Review Article

Review of Component-Specific Modelling, Optimization, and Grid Integration Strategies for Hybrid Renewable Microgrids

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ABSTRACT

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| Hybrid renewable microgrids (HRMs) integrating solar photovoltaic (PV), wind turbines, diesel generators, and battery storage systems are critical for resilient, low-carbon energy transitions. However, their inherent complexity—driven by intermittent generation, multi-objective optimization, and dynamic grid interactions—necessitates advanced modelling and control strategies to balance techno-economic and operational demands. This review synthesizes advancements in component-specific modelling, including non-linear fuel consumption curves for diesel generators, Weibull-distributed wind resource analysis, and Kalman filter-enhanced state-of-charge estimation for batteries. It highlights the transformative role of artificial intelligence (AI)-driven energy management systems and digital twin frameworks in optimizing dispatch, fault recovery, and predictive maintenance. Critical gaps in real-time adaptability, bidirectional grid synchronization, and standardized regulatory frameworks for peer-to-peer energy trading are examined. By bridging global innovations in adaptive control, blockchain-enabled transactive energy, and next-generation storage (e.g., solid-state batteries) with socio-technical insights, this review provides a roadmap for deploying HRMs that align with decarbonization targets and energy equity goals, particularly in underserved regions with volatile demand and resource constraints. |

*Keywords:* Hybrid renewable microgrids, artificial intelligence, grid integration, adaptive control, decarbonization, Kalman filter.

1. INTRODUCTION

The global energy transition toward decarbonization and resilience has intensified the deployment of hybrid renewable microgrids (HRMs), which integrate solar photovoltaic (PV), wind turbines, diesel generators, battery storage, and grid interconnections [1]. These systems address the limitations of standalone renewable sources by adopting complementary energy generation and storage technologies, enhancing reliability and reducing dependency on fossil fuels [2]. HRMs are particularly critical for remote electrification, grid stability in urban areas, and industrial decarbonization, offering a scalable framework to balance sustainability with energy security [3]. However, the inherent complexity of HRMs—arising from intermittent renewable generation, dynamic load profiles, and multi-objective operational constraints—demands advanced modelling and optimization strategies to achieve techno-economic viability [4].

Modelling HRMs requires a holistic approach to capture the transient interactions between distributed energy resources (DERs) and storage systems. Solar PV and wind generation exhibit stochastic behaviour influenced by weather variability, necessitating probabilistic forecasting models to predict output fluctuations [5]. Battery storage systems (BSS), while pivotal for load-levelling and backup power, introduce challenges such as degradation dynamics and state-of-charge (SOC) management [6]. Concurrently, diesel generators serve as dispatchable backups but contribute to emissions, requiring optimization frameworks that minimize their runtime without compromising reliability [7]. Recent studies emphasize digital twin models and real-time simulations to replicate HRM behaviour under diverse scenarios, enabling predictive maintenance and adaptive control [8].

Optimization of HRMs hinges on multi-objective algorithms that reconcile conflicting goals, including levelized cost of energy (LCOE) minimization, carbon footprint reduction, and reliability enhancement [9]. Metaheuristic techniques such as genetic algorithms (GA) and particle swarm optimization (PSO) have gained prominence for their ability to handle non-linear constraints and Pareto-optimal solutions [10]. Machine learning (ML) approaches, including reinforcement learning (RL) and neural networks, further refine dispatch strategies by learning from historical data and adapting to real-time grid conditions [11]. For instance, hybrid ML-PSO frameworks have demonstrated a 12–18% improvement in cost efficiency compared to rule-based strategies in islanded microgrids [12]. Despite these advancements, gaps persist in standardizing optimization benchmarks and scalability for large-scale HRMs with bidirectional grid interactions [13].

Grid integration remains a pivotal challenge for HRMs, particularly in maintaining stability and compliance with grid codes such as IEEE 1547-2018 [14]. Bidirectional power flow between HRMs and utility grids introduces voltage fluctuations, harmonic distortions, and synchronization issues, necessitating advanced power electronics and adaptive protection schemes [15]. Recent innovations in grid-forming inverters and virtual synchronous generators (VSGs) have improved frequency regulation and fault ride-through capabilities in HRMs [16]. Furthermore, blockchain-enabled peer-to-peer (P2P) energy trading platforms are emerging as disruptive solutions to enhance grid flexibility and economic returns [17]. This review synthesizes advancements in HRM modelling, optimization, and grid integration, providing a roadmap for researchers and policymakers to accelerate the adoption of resilient, low-carbon energy systems.

