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5G-Enabled Energy-Efficient Operation and Management of Renewable Power Generation

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ABSTRACT

To handle the growing share of renewable energy resources in a modern smart grid, efficient operation, real-time monitoring and reliable communication support are necessary. This paper proposes an operation and management framework for energy generation from renewable energy sources with the aid of 5G technology that is energy efficient. The proposed model is based on the combination of solar PV, wind and hybrid solar PV, wind and battery generation units with a fifth generation (5G) communication layer for enhanced renewable dispatch, reduced battery curtailment, load balancing and communication reliability. The mathematical model includes the following variables: renewable uncertainty, load uncertainty, battery state of charge, grid support power, renewable utilization, curtailment ratio, energy efficiency, latency, packet error rate, signal-to-interference-plus-noise ratio and communication reliability. Using several case studies, a MATLAB-based simulation has been carried out for a solar PV–only system, a wind-only system, a hybrid PV–wind system, a PV–wind–battery system, and a proposed 5G-enabled PV–wind–battery system. The results demonstrate 94.1% renewable utilization, 5.9% curtailment ratio, 0.11 MW average load mismatch, 91.3% energy efficiency, 7.6ms average latency, 24.8 dB average SINR, and 0.94 communication reliability, respectively. The results show that the optimization of renewable generation, battery storage and 5G communication jointly has a positive effect on the efficient operating of renewable power generation systems.

Introduction

Background and Motivation

The world's electric power industry is in a significant transformation as it moves from the traditional fossil fuel power generation system to renewable and digitized power systems. Application of solar photovoltaics (PV), wind resources, battery energy storage systems, hydrogen-supported generation, and hybrid renewable power plants are becoming more common in modern smart grids. It is a transition that is fueled by the increasing demand for electricity, climate change issues, decarbonization policies, fuel price volatility, and the quest for more stable and sustainable energy systems. Electricity demand has been continuously increasing at a fast pace, and solar PV and other renewable energy technologies are now a significant share of new power generation capacity globally [1, 2]. But the rising proportion of renewable energy brings new operational and management challenges, since renewable generation is intermittent, dependent on weather and uncertain. Communication technology is part and parcel of this change. For the operation of a smart grid with renewable energy, the traditional grid communication systems might not be suitable for meeting the following requirements: low latency, high reliability, high device density, and real-time response. The 5G communication technology offers a potential solution as it enables ultra-reliable low-latency communication, massive machine-type communication, network slicing, edge computing, greater bandwidth, and enables greater numbers of large IoT devices. These features can be used in smart grid applications for real-time renewable monitoring, inverter control, distributed energy resource (DER) coordination, fault detection, energy storage scheduling, and secure communication between generation units and control layers. Recent research has demonstrated that the 3 aspects of energy efficiency, flexibility in operation, utilization of renewables, and grid stability can be enhanced through 5G era coordinated scheduling, Edge-IoT-based smart-grid communication and virtual power plant optimization [3]–[5]. When renewable energy is connected to battery storage and flexible demand resources, the importance of communication-aware renewable operation becomes more critical. A variety of studies have demonstrated the potential for increasing renewable hosting capacity through the combination of hydrogen storage, demand response and uncertainty aware operation through robust optimization techniques [6]. Other recent works have optimized the scheduling of demand response in PV–wind integrated smart grid and demonstrated that hybrid forecasting and optimization could minimize the cost and increase energy efficiency [7]. It has been similarly shown that dynamic pricing, real-time feedback and load scheduling can help to lower the peak-to-average ratio and the operating cost in smart grids in the context of Stackelberg-game based demand response models [8]. In the same way, PV–battery energy management research has demonstrated the ability of battery storage to smoothen the power fluctuations of the grid, mitigate solar intermittency, and enhance the economic viability of grid-connected renewable energy (RE) systems [9]. The potential for intelligent resource allocation to optimize real-time grid operations in smart energy systems is also suggested by deep learning and IoT frameworks [10]. In addition to one single generic grid model, a series of generation-unit scenarios will be presented in the proposed case-study format. For Case Study 1, a solar PV generation unit could be installed along with a controller installed locally, which can communicate via 5G. The wind generation unit under variable wind speed with uncertain output may be selected to be included in the Case Study 2. Case Study 3 can involve a combination of PV and wind generation, with a system that needs to control two renewable generation sources, both of which are intermittent. For Case Study 4, the PV generation system can be combined with a PV–wind–battery generation system, with the battery storage system performing the same three functions as described earlier: renewable smoothing, curtailment reduction, and load balance. The simulation will test the proposed model with these case studies with varying operating conditions including Renewable Penetration, Low Renewable Penetration, High Renewable Penetration, Increased Communication Delay, Packet Loss and Variable demand.

Literature Review

Communication-aware smart-grid studies are about the role of wireless networks, IoT, edge computing and 5G in the monitoring and control of smart-grids. Uncertainty-aware energy management research is mainly about mathematical optimization, stochastic control, robust scheduling, and battery storage to mitigate the impacts of the variability of renewables. The present research will be situated at their juncture.The work of Rehmani et al. [12] was very providing in presenting the role of information and communication technologies for integrating renewable energy resources in smart grid. They also pointed out the need for sensing, communication, data collection, automation and distributed control for management of renewable energy. The study has a high relevance, as it makes the point that renewable generation is a power-system problem, as well as an ICT-coordination problem. The work primarily involved review of ICT tools and challenges of renewable integration, however. It failed to create a mathematical model in the 5G world that takes into account the operation of renewable generation, energy efficiency, and constraints on communication (e.g., latency, SINR, packet loss). Israr et al. [13] discussed sustainable 5G network infrastructure with renewable energy. Their study demonstrated that the energy consumption and carbon footprint of dense 5G networks can be reduced by renewable energy. This study is significant not only because of the link between the two sectors of renewable energy and 5G infrastructure, but also because it demonstrates the interdependency between the two sectors. The primary thrust of that work, however, was the use of renewable energy for the communications networks. The present study, on the contrary, applies the 5G communication to enhance the management of power generation units using renewables. The current research is therefore a mirror image of this scenario, and sees 5G as an enabler for the operation of renewable generation.

