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Assessment of Economic, Technical, Social and Environmental Impact of Flexibility-based Smart Microgrid Operation

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ABSTRACT

The proliferation of renewable energy sources, with their inherent uncertainty in smart microgrids, necessitates the use of flexible resources to maintain grid stability. However, implementing these flexibility-based approaches can have a multidimensional impact, including economic, technical, social, and environmental considerations. This study investigates these effects, with a particular focus on how flexibility provision influences battery aging, which is a critical aspect since batteries are the primary source of flexibility in microgrids. Here, a Lexicographic approach is used to optimize the multi-objective operation problem by minimizing costs while maximizing flexibility. Batteries act as the main source of flexibility and compensate for the uncertainty associated with solar energy production; therefore, it is important to investigate the battery's aging upon flexibility provision. The analysis shows a trade-off between flexibility and economic efficiency. Hence, from an economic point of view, increasing reliance on batteries and micro turbine production to improve flexibility leads to higher operating costs. From a social perspective, the proposed approach increases microgrid reliability by minimizing the cost of energy not supplied. Considering the technical aspect, the results indicate that increasing the use of batteries in order to increase microgrids' flexibility accelerates their aging, hence decreasing their corresponding state of health. Further, the simulation results show that flexibility comes with an environmental cost. Therefore, increasing reliance on micro turbine production and the possibility of purchasing energy from sources with more emissions to provide the required flexibility can lead to an increase in the cost of pollution.

I. Introduction

The growing concern over climate change and the depletion of fossil fuels has driven a global shift towards Renewable Energy Resources (RERs). Solar power, with its abundance and clean energy generation, has emerged as a frontrunner in this transition. However, the inherent variability of solar energy introduces challenges to grid stability. Unlike traditional power plants fueled by coal or natural gas, solar power generation fluctuates throughout the day, depending on sunshine availability. This variability can disrupt the delicate balance between supply and demand within a power grid, potentially leading to voltage fluctuations, outages, and equipment damage [1].

In order to address these challenges and ensure the seamless integration of RERs like solar power, the concept of flexibility has received a great amount of attention in the literature covering smart microgrids operation [2]. A smart microgrid is a localized, self-contained power system that integrates Distributed Energy Resources (DERs) like solar panels, wind turbines, and energy storage systems [3]. Flexibility, in this context, refers to a microgrid's ability to adapt to real-time changes in power supply and demand. This

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adaptation can involve various strategies, such as adjusting power generation from renewable resources, strategically utilizing energy storage systems, and dynamically managing consumer load profiles [4].

Previous studies have explored the concept of flexibility from various perspectives, highlighting its multifaceted nature and providing a comprehensive overview of the challenges and opportunities associated with integrating RERs into power systems. Their work emphasizes the need for flexibility as a key enabler for a reliable and efficient grid with a high penetration of renewables [5]. The integration of renewable energy sources generally leads to control challenges. From this point of view, it is very important to create control measures against the uncertainties of renewable resources in order to maintain and improve flexibility. For instance, in [6] the proposed strategy is based on deep learning to maintain the stability of the system against the fluctuations in the production of renewable power plants, which examines the technical and economic aspects of flexibility.

Building upon these definitions, researchers have introduced several metrics to quantify the energy system's flexibility. For example, [7] proposes a Flexibility Requirement Index (FRI) that considers a system's ability to manage power imbalances over different time horizons. Similarly, [8] presents the System Flexibility Index (SFI) as a measure of a system's capability of rapid response to power fluctuations. These metrics offer valuable tools for assessing and comparing the flexibility of different microgrid configurations. Beyond definitions and metrics, research efforts have delved into the practical implementation of flexibility strategies. In this regard, [9] explores the potential of demand response programs as a means to enhance flexibility. Demand response programs incentivize consumers to adjust their electricity consumption patterns during peak demand periods, thereby alleviating pressure on the grid. In [10], four different flexibility evaluation indicators are defined, which show the matching of power supply and demand with the effect of error in load forecasting. In [11] several flexibility indices are defined for real-time operations, which are modeled as the cost of flexibility in the objective function, and the economic trade-off between the cost of production and the cost of flexibility provides an acceptable level of flexibility.

