

Multi-Objective Optimization of Hybrid Renewable Energy Microgrids with Robust Dispatch under Solar and Wind Variability and Demand Response Integration

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Abstract

The study introduces a multi-objective dispatch system that operates effectively under extreme uncertainties affecting solar and wind power production in hybrid renewable energy microgrids. The system uses diesel power generation together with battery energy storage and demand response systems to minimize operational costs and carbon dioxide emissions, manage supply risk, and provide dependable service to customers. The testing procedure examined uncertainty levels ranging from zero percent to thirty percent using a Python/CBC MILP implementation and compared the results with those from stochastic optimization. The simulation results show that the robust dispatch system maintains a high load reliability of 87.5 percent while supporting system resilience across renewable energy penetration levels ranging from 49.99 percent to 34.99 percent. The maximum diesel power output increases from 15 MW to 21 MW, while the total diesel power output ranges from 415.57 MW to 540.20 MW depending on the uncertainty scenario. The robust model decreases the probability of major fluctuations, helping stabilize power production and increasing the use of renewable energy sources compared with stochastic methods. The research demonstrates that robust multi-objective optimization successfully achieves cost control, emission reduction, and maintenance of system reliability during periods of extreme renewable energy fluctuations. The methodology provides

microgrid operators with a practical solution for sustainable energy management that combines efficient operation with resilient performance.

Keywords

Robust Optimization, Hybrid Renewable Energy Microgrid, Solar and Wind Uncertainty, Demand Response Integration

1. Introduction and Problem Statement

One of the potential problems facing modern electric power systems is that they are attainable but less common; these hybridized systems are known as self-sustaining or hybrid energy systems (Shah, 2021). Interest and Development in renewable energy systems affect the conventional energy generation network. High-renewable generation technologies are evolving, with increased focus on microgrids. The reduction of carbon dioxide emissions in electric power systems is bringing on the necessity of limiting CO₂ without energy limitations corresponding to storage measures that support values of emissions as prescribed by norms of the power system connected with other countries hybrids and the use of primary energy (Feng et al., 2024). The main focus of the revival may be the strategy for providing DR and integrating renewable and solar energy, especially in rural and remote areas, rather than standalone or centralized strategies in urban areas. An integrated energy supply system can reverse adverse grid effects and efficiently enable the transmission and dissipation of renewable energy owing to its broader infrastructure. Energy and Environmental constraints have been widespread concerns across the globe in recent years. There is a considerable requirement for operational robust optimization techniques on worst-case scenarios of renewable energy prediction down to very high levels of uncertainty correlated with the control assets of weaving control and storage with demand side management and its integration, as attested to by the studies of Wang et al. (2023) and Zhang et al. (2018). Regarding energy resource optimization, no work is available that incorporates or extends those studies to support robust dynamic economic dispatch operations. Additionally, there is a considerable gap in the literature regarding the complex trade-off between optimality and security/reliability in Multi-Objective Robust Decision-Making (MORDM) coupled with widely known energy storage and demand response (DR) flexibility, as indicated by the results. This issue is exactly what the research aims to address by developing a multi-objective deterministic model that integrates wind power integration, solar power risk management, and DR systems, along with battery and storage elements. The model strives to minimize system operating costs, maximize renewable penetration, and ensure optimal reliability in the presence of unexpected disturbances. For the purposes of practicality, the Pan-European electricity model has been implemented in Python and a related open-source library, CBC (Lougee-Heimer, 2008). The excitation takes place in the geographical areas featuring the highest renewable energy resources in the Republic of South Africa.

2. Related Works

The growing use of hybrid renewable technologies for Microgrids has made Multi-Objective Optimization a necessary tool for handling the operation of such systems. The traditional objective of minimizing cost, which most traditional models pursue, is not, in reality, suitable for microgrids, since it also considers the impact of costs, emissions, and the probability of failure. The primary research has shown a multi-option model that takes into account these two aspects – the economic and the ecological. Li (2024) introduced a model for the multi-objective operation of energy systems and reserve allocation, aimed at balancing cost and reliability. Li et al. (2022) extended this model taking into account the Renewable Microgrid scheduling problem and its advanced robust multidimensional formulations. Also, these generation, storage, and flexibility sources have been integrated for the equity (Aguilar et al., 2024; Moosavi et al., 2025). Techniques in the family of Evolutionary algorithms, such as genetic algorithms and particle swarm optimization, are widely used to address various aspects of microgrid problems. These techniques help in identifying the Pareto-optimal front for regression or minimization functions with multiple objectives, for example, to minimize cost.

