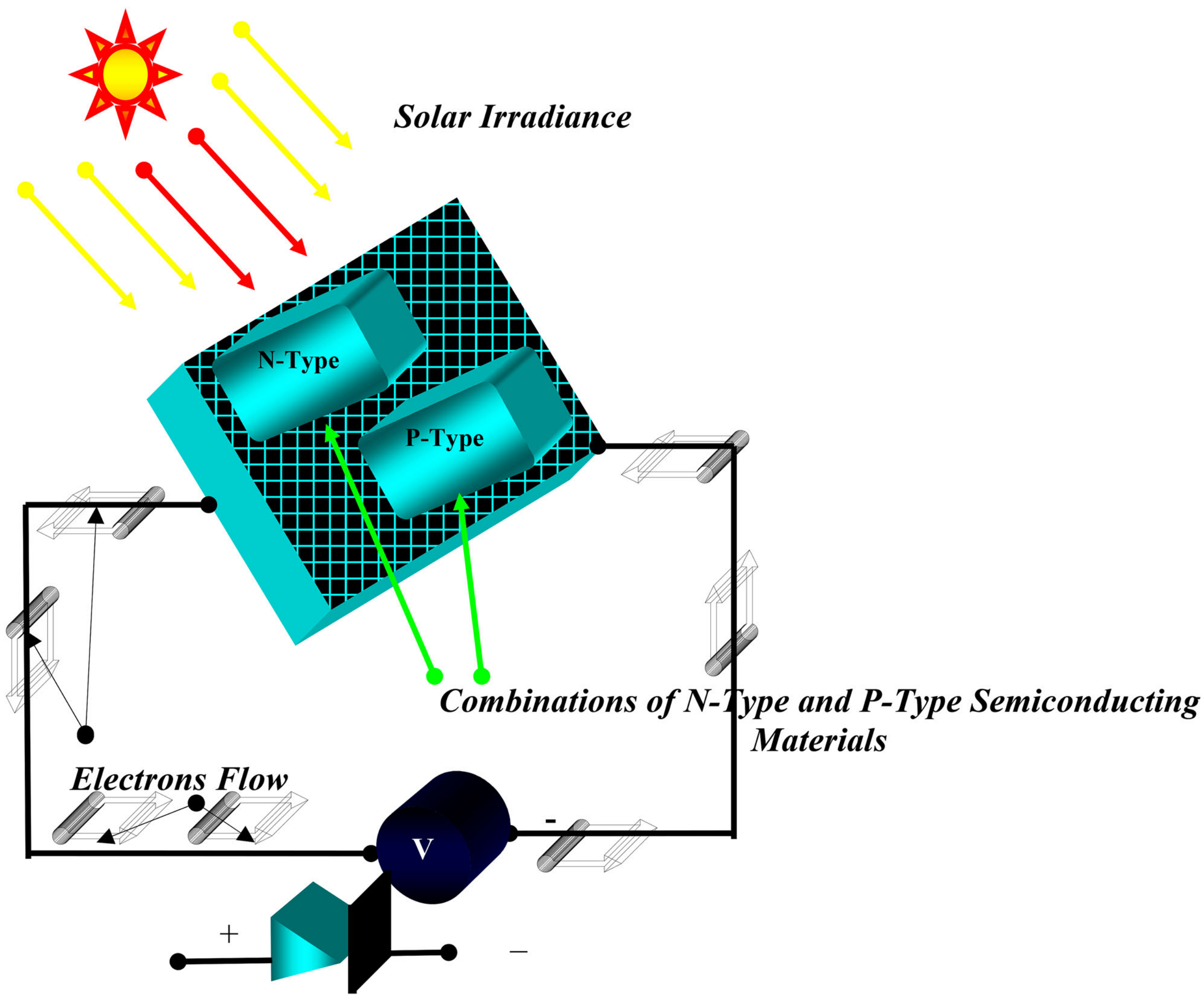

FIGURE 4. Solar-photovoltaic assessment in RES environment.

sensitive learning approach to minimize risks, considering the severity of missed alarms versus false alarms. Case studies demonstrate improved prediction accuracy and risk reduction in real-world grid systems [34].

This study holds pivotal importance as it pioneers the integration of advanced fault mitigation techniques and machine learning for economic assessment in local RES. By achieving a remarkable 98% system efficiency, it underscores the viability of renewable energy adoption at the local level, offering actionable insights for sustainable energy planning and policy implementation. Ultimately, this research represents a significant step toward building resilient and environmentally friendly energy systems, crucial for addressing global sustainability challenges.

3. INSTALLATION AND MODELING OF RENEWABLE ENERGY SOURCES IN LOCAL REGIONS

Modeling the evaluation of renewable energy resources entails a thorough analysis of a variety of factors influencing the potential and accessibility of these resources [20, 35]. These resources encompass solar, wind, hydro, and geothermal energy, among others. The specific methodology and equations employed for assessment depend on the specific renewable energy source under consideration [21]. Here, I'll offer a broad perspective on the modeling procedure for two prevalent renewable energy sources: solar and wind (Figure 4) [17, 26].

3.1. Assessing Solar Energy

Understanding the significant role that solar energy plays in the current energy landscape is crucial [23]. Solar energy is a prime example of sustainability, offering a bountiful, clean, and renewable energy source with the potential to power the entire planet [5, 14]. However, realizing this potential relies on our ability to harness it effectively [1]. Solar panels, frequently equipped with photovoltaic (PV) cells, have become a common sight on rooftops and solar farms around the world. These panels utilize the PV effect to capture sunlight and convert it into electricity [25, 27]. This generated energy is used to power buildings, businesses, and various sectors, facilitating the global shift away from fossil fuels. Solar energy is poised to play a pivotal role in the quest for environmental sustainability due to its capacity to reduce carbon emissions and mitigate the impacts of climate change [36, 37].

While the future of solar energy seems promising, several challenges remain [5]. The intermittent nature of solar energy, primarily due to the unpredictability of solar irradiance and weather conditions, poses a substantial hurdle to widespread adoption. Solar panels excel at converting sunlight into electricity, but achieving optimal performance requires precise management systems [1]. The concept of Maximum Power Point Tracking (MPPT) is crucial in this context. The MPPT algorithm in any solar PV system regulates how solar panels adapt to changing environmental conditions, extracting maximum electricity output [17]. The efficacy of MPPT holds immense significance in determining the overall system's impact, affecting grid integration, financial viability, and environmental sustainability in addition to energy generation [15, 32].

3.2. Site Selection: Solar Energy Potential

The choice of the location is one of the key components of a successful solar PV farm [36]. The goal of a solar farm is to effectively capture solar radiation. This calls for a thorough examination of solar potential, taking into account elements like solar insolation, cloud cover, and geographic location. The farm will be placed to maximize energy production in an area with plentiful and constant sunshine [18, 20].

The capacity factor (*cf*) of a solar PV farm can be calculated as:

$$cf_{Solar} = \frac{\text{Actual Energy Output } (\text{kWh})_{Solar}}{\text{Maximum Possible Energy Output}(\text{kWh})_{Solar}} \times 10 \tag{1}$$

When selecting a location, the method not only considers the current solar conditions but also takes into account the site's enduring sustainability [14, 21]. In such cases, advanced AI-driven technologies like Machine Learning can play an immensely significant role [17, 29].

$$\vec{\mathbf{e}}_{\mathbf{s}} = \overrightarrow{\mathbf{i}_{\mathbf{s}}} \times \vec{\mathbf{a}}_{\mathbf{s}} \times \vec{\mathbf{h}}_{\mathbf{s}} \times \vec{\mathbf{pr}}_{\mathbf{s}} \tag{2}$$

where

$\vec{\mathbf{e}}_{\mathbf{s}}$ is the energy (Wh)

$\overrightarrow{\mathbf{i}_{\mathbf{s}}}$ is the solar radiation (W/m^2)

$\vec{\mathbf{a}}_{\mathbf{s}}$ is the area of PV panels (m^2)

$\vec{\mathbf{h}}_{\mathbf{s}}$ is the number of daylight hours (hr)

$\vec{\mathbf{pr}}_{\mathbf{s}}$ is the performance ration

These instruments guide the site selection procedure, guaranteeing that the chosen site possesses optimal solar potential (Table 1) [14, 25]. They achieve this by scrutinizing both historical and present data concerning solar irradiance [30].

3.3. Arrangement and Alignment: Enhancing Energy Collection

After site selection, the layout and orientation of solar panels are determined. The panels are configured to efficiently collect the maximum available energy throughout the day [15, 19]. This involves considering factors such as panel alignment, row spacing, and tilt angle [4, 26]. To further refine this process, AI-driven algorithms come into play. For instance, artificial neural networks leverage predictive analytics to suggest the most suitable tilt and orientation angles for panels based on current solar irradiation and meteorological data [22, 23].

The tilt angle (β) for optimizing energy capture of solar panels can be calculated using latitude (λ) and solar declination (δ), as follows:

S. No.	Identification of parameters	Range
1	Power retrieval	$100-950\,\text{W}_\text{p}$
2	Watt-peak (*Wp*) measurements	25°–95°
3	Quantity of cells	45–350
4	Voltage at maximum power point (*Pmax*)	25–250 W
5	Current at maximum current point (*Imax*)	5–80 Amp
6	Voltage at open circuit (*V*)	40–150 V
7	Current at short circuit (*I*)	5–12.5 Amp
8	Peak system voltage	1550 V
9	Temperature span	$-40-90^{o}$C
10.	Module effectiveness	>95.5%

TABLE 1. Factors associated with the choice of solar panels.