Numerous studies have also investigated the role of energy storage systems, particularly batteries, in providing flexibility within microgrids. For instance, [12] analyzes the techno-economic feasibility of using battery storage to manage the variability of RERs. On the other hand, it highlights the trade-off between flexibility benefits and the cost associated with battery deployment and operation. Similarly, [13] focuses on the technical challenges of battery degradation due to increased cycling for flexibility purposes. This research explores strategies to mitigate battery aging and optimize battery utilization within microgrids.

Despite significant advancements in understanding and implementing flexibility within smart microgrids, further research opportunities still exist. Flexibility services, by considering the preferences of end users, can also include the social perspective in addition to technical and economic perspectives. In [14], a two-level optimization is defined for systematic evaluation to provide flexibility, where the consumers play a role in providing flexibility. In [15] flexibility is examined from the technical point of view in addition to the economic point of view. In this study, the power generation and transmission capacity is considered as a technical constraint and the results show that technical challenges are of particular importance in flexibility studies along with economic challenges. In [16], the authors examine the effect of flexibility on system reliability. Although the results show that the improvement of flexibility has a positive effect on reliability indicators, the increase of social satisfaction resulting from this planning has not been directly addressed in these studies. On the other hand, in [17], flexibility in the power grid has been investigated by considering gas-fired fast ramp power plants as a resource of flexibility. In these studies, in addition to determining the trade-off between cost and flexibility, it is also possible to check the pollution constraints, which has not been addressed in these studies. Table 1 summarizes the main topic of flexibility studies in previous literature. Flexibility studies are often looking for optimal solutions to increase flexibility, while the technical, economic, social and environmental evaluation of flexibility improvement is of special importance, which has not been dealt with in a comprehensive and integrated way in previous studies.

TABLE 1 OVERVIEW OF THE PREVIOUS LITERATURE IN FLEXIBILITY STUDIES

Ref.	Year	Aspects of flexibility provision				Battery aging	Multi objective Optimization
		Technical	Economic	Social	Environmental		
[4]	2017	×	✓	×	×	×	×
[5]	2021	×	✓	×	×	×	✓
[6]	2024	×	✓	×	✓	×	×
[7]	2021	✓	✓	×	×	×	×
[8]	2019	×	✓	✓	×	×	×
[9]	2023	✓	✓	×	✓	×	×
[10]	2023	✓	✓	×	×	×	✓
[11]	2019	×	✓	✓	×	×	×
[12]	2020	✓	✓	×	×	✓	✓
[13]	2018	✓	✓	×	×	✓	✓
[14]	2024	✓	✓	✓	×	×	×
[15]	2022	✓	✓	×	×	×	×
[16]	2022	×	✓	×	×	×	×
[17]	2020	×	✓	×	×	×	×
Current study		✓	✓	✓	✓	✓	✓

This paper investigates the multi-objective optimization problem in smart microgrids, considering both economic costs and system flexibility. In order to facilitate the multi-objective optimization a lexicographic approach is employed to prioritize objectives. Here, two primary cases are analyzed. The first case is defined by assigning the higher priority to the operation cost. Following the same principle, the second case prioritizes flexibility. Moreover, the uncertainty associated with photovoltaic (PV) generation is incorporated into the model. Key contributions and points that make this paper stand out against previous literature can be summarized as follows.

Comprehensive assessment of flexibility:

- This study extensively investigates the economic, technical, social, and environmental impacts of flexibility-based smart microgrid operations, providing a comprehensive view. Here, the trade-off between flexibility and costs, as well as the environmental implications of increased gas-fired power plant operation (for fast ramping capabilities), are analyzed. Also, social impacts are assessed through metrics such as outage duration and customer satisfaction index.
- Battery Aging Focus: This study emphasizes the impact of flexibility provision on battery aging, which is crucial since batteries are the primary source of flexibility in microgrids. Hence in this paper, the impact of flexibility on battery aging (as a flexible resource) is evaluated.
- Lexicographic Method: This paper employs a Lexicographic approach for multi-objective optimization, balancing cost and flexibility in smart microgrid operations.

Also, the uncertainties in PV generation are modeled using Monte Carlo simulation in MATLAB software, while the optimization problem is solved using the GAMS environment.

In essence, this research provides valuable insights into the trade-offs involved in optimizing smart microgrids, with a particular focus on the role of flexibility and its impact on various system aspects.

