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Techno-Economic Framework for Optimal Capacity Expansion of Active Microgrid in the Mediterranean: A Case Study of MCAST

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ABSTRACT The purpose of microgrids is to improve system flexibility and resilience during normal and emergency conditions. The ceaseless load growth mandates to increase microgrid's capacity, thereby improving the system flexibility and resilience. However, capacity expansion requires significant investments, making it essential to identify the optimal capacity of energy resources. The methodologies proposed in the literature identifies the microgrid's capacity with an assumption of investments with a single installment. This way of theoretical approach leads to unrealistic solutions. Besides, microgrid's participation in a flexible market will enhance its performance both in commercial and technical aspects. Therefore, this paper proposes a realistic framework with the concept "*expansion through time*" inspired by "Real Options Theory." This framework includes practical parameters like resource & load uncertainty, physical space required to install, revenue generated by resources, and maximum demand penalty, on top of electrical parameters; constrained with significant *return in investments* to improve the overall savings. In addition, this paper proposes a market participation model for microgrid, which defines a bidding process with two components, such as regular and flexible portions under both normal and extreme conditions. This study considers renewable-based energy resources like solar-photovoltaic plants (SPPs) and battery energy storage systems (BESSs) as microgrids' energy resources. The system chosen for testing the efficacy of the proposed framework is a real-world active-microgrid of Malta College of Arts, Science and Technology (MCAST), located on an island.

INDEX TERMS Microgrid planning, battery energy storage system, renewable energy, optimization, resilience.

I. INTRODUCTION

In recent years, the renewable penetration into the distribution system is increasing mainly to decrease the reliance on fossil fuels and reduce associated carbon emission. However, the high penetration of renewables introduces various challenges to the grid, such as reliability, power quality, etc., mainly due to their intermittent nature. The introduction of an optimal-sized battery energy storage system (BESS) increases the grid flexibility and minimizes the uncertain nature of renewables [1]. In addition, microgrids are espoused with renewable energy resources (RERs) and other distributed energy resources (DERs) to enhance their economy and reliability in a self-controlled way [2]–[6]. However, with

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the increasing demand growth, microgrids are subjected to capacity expansion, bringing investment challenges. Therefore, it is essential to optimize the investments along with the optimal allocation of energy resources.

A. BACKGROUND AND MOTIVATION

The capacity expansion of microgrids imposes various challenges out of which the investments are of more interest. In other words, one of the significant challenges for the enlargement of microgrids is high capital investment. In addition, accurate assessment of energy resources is challenging due to uncertain conditions introduced by load, RERs, and future electric vehicles (EVs). Hence, it is essential to consider uncertainty parameters for the effective planning of microgrids [7]. In recent days, microgrid's participation in flexible market at distribution system operator (DSO) level is getting more popular considering the benefits. Many researchers proposed various methodologies to formulate the market participation of microgrids at various levels [8]–[10]. Therefore, this paper proposes a realistic framework that includes the technical parameters for optimal resource expansion and a bidding process for the market participation model to improve the microgrids' overall technical and financial benefits.

B. RELEVANT LITERATURE

Earlier, the research on microgrids has mainly been focused on optimal operation and control of available resources. However, in recent years, studies on optimal planning of energy resources for microgrids are also being undertaken. Most researchers formulated the resource planning problem as a mixed-integer non-linear problem (MINLP), which minimizes the investment cost. In [4], a study on energy planning of microgrids is performed by minimizing the overall cost using HOMER and PSCAD software. The authors of [11] presented a microgrid planning study on primary distribution systems using a genetic algorithm. Here the proposed methodology identifies the optimal location and capacity of DERs like solar photovoltaic plants (SPPs), gas turbines, wind turbines, and synchronous generators by considering the availability of the grid. In [12], the authors proposed a stochastic optimal planning methodology with the primary objective to minimize the net present cost and CO_2 emission. Here, the methodology identifies the optimal capacity of SPPs and wind power plants (WPPs) for a stand-alone microgrid using a genetic algorithm. Finally, the authors of [13] present a case study investigating the planning scenarios for remote microgrids with energy resources like wind farms and energy storage. Here, a Monte-Carlo-based approach is applied to generate various scenarios for wind power generation, the availability of wind and diesel, and uncertainty of load forecast to identify the optimal size of wind farm and energy storage system with minimum capital investments for the chosen planning horizon.

In recent years, there is a considerable increase in load growth in microgrids which mandates expansion of resource capacity. For instance, studies on optimal expansion plans adding the distributed resources like SPPs, WPPs, and BESS for microgrids are performed using particle swarm optimization (PSO) considering the uncertain environment [14], [15]. Besides, the service of microgrids is extended to improve the system's resilience. The resilience enhancement framework is majorly classified into hardening and operational strategies. One of the main reasons for power outages during extreme conditions is the failure of the main feeder. Most of the hardening strategies proposed in the literature provide resource addition to improve the system's resilience. For instance, in [16], [17], the hardening measures like optimal BESS planning across the system and the combination of grid-side and demand-side resilience measures are proposed to enhance system resilience. Deployment of microgrids with minimized operational cost improves system resilience [18]–[20]. The prior installed energy resources are generally from the microgrids via optimal operation of sectionalizer switches [21]–[23]. In [24], the authors proposed the optimal interconnector which connects the available RERs across the community to form microgrids. It is essential to have sufficient operational energy resources to satisfy the demand during extreme conditions.

The authors of [25] proposed a concept named "Provisional microgrids." The provisional microgrids have sufficient energy resources without islanding capability, and for its islanding operation, it is essential to be electrically connected with conventional microgrids. In other words, the provisional microgrids will serve as an energy resource for conventional microgrids, eliminating this challenge partially. However, the reserve capacity in microgrid planning must be constrained to the jurisdiction of DSO. In [26], the authors propose a bi-level planning model to optimize the power from DERs constrained with electrical parameters and the capacity of flexible reserves (constrained with DSO jurisdiction). Considering the uncertain nature of renewable-based DERs, the authors of [27] proposed a methodology to identify the optimal capacity of BESS within a microgrid. Here, the objective function is constrained by the uncertainty of renewables and load on top of electrical parameters. Realizing the role of EVs in the future distribution system, the authors of [28] proposed utilizing EVs to enhance microgrid flexibility effectively. Here, an optimal energy trading methodology is proposed using the day-a-head and real-time energy market to maximize the flexibility of building microgrids with renewables, BESS, and EVs. Finally, a study in [29] identifies the optimal capacity of DERs by minimizing a cost-based objective function constrained with the placement of DER at less vulnerable nodes (identified via contingency analysis) to improve the microgrid resilience. A summary of recent related literature is presented in Table 1, which showcases the contribution of this article.

C. CONTRIBUTIONS AND ORGANIZATION

From the literature, it is evident that the existing microgrid planning methodologies mainly focuses on parameters like

TABLE 1. Summary of recent related literature.