A 5G RAN slicing framework for frequency regulation service provision of virtual power plant was proposed by Feng et al. [14]. They found that reliable communication between distributed energy resources (DERs) and grid operators is possible with 5G network slicing. Carrillo et al. [15] presented a smart RAN slicing solution for 5G powered smart-grid communications. Their research showed that the latencies, reliabilities and bandwidths required for various smart-grid services are different. Saleem et al. [16] explored the development of the integration of IoT and cyber-physical systems in the 5G smart-grid era. They pointed out that smart grid systems will need to incorporate sensors, smart meters, intelligent electronic devices, automated controllers, communication networks, and physical power systems. Their work is also useful for the current work since renewable power generation units are also cyber physical systems. Gholipoor et al. [17] researched the strategic use of energy storage at cellular operators for frequency regulation in smart grid. Their findings demonstrated the ability of storage services to provide reliability for cell cell services and communication services, as well as reliability for grid services. The paper is significant as it links communication infrastructure, energy storage, and energy flexibility. It advocates the concept of optimizing communication and energy systems together. Their model is based on cellular base-station storage and frequency regulation, while the present study is based on renewable generation units like PV, wind, PV–wind–battery systems etc. Bao et al. [18] also investigated the decentralized DR using large-scale 5G base stations and adaptive droop control for primary frequency support. In one of these works, they demonstrated that 5G infrastructure can be a part of the fast grid support, but they did not directly investigate the operation of the renewable generation units. In the work [19] Xue et al. introduced a fully decentralized approximate dynamic programming algorithm for stochastic energy management problem in networked microgrids. Their work is relevant not only because of the uncertainties in renewable generation and demand in microgrids, but because renewable resources are not always available. Kim et al. [20] proposed an optimal battery energy storage operation using a neural optimizer with decision-focused learning. Recent high impact renewable energy management studies also support uncertainty-aware generation operation. Kang et al. [21] proposed a framework for long-term dispatch of isolated microgrids operating under high renewable penetration, which was based on controlled evolution. They took uncertainty of renewable generation and load demand into account, with long-duration energy storage and virtual energy storage. This work is very topical as it demonstrates the need for longterm and shortterm coordination of renewable energy rich microgrids. However, the quality of the 5G communications was not included in the dispatch model. In order to operate and manage a microgrid economically, Qu et al. [22] introduced a framework based on expert behaviors and prediction intervals. They studied the uncertainty of renewable forecasting and microgrid scheduling with learning-based optimization. But it didn't take into account communication delay or packet loss for real-time dispatch decisions. By incorporating PV storage, electric vehicle charging, and demand response, Karimianfard [23] developed a comprehensive optimization model for smart home energy management that successfully addresses these challenges.Karimianfard [23] has introduced a robust optimization model to address these issues, combining PV storage, electric vehicle charging, and demand response. The study demonstrated the cost and energy management benefits of PV, battery storage and demand response under uncertainty.

In summary, the literature demonstrates significant advances in the fields of renewable integration, smart-grid communication via 5G networks, virtual power plant control, demand response, storage operation and uncertainty-aware optimization. But, the majority of the studies so far are considering communication performance independently of renewable generation management. Discussions about latency, reliability, network slicing and IoT are commonplace in communication-oriented studies, but these studies are not fully able to model the renewable utilization, curtailment and generation-load mismatch. For energy-related studies, optimization of PV, wind, battery storage and dispatch of microgrids is often considered, but 5G indicators like SINR, packet error rate, user rate and communication reliability are not fully incorporated in the optimization. This means there is a definite research gap. To fill the gap, the present study introduces a communication-aware, energy-efficient, and 5G enabled renewable generation management framework. The proposed model will employ case study generation units, as well as modified mathematical models, to jointly assess the performance of renewable power and 5G communication performance.

Contribution

This study has three main contributions.

- A novel 5G-enabled smart grid modeling framework is proposed that shifts the focus from traditional demand-response management to renewable power generation operation, thereby addressing the growing need for renewable-centric grid management.
- A comprehensive set of renewable generation case studies is developed with diverse simulation scenarios and operating conditions, making the proposed framework independent, reproducible, and readily applicable for future research and development.
- A multi-objective co-optimization strategy is introduced to simultaneously optimize renewable energy utilization, energy efficiency, renewable curtailment, generation–load mismatch, communication latency, packet error rate (PER), signal-to-interference-plus-noise ratio (SINR), user data rate, and network reliability, resulting in a practical communication-aware renewable generation management framework for next-generation smart grids.

Mathematical Monitoring Model

Sets, Indices, and System Description

Let $r \in \mathcal{R}$ denote the renewable generation unit, where $\mathcal{R}$ includes solar PV units, wind units, and hybrid PV-wind-battery units. Let $t \in \mathcal{T}$ denote the time slot, $b \in \mathcal{B}$ denote the 5G base station, and $c \in \mathcal{C}$ denote the communication cluster. The system operates over T time slots. Each renewable generation unit transmits real-time measurements to the control center through a 5G base station. The control center then sends control commands for renewable dispatch, battery charging/discharging, and curtailment management.

Solar PV Generation Model

The available solar PV power of renewable unit r at time t is modeled as:

$$P_{r,t}^{PV,av} = \eta_{PV} A_r G_t \left[1 - \beta_{PV}\left(T_{c,t} - T_{ref}\right)\right] \tag{1}$$

where $P_{r,t}^{PV,av}$ is the available PV power, η_{PV} is PV conversion efficiency, A_r is PV panel area, G_t is solar irradiance, β_{PV} is the temperature coefficient, $T_{c,t}$ is cell temperature, and T_{ref} is reference temperature. The dispatched PV power must not exceed the available PV power:

$$0 \le P_{r,t}^{PV} \le P_{r,t}^{PV,av} \tag{2}$$

where $P_{r,t}^{PV}$ is the actual dispatched PV power.

Wind Generation Model

The available wind power is modeled using the turbine power curve:

$$P_{r,t}^{W,av} = \begin{cases} 0, & v_t < v_{ci} \text{ or } v_t > v_{co} \\ P_r^{W,\,rate}\left(\dfrac{v_r^3 - v_{ci}^3}{v_r^3 - v_{ci}^3}\right), & v_{ci} \le v_t < v_r; \\ P_r^{W,\,rate}, & v_r \le v_t \le v_{co} \end{cases} \tag{3}$$

where $P_{r,t}^{W,av}$ is the available wind power, v_t is wind speed, v_{ci} is cut-in speed, v_{co} is cut-out speed, v_r is rated wind speed, and $P_r^{W,rate}$ is rated wind turbine power.

The dispatched wind power is constrained as:

$$0 \le P_{r,t}^{W} \le P_{r,t}^{W,av} \tag{4}$$

where $P_{r,t}^{W}$ is the actual dispatched wind power.

Renewable Generation Uncertainty Model

Renewable output is uncertain because solar irradiance and wind speed change with weather conditions. Therefore, uncertainty-adjusted renewable generation is expressed as:

$$\tilde{P}_{r,t}^{RE} = P_{r,t}^{RE,av}\left(1 + \varepsilon_{r,t}^{RE}\right) \tag{5}$$

where $\tilde{P}_{r,t}^{RE}$ is uncertainty-adjusted renewable generation, $P_{r,t}^{RE,av} = P_{r,t}^{PV,av} + P_{r,t}^{W,av}$, and $\varepsilon_{r,t}^{RE}$ is the renewable uncertainty factor. The uncertainty factor is bounded as:

$$-\delta^{RE} \le \varepsilon_{r,t}^{RE} \le \delta^{RE} \tag{6}$$

where δ^{RE} is the maximum renewable uncertainty bound.