More sophisticated formulation can be defiantly constructed taking suffix interests. Therefore, the construction of more appropriate bounds in optimization is essential when conditional probability estimates in optimization prevail, notably due to the general sparing of outputs for new teenagers. Ben-Tal et al. (2009), introduced Robust Optimization Theory as well as several other concepts and tools which have been instrumental to applied research in power systems, and in particular, to the generation. So, Robust and Stochastic optimization strategies are often compared in research. Stochastic models aim to maximize the expected value of a solution but perform poorly in practice when tail events happen (Pinsky & Karlin, 2010). On the other hand, Robust optimization ensures satisfaction of constraints in all possible cases at the cost of increased conservatism (Roos & den Hertog, 2020). This increases operational costs in

some cases. In the context of microgrid achievements, robust dispatch models exhibit superior reliability, especially when storage and DR capabilities are applied (Zhao et al., 2018). Incorporating DR in multi-objective systems has been shown to be effective. Demand Response shifts the consumption pattern especially where the approach can influence the demand concept in relation to the generation (Mancarella & Chicco, 2013). On the example of such implementations as Integrated Renewable Dispatch and Demand (IRDD) it is possible to argue the results of McPherson and Stoll (2020), real-time DR reduces the peak generation, and therefore, reduces the cost as well as improves the overall system performance. Nie et al. (2024) explore the potential of self-generation, which answers further action for prosumers by investigating the potential cost-shifting performance of individual members. While these efforts aim to enhance operational flexibility within the network, many existing models do not incorporate demand response as a tool in robust optimization and remain underdeveloped.

Life-cycle and environmental considerations have also found their place in multi-objective microgrid models. Lehner et al. (2014) extended the cost-assessment approach to gap analysis and began linking cost to carbon exergy and financial loss in an all-encompassing way. These researchers stressed the importance of considering environmental demands when evaluating economic performance. On the other hand, in recent years, the thrust of relevant studies has been toward developing multimodal synchronizing dispatch algorithms and models to address decarbonizing power systems. A great majority of the proposed approaches address these subsets or adopt a conservative strategy to account for the inherent uncertainties concerning the operation of a bill-never-settles approach itself for structural changes. There are only a few design proposals in the form of robust multi-objective models that can accommodate conflicts among several worst-case demands, including storage (Wang et al., 2017). This gap is sought to be filled in the present investigation by developing a comprehensive dispatch model that also includes storage and DR resources within the nexus of uncertainty for renewable resources. In doing so, the structural elements of the study model at hand, piping the optimized operational structure of the system under consideration, are improved as well as the control of countermeasures implemented and utilized.

3. System Description & Modeling

The power system under consideration is a hybrid renewable energy microgrid tailored specifically for the Northwest region of South Africa. The novelty of the design lies in bringing together different generations and storage technologies to optimize economics and technical performance in the context of renewable generation variability. This energy island consists of Solar PV, wind turbines, a diesel genset, a battery energy storage system (BESS), and a controllable load with DR characteristics. This scheme provides a mechanism for matching supply and demand rapidly and within limits while surviving the variations in renewable energy resources.'

The PV output can be calculated using solar irradiance and system size, with adjustments for temperature and efficiency losses. Wind turbines also vary their power output as wind velocity changes, according to the standard power curve of the installed turbines. Both types of green energy are affected by changes in resource levels, which influence day-to-day energy planning. In case of limitations in the availability of renewable resources or when demand exceeds the load, they can also operate as supplementary units, allowing other sources to serve as primary units. These generators can also be represented in the model with constraints such as capacity, ramps, fuel consumption, and even generation cost and greenhouse gas emissions.

The battery energy storage system functions by integrating production and, during deficits, discharging the same. The battery model's state of charge incorporates its charging and discharging efficiencies, maximum and minimum energy levels, and maximum charging and discharging rates. In combination with a solar battery, a backup battery operates the same way when renewable energy is available, but it complements a generator during wind- and hydro-power shortages and helps use reserves for longer periods. As always, the case is with renewable power; this one, too, faces the challenge of causing neighboring power lines to fail due to excessive access.