2. BACKGROUND OF THE sTUDY AND RELATED WORKS

**2.1 Renewable Microgrid**

A renewable microgrid is a localized energy system composed of distributed energy resources (DERs), primarily renewable sources such as solar photovoltaics, wind turbines, small hydro, and biomass generators. These microgrids operate autonomously or in coordination with the primary grid to enhance energy reliability, flexibility, and sustainability. Unlike centralized grids, renewable microgrids are designed for scalability and adaptability, often tailored to serve specific communities, campuses, or industrial zones. In addition to generation units, they include energy storage systems (ESS), smart meters, and intelligent controllers for real-time operation and monitoring. The core appeal of renewable microgrids lies in their ability to provide energy access in remote or disaster-prone areas where conventional grid extension is technically or economically infeasible [18]. Figure 1 shows a typical microgrid network while Fig. 2 represents a DC microgrid.



**Fig. 1: Typical microgrid network [19]**

Operational efficiency and reliability are achieved through intelligent control strategies that manage the intermittent nature of renewable energy sources. Deploying hybrid configurations—comprising multiple renewable sources alongside batteries or diesel backups—enables a more stable power output. Control techniques such as droop control, model predictive control, and hierarchical energy management systems are widely applied to balance power generation and consumption [20]. Furthermore, optimization algorithms determine the most cost-effective operation schedule based on forecasted generation and load profiles. These approaches ensure system stability during transitions between islanded and grid-connected modes. Recent advancements in machine learning and Internet of Things (IoT) integration enable microgrids to become increasingly autonomous and resilient [21].



**Fig. 2. A DC microgrid [22]**

Regarding broader impacts, renewable microgrids contribute significantly to climate change mitigation, sustainable development, and energy equity. They reduce greenhouse gas emissions by displacing diesel-based generation and decrease the vulnerability of power supply systems to environmental and geopolitical disruptions. In developing countries, microgrids can promote socio-economic development by supporting local entrepreneurship and creating green jobs [23]. Policy incentives, robust regulatory frameworks, and innovative financial models—such as pay-as-you-go or community-owned energy schemes—are essential to encourage widespread deployment. As renewable technologies and energy storage costs continue to decline, renewable microgrids are expected to play a central role in the global transition toward a decentralized, low-carbon energy future [24].

**2.2 Hybrid Renewable Microgrid**

A hybrid renewable microgrid is an advanced microgrid that integrates two or more renewable energy sources—such as solar, wind, hydro, or biomass—along with conventional energy sources and energy storage systems. The hybrid configuration leverages the complementary characteristics of different energy sources to improve the power supply’s overall reliability, stability, and efficiency. For example, solar and wind are often combined because their generation profiles are inversely correlated: solar output is highest during the day, while wind speeds may peak at night or during cloudy conditions [25]. This synergistic integration reduces reliance on fossil fuel-based backup generators and minimizes the intermittency and variability that individual renewable sources exhibit. Hybrid renewable microgrids are increasingly adopted in remote areas, island communities, and critical infrastructures where energy security and resilience are paramount [26]. An illustration of a sustainability-focused grid is presented in Fig. 3.



**Fig. 3. Sustainable energy sources for microgrid [27]**

The design and optimization of hybrid renewable microgrids involve complex multi-objective decision-making processes that account for technical, economic, and environmental factors. Vital considerations include optimal sizing of generation and storage components, real-time control strategies, and load management. Advanced optimization techniques such as genetic algorithms, particle swarm optimization, and mixed-integer linear programming have been used to determine the best configuration of resources to minimize lifecycle cost and emissions while ensuring reliable operation [28]. In addition, EMS plays a pivotal role by coordinating the dispatch of different energy resources based on weather forecasts, demand predictions, and battery state-of-charge levels. These systems enable the microgrid to operate efficiently in grid-connected and islanded modes, providing uninterrupted power supply even during grid disturbances or outages [29].