Battery Energy Storage Model

The battery state of charge is updated as:

$$E_{r,t+1}^{B} = E_{r,t}^{B} + \eta_{ch} P_{r,t}^{ch} \Delta t - \left(\frac{P_{r,t}^{dis}\Delta t}{\eta_{dis}}\right) \tag{7}$$

where $E_{r,t}^{B}$ is stored battery energy, $P_{r,t}^{ch}$ is battery charging power, $P_{r,t}^{dis}$ is battery discharging power, η_{ch} is charging efficiency, η_{dis} is discharging efficiency, and Δt is timeslot duration. The battery energy limits are:

$$E_r^{B,min} \leq E_{r,t}^{B} \leq E_r^{B,max} \tag{8}$$

where $E_r^{B,\,min}$ and $E_r^{B,\,max}$ are the minimum and maximum battery energy limits. Charging and discharging power limits are given as:

$$0 \leq P_{r,t}^{ch} \leq P_r^{ch,max}, 0 \leq P_{r,t}^{dis} \leq P_r^{dis,max} \tag{9}$$

where $P_r^{ch,max}$ and $P_r^{dis,max}$ are maximum charging and discharging power limits.

Load Demand and Power Balance

The uncertainty-adjusted load demand is defined as:

$$\tilde{L}_t = L_t(1 + \varepsilon_t^L) \tag{10}$$

where $\tilde{L}_t$ is uncertainty-adjusted load demand, L_t is forecasted load demand, and ε_t^L is load uncertainty. The load uncertainty is bounded by:

$$-\delta^L \leq \varepsilon_t^L \leq \delta^L \tag{11}$$

where δ^L is the maximum load uncertainty bound.

The power balance equation is:

$$\sum_{r\in\mathcal{R}} \left(P_{r,t}^{PV} + P_{r,t}^{W} + P_{r,t}^{dis} - P_{r,t}^{ch}\right) + P_t^G = \tilde{L}_t + M_t \tag{12}$$

where P_t^G is grid power support and M_t is generation-load mismatch. The mismatch is calculated as:

$$M_t = \left|\tilde{L}_t - \sum_{r\in\mathcal{R}} \left(P_{r,t}^{PV} + P_{r,t}^{W} + P_{r,t}^{dis} - P_{r,t}^{ch}\right) - P_t^G\right| \tag{13}$$

where a lower M_t indicates better renewable generation management.

Renewable Curtailment Model

Renewable curtailment occurs when available renewable power is not utilized due to load limitations, communication delay, storage limitation, or operational constraints. Curtailment is modeled as:

$$P_{r,t}^{cur} = P_{r,t}^{RE,av} - \left(P_{r,t}^{PV} + P_{r,t}^{W}\right) \tag{14}$$

where $P_{r,t}^{cur}$ is curtailed renewable power. The curtailment ratio is:

$$CR = \frac{\sum_{t\in\mathcal{T}} \sum_{r\in\mathcal{R}} P_{r,t}^{cur} \Delta t}{\sum_{t\in\mathcal{T}} \sum_{r\in\mathcal{R}} P_{r,t}^{RE,av} \Delta t} \tag{15}$$

where CR is the renewable curtailment ratio.

The renewable utilization ratio is:

$$RU = \frac{\sum_{t\in\mathcal{T}} \sum_{r\in\mathcal{R}} \left(P_{r,t}^{PV} + P_{r,t}^{W}\right)\Delta t}{\sum_{t\in\mathcal{T}} \sum_{r\in\mathcal{R}} P_{r,t}^{RE,av} \Delta t} \tag{16}$$

where RU is the renewable utilization ratio. A higher value of RU indicates better use of available renewable energy.

5G Communication Model

The distance between renewable generation unit r and base station b is:

$$d_{r,b} = \sqrt{(x_r - x_b)^2 + \left(y_r - y_b\right)^2} \tag{17}$$

where (x_r, y_r) and (x_b, y_b) are the coordinates of renewable unit r and base station b, respectively. The path loss between renewable unit r and base station b is:

$$PL_{r,b} = PL_0 + 10\alpha\log_{10}\left(\frac{d_{r,b}}{d_0}\right) + X_\sigma \quad (18)$$

where $PL_{r,b}$ is path loss, PL_0 is reference path loss, α is the path-loss exponent, d_0 is reference distance, and X_σ is shadow fading. The received power is:

$$P_{r,b}^{rx} = P_b^{tx} + G_b^{tx} + G_r^{rx} - PL_{r,b} \quad (19)$$

where $P_{r,b}^{rx}$ is received power, P_b^{tx} is base-station transmit power, G_b^{tx} is transmitter antenna gain, and G_r^{rx} is receiver antenna gain. The SINR is calculated as:

$$\gamma_{r,b,t} = \frac{P_{r,b}^{rx}}{\sum_{j\in\mathcal{B},j\neq b} I_{r,j,t} + N_0 B_r} \quad (20)$$

where $\gamma_{r,b,t}$ is SINR, $I_{r,j,t}$ is interference from base station j, N_0 is noise spectral density, and B_r is allocated bandwidth.

The achievable data rate is:

$$R_{r,b,t} = B_r \log_2\left(1 + \gamma_{r,b,t}\right) \quad (21)$$

where $R_{r,b,t}$ is the achievable data rate.

The transmission delay is:

$$D_{r,b,t}^{tr} = S_p / R_{r,b,t} \quad (22)$$

where $D_{r,b,t}^{tr}$ is transmission delay and S_p is packet size.

The total end-to-end latency is:

$$D_{r,b,t} = D_{r,b,t}^{tr} + D_t^q + D_t^{prop} + D_t^{proc} + D_t^{edge} \quad (23)$$

where $D_{r,b,t}$ is total latency, D_t^q is queueing delay, D_t^{prop} is propagation delay, D_t^{proc} is processing delay, and D_t^{edge} is edge-computing delay. The packet error rate is:

$$PER_{r,b,t} = \exp\left(-\gamma_{r,b,t}/\gamma_0\right) \quad (24)$$

where $PER_{r,b,t}$ is packet error rate and γ_0 is the reference SINR parameter. The communication reliability is:

$$\rho_{r,b,t} = \left(1 - PER_{r,b,t}\right)\exp\left(-D_{r,b,t}/D^{max}\right) \quad (25)$$

where $\rho_{r,b,t}$ is communication reliability and D^{max} is the maximum allowable latency.

Communication Constraints

Each renewable generation unit must be connected to one 5G base station:

$$\sum_{b\in B} x_{r,b,t} = 1 \quad (26)$$

where $x_{r,b,t}$ is a binary connection variable. If renewable unit r is connected to base station b at time t, then $x_{r,b,t} = 1$; otherwise $x_{r,b,t} = 0$. The SINR constraint is:

$$\gamma_{r,b,t} \geq \gamma^{min} x_{r,b,t} \quad (27)$$

where γ^{min} is the minimum required SINR.

The latency constraint is:

$$D_{r,b,t} \leq D^{max} \quad (28)$$

The reliability constraint is:

$$\rho_{r,b,t} \geq \rho^{min} \tag{29}$$

where ρ^{min} is the minimum required communication reliability.

Energy Efficiency Model

The useful delivered renewable energy is calculated as:

$$E^{use} = \sum_{t\in\mathcal{T}} \sum_{r\in\mathcal{R}} \left(P_{r,t}^{PV} + P_{r,t}^{W} + P_{r,t}^{dis} - P_{r,t}^{ch}\right)\Delta t \tag{30}$$

where E^{use} is the useful delivered renewable energy.