Reference	Type of Energy Resources	Optimization Objective				Practical Constraints of DERs			FMP	ALG/Solver	Test System
		CAP	LOC	OP	RE	UNC	PS	EP			
[4]	SPP, BESS, Hydro Power	✓	×	×	×	✓	×	✓	×	PSO	User-defined
[11]	Not defined	✓	✓	×	×	×	×	✓	×	Genetic Algorithm	IEEE 33 and 69 bus system
[12]	SPP, WPP	✓	×	×	×	✓	×	✓	×	Genetic Algorithm	User-defined
[13]	WPP, BESS	✓	×	×	×	✓	×	✓	×	Monte-Carlo	User-defined
[14]	WPP, SPP, BESS	✓	×	✓	×	×	×	✓	×	PSO	User-defined
[15]	SPP, WPP, Microturbine	✓	×	×	×	×	×	✓	×	PSO	IEEE 33 bus system
[18]	Microturbines, BESS	×	×	✓	✓	×	×	✓	×	User-defined	Urban LV System
[19]	SPP, WPP, BESS	×	×	✓	✓	×	×	✓	×	User-defined	DC Microgrid, IIT USA
[21]	Not defined	×	×	✓	✓	×	×	✓	×	User-defined	IEEE 37 node system
[26]	WPP, SPP, BESS, Diesel Generator	✓	×	×	×	×	×	✓	✓	CPLEX - GAMS	User-defined
[28]	SPP, EV	×	×	✓	×	×	×	✓	✓	CPLEX	User-defined
[29]	SPP, WPP	✓	✓	×	✓	×	×	✓	×	CPLEX - MATLAB	IEEE 33 bus system
Proposed Framework	*SPP & BESS*	✓	×	✓	✓	✓	✓	✓	✓	*HHO*	*MCAST Microgrid*

CAP: Capacity, LOC: Location, OP: Operation, RE: Resilience, UNC: Uncertainty, PS: Physical Space, EP: Electrical Parameters, FMP: Flexible Market Participation, ALG: Algorithms applied

voltage deviation, loading capacity of the interconnector, uncertainty offered by load, and RERs; leaving the practical constraints such as physical space available for installation of both BESS and RERs, investment burden, and the uncertainty of future EVs. Most of the approaches in the literature apply evolutionary-based optimization algorithms to solve the formulated objective function. Therefore, it is essential to identify the best suitable algorithm to solve a problem of this kind. Popular evolutionary algorithms are applied to solve the formulated cost-based objective function to determine the adequate size of BESS and SPP. Besides, to recognize the suitable algorithm among the popular ones, the results are compared based on execution time, iterations for convergence, and appropriate size. In addition, this paper proposes a market participation model for DERs of a microgrid at the DSO level. In general, the concept of microgrid capacity expansion is concerned with mainland installations. Therefore, it is essential to study the effect of microgrid capacity expansion methodologies to improve the resilience and flexibility of the systems located on islands. Hence, this paper presents the study of the capacity expansion plan inspired from real option theory for a microgrid situated on an island by considering practical constraints [30].

The significant contributions of this paper are as follows:

- Techno-economic framework for optimal capacity expansion of active microgrid based on *willingness factor of investment* (wf_i) and "*Expansion through time*" to enhance system resilience and flexibility.
- Formulation of an optimization problem with realistic constraints like the uncertainty of load, RERs, and EVs, physical space constraint for RERs and BESS, and revenue generation from DERs of the microgrid.
- Flexible market participation model at DSO level based on *willingness factor of participation* (wf_p) during normal and extreme conditions.
- The efficacy of the proposed framework is tested on real-world active microgrids of MCAST in the Mediterranean region.

This study utilizes the *pandapower* python package to develop the power system model [25] and python 3.7 for implementing the optimization algorithm. As mentioned earlier, this paper considers the MCAST microgrid located in Malta (an island in the Mediterranean) to perform numerical experiments. The rest of the article is organized as follows: Section II elaborates the proposed framework, including problem formulation, uncertainty modeling, capacity expansion model including the methodology to solve the optimization problem, and market participation model. Section III demonstrates the case study, and section IV concludes this paper.

II. PROPOSED FRAMEWORK

This section elaborates on the techno-economic framework for optimal capacity expansion of microgrids to improve their flexibility and resilience. To address the financial burden, the framework proposed is based on wf_i and

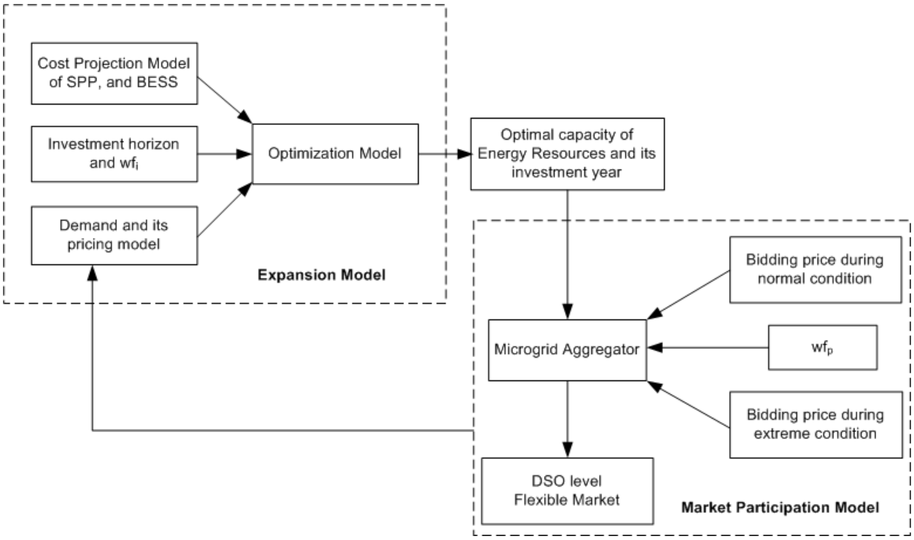

FIGURE 1. **Proposed framework.**

expansion through time. In other words, the overall investment (including the initial investment) is segmented into various investments through time, based on wf_i and the return on investments. Figure 1 shows the proposed framework with the capacity expansion and market participation model, respectively. Here the expansion model derives the optimal capacity of energy resources and its year of investment. The cost projection model estimates the yearly cost of energy resources for the entire project tenure [28]. Based on the historical data, the load and pricing model estimate the maximum annual demand and the possible penalty cost for the complete project tenure. The factor wf_i represents the investor's interest in investing in capacity expansion, taking a value between 0 and 1. The value of wf_i towards 1 indicates the reluctance of investors towards capacity expansion in the future, and 0 indicates the eagerness to invest. The market participation model determines the return in investment based on the cost of electricity purchased and sold. To address the concern of customers willing to participate in the aggregator market, wf_p is introduced. The factor wf_p represents the microgrid's customer interest to participate in the market. In other words, the customer is willing to participate in load shifting, power generation, energy storage during normal and islanding mode of operation.