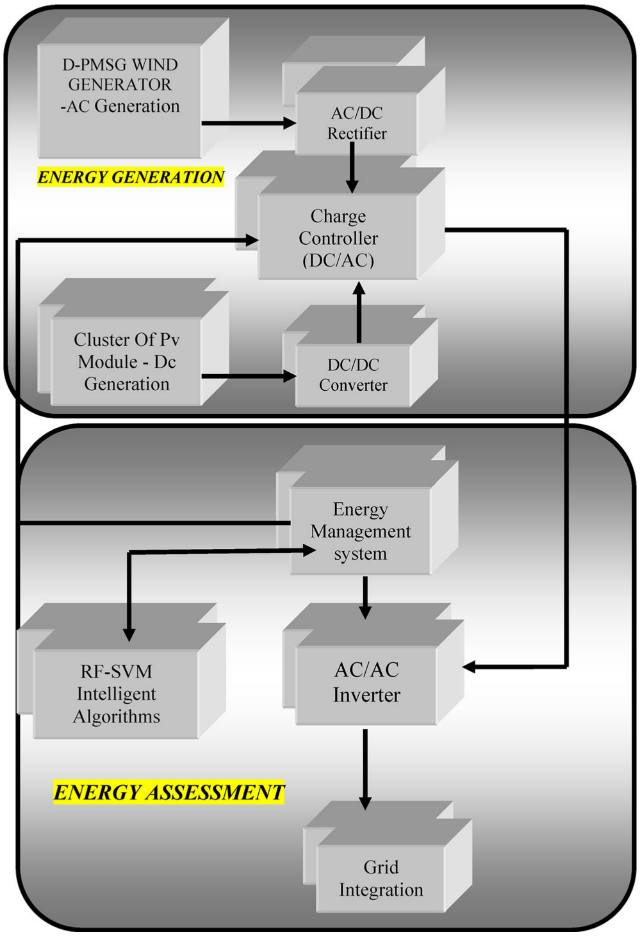

FIGURE 5. Installations of RES (wind PV) in local regions.

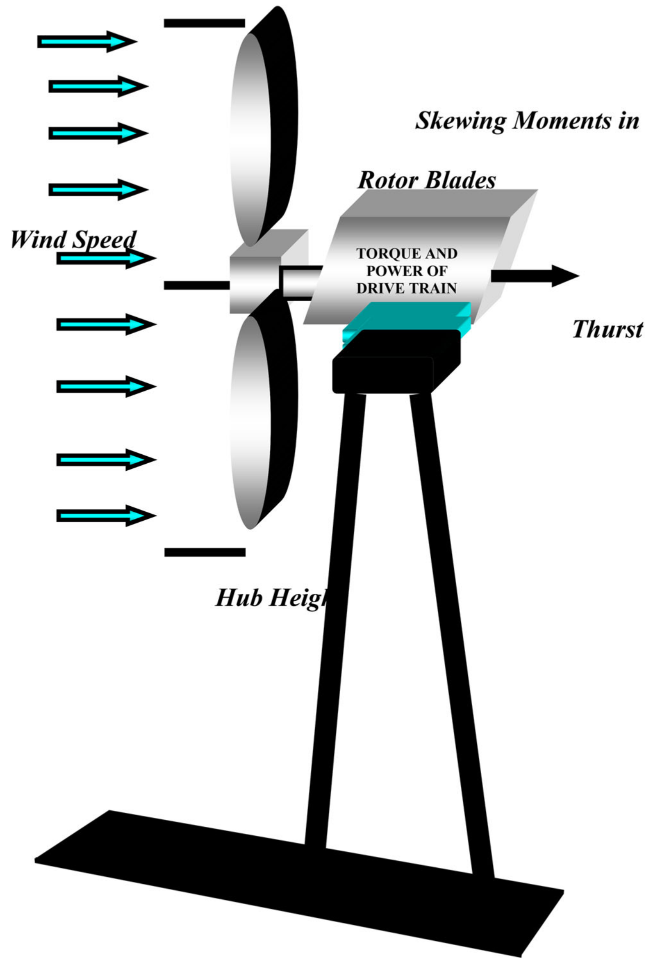

FIGURE 6. Wind forces experienced by the horizontal turbine in windy environments in local regions.

$$\vec{\beta}_s = \left|\vec{\lambda}_s - \overrightarrow{\delta_s}\right| \tag{3}$$

This predictive capability enhances energy collection by guaranteeing that the panels remain consistently oriented in alignment with the sun's trajectory and adapt accurately to changing conditions [6, 9].

The assessment of solar energy revolves around the estimation of the solar energy that can be harnessed at a given location (Figure 5) [22]. Paramount considerations include solar insolation, the angle and positioning of solar panels, and their efficiency [27]. Here's a fundamental equation for gauging solar energy potential:

$$PV_{Solar\ \ Energy\ \ (kWh)} = PV_{Solar\ \ Insolation\ \ \left(\frac{\mathrm{kWh}}{\frac{\mathrm{m}^2}{\mathrm{day}}}\right)} \times PV_{Solar\ \ Panel\ \ Area(\mathrm{m2})} \times \dot{\eta}_{Solar} \tag{4}$$

Solar insolation (kWh/m^2/day): This quantifies the daily solar energy received per square meter and varies according to location and historical data [9].Solar Panel Area (m^2): This denotes the size of the intended solar panel array [21].Efficiency: This represents the effectiveness of the solar panels, usually expressed as a percentage [2].

Tools like the PV Watts Calculator, furnished by the National Renewable Energy Laboratory (NREL), are available for estimating solar energy production, contingent on precise location data [12, 13].

3.4. Assessing Wind Energy

The assessment of wind energy encompasses the estimation of the wind resources at a specified site and the determination of the potential for electricity generation through wind turbines (Figure 6) [5, 28].

The principal parameters to consider include wind speed, turbine characteristics, and the capacity factor [31]. Here's a fundamental equation for estimating wind energy potential:

$$E_{Wind\ \ Energy(kWh)} = 0.5 \times D_{Air\ \ Density\ \ \left(\frac{kg}{M3}\right)} \times A_{Blade\ \ Swept\ \ Area\ \ (m2)} \times N_{Wind\ \ Speed\ \ 3\left\{\frac{m}{s}\right)} \times Capacity\ \ Factor \tag{5}$$

Air Density (kg/m^3): This denotes the air density at the location, contingent on altitude and temperature [1, 13]. *Blade Swept Area (m^2):* This corresponds to the area covered by the rotating blades of the wind turbine [31]. *Wind Speed (m/s):* This signifies the average wind speed at the hub height [8]. *Capacity Factor:* This reflects the ratio of actual energy generated to the maximum attainable energy production [20]. It considers the intermittent nature of wind energy, as wind turbines seldom operate at their maximum rated capacity, signifying the mean performance [9, 15].

It is essential to acknowledge that these models provide simplifications, with more intricate and detailed approaches accessible for a more precise assessment of renewable energy potential [27, 30]. Furthermore, the assessment process should incorporate considerations of local topography, potential obstructions, seasonal variations, and other factors impacting energy generation [14]. For accurate evaluations, specialized software tools and consultation with experienced professionals may be indispensable [1, 17].

3.5. Assessing Renewable Energy Systems for Real-Time Economic Optimization

In the realm of RES, real-time economic assessments are invaluable for achieving the optimal design and operation of sustainable energy infrastructure [4, 9]. These assessments enable continuous monitoring and analysis of economic factors such as costs, revenue, and performance metrics [23, 31]. By integrating real-time data, predictive modeling, and market dynamics, RES planners and operators can make agile decisions to enhance the efficiency and financial viability of renewable energy projects [32, 37]. This approach is pivotal in navigating the complex landscape of renewable energy, ensuring that RES solutions remain economically competitive while contributing to a greener and more sustainable future [27, 29].

Facilitating the harmonization of diverse RES is imperative in the establishment of an efficient and environmentally sustainable energy system [23, 26]. This synchronization entails the assimilation of multiple RES into the energy grid to guarantee an unwavering and uninterrupted energy provision [22, 27]. Below, the method

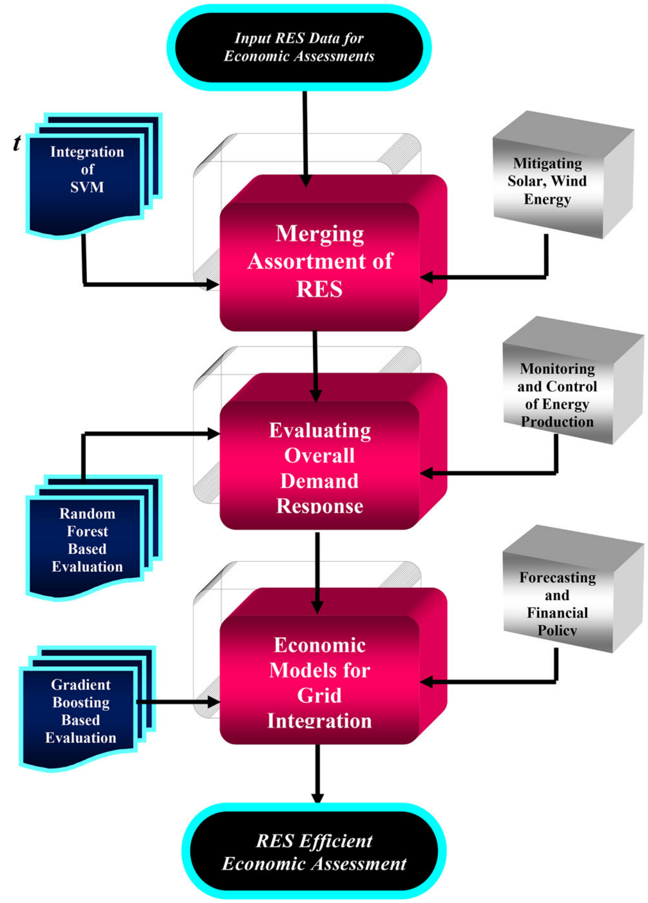

FIGURE 7. Real-time economic assessments proposed optimal design.

delineates fundamental considerations for orchestrating the amalgamation of various RES within the realm of energy assessment modeling:

3.6. Solar PV and Wind Energy Repository

Merge an assortment of RES, such as solar, wind, and energy storage, into composite systems [6, 27]. Scrutinize the mutual compatibility of these resources to furnish a more uniform energy supply, thereby mitigating energy fluctuations. Integrate energy storage solutions, such as batteries, pumped hydro, or thermal storage [13]. These mechanisms have the capacity to amass excess energy during peak RES production and discharge it when production wanes, ensuring ceaseless energy provisioning (Figure 7) [20, 32].