The rest of this paper is organized as follows: The methodology and modeling are introduced in the section II. Section III presents optimization results. Likewise, section IV provides more detailed discussions and analysis. Finally, the conclusion is given in section V.

II. Methodology

A. Smart Microgrid Optimization

In order to investigate the problem of flexible operation, a multi-objective function is defined for smart microgrid structure [8]. The first objective function is to minimize operation costs. The operating costs of the microgrid are shown in (1). In this regard, $cost^{E}$ is the cost of energy purchased from the upstream network, $cost^{ESS}$ is the cost of charging and discharging the battery and $cost^{ENS}$ is the cost of Energy Not Supplied (ENS).

In (2), $\pi^{N}_{t,s}$ is the price of purchasing energy from the upstream network and $p^{N}_{t,s}$ is the power exchanged with the upstream network. Time and scenario indices are represented by t and s. Here, T is the time interval of 1...24 hours. In (3), π^{ESS} is the price of battery charging and discharging. In the same equation, $p^{ch}_{t,s}$ and $p^{dis}_{t,s}$ are the charging and discharging power of the battery, respectively. Likewise, (4) constitutes the cost of ENS where $\pi^{ENS}_{t,s}$ represents the price of ENS and $p^{ENS}_{t,s}$ shows amount of ENS. [18].

$$F_1^{C} = Min\left\{OC = \sum_{s}\sum_{t=1}^{24}\left\{\begin{matrix} cost^{E} + cost^{ESS} \\ + cost^{ENS} \end{matrix}\right\}\right\} \quad (1)$$

$$cost^{E} = \{\pi^{N}_{t,s} p^{N}_{t,s}\} \qquad \forall t \in T \quad (2)$$

$$cost^{ESS} = \left\{\pi^{ESS}{}_{t,s}\left(p^{ch}_{t,s} + p^{dis}_{t,s}\right)\right\} \qquad \forall t \in T \quad (3)$$

$$cost^{ENS} = \left\{\pi^{ENS}_{t,s} p^{ENS}_{t,s}\right\} \qquad \forall t \in T \quad (4)$$

The second objective which aims to maximize the flexibility of the system by considering the flexibility index, is shown in (5). In this equation, $C^{a}_{(i,t)}$ and $p^{*}_{(i,t)}$ demonstrate the available capacity and instantaneous required power [8].

$$F_2^{F} = Max\left\{SFI = \sum_{s}\sum_{t=1}^{24}\frac{C^{a}_{(t,s)}}{p^{*}_{(t,s)}(t_{C^{*}_{(t,s)}} - t_{(t,s)})}\right\} \quad (5)$$

Battery degradation and aging occurs through an internal electrochemical process [10]. The degradation process occurs during operation as well as when the battery is not in the duty cycle. Hence, aging or State of Health (SOH) refers to the degree of battery damage compared to its initial state. SOH is defined in (6), where ξ_{tot} is the total battery cell capacity loss and Q_{nom} is the nominal battery capacity [19].

$$SOH = \left(1 - \frac{\xi_{tot}}{0.2Q_{nom}}\right) \quad (6)$$

The total battery aging is presented in (7) that is consisted of two parts: cycle aging and life-time aging, which are shown as ξ_{cyc} and ξ_{cal}, respectively [20].

$$\xi_{tot} = \xi_{cyc} + \xi_{cal} \quad (7)$$

$$\xi_{cyc} = \sum_i \left(k_{s1} SOC_{dev,i} e^{\left(k_{s2} SOC_{dev,i}\right)} \right) \times e^{\frac{-Ea}{R}\left(\frac{1}{T}-\frac{1}{T_{ref}}\right)} Q_{proc,i} \quad (8)$$

$$SOC_{avg,i} = \frac{1}{\Delta Q_{proc,i}} \int_{Q_{proc,i-1}}^{Q_{proc,i}} SOC \, dQ_{proc} \quad (9)$$

$$SOC_{dev,i} = \sqrt{\frac{1}{\Delta Q_{proc,i}} \int_{Q_{proc,i-1}}^{Q_{proc,i}} \left(SOC - SOC_{avg,i}\right)^2 dQ_{proc}} \quad (10)$$