From a sustainability and implementation perspective, hybrid renewable microgrids offer a pragmatic pathway toward decarbonization, particularly in areas with high energy poverty or vulnerable to climate change impacts. They enable the integration of local energy resources, promote community involvement, and foster energy independence. However, challenges persist, such as high initial capital investment, lack of standardized regulatory frameworks, and the need for skilled technical personnel for operation and maintenance. Policy support and financial mechanisms such as feed-in tariffs, green bonds, and public-private partnerships are critical for scaling deployment. With ongoing advancements in power electronics, control systems, and forecasting tools, hybrid renewable microgrids are expected to be essential in achieving global clean energy targets and enhancing grid flexibility [30].

**2.3 Hybrid Renewable Microgrid (HRM) Modelling**

Accurate Hybrid Renewable Microgrids (HRMs) modelling is essential to replicate real-world dynamics, assess operational viability, and facilitate optimal control across diverse and variable energy sources. HRM models must integrate component-level behaviour (e.g., generation units, energy storage, inverters) and system-wide interactions (e.g., power balance, control strategies, grid synchronization). Due to the stochastic nature of renewable sources and varying load demands, these models must incorporate probabilistic frameworks, degradation mechanisms, and multi-domain co-simulation capabilities. Comprehensive modelling supports critical tasks such as performance forecasting, reliability analysis, and techno-economic optimization, all of which are central to effective HRM planning and deployment [31].

3. COMPONENT MODELLING

**3.1 Solar Photovoltaic (PV) Systems**

Irradiance Forecasting: A cornerstone of PV system modelling is accurate irradiance forecasting, which directly impacts power output estimation [32]. Probabilistic methods, such as Markov Chain Models, simulate transitions between irradiance states, capturing temporal weather variations effectively. Markov Chain Transition Probability is expressed in (1).

  (1)

where  = probability of transitioning from state *i* (cloudy, for example) to *j* (sunny, for example), *Nij*​ = observed transitions, *Ni*​ = total occurrences of state *i*.

Artificial Neural Networks (ANNs) and hybrid AI models have recently shown higher prediction accuracy by learning complex non-linear relationships between solar irradiance, temperature, and historical meteorological patterns [33]. ANN-based irradiance prediction, as proposed by [34], is expressed in (2).

 (2)

*G*(*t*) = forecasted irradiance at time *t*;  ​ = neural network function trained on historical data.

These models are often trained with satellite data, sky imaging, or ground-based sensor arrays.

Degradation Modelling: Long-term PV performance declines due to thermal cycling, humidity ingress, UV exposure, and potential-induced degradation (PID). Linear models typically assume a 0.5% to 1% annual power degradation, simplifying lifetime yield estimation. However, more robust non-linear models incorporate operational stress factors and real-time environmental conditions to adjust the degradation rate dynamically. These physics-based or data-driven models are increasingly adopted in bankability studies and performance guarantees [35].

Regarding degradation modelling, (3) and (4) give the mathematical expressions for linear and non-linear degradation.

Linear degradation:

 (3)

where initial efficiency; α = annual degradation rate.

Non-Linear Degradation [36]:

 (4)

where β = stress coefficient; Stress = environmental stress factor.

Inverter Dynamics: The inverter is a critical component that converts DC output from PV panels into usable AC power. Modelling inverter behaviour involves simulating conversion losses, typically between 3–7%, depending on load conditions and inverter design. Furthermore, total harmonic distortion (THD) is a key parameter that must be kept below regulatory thresholds, commonly <5%, to prevent power quality issues. Accurate inverter models must also simulate dynamic responses to fluctuating solar input, grid disturbances, and maximum power point tracking (MPPT) efficiency [37]. Inverter efficiency is determined from (5) [38]:

 (5)

where , are loss coefficients, is the inverter-rated power output, is the AC power and is the DC power.

System-Wide Modelling Considerations: Beyond individual components, HRM modelling requires system-level integration to simulate energy flow, control coordination, and interoperability between heterogeneous resources (such as solar, wind, diesel generators, and battery storage). Tools like MATLAB/Simulink, HOMER Pro, and OpenDSS are commonly used for dynamic simulation, economic optimization, and load flow analysis. These platforms support hybrid configurations and allow the integration of custom stochastic models, energy management algorithms, and fault conditions. Incorporating Monte Carlo simulations enables risk assessment under uncertain renewable generation and load demand scenarios. Co-simulation frameworks (like FMI or Modelica-based systems) are also gaining prominence for coupling electrical, thermal, and control domains in a unified simulation environment [39].

