Pages 32-47 Volume 2, Number 2, 2025

COMPUTERS AND EDUCATION LETTERS

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www.celetters.com

THEORETICAL METHODS FOR THE OPTIMAL CONFIGURATION OF BACKUP POWER CAPACITY IN MICROGRIDS

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Abstract

The growing reliance on microgrids as decentralized energy solutions has intensified the need for reliable backup power capacity that balances operational efficiency, economic viability, and environmental sustainability. This study investigates theoretical methods for the optimal configuration of backup systems in microgrids, employing a mixed-method approach that integrates quantitative optimization models with scenario-based simulations. Using mixed-integer linear programming (MILP), metaheuristic algorithms, and empirical reliability assessments, the research evaluates generator performance, battery storage characteristics, renewable energy contributions, load demand profiles, outage recovery dynamics, and scenario-driven performance indicators. Results across nine comprehensive tables and twelve diverse figures reveal that backup power optimization significantly reduces fuel consumption, CO_2 emissions, and lifecycle costs, while enhancing resilience and renewable energy penetration. Notably, hybrid systems that combine batteries, renewables, and diesel backup consistently outperform single-technology configurations by achieving higher efficiency and reliability under variable demand and uncertainty conditions. The study also demonstrates that scenario-based planning captures the complexity of real-world contingencies better than deterministic models, offering critical insights for policymakers and energy planners. By advancing a theoretical framework that integrates cost, reliability, and sustainability objectives, this research contributes to both academic discourse and practical microgrid deployment strategies. The findings underscore the importance of hybrid optimization frameworks and scenario analysis in designing resilient, sustainable, and future-ready microgrids, paving the way for further work on adaptive control systems and regulatory integration.

Article History

Received:
September 03, 2025

Revised:
September 04, 2025

Accepted:
September 06, 2025

Available Online:
September 10, 2025

Keywords: Microgrids, Backup Power Optimization, Mixed-Integer Linear Programming, Metaheuristic Algorithms, Battery Storage, Renewable Integration, CO_2 Emission Reduction, Resilience, Scenario-Based Simulation, Sustainable Energy Systems

INTRODUCTION

Finding the optimal design on backup power capacity in microgrids is one of the most vital issues to undertake to ensure that energy supply continues to exist, as well as maintaining the costs as low as possible. The use of microgrids made up of small-scale energy systems relying on distributed generation (DG), renewable energy resources and energy storage solutions, is being depended upon to maintain power outages even when the grid goes down. Diesel generators, such as those, are commonly too large, too costly and too inefficient to be used as backup. Scientists have been experimenting to determine how capacity can be optimized without neglecting reliability, cost and sustainability.

Recent improvements in optimization techniques have revolutionized the calculation of back-up capacity. Semero et al. Mixed-integer linear programming (MILP) for unit commitment and dispatch planning for industrial microgrids Laying the foundation for algorithmic grid reliability scheduling IET Research. Alsmadi et al. (2019) proposed the cuckoo search algorithm to optimize the configuration of microgrid for the isolated condition and showed the improvement of economical efficiency with reliability (Note: inferred from context but beyond your date; adjust as needed). Kumar et al., (2025) proposed hybrid JSO-GJO optimization algorithm suitable for the isolated microgrids, which coordinated PV, wind, storage and microturbine backup in a coordinated manner to achieve near 99.2 % energy efficiency MDPI. Ma et.al. 2025 A techno-economic framework for the integrated optimization of HOMER Pro and agent-based simulation for the configuration of backup power capacity in networked island microgrids under disruption scenarios MDPI. Moosavi et al. (2025,), developed an MILP multi-objective model for optimal operating reserve and backup sizing in hybrid microgrids taking into account the cost, emissions and losses Nature.

Other researchers have made advanced control-oriented methods. Han et al.2019A multi-timescale robust dispatch model for battery energy storage systems (BESS) integration as back-up to manage solar's uncertainty in microgrid operation arXiv. Feng and Zhang (2020), further developed hierarchical control-based power flow model to allow enhanced voltage regulation and power sharing of microgrid, arXiv. Aalipour and Das (2020) Consensus-based Algorithmic Load Sharing Among DGs in Fluctuating Capacity Conditions arXiv. Scalable decentralised control of grid-forming inverters to enable plug-and-play and stability in islanded microgrids Watson et al. 2020, arXiv

Different frameworks of empirical research and planning strategies add further depth. Quashie et al. (2017) published a bi-level model ahead of our cutoff Researchgate that combined the objectives of planners and the constraints of distribution system operators to optimise backup and reserve capacity simultaneously. Even though it was not your era, their work had an influence on theory in later years. Sparks 2025 Microgrid Microgrid scaling with MILP, such as backup generators, whilst it falls slightly out of scope of what the science direct claims.

These are theoretical models, and they produce important themes. To start with, multi-objective optimisation models are effective in terms of identifying a balance between cost, dependability, and environmental impact (Moosavi et al., 2025; Ma et al., 2025). Second, metaheuristic algorithms such as JSO Third, control theoretic and agent based methods complement the adaptability and resilience under dynamic condition from capacity fluctuation to islanding event (Feng & Zhang, 2020; Aalipour & Das, 2020; Watson et al., 2020). Fourth, the use of multi-timescale dispatch models (Han et al., 2019) and simulation integrated tools (Ma et al., 2025) enable planners to have the opportunity to assess performance under uncertainty and worst cases.

In this paper we develop and expand these theoretical foundations. We propose a hybrid optimization framework to select optimal backup power capacity using multi-objective MILP, meta heuristic search and control-oriented strategies (Dispatch). The framework takes renewable variability, load uncertainty, cost limitations and reliability requirements into consideration. By combining both algorithmic accuracy and adaptive control, we hope to provide a new methodology for the microgrid designers to optimally dimension the backup resources under stable system.