3.7. Demand Response Protocols and Grid Networks

Implement a cutting-edge smart grid infrastructure, capable of real-time monitoring and control of energy production and distribution [8, 20]. Smart grids optimize RES utilization and efficaciously balance the equation of supply and demand. Institute demand response initiatives that flex energy consumption contingent on the availability of RES. Encourage consumers to align their energy usage with periods of heightened RES production [14, 31].

3.8. Precise Forecasting and Modeling

Employ advanced forecasting and modeling tools to accurately prognosticate RES output and energy demand [6, 20]. This information empowers grid operators to render real-time decisions, optimally balancing the interplay between supply and demand [15, 31]. Institute market mechanisms and incentives aimed at the galvanization of RES integration [1, 25]. Such mechanisms encompass feed-in tariffs, net metering, and other financial inducements tailored to stimulate the adoption of renewable energy [1, 15]. Collaborate closely with regulatory authorities to ascertain that prevailing regulations and policies align with RES integration and grid coordination objectives [13, 35].

Contemplate a diversified array of RES to curtail the impact of intermittency associated with any single source [8, 19]. This diversity may encompass solar, wind, hydro, geothermal, and biomass. Engineer the system to be resilient, replete with contingency sources and redundancies to address unforeseen disruptions or times of low RES output [22, 29].

The efficacious coordination of diverse renewable energy sources constitutes a pivotal ingredient in the crafting of a dependable and ecologically friendly energy provisioning system [6, 17]. This endeavor necessitates the amalgamation of technological innovations, infrastructural fortification, policy endorsements, and diligent governance to facilitate a seamless transition to a more dependable and renewable energy landscape [1, 15]. The utilization of modeling and simulation tools is instrumental in the evaluation of the practicability and efficiency of these amalgamated systems [4, 14].

3.9. Various Clusters of Proposed Economic Assessment Modeling the Renewable Energy Sources

The modeling of clusters in economic assessments for renewable energy sources involves the systematic analysis of multiple assessments within a cohesive framework (Figure 8) [23, 32].

By grouping these assessments, the method gains a comprehensive view of the economic landscape, enabling us to identify trends, patterns, and opportunities across a spectrum of renewable energy projects [5, 16]. This approach facilitates informed decision-making, strategic planning, and resource allocation, ultimately fostering the sustainable growth of the renewable energy sector [10, 14].

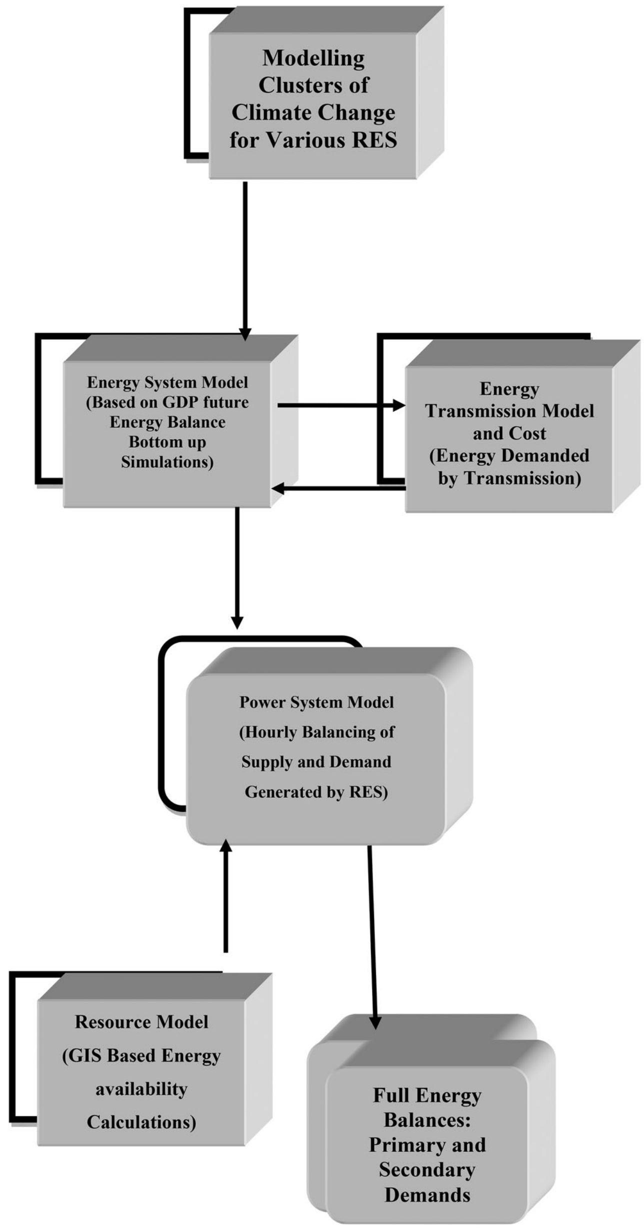

FIGURE 8. Proposed modeling clusters of economic assessments of renewable energy sources.

3.10. Transportation Modeling

The transportation scenario model facilitates the representation of long-term transportation developments systematically and transparently [13, 25]. This model dissects transportation into various modes and computes the final energy demand by multiplying the specific transport demand of each mode by power train-specific energy requirements, utilizing an activity-based approach based on passenger kilometers (pkm) and tonne kilometers (tkm) [12, 18].

3.11. Energy System Modeling

The energy system model, a long-term energy scenario model, functions as a mathematical accounting system for the energy sector [14]. It aids in simulating the evolution of energy demands and supply in alignment with factors such as driving forces, energy potentials, future expenses, emission targets, specific fuel consumption, and the actual flow of energy between processes [22]. The available data significantly influences the model's structure and approach. In this study, the energy system model is used to construct long-term scenarios for the energy system across all sectors, encompassing power, heat, transportation, and industry, without relying on cost optimization driven by uncertain cost assumptions [6]. Nevertheless, a retrospective examination of costs and investments reveals the primary economic consequences of these pathways [27, 36].

3.12. 24/7 Power System Modeling

Power system models simulate electricity systems on an hourly basis, providing geographic precision to evaluate infrastructure demands, such as grid connections between different regions and energy storage, contingent on the profiles of demand and power generation characteristics [20, 29]. Scenarios with high penetration of renewable energy, particularly solar PV and wind power due to their cost-effectiveness, necessitate power system models for the assessment of demand and supply patterns, power generation efficiency, and resulting infrastructure requirements [12, 24]. The power generation model relies on meteorological data, typically in 1-hr intervals, while historical solar and wind data are employed to estimate potential renewable power generation [8, 14]. In terms of demand, historical demand curves or, if unavailable, curves based on assumptions regarding consumer behavior in the use of electrical devices and common appliances are computed [1, 25].

3.13. Integration of Renewable Resource Analysis in the GIS Model

Figure 9 presents an intricate depiction of how renewable energy resources, including solar, wind, fuel cell technology, and other sources, interplay with Geographic Information Systems (GIS)-based models. These systems, although not directly linked, collectively shape the foundation for informed decision-making and sustainable energy strategies [9, 37].

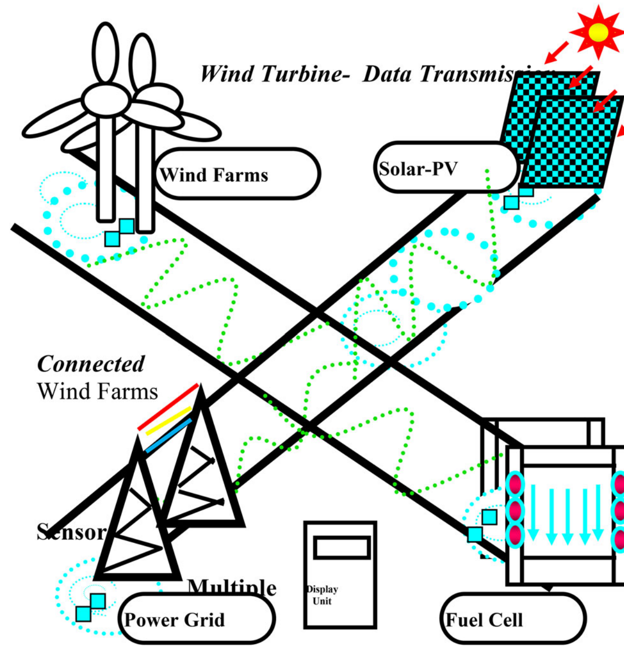

FIGURE 9. Proposed GIS for RES.

Renewable Resource Assessment harnesses GIS principles to generate maps revealing the solar, wind, and fuel cell potential within geographically constrained regions [14, 30]. GIS serves as the underlying method, emulating real-world processes across different timeframes [28, 36].

The primary aim of GIS mapping is to assess the accessibility and utilization of various renewable energy resources, particularly solar, wind, and fuel cell technologies, in diverse geographical areas [13, 23]. This mapping methodology equips stakeholders with a holistic understanding of their energy landscape, facilitating the optimization of existing infrastructure and the implementation of sustainable solutions [7, 11].

