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Original Scientific Article

Prioritized Objective Hierarchies for Sustainable and Resilient Microgrid Energy Management

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Abstract— **Renewable energy resources are becoming more prevalent in modern microgrids. This means that operators face a growing need for optimization strategies. These strategies must balance technical, economic and environmental objectives. This is especially true when battery degradation is considered. Researchers are struggling to achieve this balance between short-term cost savings and long-term system durability. The issue is addressed in this study through the implementation of a two-stage approach. In the first stage, photovoltaic (PV) capacity and battery size are determined using particle swarm optimization (PSO) to ensure both economic feasibility and realistic lifecycle performance. A mixed-integer linear programming (MILP) model implemented in Python through Gurobi is employed in the second stage for the management of daily energy operations. The analysis examines how different objective-function priorities affect prosumers with varied consumption and generation profiles in a multi-stage microgrid setting. A comparison is made between three alternative formulations. (i) minimizing operating costs, (ii) preserving battery health and (iii) maximizing renewable energy use, as well as combined bi- and tri-objective versions. Simulation outcomes show that the ranking of objectives strongly shapes system performance, which is important to consider when designing and implementing systems. Indicators such as self-consumption, self-sufficiency, curtailed power, CO2 emissions and storage ageing show variations. Overall, practical guidance is offered by the findings for engineers and planners aiming to design energy-management strategies that link immediate operational goals with long-term sustainability and resilience in prosumer-oriented microgrids.**

Keywords - microgrid energy management, multi-stage optimization, prioritized objective hierarchies, battery aging model, cycle and calendar degradation.

I. INTRODUCTION

Renewable energy sources are becoming a larger part of modern power systems, especially through the growth of microgrids that operate independently. These microgrids, which are often set up in remote or rural areas, bring together distributed generation, energy storage, and controllable demand. This combination helps to keep the local energy system reliable and independent [1]. Renewables make a clean and reliable power supply possible, but they also cause problems. These problems include changes

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in how much power is produced, costs that are hard to predict, and problems making sure the system works well. These challenges require optimization frameworks that can guarantee sustainable and profitable operation [2]. Conventional single-objective control strategies are often designed for cost minimization. They fail to manage the multiple, sometimes conflicting, goals of microgrid operation under high renewable penetration [3]. To address these limitations, multi-objective approaches have been increasingly adopted by researchers that jointly consider economic, environmental, and technical performance [4].

Researchers have recently investigated the potential of heuristic and metaheuristic optimization algorithms to improve the performance of microgrid scheduling. For instance, advanced techniques like the oppositional gradient-based grey wolf optimizer (OGGWO) have demonstrated the ability to prevent premature convergence and attain robust solutions for cost reduction and emission control [5]. In a similar way, hybrid metaheuristic frameworks, such as the predatory pelican optimization algorithm (PPOA), have shown significant advancements in cost and emission performance while preserving grid stability [2]. Multi-stage and hybrid control architectures build on these efforts by introducing dynamic energy management across multiple time horizons, achieving consistent results in both grid-connected and islanded operating modes [6]–[10].

Additionally, value-based objective formulations have assisted microgrid operators in identifying balanced, Pareto-optimal trade-offs among competing criteria, which reduces renewable intermittency and improves service reliability [3]. The addition of demand-response (DR) schemes, like real-time pricing and direct load control, has made the system even more flexible. This has resulted in noticeable decreases in cost, emissions, and energy losses [4], [11], [12]. Finally, studies that focus on uncertainty management and strong optimization have shown that it is very important to plan for changes in the generation and demand of electricity. This is necessary for microgrids to be reliable and strong [13], [14].

At the same time, many recent studies emphasize that battery aging and degradation should be treated as key factors in long-term microgrid planning. Disregarding these effects frequently results in impractical outcomes, increased lifetime expenses, and a reduction in system dependability [15]. In response, several works have proposed layered optimization methods that integrate battery health with economic and environmental goals. These methods underscore the need for frameworks that weigh short-term financial performance against long-term technical stability [16], [17].

Despite these advances, there is still no clear consensus on how multi-stage objective functions should be structured and prioritized for prosumers operating within microgrids. The research findings indicate that a balanced outcome across cost, environmental, and technical criteria is achieved with a two-layer configuration or a three-layer configuration. In particular, further study is warranted by the trade-offs among electricity cost minimization, battery health preservation, and renewable energy utilization, especially in systems with diverse consumption and generation behaviors.

