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

BALAJI VENKATESWARAN V¹, (Senior Member, IEEE), VIBHU JATELY², (Member, IEEE) and BRIAN AZZOPARDI², (Senior Member, IEEE)

¹ Electrical and Electronics Engineering Department, University of Petroleum and Energy Studies, Dehradun 248007, India

² MCAST Energy Research Group, Institute of Engineering and Transport, Malta College of Arts, Science and Technology, 9032 Paola, Malta

Corresponding author: Balaji Venkateswaran V (balajivenkateswaran.v@gmail.com).

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ABSTRACT The purpose of microgrids is to improve system flexibility and resilience during normal and emergency conditions, respectively. 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 instalment. 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 and 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 for both normal and extreme conditions. This study considers renewable-based energy resources like solar-photovoltaic plants (SPPs) and battery energy storage systems (BESSs) as energy resources for the microgrid. 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 distribution system is increasing mainly to decrease the reliance on fossil fuels and reduce associated carbon emission. The high penetration of renewables introduces various challenge to the grid such as reliability, power quality, etc., mainly due to their intermittent nature. Introducing the optimal-sized battery energy storage system (BESS) increases the grid flexibility and minimizes the uncertain nature of renewables [1]. In addition, the microgrids are espoused with renewable energy resources (RERs) and other distributed energy resources (DERs) to enhance its economy and reliability in a self-controlled way [2]–[4]. With the increasing demand growth, microgrids are subjected capacity expansion, which brings with challenges in investments. Therefore, it is essential to optimize the investments along with optimal allocation of energy resources.

The capacity expansion of microgrids imposes various challenges out of which the investments is of more interest. In other words, one of the major challenges for 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 effective planning of microgrids [5]. 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 [6]–[8]. Therefore, this paper proposes a realistic framework which includes the technical parameters for optimal resource expansion and a bidding process for market participation model to improve the overall technical and financial benefits from microgrids.

A. BACKGROUND AND MOTIVATION

B. RELEVANT LITERATURE

Earlier the research on microgrids are mainly focused on optimal operation and control of available resources. However, in recent years, studies on optimal planning of energy resources for microgrids are presented. Most of the 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 [9] presented a microgrid planning study on primary distribution system using genetic algorithm. Here the proposed methodology identifies the optimal location and capacity of DERs like solar photovoltaic plants (SPPs), gas turbine, wind turbine, and synchronous generators considering the availability of the grid. In [10], the authors proposed a stochastic optimal planning methodology with the main objective to minimize the net present cost and CO₂ emission. Here, the methodology identifies the optimal capacity of SPPs and wind power plants (WPPs) for a stand-alone microgrid using genetic algorithm. The authors of [11] presents a case study which investigates 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 of load growth in microgrids which mandates to expand its resource capacity. For instance, studies on optimal expansion plans using the distributed resources like SPPs, WPPs, and BESS for microgrids are performed using particle swarm optimization (PSO) considering the uncertain environment [12], [13]. Besides, the service of microgrids are extended to improve the system 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 main feeder. Most of the hardening strategies proposed in the literature provide resource addition to improve the system resilience. For instance in [14], [15], the hardening measures like optimal planning of BESS across the system along with combination of grid-side and demand-side resilience measures are proposed to enhance the system resilience. Deployment of microgrids with minimized operational cost improves system resilience [16]–[18]. The prior installed energy resources generally form the microgrids via optimal operation of sectionalizer switches [19]–[21]. In [22], the authors proposed the optimal interconnector which connect the available renewable energy resources (RERs) across the community to form microgrids. It is essential to have sufficient energy resources operational to satisfy the demand during extreme conditions.

The authors of [23], proposed a concept named “Provisional microgrids”. The provisional microgrids have sufficient energy resources without the capability of islanding; 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 which will therefore eliminate this challenge partially. The reserve capacity in microgrid planning must be constrained to the jurisdiction of DSO. In [24], 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 [25] proposed a methodology to identify the optimal capacity of BESS within a microgrid. Here, the objective function is constrained with the uncertainty of renewables and load on top of electrical parameters. Realizing the role of EVs in future distribution system, the authors of [26] proposed to effectively utilize EVs to enhance the microgrid flexibility. Here, an optimal energy trading is proposed using the day-a-head and real-time energy market to maximize the flexibility of building microgrids with renewables, BESS and EVs. A study in [27] 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 I which showcase 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 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. To identify the effective size of BESS and SPP, popular evolutionary algorithms are applied to solve the formulated cost-based objective function. Besides, to recognize the suitable algorithm among the popular ones, the results obtained are compared based on parameters such as execution time, number of iterations for convergence, and suitable size. In addition, this paper proposes a market participation model for DERs of microgrid at DSO level. In general, the concept of microgrid capacity expansion is concerned with the 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 for a microgrid located on an island by considering practical constraints.

