Robust Multi-Objective Dispatch of Hybrid Renewable Energy Microgrids Considering Solar and Wind Uncertainties with Demand Response Integration

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Abstract—**In this paper, a novel robust multi-objective energy management strategy is proposed for a standalone Hybrid Renewable Energy Microgrid (HREM) comprising solar, wind, diesel generators, energy storage systems, and demand response programs. The strategy accounts for the uncertainty in solar and wind power over a 24-hour look-ahead horizon. Six performance metrics are used to compare the proposed robust energy management strategy with the stochastic dispatch strategy. These metrics are divided into two categories, including two operational metrics: peak and total diesel energy consumption; three reliability metrics: renewable share of renewable resources, load reliability, and resilience; and one flexibility metric. The results reveal that robust dispatch primarily aims to maximize the microgrid's reliability and resilience under both normal and extreme operating conditions. Thus, by accounting for 30% uncertainty in renewable resources, the proposed strategy achieves a reliability level exceeding 99%. However, as expected, using the robust dispatch strategy results in a lower share of renewable resources and flexibility than the stochastic dispatch strategy. In such cases, the latter strategy maximizes the share of renewable resources and enhances system flexibility, albeit at the expense of reliability. Trade-offs between robustness and efficiency are also investigated, and the results provide valuable insights for the planning and operation of an HREM in the presence of uncertainty.**

Keywords: Robust Optimization, Hybrid Renewable Energy Microgrid, Real-Time Demand Response, Renewable Uncertainty, Flexible Multi-Objective Dispatch

I. INTRODUCTION

The operational environment of contemporary microgrids has changed due to the rapid deployment of renewable energy systems, including solar photovoltaic (PV) and wind. These hybrid systems provide significant environmental and economic benefits by reducing fossil fuel dependence and greenhouse gas emissions [1]. Solar and wind energy systems generate power intermittently and are inherently variable, creating major operational problems that undermine their ability to deliver dependable and affordable electricity services. The expanding use of renewable energy sources requires microgrid systems to operate flexibly by adjusting their power generation, energy storage, and load management in response to rapid changes in the power supply [2]. Flexibility enables microgrids to respond effectively to changes in renewable power generation while controlling operating expenses and maintaining power quality, resulting in reliable and eco-friendly energy distribution for urban areas and remote regions [3].

Renewable energy systems require operational flexibility, yet uncertainty in renewables continues to disrupt standard dispatch operations [4]. Microgrid operators face the challenge of managing variations in solar irradiance, wind speed, and demand patterns, which create supply-demand imbalances, lead to excessive use of backup diesel generators, and result in inefficient use of renewable energy sources [5]. Conventional deterministic dispatch methods, together with stochastic dispatch techniques, do not capture rapidly changing extreme conditions due to their limitations [6]. The current situation requires real-time, adaptable dispatch strategies that can handle fluctuations in renewable energy output, helping organizations achieve operational efficiency while meeting their reliability objectives. Research studies have made significant progress in creating robust and stochastic optimization methods for microgrid dispatch systems [7]. The aim of this study is to present a robust multi-objective energy management solution for hybrid renewable sources-based microgrids. The framework proposed in this article can address the uncertainties associated with solar and wind power sources. The energy stored in batteries is used for demand management. The main objectives of the framework are to maximize the share of renewable energy sources, minimize diesel usage, reduce emissions, and achieve robustness and high performance within 24 hours.