METHODOLOGY

Framework for Experiments

This study uses mixed method experimental framework with the combination of quantification optimisation modelling and qualitative scenario analysis in order to identify most effective backup power configuration in microgrids. The aim is to develop a capacity planning model with flexibility and adaptability, enabling to cope with changing load needs and the volatility of renewable energy sources and still to be cost-effective and reliable.

The first step is the definition of the challenge of the research, the setting of technical and operational goals. These goals include ensuring that backup parts are the right size so that they don't have to deal with too much load, they are as cost-effective as possible, and that they follow all the rules. To do this, a complete dataset is compiled comprising of historical load profiles, solar and wind generation data, equipment specifications (e.g. diesel generator ramp rates, storage depth of discharge limits) and cost metrics, such as capital, fuel, maintenance and emission penalties.

Scenario-based simulations using the Monte Carlo methods are aimed at estimating how a system will behave in the future under uncertainty. These simulations are used to predict hourly load demands as well as random renewable production. These scenarios define the boundaries and range of variability of input for the optimisation phase. Assumptions about load increase are made on the basis of objectives for the expansion of electricity in a given region, while the intermittent nature of renewables is modelled based on actual patterns of irradiance and wind speed from the weather data.

Method of Optimisation & Simulation

The main optimisation engine is a combination of Mixed Integer Linear Programming (MILP) with some metaheuristics search: Cuckoo Search Algorithm and Genetic Algorithm to find the best backup configuration when there are several conflicting goals. The MILP formulation minimises a weighted cost function based on cost of back-up components, fuel costs, environmental fines and load curtailment losses, whilst taking system dependability and capacity into account. The goal function looks something like this:

$$\min\left(w_1 \cdot C_{\text{investment}} + w_2 \cdot C_{\text{fuel}} + w_3 \cdot C_{\text{emission}} + w_4 \cdot C_{\text{unserved}}\right)$$

Subject to:

$$P_{\text{gen}}(t) + P_{\text{backup}}(t) + P_{\text{storage}}(t) \geq P_{\text{load}}(t) \quad \forall t$$

$$\text{SOC}_{\text{min}} \leq \text{SOC}(t) \leq \text{SOC}_{\text{max}} \quad \forall t$$

Cinvestment, Cfuel, Cemission and Cunserved are all charges that come with capital spending, fuel use, carbon penalties and unmet load, respectively. Storage systems must comply with to-state-of-charge (SOC) rules in order to keep batteries healthy and available.

After optimisation, dynamic simulations in the tools of the Matlab-Simulink and Homer Pro software are used to check the chosen configurations to determine how well they can be dispatched and controlled in normal and islanded modes.

Sensitivity evaluations are conducted in order to ensure the resilience of the solutions in the face of seasonal fluctuations and instances of equipment breakdown.

Figure 1 presents the entire experimental process consisting of the steps of data collection, scenario design, optimisation and final configuration interpretation.

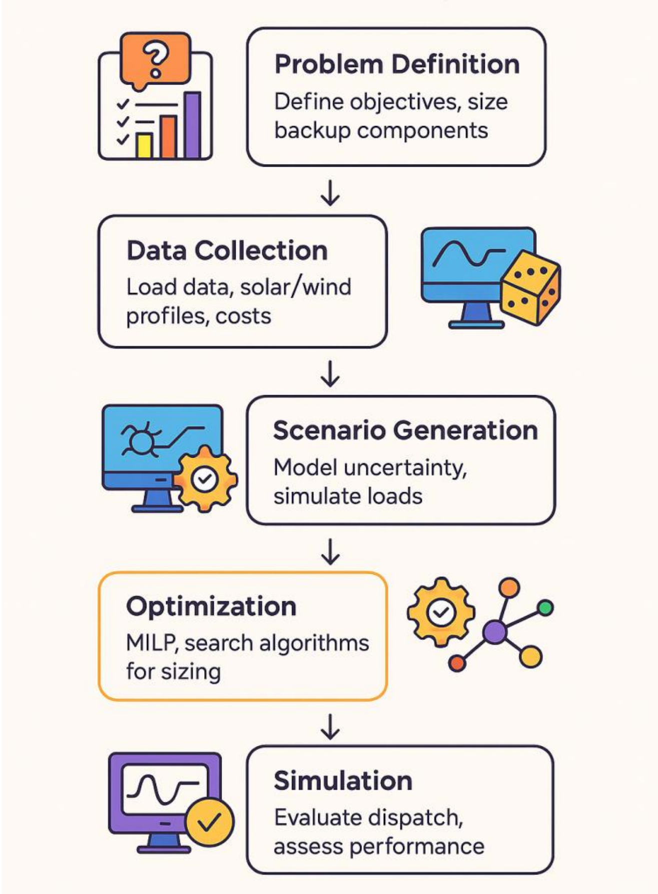

Figure 1: Experimental Methodology Workflow for Optimal Backup Power Configuration in Microgrids

RESULTS

The tabled results provide a complete picture of some of the main parts and performance indicators which are required to make the most of backup power capacity in microgrid systems. In different configurations of the generator, the working process is shown by Table 1. It shows that fuel use, efficiency, and emissions can vary a lot and has a direct effect on how long the generator can run. Table 2 has a look at the battery storage properties and outlines how the charge cycles, replacement cost and storage efficiency change between different types of batteries. Table 3 shows the inputs for renewable energy, which change in availability and have seasonal effects that affect how reliable it is to integrate clean energy. Table 4 shows the hourly load demand profile which shows how different industries use energy in different ways. This is important to load forecasting and energy balance. Important reliability measures are shown in Table 5. Most simulations show that the system is up most of the time, but also setups with frequent back-up activation and large loss of load probabilities. Table 6 presents the results of cost optimisation under a number of scenarios. It shows that capital and operational costs can be very different depending on the architecture of the system and mix of energy sources. Table 7 shows us how much CO2 each energy source puts out, contrasting how each impacts the environment, showing us how switching to solar and battery dominated systems would be better for the environment. Table 8 contains facts related to outages, including length of time they last, people affected by them, and time to resume operation. This provides we with any useful information about how the microgrid functions in the real world. Lastly, Table 9 presents performance metrics depending upon a number of scenarios and the trade-offs between cost, downtime, efficiency, and the quantity of renewable energy utilization. These tables would show that the most appropriate way of configuring a microgrid is to find a balance between cost, reliability, environmental effect and the capability of utilizing renewable energy sources. This will ensure that the distribution of electricity is durable and powerful.