TABLE 1
SUMMARY OF RECENT RELATED LITERATURE

Ref	Type of Energy Resources	Optimization Objective				Practical Constraints of DERs			Flexible Market Participation	Algorithm / Solver	Test System
		Capacity	Location	Operation	Resilience	Uncertainty	Physical space	Electrical Parameters			
[4]	SPP, BESS, Hydro Power	✓	×	×	×	✓	×	✓	×	PSO	User defined
[9]	Not defined	✓	✓	×	×	×	×	✓	×	Genetic Algorithm	IEEE 33 and 69 bus system
[10]	SPP, WPP	✓	×	×	×	✓	×	✓	×	Genetic Algorithm	User defined
[11]	WPP, BESS	✓	×	×	×	✓	×	✓	×	Monte-Carlo	User defined
[12]	WPP, SPP, BESS	✓	×	✓	×	×	×	✓	×	PSO	User defined
[13]	SPP, WPP, Micro turbine	✓	×	×	×	×	×	✓	×	PSO	IEEE 33 bus system
[16]	Micro turbines, BESS	×	×	✓	✓	×	×	✓	×	User defined	Urban LV System
[17]	SPP, WPP, BESS	×	×	✓	✓	×	×	✓	×	User defined	DC Microgrid, IIT USA
[19]	Not defined	×	×	✓	✓	×	×	✓	×	User defined	IEEE 37 node system
[24]	WPP, SPP, BESS, Diesel Generator	✓	×	×	×	×	×	✓	✓	Cplex - GAMS	User defined
[26]	SPP, EV	×	×	✓	×	×	×	✓	✓	Cplex	User defined
[27]	SPP, WPP	✓	✓	×	✓	×	×	✓	×	Cplex - MATLAB	IEEE 33 bus system
Proposed Framework	SPP & BESS	✓	×	✓	✓	✓	✓	✓	✓		MCAST Microgrid

The major contributions of this paper are as follows:

- Techno-economic framework for optimal capacity expansion of active microgrid based on “*Expansion through time*” to enhance system resilience and flexibility.
- Formulation of optimization problem with realistic constraints like uncertainty of load, RERs, and EVs, physical space constraint for RERs and BESS, and revenue generation from DERs of microgrid.

- Flexible market participation model at DSO level during normal and extreme conditions.

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 Mediterranean) to perform numerical experiments. The rest of the paper is organized as follows: Section II elaborates the proposed framework, which includes the formulation of the

optimization problem for capacity expansion plan through time, flexible market participation of DERs at DSO level and the methodology to solve the problem. Section III demonstrates the case study and section IV concludes this paper.

II. PROPOSED FRAMEWORK

This section elaborates the proposed framework for capacity expansion of microgrids that improves system flexibility and resilience. This framework takes the practical parameters like initial investments for energy resources, including the cost of land space required, yearly expenditure and revenue for the complete project, and grid performance parameters. Besides, the financial burden on initial investment is addressed by “*expansion through time*”. In other words, the initial investment is segmented into various investments through time, based on the return.

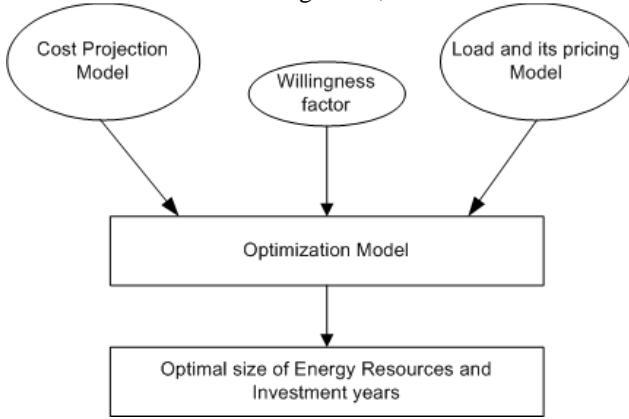


FIGURE 1. Generalized structure of Proposed Framework

The *willingness factor*, modeled in the framework derives segments of investment. A generalized structure of the proposed framework is shown in figure 1. Here, the cost projection model estimates the yearly cost of energy resources for the complete project tenure [26]. Based on the historical data, the load and its pricing model estimate the yearly maximum demand and the possible cost of penalty for the complete project tenure. The willingness factor represents the investor’s interest in investing in capacity expansion taking a value between 0 and 1. The willingness factor towards 1 indicates the reluctance of investors towards capacity expansion in the future and 0 indicates the eagerness to invest. The following sub-sections elaborate on the problem formulation, uncertainty modeling, and the capacity expansion strategy based on the willingness factor.