A. Related Works

The design and operation of hybrid renewable energy microgrids depend on their ability to adapt to changing operational requirements. The system assessment method called flexibility metrics evaluates how well a system can adjust its electricity output and power consumption to handle supply-demand imbalances arising from changes in renewable energy production [8]. The flexibility strategies of the system use three main methods, which include flexible generation scheduling, energy storage management, and load management, to handle the unpredictable nature of solar and wind energy [9]. The three flexibility metrics, which include ramping capability, reserve margins, and demand response capacity, enable assessment of microgrid systems that operate in real time. The metrics support dispatch decisions that improve system reliability while decreasing the need for backup fossil fuel sources. Demand response (DR) integration has attracted significant attention as a key enabler of flexibility. The DR strategies use supply conditions, market signals, and price incentives to adjust or shift end-user loads [10]. The research conducted by Besançon [11] demonstrated that time-of-use-based DR systems reduce peak demand and improve reliability under uncertainty by achieving greater load reduction and improved forecasting capacity. The research conducted by Babu, et al. [12] found that their MILP-based DR optimization framework achieved cost reductions and peak load decrease through the system's ability to synchronize renewable energy production with DR activities. The studies demonstrate that DR technology enables microgrid systems to achieve greater flexibility while reducing operational expenses and managing energy demand fluctuations. The majority of DR research currently available examines static and day-ahead operational planning rather than studying systems that must adjust their operations in real time. The existing literature has not examined the need for real-time demand response, which requires automatic load changes in response to immediate changes in renewable energy production. The research conducted by Zippenfenig et al. [13] revealed the difficulties that arise from demand-side management, as it requires flexible scheduling that must function properly even with limited information; however, the study did not use real-time data.

II. SYSTEM DESCRIPTION AND MODELLING

This research paper investigates a microgrid system that operates as a hybrid renewable energy network, providing electricity to meet the standard energy demands of the North West Province in South Africa. The system unites solar PV arrays with wind turbines, diesel generators, battery energy storage systems, and flexible loads that operate through real-time DR functions. All system elements work together to supply power needs while enabling both operational freedom and dependable service during times of renewable power shortfall. This section explains the physical system elements, how generation and demand change together, and the main performance metrics researchers use to track system efficiency in real time.

A. Microgrid Components

Solar PV arrays convert solar irradiance into electrical power. The PV system output depends on actual solar irradiance levels, which vary hourly and seasonally. The Solcast and Open-Meteo APIs provides data on solar irradiance, enabling researchers to capture authentic temporal fluctuations [13]. The PV system capacity has been designed to support scenarios with high levels of renewable energy integration. Wind turbines harness wind energy using hourly wind speed profiles, which are also obtained from the Solcast and Open-Meteo APIs. Wind power generation depends on atmospheric conditions, which introduce additional unpredictability that the dispatch model must account for. The turbine output calculation uses standard power curves that relate wind speed to electrical output. Diesel generators serve as controlled power sources that supply electricity when renewable energy production and storage capacity fall short of demand.

B. Load and Renewable Variability Profiles

The microgrid's load profile uses hourly modeling to show both daily and annual demand patterns. The system creates synthetic load data using standard demand patterns and modifies them to match local demand characteristics. The dispatch model uses real-time DR to update its net load assessment in response to fluctuations in renewable power and operational stresses on the system. The forecasts establish the foundation for modeling uncertainty. The system normalizes solar and wind generation outputs and scales them by their installed capacity, resulting in authentic hourly production data. The model generates scenario-based variations that create new paths leading to different outcomes and improve the ability to predict future events. The generated scenarios represent typical operating conditions and varying degrees of operational challenges, including unexpected reductions in irradiance and wind speed.

C. Flexibility and Reliability Metrics

The assessment of microgrid performance under uncertain conditions requires reliable measurement tools that can evaluate both system operational flexibility and reliability. Flexibility metrics measure system performance because it needs to handle changes in both renewable energy production and electricity demand. The system uses these metrics to measure its ability to handle variable renewable energy generation and electricity demand. The system can handle renewable generation changes for up to one hour because its generation output can change at maximum sustaining capacity. The system uses storage utilization to measure how much renewable energy it stores and uses to mitigate fluctuations in energy production.

III. ROBUST MULTI-OBJECTIVE DISPATCH FORMULATION

The operation of a hybrid renewable energy microgrid under uncertain conditions requires a robust multi-objective optimization system that accounts for variations in solar and wind generation while reducing operational expenses and carbon dioxide emissions and increasing system flexibility and reliability. The dispatch model is formulated as a dynamic hourly Mixed-Integer Linear Programming (MILP) model across the entire planning horizon. At each hour, the solver determines diesel output, battery charge and discharge, and demand-response moves, while still satisfying power balance, SOC evolution, and the usual operating limits. In robust dispatch, PV and wind are treated as bounded, uncertain inputs, so the model looks for a schedule that remains feasible even under the worst-case renewable availability, all within the polyhedral bounds. The objective then combines diesel costs, CO_2 emissions, and flexibility-related actions using a weighted-sum approach, while the ε-constraint method is also used to identify other trade-offs among the objectives.