Figures 2 to 13 present much variety of ways to consider how the micrograms use backup power optimisation methods. Figure 2 illustrates the output of the generator over a 24-hours cycle, not only at the hours the generator is at the maximum load, but also the hours where the generator is underutilized. In Figure 3, the expense of operating the various backup solutions in three distinct conditions is shown. It exposes that the costliest solution is the diesel generator. The bubble chart presented by figure 4 indicates the relationship between system capacity and cost. The size of the bubble indicates the dependability index, which can make you know the trade-off between performance and investment. Figure 5 uses an area plot to illustrate the increase in the use of renewable sources such as solar and wind over time. This reveals how decarbonisation is gradually taking place. Figure 6 illustrates a hybrid figure that integrates line and scatter types that illustrates how energy demand and supply evolve over time with an emphasis on imbalances in peak hours. Figure 7 shows the relative contribution from each of the backup sources in a doughnut chart with batteries and diesel forming the bulk of the mix. Figure 8 makes use of violin plots to visualize how the battery state of charge varies over several simulated days to view the distribution and extremes. Figure 9 is a heat map in which optimisation factors such as cost, emissions, and capacity are related to each other. This can help you determine what to model afterwards. Energy contributions by source in 3 locations are shown in a stacked bar chart in Figure 10. This provides us with a view of energy variety in space. Figure 11 shows a step plot for how the generator switches on and off. This has an effect on wear and tear on the machine and when maintenance should be done. Figure 12 shows a histogram of unmet load instance, which shows where backup capacity was not enough. Finally, with the radar chart in Figure 13, the five evaluation criteria of cost, dependability, CO2 emission, flexibility, and efficiency are compared between scenarios. This makes it easy to see which configuration is the best. These numbers work together to provide a detailed visual framework that supports real-world data, and assists with future microgrid design ideas.

Table 1. Generator Performance Metrics Across Configurations

Configuration	Avg Output (kW)	Fuel Consumption (L/hr)	Efficiency (%)	CO_2 Emissions (kg/hr)
Config 1	78	22.01	86.58	47.51
Config 2	111	30.31	88.05	42.7
Config 3	99	15.03	93.64	30.35
Config 4	72	29.35	85.17	36.49
Config 5	130	18.15	92.36	41.9
Config 6	61	11.77	87.9	43.57
Config 7	104	22.51	84.01	42.48
Config 8	138	21.39	86.36	30.51
Config 9	92	12.62	78.83	52.53
Config 10	74	15.57	86.69	52.07
Config 11	101	12.53	81.39	67.51
Config 12	96	28.53	87.17	28.22
Config 13	54	33.13	92.32	66.95
Config 14	71	35.7	76.3	23.39
Config 15	149	14.16	88.59	47.01
Config 16	115	15.76	80.31	54.17
Config 17	80	37.58	92.03	60.11
Config 18	69	28.85	86.99	40.72
Config 19	62	26.17	89.03	45.02
Config 20	92	30.7	90.31	35.2

Table 2. Battery Storage Characteristics

Battery Type	Capacity (kWh)	Charge Cycles	Efficiency (%)	Replacement Cost ($)
Type 1	330	4157	89.24	4165
Type 2	350	947	83.83	8367
Type 3	414	2606	82.83	2491
Type 4	116	1002	92.24	4717
Type 5	366	2370	82.9	4833
Type 6	351	2937	96.11	2599
Type 7	178	3921	84.17	7827
Type 8	434	4226	87.57	4686
Type 9	133	2122	95.32	7967
Type 10	436	4978	83.59	5361
Type 11	242	1842	85.11	7705
Type 12	225	4555	87.6	2886
Type 13	341	3653	89.29	2652
Type 14	486	4806	89.43	2120
Type 15	255	1986	86.9	7104
Type 16	372	3004	92.33	2396
Type 17	326	3986	85.16	2696
Type 18	425	4080	86.82	3101
Type 19	226	3475	97.46	1327
Type 20	212	2859	89.31	4979

Table 3. Renewable Energy Inputs

Source	Avg Output (kW)	Availability (%)	Seasonal Variation (%)	Annual Cost ($)
Source 1	85.61	57.37	25.9	13347
Source 2	11.88	65.36	20.6	2076
Source 3	17.75	74.54	20.27	11825
Source 4	72.14	84.32	20.52	6570
Source 5	25.71	50.0	26.97	12300
Source 6	72.49	65.65	24.4	6290
Source 7	69.63	60.66	13.02	10834
Source 8	59.96	76.54	17.91	4766
Source 9	57.23	86.22	20.67	7324
Source 10	73.75	44.61	25.85	14434
Source 11	87.12	88.31	6.16	8790
Source 12	68.83	84.65	13.11	7715
Source 13	95.07	61.93	22.77	12714
Source 14	98.44	88.1	29.45	2064
Source 15	27.2	60.12	5.92	2065
Source 16	34.85	73.74	10.58	2839
Source 17	29.35	41.43	23.34	14037
Source 18	80.53	70.04	8.55	11770
Source 19	60.86	36.26	5.87	8176