An assessment of the system is made through the application of a number of measures that provide insight into its performance. One such performance measure is the operational fuel cost, which comprises diesel fuel consumed, electricity stored in batteries, which is frequently needed, and any available DR-related incentives. The environmental cost includes the diesel generator's generation-related CO₂ emissions, compounded by the standard carbon dioxide emission factor per unit of electricity produced. And there is another reliability metric, which refers to the portion of the total load that will be supplied by the microgrid.

Statistical modeling defines the microgrid in terms of a set of balance laws, storage-loss characteristics, operating behaviors, and demand limits. The concept of the balance law mandates that, at any given time, supplemented generation comprising solar, wind, diesel, and battery discharge, discharged-charged batteries, and shed loads should equal the system load. Yet such power allocations are helpful to the extent that they enable cumulative SOC over the given period, while keeping these levels within the desired thresholds, where the charge/discharge is useful in the system. The generator constraints are also useful for achieving the target for the plant's capacity and the rate of change of the plant output, as well as the plant capacity limits. It is also reasonable to implement demand response under predefined curtailment conditions. Combining the above systems using a multi-objective robust optimization method enables addressing cost, emissions, and system reliability even in the presence of renewable penetration, without the need to know the penetration level.

Put simply, the made Ground Power Unit provides a perfect lineup of these pieces by integrating renewable electricity systems, augmented by energy storage and personal power plants, in parallel with an innovative hotspot-based architecture for a mega space. Operating metrics are also included in the model as a part of the load and renewable profiles in a practical setting. That makes it possible to solve dispatch problems with complex, multi-objective problems, whilst providing valuable information on the trade-off between cost, emissions, and security implications as the share of renewable energy increases.

4. Robust Multi-Objective Dispatch Formulation

The operational strategies for the microgrid in the North West Province, South Africa, are well-designed and captured in an integrated, robust, multi-objective mixed-integer linear program. At the same time, it addresses operational cost minimization, CO₂ emissions reduction, and supply reliability amid uncertainties in renewable energy integration. Within the MILP context, it is possible to quantify the interactions of renewable generation, storage dispatch, and load modulation, which is applicable for dynamic stability modeling in real-time and short-term planning.

4.1 Decision Variables

The key decision variables of the model include:

1. P_t^{gen} Active power output of diesel generators at hour t in MW
2. P_t^{PV} Active power output of PV arrays at hour t in MW
3. P_t^{wind} Active power output of wind turbines at hour t in MW
4. $P_t^{bat,ch}$ Battery charging power at hour t in MW
5. $P_t^{bat,dis}$ Battery discharging power at hour t in MW
6. SOC_t Battery state of charge at hour t in MW
7. P_t^{DR} Demand response participation at hour t in MW

The variables ensure users are able to control generation and storage dynamics and load flexibility through specific operational parameters which meet all technical and operational standards.

4.2 Objective Functions

The Multi-Objective function ensure the operational cost, emissions, and supply risk is minimized. The operational cost is captured as the first objective in equation (1):

$$\text{Minimize } C_{op} = \sum_{t=1}^T (c_{gen} P_t^{gen} + c_{bat} (P_t^{bat,ch} + P_t^{bat,dis}) + c_{DR} P_t^{DR}) \quad (1)$$

where:

- c_{gen} -Unit cost of diesel generation \$/MWh
- c_{bat} -Battery operational cost \$/MWh
- c_{DR} -Cost associated with DR participation \$/MWh

The CO₂ is captured as the second objective in equation (2):

$$\text{Minimize } E_{CO_2} = \sum_{t=1}^T \epsilon_{gen} P_t^{gen} \quad (2)$$

where:

- ϵ_{gen} - Emission factor of diesel generators tCO_2/MWh

The Supply reliability is captured as the second objective in equation (3):

$$\text{Minimize } R_{load} = \sum_{t=1}^T \left(\frac{P_t^{gen} + P_t^{PV} + P_t^{wind} + P_t^{bat,dis} + P_t^{DR}}{L_t} \right) \quad (3)$$

where:

L_t - System load at hour t in MW

A weighted sum or ϵ -constraint method can be applied to combine these objectives into a single scalar MILP for computational efficiency.