The question is addressed in this study through an examination of the selection and prioritization of multi-stage objectives using a Mixed-Integer Linear Programming (MILP) model. This model is implemented through the Gurobi solver in Python. The analysis offers practical insight. It looks at how different combinations of objectives affect the economic, environmental, and technical feasibility of microgrid operation. It considers various scenarios. In doing so, the work contributes not only to the methodological development of optimization-based microgrid management but also to the creation of a decision-support tool aimed at improving the long-term sustainability of prosumer-oriented energy systems.

II. Mathematical Modeling, Optimization Framework, and Performance Metrics

The optimization process was carried out in a Python environment. The Gurobi solver was used. Synthetic datasets were prepared. These datasets represent both electrical demand and photovoltaic (PV) generation. The case study location was Antalya, a region with high solar potential. PV production data were derived from satellite-based reanalysis and irradiance sources. These sources include SARAH and ERA5. The city's coordinates were used to access the PVGIS database. At the same time, HOMER software was used to make electricity use profiles. This

software looks at random and repeated patterns. The optimal capacities of PV and energy storage systems (ESS) were determined using Particle Swarm Optimization (PSO), as outlined in [18]. The objective was to reduce both electricity and lifecycle costs (LCC). The resulting PV capacities for the five prosumers were 5, 5, 4, 5, and 4.5 kW, while the corresponding ESS capacities were 4, 5.5, 5.5, 5.5, 3, and 4 kWh, respectively. These parameter values formed the basis for subsequent simulations and performance evaluations within the proposed framework.

In the Gurobi-based energy management framework, hourly load and PV generation data are imported from Excel files as model inputs. For each prosumer k and time step t, the total load demand ($P_{k,t}^{L}$) is met through contributions from PV-to-load ($P_{k,t}^{PV2L}$), ESS-to-load ($P_{k,t}^{B2L}$), and grid-to-load ($P_{k,t}^{G2L}$), as shown in (1). Simultaneously, the total PV generation ($P_{k,t}^{PV_{gen}}$) is distributed among $P_{k,t}^{PV2L}$, PV-to-ESS ($P_{k,t}^{PV2B}$), PV-to-grid ($P_{k,t}^{PV2G}$), and curtailed energy ($P_{k,t}^{PV_{cur}}$), following (2).

$$P_{k,t}^{L} = P_{k,t}^{PV2L} + P_{k,t}^{B2L} + P_{k,t}^{G2L} \quad , \quad \forall k,t \tag{1}$$

$$P_{k,t}^{PV_{gen}} = P_{k,t}^{PV2L} + P_{k,t}^{PV2B} + P_{k,t}^{PV2G} + P_{k,t}^{PV_{cur}} \quad , \quad \forall k,t \tag{2}$$

To reduce grid stress, PV export ($P_{k,t}^{PV2G}$) is limited to 40% of the installed PV capacity (C_{k}^{PV}), even when higher exports could be economically favorable, as expressed in (3). The total energy exported to the grid ($P_{k,t}^{G_{injected}}$), combining PV and ESS contributions ($P_{k,t}^{B2G}$), is managed through a binary variable u_{t1}, which prevents simultaneous buying and selling of power (4)–(6). Another binary variable u_{t2} ensures that ESS charging and discharging do not occur at the same time, as represented in (7)–(8). Constants M and c are introduced to linearize these relationships while maintaining the state-of-charge (SoC) boundaries.

$$P_{k,t}^{PV2G} \le 40\% C_{k}^{PV} \quad , \quad \forall k,t \tag{3}$$

$$P_{k,t}^{G_{injected}} = P_{k,t}^{PV2G} + P_{k,t}^{B2G} \quad , \quad \forall k,t \tag{4}$$

$$P_{k,t}^{G_{injected}} \le M\, u_{t1} \quad , \quad \forall k,t \tag{5}$$

$$P_{k,t}^{G_{used}} = P_{k,t}^{G2L} \le M\left(1-u_{t1}\right) \quad , \quad \forall k,t \tag{6}$$

$$P_{k,t}^{ESS_{chr}} \le c\, u_{t2} \quad , \quad \forall k,t \tag{7}$$

$$P_{k,t}^{ESS_{disch}} = c\left(1-u_{t2}\right) \quad , \quad \forall k,t \tag{8}$$

