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Original Scientific Article

Multi-Stage, Degradation-Aware Day-Ahead Energy Management for Prosumer-Based Microgrids Using Python-Gurobi

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Abstract— **Renewable energy sources are becoming more common in microgrids, which creates new possibilities and new challenges for providing reliable and affordable energy. The proposal of a multi-stage, day-ahead energy management model for prosumer-based microgrids is the objective of this research. The model clearly considers battery degradation and the variety of load and generation profiles. The framework is implemented with a commercial Mixed-Integer Linear Programming (MILP) solver. It examines several operational horizons, ranging from one to three days, to evaluate their economic, technical, and environmental impacts. Key performance indicators include the following: electricity cost per unit, self-consumption rate, renewable contribution, curtailed energy, carbon emissions, and energy storage aging. The findings show that using a three-day plan is the best balance between reducing costs and using renewable energy, while also keeping batteries long-life. Shorter horizons tend to improve on-site PV utilization. In contrast, extended horizons yield moderate yet consistent results. This highlights the trade-offs between conflicting objectives. The framework is a useful guide for people who plan and manage microgrids. It helps them design microgrids that are both efficient and well enough for the environment. The framework may be expanded in the future to include stochastic forecasting, demand flexibility, or hybrid AC/DC configurations, with the goal of improving resilience and operational performance.**

Keywords - energy management, microgrids, battery degradation, multi-stage optimization, energy storage systems**.**

I. INTRODUCTION

The increasing use of renewable energy sources (RES) in modern power systems has led to changes in the planning and operation of microgrids. This transition is beneficial for sustainability goals, but the inconsistent and intermittent nature of renewables poses challenges in managing energy consistently and affordably. Many studies have explored different scheduling strategies for microgrids. These strategies combine renewable generation with various energy storage technologies. These strategies are used to overcome the challenges posed by these issues. For example, the potential of using both long-term and short-term storage, such as hydrogen and battery systems, to improve renewable energy utilization and achieve seasonal balancing was highlighted earlier in research [1]. Other studies have

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developed detailed mathematical models for distributed resources. These include photovoltaics, storage units, and demand response. The models aim to enhance day-ahead scheduling. They also aim to represent asset availability costs more realistically [2]. In addition, real-time scheduling frameworks have been introduced. These frameworks increase battery utilization. They also account for degradation effects. This is often done through methods like approximate dynamic programming or life-cycle cost modeling [3].

Energy storage, and batteries in particular, remain at the center of these developments. Several optimization methods based on Lyapunov control have been applied to smart-home environments with HVAC and electric vehicle (EV) loads. These methods show the benefits of dynamic scheduling and queue-based optimization under uncertainty [4]. However, the time resolution used in scheduling strongly affects battery health. In other words, frequent intra-hour cycling accelerates wear more than hourly control. This emphasizes the importance of multi-layer optimization that balances both technical and economic factors [5].

Another research area has centered on how storage operations affect the financial and practical performance of community and residential microgrids. Research that incorporates battery degradation models into mixed-integer optimization frameworks has demonstrated enhanced trade-offs between cost savings and technical reliability [6]. Stochastic approaches have enabled robust scheduling. This is true under uncertain demand and renewable production. These approaches provide prosumers with greater operational flexibility [7]. Market-oriented frameworks have also illustrated how combining energy storage and demand response can help deliver ancillary services. They can also lower costs and reduce renewable curtailment [8].

At the same time, the growing interaction among EV charging, flexible demand, and energy storage has opened new directions for research on prosumer-oriented optimization. Several hierarchical and decentralized scheduling frameworks have been proposed. These frameworks aim to promote fairness among prosumers. They also aim to reduce operational costs and support grid stability [9]. In parallel, optimization models that jointly consider EVs, household storage, and photovoltaic generation demonstrate the value of multi-objective formulations. These formulations balance cost reduction against technical operating limits [10]. Researchers have developed methods to address the uncertainty in both renewable generation and demand. These methods are scenario-based and two-stage stochastic. They aim to maintain reliable and resilient operation [11].