Arrhenius equation is used in (8), which is a well-established principle in chemistry, to explain the effect of temperature on battery aging. This equation includes the base temperature of the cell (T_{ref}) and T defines the temperature during operation. R is the gas constant, E_a is a parameter that represents the activation energy, and $Q_{proc,i}$ is the processed charge at the end of i^{th} event. In this regard the value deviation from the reference state of charge is shown as SOC_{dev}. k_{sn} SOC during a specific cycle is shown using SOC_{avg}. In (10), SOC_{dev} is fully described [20].

$$\frac{d\xi_{cal}}{dt} = k(T, SOC) = \left(1 + \frac{\xi_{cal}(t)}{Q_{nom}}\right)^{-\alpha(T)} \quad (11)$$

$$k(T, SOC) = k_A e^{\frac{-E_A}{R}\left(\frac{1}{T}-\frac{1}{T_{ref}}\right)} SOC + k_B e^{\frac{-E_B}{R}\left(\frac{1}{T}-\frac{1}{T_{ref}}\right)} \quad (12)$$

$$\xi_{cal} = Q_{nom}\left(\left(\frac{k(T, SOC)(1+\alpha(T))t}{Q_{nom}} + 1\right)^{\frac{1}{1+\alpha(T)}} - 1\right) \quad (13)$$

The calendar aging structure uses Arrhenius equations. In this regard, calendar aging is influenced by an empirical equation between SOC and temperature. For describing the calendar aging of batteries $K\sqrt{t}$ is often used. Also, parameter $\alpha(T)$ is provided which is related to temperature. The $\alpha(T)$ parameter follows the experimental data using non-linear regression. ξ_{cal} calendar aging at the time t is calculated in (11). $k(T, SOC)$ expresses the kinetic dependence of capacity reduction based on temperature and SOC. Kinetic dependence is shown in (12). In this equation, k_A and k_B are model parameters, E_A and E_B are experimental parameters that determine the activation energy SOC and temperature are assumed constant in these equations. Therefore, (11) is rewritten as (13) [21].

$$P_{t,s}^{MT} + P_{t,s}^{G} + P_{t,s}^{PV} + ENS_{t,s} + P_{t,s}^{dis} = P_{t,s}^{ch} + P_{t,s}^{D} + P_{t,s}^{S} \quad (14)$$

$$SoC_{t,s} = SoC_{t-1,s} + \frac{\left(P_{t,s}^{ch}\eta^{ch} - \frac{P_{t,s}^{dis}}{\eta^{dis}}\right)}{E} \quad (15)$$

$$SoC_{Min} \le SoC_{t,s} \le SoC_{Max} \quad (16)$$

$$P_t^{ch} \le u_{t,s}^{ch} P^{ch_Max} \quad (17)$$

$$P_{t,s}^{dis} \le u_{t,s}^{dis} P^{dis_Max} \quad (18)$$

$$u_{t,s}^{ch} + u_{t,s}^{dis} = 1 \quad (19)$$

$$P^{MT_min} \le P_{t,s}^{MT} \le P^{MT_Max} \quad (20)$$

$$P_D^{MT} \le P_{t,s}^{MT} - P_{t-1,s}^{MT} \le P_U^{MT} \quad (21)$$

$$0 \le P_{t,s}^{B} \le P_B^{Max} \quad (22)$$

$$0 \le P_{t,s}^{s} \le P_s^{Max} \quad (23)$$

$$MCe = \varepsilon . \sum_s \sum_t \upsilon . P_{t.s}^{B} + \sigma . P_{t.s}^{MT} \quad (24)$$

Load balance constraint is shown in (14). In this equation, $P_{t,s}^{MT}$ is the micro turbine (MT) production power, $P_{t,s}^{G}$ is the power purchased from the upstream network, $P_{t,s}^{D}$ is the microgrid load, and $P_{t,s}^{S}$ is the power sent to the upstream network. This constraint balances the power at time t and under scenario s. The process of changing battery's SOC is explained in (15). In this equation, η^{ch} and η^{dis} are the charging and discharging efficiency of the battery, respectively. Maximum and minimum limit of SOC is shown in (16). In this equation, SOC_{Max} and SOC_{Min} are the maximum and minimum limits of SOC, sequentially. The charging and discharging power limits are explained in (17) and (18), respectively. In these equations, the maximum charge and discharge power of the battery are shown by P^{ch_Max} and P^{dis_Max}. (18) introduces two binary variables, denoted as