The state of energy (SoE) of each ESS unit ($SoE_{k,t}^{ESS}$) evolves according to (9), which accounts for charging and discharging power and their efficiencies (η_{chr} and η_{disch}). The SoC is constrained between 20% and 90%. Battery degradation mechanisms are modeled through cycle aging ($Q_{k,t}^{cyc}$) and calendar aging ($Q_{k,t}^{cal}$), as described in [19] and [20]. The cumulative degradation ($Q_{k,t}^{tot}$) and the effective ESS capacity at time t ($C_{k,t}^{ESS_{new}}$) are computed using (12)–(13). Here, $L_{k,t}^{cyc}$ indicates the expected battery lifetime, while $P_{k,t}^{ESS_{chr}}$ and $P_{k,t}^{ESS_{disch}}$ represent charging and discharging powers, respectively. The empirical coefficients in these degradation equations are based on experimental data reported in previous studies.

$$SoE_{k,t}^{ESS} = SoE_{k,t-1}^{ESS} + P_{k,t}^{ESS_{chr}}\eta_{chr} - \frac{P_{k,t}^{ESS_{disch}}}{\eta_{disch}} \quad , \quad \forall k,t \tag{9}$$

$$Q_{k,t}^{cyc} = \frac{1}{2}\sum_{k,t}\frac{\eta_{chr}P_{k,t}^{ESS_{chr}} - \eta_{disch}P_{k,t}^{ESS_{disch}}}{L_{k,t}^{cyc}\, C_{k}^{ESS}} \quad , \quad \forall k,t \tag{10}$$

$$Q_{k,t}^{cal} = \sum_{k,t} 6.6148.10^{-6} P_{k,t}^{ESS} + 4.6404.10^{-6} \quad , \quad \forall k,t \tag{11}$$

$$Q_{k,t}^{tot} = Q_{k,t}^{cyc} + Q_{k,t}^{cal} \quad , \quad \forall k,t \tag{12}$$

$$C_{k,t}^{ESS_{new}} = C_{k}^{ESS}\left(1-Q_{k,t}^{tot}\right) \quad , \quad \forall k,t \tag{13}$$

In this study, three objective functions are examined. For the third objective, which aims to maximize renewable utilization, specific variables and constraints are defined. Equation (14) expresses the renewable power contribution ($P_{k,t}^{RE}$), obtained from the cumulative power delivered from $P_{k,t}^{PV2L}$ and $P_{k,t}^{PV2B}$. Equation (15) defines the total electrical load served ($P_{k,t}^{LS}$), which aggregates the contributions of PV, ESS, and grid power. Finally, Equation (16) calculates the renewable fraction (RF) as the ratio of renewable-supplied energy ($P_{k,t}^{RE}$) to total demand.

$$P_{k,t}^{RE} = \sum_{k,t} P_{k,t}^{PV2L} + P_{k,t}^{PV2B} \ , \quad \forall k,t \qquad (14)$$

$$P_{k,t}^{LS} = \sum_{k,t} P_{k,t}^{PV2L} + P_{k,t}^{PV2B} + P_{k,t}^{G2L} \ , \quad \forall k,t \qquad (15)$$

$$P_{k,t}^{RE} = RF\, P_{k,t}^{LS} \ , \quad \forall k,t \qquad (16)$$

The cost minimization problem is formulated in (17). It includes grid purchase costs based on a three-tier time-of-use (ToU) tariff ($P_{k,t}^{G_{used}} \operatorname{Cos} t_{k,t}^{GP}$), revenues from grid exports at a fixed rate ($P_{k,t}^{G_{injected}} \operatorname{Cos} t_{k,t}^{GS}$), lifecycle costs (LCC) of PV and ESS capacities ($C_{k,t}^{ESS_{new}} LC\, C_{k,t}^{ESS}$ and $C_k^{PV} LC\, C_{k,t}^{PV}$), and the depreciation of ESS components ($\left(C_k^{ESS} - C_{k,t}^{ESS_{new}} \right) \operatorname{Cos} t_{k,t}^{depr.}$). The analysis evaluates which bi-objective or tri-objective combination implemented in Python–Gurobi yields the most balanced results for prosumers with distinct consumption and production profiles.

The optimization framework prioritizes different objectives across three configurations:

- **Objective 1:** cost minimization as the primary goal, with battery health preservation as secondary.
- **Objective 2:** reverse prioritization, battery health first, cost minimization second.
- **Objective 3:** RF maximization as the leading objective, followed by cost minimization, and optionally ESS health preservation.

