Multi-objective optimisation framework for standalone DC-microgrids with direct load control in demand-side management

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Renewable energy-powered DC microgrids have emerged as a sustainable alternative for standalone power systems in remote locations, which were traditionally reliant on diesel generators (DIG) only. To ensure power quality and reliability, energy storage systems (ESS) and demand-side management (DSM) techniques are employed, addressing the intermittent nature of renewable energy sources (RES). This manuscript presents a novel multi-objective optimisation framework to determine the equipment sizing, depth of discharge (DoD) of ESS, and share of controllable loads contributing to DSM in a standalone DC microgrid incorporated with RES as a primary energy source and a backup DIG. The proposed optimisation strategy utilises genetic algorithm with the objectives of minimizing lifecycle cost and carbon footprint. A novel battery energy storage system (BESS) management criterion is introduced, which accounts for battery degradation in the lifecycle cost calculation. The minimum allowable DoD of the BESS is considered a decision variable in the optimisation problem to assess the impact of higher DoD on lifecycle cost improvement. MATLAB simulation results demonstrate that the proposed optimisation model significantly reduces the levelized cost of electricity and per unit carbon footprint compared to previous models. Additionally, it identifies an optimal range of DoD for the BESS to enhance the lifecycle cost of a standalone DC microgrid.

Introduction: Standalone power systems are essential for powering remote areas where grid connections are not feasible due to inaccessibility. Traditionally, diesel generators (DIGs) have been the primary energy source for these systems, valued for their ease of deployment, operational reliability, and the global availability of diesel fuel. However, DIGs pose several issues, including high fuel costs, noise pollution, and a significant carbon footprint when used as the sole energy source [1]. Renewable energy sources (RES) have emerged as a sustainable alternative for replacing DIGs in standalone power systems. RESs offer advantages such as low operational costs, zero carbon emissions, and minimal environmental impact. Despite these benefits, integrating RES into power systems is challenging due to their intermittent nature. To address these challenges, energy storage systems (ESS) and demand-side management (DSM) technologies have been incorporated within the microgrid framework. For standalone power systems, the islanded microgrid concept has been employed. Key ESS technologies, such as batteries, supercapacitors, flywheels, and hydrogen energy storage, are used to store excess energy generated by RES when generation exceeds demand and to supply energy when demand is higher. Since ESS outputs and RES like solar PV often produce direct current (DC), DC microgrids are advantageous, especially if most loads can be easily converted to DC.

DSM technologies play a crucial role in managing demand during peak periods when the available generation and energy storage are insufficient. DSM encompasses three main strategies: (a) energy conservation, (b) load management, and (c) demand response (DR). DR involves modifying electricity consumption patterns in response to signals from grid operators or suppliers and is typically categorized into incentive-based and time-based programs [2]. However, many standalone DC microgrids, often built-own-operate (BOO) projects, face challenges in integrating traditional DR programs. Direct load control (DLC) presents a viable DR strategy for standalone microgrids which allows utilities or grid operators to directly control or adjust specific appliances or equipment, providing a practical solution [3].

The main outcome of the design of a microgrid is to reduce costs and the carbon footprint. Optimisation techniques and energy management strategies can be utilised to design the microgrids to achieve the expected outcomes. The design of the microgrid should minimize the levelized cost of electricity (LCOE, a measure of the lifetime cost of a microgrid) and carbon footprint using optimisation algorithms while improving performance by utilising suitable energy management strategies [4].

Integration of DSM techniques into a DC microgrid may have a positive impact on cost reduction. However, there is still a cost associated with shedding the loads in terms of operational behaviour changes in the microgrid. When designing the operation of the microgrid, it is necessary to incorporate the associated cost of DSM into the optimisation [5].

There were only limited number of DSM studies for standalone microgrids found in the current literature. An optimisation strategy based on HOMER software was developed for a standalone residential microgrid in India, as detailed in [6]. This strategy optimises the microgrid using only a rule-based approach to battery energy storage system (BESS) management, assuming full charging and discharging cycles without any set limits on the depth of discharge. In [7], a multi-objective optimisation approach for designing a standalone DC microgrid was developed, incorporating a BESS management strategy that uses a DIG when the BESS reaches its minimum designed state of charge (SOC) until it is fully charged. However, this approach does not account for DSM and battery degradation over its cycle life.