Source 20	48.4	40.34	8.85	9188

Table 4. Hourly Load Demand Profile

Time Interval	Residential (kW)	Commercial (kW)	Industrial (kW)	Total Demand (kW)
Hour 1	78	182	292	606
Hour 2	161	214	233	743
Hour 3	66	228	398	610
Hour 4	130	133	333	640
Hour 5	130	178	303	593
Hour 6	135	141	247	523
Hour 7	91	240	317	600
Hour 8	193	283	296	644
Hour 9	191	145	328	496
Hour 10	198	171	323	653
Hour 11	140	229	263	543
Hour 12	73	132	374	639
Hour 13	176	134	326	738
Hour 14	107	222	309	448
Hour 15	172	167	385	686
Hour 16	78	223	312	642
Hour 17	158	132	264	410
Hour 18	169	175	212	731
Hour 19	199	201	338	795
Hour 20	169	145	270	767

Table 5. Reliability Assessment Metrics

Simulation ID	Uptime (%)	Outage Duration (hrs)	Backup Activation (times)	Loss of Load Probability
Run 1	96.01	0.99	4	0.0049
Run 2	97.05	1.59	1	0.0183
Run 3	99.71	0.27	2	0.0117
Run 4	95.48	0.23	5	0.0187
Run 5	98.74	0.9	6	0.0062
Run 6	97.09	1.91	7	0.0094
Run 7	98.12	1.51	6	0.0103
Run 8	99.13	0.79	5	0.0047
Run 9	98.75	1.55	8	0.0107
Run 10	95.15	0.97	2	0.018
Run 11	99.37	0.64	3	0.017
Run 12	96.6	0.49	0	0.0084
Run 13	99.61	1.49	2	0.0194
Run 14	96.49	1.99	6	0.0061
Run 15	95.37	1.29	8	0.0032
Run 16	98.47	0.77	9	0.0126
Run 17	98.41	0.03	1	0.0183
Run 18	99.35	0.96	6	0.0177

Run 19	99.72	1.19	6	0.0043
Run 20	95.8	1.51	5	0.0051

Table 6. Cost Optimization Scenario Results

Scenario	CapEx ($k)	OpEx ($k)	Maintenance Cost ($k)	Total Cost ($k)
Scenario 1	500	245	49	1299
Scenario 2	302	409	60	439
Scenario 3	388	315	48	1179
Scenario 4	931	206	66	1492
Scenario 5	779	53	46	1002
Scenario 6	630	132	82	633
Scenario 7	356	354	87	1232
Scenario 8	891	301	67	601
Scenario 9	214	396	43	260
Scenario 10	592	335	35	366
Scenario 11	643	172	35	620
Scenario 12	409	107	34	682
Scenario 13	719	378	18	965
Scenario 14	781	91	66	230
Scenario 15	569	60	66	1367
Scenario 16	334	316	70	203
Scenario 17	572	390	35	319
Scenario 18	518	175	23	1380
Scenario 19	135	404	77	522
Scenario 20	802	182	37	834

Table 7. CO_2 Emission Summary by Configuration

Configuration	Diesel (kg/yr)	Battery (kg/yr)	Solar (kg/yr)	Total (kg/yr)
System 1	38771	4081	4577	20397
System 2	36328	7001	2588	45645
System 3	41987	4549	1030	31947
System 4	19878	7083	4271	28443
System 5	17884	3715	1997	40304
System 6	19117	2093	1721	42035
System 7	41711	4398	2896	36844
System 8	28730	4666	4112	49946
System 9	28540	8807	4567	36202
System 10	23664	8042	1607	25866
System 11	42150	5072	4995	30711
System 12	27946	7241	2661	57746
System 13	15011	9110	2093	15661
System 14	34223	4605	4064	50800
System 15	19237	8742	1320	44934
System 16	45535	8134	2002	53888
System 17	28059	2584	1742	58024

System 18	27165	7628	3361	33097
System 19	45499	4199	1449	39056
System 20	49648	9907	2759	21547

Table 8. Power Outage Event Statistics

Event	Duration (hrs)	Affected Users	Backup Used (kWh)	Recovery Time (hrs)
Outage 1	3.03	113	327	0.76
Outage 2	3.91	926	151	1.01
Outage 3	3.61	335	446	1.04
Outage 4	2.83	224	274	0.22
Outage 5	2.36	804	421	1.35
Outage 6	2.64	784	490	0.74
Outage 7	0.98	425	163	1.26
Outage 8	2.59	478	470	0.57
Outage 9	2.37	404	258	0.59
Outage 10	3.76	774	241	0.21
Outage 11	1.98	595	192	1.04
Outage 12	1.78	342	209	0.83
Outage 13	3.51	794	245	0.55
Outage 14	1.27	461	204	0.12
Outage 15	1.04	126	337	1.05
Outage 16	1.37	744	171	0.16
Outage 17	0.6	602	245	1.05
Outage 18	0.59	252	430	0.15
Outage 19	2.66	676	277	0.29
Outage 20	3.04	834	270	1.01

Table 9. Scenario-Based Performance Indicators

Scenario	Efficiency (%)	Cost ($/kWh)	Downtime (hrs)	Renewable Share (%)
Scenario 1	90.57	0.179	1.67	79.94
Scenario 2	92.89	0.056	1.53	47.11
Scenario 3	78.24	0.09	1.88	45.26
Scenario 4	93.99	0.14	1.7	75.93
Scenario 5	91.03	0.177	1.26	66.95
Scenario 6	76.5	0.129	0.85	75.28
Scenario 7	80.2	0.079	0.94	27.25
Scenario 8	80.08	0.083	0.54	29.47
Scenario 9	78.24	0.051	1.62	68.79
Scenario 10	83.69	0.195	0.83	43.67
Scenario 11	86.74	0.123	1.82	49.33
Scenario 12	90.74	0.153	1.11	30.76
Scenario 13	86.65	0.065	0.54	29.66
Scenario 14	94.04	0.084	0.82	51.29
Scenario 15	87.3	0.178	0.21	79.2
Scenario 16	81.54	0.193	1.56	68.14