A. PROBLEM FORMULATION

This section elaborates the formulation of the cost-based objective function to derive the optimal capacity expansion of a microgrid. The objective function formulated comprises four components such as 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).

$$ObjF = C_{INV} + C_{yr}^{Ex} + C_{\mu G} - C_{yr}^{Rev} \quad (1)$$

$$C_{INV} = \sum_{n=1}^{N_{SPP}} C_{FI}^{SPP,n} + A^{SPP,n} \times C_{land} \times S_{rated}^{SPP,n} + \sum_{n=1}^{N_{BESS}} C_{FI}^{BESS,n} + C_{PI}^{BESS,n} + C_{EI}^{BESS,n} + C_{land} \times A^{BESS,n} \times S_{rated}^{BESS,n} \quad (2)$$

$$C_{yr}^{Ex} = \sum_{yr=1}^{P_T} \sum_{n=1}^{N_{SPP}} C_{OM}^{SPP,yr} \times S_{rated}^{SPP,n} + \sum_{yr \in N_{Rpl,yr}} C_{Rpl}^{SPPInv,yr} \times \mathbb{D}_f^{yr} + \sum_{n=1}^{N_{BESS}} C_{OM}^{BESS,yr} \times S_{rated}^{BESS,n} + \sum_{t \in N_{Rpl,yr}} \sum_{n=1}^{N_{SPP}} C_{Rpl}^{SPPInv,n} \times \mathbb{D}_f^{yr} + C_{grid}^{penalty,yr} \quad (3)$$

$$C_{\mu G} = C_{ll}^L + C_{Vdev}^{N_n} + C_{Sp}^L \quad (4)$$

$$C_{ll}^L = \{\sum_{l=1}^L \%LL^{BESS} + \%LL^{SPP}\} \times C_{ll} \quad (5)$$

$$C_{Vdev}^N = \sum_{n=1}^{N_n} |V_{rated} - (V_n^{BESS} + V_n^{SPP})| \times C_{Vdev} \quad (6)$$

$$C_{Sp}^L = \sqrt{\sum_{l=1}^L (P_{loss,l}^2 + Q_{loss,l}^2)} \times C_{loss} \quad (7)$$

$$C_{yr}^{Rev} = \sum_{yr=1}^{P_T} \sum_{n=1}^{N_{SPP}} C_{grid}^{SPP,yr} \times S_{rated}^{SPP,n} + \sum_{n=1}^{N_{BESS}} C_{grid}^{rev,yr} \times S_{rated}^{BESS,n} \quad (8)$$

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

The formulated objective function subjects 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 BESS (during peak hours) or absorbed (during off-peak hours) by BESS. The optimization constraints for capacity expansion of microgrid is given by equations (9) – (18).

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

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

$$P_{flow}^{n_i} = V^{n_i} \times \sum_{n_i, n_j \in N} V^{n_j} (G_{n_i n_j} \cos \theta_{n_i n_j} + B_{n_i n_j} \sin \theta_{n_i n_j}) \quad (11)$$

$$Q_{flow}^{n_i} = V^{n_i} \times \sum_{n_i, n_j \in N} V^{n_j} (G_{n_i n_j} \sin \theta_{n_i n_j} - B_{n_i n_j} \cos \theta_{n_i n_j}) \quad (12)$$

$$V_{min} < V^n < V_{max} \quad \forall n = 1, 2, 3, \dots, N \quad (13)$$

$$\%LL^l < \%LL_{max}^l \quad \forall l = 1, 2, 3, \dots, L \quad (14)$$

$$P_{BESS}^n \geq \sum_{i=1}^{N_{ESSD}} P_{ESSD,i}^n \quad (15)$$

$$E_{BESS}^n \geq \sum_{i=1}^{N_{ESSD}} P_{ESSD,i}^n \times EET \quad (16)$$

$$E_{SPP} \geq E_{BESS} \quad (17)$$

$$ObjF \leq Budget_{max} \quad (18)$$

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

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

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

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

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 the 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 $\sigma[]$ represent the mean and standard deviation, respectively.

C. CAPACITY EXPANSION STRATEGY

This section elaborates on the strategy followed to minimize the overall expenditure over the project tenure to derive the optimal size of SPP, BESS, and the year of investments based on the willingness factor. 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 load profile, 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.

Step 4: Choose an appropriate optimization algorithm and read the parameters required for optimization and develop the system to perform power flow studies.

Step 5: Set the iteration count.

Step 6: Generate the initial solution using a chosen optimization algorithm. After that, run the power flow analysis.

Step 7: Execute step 7 to step 9 throughout the project tenure.

Step 8: Evaluate the objective function parameters mentioned in equations (2) - (8) and check for the constraints (9) – (17).

Step 9: For the given willingness factor, check the value of equation (8). If the value is greater than or equal to the $w_f \times ObjF$, add the size of SPP & BESS generated by step 7 and its corresponding investment, else go to the next step directly.

Step 10: Evaluate the objective function using equation (1) and check for the budget constraint mentioned in equation (18).

Step 11: Update the local and global best solution obtained from the optimization algorithm.

Step 12: Update the size of BESS & SPP to a new position according to the procedure followed in the optimization algorithm.

Step 13: Check for the maximum number of iterations and display the optimal size of BESS & SPP and the optimal years of investments.