A. *Decision Variables*

The decision variables considered in this model include:

$P_{gen,h}$	power output of diesel generators at hour h (MW).
$P_{bat,ch,h}$	battery charging power at hour h (MW)
$P_{bat,dis,h}$	battery discharging power at hour h (MW).
SOC_h	battery state of charge at hour h (MWh)
$P_{DR,h}$	adjustable load due to demand response at hour h (MW).

B. *Constraints*

Power Balance

The total generation and storage injection, minus battery charging and demand response curtailment, must equal the load, and this is captured mathematically in equation (1):

$$P_{gen,h} + P_{PV,h} + P_{wind,h} + P_{bat,dis,h} - P_{bat,ch,h} - P_{DR,h} = L_h, \forall h \quad (1)$$

where:

$P_{PV,h}$ and $P_{wind,h}$ are worst-case solar and wind outputs (MW).

L_h is the system's load at hour h (MW)

This constraint ensures a rapid and responsive balance between electricity supply and demand.

Capacity Limits

Battery state of charge is governed by charging and discharging as shown in equation (2).

$$SOC_{h+1} = SOC_h + \eta_{ch} P_{bat,ch,h} - \frac{P_{bat,dis,h}}{\eta_{dis}}, \forall h \quad (2)$$

where η_{ch} and η_{dis} are charging and discharging efficiencies $(0-1)$. This equation represents energy conservation within the storage system, accounting for conversion losses.

Capacity Limits

Physical and operational limits would restrain diesel generator systems, battery systems, and demand response as shown in equation (3).

$$0 \le P_{gen,h} \le P_{gen}^{max}, 0 \le P_{bat,ch,h} \le P_{bat,ch}^{max}, 0 \le P_{bat,dis,h}, 0 \le P_{DR,h} \le DR^{max} \quad (3)$$

These limits ensure safe operation and prevent overloading.

Ramping Constraints

The output of a generator cannot change in an abrupt fashion because of mechanical limitations, as shown in equation (4).

$$\left|P_{gen,h} - P_{gen,h-1}\right| \le R^{max}, \forall h > 0 \quad (4)$$

R^{max} is the maximum allowed ramping per hour (MW). Ramping constraints reflect generator physical response limitations.

C. *Uncertainty Modeling*

The generation capacity of solar and wind energy sources is unpredictable. The system uses polyhedral uncertainty sets to create a dependable framework that establishes its operational requirements; see equation (5).

$$P_{PV,h}^{min} \le P_{PV,h} \le P_{PV,h}^{max}, P_{wind,h}^{min} \le P_{wind,h} \le P_{wind,h}^{max} \quad (5)$$

The bounds define the worst-case scenarios for each hour, ensuring robustness under extreme conditions.

D. *Objective Function*

The multi-objective function balances cost, emissions, and operational flexibility. Using a weighted-sum approach as shown in equation (6):

$$\min Z = \omega_1 \sum_h c_{gen} P_{gen,h} + \omega_2 \sum_h \epsilon CO_2 \, P_{gen,h} + \omega_3 \sum_h \left(P_{bat,ch,h} + P_{bat,dis,h} + P_{DR,h}\right) \quad (6)$$

where :

c_{gen} −cost coefficient for diesel generation (\$/MWh).

ϵCO_2 −emission factor for diesel generation (tCO_2/MWh).

$\omega_1, \omega_2, \omega_3$ normalized weights representing decision-maker priorities. Normalized weights $(\omega_1, \omega_2, \omega_3)$ balance economic cost, CO_2 emissions, and operational flexibility. Adjusting these weights allows prioritization between sustainability and economic efficiency.

The final term measures operational flexibility, as better storage capabilities and increased DR usage lead to greater adaptability. The function establishes a dispatch system that allocates resources among three objectives: operational costs, greenhouse gas emissions, and operational flexibility.