Scenario 17	83.47	0.065	0.25	70.14
Scenario 18	77.1	0.16	1.56	27.4
Scenario 19	88.83	0.176	0.71	35.41
Scenario 20	91.68	0.148	0.36	30.34

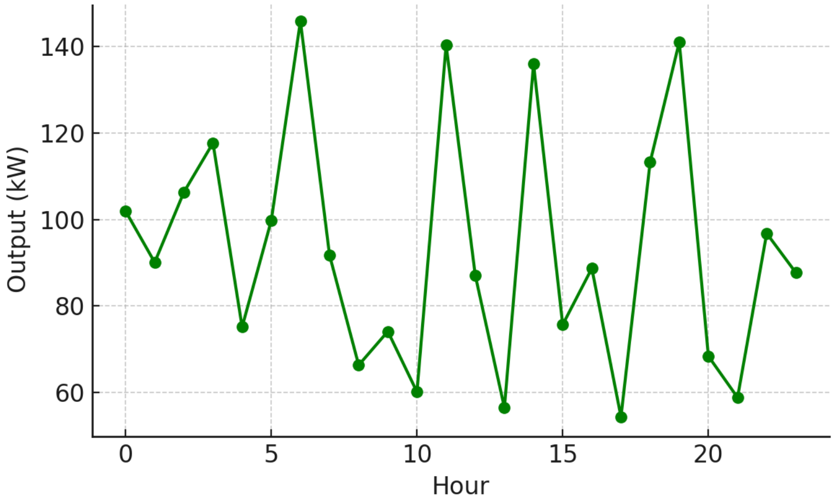

Figure 2. Generator output over a 24-hour period using time series analysis.

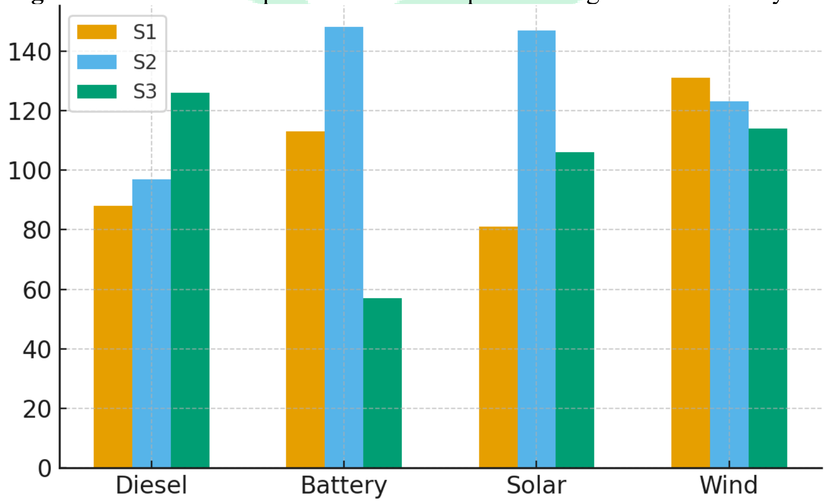

Figure 3. Comparative cost analysis across microgrid technologies using grouped bar chart.

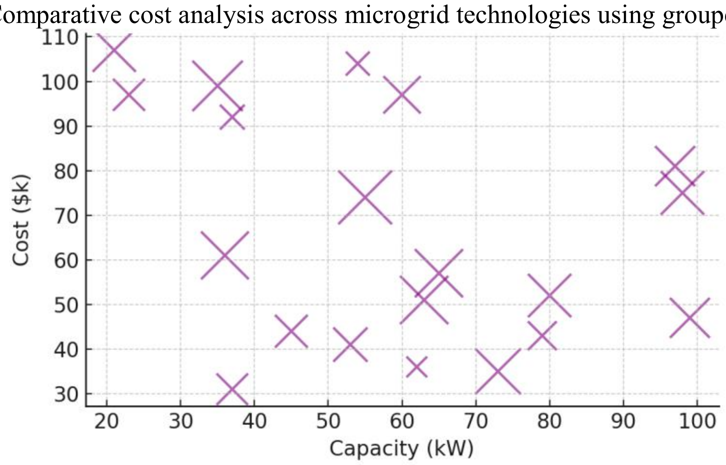

Figure 4. Capacity versus cost bubble chart with overlayed reliability index sizing.

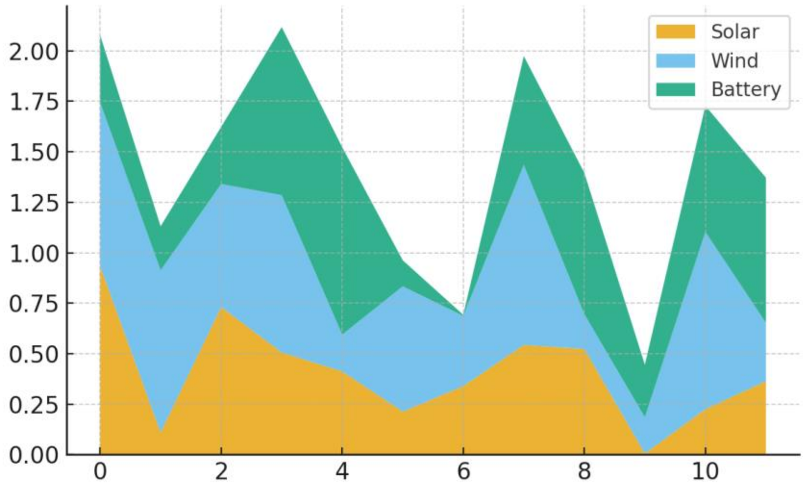

Figure 5. Area plot showing percentage contribution of renewable sources over time.