Therefore, a significant research gap remains in integrating battery degradation into lifecycle cost assessments for standalone microgrid design, and in applying DSM techniques for optimization. This manuscript proposes a multi-objective genetic algorithm-based optimization technique that determines the optimal capacities of equipment in a renewable energy-powered DC microgrid, while incorporating a novel BESS management algorithm accounting for battery degradation by analysing the cycle life. Depth of discharge (DoD) of the BESS is considered as a decision variable (DEV) to optimize the BESS management algorithm. The upper and lower bounds for DoD are selected based on the safe operating range provided by the BESS manufacturers. Furthermore, the proposed method employs DLC as a DSM strategy to reduce demand by shutting down some controllable loads.

Model of the standalone DC microgrid: There are three major parts of a DC microgrid: generation, loads, and energy storage. In this study, solar PV and wind energy are utilised as the primary energy sources. A DIG has been used as a backup power source. BESS has been used as the ESS. The proposed microgrid is controlled via a centralized controller as shown in Figure 1. In addition to the loads, a dynamic load (DYL) has been utilised in the design to absorb the surplus generation from renewable energy sources and to dissipate power transients when the BESS is fully charged.

When designing the required capacity of a solar PV system for a microgrid, the maximum power output that can be obtained in a certain location by a solar module should be calculated [8]. It can be calculated by the measured values of solar irradiance and temperature on a given location using Equation (1).

$$P_{PV} = \eta \times PR_{PV} \times A_{PV} \times Irr \times \left(1 - \left(k \times T_C - T_{ref}\right)\right) \tag{1}$$

where P_{PV} is the maximum power output of the solar PV system, η is the efficiency of a solar panel, PR_{PV} is plant's performance ratio, A_{PV} is the required area of the solar panels, Irr is the solar irradiance, k is the temperature coefficient, T_c is the cell temperature, and T_{ref} is the reference cell temperature.

Wind turbine converts the kinetic energy of the wind to electrical energy by a generator coupled to the turbine shaft [9]. The total power output of a wind turbine system can be calculated by measuring the

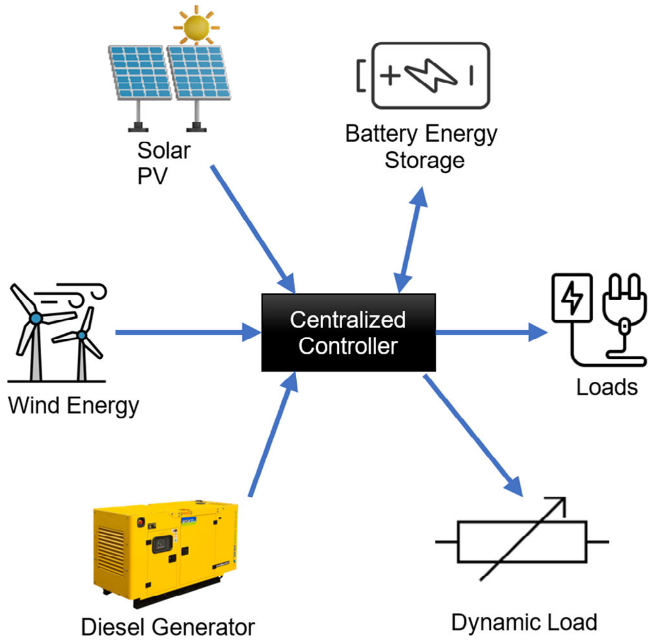

Fig. 1 *Schematic of the standalone DC microgrid being proposed*

wind speed at the location as given in Equation (2).

$$P_{Wind-T} = \begin{cases} \frac{1}{2}.\eta_{Gen} \times \eta_{GB} \times C_P \times A_s \times \rho_{Air} \times V_{Wind}^3\ ;\ V_{cut-in} \leq V_{Wind} \\ \leq V_{rated} P_{rated};\ V_{rated} \leq\ V_{Wind}\ \leq\ V_{cut-off} \\ 0;\ V_{wind} \langle\ V_{cut-in} \text{ or } V_{wind} \rangle\ V_{cut-off} \end{cases} \tag{2}$$

where P_{Wind-T} is the cumulative power generated by the wind turbine setup, η_{Gen} is the wind generator's efficiency, η_{GB} is the gear system's efficiency of a wind turbine, C_P is the wind turbine's power coefficient, A_S is the rotor-swept area of the wind turbine, ρ_{Air} is the density of air, V_{wind} is the wind speed, P_{rated} is the rated power of the wind turbine, V_{rated} is the rated speed of the wind turbine, V_{cut-in} is the cut in velocity of the wind turbine and $V_{cut-off}$ is the cut-off velocity of the wind turbine.