Accordingly, the three objective functions under consideration are introduced from (18) to (20).

$$TC_{k,t}^{MG} = P_{k,t}^{G_{used}} \operatorname{Cos} t_{k,t}^{GP} - P_{k,t}^{G_{injected}} \operatorname{Cos} t_{k,t}^{GS} + C_{k,t}^{ESS_{new}} LC\, C_{k,t}^{ESS} + C_k^{PV} LC\, C_{k,t}^{PV} + \left(C_k^{ESS} - C_{k,t}^{ESS_{new}} \right) \operatorname{Cos} t_{k,t}^{depr.}, \quad \forall k,t \qquad (17)$$

$$objective\ 1 = \min \left(\sum_{k,t} \left(TC_{k,t}^{MG} \right) \right) \qquad (18)$$

$$objective\ 2 = \min \left(\sum_{k,t} \left(TC_{k,t}^{MG} + Q_{k,t}^{tot} N \right) \right) \qquad (19)$$

$$objective\ 3 = \min \left(\sum_{k,t} \left(TC_{k,t}^{MG} - RF.K \right) \right) \qquad (20)$$

Trade-offs among economic, environmental, and technical outcomes can be evaluated through the use of these objective structures. Tariff rates are set to 0.0767 \$/kWh from 6:00 a.m. to 5:00 p.m., 0.112 \$/kWh from 5:00 p.m. to 8:00 p.m., and 0.04854 \$/kWh from 8:00 p.m. to 6:00 a.m. The grid sale is set at 0.04 \$/kWh, and the lifecycle cost estimation follows the procedure outlined in [18].

The Gurobi solver in Python was used to solve the optimization problems. Subsequent to each iteration, the results were exported to Excel as hourly datasets for all prosumers and analyzed according to the evaluation metrics summarized in Table I.

These performance metrics include the unit cost of electricity (COE), the RF, the self-consumption ratio (SCR), the self-sufficiency ratio (SSR), the carbon emissions (CO_2), and the curtailed energy (CE). A detailed basis for evaluating the operational behavior of the microgrid under different optimization strategies is provided by these indicators.

TABLE I. DECISION CRITERIA

Metric	Formulation	Metric	Formulation
COE	$\frac{\sum Total\,\mathrm{Cos}\,t}{\sum P_{load}}$	SCR	$\frac{\int P_{PV}dt-\int P_F dt}{\int P_{PV}dt}$
RF	$1-\frac{\sum(P_{GP})}{\sum(P_{load})}$	SSR	$\frac{\int P_L dt-\int P_G dt}{\int P_L dt}$
CO_2	$0.4261\sum P_{GP}$	CE	$\sum P_{k,t}^{PVcur}$

The unit cost of electricity (COE, $/kWh) is calculated by dividing the total operating cost of the microgrid by the total demand for electricity across all time periods. The RF expresses the portion of total demand that renewable sources supply. It is determined by subtracting the electricity imported from the utility grid from the total load and then normalizing the remainder with respect to total demand. The amount of CO_2 released per kilowatt-hour of imported grid electricity in Turkey is estimated to be around 0.426 kg. This is used as a basis for the country's carbon accounting. CO_2 associated with microgrid operation are estimated using this factor.

During periods when PV generation exceeds instantaneous load, the exported energy (P_F) represents the residual power remaining after local demand is satisfied and the ESS has been charged. In other words, it is the difference between PV generation, ESS discharge, and the load requirement. Conversely, when the load surpasses PV output, the imported energy (P_G) is defined as the deficit between the total demand and the combined supply from PV and ESS.

The SCR measures how efficiently the system uses on-site PV energy. It is calculated by determining the part of PV generation that isn't exported to the grid and then dividing it by the total PV output. The SSR is a different measure. It shows the share of total demand met by local generation and storage. In other words, it is the fraction of demand that does not rely on grid supply. Thus, PV utilization efficiency is evaluated by SCR, while the degree of grid independence is indicated by SSR.

Finally, when PV generation exceeds both the load requirement and the available ESS storage capacity, the system records any unutilized energy as waste energy. CE is expressed as a percentage of total PV generation. It serves as an indicator of renewable energy losses. These losses are caused by storage and load limitations.

III. OPTIMIZATION RESULTS AND DISCUSSION

The results of the multi-stage microgrid optimization are shown in Table II. This table lists the most important performance measurements for the three objective formulations. These include COE, SCR, SSR, RF, CE, CO_2, and the cumulative battery degradation. The findings are further complemented by Table III, which provides a ranking of the three formulations based on their techno-economic and environmental performance. This ranking offers a comparative perspective on the trade-offs among competing objectives.