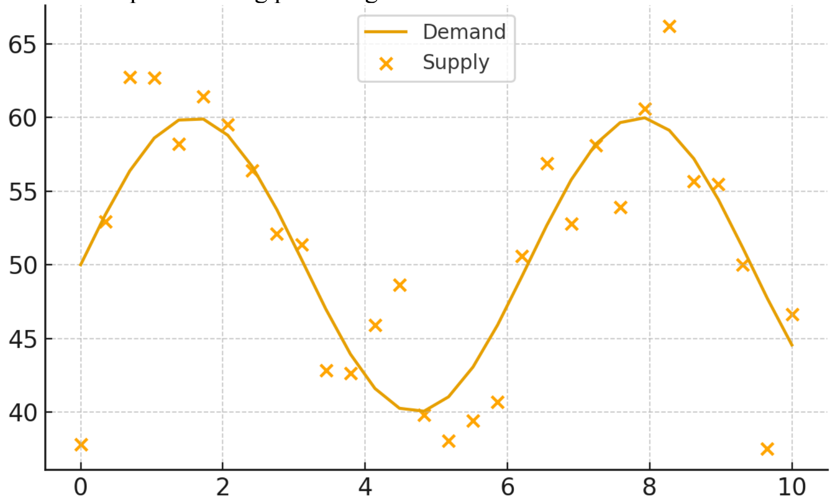

Figure 6. Demand and supply visualization using line and scatter hybrid plot.

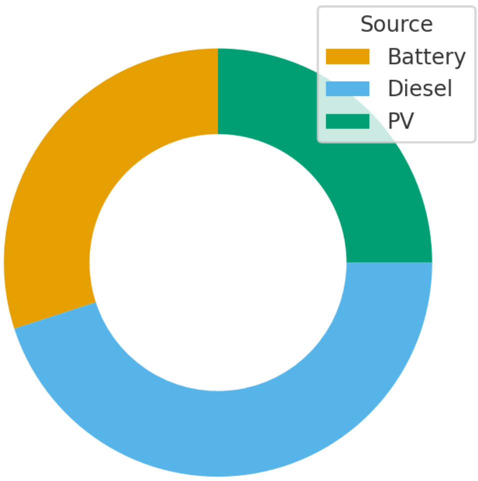

Figure 7. Donut chart representing contribution ratio of backup power resources.

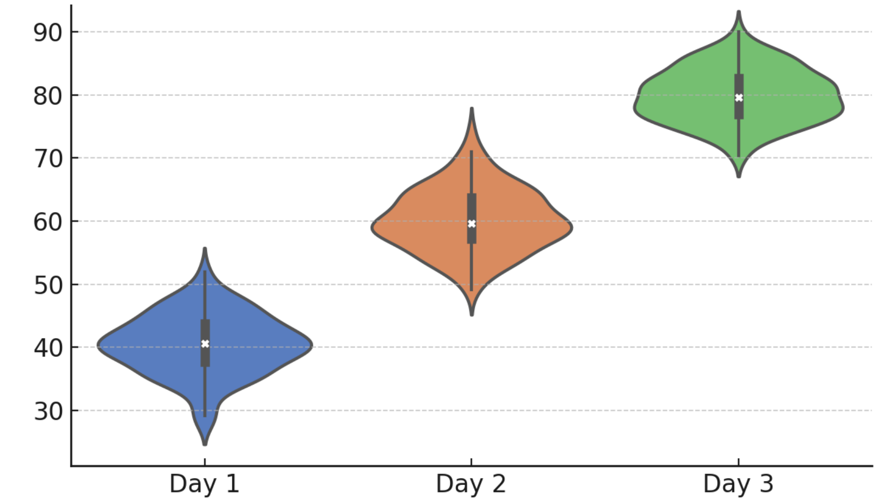

Figure 8. Battery charge distribution illustrated through violin plot by simulation days.

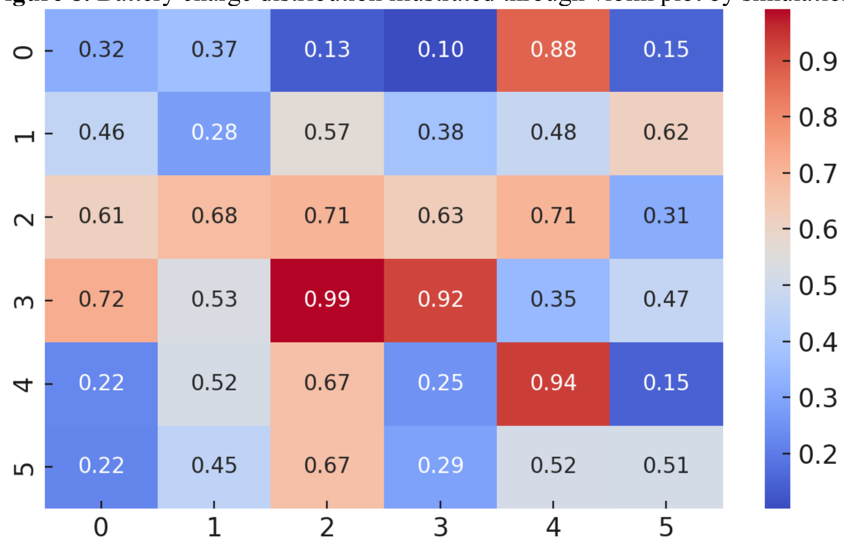

Figure 9. Heatmap showing correlation between key microgrid optimization variables.