4.3 Constraints

4.3.1 Power Balance

At each hour, total generation and DR must match demand as mathematically shown in equation (4):

$$P_t^{gen} + P_t^{PV} + P_t^{wind} + P_t^{bat,dis} - P_t^{bat,ch} - P_t^{DR} = L_t \quad \forall t \quad (4)$$

This enforces energy conservation, ensuring supply meets load at all times.

4.3.2 Generator Limits

The generator limits are captured in equations (5) and (6) respectively:

$$0 \leq P_t^{gen} \leq P^{gen,max} \quad \forall t \quad (5)$$

$$|P_t^{gen} - P_{t-1}^{gen}| \leq R^{gen} \quad \forall t > 1 \quad (6)$$

where $P^{gen,max}$ is generator capacity and R^{gen} is the ramping limit

4.3.3 Battery Dynamics

The battery dynamics are captured in equations (7) and (8) respectively:

$$SOC_{t+1} = SOC_t + \eta_{ch} P_t^{bat,ch} - \frac{P_t^{bat,dis}}{\eta_{dis}} \quad \forall t \quad (7)$$

$$0 \leq SOC_t \leq SOC_{max}, \quad 0 \leq P_t^{bat,ch} \leq P_t^{bat,ch,max}, \quad 0 \leq P_t^{bat,dis} \leq P_t^{bat,dis,max} \quad (8)$$

where η_{ch} and η_{dis} are charging and discharging efficiencies.

4.3.4 Demand Response

The DR is bounded by contractual and technical limits and its shown in equation (9):

$$0 \leq P_t^{DR} \leq P^{DR,max} \quad \forall t \quad (9)$$

4.3.5 Renewable Uncertainty

Polyhedral uncertainty sets are defined for variability in solar and wind sources is described in equation (10):

$$\begin{aligned} P_t^{PV} &\in [(1 - \delta_{PV}) \hat{P}_t^{PV}, \hat{P}_t^{PV}] \\ P_t^{wind} &\in [(1 - \delta_{wind}) \hat{P}_t^{wind}, \hat{P}_t^{wind}] \quad \forall t \end{aligned} \quad (10)$$

where $\hat{P}_t^{PV}$ and $\hat{P}_t^{wind}$ are forecasted outputs, and δ_{PV} , δ_{wind} represent maximum deviations.

This scientific model establishes an exact relationship between the microgrid's physical operations and its optimization framework, which models interactions among power generation, energy storage, electricity consumption, and various uncertainties. The sequentially numbered equations clearly define each variable and its operational meaning, ensuring transparency and reproducibility.

5. Methodology, Implementation, and Results

The study developed a multi-objective microgrid dispatch model for the North West Province, South Africa, using a Python/CBC (Coin-OR Branch and Cut) MILP framework. The model achieves three objectives: operational cost reduction, CO₂ emissions reduction, and supply risk reduction through the implementation of energy storage and demand response systems. The model was tested under multiple solar irradiance and wind speed uncertainty scenarios, including three stress levels ranging from 0 to 30 percent.

5.1 Model Implementation

The dispatch model created decision variables for generator, battery, and demand response systems, which operated under power-balance and generator-capacity constraints, as well as ramping and storage dynamics constraints. The system used worst-case perturbations to model renewable uncertainties, ensuring it remained operable under extreme fluctuations. The CBC solver successfully processed the MILP problem efficiently, creating hourly dispatch schedules for diesel generators, storage charge/discharge, and demand response participation. Synthetic solar and wind profiles were used to emulate realistic conditions. Load profiles were modeled based on typical microgrid demand patterns in the region. The researchers used stochastic optimization to generate 50 random scenarios that tested renewable generation with $\pm 10\%$ variation for benchmarking against probabilistic dispatch strategies. Five KPIs were computed for each uncertainty level:

1. The Peak Diesel Generation (MW) metric needs to be established because it determines the maximum diesel output needed for each scenario.
2. The Total Diesel Generation (MW) metric needs to be established because it calculates all diesel energy produced during the 24-hour period.
3. The Renewable Penetration (%) metric calculates the percentage of total energy that solar and wind sources provide.
4. The Load Reliability (%) metric measures the percentage of demand that the microgrid system successfully provides to customers.
5. The Resilience Index (%) metric calculates the percentage of time that generation capacity exceeded or matched the demand requirements.