**3.2 Wind Turbines**

Wind turbines are integral to Hybrid Renewable Microgrids (HRMs), offering clean, distributed power that complements solar and diesel sources. Accurate modelling of wind energy systems is essential for performance prediction, resource assessment, and reliable grid integration. Wind speed, being inherently stochastic and location-dependent, significantly affects the output of wind turbines. Therefore, system-level simulations rely on accurate wind speed modelling, turbine dynamics, and advanced control strategies to maintain operational stability and efficiency under variable atmospheric conditions [40].

Power curve modelling is fundamental in wind turbine simulation. The power output is a non-linear function of wind speed and turbine-specific characteristics such as cut-in, rated, and cut-out speeds. The Weibull distribution is often applied to historical wind speed data to represent wind resource availability accurately. The two-parameter Weibull model provides a good statistical fit for most geographic locations and allows estimation of the frequency and intensity of wind speeds over time. In addition, turbulence intensity, a measure of short-term wind speed fluctuation, is crucial in determining mechanical stress and fatigue on turbine blades and shafts. Elevated turbulence increases component wear and reduces the lifespan of turbines, which is thus incorporated into mechanical stress models and maintenance schedules [41]. Weibull wind speed distribution is as expressed in (6) [42]:

 (6)

where v is wind speed, k is the shape factor, and is the scale factor.

Wind turbine output is approximated from (7) [43]:

 (7)

where is the air density, A is the rotor-swept area, is the power coefficient, is the mechanical efficiency, , , and are turbine operational thresholds.

Pitch control mechanisms optimize performance and protect components under variable wind conditions. These systems adjust the blade pitch angle to regulate the aerodynamic force the rotor captures, especially when wind speeds exceed rated values. The most common strategy is the Proportional-Integral-Derivative (PID) controller, which minimizes the error between the desired and actual rotor speed. More advanced schemes, such as fuzzy logic controllers, adapt flexibly to rapid gusts and uncertain environmental changes, improving energy capture and reducing overloading risks. Control models are integrated into dynamic simulations to analyze system response during transients, load sharing, and fault conditions in HRMs [44]. Typically, PID controllers are used for pitch control dynamics and are modelled using (8) [44].

 (8)

where is the blade pitch angle, e is the error between the actual and desired rotor speed and , , are proportional, integral and derivative gains.

**3.3 Diesel Generators**

Diesel generators (DGs) serve as backup or primary generation units in Hybrid Renewable Microgrids (HRMs), particularly during periods of low renewable output or peak demand. Accurate modelling of DGs is crucial to reflect their dynamic behaviour, optimize fuel usage, and mitigate environmental impacts. The performance of diesel generators is susceptible to the load profile and operational scheduling; thus, a precise mathematical representation is required for system simulation and economic dispatch optimization. In hybrid systems, DGs often complement intermittent sources like solar or wind, but their inclusion introduces operational trade-offs regarding fuel costs, emissions, and maintenance requirements [45].

A vital aspect of DG modelling involves fuel efficiency curves, which capture the non-linear relationship between output power and fuel consumption. The fuel usage in litres per kilowatt-hour (L/kWh) is typically expressed as a second-order polynomial, as given in (9) [46]:

 (9)

where *F(P)* is the fuel consumption rate and, *P* is the generator output power, the coefficients *a*, *b*, and *c* are empirical constants specific to the modelled DG. They define the non-linear relationship between *P* and *F*(*P*).  *F(P)* accounts for diesel engines operating most efficiently at a specific load range (typically 70–85% of rated capacity), while efficiency drops significantly at lower loads.

Correct parameterization of the curve in (1) using empirical data enables realistic simulation of fuel demand under different load conditions and dispatch strategies [47]. Some models further integrate startup fuel consumption, ramp rate limitations, and engine wear considerations for enhanced reliability analysis. Startup fuel penalty, is approximated from (10) [48].

 (10)

where base fuel consumed during startup, is the fuel decay rate, and is the time since the last shutdown.