The inclusion of a DIG in this microgrid design ensures power reliability during emergency situations. To optimise its efficiency, the DIG is designed to operate within the 75%–85% load range, with capacity set to cater to 80% of the peak demand in the DC microgrid [10].

In this study, commonly used Li-ion BESS has been employed. Furthermore, DLC has been selected as the DR strategy to assess the effectiveness of DSM.

Optimisation approach: The aim of this optimisation study is to design a standalone DC microgrid while minimizing the lifetime cost and carbon footprint. Multi-objective genetic algorithm-based optimisation problem has been solved. A total of six DEVs have been defined in this optimisation problem: number of solar PV panels (N_{PV}), number of wind turbines (N_{WT}), full load rating of DIG (P_{DG}), total capacity of BESS (E_{BS}), designated minimum SOC limit for BESS (DOD_{Bat}), and the percentage of controllable loads under DLC (P_{DLC}).

Two objective functions were defined to design the optimisation problem. Equation (3) represents the first objective function that addresses the minimization of the total lifetime cost of the DC microgrid. C represents the total lifecycle cost including the investment costs, replacement costs as well as operation and maintenance costs.

$$C = C_{PV} + C_{Wind} + C_{DG} + C_{BESS} + C_{DLC} \tag{3}$$

where C_{PV} is the lifetime cost related to solar PV system, C_{Wind} is the lifetime cost related to wind energy system, C_{DG} is the lifetime cost related to DIG system, C_{BESS} is the lifetime cost related to BESS, and C_{DLC} is the total cost associated with the curtailment of controllable loads with DLC in the lifetime of DC microgrid. The individual cost item in (3), is related to separate systems within the DC microgrid, and each cost related to DLC is calculated in the following Equations (4)–(8), respectively. Any future costs will be converted to net present value considering the interest rate.

$$C_{PV} = N_{PV} \times P_{PV} \left(i_{PV} + \sum_{n=0}^{T_{MG}-1} \frac{om_{PV}}{(1+r)^{T_{MG}-n}} \right) \tag{4}$$

where i_{PV} is the capital cost of solar PV per kW, om_{PV} is the annual operational and maintenance cost of solar PV per unit, T_{MG} is the expected lifetime of the DC microgrid, and r is the interest rate.

$$C_{Wind} = N_{WT} \times P_{Wind-T} \left(i_{WT} + \sum_{n=0}^{T_{MG}-1} \frac{om_{WT}}{(1+r)^{T_{MG}-n}} \right) \tag{5}$$

where i_{WT} is the capital cost of wind energy per kW, and om_{WT} is the annual operational and maintenance cost of wind turbine per kilowatt.

$$C_{DG} = P_{DG} \left(\sum_{n=0}^{\alpha T_{MG}} \frac{i_{DG}}{(1+r)^{\left(T_{MG}-\frac{n}{\alpha}\right)}} + \sum_{n=0}^{T_{MG}-1} \frac{\alpha FC_{DG} P_D RH_{DG} + om_{DG}}{(1+r)^{T_{MG}-n}} \right) \tag{6}$$

where i_{DG} is the capital cost of DIG per kilowatt, om_{DG} is the annual operational and maintenance cost of DIG per kilowatt, FC_{DG} is the fuel consumption of the DIG, P_D is the unit price of diesel, RH_{DG} is the rated maximum running hours per one DIG, and α is the usage of DIG per year, that is, the ratio between running hours per year and maximum running hours.