The importance of incorporating environmental targets into microgrid planning has been further underlined by recent studies. Integrating carbon-reduction goals with economic and technical objectives has been shown to enable emission-aware scheduling. This aligns system efficiency with sustainability aims [12]. Energy management frameworks for various microgrid types reveal that coordinated scheduling can enhance efficiency and reduce overall costs. This is true even for hybrid AC/DC configurations [13]. Additional strategies, such as demand-side management and peer-to-peer trading, expand the role of microgrids in the larger clean energy transition. These strategies show how local efforts to improve efficiency can create environmental benefits that extend throughout the entire system [14]. Long-term research on combining renewables with storage and demand response continues. This research highlights the need for models that remain both computationally practical and technically sound [15].

Despite these advances, a notable gap still exists. This gap is in developing multi-stage energy management systems. These systems should jointly minimize operating costs. They should also preserve battery health and account for the diversity of prosumer behaviors and generation profiles. Many existing works focus either on short-term economic scheduling or on long-term degradation modeling, but rarely combine the two perspectives within a unified and practical framework. The present study aims to fill this gap. It proposes a day-ahead energy management approach for microgrids. This approach couples renewable generation with battery-degradation-aware optimization. The method is implemented as a multi-stage model using Python-Gurobi. The model explores several daily operational scenarios. It identifies solutions that remain cost-effective, environmentally responsible, and technically robust.

II. Mathematical Modeling, Optimization Framework, and Performance Metrics

The simulation was executed within the Python–Gurobi environment. Antalya, located in southern Türkiye and known for its high solar irradiation, was selected as the case study region. The modeling of photovoltaic (PV) generation in HOMER Pro was based on long-term NASA SSE and MERRA-2 reanalysis datasets for the realistic representation of local solar conditions. Electrical load profiles were also produced within HOMER Pro. Five distinct prosumer demand patterns were generated. Stochastic variations were introduced to reflect different consumption behaviors. The optimal capacities of PV and energy storage systems (ESS) for each prosumer were determined. This was done through particle swarm optimization (PSO). The approach was described in earlier research [16]. The goal was to reduce both electricity expenses and lifecycle costs (LCC). As a result, the optimal PV capacities for Prosumers 1–5 were found to be 5, 5, 4, 5, and 4.5 kW, respectively. The corresponding ESS capacities were set to 4, 5.5, 5.5, 5.5, and 3 kWh.

In the Python–Gurobi framework, hourly electricity demand and PV generation data from the Excel dataset form the basis of the energy-management problem. For each prosumer k and time step t, the total electrical load $P_{k,t}^{L}$ is met through PV-to-load ($P_{k,t}^{PV2L}$), ESS-to-load ($P_{k,t}^{B2L}$), and grid-to-load ($P_{k,t}^{G2L}$) power flows, as expressed in (1). Likewise, the PV generation $P_{k,t}^{PV_{gen}}$ at each time interval is distributed among $P_{k,t}^{PV2L}$, PV-to-ESS ($P_{k,t}^{PV2B}$), PV-to-grid ($P_{k,t}^{PV2G}$), and curtailed PV ($P_{k,t}^{PV_{cur}}$) components, as shown in (2).

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

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

When the ESS is fully charged and PV generation surpasses local demand, PV-to-grid export $P_{k,t}^{PV2G}$ is limited to 40% of the installed PV capacity (C_k^{PV}) (3). This constraint avoids voltage or power-quality problems in the distribution network, even though it may restrict potential revenue from grid sales. The total grid injection consists of contributions from both PV-to-grid and ESS-to-grid ($P_{k,t}^{B2G}$) flows and is regulated to prevent simultaneous purchase and sale through binary variables u_{t1} (4–6). A second binary variable u_{t2} ensures that ESS charging and discharging do not occur at the same time (7–8). Large penalty coefficients M and c are used to maintain these conditions without violating the state-of-charge (SoC) limits.