In addition to fuel usage, emission modelling is essential to evaluate the environmental footprint of diesel generators in HRMs. Diesel combustion emits significant amounts of carbon dioxide (CO₂), characteristically 650–1000 g/kWh, and nitrogen oxides (NOx), both regulated pollutants. Emission rates depend on generator loading, maintenance conditions, and fuel quality. As the load factor decreases, the specific emissions per unit energy tend to increase due to incomplete combustion and lower thermal efficiency. Therefore, emissions are often modelled as a function of output power and operational cycles, sometimes incorporating degradation factors and engine-specific emission coefficients derived from lab or field tests [49]. Accurate emission profiles are necessary for lifecycle assessment (LCA), regulatory compliance, and optimizing microgrid dispatch to minimize environmental impacts, especially in grid-isolated or environmentally sensitive areas. CO₂ emissions are approximated using the expression in (11) [49]:

 (11)

where is the CO₂ emission factor, linking fuel use to carbon output.

**3.4 Battery Storage Systems (BSS)**

Battery storage systems (BSS) are essential for enhancing the flexibility and reliability of HRMs. They enable energy balancing, frequency regulation, and load shifting by storing excess energy from intermittent sources like wind and solar and discharging during peak demand or renewable shortfalls. Accurate modelling of BSS behaviour is critical to ensure operational efficiency, lifecycle optimization, and safe integration into microgrids. Two central considerations in battery modelling are degradation mechanisms and state of charge (SOC) estimation, which influence control strategies and economic dispatch algorithms [49]. The expression for SOC is given in (12) [50].

 (12)

Q is the battery capacity, is Coulombic efficiency, and I is the current.

Degradation mechanisms in lithium-ion and other advanced batteries are typically categorized into cycle ageing and calendar ageing. Cycle ageing depends on the depth-of-discharge (DoD), charge/discharge rates, and frequency of cycles, while calendar ageing is primarily influenced by temperature and storage conditions. Studies indicate that capacity can be reduced by approximately 10–20% over five years due to these mechanisms, even under moderate cycling conditions. Capacity fade (cycle ageing) of batteries is estimated using (13) [51].

 (13)

where , are empirical constants, is the number of charges/discharge cycles, and DoD is the depth of discharge.

Some authors have also used the Kalman filter for SOC estimation, as given in (14) [52].

 (14)

where is the updated SOC estimate, is the sensor measurements (voltage and current) and is the Kalman gain matrix.

Therefore, modern battery models incorporate empirical or semi-empirical degradation functions that dynamically update internal resistance, capacity fade, and efficiency over time. This allows more realistic performance and maintenance scheduling prediction in HRMs, especially for long-term planning [53].

Accurate SOC management is equally vital, as errors in estimating the battery’s charge level can lead to overcharging, deep discharging, and reduced battery life. Coulomb counting is the most widely adopted technique, integrating current over time to estimate SOC. However, due to sensor drift and non-linear behaviour under varying temperatures and loads, Coulomb counting alone may yield significant errors. To overcome this, Kalman filter-based algorithms correct and refine SOC estimates in real-time. These methods have demonstrated SOC estimation errors of less than 2%, making them highly reliable for embedded EMS. Incorporating such algorithms in HRM simulations ensures robust control, extends battery lifespan, and improves system-wide efficiency [54].

**3.5 Load Demand**

Load demand modelling is a cornerstone of Hybrid Renewable Microgrid (HRM) design and operation. It directly influences the sizing of generation and storage units, dispatch optimization, and system stability. Unlike centralized grids with more predictable aggregate loads, microgrids often serve small, localized communities or industrial clusters, where demand profiles can be highly variable and non-linear. Precise load forecasting and adaptive demand response (DR) mechanisms are critical for maintaining supply-demand balance and minimizing operational costs. These models must also capture socio-economic factors, occupancy behaviour, and seasonal or temporal consumption trends [55].

Probabilistic forecasting methods such as Monte Carlo simulations represent variability and uncertainty in load patterns. These simulations generate thousands of possible load profiles based on historical data distributions and stochastic variables, capturing uncertainties arising from daily usage habits, appliance scheduling, and industrial processes. Typically, residential and commercial loads can fluctuate within a ±15% margin, and Monte Carlo methods enable planners to evaluate worst-case, average, and best-case scenarios as mathematically represented in (15) [56].

 (15)

where is the deterministic base load, is the stochastic load deviation, and is the standard deviation of load variability.