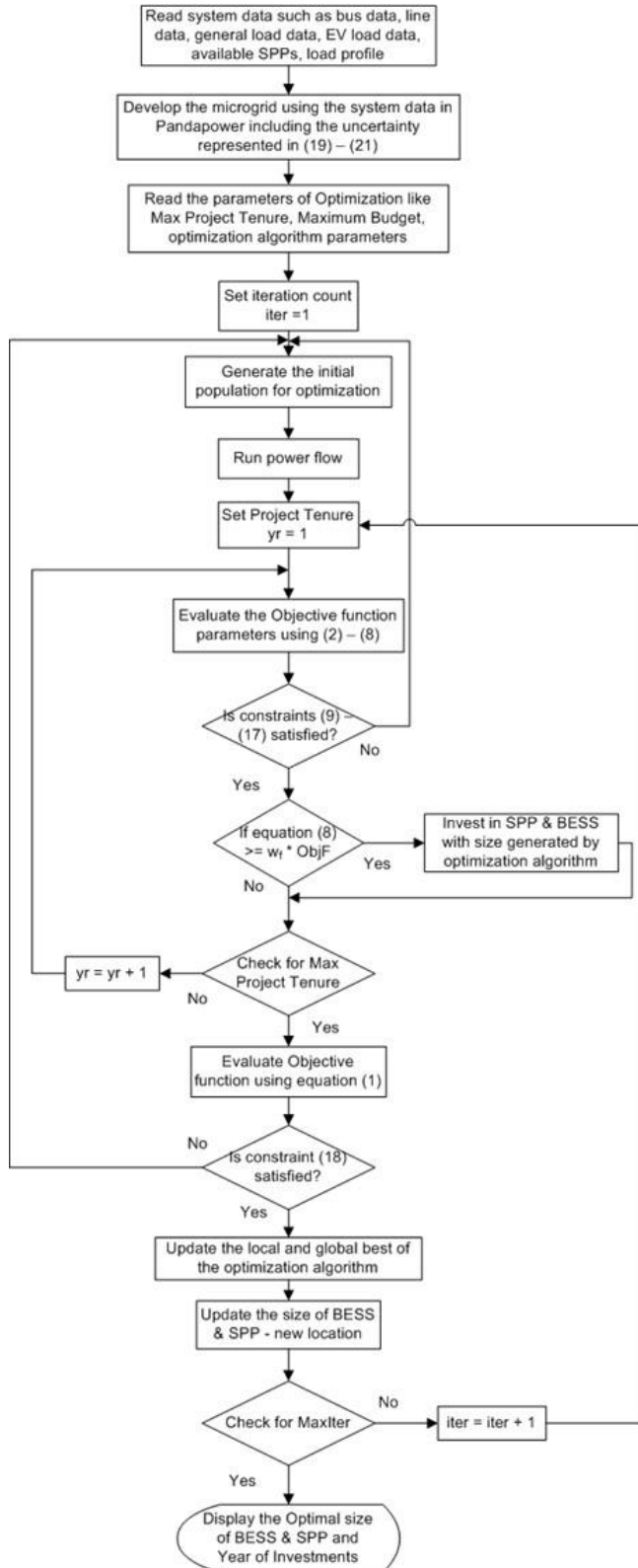


FIGURE 2. Flowchart of the Proposed Framework

III. CASE STUDIES AND RESULTS

This paper considers the real-world active microgrid of MCAST (shown in figure 3) to perform the 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 through a 153-meter AL XLPE cable. Table I shows the detailed system data. This microgrid lies on an island called Malta. Fifty percent of the island's demand is satisfied from local generation and the rest from Sicily, Italy in the mainland via interconnector by 'Enemalta' distribution company. Loads of this microgrid are the building loads located in Blocks D, F, and J with underground parking. The total area of MCAST Campus shown in figure 4 covers an area of 40,000 sq.m. Presently, the microgrid has three SPPs with an installed capacity of 63.36 kWp, 21.12 kWp each on Block D, J, and F, respectively. From figure 4, 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 4, 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 II. The nomenclature 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 nomenclature: [Building] _ [Type] _ [Category]. Here the category specifies its essentiality. For instance, J_AC_NE represents the HVAC load in the J building, which comes under the non-essential category. The essential loads under the car parking distribution board (DB) represent the EV load in the system. The load data, load profile, and annual average solar irradiance at the MCAST campus are shown in figure 3, figure 5, and figure 6, respectively. The values of depreciation factor (Df) for SPP and BESS over the project tenure are derived from the cost projection model presented in [26], [27].