$u_{t,s}^{ch}$ and $u_{t,s}^{dis}$. These variables can only take on the values of 0 or 1. Variable $u_{t,s}^{ch}$ represents the charging state of the battery ($u_{t,s}^{ch}$ = 1 indicates charging), while variable $u_{t,s}^{dis}$ represents the discharging state ($u_{t,s}^{dis}$ = 1 indicates discharging). This mathematical relationship enforces the constraint that the battery cannot be in both charging and discharging states simultaneously. (20) defines the upper and lower boundaries of MT, which P^{MT_Max} and P^{MT_min} are the maximum and minimum production power values of the MT. Furthermore, the MT ramp speed limit is explained by (21). In this equation, P_U^{MT} and P_D^{MT} show the ramp-up and ramp-down of the MT. The limit of buying and selling power from the main network are shown by (22) and (23). These equations state that the power purchased from the upstream and the power sent to the upstream is less than the values of P_B^{Max} and P_s^{Max}, respectively [21]. The carbon emission cost is the equivalent emission cost for electricity purchased from the upstream grid and the MT. If υ and σ are the equivalent emission factors for upstream grid electricity and MT electricity, and ε is the CO_2 processing cost per kg, then the carbon emission cost is expressed as (24) [22].

B. *Modeling the output power of the solar power plant with the Monte Carlo method*

Previous research has shown that the beta distribution function provides the most accurate and closest values for radiation modeling compared to other distribution functions used for this purpose. The probability density distribution function for the beta distribution is as provided in (25) where B can be expressed by the gamma function (Γ) which is shown in (26). Also, α and β are parameters of beta probability distribution function. After fitting the beta distribution function to the historical data, the parameters of the beta distribution function are obtained with the help of MATLAB Learning Toolbox. After obtaining the probability distribution function, the solar radiation is predicted for the required time interval with the help of the inverse transformation of the beta function. (27) presents the amount of solar power resulting from different amounts of radiation. In this equation; G is the modeled solar radiation in terms of w/m^2, G_{std} is solar radiation in the standard environment. In addition, R_c is a certain amount of radiation. Finally, P_{sn} is the nominal output power of solar panels, which is determined according to the structure of the panel [23].

$$f(x) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha,\beta)} \tag{25}$$

$$B(\alpha,\beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)} \tag{26}$$

$$P_{pv} = \begin{cases} P_{sn}\dfrac{G^2}{G_{std}+R_c} & 0 \le G \le R_c \\ P_{sn}\dfrac{G}{G_{std}} & R_c \le G \le G_{std} \\ P_{sn} & G_{std} \le G \end{cases} \tag{27}$$

C. *Mathematical approach: Lexicographic Method*

Multi-objective optimization problems are challenging due to the inherent conflicts between the objective functions. Multi-objective optimization problems inherently lack a single solution that can simultaneously achieve optimal values for all objectives. The Lexicographic method serves as an efficient approach to optimize these problems by relying on a pre-defined ordering among the objectives. This method involves sequentially solving a series of single-objective optimization problems after prioritizing the objectives. At each stage, one objective is optimized while considering the constraints imposed by the previously optimized objectives. This process continues until all objectives are optimized in the desired order. The implementation of the Lexicographic method consists of optimizing the objective with the first priority at the beginning and obtaining the optimum value of $F_1(x) = F_1^*$. Then, the second step is to optimize the objective with the second priority by adding the constraint $F_1(x) \le F_1^*$ (for minimization objectives) to preserve the optimal solution of the first optimization. Hence, minimizing $F_2(x) = F_2^*$ subject to $F_1(x) \le F_1^*$ will be the optimal solution for the multi-objective problem that shown in (28) [24]:

$$\begin{aligned} &Min\, F_i(x) = \\ &\quad subject\ to: F_j(x) \le F_j(x_j^*) \\ &\quad\quad j = 1,2,\ldots,i-1 \\ &\quad\quad i = 1,2,\ldots,n \end{aligned} \tag{28}$$

where i presents an objective status in the preferred order and $F_j(x_j^*)$ denotes the optimal value of $F_j(x)$ [24].