$$C_{BESS} = E_{BS} \left(\sum_{n=0}^{\beta T_{MG}} \frac{i_{BS}}{(SOC_{Max} - DOD_{Bat}) \times (1+r)^{\left(T_{MG}-\frac{n}{\beta}\right)}} + \sum_{n=0}^{T_{MG}-1} \frac{om_{var}}{(1+r)^{T_{MG}-n}} \right) + P_{MG} \left(i_{CVT} + \sum_{n=0}^{T_{MG}-1} \frac{om_{fixed}}{(1+r)^{T_{MG}-n}} \right) \tag{7}$$

where i_{BS} is the capital cost of BESS per kilowatt hour, om_{var} is the annual variable O&M cost of BESS per kilowatt hour, om_{fixed} is the annual fixed O&M cost of BESS, SOC_{Max} is the maximum allowed SOC for BESS, P_{MG} is the rated capacity of the DC microgrid, i_{CVT} is the capital cost of all power converters per kilowatt, and β is the inverse of the lifetime of BESS.

$$C_{DLC} = P_{MG} \times K_{Con} \times P_{DLC} \times \sum_{n=0}^{T_{MG}-1} \frac{UC_{DLC}}{(1+r)^{T_{MG}-n}} \tag{8}$$

where K_{Con} is the percentage of controllable loads from the rated capacity of DC microgrid, and UC_{DLC} is the cost of interrupting the controllable loads per kilowatt.

In this research, a novel strategy has been applied for the BESS management to account for the state of charge (SOC). In the design of a standalone microgrid, battery degradation must be considered to prevent premature failures of the BESS, which would incur high replacement costs. While maintaining a lower DoD in lithium-ion (Li-Ion) batteries extends their lifespan, sustaining in deep DoD for extended periods reduces the life of BESS [11]. To address this, DOD_{Bat} has been considered as a DEV for the optimisation problem. Specifically, it recommends the continuous operation of the DIG when the BESS reaches DOD_{Bat} until it achieves the SOC_{Max}. Table 1 presents the actions of BESS, DIG, and DYL according to the instant value of $P_{DEF}(t)$ in this optimisation problem according to the designed BESS management strategy. Equation (9) determines the power that BESS should supply in an instant ($P_{DEF}(t)$) where $P_L(t)$ is the total power demand at the instant t.

$$P_{DEF}\ \ (t) = P_L\ (t) -\ P_{DLC}\ (t) - [P_{PV}\ (t) + P_{Wind}\ (t)] \tag{9}$$

To assess the enhancement in the cycle life of the BESS, the rainflow cycle counting algorithm, which is a well-established method for

Table 1. Designed BESS management strategy

Criteria	SOC level	BESS action	Action of DIG	Action of DYL
$P_{DEF}(t) = 0$	All	No action	No action	No action
$P_{DEF}(t) < 0$	$SOC(t) < SOC_{Max}$	Charging	No action	No action
	Otherwise	No action	No action	Dissipate excess power
$P_{DEF}(t) > 0$	$SOC(t) > DOD_{Bat}$	Discharging	No action	No action
	$SOC(t) \leq DOD_{Bat}$	Charging	Operating until SOC reaches SOC_{Max}	No action

counting cycles in BESS, is utilised [12]. The required number of replacements in BESS in the lifetime of the microgrid is then calculated using Equation (10).

$$NR_{Bat} = \frac{Cyc_{BESS}}{(Cyc_{max})_{avg-DOD}} \tag{10}$$

where NR_{Bat} is the required number of replacements of BESS throughout the lifetime of a standalone microgrid, Cyc_{BESS} is the total number of cycles of BESS in the lifetime of the microgrid, and $(Cyc_{max})_{avg-DOD}$ is the maximum achievable number of cycles of BESS according to the average DoD before failure.

The second objective of the optimisation problem in this study is to minimize the carbon footprint from the DC microgrid. In this design, the utilisation of the DIG leads to carbon emissions. The amount of CO_2 emissions, measured in metric tonnes, can be computed using the Equation (11) provided below.

$$CF_{MG} = \frac{FC_{DG} \times ECF_{Diesel} \times EF_{Diesel} \times T_{MG}}{1000} \tag{11}$$

where CF_{MG} is the carbon footprint of the microgrid throughout its lifetime, FC_{DG} denotes the yearly fuel consumption of DIG, EF_{Diesel} is the diesel's emission factor, and ECF_{Diesel} is the energy content of diesel.