The total communication energy consumption is:

$$E^{com} = \sum_{t\in\mathcal{T}} \sum_{r\in\mathcal{R}} \sum_{b\in\mathcal{B}} x_{r,b,t} P_b^{tx} D_{r,b,t} \tag{31}$$

where E^{com} is the 5G communication energy consumption.

The proposed energy efficiency index is:

$$EE = \frac{E^{use}}{\sum_{t\in\mathcal{T}} \sum_{r\in\mathcal{R}} P_{r,t}^{RE,av}\Delta t + E^{com}} \tag{32}$$

where EE is the energy efficiency index. A higher value of EE indicates better renewable generation management.

Objective Function

The objective function is formulated as:

$$\min J = \sum_{t\in\mathcal{T}} \left[w_1\left(\frac{M_t}{L_t}\right) + w_2 CR + w_3 C_t^G P_t^G \Delta t + w_4 \bar{D}_t + w_5 \overline{PER}_t \right. \tag{33}$$

$$\left. + w_6 C_t^B - w_7 RU - w_8 \bar{\rho}_t\right] \tag{33}$$

where J is the total objective value; w_1 to w_8 are weighting coefficients; C_t^G is grid power cost; C_t^B is battery degradation cost; $\bar{D}_t$ is average latency; $\overline{PER}_t$ is average packet error rate; $\bar{\rho}_t$ is average communication reliability CR is curtailment ratio; and RU is renewable utilization ratio.

The average latency is:

$$\bar{D}_t = \frac{1}{|\mathcal{R}|} \sum_{r\in\mathcal{R}} \sum_{b\in\mathcal{B}} x_{r,b,t} D_{r,b,t} \tag{34}$$

where $\bar{D}_t$ is the average latency of all connected renewable generation units. The average packet error rate is:

$$\overline{PER}_t = \frac{1}{|\mathcal{R}|} \sum_{r\in\mathcal{R}} \sum_{b\in\mathcal{B}} x_{r,b,t} PER_{r,b,t} \tag{35}$$

where $\overline{PER}_t$ is the average packet error rate of all connected renewable generation units. The average communication reliability is:

$$\vec{\rho}_t = \frac{1}{|\mathcal{R}|} \sum_{r\in\mathcal{R}} \sum_{b\in\mathcal{B}} x_{r,b,t} \rho_{r,b,t} \tag{36}$$

where $\vec{\rho}_t$ is the average communication reliability of all connected renewable generation units. The final outputs of the model include renewable utilization, curtailment ratio, load mismatch, energy efficiency, average latency, packet error rate, SINR, communication reliability, and grid support cost.

Table 1. Simulation Parameters

Parameter	Symbol	Value
Renewable generation units	(N_R)	60
Solar PV units	N_{pv}	20
Wind units	N_w	20
Hybrid PV–wind–battery units	N_H	20
5G base stations	N_B	6
Simulation area	A_S	$(1.5\ \times 1.5)\text{km}^2$
Time slots	(T)	24 h
Carrier frequency	(f_c)	28 GHz
System bandwidth	(B)	80 MHz
Maximum latency	$\left(D^{\{max\}}\right)$	15 ms
Minimum reliability	$\left(\rho^{\{min\}}\right)$	0.85
Battery SOC range	$\left(SOC^{\{min\}}\right) - \left(SOC^{\{max\}}\right)$	$20\% - 90\%$
Load demand range	(L_t)	$1 - 5$ MW
Renewable uncertainty	$\left(\delta^{\{RE\}}\right)$	$10\% - 30\%$
Convergence tolerance	$\left(\epsilon^{\{conv\}}\right)$	$\left(10^{\{-4\}}\right)$

Simulation Model and Case Study Setup

Proposed Algorithm

In this section, an algorithm for the operation and management of renewable power generation with 5G technology and energy efficiency is proposed. The algorithm takes into account renewable generation, battery operation, load demand, renewable curtailment, as well as 5G communication performance. The primary goal is to reduce the total objective function defined in (33), while meeting renewable generation constraints, battery constraints, load balance constraints, curtailment constraints and communication constraints resulting from the 5G communication system where the simulation parameters rae shown in Table.1.

The scheduling horizon of (T) time slots is considered for the proposed algorithm as shown in Table. 2. The solar PV output, wind output, load demand, battery state of charge and 5G communication parameters are updated at every time slot. The renewable generation units are then installed in appropriate 5G base stations in terms of distance, SINR, latency, packet error rate and communication reliability. Then, power dispatch of PV, wind, charging/discharging power of batteries, and grid support power is optimized. The algorithm is repeated until a convergence of the objective function or a maximum number of iterations is reached as shown in Figure.1.

Table 2. Proposed 5G-Enabled Renewable Generation Management Algorithm

Algorithm Item	Description
Input	Renewable generation units (R), time slots (T), base stations (B), solar irradiance (G_t), wind speed (v_t), load demand (L_t), battery parameters, 5G communication parameters, uncertainty bounds, and weighting coefficients (w_1) to (w_8).
Output	Optimal renewable dispatch, battery schedule, grid support power, renewable utilization, curtailment ratio, load mismatch, energy efficiency, latency, packet error rate, SINR, and communication reliability.
Step 1: Initialization	Initialize all renewable generation units, 5G base stations, battery storage units, simulation area, time slots, and communication clusters. Set initial battery energy $\left(E^{\{B\}}_{\{r,1\}}\right)$, initial renewable uncertainty $\epsilon^{RE}_{r,t}$, load uncertainty, maximum iterations I^{max}, and convergence tolerance ϵ^{conv}.
Step 2: Renewable Generation Calculation	For each renewable generation unit (r) and time slot (t), calculate the available solar PV power using (1). Then calculate the available wind power using the wind turbine power curve in (3). The total available renewable power is obtained from the sum of available PV and wind generation.
Step 3: Uncertainty Adjustment	Apply renewable generation uncertainty using (5) and (6). Apply load demand uncertainty using (10) and (11). This step produces uncertainty-adjusted renewable generation and uncertainty-adjusted load demand for each time slot.
Step 4: 5G Base Station Association	For each renewable generation unit, calculate the distance to each 5G base station using (17). Then calculate path loss using (18), received power using (19), SINR using (20), data rate using (21), transmission delay using (22), total latency using (23), packet error rate using (24), and

	communication reliability using (25). Each renewable generation unit is assigned to the base station that satisfies SINR, latency, and reliability constraints in (27)–(29).
Step 5: Battery Scheduling	For each hybrid PV–wind–battery unit, update the battery state of charge using (7). If renewable generation is higher than load demand, the battery is charged within the limit given in (9). If renewable generation is lower than load demand, the battery is discharged within the allowable discharging limit. The battery energy is maintained within its minimum and maximum limits using (8).
Step 6: Renewable Dispatch and Power Balance	Dispatch available PV and wind power subject to the constraints in (2) and (4). Then apply the power balance equation in (12). If renewable generation and battery output cannot fully supply the load, grid support power P_t^G is used. The mismatch M_t is calculated using (13).
Step 7: Curtailment and Utilization Calculation	Calculate renewable curtailment using (14). Then calculate the renewable curtailment ratio using (15) and renewable utilization ratio using (16). Lower curtailment and higher renewable utilization indicate better operation of renewable generation units.
Step 8: Objective Function Evaluation	Calculate useful delivered renewable energy using (30), communication energy consumption using (31), and energy efficiency using (32). Then evaluate the total objective function in (33). The algorithm aims to reduce mismatch, curtailment, grid support cost, latency, packet error rate, and battery degradation cost, while improving renewable utilization and communication reliability.
Step 9: Iterative Update	Update the renewable dispatch, battery schedule, base-station association, and communication reliability. Recalculate all performance indicators. The iteration continues until the convergence condition.
Step 10: Final Output	After convergence, record the final values of renewable utilization, curtailment ratio, load mismatch, energy efficiency, average latency, packet error rate, SINR, communication reliability, grid support cost, and battery state of charge.