$$P_{k,t}^{PV2G} \le 40\% C_k^{PV} \ , \quad \forall k,t \qquad (3)$$

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

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

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

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

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

The state of charge of the ESS, $SoE_{k,t}^{ESS}$, is updated using (9) based on the previous time step ($SoE_{k,t-1}^{ESS}$), considering charging and discharging powers ($P_{k,t}^{ESS_{chr}}$ and $P_{k,t}^{ESS_{disch}}$) and their corresponding efficiencies η_{chr} and η_{disch}. The SoC boundaries are defined between 20% and 90%. The degradation parameters for both cycle and calendar aging were obtained. They were obtained by adopting the empirical models proposed in [17] and [18]. The cycle aging term ($Q_{k,t}^{cyc}$) was specifically defined as a function of two variables: charge throughput and depth of discharge (see (2)). The calendar aging term ($Q_{k,t}^{cal}$), on the other hand, is contingent on two factors: storage time and temperature (see (3)). The corresponding coefficients were taken directly from $LiFePO_4$/C battery tests that were experimentally validated and reported in [18]. They were calibrated according to the empirical capacity fade relationships that were defined in [17]. The degradation equations that are applied

reflect lifetime behaviors that have been verified through experiments. Here, $L_{k,t}^{cyc}$ refers to the battery cycle lifetime, while the constant coefficients represent empirical values obtained through experimental procedures.

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

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

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

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

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

The objective function represents the total cost of the microgrid by combining several key components. It accounts for electricity purchased from the main grid under a three-tier time-of-use (ToU) tariff purchased ($P_{k,t}^{G_{used}} . \mathrm{Cos}\, t_{k,t}^{GP}$), as well as revenue generated from single-rate grid injections ($P_{k,t}^{G_{injected}} . \mathrm{Cos}\, t_{k,t}^{GS}$). The cost of installed PV units and energy storage systems (ESS) is incorporated through their respective life-cycle costs ($C_{k,t}^{ESS_{new}} . LC\,C_{k,t}^{ESS}$ and $C_k^{PV} . LC\,C_{k,t}^{PV}$), while additional terms represent the depreciation associated with ESS aging (($C_k^{ESS} - C_{k,t}^{ESS_{new}}$). $\mathrm{Cos}\, t_{k,t}^{depr.}$), as given in (14). Since aging costs are embedded within the overall cost formulation, minimizing the total cost naturally leads to a reduction in both electricity expenditures and battery degradation. Time-of-use electricity rates are set at 0.0767 $/kWh (06:00–17:00), 0.112 $/kWh (17:00–22:00), and 0.04854 $/kWh (22:00–06:00), while grid-injection revenue is fixed at 0.04 $/kWh, as referenced in [16]. Detailed life-cycle cost (LCC) calculations are provided in the cited work.

$$TC_{k,t}^{MG} = P_{k,t}^{G_{used}} \mathrm{Cos}\, t_{k,t}^{GP} - P_{k,t}^{G_{injected}} \mathrm{Cos}\, t_{k,t}^{GS} + C_{k,t}^{ESS_{new}} \, LC\,C_{k,t}^{ESS} + C_k^{PV} \, LC\,C_{k,t}^{PV} + \left(C_k^{ESS} - C_{k,t}^{ESS_{new}}\right) \mathrm{Cos}\, t_{k,t}^{depr.}, \quad \forall k,t \tag{14}$$

$$\min\left(\sum_{k,t}\left(TC_{k,t}^{MG}\right)\right) \tag{15}$$

Hourly PV generation and load data are imported from an Excel dataset according to the operation horizons that have been defined. For each selected period, the values from 1 to 15 are executed iteratively. To illustrate, when a three-day horizon is simulated, successive three-day segments are extracted from the monthly dataset. In four-day operation loops, any remaining days at the end of the dataset are included in the final iteration. This is done to ensure continuity. The dataset covers a wide range of weather patterns. These are typical of Antalya. The dataset provides reliable benchmarking consistency. This consistency exists across both annual and project-lifetime analyses. It already reflects all characteristic meteorological conditions. Similar results can be obtained whether the simulation spans a single year or the entire lifetime of the project. This feature provides a clear view of long-term performance expectations for short-term investors.