E. Solution Approach

The MILP problem is solved using Python/CBC, which employs the weighted sum and ε-constraint methods for multi-objective optimization [14]. The weighted-sum approach combines objectives into a single scalar, while ε-constraint allows one objective to be optimized while constraining the others, providing a Pareto frontier of solutions. The robust formulation ensures that dispatch decisions remain operationally feasible across all established renewable uncertainty boundaries, while system reliability and operational flexibility improve through the adaptive scheduling of storage and demand response.

IV. METHODOLOGY, IMPLEMENTATION, AND RESULTS

The PuLP solver is used to solve the MILP problems within the proposed approach. All computations were performed on a standard desktop running Windows 10 with an Intel Core i7 CPU and 16 GB of RAM. The resulting dashboard and performance analysis functionality use standard Python libraries to create plots. The research uses Python to create a mixed-integer linear programming model, which the CBC solver processes to develop dispatch methods for a hybrid renewable microgrid system in North West Province, South Africa. The study collected hour-by-hour data on all microgrid-related variables over a 24-hour span and then used them for evaluation. For the stochastic benchmarking part, 30 Monte Carlo scenarios were generated, yielding 4,320 total points, which they used to assess the behavior of both robust and stochastic dispatch strategies. The objective function balances operational costs with CO_2 emissions control, system reliability requirements, and operational flexibility needs.

A. Dispatch and Scenario Generation

The study used hourly solar irradiance and wind speed data, accessed via the Solcast and Open-Meteo APIs, to obtain current renewable energy profiles at specific locations in the North West Province, South Africa. Solcast provided high-resolution solar radiation forecasts, while Open-Meteo delivered wind speed information; researchers normalized both datasets to installed PV and wind capacity.

Two dispatch strategies are implemented: Robust and Stochastic dispatch. Robust Dispatch uses worst-case renewable output to ensure the system remains feasible, even under extreme conditions. Therefore, it relies heavily on reliability and aims to minimize load shedding. Stochastic dispatch uses Monte Carlo scenarios to capture the probabilistic nature of renewable variability. The idea is to optimize expected performance while maintaining greater operational flexibility, rather than just guarding against the worst single snapshot. The system performance indicators (KPIs) are evaluated using both approaches, enabling comparison of flexibility utilization, load reliability, renewable energy utilization, peak diesel generation, total diesel generation, and resilience. The datasets enabled researchers to model renewable energy uncertainty across different scenarios, including both daily and random variations, which were essential for operational dispatching. The model acquired API-derived data and integrated it into the MILP framework to enable realistic assessments of robust and stochastic dispatch methods that capture the operational challenges faced by hybrid microgrid systems during periods of fluctuating renewable energy output.

B. Key Performance Indicators and Analysis

For each uncertainty level, a set of results is collected and then compared, with a focus on how robust versus stochastic strategies perform. The robust dispatch keeps operations safe even under extreme conditions, such as high variability, whereas the stochastic dispatch tends to be more adaptive, offering greater flexibility and better utilization of renewables in more typical situations. The model's output is evaluated using six key performance indicators: Peak Diesel Generation, Total Diesel Generation, Renewable Utilization, Load Reliability, Resilience Index, and Flexibility Utilization. Fig. 1, which shows peak diesel generation, demonstrates that the dispatch system, with its robust design, relies on renewable energy sources to handle varying degrees of uncertainty in renewable output. The robust strategy ensures sufficient diesel availability to maintain load reliability. Fig. 2, which displays total diesel generation, shows an upward trend that continues amid increasing uncertainty until reaching 664.12 MW at 30% uncertainty. The stochastic dispatch system maintains a steady output of approximately 541 MW under varying uncertainty levels.