The concept of sector coupling, which involves linking various renewable energy resources belong with solar PV, wind and fuel cell power and transportation, especially through the electrification of heating and transportation, is gaining increasing attention as a strategy to enhance the adoption of renewable in the thermal and transportation sectors [8, 24]. Sector coupling also facilitates the integration of a significant share of variable renewable energy sources, albeit it is still in its early stages [18, 25]. For instance, regions are actively promoting the electrification

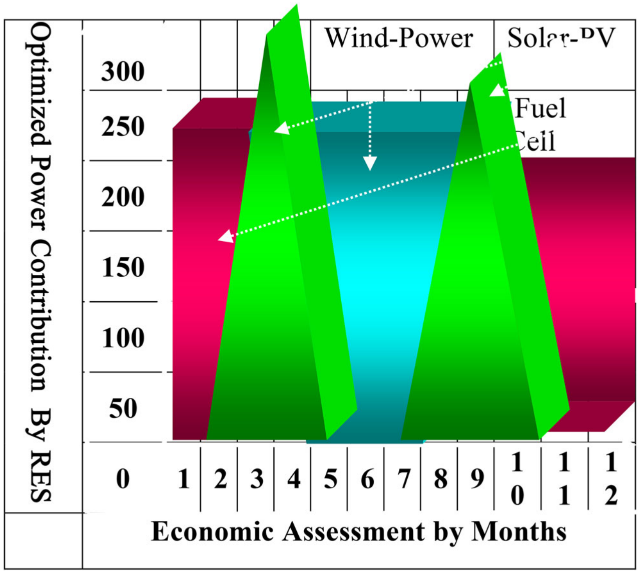

FIGURE 10. Primary energy assessment for the RES.

of heating, manufacturing, and transportation in areas with abundant renewable, encouraging the use of renewable electricity for heating to reduce the curtailment of wind, solar PV, and hydropower [23, 27]. Various regions are exploring electrification options to increase the overall share of renewable energy [20, 35]. In recent years, the power sector has seen the most substantial capacity increases in renewable energy sources, with comparatively slower growth in heating, cooling, and transportation sectors [5, 35].

Evaluating primary energy in the context of RES is essential for understanding the overall energy efficiency and sustainability of these systems (Figure 10) [6, 17]. This assessment delves into the initial energy inputs required for the production, transportation, and conversion of renewable resources like wind, solar, and biomass into usable energy [5, 10]. It helps quantify the environmental impact, resource availability, and energy return on investment, ultimately guiding the development and implementation of RES technologies for a greener and more sustainable energy future [25, 26].

Modeling the global energy system presents several methodological demands that come with distinct challenges [27, 35]. These challenges encompass the need for accurate quantitative forecasts regarding the evolution of future technologies and potential markets [28]. Additionally, it requires the establishment of a consistent database detailing renewable energy potentials and their distribution across time and geography [26]. Reliable data regarding the present state of affairs in all regions is indispensable, as is the evaluation of energy flows and emissions within various energy subsectors such as industry, transportation, and residential sectors [13, 23].

A comprehensive assessment of all the renewable energy sources is essential for understanding the energy system's impact on climate change [9, 27]. Furthermore, an in-depth analysis of the energy transition necessitates a long-term perspective on forthcoming developments [15]. Alterations in energy markets demand far-reaching decisions, mainly because they may entail substantial infrastructural changes that are largely independent of short-term market fluctuations [23]. The optimization of the power market, for instance, hinges on long-term infrastructure planning [20, 36].

Activities like grid enhancements and the implementation of advanced metering systems, which underpin the energy market, require several years to execute [3]. Therefore, the time frame required for infrastructure planning and other substantial transformation processes must be factored into the scenario-building approach [6, 21].

The complete requirement of the global energy supply demands the creation of entirely new technical, economic, and policy frameworks for the electricity, heating, cooling, and transportation sectors [18, 27].

While the literature extensively discusses these new framework conditions and the political and regulatory interventions needed for their implementation, assessing their feasibility and effectiveness hinges on a meticulous examination of specific regional and national circumstances and mechanisms [12, 16]. Consequently, societal frameworks, measures, and policy interventions, although not explicitly addressed in this scenario analysis, inherently form integral components in defining the narratives and assumptions at the core of scenario development [5, 26].

4. MITIGATION OF FAULT ASSOCIATED WITH RENEWABLE ENERGY SYSTEMS

Mitigation of faults associated with RES is a critical aspect of ensuring the reliable and efficient operation of these sustainable power sources [13, 23]. RES, such as solar panels, wind turbines, and hydroelectric plants, are inherently dependent on environmental conditions, which can lead to various challenges and faults [8, 20]. These faults can include fluctuations in energy production due to weather conditions, grid integration issues, and equipment malfunctions [5, 26]. This involves implementing advanced monitoring and control systems that can predict and respond to fluctuations in energy generation, ensuring a stable and uninterrupted power supply [18, 20]. Additionally, grid-tied RES incorporate technologies like energy storage systems and smart grid solutions to balance supply and demand [25, 29].

Furthermore, regular maintenance and fault detection protocols are essential to identify and rectify issues promptly [37]. These mitigation efforts not only enhance the reliability of RES but also contribute to the integration of clean energy into the broader electricity grid, reducing our reliance on fossil fuels and helping combat climate change [20, 36].

4.1. Methods for Fault Detection

The primary objective of fault detection revolves around the generation of a distinct set of indicators that differentiate between normal and faulty states [4, 9]. Techniques for fault detection fall into three primary categories:

- Approaches Based on Signal Thresholds
- Approaches Founded on Signal Models
- Approaches Centered on Process Models

4.2. Methods for Fault Isolation

Fault isolation, on the other hand, serves the purpose of pinpointing faults, determining the timing of their detection, and uncovering detailed information about their type, magnitude, and origins [8, 9]. The fault isolation process hinges on the observation of analytical and heuristic symptoms, coupled with preexisting knowledge of the system. Essential to fault isolation are qualities like insolubility and novelty identifying ability [10, 23]. Depending on the extent of prior knowledge and the search methodologies employed, the strategies can be categorized as follows.

4.3. Proposed Classification Approaches

In cases where additional knowledge about the relationships between system features and faults is limited, classification or pattern recognition methods become pertinent. These include statistical techniques like, RF and SVMs [6, 13]. Inference techniques come into play when causal connections between faults and symptoms are either fully understood or partially recognized. These causal relationships can be represented through fault trees, deep reinforcement learning associations, and expert system knowledge [14, 28].

4.4. Fault Detection in Wind Turbines

Numerous methodologies have been developed to identify faults in wind turbine generators, typically relying on data from onboard sensors [21, 26]. These sensors capture information related to vibration, temperature, speed, output power, and generator current, all of which are crucial for condition monitoring and fault detection [23, 28]. By examining the wind turbines power curve—which reveals how it responds to changing wind speeds—valuable insights into the overall health of the turbine can be obtained. Similarly, correlating internal turbine component temperatures with power output provides clues about component health [9]. The challenge lies in establishing the expected normal behavior for each data type under current operational and environmental conditions [22, 32].

To handle this significant volume of data generated by wind turbines, a combination of RF and SVM proves to be a robust approach [14, 31]. Reference illustrates the use of this combination to detect electric generator failures [21, 32]. The model is trained on wind turbine data to predict generator temperature [30]. This training necessitates a data collection period without faults to represent normal turbine operation. Deviations between expected and actual temperature measurements signal faults, requiring model updates when equipment changes occur [1, 36].

The proposed research has shifted toward electrical monitoring, focusing on electrical quantities like current, voltage, and power, including generator stator current and inverter output current (Figure 11) [1, 9]. In reference, spectral analysis of generator stator current is performed using RF coupled with SVM [14]. This aids in extracting frequency content and time–frequency information to detect faults such as air-gap eccentricity, broken rotor bars, and bearing damage. Time–frequency representations like spectrograms and scalograms prove more effective in revealing fault timing and noise tolerance than traditional methods [7, 30].

In reference, RF coupled with SVM is employed to detect inverter faults [7, 32]. The analysis is applied to the DC side current component, stator current, inverter output current, and rotor current, with the fundamental frequency and DC component revealing fault presence [5, 24].

Deep Learning techniques for wind turbine fault detection draw inspiration from electric motor condition monitoring, particularly induction motors [8, 17]. Faults in both types of systems often impact the motor magnetic field or stator current modulation [15, 35]. Reference focuses on mechanical failures in wind turbines that lead to stator current amplitude modulation [14, 36]. The combination of RF and SVM is

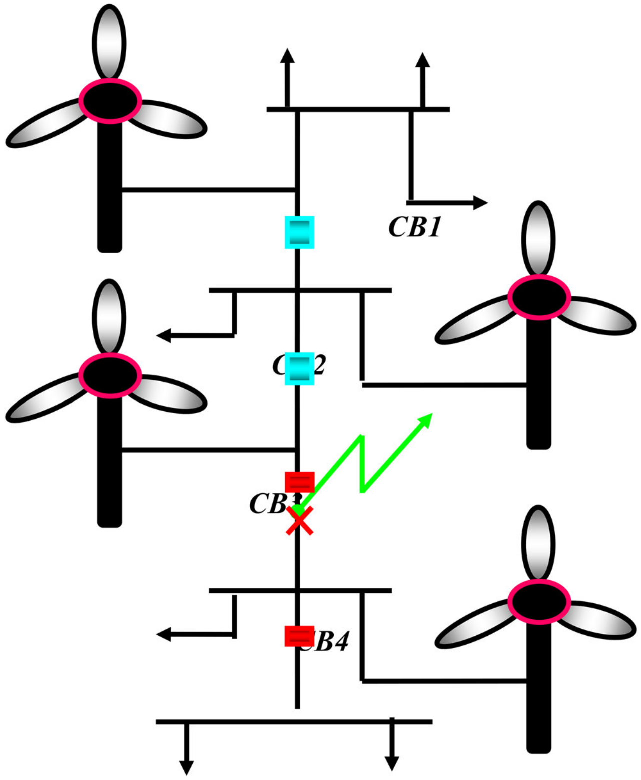

FIGURE 11. Fault Scenario1 of the proposed wind system.