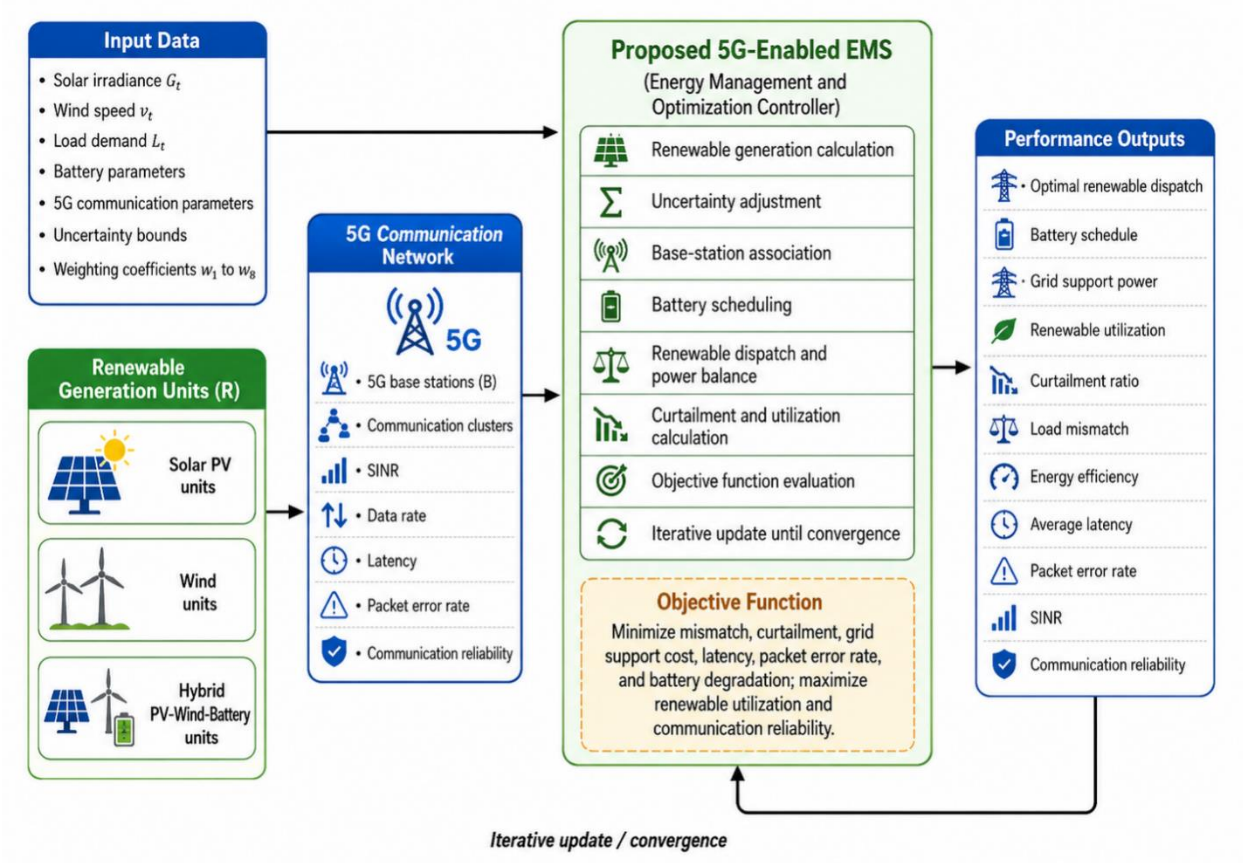

Figure 1. IoT-enabled fault monitoring system architecture for power distribution lines and distribution transformers.

To compare the performances, there are three benchmark methods for comparison with the proposed method. The first benchmark is a renewable-only model in which the optimization of renewable dispatch is done without taking into account the 5G communication performance. The second is distance-based communication model, which assigns each renewable unit to the base station that is closest to it, without taking account of SINR, packet error rate, and/or reliability. The third benchmark is a no-storage one, using PV and wind generation without battery support. The proposed method is likely to be more effective as it takes into account the availability of renewables, flexibility of the battery, mismatch in load, curtailment, and quality of 5G communication

Table 3. Simulation Case Studies

Case Study	Generation Unit Type	Main Purpose
Case 1	Solar PV only	To evaluate PV output variation and solar curtailment
Case 2	Wind only	To evaluate wind-speed uncertainty and wind dispatch
Case 3	Hybrid PV–wind	To evaluate combined renewable generation without storage
Case 4	Hybrid PV–wind–battery	To evaluate storage-supported renewable management
Case 5	Proposed 5G-enabled PV–wind–battery system	To evaluate joint renewable and communication-aware optimization

Table 4. Benchmark Methods

Method	Description
Renewable-only optimization	Optimizes PV and wind dispatch without 5G communication constraints
Distance-based association	Connects renewable units to the nearest 5G base station only
No-storage operation	Operates PV and wind generation without battery energy storage
Proposed method	Jointly optimizes renewable generation, battery operation, and 5G communication performance

Results

Case-Study Performance Comparison

Five operating cases were considered in the MATLAB results: solar PV only, wind only, hybrid PV-wind, PV-wind-battery and 5G-enabled PV-wind-battery as shown in Table. 3. As seen in Figure. 1, the proposed 5G enabled system resulted in the maximum renewable utilization, energy efficiency and minimum curtailment ratio. The proposed case, the renewable utilization was around 94.1%, the curtailment ratio was around 5.9% and the energy efficiency was around 91.3%. The solar PV-only case, on the other hand, had around 71.6% renewable utilization, and the wind-only case around 73.8% renewable utilization. The hybrid renewables generation, battery energy storage, and 5G communication-aware control were all combined in the proposed case to achieve the improvement. Solar-only and wind-only systems rely on a single renewable energy source and their production is highly volatile with weather and time. The case study for PV-wind was a hybrid configuration that gave better performance due to the complementarity between solar and wind generation. Without battery storage and communication-aware control, however, surplus energy would not be able to be fully utilized. The proposed 5G-enabled PV-wind-battery case has performed better due to the real-time communication indicators (SINR, latency, PEC, reliability) were used to optimize dispatch and storage scheduling decisions for the system.