The factor wf_p is a binary variable that takes the value 0 when the customer is unwilling for market participation. The following subsections elaborate on the problem formulation, uncertainty modeling, capacity expansion, and market participation models.

A. PROBLEM FORMULATION

This section elaborates the formulation of the cost-based objective function to derive the optimal capacity expansion. The objective function formulated comprises four components: investment cost, yearly expenses, yearly revenue, and cost of microgrid performance such as line loading, voltage deviation, and power loss shown in equations (1) – (8).

$$ObjF = C_{INV} + C_{yr}^{Ex} + C_{\mu\mathbb{G}} - C_{yr}^{Rev} \tag{1}$$

$$\begin{aligned} C_{INV} = & \sum\nolimits_{n=1}^{N_{SPP}} C_{FI}^{SPP,n} + A^{SPP,n} \times C_{land} \times S_{rated}^{SPP,n} \\ & + \sum\nolimits_{n=1}^{N_{BESS}} C_{FI}^{BESS,n} + C_{PI}^{BESS,n} + C_{EI}^{BESS,n} \\ & + C_{land} \times A^{BESS,n} \times S_{rated}^{BESS,n} \end{aligned} \tag{2}$$

$$\begin{aligned} C_{yr}^{Ex} = & \sum\nolimits_{yr=1}^{P_T} \sum\nolimits_{n=1}^{N_{SPP}} C_{OM}^{SPP,yr} \times S_{rated}^{SPP,n} \\ & + \sum\nolimits_{yr\in N_{Rpl_{yr}}^{SPP}} C_{Rpl}^{SPP_{Inv},yr} \times \mathbb{D}_f^{yr} + \sum\nolimits_{n=1}^{N_{BESS}} C_{OM}^{BESS,yr} \\ & \times S_{rated}^{BESS,n} + \sum\nolimits_{t\in N_{Rpl_{year}}^{SPP}} \sum\nolimits_{n=1}^{N_{SPP}} C_{Rpl}^{SPP_{Inv},n} \\ & \times \mathbb{D}_f^{yr} + C_{grid}^{penalty,yr} \end{aligned} \tag{3}$$

$$C_{\mu\mathbb{G}} = C_{ll}^{L} + C_{V_{dev}}^{N_n} + C_{S_p}^{L} \tag{4}$$

$$C_{ll}^{L} = \left\{ \sum\nolimits_{l=1}^{L} \%LL^{BESS} + \%LL^{SPP} \right\} \times \mathcal{C}_{ll} \tag{5}$$

$$C_{V_{dev}}^{N} = \sum\nolimits_{n=1}^{N_n} \left| V_{rated} - (V_n^{BESS} + V_n^{SPP}) \right| \times \mathcal{C}_{V_{dev}} \tag{6}$$

$$C_{S_p}^{L} = \sqrt{\sum\nolimits_{l=1}^{L} \left(P_{loss,l}^2 + Q_{loss,l}^2 \right)} \times \mathcal{C}_{loss} \tag{7}$$

$$\begin{aligned} C_{yr}^{Rev} = & \sum\nolimits_{yr=1}^{P_T} \sum\nolimits_{n=1}^{N_{SPP}} C_{grid}^{SPP,yr} \times S_{rated}^{SPP,n} \\ & + \sum\nolimits_{n=1}^{N_{BESS}} C_{grid}^{rev,yr} \times S_{rated}^{BESS,n} \end{aligned} \tag{8}$$

As shown in equation (1), the cost-based objective function represents the project expenditure in €(Euros) for capacity expansion with BESS and SPP in the microgrid. Here, the first term means the cost of initial investments towards building SPP, BESS, and the land required for installation. The second term represents the expenses that occur during the operation stage of the project, like the operation & maintenance cost of SPP & BESS and the replacement cost of SPP inverter & BESS after its lifespan. The third term represents the microgrid performance cost, which includes cost due to line loading, voltage deviation, and power loss. Finally, the last term denotes the revenue from the feed-in tariff of SPP and peak management using BESS to avoid the maximum demand penalty.

The formulated objective function is subjected to the following constraints:

1) OPTIMIZATION CONSTRAINTS

The power demand (including EVs) at any time of the day must be satisfied by the power from the grid, SPPs, power loss, and the power injected (during peak hours) or absorbed (during off-peak hours) by BESS, respectively. The optimization constraints for capacity expansion of microgrid are given by equations (9) – (18).

$$P_D^n + P_{EV}^n = P_{SPP}^n + P_{BESS}^n + P_{grid}^{LG} + P_{grid}^{IC} + P_{loss} \tag{9}$$

$$Q_D^n + Q_{EV}^n = Q_{SPP}^n + Q_{BESS}^n + Q_{grid}^{LG} + Q_{grid}^{IC} + Q_{loss} \tag{10}$$

$$P_{flow}^{n_i} = V^{n_i} \times \sum\nolimits_{n_i, n_j \in N} V^{n_j} \left(G_{n_i n_j} cos\theta_{n_i n_j} + B_{n_i n_j} sin\theta_{n_i n_j} \right) \tag{11}$$

$$Q_{flow}^{n_i} = V^{n_i} \times \sum\nolimits_{n_i, n_j \in N} V^{n_j} \left(G_{n_i n_j} sin\theta_{n_i n_j} - B_{n_i n_j} cos\theta_{n_i n_j} \right) \tag{12}$$

$$V_{min} < V^n < V_{max} \quad \forall n = 1, 2, 3, \ldots.., N \tag{13}$$

$$\%LL^l < \%LL_{max}^l \quad \forall l = 1, 2, 3, \ldots.., L \tag{14}$$

$$P_{BESS}^n \geq \sum\nolimits_{i=1}^{N_{ESS_D}} P_{ESS_{D,i}}^n \tag{15}$$

$$E_{BESS}^n \geq \sum\nolimits_{i=1}^{N_{ESS_D}} P_{ESS_{D,i}}^n \times EET \tag{16}$$

$$E_{SPP} \geq E_{BESS} \tag{17}$$

$$ObjF \leq Budget_{max} \tag{18}$$

Equations (9) – (12) represent the power balance and power flow constraints of real and reactive power, respectively. Equations (13) – (14) represent voltage deviation and line loading constraints due to grid-tied SPP. The selection of energy to power ratio plays a vital role in demand satisfaction (at least the essential loads) during the expected emergency time (EET), and equations (15 – 17) ensure the same. Finally, equation (18) restricts the overall expenditure within the maximum budget of the project.