III. Test Results

The structure investigated in this paper includes a smart microgrid containing an MT, a PV and an energy storage. In this structure, the battery plays the role of the energy storage, and working alongside the MT, it is also a source of flexibility in addition to supplying energy. In this research, the problem of flexibility-based operation is investigated using the Lexicographic method in two cases, with cost priority in the first case and flexibility in the second one. Hence, in the first case, the cost objective is minimized initially, and the flexibility objective is optimized with an additional constraint of $Cost(x) \le Cost^*$ which leads to the optimum value

considering both objectives. Likewise, the second case assigns the flexibility with a higher priority and optimizes the operation cost in accordance to that. In this regard, the scheduling results of the MT, battery and the exchanged energy with the upstream network are presented in this section. In addition, the effect of providing flexibility using the battery on its aging and health is numerically compared in both cases. In order to examine the results obtained from solving the stochastic scheduling problem, 1000 scenarios are generated using Monte Carlo, and the number of these scenarios has been reduced to 10 using the k-means method. The utilized historical data were acquired from the modified Rye microgrid [25]. Fig. 1 shows the production power of the solar power plant in the 10 scenarios. In addition, the probability of these scenarios is shown in Table 2.

Fig. 2 shows the electrical demand of the studied microgrid in a 24-hour period. Additionally, in order to exchange energy with the upstream network, the corresponding prices are shown in Fig. 3. It's worth mentioning that the electrical demand and electricity prices are acquired from [26]. Although these values can have considerable uncertainties, in this study they are regarded as deterministic entities for the ease of calculation. This is since the main idea of this research is to provide a comprehensive study regarding different aspects of flexibility provision and considering the uncertainties of PV generation can sufficiently impose a high amount of flexibility requirement.

Fig. 4 shows the scheduling of the smart microgrid energy resources in the first case. Since in this case the scheduling cost is prioritized, as can be observed in this figure, the MT is operating at its minimum capacity for most of the time intervals. On the other hand, the battery is discharged in certain hours and charged in hours with the lowest price of energy purchased from the upstream network.

Since there are spikes in the consumption profile at some hours such as 8 and 22, it is necessary for the network to have the required flexibility in order to supply the load. Hence, the fast-ramp resource (battery) is discharged for this purpose.

Fig. 5 shows the values of ENS for the two cases. In this optimization problem, the maximum amount of ENS is limited to 50 kW. However, despite setting the Value of the Lost Load (VOLL) equal to 2 $\$/_{kW}$, due to the consideration of the cost of pollution, the optimization results show that there is unsupplied energy in several time intervals.

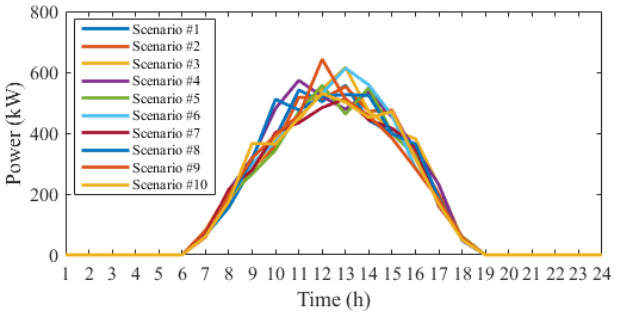


Fig. 1. Production power of the solar power plant in the 10 scenarios

TABLE 2 PV SCENARIOS AND THE CORRESPONDING PROBABILITIES

Scenario	***1***	***2***	***3***	***4***	***5***
Probability	0.105	0.09	0.102	0.123	0.103
Scenario	**6**	**7**	**8**	**9**	**10**
Probability	0.095	0.097	0.102	0.106	0.077