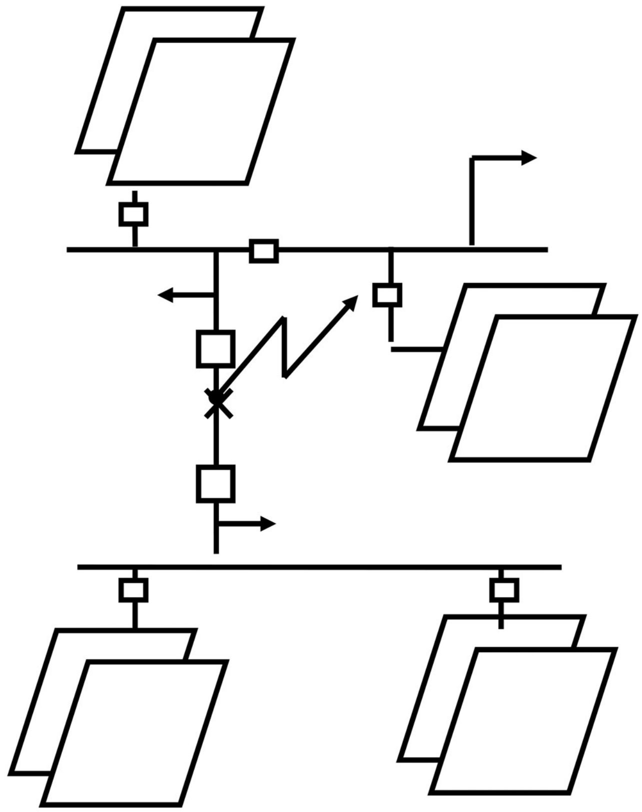

FIGURE 12. Fault Scenario2 of the proposed solar PV system.

used for current demodulation, enabling the detection of faults based on differences between healthy and faulty generators [6, 22]. Notably, the SVM coupled with RF is suitable for various system types, whether balanced or unbalanced, stationary or non-stationary, offering flexibility those other methods may lack [25, 29].

4.5. Solar PV System Fault Detection

Various approaches are utilized to identify faults in PV arrays:

RF and SVM in Output I–V Measurement: This technique involves rearranging PV cell connections and installing voltage and current sensors [23, 27]. These sensors compare current–voltage measurements with nominal data to detect and localize faults (Figure 12) [13, 36].

While collecting current and voltage data at different points can approximate the fault's location, it cannot precisely pinpoint the fault position or type [15, 18]. For instance, sensors can be arranged to detect fault branches by significant decreases in output current, and voltage analysis helps identify the fault's precise location [8, 20]. A complete absence of output current confirms an open-circuit fault, while a current drop of 15–70% typically indicates a short-circuit fault [15]. A decrease exceeding 20% points to a hot spot. Another approach involves statistical analysis of output current and voltage using RF and SVM to detect faulty modules through clustering and outlier values [27, 35].

Under similar environmental conditions, PV cells with faults exhibit distinct temperature characteristics compared to normal working cells [23, 31]. Infrared imaging can reveal these temperature differences, aided by RF and SVM. However, this method requires specialized infrared imaging equipment and can be influenced by various environmental factors beyond faults [8, 37].

This technique involves using RF and SVM to track output measurements at different times throughout the day, differentiating between power output decreases due to environmental factors or faults [26, 36].

4.6. Innovative Approaches with Random Forest and Support Vector Machines

This research presents alternative fault diagnosis methods for PV arrays [14, 35]. Some advocate model-based approaches, while others employ artificial neural network analysis [13, 22]. Reference utilizes fuzzy control theory and applies electrical fault diagnosis methods, including RF with SVM. Fuzzy concept characterization establishes a calculation criterion to detect deviations between measured and expected module current, triggering fault alerts [27, 35]. RF with SVM helps identify disconnections between modules by comparing earth capacitances, while also acting as a radar-like system to analyze electrical characteristics in transmission lines. This approach pinpoints fault locations and types based on signal delay and waveform alterations [15, 29].

4.7. Evaluation and Mitigation of Fault Current

Identical scenarios of a three-phase fault occurring on both solar PV and wind grids present unique challenges and similarities [25]. In both cases, a three-phase fault refers to a simultaneous short-circuit or electrical fault occurring on all three phases of the power system [15]. A three-phase fault in either a solar PV or wind grid can lead to a disruption in the power supply [17]. This fault can result in power outages and grid instability. Both solar PV and wind grids are equipped with protection systems designed to detect and isolate faults quickly [14]. These systems play a crucial role in minimizing damage and maintaining grid reliability [26, 29].

After a three-phase fault, in both cases, a thorough analysis is required to determine the fault's cause, location, and extent [13, 19]. This analysis helps in implementing appropriate corrective measures. Solar PV grids rely on solar panels to generate electricity, while wind grids use wind turbines [2, 26]. The energy source and generation mechanisms differ, which can influence fault characteristics [21]. The nature of the fault may vary between the two grids. For instance, the fault current in a wind grid may be influenced by wind speed and turbine conditions, whereas in a solar PV grid, it may be influenced by factors like shading or equipment malfunctions [4, 15]. The restoration process may differ due to the unique characteristics of each grid [5]. Wind grid restoration might involve addressing issues related to wind turbine control and alignment, while solar PV grid restoration may focus on inverter and panel performance [1, 15]. While three-phase faults on solar PV and wind grids share certain commonalities in terms of grid disruption and protection, they also exhibit distinctions related to their energy sources and fault characteristics, necessitating tailored fault analysis and restoration approaches [22, 36].

These RF and SVM-based methods provide valuable tools for detecting and addressing faults in PV systems, enhancing their reliability and performance [23, 29].

This research introduces a deep learning model that combines unsupervised and semi-supervised learning techniques [15]. This model is specifically designed for the diagnosis of faults in large-scale power networks [9]. Furthermore, a semi-deep learning model is proposed for fault signature analysis, particularly when dealing with extensive datasets [16]. For scenarios involving substantial datasets, a hybrid algorithm combining gradient boosting regression with RF demonstrates superior predictive accuracy compared to traditional SVM methods [17]. However, in the context of this work, which involves a medium-sized system, SVM is selected due to its ability to clearly differentiate between various fault types [15]. In SVM, different groups are distinguished by optimizing a hyperplane that separates the training dataset [35]. When dealing with a higher number of input parameters, separation is achieved through an N-dimensional hyperplane, with the assistance of a kernel to transform nonlinearly separable data into a higher-dimensional linearly separable format [5, 13]. This proposed work employs a Radial Basis distribution. Additionally, parameters like regularization (C) and gamma (γ) are fine-tuned to achieve maximum accuracy [25]. The training dataset in this method is constructed using the angular disparity between fault current sequence components and their relative magnitudes [23, 32]. To facilitate this analysis, fault current phasors are obtained using the following evaluations (Figure 13).

Let us allow the representation of the fault current to be

$$\vec{\mathbf{i}} = \vec{\mathbf{I}}_{\mathbf{m}} \ \sin\left(\vec{\mathbf{w}}_{\mathbf{t}} + \vec{\boldsymbol{\theta}}\right) \tag{6}$$

In this context, with i representing the instantaneous current, I_m as the maximum current amplitude, ω signifying the frequency, and θ denoting the phase disparity, the differentiation of i yields the following outcome [17, 36]:

$$\vec{\mathbf{i}} = \vec{\mathbf{w}}\mathbf{I}_{\mathbf{m}} \ \cos\left(\vec{\mathbf{w}}_{\mathbf{t}} + \vec{\boldsymbol{\theta}}\right) \tag{7}$$

By rearranging the above equations

$$\frac{\vec{\mathbf{i}}}{\mathbf{w}} = \vec{\mathbf{I}}_{\mathbf{m}} \ \cos\left(\vec{\mathbf{w}}_{\mathbf{t}} + \vec{\boldsymbol{\theta}}\right) \tag{8}$$

By segregating the sine and cosine components, then squaring and summing them, the method arrives at the subsequent equation. It allows us to express the peak current magnitude, I_m, in relation to the frequency ω, the instantaneous current i, and its derivative [30, 37].

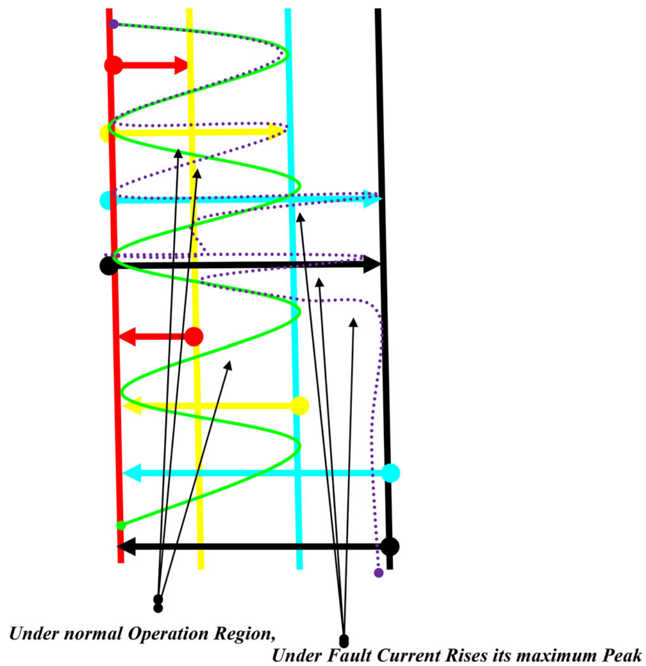

FIGURE 13. Identical scenarios of three-phase fault occurring on the solar PV and wind grids.