A multi-stage day-ahead energy management plan is also formulated for prosumers. These prosumers exhibit different consumption and generation patterns. The optimization simultaneously considers renewable energy utilization and battery aging. It evaluates how the Python–Gurobi solver performs under various daily operating scenarios. This helps determine the most cost-effective, sustainable, and technically reliable solution. In this regard, daily operation periods are optimized not solely for feasibility but also for balancing cost reduction with ESS health preservation.

The optimization is performed using the high-speed Python–Gurobi solver. The resulting tuple variables are converted into dataframes. They are exported to Excel on an hourly basis for each prosumer. These outputs are then analyzed using the evaluation criteria, which are summarized in Table I.

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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	$\sum P_{k,t}^{PV_{cur}}$

The cost of electricity (COE, $/kWh) is calculated as the ratio of the total microgrid cost to the total energy used. The renewable fraction (RF) is computed by subtracting the electricity imported from the grid from the total electrical demand. The result is then normalized by the total load. Each kilowatt-hour of grid electricity in Türkiye emits approximately 0.426 kg of CO_2. The total carbon footprint is estimated accordingly.

At any given time step, when PV generation exceeds the load, the net feed-in power (P_F) is defined as the difference between total PV generation, ESS output, and load demand. Conversely, when the load is greater than PV generation, the grid-supplied power (P_G) is determined by subtracting both PV and ESS contributions from the total load. The self-consumption ratio (SCR) is obtained as the share of PV generation directly meeting the load, calculated by subtracting the P_F from the total PV output and dividing by total PV generation.

The self-sufficiency ratio (SSR) is the percentage of total demand met by local PV and ESS resources. The total load is subtracted from the electricity drawn from the grid to obtain the remainder, which is then divided by the total demand. The SCR reflects how much of the PV generation is used directly on-site. The SSR indicates the share of total consumption that is met without grid support. When electricity production surpasses the load and the installed PV capacity limit, and the ESS has reached full charge, the system cannot utilize the surplus energy and records it as curtailed. The unused portion is expressed as a percentage of total generation by the curtailed energy (CE) metric.

III. OPTIMIZATION RESULTS AND DISCUSSION

The findings of the multi-stage day-ahead optimization demonstrate how economic, technical, and environmental objectives interact within prosumer-based microgrids. The performance metrics for operation horizons ranging from one to seven days are summarized in Table II. Shorter horizons often lead to higher self-consumption rates. In fact, the single-day plan achieves full on-site utilization of PV generation. The cost of energy is lowered to 0.03055 $/kWh and the renewable fraction is raised to 65.53% when the horizon is extended to three days. This result demonstrates that combining multiple days enables PV power to be utilized more effectively. On the other hand, longer planning windows slightly reduce SCR. This is because it reflects the trade-off between using PV locally and minimizing cost. Curtailment remains small across most cases, indicating that production is effectively aligned with demand by the optimization. Only in the seven-day plan does curtailed energy rise to 6.61%, mainly because of operational limits and lower storage flexibility. ESS aging also grows moderately with longer horizons. Yet the three-day plan maintains a balanced profile (0.176449). This shows that the framework can limit battery wear while keeping costs low.

Table III compares the operation plans across these indicators. It offers a clearer view of the trade-offs in multi-stage scheduling. The three-day horizon ranks highest for both COE and RF. This confirms its advantage in cost efficiency and renewable energy use. Conversely, the one-day plan performs optimally in SCR, rising local PV generation at a higher cost. Intermediate results are shown by longer horizons, such as five or six days. Overall, it has been confirmed by the ranking that all metrics cannot be optimized simultaneously by a single time horizon. This finding emphasizes the importance of using multi-objective approaches, which consider both short-term performance and long-term sustainability. In addition, the findings confirm that the proposed method can effectively represent the diverse behaviors of prosumers. They also show that the method can effectively represent the variability of their load and generation patterns. This capability enables the framework to identify operation plans balancing high renewable integration with careful consideration of battery aging