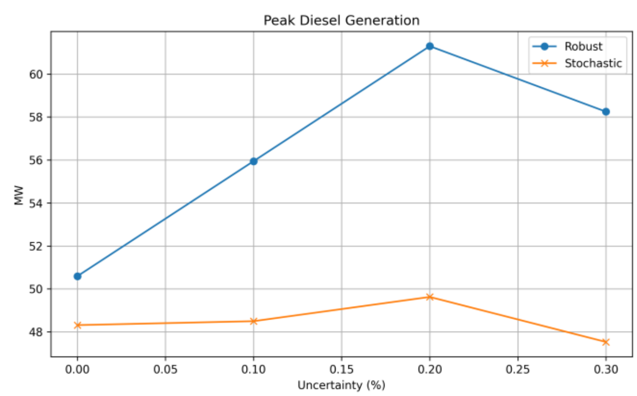

Fig. 1. Peak Diesel Generation

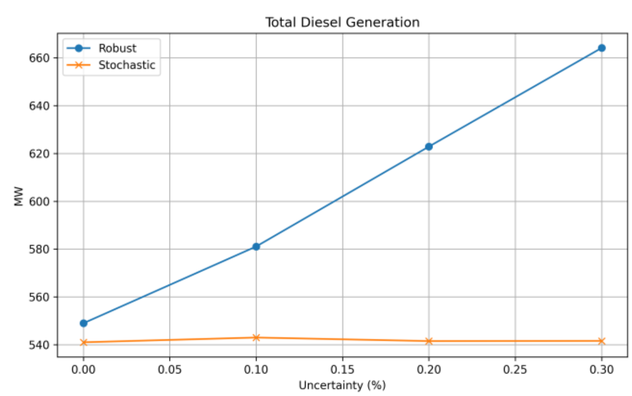

Fig. 2. Total Diesel Generation

Fig. 3 (Renewable Utilization) shows that dependable renewable resource usage decreases from 416 MW at 0% to 291 MW at 30% due to operational changes made to ensure reliable performance. The stochastic dispatch system provides steadier renewable energy distribution, yet its ability to handle extreme weather conditions may be diminished. Fig. 4 (Load

Reliability) shows that the robust dispatch system achieves total reliability by operating under moderate uncertainty levels, ranging from 10% to 20%. The real-time adaptive planning system provides operational advantages according to the research because it delivers better results than the stochastic dispatch system, which achieves 99.21% to 99.39% reliability.

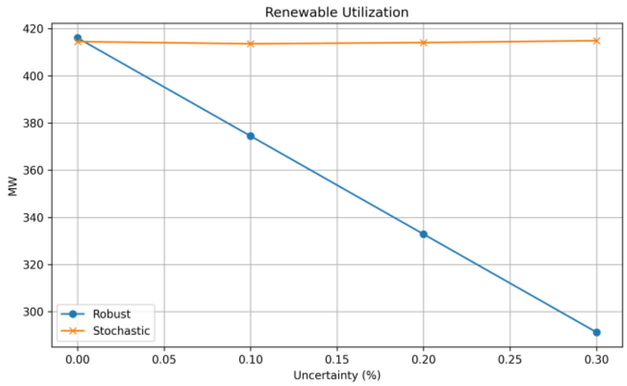

Fig. 3. Renewable Utilization

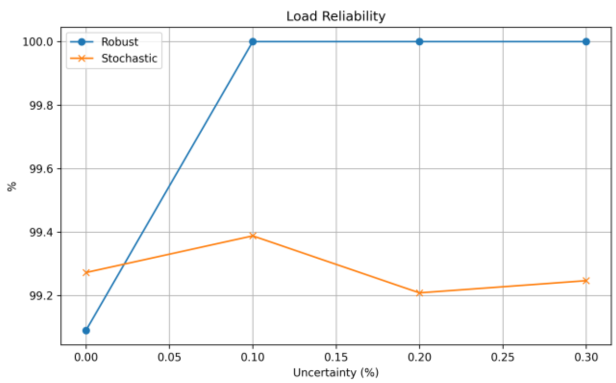

Fig. 4. Load reliability

Fig. 5 demonstrates that robust strategies require less energy storage and demand response resources to handle uncertainty, reducing storage requirements from 12.4% at 0% uncertainty to 7.6% at 30% uncertainty. Fig. 6 demonstrates that robust dispatch systems achieve 50%-62% resilience, while stochastic scenarios reach their maximum of 66% under moderate uncertainty. The stochastic method leverages favorable outcomes in its operations while facing risks from worst-case scenarios.