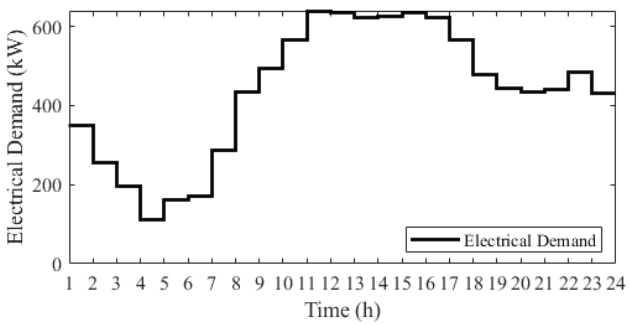


Fig. 2. Electrical demand

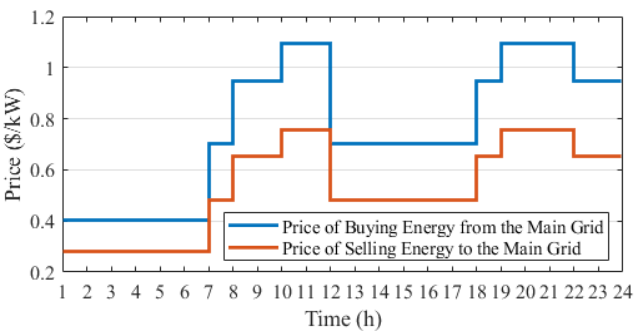


Fig. 3. Main grid energy trading price

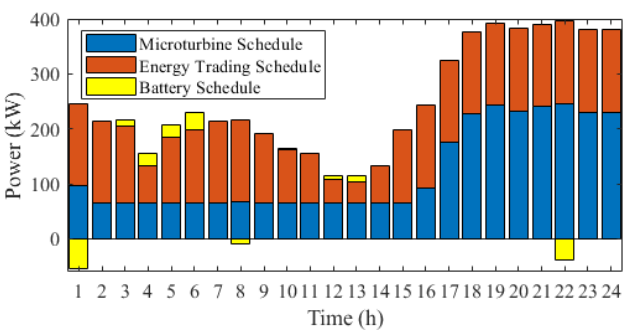


Fig. 4. Scheduling of smart microgrid energy resources in the first case

Similarly, Fig. 6 shows the scheduling results in the second case. Since flexibility is a priority in this case, as can be seen in the figure, fast-ramp resources (batteries) have many time intervals of energy production. Therefore, the flexibility of the network is increased and a greater share of the load profile is supplied. This result can also be seen in Fig. 5. It can be seen that during these hours the value of ENS has decreased which indicates more demand coverage.

Assigning priorities to each of the objective functions in the flexibility-based optimization problem has different effects from economic, social, environmental and technical points of view. In this paper, the economic aspect considers the cost of operation. The social aspect is defined in the form of the cost of ENS. Likewise, the environmental and the technical aspects are modeled in the form of the emission cost of the MT and the upstream network, and battery aging, respectively. Table 3 presents the comparison of two cases from economic, social, and environmental aspects as well as grid flexibility index.

It is clear that in the second case, by assigning the higher priority to flexibility and increasing the presence of fast-ramp resources, as well as increasing the purchase of energy from the upstream network, the cost of operation increases drastically. Furthermore, due to the increase in the production of resources and the purchase of energy, the cost of emission increases compared to case 1. This increase is 27.9% for operating cost and 8.5% for emission cost. In this case, due to the improvement of flexibility, load supply has been better and the total cost of unsupplied energy has decreased by 20.8%, which demonstrates a rise in social welfare.

It should be noted that providing flexibility using the battery increases its aging. Bearing in mind that the degradation of the battery health in a 24-hour period is very small, these changes are shown in Fig. 7 for both cases in a one-year period considering how the battery had to perform in the 24-hour operation time interval. As shown in the figure, by prioritizing the flexibility index and consequently charging and discharging the battery in more cycles, the aging rate of the battery increases.

IV. Discussion and Analysis

The findings of this study reveal a significant trade-off between flexibility and economic efficiency in microgrids. The increased reliance on batteries and micro turbine production to enhance flexibility results in higher operating costs, with a notable 27.9% increase in overall expenses. This economic impact underscores the need for careful consideration of cost management strategies when implementing flexibility measures.

From a technical perspective, the provision of flexibility accelerates battery aging, leading to a reduction in their state of health by more than 20% over a year. This technical challenge highlights the importance of developing advanced battery management systems and exploring alternative energy storage solutions to ensure long-term sustainability.