Minimising the energy wastage due to curtailment of RES can be done to utilise the maximum output of RES. A resistive DYL has been integrated to dissipate the additional energy content generated by RES. Energy wastage is calculated as in Equation (12) below where E_{WST} is the energy wastage throughout the designated lifetime of the DC microgrid.

$$E_{WST} = \sum_{t=0}^{T_{MG}-1} Max\{0, [P_{PV}(t) + P_{Wind}(t)] - [P_L(t) - P_{DLC}(t)]\},$$
$$when\ SOC(t) = SOC_{Max} \tag{12}$$

To minimize energy wastage from RES in the optimisation problem, the following constraint (13) has been added, defining a maximum allowable energy wastage from the microgrid, denoted as EWT_{max}.

$$E_{WST} \leq EWT_{max} \tag{13}$$

LCOE of the standalone DC microgrid has been calculated as in the below Equation (14) to analyse the performance of the proposed method compared to previous works.

$$LCOE = \frac{C}{Total\ energy\ consumption\ in\ the\ lifespan} \tag{14}$$

The following inequalities (15) and (16) represent the constraints added based on the load flow equation and BESS management.

$$P_L(t) \leq P_{PV}(t) + P_{Wind}(t) + P_{DG}(t) + P_{BS}(t) + P_{DLC}(t) \tag{15}$$
$$DOD_{Bat} \leq SOC_{min} < SOC(t) \leq SOC_{Max} \tag{16}$$

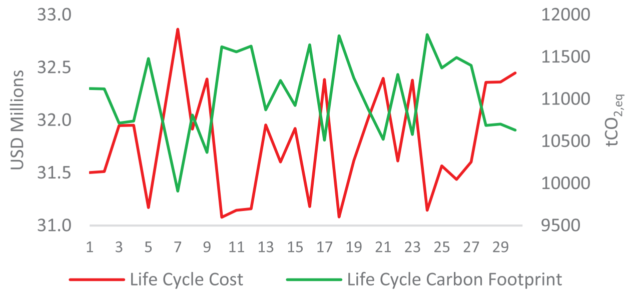

Fig. 2 *Variation of total cost and carbon footprint for the 30 optimised cases*

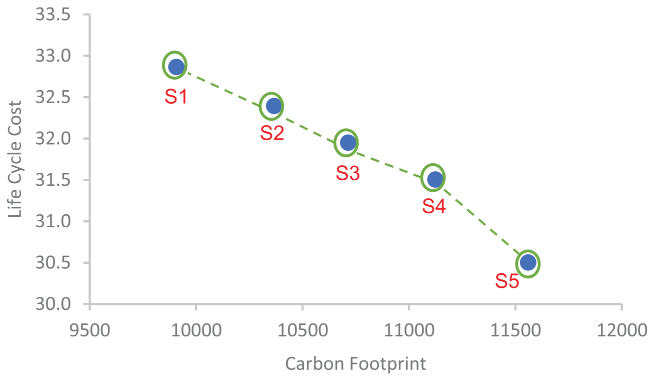

Fig. 3 *Pareto optimal chart for total cost and carbon footprint*

MATLAB simulation: This study proposes a multi-objective optimisation approach based on a genetic algorithm to optimise the sizing of equipment in a DC microgrid comprising wind energy, solar PV, and a DIG as energy sources, BESS as energy storage, and DLC as demand-side management technology. Simulations have been conducted to assess the performance of the method in two cases: area of (a) high penetration of RES and (b) low penetration of RES. To analyse the effectiveness of the proposed method in achieving the objectives, results have been compared with a baseline approach [6], and a modified version of the baseline approach [7]. The difference of the proposed method with those two approaches is presented in Table 2.

The simulation was conducted for a duration of 7 days for both cases of high and low renewable energy outputs, with input data available at 5-min intervals. The load demand data exhibited a peak load of 1196 kW, sourced from freely available power datasets in IEEE PES [13]. The upper boundary (UB) and lower boundary (LB) values used for DEVs are detailed in Table 3. The simulation was performed using MATLAB software version R2023a, employing a multi-objective genetic algorithm solver.