B. UNCERTAINTY MODELING

The capacity expansion of microgrids is a planning activity; therefore, it is essential to model the uncertainty of parameters like load (both general and EV) and power generation from SPPs. The probabilistic behavior of these parameters reflects its uncertainty. For instance, the power output from SPP depends on the level of solar irradiance at the chosen site. Here, the beta and normal distribution function reflect the uncertainty of solar irradiance, general load, and EV load as given by equations (19), (20), and (21), respectively.

$$PDF_{SPP}(G_n) = \begin{cases} \frac{1}{\mathrm{B}(\alpha,\beta)} \times G_n^{\alpha-1} \times (1-G_n)^{\beta-1} & if\ G_n \in [0,1] \\ 0 & otherwise \end{cases} \tag{19}$$

$$PDF_P(S_n) = \frac{1}{\sqrt{(2\pi)}\,\sigma\,[S_n]} \times e^{-\left(S_n - \mathrm{E}(S_n) / \sqrt{2\sigma\,[S_n]}\right)^2} \tag{20}$$

$$PDF_{EV}\left(P_{EV_n}\right) = \frac{1}{\sqrt{(2\pi)}\sigma[P_{EV_n}]} \times e^{-\left(P_{EV_n} - \mathrm{E}(P_{EV_n}) / \sqrt{2\sigma\,[P_{EV_n}]}\right)^2} \tag{21}$$

where G^n indicates solar irradiance, at n^{th} location in W/m^2, B denotes the beta distribution function, α, and β represents the shape parameters of the probability density function, which takes values greater than zero. S_n refers to the apparent power of general load and P_{EV_n} represents the EV load, at n^{th} location, respectively. $E[]$ and σ [] represent the mean and standard deviation, respectively.

C. CAPACITY EXPANSION MODEL

This section elaborates on the strategy to minimize the overall expenditure over the project tenure to derive the optimal size of SPP, BESS, and the year of investments based on wf_i. The flowchart of the proposed framework is shown in figure 2. The steps of the proposed capacity expansion strategy are as follows:

Step 1: Fetch the system data required for power flow calculation, e.g., line data, bus data, the capacity of prior installed energy resources like SPP (if any), historical profile of general and EV load, etc.

Step 2: Derive the estimated cost of energy resources using the cost projection model.

Step 3: Derive the maximum demand and penalty against maximum demand using load and its pricing model. Besides, obtain the bidding price data from the market participation model for normal and extreme conditions to derive an effective pricing model.

Step 4: Choose an appropriate optimization algorithm and read the parameters required for optimization.

Step 5: Develop the system to perform power flow studies using pandapower.

Step 6: Set the iteration count.

Step 7: Generate the initial solution using a chosen optimization algorithm and run the power flow analysis.

Step 8: Execute step 9 and step 10 throughout the project tenure.

Step 9: Evaluate the objective function parameters mentioned in equations (2) - (8) and check for the constraints (9) – (17). If any violation in constraints, go to step 7.

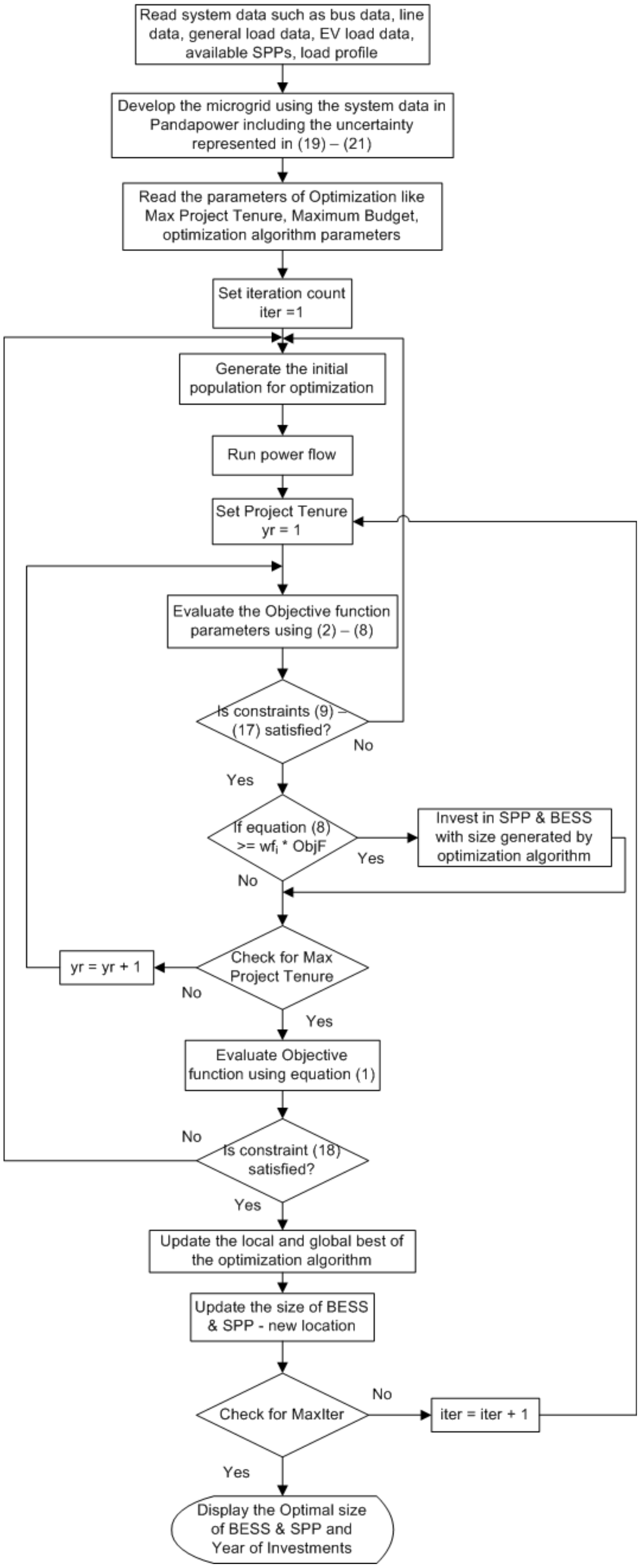

FIGURE 2. Flowchart of the proposed framework.

Step 10: For the given value of wf_i, check the value of equation (8). If the value is greater than or equal to $wf_i \times ObjF$, add the size of SPP & BESS generated by step 7, its cost calculated using step 9, and store the year, else go to the next step directly.

Step 11: Evaluate the objective function using equation (1) and check for the budget constraint mentioned in equation (18).

Step 12: Update the local and global best solution obtained from the optimization algorithm.

Step 13: Update the size of BESS & SPP to a new position according to the procedure followed in the optimization algorithm.

Step 14: Check for the maximum number of iterations and display the optimal size of BESS & SPP and the optimal years of investments.

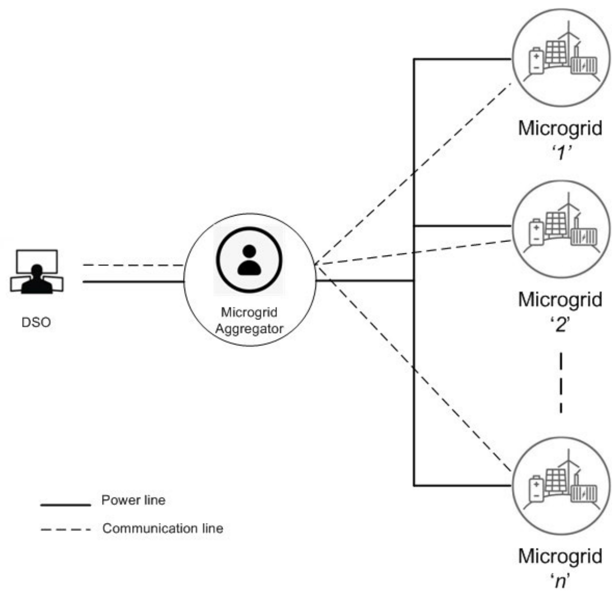

FIGURE 3. Market participation model.