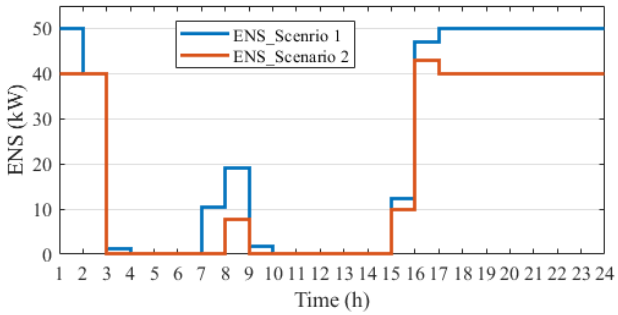


Fig. 5. Values of ENS in the two cases

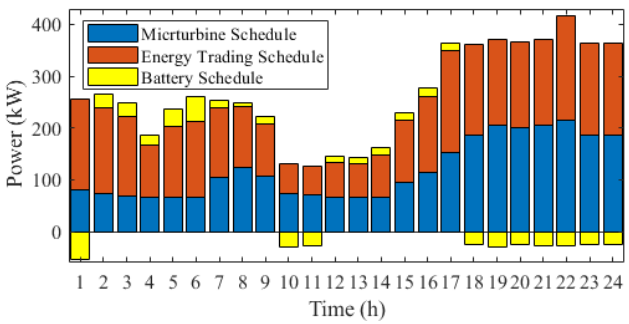


Fig. 6. Scheduling of the smart microgrid energy resources in the second case

TABLE 3 COMPARISON IN TERMS OF ECONOMIC, SOCIAL, AND ENVIRONMENTAL ASPECTS AS WELL AS NETWORK FLEXIBILITY INDEX.

Priority cases	*Operation Cost*	*Emission Cost*	*Total ENS Cost*	*Flexibility Index*
Case 1	32964.64	4601.52	1163.45	0.637
Case 2	42170.05	4990.22	921.68	0.78

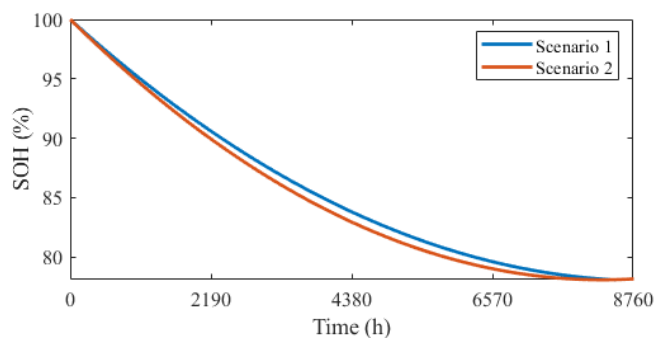


Fig. 7. Battery degradation in both cases in one-year period.

Socially, the proposed approach enhances microgrid reliability by minimizing the cost of energy not supplied, resulting in a 20.8% improvement in social welfare. This improvement in reliability is crucial for maintaining the quality of life and economic stability in communities reliant on microgrids.

However, the environmental impact of increased flexibility cannot be overlooked. The reliance on micro turbine

generation and higher-emission energy sources leads to an 8.5 % rise in pollution costs. This environmental cost necessitates the exploration of cleaner energy alternatives and the implementation of stringent emission control measures. cleaner energy alternatives and the implementation of stringent emission control measures.

V. Conclusions

In this study, the effects of implementing approaches based on flexibility in smart microgrids, considering the economic, technical, social and environmental consequences have been investigated. For this purpose, the lexicographic method was used to solve the optimization problem with the aim of optimizing operations by minimizing costs and at the same time maximizing flexibility. In this research, the battery is considered as the main source of flexibility. The simulation performed compares microgrid resource planning as well as operation cost, emission cost, unsupplied energy cost, microgrid flexibility index and in addition compares the impact of flexibility provision on battery aging in two cases. Considered cases are proposed by setting priorities for cost and flexibility in the lexicographic method. The results show that prioritizing cost flexibility from an economic point of view, increasing reliance on batteries and MT production to improve flexibility leads to a 27.9% increase in operating costs. From a social perspective, the proposed approach increases microgrid reliability by providing a 20.8% reduction in the cost of unsupplied energy. From a technical perspective, the results show that increasing the use of batteries accelerates their aging. On the other hand, it was observed that with a 14.3 % increase in flexibility, the emission cost also increased by 8.5%.

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