The resulting synthetic profiles are used to stress-test microgrid reliability, evaluate spinning reserve requirements, and inform battery dispatch algorithms under variable demand conditions [57].

On the control side, demand response (DR) programs are integrated into HRM management systems to reshape consumption patterns based on grid conditions or price signals. Price elasticity models, which quantify consumer responsiveness to changes in electricity pricing, are central to these strategies. The price elasticity model on load demand, as put forward by [58], is expressed in (16).

 (16)

where is the change in demand, is the elasticity coefficient, and is the change in the electricity price.

Through real-time pricing, time-of-use tariffs, or incentive-based load curtailment schemes, peak loads can often be reduced by 10–30%, lowering system stress and operational costs. DR modelling considers elastic load components—such as HVAC systems or deferrable appliance loads—that can be shifted without significantly impacting end-user satisfaction. These models are embedded into energy management systems to enable dynamic load shifting in response to renewable generation variability and grid contingencies [59].

For energy balance, (17) is used for the approximation [58, 59].

 (17)

The expression in (17) ensures that the power supply matches demand, including storage and losses.

However, the priority is ensuring minimal cost is maintained for the energy balance. This is achieved by setting a cost-minimization objective as outlined in (18).

 (18)

where:

 (19)

 (20)

 (21)

4. LITERATURE SURVEY AND FUTURE PROSPECTS

**4.1 Literature Survey**

Table 1 is an exhaustive review of previous works on modelling, optimization, and grid integration. The table summarizes methodologies, objectives, and research gaps.

**Table 1. Review of related past works**

| **Reference**  | **What Was Done** | **Method Used** | **Research Gap** |
| --- | --- | --- | --- |
| [60] | Developed a wavelet-SVM model for transient fault detection in grids. | Wavelet transform + SVM | Limited to fault detection; no integration with energy management systems. |
| [61] | ANN-based fault detection in PMU-enabled grids. | Artificial Neural Networks (ANN) | Focused only on fault detection; ignored economic dispatch. |
| [62] | Hybrid SVM-ANN models for real-time fault classification. | SVM + ANN | It did not address scalability for large-scale HRMs. |
| [63] | ANN-based power quality compensator for voltage sag mitigation. | ANN + Rule-based control | There is no integration with renewable sources or storage. |
| [64] | Reviewed AI applications in power system stability and control. | Literature review + Comparative analysis | Focused on stability; lacked HRM-specific optimization insights. |
| [65] | Deep learning for transient stability assessment in power systems. | Convolutional Neural Networks (CNN) | Limited to stability analysis; excluded cost or emission optimization. |
| [66] | Combined TCN-LSTM for short-term voltage stability. | Temporal CNN + LSTM | Did not integrate DERs or storage systems. |
| [67] | ANN-based fault detection for Nigerian 330kV lines. | ANN + Travelling wave theory | Limited to fault detection; no grid interconnection analysis. |
| [68] | ANN-based fault identification in Onitsha-New Haven line. | ANN + Signal processing | Narrow focus on faults; no optimization or cost analysis. |
| [69] | Modelled insulation defects in the Onitsha-New Haven line. | MATLAB/Simulink simulations | Did not propose mitigation strategies or optimization frameworks. |
| [70] | Transient stability analysis of Nigeria’s 330 kV grid. | PSCAD/EMTDC simulations | Outdated; no integration of ML/AI techniques. |
| [71] | Adaptive auto-reclosing using harmonic signatures. | Harmonic analysis + Adaptive logic | Limited to transmission lines; excluded microgrids or DERs. |
| [72] | Multifunctional DVR for power quality improvement. | Dynamic Voltage Restorer (DVR) + PI control | No renewable energy integration. |
| [73] | PSO-ANN for voltage sag mitigation in HRMs. | PSO + ANN | Ignored battery degradation and grid synchronization. |
| [74] | BOA-based unified power quality conditioner for DG systems. | Butterfly Optimization Algorithm (BOA) | Limited to single-objective optimization. |
| [75] | DVR for voltage quality improvement. | PI control + DVR | It did not consider renewable sources or hybrid systems. |
| [76] | Transformerless DVR topology for voltage sag mitigation. | Multilevel inverter design | No integration with HRMs or optimization frameworks. |
| [77] | Fuzzy-PI controller for DVR in distribution systems. | Fuzzy logic + PI control | Limited to distribution networks; excluded transmission-level HRMs. |
| [78] | Fuzzy neural controller for DVR in HRMs. | Fuzzy logic + ANN | It did not address grid interconnection stability. |
| [79] | AI-based energy prediction for solar systems. | ANN + Regression models | Focused only on solar; excluded wind, storage, or hybrid optimization. |
| [80] | Hybrid classification for student performance (non-energy). | ML classifiers (SVM, DT) | Irrelevant to HRMs; included for methodology comparison. |
| [81] | Adaptive ant colony clustering in WSNs. | Ant Colony Optimization (ACO) | Focused on WSNs; no link to HRM energy management. |
| [82] | Semi-supervised ML for power system security. | Multi-task learning | It did not address HRM-specific challenges like bidirectional power flow. |
| [83] | Deep learning for short-term voltage stability. | CNN + LSTM | Excluded economic or environmental optimization. |
| [84] | Harmonic-based SVM for transient fault detection. | SVM + Harmonic analysis | Limited to HV networks; no microgrid application. |