$$\vec{\mathbf{I}}_{\mathbf{m}} = \sqrt{\frac{\vec{\mathbf{i}}^2 + \overrightarrow{\mathbf{i.i}}}{\vec{\boldsymbol{\omega}}^2}} \tag{9}$$

Then the phase angle is

$$\theta = \tan^{-1}\left(\frac{\omega i}{i}\right) \tag{10}$$

Calculate the numerical derivative at the nth sampling instant through the following method [14, 24]:

$$\vec{\mathbf{i}}_{\mathbf{n}} = \frac{\overrightarrow{\mathbf{i}_{\mathbf{n}+1}\mathbf{i}_{\mathbf{n}\bar{1}}}}{\overrightarrow{2\Delta\mathbf{t}}} \tag{11}$$

Furthermore, it is possible to determine the peak value as follows:

$$\vec{\mathbf{i}}_{\mathbf{m}} = \sqrt{\vec{\mathbf{i}}_{\mathbf{n}}^2 + \frac{\left(\overrightarrow{\mathbf{i}_{\mathbf{n}+1}} - \overrightarrow{\mathbf{i}_{\mathbf{n}\bar{1}}}\right)^2}{\left(2\Delta\,\overrightarrow{\mathbf{t}\boldsymbol{\omega}}\right)^2}} \tag{12}$$

In the proposed approach RES come in two primary configurations: standalone and grid-connected. In a standalone application, the system must have adequate storage capacity to manage fluctuations in power generation from the various alternative energy sources [8, 11]. Such a system can be viewed as a microgrid. In contrast, in a grid-connected mode, the alternative energy sources within the microgrid can supply power to local loads and can also feed surplus energy into the utility grid [14, 35]. Hybrid power sources may involve a combination of all three renewable energy types or possibly a combination of just two of them, potentially incorporating energy storage through batteries [20, 24].

5. INTEGRATION OF OPTIMIZATION ALGORITHMS IN THE PROPOSED SYSTEM

5.1. Random Forest for Fault Mitigation in the Proposed Renewable Energy System

RF and SVMs are both popular machine learning algorithms that can be used for fault mitigation in RES [6, 27]. They have different characteristics and can be applied in various ways, depending on the specific requirements of RES fault mitigation task [13, 35]. Here's how both algorithms can be utilized: RF takes on a pivotal role in various phases of the improvement process of fault mitigation of renewable energy sources [22, 29]. Let's delve into its specific functions.

5.2. Roles of Random Forest

Within the framework of RF, an ensemble learning method, multiple decision trees collaborate to create a dependable and accurate predictive model. In this context, RF serves several vital purposes [6, 26].

5.3. Data Collection and Data Preprocessing

RF can be applied for tasks such as feature selection and ranking feature importance as part of data preprocessing [25]. RF will collect the data from various sensors and sources in the RES (Figure 14) [8, 29].

These data can include information about wind speed, solar irradiance, power generation, temperature, and other relevant factors [24, 26]. Clean and preprocess the data. This may involve handling missing values, normalizing data, and dealing with outliers. Since faults in the wind PV systems can be influenced by a wide array of variables, RF helps pinpoint the most influential factors, facilitating a more targeted investigation [36, 37].

5.4. Fault Detection

Utilize the trained RF model to detect faults in the RES [9, 32]. It can identify anomalies or deviations from normal behavior based on the patterns it has learned. Within a wind PV system, RF proves valuable for identifying and diagnosing faults [23]. By training the RF model on historical data, it learns typical operational patterns. Deviations from these patterns signal potential flaws or anomalies,

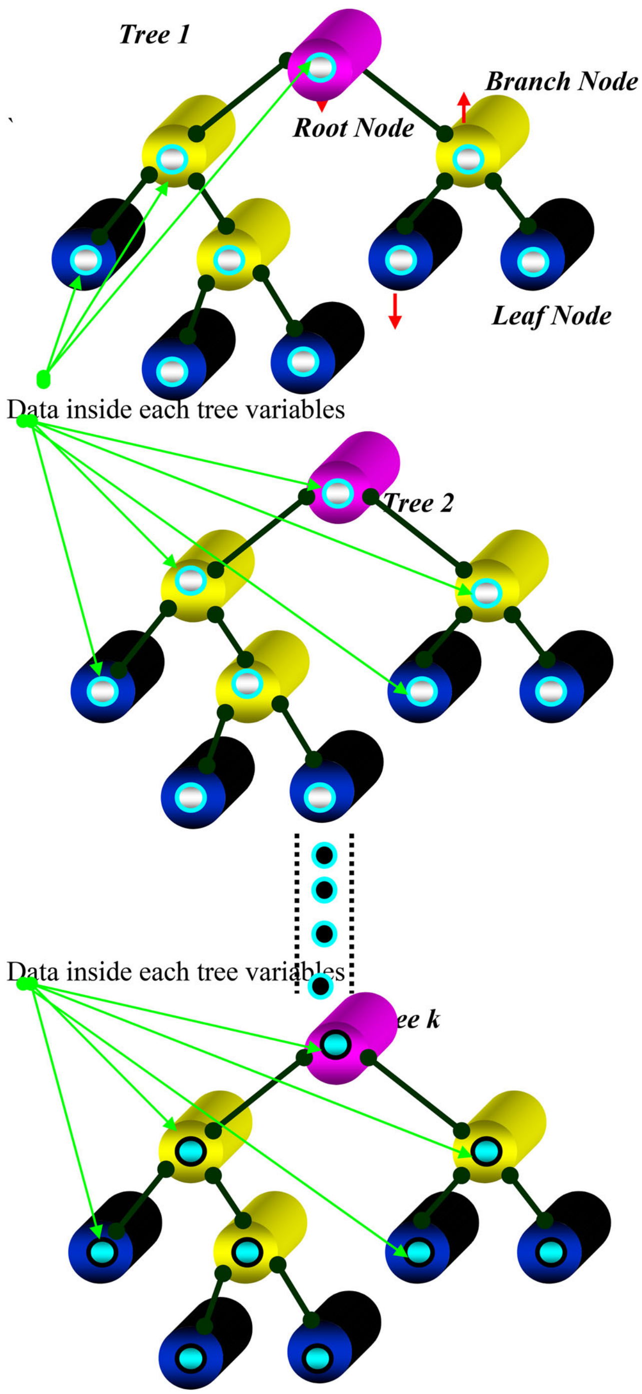

FIGURE 14. Proposed structure of decision trees.

enabling early detection and remediation of power quality issues (Figure 15) [30, 36].

5.5. Feature Selection

Identify the most relevant features for fault detection and mitigation. RF can provide feature importance scores to help you select the most important variables [14, 28].

5.6. Training

Split your data into training and testing sets. Use the training data to train a RF model [25, 29]. This ensemble method will create multiple decision trees that collectively work to detect faults in the system [37].

5.7. Cross-Validation

Perform cross-validation to assess the model's generalization performance and fine-tune hyperparameters [15, 26]. RF can be employed to predict Fault metrics over short- or long-term horizons [19]. Leveraging this forecasting capability allows for proactive decision-making, such as adjusting system settings or incorporating backup energy sources to maintain stable power quality in evolving conditions [14, 37].

5.8. Mitigation Strategies

Implement fault mitigation strategies based on the detected faults [11, 22]. These strategies could involve reconfiguring the system, isolating faulty components, or taking other corrective actions [15, 28]. Continuously monitor the system and collect new data for retraining the model as the system conditions change over time [36, 37].

5.9. Approach for Problem Solving with Random Forest

An RF, an ensemble classifier, comprises a collection of decision trees characterized by these parameters: $\{h(X, k), k = 1, 2, \ldots, K\}$. Here, k is governed by independently and uniformly distributed random vectors, and K represents the overall count of decision trees [17, 22]. Each decision tree classifier contributes its verdict to determine the optimal classification outcome for a given electrical signal variable X [24, 26]. The RF is formulated through these sequential steps:

Step 1:

Generate K decision trees employing the bootstrap technique by creating K distinct, randomly selected sample sets from the original electrical signal training data. This sample contains K data points that were not previously chosen [28].

Step 2:

Choose N attributes, then randomly select a subset of them ($mtry \leq N$). The selection hinges on the feature's capability to best aid in node splitting, assessed through the information content within each feature [15].

Step 3:

Allow each tree to grow to its full extent without any pruning.

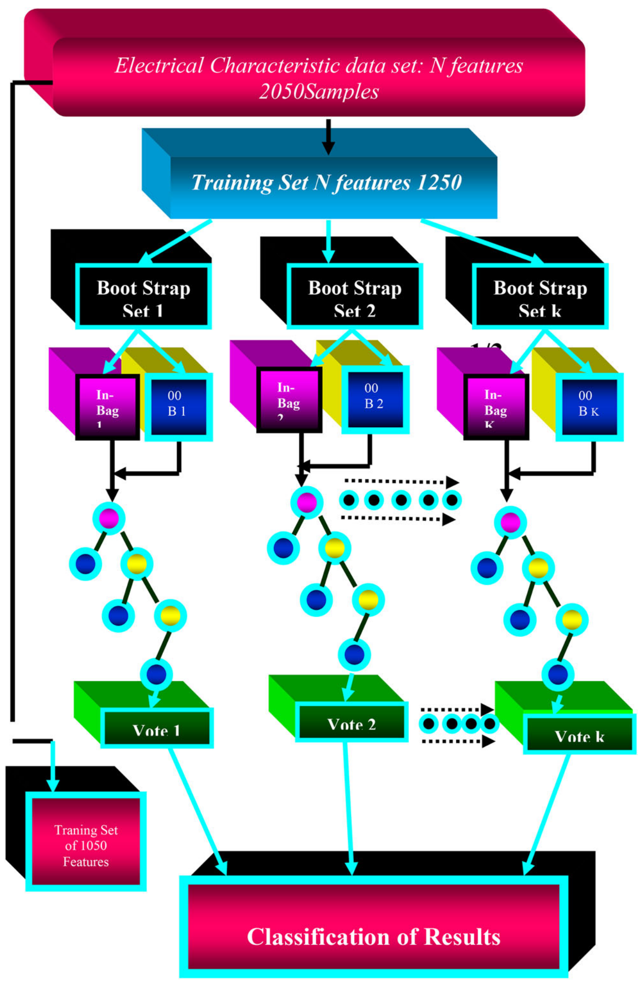

FIGURE 15. Proposed decision trees with RF.