D. MARKET PARTICIPATION MODEL

In recent days, the market participation model for microgrids is getting popular. The main objective of these models presented in the literature is to enhance the commercial and technical benefits at the microgrid and DSO levels. This paper adopts a similar concept of generalized market participation model, as shown in figure 3. Here, various microgrids form a microgrid aggregator to communicate with DSO for both commercial and technical transactions. The bidding process initiated will be communicated via communication lines and the power delivery via power lines, as shown in figure 3. This paper proposes a bidding process addressing both normal and extreme conditions assuming that the power and communication lines are in operation during both conditions. This process is defined with two components, such as regular and flexible portions. The microgrids adopted for the regular portion are subjected to a fixed price model (for both conditions) for power production (using SPPs) and the demand consumption as per the contract between DSO and the microgrid aggregator. This paper considers that the role of

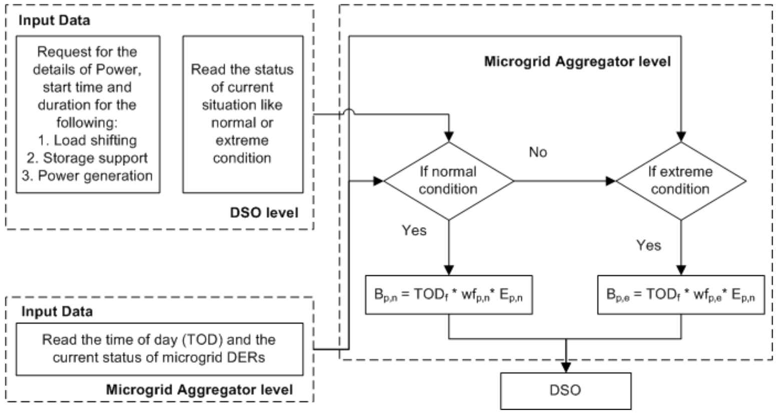

FIGURE 4. Flowchart of flexible bidding portion.

the energy storage system is restricted within the n^{th} microgrid for demand-side management. The microgrids espoused for the flexible portion are subjected to the bidding process, as shown in figure 4.

In the flexible portion, the DSO provides specific data like power required, time duration for which the power is required, and the start time of requirement concerning load shifting, storage support, and power generation. For instance, if DSO requires a specific amount of load to be shifted to a particular interval of time (for a given day) to meet the technical constraints, a request will be sent to the microgrid aggregator in prior as shown in figure 4. Then, based on the received requirement from DSO, the status of microgrid DERs, and the condition (either normal or extreme), a bidding price (B_p) is quoted to DSO as shown in figure 4. Here, the bidding price for both normal ($B_{p,n}$) and extreme conditions ($B_{p,e}$), is calculated based on *willingness factor for participation* (wf_p) and time of day factor (TOD_f); where TOD_f reflects whether the given time lies on peak or off-peak condition.

III. CASE STUDIES AND RESULTS

This paper considers a real-world active microgrid of MCAST located on an island to perform numerical experiments. The system consists of two 11 kV substations SS1 and SS2, where SS1 is connected to an external grid, and SS2 is connected to SS1 via a 153-meter AL XLPE cable. Table 2 shows the detailed system data. This microgrid lies on an island called Malta. In Malta, fifty percent of the energy demand is satisfied from local power generation and the rest from Sicily, Italy in the mainland via interconnector by 'Enemalta' distribution company. This microgrid's load is the building load located in Blocks D, F, and J with underground parking. The total area of MCAST Campus shown in figure 5 covers an area of 40,000 sq.m. Presently, the microgrid has three SPPs with an installed capacity of 63.36 kWp, with 21.12 kWp each on Block D, J, and F, respectively. From figure 5, it is evident that the MCAST campus has more rooftop space to install similar SPPs. However, to formulate a practical optimization problem, the objective function includes land cost as one of its features. In Figure 5, the yellow and orange box represents substation 1 (SS1) and substation 2 (SS2), respectively. The description of the blocks in the MCAST campus is shown in Table 3. The terminology used in this study to represent the HVAC system, main distribution board, pumping room, and car parking are AC, MDB, PR, and CP, respectively. For better understanding, the loads are represented using a jargon: [Building]_[Type]_[Category]. Here, the category specifies the importance of a chosen load. For instance, J_AC_NE represents the HVAC load in the J building, which comes under the non-essential category of load. The essential loads under the car parking distribution board (DB) represent the system's EV load Figure 6 shows the single line diagram of MCAST the microgrid. The load data, load profile of both essential and non-essential loads, and annual average solar irradiance at MCAST campus are shown in Figures 6, 7, 8, and 9, respectively. The value of depreciation factor (D_f) for SPP and BESS over the project tenure is derived from the cost project model presented in [31], [32].

TABLE 2. Component details of MCAST microgrid.

Component	Rating
SS1 & SS2	11 kV
B1 & B2	0.433 kV
T1 & T2	1600 kVA
Interconnector 1 & 2	AL XLPE cable. (153 m length)
L1 & L2	NYY-J cable. (5 m length)

In general, the market participation of DSO and microgrid aggregator is encouraged to ensure a reliable power supply. In this paper, the concept of the flexible market is extended to improve system flexibility and resilience by load shifting, energy storage support, and power generation requirement during normal and extreme conditions. As discussed in Table 1, many researchers attempt to solve a problem of this kind using popular meta-heuristic algorithms. Therefore, to identify a better suitable algorithm, popular algorithms like PSO, WOA, Grey Wolf Algorithm (GWO), Harris Hawks Optimization (HHO) algorithm, and BAT algorithm are applied to solve the proposed framework. Table 4 shows the input parameters for optimization. Considering the present scenario of Malta, which promotes renewable energy solutions on the island and decreases the dependency on the interconnector, this study is performed for $wf_i = 0.05, 0.1$ & 0.5.

TABLE 3. Description of buildings in MCAST campus.