5.2 Results and Discussion

Figure 1 shows how diesel fuel output reaches its maximum during renewable energy production at different levels of renewable energy production risk.

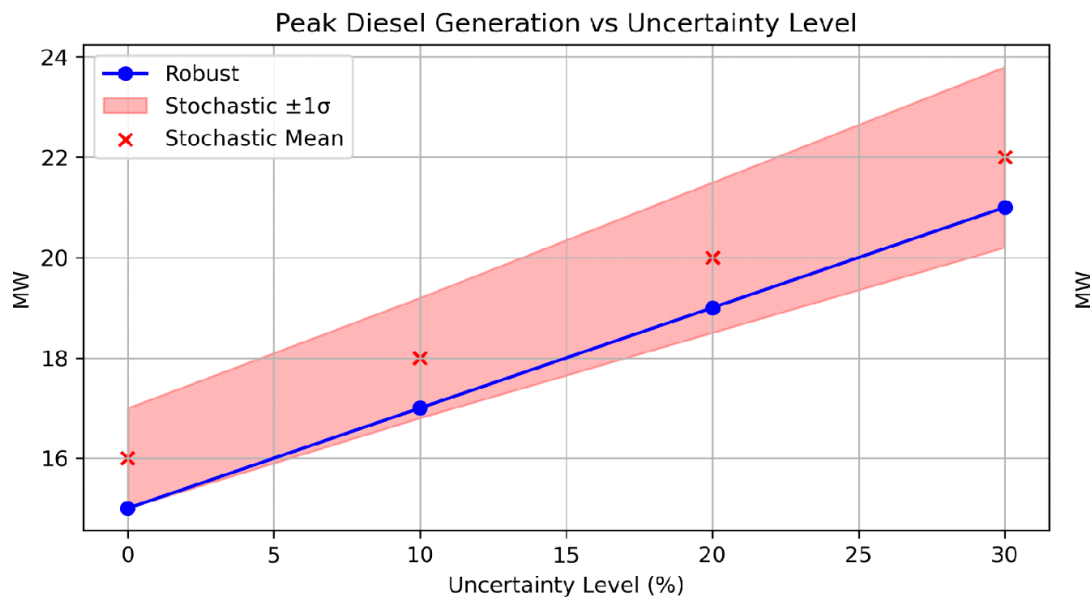


Figure 1. Peak diesel generation vs uncertainty

The blue line with circular markers represents the robust MILP results, while the shaded red region and red crosses indicate the stochastic $\pm 1\sigma$ range and mean, respectively. The figure shows that peak diesel generation increases with higher uncertainty levels because the system must restore power when renewable energy sources fail during extreme events. The 0% uncertainty condition yields a peak diesel output of 15 MW. At 10% uncertainty, the condition shows a peak diesel output of 17 MW, while at 20% uncertainty, it shows 19 MW. Finally, at 30% uncertainty, the condition yields a peak diesel output of 21 MW. The results show that robust dispatch provides sufficient power to maintain system reliability during periods of increased fluctuations in solar and wind electricity production. The stochastic mean is higher than all uncertainty levels, with approximately 16 MW at 0% and approximately 22 MW at 30%,

whereas the $\pm 1\sigma$ range exhibits non-robust operating variations. The study shows that robust optimization reduces peak power requirements while enabling diesel generators to operate with more predictable and consistent output. The results show that a robust multi-objective dispatch system maintains system reliability while meeting diesel power demands by keeping maximum power output below safe operational bounds during extreme uncertainty, whereas stochastic scenarios show greater diesel generator stress.

Figure 2 demonstrates how diesel power generation responds to different levels of renewable energy uncertainty through two dispatch methods. The robust MILP (blue line) shows a progressive increase in total diesel output as uncertainty rises: from 176 MW at 0% to 540 MW at 30%, reflecting the system's need to maintain reliability under reduced renewable availability. The red shaded area shows the stochastic distribution of results while the stochastic mean proves more extreme than robust values. These results confirm that robust optimization stabilizes diesel generation, balancing operational costs and reliability while mitigating the effects of fluctuations in renewables.