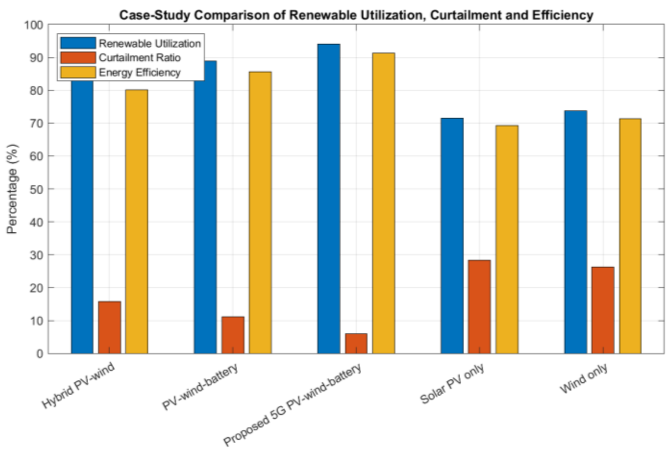

Figure 2. Case-study comparison of renewable utilization, curtailment ratio, and energy efficiency.

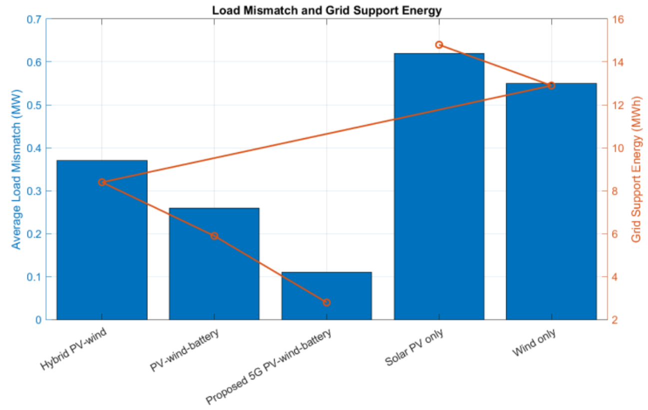

Figure 3. Load mismatch and grid support energy for different renewable generation cases.

Renewable Utilization and Curtailment Analysis

The same applies for the renewable curtailment which was maximum for solar PV-only and wind-only. The solar PV-only case yielded curtailment of around 28.4% and the wind-only case yielded curtailment of around 26.2%. These values establish that it is not always effective to match the load demand efficiently with only one renewable source. This hybrid PV-wind case has shown that curtailment was around 15.8%, confirming that the use of two renewable energy sources is beneficial in terms of generation availability, as well as the reduction of unused renewable energy. With the PV-wind-battery case, curtailment was reduced to around 11.1%, highlighting the importance of energy storage for the management of renewable generation. The proposed PV-wind-battery system with 5G was, however, the system with the lowest curtailment ratio, 5.9%. This reduction was due to the proposed method which utilized a reliable 5G communication layer to coordinate the dispatch of renewables and charging/discharging of batteries. So, renewable energy was more effectively used and less clean energy was wasted.

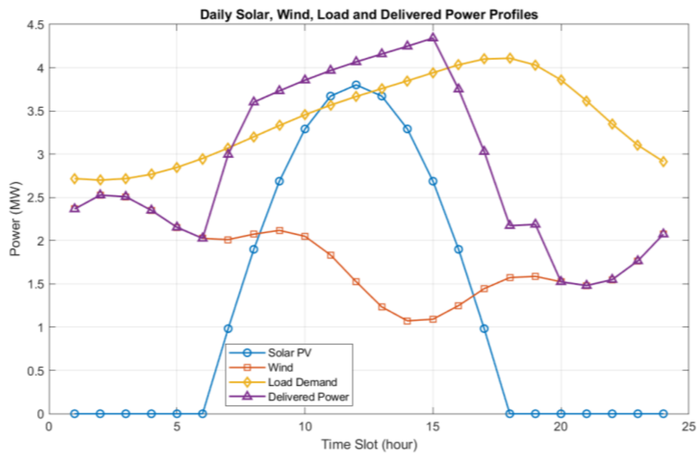

Figure 4. Daily solar PV, wind, load demand, and delivered power profiles over 24 time slots.

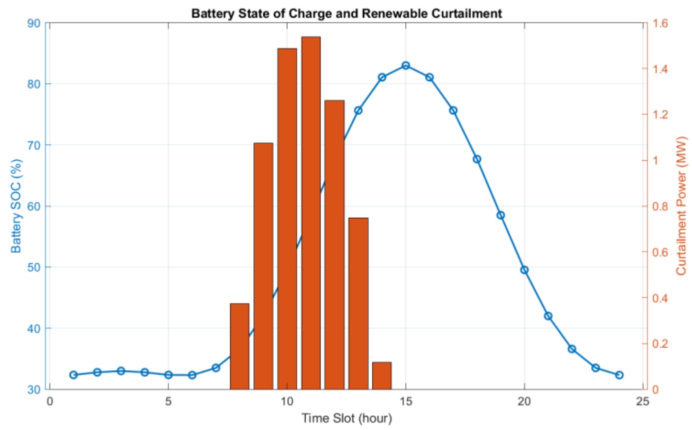

Figure 5. Battery state of charge and renewable curtailment behavior over the 24-hour simulation period.

Load Mismatch and Grid Support Energy

The load mismatch and the results of the grid support are displayed in Figure 3. The solar PV-only case exhibited the highest average load mismatch of ~0.62 MW, while the wind-only case exhibited ~0.55 MW of load mismatch. The mismatch was around 0.37 MW for the hybrid PV-wind system, and around 0.26 MW for the PV-wind-battery system. The mismatch of the proposed 5G enabled PV-wind-battery system was minimum around 0.11 MW. The mismatch reduction validates this is the method that resulted in a more balanced balance between the uncertainty and the load demand and renewable supply. The energy supplied by the grid was also highest for solar PV only and lowest for the proposed case as can be seen in Figure 3. The proposed system needed approximately 2.8 MWh of support energy from the grid as compared to approximately 14.8 MWh of support energy for the solar PV system on its own, and 12.9 MWh for the wind system on its own. The outcome shows that the suggested approach can decrease reliance on external grid and enhance the local renewable self-sufficiency.

Daily Solar, Wind, Load, and Delivered Power Profiles

The daily solar PV, wind, load demand and delivered power profiles are shown in Figure 4 over 24 time slots. Solar PV generation was nearly non-existent in the early morning and early evening hours, but grew after sunrise and peaked around midday. This is the normal pattern of solar energy generation. Wind generation was available all day, but depended upon wind-speed fluctuations. The load demand mounted steadily throughout the day, and was higher in the afternoon and evening. When both solar and wind generation were available, the delivered power was very responsive to the load demand. PV system was a major source of delivered power during peak solar production hours. Batteries and wind production assisted supply during the low solar times. This outcome verifies that a combination of renewables and storage is more stable in its operation than a single renewable source.

Battery State of Charge and Curtailment Behavior

Figure 5 illustrates the battery state of charge and renewable curtailment behaviour. The SOH (State of Charge) of the battery increases during high Renewable energy production hours, particularly on high solar PV playing hours. This means there was no waste of excess renewable energy, as it was stored in the battery. Later on, when renewables dropped, the battery provided the load demand. Renewable curtailment seemed to occur primarily during high generation periods when renewable power generation and available battery charging capacity is more than the demand for electricity. Curtailment after the battery absorbed the excess renewable energy, however. The range of battery operating limits was not breached, thereby indicating that the proposed scheduling method has satisfied battery operating limits while increasing use of renewable energy.