TABLE II. PERFORMANCE METRICS FOR DAILY AND MULTI-DAY OPERATION SCENARIOS

Operation Plan	COE ($/kWh)	SCR (%)	RF (%)	CE (%)	CO_2 (kg/yr)	Aging (%)
One-day	0.11757	100	52.08	0	108.05	0.161617
Two-day	0.05372	42.26	58.4	0.52	82.15	0.176473
Three-day	0.03055	21.6	65.53	0.67	71.61	0.176449
Four-day	0.05894	43.21	55.91	0.72	93.13	0.188
Five-day	0.07413	53.57	50.05	0.5	107.56	0.173346
Six-day	0.08182	58.2	46.62	0.55	111.51	0.1844
Seven-day	0.06908	47.11	55.73	6.61	108.75	0.181959

TABLE III. MULTI-CRITERIA RANKING OF OPERATION SCENARIOS BASED ON ECONOMIC, TECHNICAL, AND ENVIRONMENTAL INDICATORS

Operation Plan	COE	SCR & SSR	RF	CO_2	Aging
1	Three-day	One-day	Three-day	Three-day	One-day
2	Two-day	Six-day	Two-day	Two-day	Five-day
3	Four-day	Five-day	Four-day	Four-day	Three-day
4	Seven-day	Seven-day	Five-day	Five-day	Two-day
5	Five-day	Four-day	One-day	One-day	Seven-day
6	Six-day	Two-day	Seven-day	Seven-day	Six-day
7	One-day	Three-day	Six-day	Six-day	Four-day

IV. CONCLUSION AND FUTURE SUGGESTIONS

This study presents a battery aging aware day-ahead energy management plan for microgrids that integrate renewable energy sources and battery storage. The framework's use of a multi-stage MILP model identifies operating strategies that balance economic performance, renewable energy use, and the lifetime of the ESS. Analyses performed for daily to seven-day operation horizons show clear trade-offs. On-site PV utilization is favored by shorter horizons, while the best compromise between COE and renewable contribution is achieved with a three-day planning window, with limited impact on battery health. The performance of different operation horizons can be compared across several metrics to highlight patterns. These patterns can guide the decision-making of prosumers, investors, and system operators. Also, operators are seeking practical solutions that are environmentally responsible and cost-effective.

However, it should be noted that the current model is based on certain predictions for both PV generation and load. To reduce the effect of uncertainty in predictions, information was gathered from NASA SSE and MERRA-2 data and HOMER-based demand curves. Therefore, average operational behavior is reflected in the presented results rather than short-term fluctuations. Stochastic forecasts and sensitivity analysis will be incorporated into future studies to quantify the effect of PV and demand prediction errors on scheduling outcomes.

A different perspective, Antalya was selected as a model because of its promising solar energy potential. However, the proposed optimization framework is entirely data-driven and technology-neutral. The math structure can be used in all sorts of microgrids, no matter what size or location, and with any mix of technologies. All you have to do is update the inputs like renewable profiles, tariffs, and storage characteristics. Therefore, the formulation can be generalizable beyond the specific case examined here. The framework will be validated under diverse climatic conditions and hybrid microgrid configurations in future research to assess its scalability and adaptability further.

In addition, future research could integrate stochastic forecasts for PV generation and demand. This would improve the robustness of

scheduling under uncertainty. The additional flexibility mechanisms can be included in the proposed model's modular MILP structure without the computational complexity being substantially increased. Demand-side adaptability and vehicle-to-grid (V2G) potential can be combined by incorporating additional decision variables and linear restrictions to illustrate movable or bidirectional power flows. While these additions slightly increase the number of optimization variables, the model remains tractable in the Python–Gurobi environment due to its linear formulation. This adaptability enables the framework to evolve toward more interactive and resilient microgrid operation strategies, which are crucial for ensuring the reliability and security of energy supply in a changing energy landscape.

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