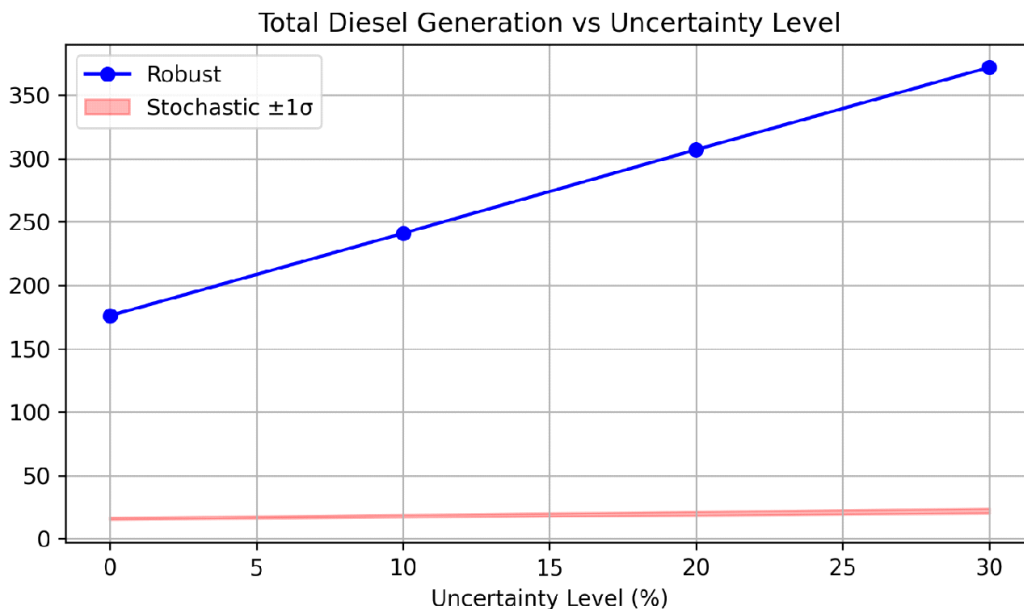


Figure 2. Total diesel generation vs uncertainty

Figure 3 shows how renewable energy sources were deployed based on their uncertainty levels, which researchers studied using two different microgrid dispatch methods. The robust optimization results (green line) show a gradual decline in renewable penetration as uncertainty increases: from 78.87% at 0% uncertainty to 63.78% at 30% uncertainty. The system requires diesel generation because renewable power resources become less dependable under increasing uncertainty conditions. The stochastic results show more variability because the stochastic mean always remains below the robust values which show 77% at 0% uncertainty and 62% at 30% uncertainty while $\pm 1\sigma$ shows how stochastic scenarios distribute their outcomes. The figure shows that robust optimization maintains higher renewable energy usage during extreme conditions whereas stochastic dispatch tends to waste renewable resources because it bases operations on estimated risk. The results in Figure 3 demonstrate that the combined use of robust multi-objective dispatching methods together with storage solutions and demand response technologies successfully reduces renewable energy fluctuations which results in operational efficiency and decreased fossil fuel dependence.