5G Communication Performance

The performance of 5G communication is illustrated in Figure.6 as the number of cells is increased. The latency rose from 5.8 to 14.2 ms, while the average SINR dropped from 28.9 to 17.2 dB, and the ratio of correct communication decreased from 0.96 to 0.86 with an increase in the cell load from 0.3 to 0.9. This trend is likely to continue as the networks become more congested and interfered with with higher cell load, thus impacting the quality of the communication. While communication performance decreased as the cell load increased, communication latency did not exceed 15 ms (the maximum allowed value), and communication reliability stayed above 0.85 (the minimum allowed value). The results show that the 5G communication layer was still applicable for the control of renewable generation under the tested conditions. The results also confirm that the communication performance has a direct influence on managing renewable generation. An excessive latency or packet error rate can result in delayed or lost control messages, increasing the mismatch of load and renewable curtailment.

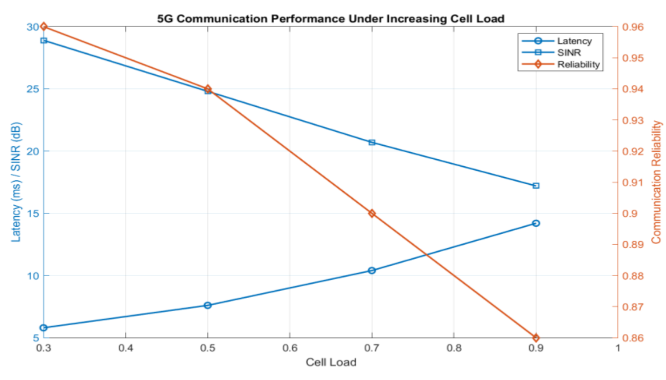

Figure 6. 5G communication performance under increasing cell load.

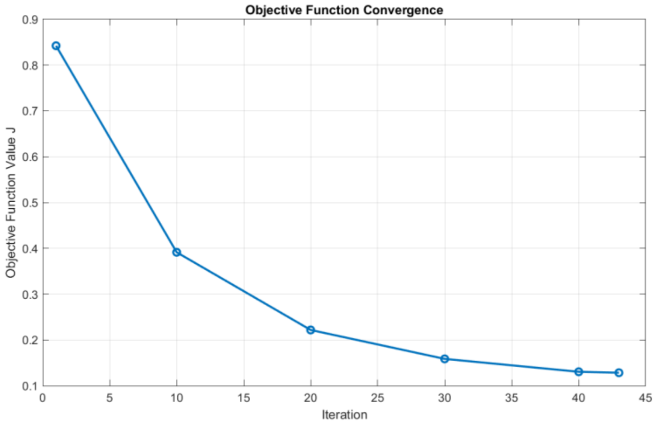

Figure 7. Objective function convergence of the proposed optimization algorithm.

Objective Function Convergence

The convergence property of proposed optimization algorithm is presented in Figure 7. The objective function value dropped from about 0.8421 in the 1st iteration to about 0.3914 in the 10th iteration. It was also reduced to approximately 0.2218 at the 20th iteration, to approximately 0.1587 at the 30th iteration, and almost converged to the value 0.1285 at the 43rd iteration. The successive decrease of the objective function indicates the stability and effectiveness of the proposed algorithm. The initial performance drops in the first few iterations indicate the algorithm was able to rapidly enhance the dispatching of renewables, scheduling the batteries, and base-station association. The number of iterations taken was 30, suggesting that the algorithm was continuing to improve the solution until the convergence criteria was met, which is reflected by the smaller reduction after 30 iterations. Thus, this iterative method can be used for optimizing the management of renewable generation resources in both energy and communication constraints.

Overall Discussion

On a whole, the results provided in Fig. 2–Fig. 7 have shown that the proposed 5G enabled PV-wind-battery framework has better performance than the other operating cases as shown in Table.4. It had the highest renewable utilization, least curtailment, least load mismatch, highest energy efficiency and least grid support requirement. The findings in this study substantiate what is observed in practice: the use of a combination of renewable generation management, hybrid renewable generation, battery storage and communication-aware optimization brings benefits for renewable generation management.

Conclusion and Future Work

In this paper, a framework for the operation and management of renewable power generation in 5G environment was proposed, which was energy efficient. The proposed model consisted of 5G communication layer and solar PV, wind, hybrid PV–wind and PV–wind–battery generation units. The framework took into account uncertainty of renewables, load uncertainty, battery scheduling, grid support, renewable curtailment, energy efficiency, latency, packet error rate, SINR, and communication reliability.

The MATLAB simulation results showed that the proposed 5G supported PV–wind–battery system gave the optimum performance in all the tested cases. The proposed system was able to attain 94.1% renewable utilization as compared to 71.6%, 73.8%, 84.2% and 88.9% being obtained in PV only, wind only, hybrid PV and wind, and PV, wind, and battery operation, respectively. Renewable curtailment ratio decreased to 5.9% due to wind-only and solar PV-only cases being 26.2% and 28.4% respectively. Likewise, the proposed method has resulted in an average load mismatch of 0.11 MW, compared with 0.62 MW and 0.55 MW for the solar PV-only and wind-only cases, respectively. The energy efficiency of the proposed system was 91.3% which is better than the PV only system (69.2%), wind only system (71.4%), hybrid PV–wind system (80.1%), and PV–wind–battery system (85.7%).

The communication results also indicated that the proposed 5G layer is appropriate for the control of renewable generation. With the load of cells gradually raised from 0.3 to 0.9, the latency rose from 5.8ms to 14.2ms, which is still within the maximum latency limit of 15ms. The SINR went down from 28.9 dB to 17.2 dB, and the reliability of communication went down from 0.96 to 0.86 (but still above the minimum reliability level of 0.85). The results indicate that the proposed model achieved good communication quality even when the cell is highly loaded. The objective function also converged to 0.1285 from 0.8421 at the first iteration to 43rd iteration, showing the stability of the proposed optimization algorithm.

The proposed framework can be extended in future work by implementing the proposed framework in real time in the hardware using a renewable energy testbed with at least 20–60 distributed generation units, 6 or more 5G base stations and a real-time monitoring horizon of 24 h. The model can also be tested in future studies with a more severe level of renewable uncertainty, e.g., 30%–40%, and load uncertainty, e.g., 15%–25%, to assess model robustness in extreme operating conditions. Furthermore, the framework can be extended by adding in electric vehicle charging stations, hydrogen storage, and bigger batteries with SOC limits ranging from 20% to 90%. Further future work could also involve renewable forecasting using machine learning techniques, detecting cybersecurity attacks, event logging, fault location methods, and real datasets from the utility grid to more rigorously test the practical performance of the proposed renewable generation management system in 5G.

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References

[1] International Energy Agency, Global Energy Review 2025. Paris, France: IEA, 2025.

[2] International Energy Agency, Renewables 2025: Analysis and Forecasts to 2030. Paris, France: IEA, 2025.