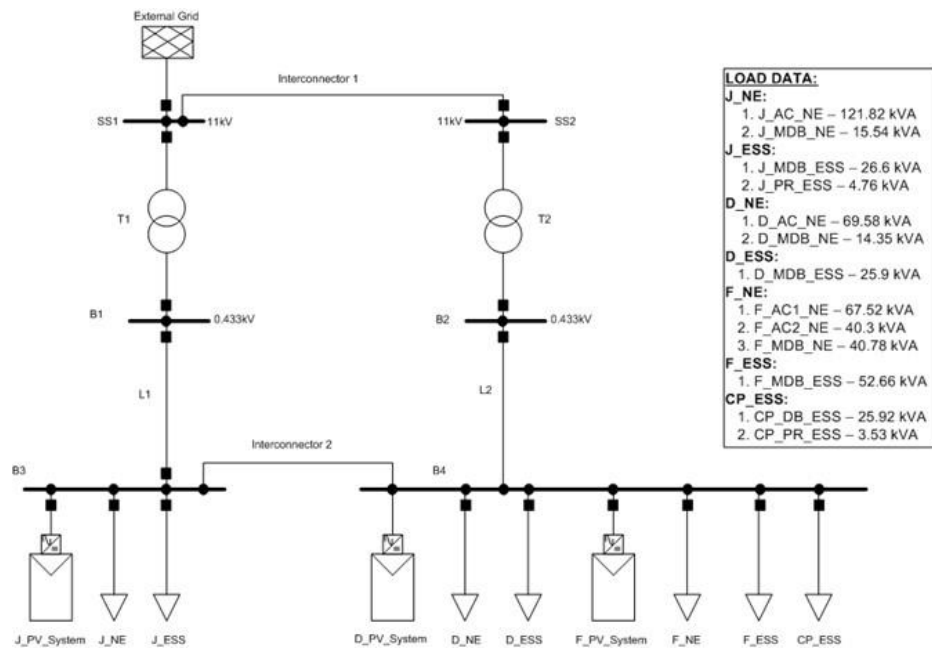


FIGURE 3. Single line diagram of MCAST Microgrid



FIGURE 4. Aerial-view 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	NY-Y cable. (5 m length)

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

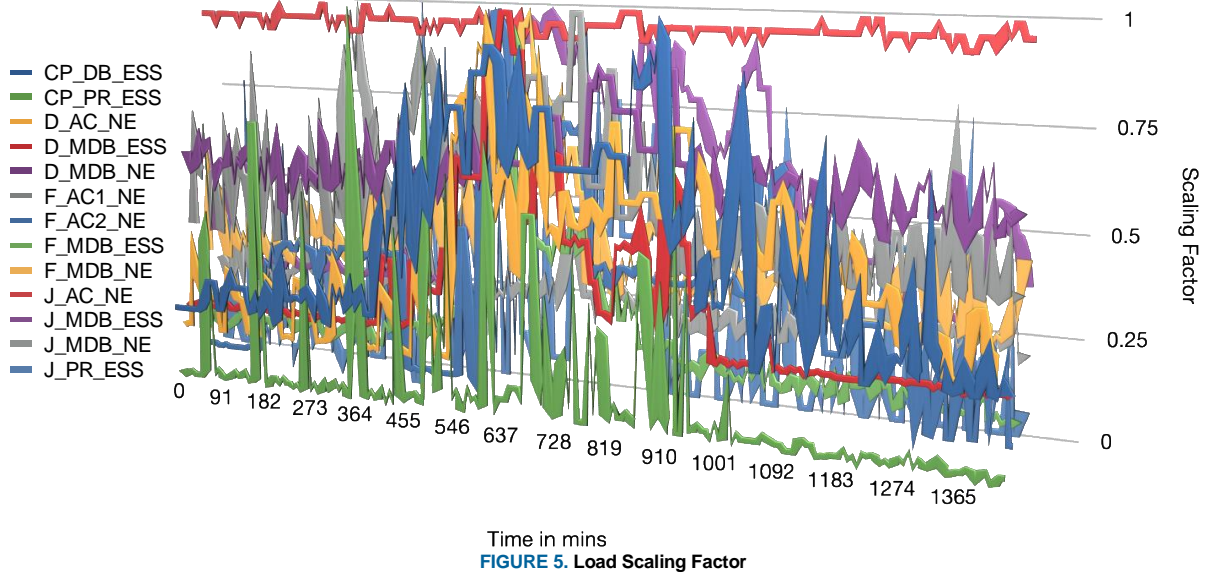


FIGURE 5. Load Scaling Factor

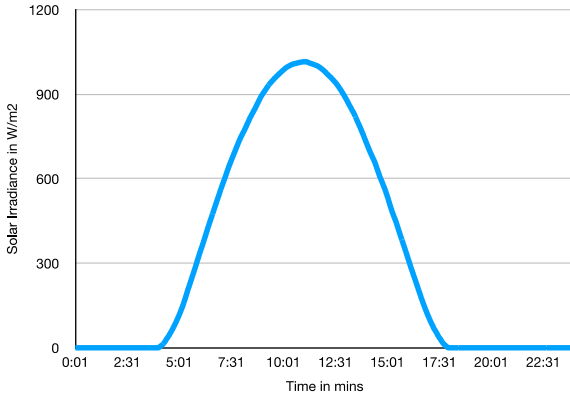


FIGURE 6. Annual average Solar irradiance at MCAST Campus in W/m²

PSO parameters	$w_{min} = 0.2, w_{max} = 0.9, \Delta w = 0.1, c_1 = c_2 = 2$
Max Iterations	60
Range of BESS	[0.04, 0.2] MVA
Range of SPP	[0.12, 0.6] MWp
C_{ll}	0.42 €/p.u.
C_{vdev}	0.12 €/p.u.
C_{loss}	0.22 €/p.u.
$[V_{min}, V_{max}]$	[0.95 p.u., 1.05 p.u.]
$\%LL_{max}^l$	80% of line capacity