**4.2 Future Prospects in Hybrid Renewable Microgrid (HRM) Research**

Integrating artificial intelligence (AI) and advanced machine learning (ML) algorithms presents a transformative avenue for optimizing HRM operations. As [85] demonstrated in their work on adaptive energy management systems, recent advancements in reinforcement learning and deep neural networks enable real-time decision-making under stochastic renewable generation and load variability. These systems could dynamically recalibrate dispatch strategies, predictive maintenance schedules, and fault-response protocols, minimizing reliance on deterministic models. Furthermore, the emergence of digital twin technology, as explored by [86] in their framework for virtual HRM prototyping, allows for high-fidelity simulation of physical microgrids, incorporating real-time sensor data to predict component degradation and optimize lifecycle costs. Such innovations promise to bridge the gap between theoretical models and operational resilience, particularly in remote or resource-constrained environments.

A second critical prospect lies in developing next-generation energy storage systems, including solid-state batteries and hydrogen-based storage, which could revolutionize HRM scalability and sustainability. Chen et al. [87] research on lithium-sulfur batteries highlights potential energy density improvements exceeding 500 Wh/kg, addressing current limitations in battery storage capacity and cycle life. Concurrently, hybrid storage architectures integrating supercapacitors for rapid charge-discharge cycles, as [88] proposed, could mitigate the intermittency of solar and wind resources more effectively. Policy-driven initiatives, such as the European Union’s Green Deal and the International Renewable Energy Agency’s (IRENA) roadmap for decarbonization, further emphasize the need for standardized regulatory frameworks to incentivize HRM adoption. These frameworks must address techno-economic barriers, such as tariff structures for peer-to-peer energy trading and carbon pricing mechanisms, as [89] analysed in their cross-national study of microgrid financing. Lastly, converging decentralized energy systems with blockchain-enabled transactive energy platforms, as piloted in the Brooklyn Microgrid Project, could democratize energy access while ensuring grid stability through distributed consensus algorithms. Collectively, these prospects align with global decarbonization goals while addressing the technical, economic, and socio-political complexities inherent in HRM deployment.

4. Conclusion

Hybrid Renewable Microgrids represent a pivotal advancement in sustainable energy systems, integrating solar, wind, diesel, and storage technologies to address intermittency, enhance reliability, and reduce carbon footprints. Through component-specific modelling—such as non-linear fuel consumption curves for diesel generators, Weibull-distributed wind resource analysis, and Kalman filter-enhanced battery state-of-charge estimation—HRMs achieve optimized dispatch and lifecycle management. Challenges persist in balancing economic viability, technical interoperability, and regulatory compliance, particularly in regions with resource constraints or volatile demand. However, emerging innovations in AI-driven energy management, digital twins for predictive maintenance, and next-generation storage solutions (such as solid-state batteries and hydrogen systems) offer pathways to scalable, resilient microgrid deployment. Policy frameworks and blockchain-enabled transactive energy platforms further highlight the socio-technical synergy required for global HRM adoption. Through the harmonization of advanced analytics, material science breakthroughs, and decentralized governance models, HRMs are poised to play a central role in achieving decarbonization targets while ensuring energy equity and grid stability in diverse geographies.

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