[3] N. Zhang, D. Liu, T. Liu, X. Zhang, J. Guo, F. Lan, Q. Li, W. Lu, and X. Yang, “A win-win coordinated scheduling strategy between flexible load resource operators and smart grid in 5G era,” Energies, vol. 18, no. 6, Art. no. 1510, 2025, doi: 10.3390/en18061510.

[4] Z. Fu, A. S. Al Shammre, S. F. Akhtar, R. A. Almasri, A. Emara, and M. J. F. Alenazi, “An efficient algorithm for demand-response optimization in smart grid power communication based on Edge-IoT,” International Journal of Energy Research, vol. 2025, Art. no. 2245366, 2025, doi: 10.1155/er/2245366.

[5] X. Tang and J. Wang, “Deep reinforcement learning-based multi-objective optimization for virtual power plants and smart grids: Maximizing renewable energy integration and grid efficiency,” Processes, vol. 13, no. 6, Art. no. 1809, 2025, doi: 10.3390/pr13061809.

[6] S. A. Jazayeri, M. S. Moghaddam, M. Moazzami, G. Shahgholian, and M. Hashemi, “Enhancing renewable hosting capacity in smart grids: A robust optimization framework integrating hydrogen systems and demand response,” Energy Conversion and Management: X, vol. 27, Art. no. 101063, 2025, doi: 10.1016/j.ecmx.2025.101063.

[7] M. Ayyakrishnan, M. Lakshmanan, S. Srinivasan, and G. G. R. Sekhar, “Enhancing demand response scheduling in smart grids with integrated renewable energy sources PV and wind systems using hybrid epistemic neural networks—Clouded leopard optimization algorithm,” Advanced Theory and Simulations, vol. 8, Art. no. 2500099, 2025, doi: 10.1002/adts.202500099.

[8] S. A. Ali, S. Imran Saeed, S. Ahmad, M. Waqas, S. H. Ali, D. Shah, S. Ali, and M. Tahir, “Optimizing smart grid demand response: A Stackelberg game framework for priority-aware dynamic pricing and load scheduling,” Engineering Reports, vol. 7, no. 8, Art. no. e70341, 2025, doi: 10.1002/eng2.70341.

[9] S. Panda, P. K. Rout, B. K. Sahu, W. F. Mbasso, P. Jangir, and A. Elrashidi, “Optimization-based energy management for grid-connected photovoltaic–battery systems in smart grids using demand response and particle swarm optimization,” Engineering Reports, vol. 7, no. 7, Art. no. e70305, 2025, doi: 10.1002/eng2.70305.

[10] A. R. Singh, M. S. Sujatha, A. D. Kadu, M. Bajaj, H. K. Addis, and K. Sarada, “A deep learning and IoT-driven framework for real-time adaptive resource allocation and grid optimization in smart energy systems,” Scientific Reports, vol. 15, Art. no. 19309, 2025, doi: 10.1038/s41598-025-02649-w.

[11] S. Rabbani, A 5G Enabled Efficient Operations in Smart Grid, Ph.D. dissertation, Department of Electrical Engineering, Superior University, Lahore, Pakistan, 2026.

[12] M. H. Rehmani, M. Reisslein, A. Rachedi, M. Erol-Kantarci, and M. Radenkovic, “Integrating renewable energy resources into the smart grid: Recent developments in information and communication technologies,” IEEE Transactions on Industrial Informatics, vol. 14, no. 7, pp. 2814–2825, Jul. 2018, doi: 10.1109/TII.2018.2819169.

[13] A. Israr, Q. Yang, W. Li, and A. Y. Zomaya, “Renewable energy powered sustainable 5G network infrastructure: Opportunities, challenges and perspectives,” Journal of Network and Computer Applications, vol. 175, Art. no. 102910, 2021, doi: 10.1016/j.jnca.2020.102910.

[14] C. Feng, Q. Chen, Y. Wang, J. Ma, and X. Wang, “Frequency regulation service provision for virtual power plants through 5G RAN slicing,” IEEE Transactions on Smart Grid, vol. 13, no. 6, pp. 4943–4956, Nov. 2022, doi: 10.1109/TSG.2022.3177765.

[15] D. Carrillo, C. Kalalas, P. Raussi, D. S. Michalopoulos, D. Z. Rodríguez, H. Kokkoniemi-Tarkkanen, K. Ahola, P. H. J. Nardelli, G. Fraidenraich, and P. Popovski, “Boosting 5G on smart grid communication: A smart RAN slicing approach,” IEEE Wireless Communications, vol. 30, no. 5, pp. 170–178, Oct. 2023, doi: 10.1109/MWC.004.2200079.

[16] M. U. Saleem, M. R. Usman, M. A. Yaqub, A. Liotta, and G. Exarchakos, “Smarter grid in the 5G era: Integrating the Internet of Things with a cyber-physical system,” IEEE Access, vol. 12, pp. 36769–36791, 2024, doi: 10.1109/ACCESS.2024.3372379.

[17] N. Gholipoor, F. H. Aghdam, M. Rasti, and H. Zarini, “Strategic utilization of cellular operator energy storage for smart grid frequency regulation,” IEEE Transactions on Smart Grid, vol. 16, no. 5, pp. 3961–3975, Sept. 2025, doi: 10.1109/TSG.2025.3581770.

[18] P. Bao, Y. Wang, X. Jiang, Y. Wang, and Y. Xu, “A statistical-based approach for decentralized demand response toward primary frequency support: A case study of large-scale 5G base stations with adaptive droop control,” IEEE Transactions on Smart Grid, early access, 2025, doi: 10.1109/TSG.2025.3535729.

[19] X. Xue, X. Ai, J. Fang, S. Cui, Y. Jiang, Y. Xu, and J. Wen, “Fully decentralized approximate dynamic programming for stochastic energy management of a networked microgrid system,” IEEE Transactions on Industrial Informatics, vol. 21, no. 6, pp. 4412–4422, Jun. 2025, doi: 10.1109/TII.2025.3538113.

[20] H. Kim, A. Das, and D. Wu, “A neural optimizer with decision-focused learning for optimal energy storage operation,” IEEE Transactions on Industrial Informatics, vol. 21, no. 12, pp. 9286–9296, Dec. 2025, doi: 10.1109/TII.2025.3597951.

[21] K. Kang, Y. Su, P. Yang, Z. Wang, and F. Liu, “Securing long-term dispatch of isolated microgrids with high-penetration renewable generation: A controlled evolution-based framework,” Applied Energy, vol. 381, Art. no. 125140, 2025, doi: 10.1016/j.apenergy.2024.125140.

[22] K. Qu, G. Si, Q. Wang, M. Xu, and Z. Shan, “Improving economic operation of a microgrid through expert behaviors and prediction intervals,” Applied Energy, vol. 383, Art. no. 125391, 2025, doi: 10.1016/j.apenergy.2025.125391.

[23] H. Karimianfard, “A robust optimization framework for smart home energy management: Integrating photovoltaic storage, electric vehicle charging, and demand response,” Journal of Energy Storage, vol. 110, Art. no. 115259, 2025, doi: 10.1016/j.est.2024.115259.