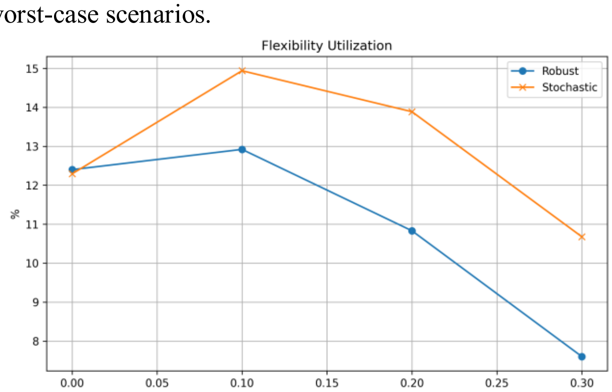

Fig. 5. Flexibility utilization

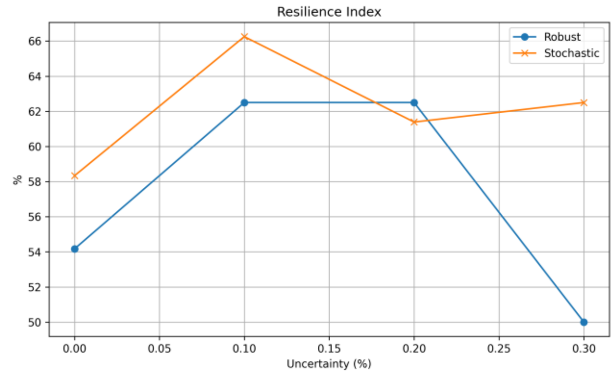

Fig. 6. Resilience index

C. *Research Implications*

The research findings show that an effective multi-objective dispatching system that employs robust dispatch methods can strike an appropriate balance among system reliability, operational flexibility, and renewable energy consumption. The robust strategies maintain system reliability during high-load periods while dynamically adjusting diesel power generation to compensate for reduced output from renewable energy sources. The stochastic dispatch system enables better average utilization of flexibility and greater adoption of renewable energy under normal conditions, while its performance declines during periods of extreme uncertainty. Table 2 gives a summary of the MILP size and computational complexity.

Table 2. Summary of MILP size and computational complexity for a 24-hour microgrid dispatch scenario

Category	**Details**	**Count per 24-hour Scenario**	**Notes**
Decision Variables	Diesel generator power	24	One per hour
	Battery charge/discharge	48	Two per hour
	Demand response adjustment	24	One per hour
	Battery SOC	24	One per hour
Total Variables		120	Continuous variables
Constraints	Power balance	24	One per hour
	SOC dynamics	24	One per hour
	Operational limits (gen, battery, DR)	96	3×24 + 24
Total Constraints		≈144	Per scenario
Complexity	Single 24-hour MILP	120 variables, 144 constraints	Moderate, seconds per scenario using CBC

Stochastic Benchmarking	30 scenarios	30 MILPs sequentially	Feasible on standard hardware
Large-Scale Implications	7-day horizon	~840 variables per scenario	Parallelization recommended
	30 scenarios × 7 days	25,200 variable evaluations	Requires careful memory management or decomposition

The computational dimensions of the model proposed in this paper for a single 24-hour scenario are depicted in Table 2. The size of the problem and the computational effort to solve it for stochastic benchmarking, i.e., for a growing number of scenarios, is then addressed. The models for scenarios with a 24-hour time horizon consist of 120 decision variables and about 144 constraints each. For stochastic benchmarking, for example, 30 MILPs are solved for the 30 scenarios. However, although the models for a single day are already of moderate size, the number of variables and constraints increases linearly with the number of time steps, so that large-scale instances (e.g. for several days) are still solvable as MILP problems in normal or also in parallel computation.

V. CONCLUSION AND FUTURE WORK

The paper investigates robust multi-objective dispatch for reliable and resilient microgrid operation and stochastic dispatch for efficient energy generation by maximizing renewable penetration and the flexible utilization of resources. While the stochastic dispatch operates the microgrid in a less reliable way, it can still be used for energy-efficient operation with a high level of flexibility. This paper highlights a trade-off among robustness, renewable penetration, and flexible usage. The paper provides a detailed quantitative analysis, enabling the microgrid operator to trade off among six performance metrics when dispatching resources in the smart microgrid. In the future, the author would like to extend this work by applying dynamic weight assignment to investigate the environmental and economic objectives of the smart microgrid under extreme scenarios for battery and demand response operations.

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