Block	Description
Block M	Administration Building
Block L	Library & Learning Resource Centre
Block J	Institute of Applied Sciences
Block D	Institute of Business Management & Commerce
Block C	Institute of Community Services
Block E	Institute of Engineering & Transport
Block T	Institute of Information & Communication Technology
Block W	Apprenticeship & Work-Based Learning Department
Block G	Gymnasium
Block K	Canteen
Block F	Students' House

Table 5 shows the optimization results obtained after solving the formulated problem using popular meta-heuristic algorithms, as mentioned earlier. Figure 10 shows the convergence curve of the proposed optimization obtained from popular meta-heuristic algorithms. Table 5 and figure 10 show that PSO and GWO algorithms converge at local minima by taking many iterations to convergence and large execution time compared to other algorithms. The optimal solution obtained from WOA, HHO, and BAT are very close to each other. However, by comparing the number of iterations to converge and the execution time, the HHO algorithm's performance is better than other algorithms. Therefore, the optimal solution obtained from the HHO algorithm is considered for numerical experiments on the market participation model of the proposed framework. The numerical experiments performed to showcase the efficacy of the proposed framework consider two cases such as *Case I* : the customers of microgrid (DERs) opting for the regular bidding process, and *Case II:* the customers of microgrid (DERs) opting for a flexible bidding process. Further subsections discuss the results obtained from the proposed framework for both the cases with the market participation parameters like load shifting, energy storage support and power generation. In this study, the load shifting is assumed to be a part of the flexible portion of the bidding process by default.

FIGURE 5. Aerial view of MCAST microgrid.

TABLE 4. Input parameters for optimization.

PSO parameters	$w_{min} = 0.2, w_{max} = 0.9, \Delta w = 0.1, c_1 = c_2 = 2$
BAT parameters	$A = r = 0.5, Q_{min} = 0, Q_{max} = 2$
Max Iterations	100
Range of BESS	[0.04, 0.2] MVA
Range of SPP	[0.12, 0.6] MWp
C_{ll}	0.42 €/p.u.
$C_{V_{dev}}$	0.12 €/p.u.
C_{loss}	0.22 €/p.u.
$[V_{min}, V_{max}]$	[0.95 p.u. , 1.05 p.u.]
$\%LL^l_{max}$	80% of line capacity
Electricity price (E_p)	0.14 €
E/P ratio	1.4

TABLE 5. Comparison of optimization results among the chosen algorithms.

Features	PSO	WOA	HHO	GWO	BAT
Objective Function Value	19094140.5	10922164.8	10007463.5	18467669.7	10055196.1
Iterations to Converge	71	29	24	49	75
Execution time (in seconds)	1343.05736	778.34991	751.60138	1297.44929	987.07988
Size of BESS (in kVA)	65.783	37.069	33.743	63.892	34.986
Size of SPP (in kWp)	394.701	222.419	202.462	383.364	202.089

A. RESULTS FROM CASE I

This case presents the results if the microgrid customers (DERs) opted for the regular bidding process. As mentioned earlier, the regular bidding process is subjected to a fixed price model for normal and extreme conditions. Therefore, the effectiveness of the capacity expansion strategy lies in the selection of wf_i. Considering various values of wf_i like 0.05, 0.1, and 0.5, the net cash flow during the project tenure is shown in figure 11.

From figure 11, it is evident that for $wf_i = 0.5$, the net cash flow is approximately constant throughout the project tenure. However, for $wf_i = 0.1$, the net cash flow improves, and it further improves for $wf_i = 0.05$. From this, it is clear that the payback period can be improved with proper selection of wf_i concerning the present market scenario. Figure 12 shows

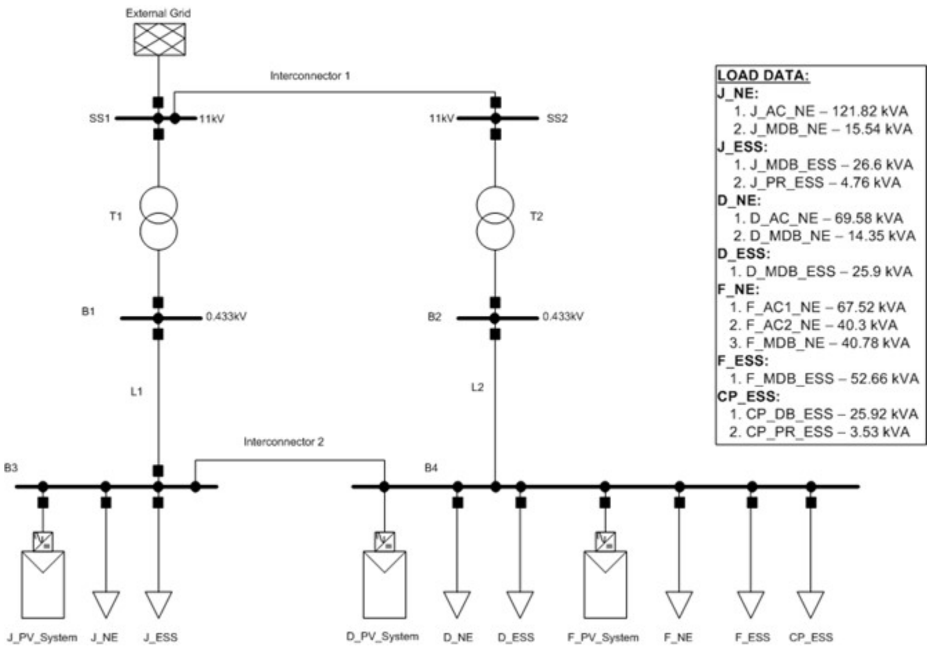

FIGURE 6. Single line diagram of MCAST microgrid.

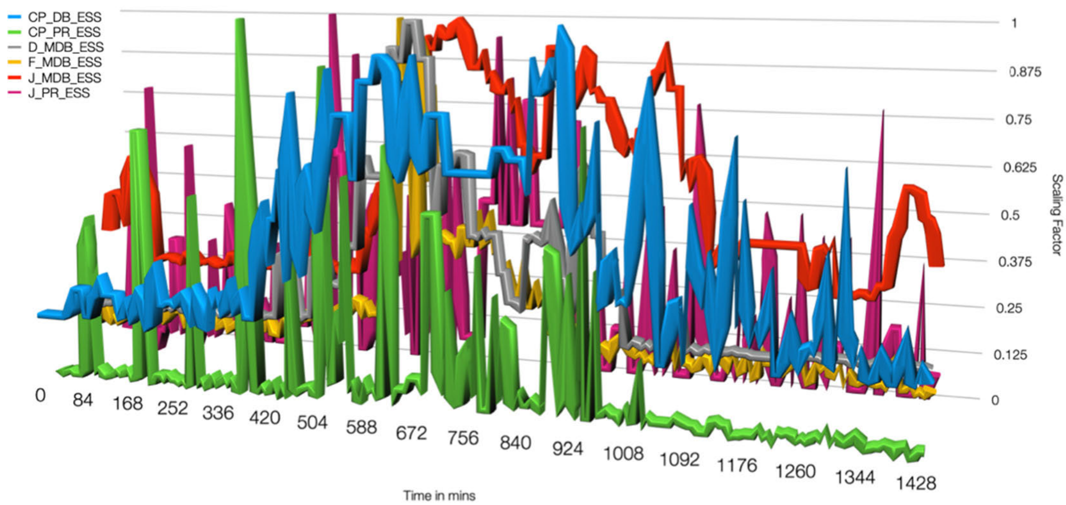

FIGURE 7. Load scaling factor of essential loads.

the steady-state performance of microgrid during the project tenure after installation of BESS and SPP.