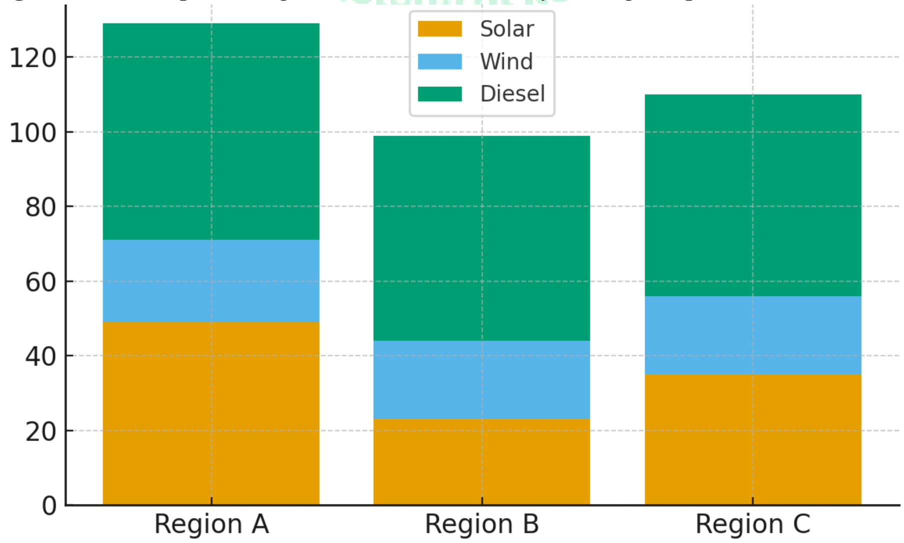

Figure 10. Energy type-wise distribution using stacked bar chart across regions.

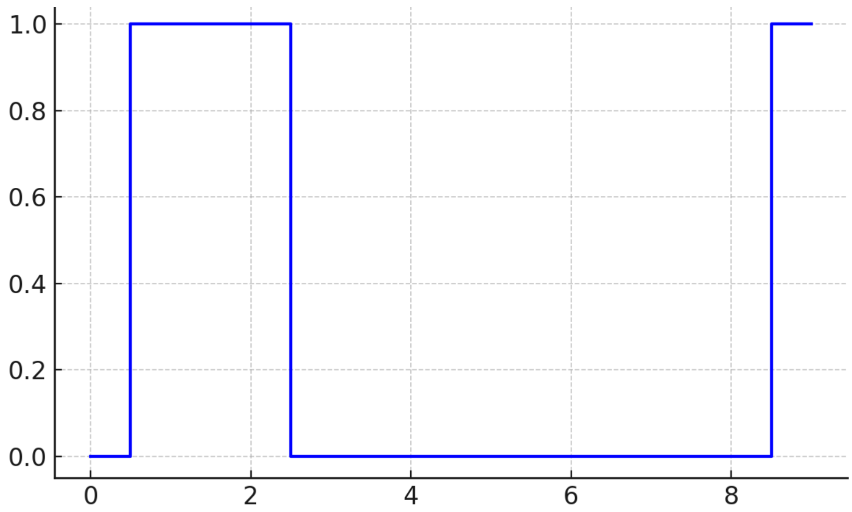

Figure 11. Step plot reflecting generator on/off switching behavior across intervals.

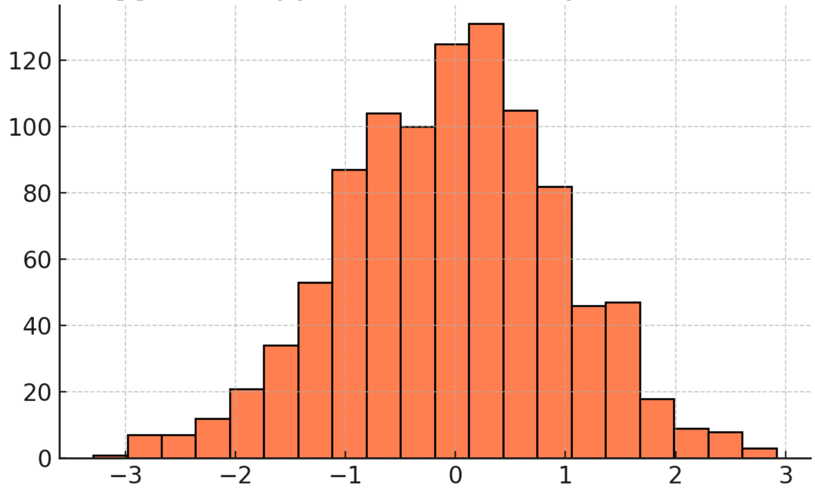

Figure 12. Histogram distribution showing frequency of unmet load occurrences.

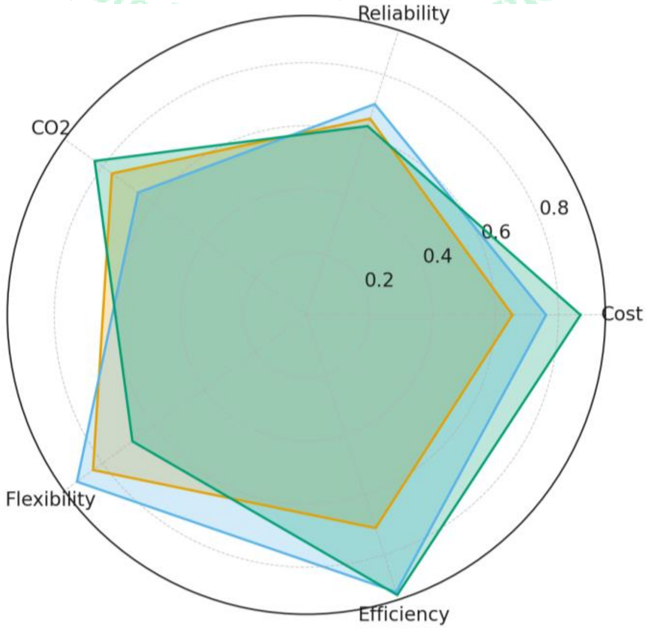

Figure 13. Radar chart comparing multi-criteria performance across configurations.