Results and discussion: In this section, approach utilised to solve the optimisation problem has been described considering high-RES output scenario. The optimisation problem was solved multiple times, resulting in nearly seven hundred optimised cases. Among these solutions, the thirty most optimised cases were identified by minimizing the sum of the ratios of three objective function outputs to the average values of objective function outputs. The variation in the total cost and carbon footprint for the life cycle of the DC microgrid, for these 30 optimisation cases has been depicted in Figure 2.

To determine the most optimum solution from the thirty optimised cases, a Pareto optimal chart was constructed, employing the total cost on the horizontal axis and carbon footprint on the vertical axis, as depicted in Figure 3. The green hachure line represents the Pareto front, which showcases the trade-offs between total cost and carbon footprint. Within the Pareto front, five extreme solutions are identified as 'S1', 'S2', 'S3', 'S4', and 'S5' which are circled in green colour.

To determine the most optimised solution among the five extreme solutions, a carbon tax was added to the carbon footprint, and the total life cycle cost, including the carbon tax, was compared. A benchmark rate of 39 USD/tCO_2 was used for the carbon tax calculation [14]. Table 4 presents the lifecycle cost including carbon tax for each five optimum solutions.

Table 2. *Difference of the proposed method with previous two approaches*

	BESS management algorithm	Consideration of battery degradation	Allowable minimum DoD	DSM
Baseline approach [6]	Rule based	No	10%	No
Modified Version [7]	Rule based with DIG operation as cyclic charging	No	10%	No
Proposed Method	Rule based with DIG operation as cyclic charging	Yes	DEV	DLC

Table 3. *Lower and upper boundaries for decision variables*

DEV	LB	UB	Selection criteria
N_{PV}	0	12770	UB—No. of modules required for supply total demand with 5 peak sun hours
N_{WT}	0	80	UB—No. of turbines required to cater to the total demand alone
P_{DG}	1650	2200	LB—Capacity required to supply the total load with 10% LOLP UB—Capacity required to supply total load with 10% overloading (80% of full load operation is assumed)
E_{BS}	0	12770	UB—Capacity required to supply half of daily energy demand
DOD_{Bat}	20%	90%	LB/UB—Minimum and maximum levels of DoD to reduce the impact of battery degradation [9]
P_{DLC}	0	0.5	UB—Assumption of 50% of controllable non-critical loads can always be disconnected from the system

Table 4. *Optimum capacities of solutions in Pareto front in high RES output scenario*

	S1	S2	S3	S4	S5
N_{PV} (No. of PV Modules)	5093	4910	4623	4803	4651
N_{WT} (No. of wind turbines)	53	52	50	51	49
E_{BS} (kWh)	11,428	11,674	12,234	11,962	12,525
DOD_{Bat} (Min)	37.4%	41.5%	42.3%	43.7%	43.5%
P_{DG} (kW)	2184	2174	2182	2168	2166
P_{DLC} (% from controllable loads)	48.4%	47.9%	48.1%	47.8%	48.5%
Lifecycle cost (USD millions)	32.9	32.4	31.5	31.9	30.5
Carbon footprint (tCO_2, eq)	9908	10,368	11,125	10,715	11,561
Carbon tax (USD millions)	0.4	0.4	0.4	0.4	0.5
Lifecycle cost including carbon tax (USD millions)	33.2	32.8	31.9	32.4	31.0

From the results, the optimum DOD_{Bat} is turned out as 43.5%. This indicates that maintaining a higher DoD for the BESS can increase the lifetime of BESS in a standalone microgrid system. The optimal range for DoD is approximately around 40%–45%.

The proposed methodology was then applied to a different dataset from the IEEE PES datasets, which has a lower output of RES [13]. The same methodology used for the high-RES output dataset was applied in this optimisation as well. The most optimal result for the low-RES output dataset is shown in Table 5 below.

As previously mentioned, the solution derived from the proposed method is compared with two previous approaches: a baseline approach [6] and a modified version [7]. To compare the results, LCOE and per unit carbon footprint have been utilised, as the proposed model includes the shutdown of some loads due to DSM. The comparison of results for both high-RES output and low-RES output scenarios is presented in Table 6.