B. RESULTS FROM CASE II

This case presents the results if the microgrid customers (DERs) opted for a flexible bidding process. As mentioned earlier, the microgrid customers (like general load) are considered under a flexible bidding process for load shifting. To perform the flexible market participation regarding load shifting, energy storage support, and power generation, the MCAST microgrid data is considered as input. For numerical experiments, the load data and outage data throughout a year are taken from the MCAST microgrid, and the size of BESS and SPP is considered from the optimal solution derived using the proposed framework. In addition, the values of TOD_f considered in this study for both normal and extreme conditions is shown in Table 6. Figure 13 represents the per-year outage data of the MCAST microgrid. The outage duration considered for this study is thirty minutes for normal conditions and three hours for extreme condition. Figure 14 shows the load duration curve of the MCAST Microgrid. Finally, the allowable %load shifting is evaluated in terms of maximum demand shown in figure 15.

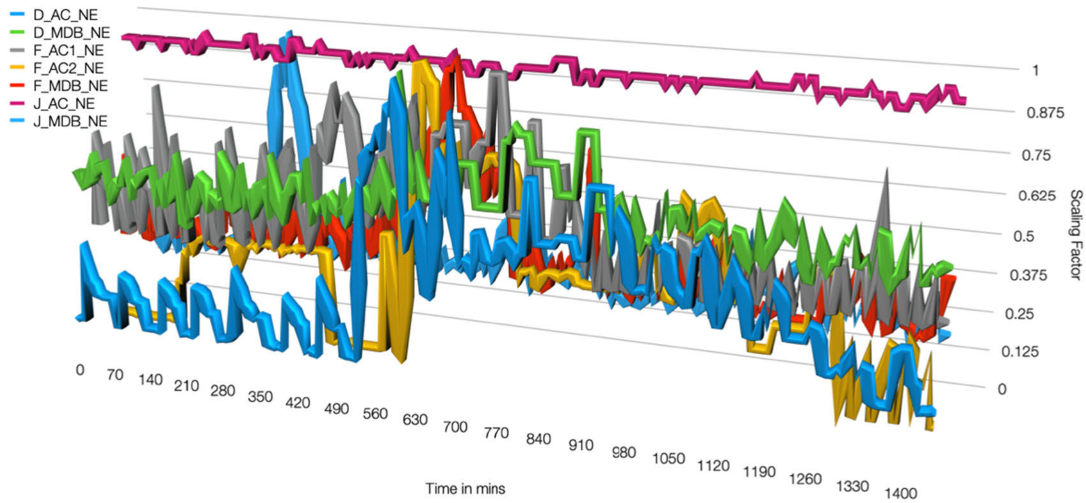

FIGURE 8. Load scaling factor of non-essential loads.

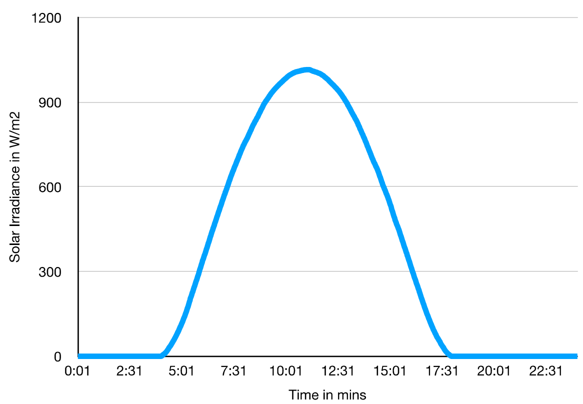

FIGURE 9. Annual average solar irradiance at MCAST campus in W/m^2.

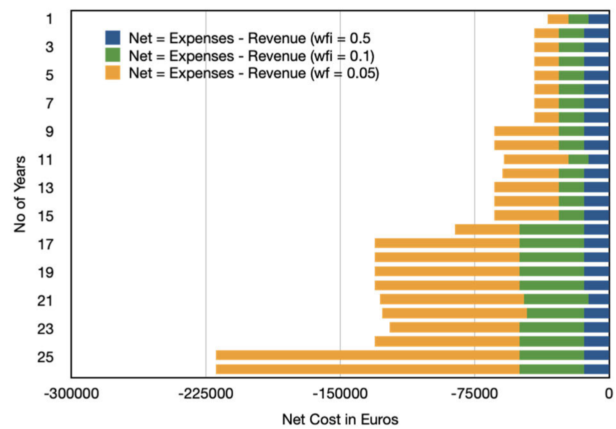

FIGURE 11. Net income throughout the project for various wf_i: Case I.

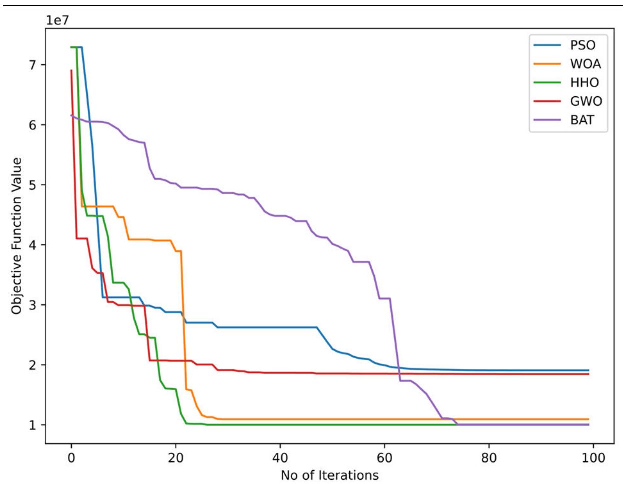

FIGURE 10. Convergence curve of proposed optimization.

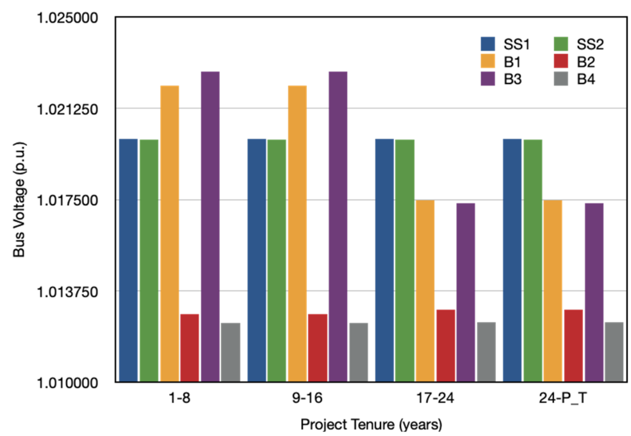

FIGURE 12. Bus voltage profile: Case I.