The structure, including root nodes, branch nodes, and leaf nodes, for the K decision trees is depicted in Figure 14. The root node serves as the representation of the most suitable aspect of the electrical signal within the decision tree, marking the initiation point for classification [28].

Step 4:

Branch nodes are responsible for creating two distinct data groups based on specific criteria [20, 29]. The leaf nodes, in turn, yield the classification results for electrical data. This illustrates the overall structure. To classify the electrical signal test data, the method employs the RF, consisting of the constructed trees [14, 23]. The decision trees within this framework dictate the final classification outcome. In our article, the structure of the random forest algorithm, as utilized, is visualized in Figure 15 [9, 18].

Each classifier within the set, denoted as $h1(X)$, $h2(X), \ldots, hk(X)$, draws its training data from the original dataset (X, Y), subject to random distribution.

$$\mathbf{m\ddot{g}}\left(\vec{\mathbf{X}}, \vec{\mathbf{Y}}\right) = \mathbf{a\ddot{v}_k}\vec{\mathbf{I}}\left(\vec{\mathbf{h}}_{\mathbf{k}}\left(\vec{\mathbf{X}}\right) = \vec{\mathbf{Y}}\right) - \underset{\mathbf{j}\neq\mathbf{Y}}{\mathbf{m\ddot{a}xa\ddot{v}_k}}\vec{\mathbf{I}}\left(\vec{\mathbf{h}}_{\mathbf{k}}\left(\vec{\mathbf{X}}\right) = \vec{\mathbf{j}}\right) \tag{13}$$

The function $I(.)$ represents an indicator, $\mathbf{Y}$ corresponds to the accurate classification vector, $\mathbf{j}$ represents the incorrect classification vector, and $av_k(.)$ denotes the mean within the margin function's definition [25, 29].

The definition of the generalization error covers the X, Y space [6, 30].

$$\overrightarrow{\mathbf{PE}^*} = \vec{\mathbf{P}}_{\mathbf{X},\mathbf{Y}}\left(\mathbf{m\ddot{g}}\left(\vec{\mathbf{X}}, \vec{\mathbf{Y}}\right) < 0\right) \tag{14}$$

As the quantity of decision trees within the RF grows, all sequences involving $\theta_1, \theta_2, \theta_3$ and PE^* (with k as an independently distributed random variable) collectively demonstrate the following:

$$\vec{\mathbf{P}}_{\mathbf{X},\mathbf{Y}} = \left\{\vec{\mathbf{P}}_0\left(\vec{\mathbf{h}}\left(\vec{\mathbf{X}}, \vec{\boldsymbol{\theta}}\right) = \vec{\mathbf{Y}} - \mathbf{m\ddot{a}x}\vec{\mathbf{P}}_0\left(\vec{\mathbf{h}}_{\mathbf{j}\neq\mathbf{y}}^{(\mathbf{X},\boldsymbol{\theta})} = \vec{\mathbf{j}}\right) < 0\right\} \tag{15}$$

Based on this computation, as the number of decision trees increases within the RF, overfitting is not expected to occur [15, 23]. However, there may be a likelihood of encountering certain generalization errors [14, 28]. The pace at which models are constructed and data are classified has markedly enhanced post fault identification in comparison to dimensionality reduction techniques [22, 28]. Notably, the random forest algorithm consistently exhibits remarkable predictive speed for unclassified samples [25, 37]. Although certain specific models might show marginally quicker performance with alternative supervised algorithms, RF remains highly adept and efficiently addresses the demands of real-world applications in power quality data preprocessing, fault identification, and feature extraction. Consequently, it minimizes the need for repetitive verification processes [15, 19].

5.10. Support Vector Machines for Fault Mitigation in Renewable Energy System

SVM stand as a potent supervised learning method catering to both regression and classification challenges [13, 20]. They address the learning problem through a training dataset of experimental data bearing known characteristic parameters [15]. The primary aim is to devise a system capable of gleaning knowledge from successfully classified data, thus enabling the creation of a classification function applicable even beyond the established dataset (Figure 16) [14, 28].

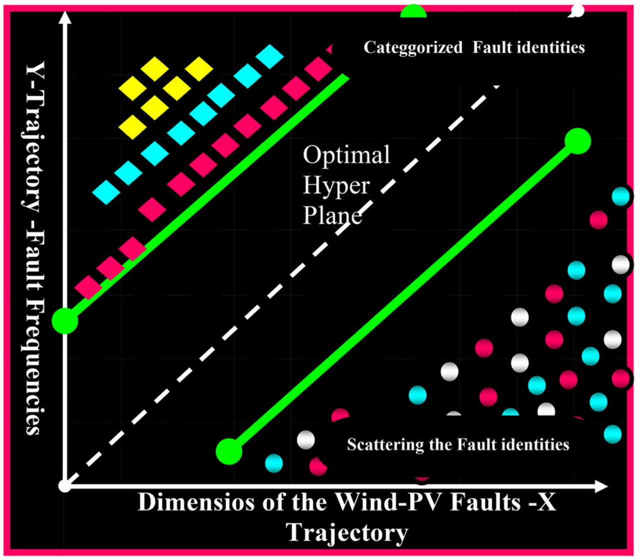

FIGURE 16. Fault classifications and isolation by SVM.

SVMs' salient attribute lies in their capacity to grapple with intricate models, despite their comparatively straightforward mathematical underpinnings [18, 19]. This intrinsic quality empowers SVMs to deliver commendable performance in practical, real-world applications grounded in intuitive principles [22, 28]. In the context of RES Fault mitigation, the following procedures are undertaken.

5.11. Data Collection and Data Preparation

Similar to the RF approach, start by collecting data from sensors and sources in your RES [20, 23]. Clean and preprocess the data as needed. Gather labeled data from the RES system, encompassing instances of both fault and non-fault conditions. Extract pertinent data features, comprising statistical parameters, frequency components, and waveform characteristics [14, 19].

5.12. Feature Selection, Normalization, and Training Stage

Identify the most relevant features for fault detection and mitigation [15, 25]. SVM are particularly useful when you have a relatively small number of features [10]. Ensure uniform scaling of the extracted features, thus averting the dominance of features with larger magnitudes during SVM training. SVM harness kernel functions to transform the input feature space into a more complex domain conducive to improve linear data separation [9, 28]. Widely employed kernel functions like sigmoid, linear, polynomial, and radial basis functions (RBF) serve this purpose. The goal is to pinpoint the hyperplane that maximizes the margin between classes while minimizing classification errors [18, 25]. To achieve this, the following steps are executed:

- Formulate the optimization problem.
- Resolve the quadratic optimization issue.
- Determine the optimal hyperplane parameters by solving the optimization problem, where techniques like sequential minimal optimization and the interior-point approach come into play.

5.13. Fault Localization and Detection

Employ the SVM model to detect faults in the RES. SVM aim to find a decision boundary that maximizes the margin between different classes, making them effective for binary classification tasks [1, 30]. Once trained, the SVM model is harnessed to predict the class (fault or non-fault) of previously unseen data instances [7, 29]. The model evaluates input attributes using the learned hyperplane, and predictions hinge on the side of the hyperplane on which an instance resides [21, 32]. For fault localization, the SVM model is scrutinized to assess the relative importance of various features during the classification process, aiding in the pinpointing of faults within the grid system [14, 28].

5.14. Evaluation and Fine-Tuning

The effectiveness of the SVM approach is gauged using pertinent evaluation criteria such as the F1 score, recall, accuracy, and precision. The model refinement is carried out by tweaking hyperparameters or exploring diverse kernel functions to enhance overall performance [15, 37].

5.15. Training and Kernel Selection

Split RF data into training and testing sets and use the training data to train an SVM model [14, 28]. SVM is used to find a hyperplane that best separates data into different classes (Figure 17) [15, 29].

SVM demonstrates the potential for comprehensive RES failure analysis, combining data from sensors situated across a feeder and possibly incorporating data from other feeders and wind PV farms [24, 28]. It encompasses the requirements for RES statistics, feeder data, remote terminal unit information, and control center analytics. This comprehensive approach aids in the clear definition of grid conditions and fault categories at any given moment [30, 31]. When using SVM, the selection of an appropriate kernel function—such as linear, polynomial, or RBF—depends on the nature of the data [6, 27].