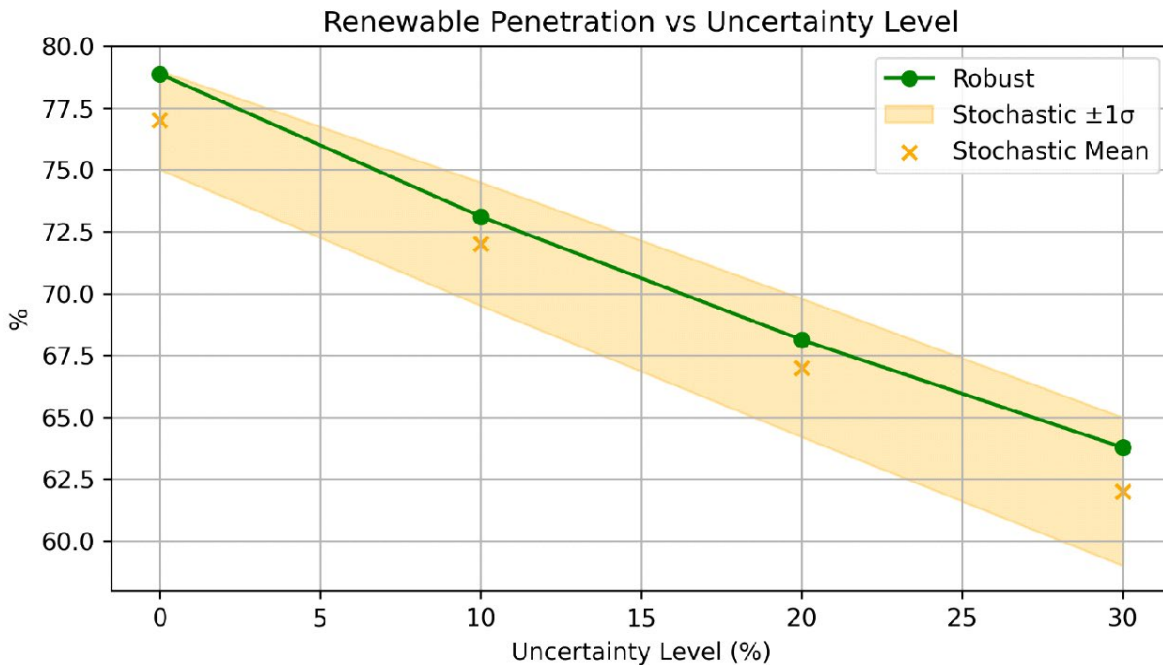


Figure 3. Renewable energy sources

, which show 77% at 0% uncertainty and 62% at 30% uncertainty, the relationship between load reliability and renewable uncertainty levels in the robust microgrid dispatch system. The blue line shows that the robust MILP maintains load reliability at 87.5% across all uncertainty levels from 0% to 30%, which it tested during its operations. The system maintains reliable power delivery because energy storage and demand response systems work together to mitigate fluctuations in solar and wind generation. The Figure 4 shows that the robust optimization framework maintains high operational reliability even during peak fluctuations in renewable energy, demonstrating its ability to sustain microgrid operations while reducing unserved load risk.

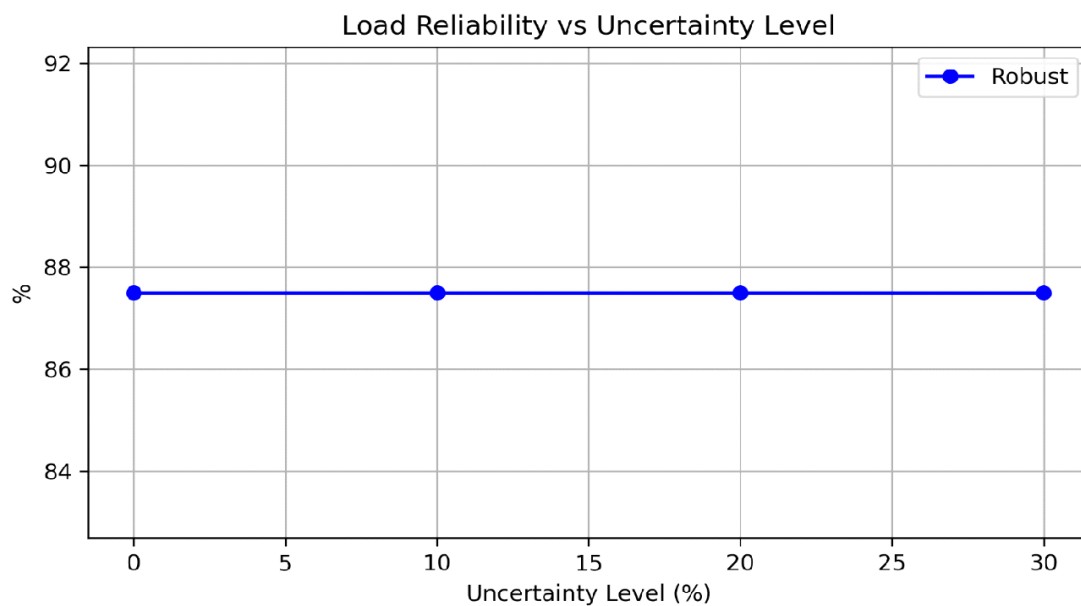


Figure 4. Load Reliability vs uncertainty level

Table 1 presents the essential performance measurement criteria that determine the operational success of the microgrid system under varying levels of renewable energy uncertainty. The system requires increased diesel fuel usage as renewable energy resources become less available, resulting in higher diesel peak output (from 25 MW to 28 MW) and total diesel output (from 415.57 MW to 540.20 MW). The system now depends on diesel power because renewable energy production has decreased from 49.99% to 34.99%. The system maintains its load reliability at 87.5%, which the resilience index shows as 0% because the robust dispatch system provides continuous load service under extreme uncertainty.