In [28], the authors claim that the particle swarm optimization (PSO) algorithm is better suitable for an optimization problem of this kind. However, in [29], the whale optimization algorithm (WOA) provides better results. Therefore, in this study, both optimization algorithms are applied to solve the proposed framework, to identify the suitable algorithm and optimal solution. Table III shows the input parameters for optimization considered in this study. Considering the present scenario of Malta, which promotes renewable solutions on the island and decreases the dependency on the interconnector, this study is performed for $w_f = 0.05$ & 0.1. Table IV shows the optimization results obtained after solving the formulated problem using PSO and WOA. From figure 7, it is evident that WOA converges with fewer iterations to obtain the minimum solution. Besides, WOA takes less execution time to solve this problem compared to PSO. Since the PSO algorithm does not provide the optimal solution for this problem, the optimal investment year obtained is no more valid. Therefore, the discussion on capacity expansion strategy based on willingness factor is restricted with the results of WOA.

TABLE V
COMPARISON OF OPTIMIZATION RESULTS AMONG THE CHOSEN
ALGORITHMS

Features	PSO Algorithm	WOA Algorithm
Size of BESS	18.134 kVA	8.97 kVA
Size of SPP	106.65 kWp	53.848 kWp
Objective Function Value	5835558.915	3233207.090
No of Iterations to convergence	47	25
Execution time (in seconds)	2840.9693	1324.8362

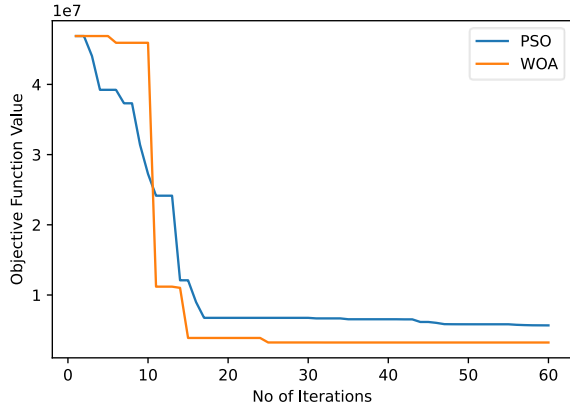


FIGURE 7. Convergence Curve of the Proposed Optimization

The effectiveness of the capacity expansion strategy lies in the selection of the willingness factor. For the willingness factor of 0.1 and 0.05, the optimal number of investments are two and four, respectively during the project tenure. Figure 8 demonstrates the net cash flow during the project tenure, which derives the payback period. From this figure, it is evident that for $w_f = 0.1$, the payback period is fifteen years; whereas, for $w_f = 0.05$, the payback period is eight years. Figure 9 shows the performance of microgrid during the project tenure after the installation of BESS and SPP.