According to Table II, the lowest COE, 0.03055 $/kWh, is yielded by Objective 1, which places primary emphasis on minimizing operational cost, while moderate SCR and SSR values of 21.6% and 28.98%, respectively, are maintained. Objective 2 gives priority to maintaining ESS health. It produces a higher COE of 0.0484 $/kWh. However, it substantially decreases battery aging to 0.1046%. This suggests that extending the storage system's lifespan comes with a higher operating cost. The goal of objective 3 was to use renewable energy as much as possible. It achieves the highest RF at 77.32%, along with significant improvements in SCR (56.34%) and SSR (75.61%). However, this enhanced renewable contribution comes with a higher cost of 0.06631 $/kWh and accelerated battery wear of 0.35494%.

Overall, the comparison highlights the expected trade-offs among economic efficiency, renewable energy integration, and energy-storage durability. The results suggest that no single configuration universally dominates. Instead, the optimal choice depends on whether cost savings, renewable penetration, or asset ESS lifetime is prioritized within the specific microgrid context.

The three objective functions' comparative performance is summarized in Table III. Objective 3 is the most successful in increasing the renewable energy fraction and the amount of local PV utilization. Objective 1 is the most successful in cost-related metrics and reducing the amount of curtailed energy.

TABLE II. PERFORMANCE METRICS UNDER MULTI-STAGE OBJECTIVE FUNCTIONS

Objective Function	COE ($/kWh)	SCR (%)	SSR (%)	RF (%)	CE (%)	CO_2 (kg/yr)	Aging (%)
1	0.03055	21.6	28.98	65.53	0.67	71.61	0.176449
2	0.0484	8.3	11.13	46.98	9.92	92.69	0.104598
3	0.06631	56.34	75.61	77.32	27.16	70.24	0.35494

TABLE III. RANKING OF OBJECTIVE FUNCTION PERFORMANCE ACROSS KEY INDICATORS

Objective Function Ranking	COE	SCR	CE	RF	CO_2	Aging
1	Objective 1	Objective 3	Objective 1	Objective 3	Objective 3	Objective 2
2	Objective 2	Objective 1	Objective 2	Objective 1	Objective 1	Objective 1
3	Objective 3	Objective 2	Objective 3	Objective 2	Objective 2	Objective 3

The results for battery-aging mitigation are strongest for Objective 2, which emphasizes extending storage lifespan. These rankings indicate that no single formulation can optimize all metrics at once. This reinforces the need for multi-stage optimization strategies. These strategies should balance the diverse priorities of different prosumers. When the results are interpreted in light of existing research, they align with recent literature advocating for multi-objective and hierarchical optimization for renewable-intensive microgrids. The observed tension between increasing renewable usage and limiting battery degradation mirrors challenges discussed in hybrid optimization studies. These include PSO-based capacity design and multi-level energy management frameworks. Moreover, it has been demonstrated that energy autonomy can be significantly strengthened and grid dependency can be reduced by targeted objective hierarchies, as shown by the higher SCR and SSR values achieved under Objective 3. This outcome is aligned with the resilience goals highlighted in prior works.

In summary, the comparative analysis suggests that each system operator should choose an objective structure that reflects their priorities. Those responsible for decision-making who prioritize short-term economic benefits may favor configurations similar to Objective 1. However, those seeking to maintain ESS durability might find approaches similar to Objective 2 more beneficial. On the other hand, operators aiming to maximize renewable integration might adopt a structure similar to Objective 3. The framework developed in this study is implemented in Python with the Gurobi solver. This provides a systematic and flexible means of tailoring multi-objective optimization to practical microgrid planning needs.

IV. CONCLUSION AND FUTURE SUGGESTIONS

This study shows that how people structure and prioritize multi-stage objective functions has a decisive influence on the economic, technical, and environmental behavior of renewable-based microgrids. The results of the comparison show that the best performance across key indicators is achieved by a three-stage configuration. In this configuration, renewable energy utilization is prioritized first, followed by cost reduction and battery health preservation. Two-stage formulations, on the other hand, often prioritize short-term economic benefits or prolonging battery life, which can come at the cost of increasing renewable energy use and overall system independence. These findings emphasize the importance of designing objective hierarchies. These hierarchies should align with specific operational targets. They should also align with the characteristics of prosumer-driven systems. In the future, the proposed framework can be expanded to include stochastic renewable generation, real-time demand response strategies, and more detailed battery degradation modeling. This would improve the robustness and scalability of the optimization process. In summary, the research shows that using multi-stage, multi-objective optimization to manage energy in prosumer-oriented microgrids leads to sustainable, resilient, and cost-effective results.

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