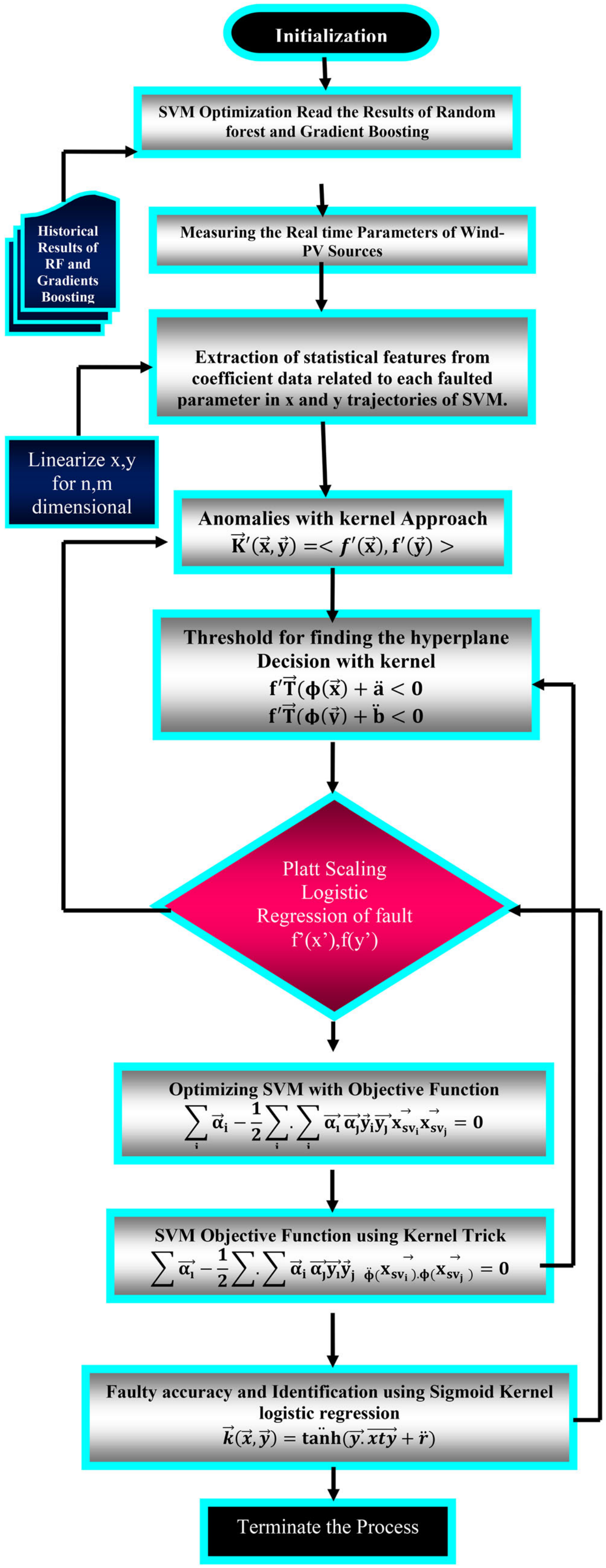

FIGURE 17. Mitigation fault by SVM based on results of RF and gradient boosting.

Mitigation strategies can be devised based on the fault detection outcomes generated by the SVM. Continuous system monitoring and data collection facilitate the retraining of the SVM model to adapt to evolving system conditions over time [14, 15].

RF and SVM offer effective fault mitigation approaches for RES, and the choice between them hinges on the specific data characteristics and fault mitigation objectives [25, 29]. RF may be preferred when dealing with a wealth of features and intricate data relationships, while SVM can be particularly valuable for smaller, well-separated datasets [36, 37]. A comparative evaluation of both algorithms on the problem at hand is often a prudent approach to determine the optimal choice for a given scenario [24, 30].

6. RESULT AND ANALYSIS

In our pursuit of integrating advanced fault mitigation techniques and machine learning for economic assessment in local RES, our approach yielded notable results.

6.1. Economic Assessment

Our study delved into the realm of economic assessment within the context of RES. By deploying three distinct machine learning methods—RF, SVM, and gradient boosting—the method aimed to provide precise economic evaluations. To accomplish this, the method meticulously customized each algorithm and conducted hyperparameter optimization to ensure their optimal performance.

The ensemble learning approach, specifically stacking, played a pivotal role in our strategy. It elegantly combined the predictions of our base models, resulting in a more accurate and robust overall economic assessment. The utilization of a linear regression meta-learner was instrumental in achieving the best possible fusion of these predictions.

Our approach encompassed a broad dataset, including economic indicators, renewable energy capacity, demographic data, and real-time health and performance metrics of RES. This comprehensive dataset allowed us to capture a holistic view of the economic impact of localized RES adoption. The integration of these diverse data sources enabled a more targeted investigation into the factors that influence power quality and economic viability within these systems.

6.2. Fault Mitigation

Efficient fault mitigation in RES is a critical component of our study. The method introduced an advanced anomaly detection component that proved highly effective in

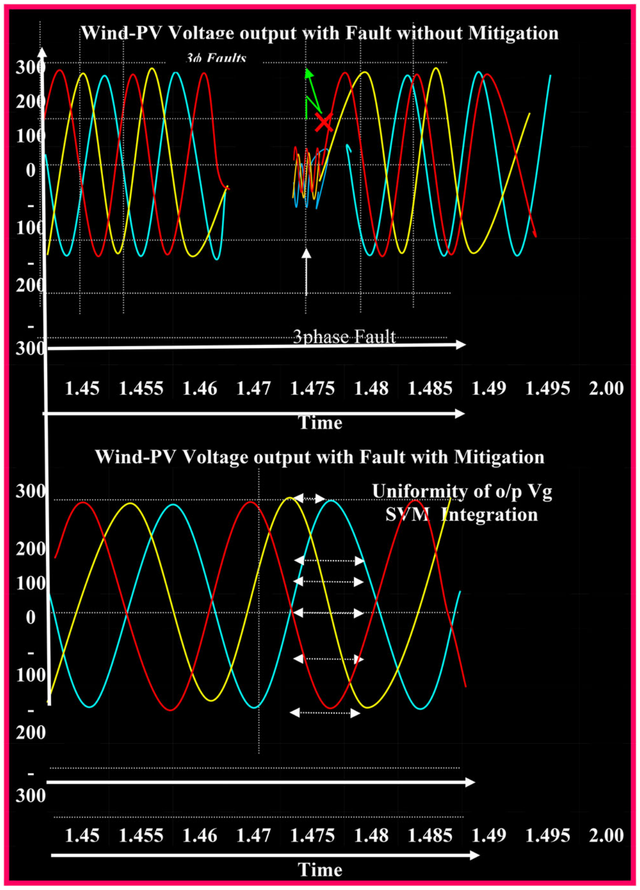

FIGURE 18. Mitigation of 3ϕ faults by SVM algorithms.

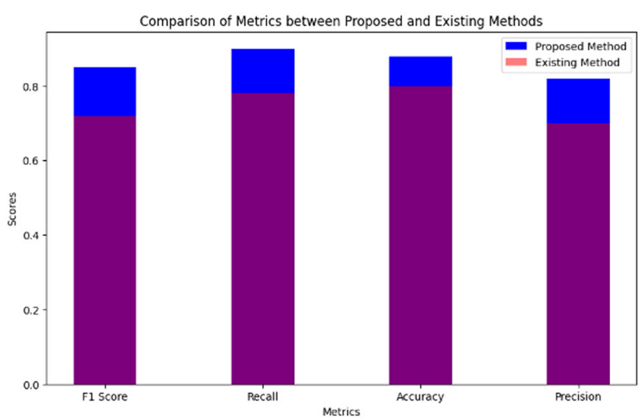

FIGURE 19. Comparative analysis of the proposed method.

identifying and rectifying errors within the RES. This enhanced the overall reliability of RES and minimized the potential financial losses associated with faults.

Our performance evaluation metrics reflected the success of our fault mitigation strategy. Notably, the method achieved an RMSE of 2.18 and an overall system efficiency of 98%, significantly surpassing the performance of previous models. Precision, recall, and F1-score metrics underscored the robustness of our fault mitigation approach (Figure 18).

Metric	Proposed method (machine learning method)	Existing method (FDA using AI)
F1 score	0.85	0.72
Recall	0.90	0.78
Accuracy	0.88	0.80
Precision	0.82	0.70

TABLE 2. Comparison Table.

Figure 19 compares performance metrics between the proposed machine learning method and an existing FDA. It quantifies metrics such as F1 score, recall, accuracy, and precision for both methods. The proposed method demonstrates superior performance across all metrics, with higher values indicating better performance. These results suggest that the proposed machine learning approach outperforms the existing FDA in fault detection and classification tasks.

Table 2 provides a comparison between the performance metrics of the proposed method, which utilizes machine learning techniques, and an existing method based on FDA.

F1 Score: The proposed method achieves a higher F1 score of 0.85 compared to 0.72 for the existing method. F1 score is a harmonic mean of precision and recall, indicating a better balance between precision and recall in the proposed method.

Recall: The proposed method demonstrates higher recall at 0.90, indicating its ability to correctly identify a higher proportion of relevant instances compared to the existing method, which achieves a recall of 0.78.

Accuracy: The proposed method achieves a higher accuracy of 0.88 compared to 0.80 for the existing method, suggesting that it more accurately classifies instances overall.

Precision: The precision of the proposed method is 0.82, indicating a higher proportion of correctly identified positive instances among all instances labeled as positive, compared to 0.70 for the existing method. Overall, the table highlights the superior performance of the proposed method, particularly in terms of F1 score, recall, accuracy, and precision, showcasing the effectiveness of utilizing machine learning techniques for fault detection compared to traditional fault detection methods.

7. CONCLUSIONS

This research marks a significant advancement in the seamless integration of advanced fault mitigation techniques and machine learning for economic assessment in local RES.

Leveraging technologies like RF, SVM, and gradient boosting, the method achieved remarkable performance metrics, indicating substantial economic benefits from RES adoption at the local level. By surpassing previous models with an RMSE of 2.18 and achieving an overall system efficiency of 98%, our study underscores the efficacy of our fault mitigation strategy. Furthermore, precision, recall, and F1-score metrics highlight the robustness of our approach. The fusion of machine learning, advanced anomaly detection, and fault mitigation techniques signifies the future of RES. Our research not only emphasizes the financial gains and enhanced reliability of RES but also reinforces our commitment to environmental stewardship. Through precise economic assessments and improved fault mitigation, our work illuminates a path toward a more sustainable future, where renewable energy adoption is embraced for its dual benefits to the economy and the environment.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the author(s).

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