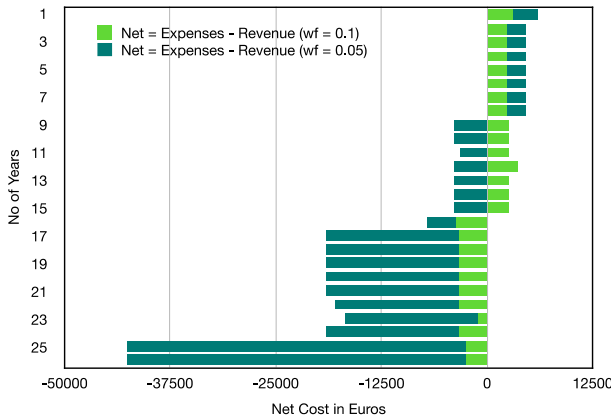


FIGURE 8. Net income throughout the project for various w_f

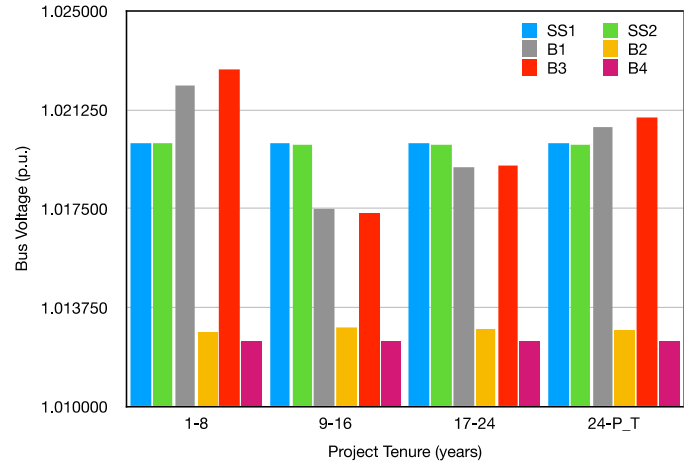


FIGURE 9. Bus voltage profile of Proposed methodology

V. CONCLUSION

In this paper, capacity expansion strategy through time is proposed to enhance the microgrid flexibility and resilience by considering the practical constraints such as initial investments for energy resources, including the cost of land space required, yearly expenditure, revenue for the complete project, and uncertainty of SPP, general load and EV load on top of grid performance parameters. The paper also compares the optimization results obtained from the most suitable algorithms like PSO and WOA (as suggested in the literature). From the obtained results, it is evident that, WOA converges quickly and provides better optimal solution compared to PSO. In addition, the consideration of capacity expansion strategy based on willingness factor proves to be beneficial for the investor by improving the overall saving from the project.

REFERENCES

- [1] V. B. Venkateswaran, D. K. Saini, and M. Sharma, "Environmental Constrained Optimal Hybrid Energy Storage System Planning for an Indian Distribution Network," *IEEE Access*, vol. 8, pp. 97793–97808, 2020, doi: 10.1109/ACCESS.2020.2997338.
- [2] Liang Che, M. Khodayar, and M. Shahidehpour, "Only Connect: Microgrids for Distribution System Restoration," *IEEE Power Energy Mag.*, vol. 12, no. 1, pp. 70–81, Jan. 2014, doi: 10.1109/MPE.2013.2286317.
- [3] E. Planas, J. Andreu, J. I. Gárate, I. Martínez de Alegría, and E. Ibarra, "AC and DC technology in microgrids: A review," *Renew. Sustain. Energy Rev.*, vol. 43, pp. 726–749, Mar. 2015, doi: 10.1016/j.rser.2014.11.067.
- [4] A. M. A. Haidar, A. Fakhar, and A. Helwig, "Sustainable energy planning for cost minimization of autonomous hybrid microgrid using combined multi-objective optimization algorithm," *Sustain. Cities Soc.*, vol. 62, no. December 2019, p. 102391, 2020, doi: 10.1016/j.scs.2020.102391.
- [5] A. Khodaei, S. Bahramirad, and M. Shahidehpour, "Microgrid Planning Under Uncertainty," *IEEE Trans. Power Syst.*, vol. 30, no. 5, pp. 2417–2425, 2015, doi: 10.1109/TPWRS.2014.2361094.
- [6] K. Buayai, W. Ongsakul, and N. Mithulanathan, "Multi-objective micro-grid planning by NSGA-II in primary distribution system," *Eur. Trans. Electr. Power*, vol. 22, no. 2, pp. 170–187, Mar. 2012, doi: 10.1002/etep.553.
- [7] L. Guo, W. Liu, B. Jiao, B. Hong, and C. Wang, "Multi-objective stochastic optimal planning method for stand-alone microgrid system," *IET Gener. Transm. Distrib.*, vol. 8, no. 7, pp. 1263–1273, 2014, doi: 10.1049/iet-gtd.2013.0541.