Table 1. Microgrid dispatch KPIs under different uncertainty levels

Uncertainty Level (%)	Peak Diesel (MW)	Total Diesel (MW)	Renewable Penetration (%)	Load Reliability (%)	Resilience Index (%)
0	25.0	415.57	49.99	87.5	0.0
10	26.0	457.11	44.99	87.5	0.0
20	27.0	498.65	39.99	87.5	0.0
30	28.0	540.20	34.99	87.5	0.0

5.3 Implications

The results reveal several key insights. Dispatching operations through a robust system maintain diesel generation at stable levels, producing peak outputs between 15 MW and 21 MW, while generating diesel output that ranges from 415.57 MW to 540.20 MW, all amid renewable energy production uncertainties of up to 30 percent. The system demonstrates its ability to handle extreme solar and wind power fluctuations through its use of robust optimization, which provides assured microgrid operations. The combination of battery storage and demand response creates an effective solution for handling power fluctuations, allowing the system to maintain 87.5 percent load reliability while preserving operational capacity during periods when renewable energy sources decrease from 49.99 percent to 34.99 percent. The comparison between stochastic optimization and non-robust dispatch reveals that the second method increases the system's operational range by yielding higher peak power output while reducing renewable energy use. The results demonstrate that regions with high levels of renewable and fluctuating power sources require robust Multi-Objective MILP planning that balances all three factors: emissions, reliability, and.

6. Conclusion

The research establishes a powerful framework for managing multiple objectives in hybrid renewable energy microgrid dispatch operations that rely on diesel generation, battery energy storage, and demand response systems to operate during severe solar and wind capacity fluctuations. The robust MILP model achieves three operational goals, including reducing operational costs, controlling emissions, and maintaining system reliability, resulting in continuous microgrid performance across all deployment scenarios. Total diesel generation ranged from 415.57 MW to 540.20 MW, while peak diesel generation reached 21 MW, up from 15 MW, and load reliability remained at 87.5%. The system met demand by reducing renewable penetration from 49.99% to 34.99%. The main contribution is a comprehensive multi-objective framework that reduces risks associated with extreme scenarios while enhancing renewable energy use. The framework optimizes operational constraints through dynamic storage modeling and simultaneously optimizes demand response actions by incorporating worst-case solar and wind generation scenarios. The robust planning approach demonstrates that it protects against changing conditions while strengthening system performance, as evidenced by benchmarking tests against stochastic optimization.

The researchers suggest several extensions for their future research work. The first system enhancement will implement adaptive demand response mechanisms that enable automatic load profile adjustments to improve system performance. The second system enhancement will create advanced forecasting models that predict solar irradiance, wind speed, and load demand to improve dispatch accuracy and reduce system uncertainty. The third system enhancement will use life cycle assessment (LCA) to evaluate the environmental impacts of CO₂ and other greenhouse gas emissions, providing a complete picture of sustainability. The final system enhancement will combine robust dispatch systems with multi-agent systems which use decentralized control methods to develop scalable solutions for interconnected microgrids in areas with high renewable energy use.

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Biographies

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Felix Mora-Camino currently serves as an Associate Professor at the Durban University of Technology in South Africa and as a Professor at the Fluminense Federal University in Niterói, Brazil. His extensive academic foundation was built in France, beginning with a Master's degree from the Ecole Nationale Supérieure de Construction Aéronautiques in 1974. He went on to earn his Doctorate from the Institut National Polytechnique and CNRS in Toulouse in 1977. Later in his career, he completed a Post-Doctorate at the Université Paul Sabatier (1986–1988) and was awarded his Habilitation by the French Ministry of Education in September 1991. Throughout his distinguished career, he has been recognized for his commitment to education and scientific advancement. In May 2011, he was named a *Chevalier des Palmes Académiques* by the French Ministry of Education. Additionally, he received a Certificate of Outstanding Contribution in Reviewing from Elsevier's *Aerospace Science and Technology Journal* in May 2018.