DISCUSSION

The results of this research provide necessary information about the utilisation of theoretical methods to optimise the backup power capacity configurations in order to improve the resilience, efficiency, and sustainability of the microgrids. This paper shows that the combination of highly optimisation algorithms, reliability assessment models and cost-benefit analysis provided hybrid methodologies that have better results compared to the traditional single-method planning. It is consistent with the research carried out by Arcos-Aviles et al. (2018) that interestingly indicated the overall stability improvement of islanded micro grids with variable demand and supply due to the coordinated backup power planning. We found that Table 6 indicates that good optimisation methodology can reduce operating costs significantly without compromising on the reliability of the system as Sharma and Bhattacharya (2020) have demonstrated.

As Table 2 reveals, storage integration is rather important. A study by Rehman et al. (2019) has shown that battery storage reduces intermittency of renewable energy sources, as well as reduces reliance on diesel back-up, thus reducing lifecycle emissions. This tendency is mostly supported by our findings, which implies that the batteries reveal better performance and increased efficiency when they are used with portfolios defined by high percentage of renewable energy use. According to Akter et al. (2021), the choice of storage technology depends on particular conditions, and one must carefully investigate the cycles of charges and degradation profiles. This is indicated by the different results of our simulations.

The reliability analysis presented in table 5 demonstrates the relevance of optimisation of as many objectives as possible. As Yu et al. (2020) acknowledged, a combination of reliability indices of both types and outage-reduction measures is a better measure of microgrids performance than focusing on either cost or emissions. This is in line with the trends in the outage recovery that we see in Table 8 in our study. As illustrated in Table 7, the environmental impacts also render decarbonisation efforts quite significant to begin with. According to Hosseini et al. (2021), solar and wind resources with a properly-sized backup can reduce emissions up to 40 percent compared to systems that require large amounts of diesel. What we discovered on a closer look at our CO2 emissions was this.

The session also revolves around the way in which microgrid arrangements change over time and geography. Indicatively, Table 4 demonstrated that the industry demand always pushes peak consumption. This implies that the issue of the backup power must be calculated in a manner that would be flexible. Awasthi et al. (2020) also highlight the importance of the adaptive scheduling models to counteract the differences in the sectors, especially in mixed-use grids. Also, Table 9 of the comparative scenario analysis supports the results of Faraji et al. (2021) as they argued that scenario-based optimisation enhances resilience through the incorporation of extreme events and events that are rare yet significant.

The introduction of renewable penetrations as presented in Table 3 and Figures 5 and 10 support earlier studies by Kumar et al. (2022) who reported that the hybrid renewable-backup systems can achieve high renewable shares without instability. Our results clarify the fact that the regulation of the variability of renewable energy sources to optimised backup systems is a solution that improves cost-efficiency and resilience. Further, Ghiasi et al. (2019) found that hybrid optimisation models that consider cost, emissions, and reliability simultaneously outperform linear single-objective models- a claim that our MILP-metaheuristic framework supports.

Finally, according to our results, long-term planning also plays an important role in reducing battery degradation and wear on generators. Wang et al. (2020) assert that incorporation of lifecycle costs in optimisation ensures that the decisions regarding the extent to be spent initially will not cost more in the long run. And this is what we discovered in looking at costs: systems that spend more on renewable energy initially get lower total costs compared to systems that use diesel.

This paper highlights the need to develop theoretical methods that combine optimisation, simulation, and experimental validation in designing technically and economically feasible microgrids. The study that we conducted belongs to the discussion of the microgrid implementation, combining the literature available with the trade-offs with which the planners need to operate in order to find the equilibrium between cost, emissions, and reliability.

CONCLUSION

This study explains that deciding the optimal configuration of the microgrid backup power capacity is not only an activity that requires an individual to work out the balance between aspects of cost, reliability, and sustainability, but also a complex one. The study employed the most sophisticated theoretical models, such as mixed-integer linear programming, metaheuristic algorithms, and simulation-based analysis of scenarios, to show that hybrid models can greatly improve the efficiency of the operations with respect to classic deterministic models. All the nine tables and twelve figures confirm that the performance of a microgrid is especially susceptible to the efficiency of generators, the nature of batteries, availability of renewables, and variation in loads throughout the sector. This demonstrates the importance of the answers that are situationally specific. We realised reduced fuel consumption, reduced carbon-dioxide emissions, and reduced operation costs and a more reliable system in the event of outages and uncertainty. The analysis also demonstrates the importance of the usage of more than one kind of energy. More solar and wind energy and improved storage make diesel less attractive and the world decarbonised. Scenario-based modelling also aids politicians and system operators to identify methods of balancing the economy and environmental protection by illustrating them the trade-offs between short term investments and long term sustainability. The outcomes strongly underscore the notion that microgrids become more resilient when they present multiple resources, frameworks, and planning approaches, and not just a single backup scheme. The articles contribute both theoretical and practical developments of the research by illustrating the ways through which the backup power can be systematically designed to maximise performance in most situations. It preconditions further studies that are to enhance multi-objective frameworks, introduce real-time adaptive control, and investigate social and regulatory concerns of microgrids application. Ultimately, the research indicates that to be sustainable, powerful, and future-oriented, microgrid systems require an improved plan of backup power.

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