- [8] E. Hajipour, M. Bozorg, and M. Fotuhi-Firuzabad, "Stochastic Capacity Expansion Planning of Remote Microgrids with Wind Farms and Energy Storage," *IEEE Trans. Sustain. Energy*, vol. 6, no. 2, pp. 491–498, 2015, doi: 10.1109/TSTE.2014.2376356.
- [9] Z. Wang, Y. Chen, S. Mei, S. Huang, and Y. Xu, "Optimal expansion planning of isolated microgrid with renewable energy resources and controllable loads," *IET Renew. Power Gener.*, vol. 11, no. 7, pp. 931–940, 2017, doi: 10.1049/iet-rpg.2016.0661.
- [10] N. Kanwar, N. Gupta, K. R. Niazi, and A. Swamkar, "Optimal distributed resource planning for microgrids under uncertain environment," *IET Renew. Power Gener.*, vol. 12, no. 2, pp. 244–251, 2018, doi: 10.1049/iet-rpg.2017.0085.
- [11] B. V. V. D. K. Saini, and M. Sharma, "Approaches for optimal planning of the energy storage units in distribution network and their impacts on system resiliency — A review," *CSEE J. Power Energy Syst.*, 2020, doi: 10.17775/CSEEJPES.2019.01280.
- [12] B. Venkateswaran V, D. K. Saini, and M. Sharma, "Techno-Economic Hardening Strategies to enhance Distribution System Resilience against Earthquake," *Reliab. Eng. Syst. Saf.*, vol. 213, no. December 2020, p. 107682, Apr. 2021, doi: 10.1016/j.res.2021.107682.
- [13] C. Gouveia, J. Moreira, C. L. Moreira, and J. A. Peças Lopes, "Coordinating Storage and Demand Response for Microgrid Emergency Operation," *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 1898–1908, Dec. 2013, doi: 10.1109/TSG.2013.2257895.
- [14] L. Che and M. Shahidehpour, "DC microgrids: Economic operation and enhancement of resilience by hierarchical control," *IEEE Trans. Smart Grid*, vol. 5, no. 5, pp. 2517–2526, 2014, doi: 10.1109/TSG.2014.2344024.
- [15] Y. Wang, A. O. Rousis, and G. Strbac, "On microgrids and resilience: A comprehensive review on modeling and operational strategies," *Renew. Sustain. Energy Rev.*, vol. 134, no. August, 2020, doi: 10.1016/j.rser.2020.110313.
- [16] C. Chen, J. Wang, F. Qiu, and D. Zhao, "Resilient Distribution System by Microgrids Formation After Natural Disasters," *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp. 958–966, Mar. 2016, doi: 10.1109/TSG.2015.2429653.
- [17] X. Liu, M. Shahidehpour, Z. Li, X. Liu, Y. Cao, and Z. Bie, "Microgrids for Enhancing the Power Grid Resilience in Extreme Conditions," *IEEE Trans. Smart Grid*, vol. 8, no. 2, pp. 589–597, 2017, doi: 10.1109/TSG.2016.2579999.
- [18] M. A. Gilani, A. Kazemi, and M. Ghasemi, "Distribution system resilience enhancement by microgrid formation considering distributed energy resources," *Energy*, vol. 191, p. 116442, 2020, doi: 10.1016/j.energy.2019.116442.
- [19] L. Che, X. Zhang, M. Shahidehpour, A. Alabdulwahab, and A. Abusorrah, "Optimal Interconnection Planning of Community Microgrids with Renewable Energy Sources," *IEEE Trans. Smart Grid*, vol. 8, no. 3, pp. 1054–1063, 2017, doi: 10.1109/TSG.2015.2456834.
- [20] A. Khodaei, "Provisional Microgrid Planning," *IEEE Trans. Smart Grid*, vol. 8, no. 3, pp. 1096–1104, 2017, doi: 10.1109/TSG.2015.2469719.
- [21] M. Quashie, C. Marnay, F. Bouffard, and G. Joós, "Optimal planning of microgrid power and operating reserve capacity," *Appl. Energy*, vol. 210, no. August, pp. 1229–1236, 2018, doi: 10.1016/j.apenergy.2017.08.015.
- [22] I. Alsaidan, A. Khodaei, and W. Gao, "A Comprehensive Battery Energy Storage Optimal Sizing Model for Microgrid Applications," *IEEE Trans. Power Syst.*, vol. 33, no. 4, pp. 3968–3980, 2018, doi: 10.1109/TPWRS.2017.2769639.
- [23] A. T. Eseye, M. Lehtonen, T. Tukia, S. Uimonen, and R. J. Millar, "Optimal Energy Trading for Renewable Energy Integrated Building Microgrids Containing Electric Vehicles and Energy Storage Batteries," *IEEE Access*, vol. 7, pp. 106092–106101, 2019, doi: 10.1109/ACCESS.2019.2932461.
- [24] X. Wu, Z. Wang, T. Ding, X. Wang, Z. Li, and F. Li, "Microgrid planning considering the resilience against contingencies," *IET Gener. Transm. Distrib.*, vol. 13, no. 16, pp. 3534–3548, 2019, doi: 10.1049/iet-gtd.2018.6816.
- [25] L. Thurner et al., "Pandapower—An Open-Source Python Tool for Convenient Modeling, Analysis, and Optimization of Electric Power Systems," *IEEE Trans. Power Syst.*, vol. 33, no. 6, pp. 6510–6521, Nov. 2018, doi: 10.1109/TPWRS.2018.2829021.
- [26] W. Cole and A. W. Frazier, "Cost Projections for Utility- Scale Battery Storage," *Natl. Renew. Energy Lab.*, no. June, p. NREL/TP-6A20-73222, 2019, [Online]. Available: <https://www.nrel.gov/docs/fy19osti/73222.pdf>.
- [27] Statista Research Department, "Installation cost of solar photovoltaics worldwide," Statista. .
- [28] Z. Abdmouleh, A. Gastli, L. Ben-Brahim, M. Haouari, and N. A. Al-Emadi, "Review of optimization techniques applied for the integration of distributed generation from renewable energy sources," *Renew. Energy*, vol. 113, no. November, pp. 266–280, 2017, doi: 10.1016/j.renene.2017.05.087.
- [29] A. A. Zaki Diab, H. M. Sultan, I. S. Mohamed, N. Kuznetsov Oleg, and T. D. Do, "Application of different optimization algorithms for optimal sizing of pv/wind/diesel/battery storage stand-alone hybrid microgrid," *IEEE Access*, vol. 7, pp. 119223–119245, 2019, doi: 10.1109/ACCESS.2019.2936656.