The revenue generated from bidding prices for normal and extreme conditions is calculated using TOD_f, wf_p, & E_p as shown in figure 4. As mentioned earlier, the revenue with a flexible portion is obtained for load shifting, energy storage support, and power generation. Here, the energy storage support from BESS is obtained for a reduced price based on the discount rate.

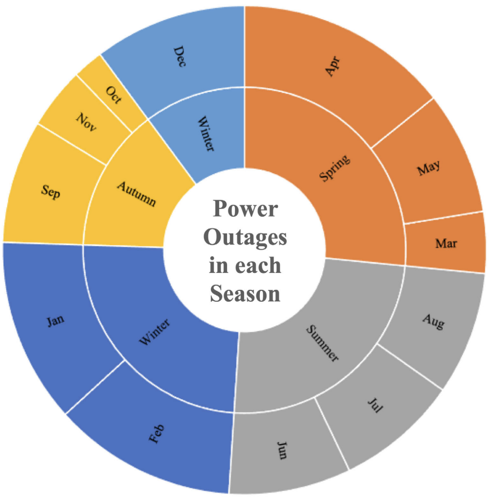

FIGURE 13. Power outages in MCAST microgrid during various seasons.

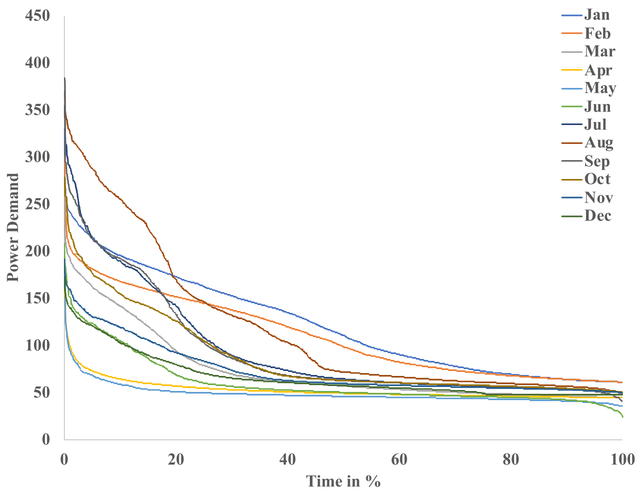

FIGURE 14. Load duration curve of MCAST microgrid.

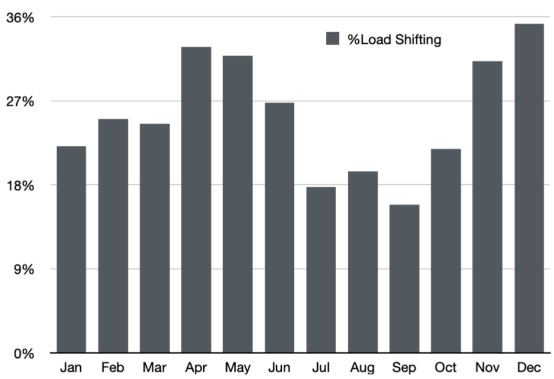

FIGURE 15. Allowable % load shifting.

In other words, the BESS will behave like a general load for a compensating price to maintain the grid performance. For the optimal size of BESS with an E/P ratio of 1.4 and a discount rate of 5% & 10% during peak and off-peak

TABLE 6. Time of day factor.

Condition \ TOD	Peak	Off-Peak
Normal	1.2	1
Extreme	1.5	1.1

TABLE 7. Monthly revenue by load shifting.

Month	R_NP (€)	R_NOP (€)	R_EP (€)	R_EOP (€)
Jan	56.7705914	47.3088262	70.9632393	52.0397088
Feb	64.3842744	53.653562	80.4803431	59.0189182
Mar	20.9791706	17.4826421	78.6718897	57.6927191
Apr	98.123181	81.7693175	105.13198	77.0967851
May	54.4445236	45.3704364	102.083482	74.86122
Jun	45.8480199	38.2066833	85.9650373	63.0410274
Jul	30.3662414	25.3052011	56.9367025	41.7535819
Aug	33.2973457	27.7477881	62.4325232	45.7838504
Sep	27.1817525	22.6514604	50.9657859	37.3749097
Oct	9.35286108	7.7940509	70.1464581	51.4407359
Nov	26.73615	22.280125	100.260563	73.5244125
Dec	75.4175792	62.8479827	113.126369	82.9593371

TABLE 8. Monthly revenue by power generation.

Month	R_NP (€)	R_NOP (€)	R_EP (€/day)	R_EOP (€/day)
Jan	4117.43762	3431.19802	166.025711	121.752188
Feb	4632.11732	3860.09777	206.790952	151.646698
Mar	5790.14665	4825.12221	233.473655	171.214014
Apr	6433.49628	5361.2469	268.062345	196.579053
May	7720.19554	6433.49628	311.298207	228.285352
Jun	8492.21509	7076.84591	353.842296	259.48435
Jul	9264.23465	7720.19554	373.557849	273.942422
Aug	8492.21509	7076.84591	342.428028	251.113887
Sep	6433.49628	5361.2469	268.062345	196.579053
Oct	5790.14665	4825.12221	233.473655	171.214014
Nov	4632.11732	3860.09777	193.004888	141.536918
Dec	3988.7677	3323.97308	160.837407	117.947432

TOD during the normal condition, the revenue generated is 361.11 €/year. This is evaluated by considering a minimum of one energy support request per day in a year. With the same input values, the revenue generated per energy support during extreme conditions is 10 €/support and 7 €/support during peak and off-peak TOD, respectively. For the given outage data (shown in figure 13), the revenue generated by load shifting and power generation throughout the year for both normal and extreme conditions is shown in Table 7 and Table 8, respectively. Here, the notation R_NP, R_NOP, R_EP, and R_EOP represents the revenue in Euros during peak and off-peak for normal and extreme conditions. The revenue during extreme conditions is calculated on per day basis during the specified month.

IV. CONCLUSION

This paper proposes an improved optimal capacity expansion framework with a market participation model to enhance the microgrid flexibility and resilience. The optimization problem formulated in this framework includes the practical parameters like initial investments, cost of land required to install BESS and SPP, yearly expenditure and yearly revenue, uncertainty of SPP, general load, and EV on top of grid performance parameters. In addition, this paper compares the efficacy of popular meta-heuristic algorithms such as PSO, GWO, HHO, WOA, and BAT for an optimization problem of this kind based on convergence, execution time, and optimal size of BESS and SPP. The results show that formulation of optimal planning problem with capacity expansion strategy based on wf_i largely improves the financial benefits for the investor by increasing the overall net cash flow during the project tenure. Besides, the market participation model with regular and flexible portion further enhance the revenue generation. For instance, with the proposed flexible bidding process, a significant amount of revenue could be generated from load shifting, energy storage support, and power generation in both normal and extreme conditions. Concerning the current scenario of Malta, a flexible bidding model with load shifting and power generation model along with significant energy storage support will be very effective in reducing the dependency on interconnectors.

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