Table 5. *The most optimum solution of Pareto front in a low RES output scenario*

Parameter	Most optimum solution for low RES output
N_{PV} (No. of PV modules)	12,734
N_{WT} (No. of wind turbines)	33
E_{BS} (kWh)	12,513
DOD_{Bat} (Minimum)	43.1%
P_{DG} (kW)	2197
P_{DLC} (% from controllable loads)	49.9%
Lifecycle cost (USD millions)	34.6
Carbon footprint (tCO_2, eq)	45,793

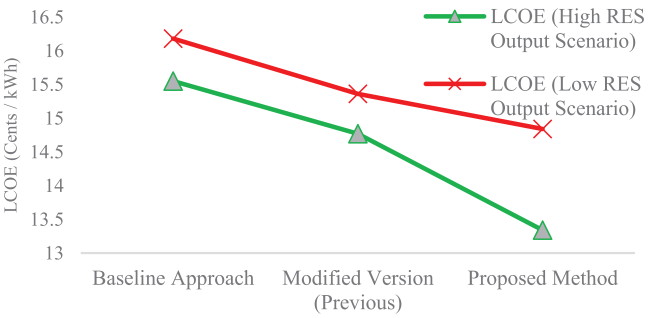

Fig. 4 *Comparison of LCOE from the proposed method with previous works*

As shown in the comparison, the LCOE of the microgrid has been significantly reduced by utilising the proposed multi-objective optimisation method, which includes a novel BESS management algorithm and DSM. For the high-RES output scenario, the proposed methodology reduced the LCOE by more than 10% compared to the benchmark approach. Additionally, the per unit carbon footprint has also been slightly reduced compared to previous approaches. A graphical comparison of LCOE from the proposed method with previous works is presented in Figure 4.

In previous research, the average LCOE for renewable energy-based hybrid standalone microgrids was found to range between 0.15 to 0.25 USD/kWh [15]. However, in this optimisation problem, the LCOE of the microgrid is below 0.15 USD/kWh. This indicates a significant improvement in the cost of standalone microgrids, representing a notable achievement. The main reason for this is the integration of DSM for the DC microgrid design.

Conclusion: In this manuscript, we propose a DC microgrid for a standalone power system consisting of solar PV, wind as RES, DIG, and BESS. A novel multi-objective optimisation strategy based on a genetic algorithm has been introduced to determine the optimal sizes of the different components within the DC microgrid. The objective functions of this optimisation problem aim to minimize both the lifecycle cost and the carbon footprint of the DC microgrid. To address battery degradation, the DoD of the BESS is included as a DEV in the optimisation algorithm. The rainflow counting algorithm was used to calculate the cycles and determine the cycle life of the BESS. DLC has been incorporated as a DSM technique to shut down a portion of controllable loads from the demand.

Table 6. Comparison of results from the proposed method with previous work in both scenarios

		Baseline approach	Modified version (Previous)	Proposed method
High-RES Output scenario	LCOE (Cents/kWh)	15.55	14.77 (5.02% ↓)	13.34 (14.21 ↓)
	Per unit carbon footprint ($kgCO_{2,\ eq}$/kWh)	0.056	0.054 (4.13% ↓)	0.050 (11.89% ↓)
Low-RES output scenario	LCOE (cents/kWh)	16.18	15.36 (5.04% ↓)	14.84 (8.20%)
	Per unit carbon footprint ($kgCO_{2,\ eq}$/kWh)	0.2150	0.2017 (6.16% ↓)	0.1965 (8.57% ↓)

Simulations were conducted under two scenarios: high-RES output and low-RES output. For the high-RES output scenario, the LCOE of the DC microgrid was found to be 13.34 cents/kWh, with a per unit carbon footprint of 0.05 $kgCO_2$ eq/kWh. In the low-RES output scenario, the LCOE was 14.84 cents/kWh, with a per unit carbon footprint of 0.1965 kg CO_2 eq/kWh. This represents a 14.21% reduction in LCOE compared to the baseline approach in the high-RES scenario and an 8.2% reduction in the low-RES scenario. In terms of carbon footprint, the proposed approach shows an 11.89% reduction in the high-RES output scenario and an 8.57% reduction in the low-RES output scenario. These results indicate that incorporating proper BESS management strategies and DSM into the design of standalone DC microgrids can significantly reduce lifecycle costs and carbon emissions compared to current approaches. The proposed method is particularly advantageous for designing standalone DC microgrids with higher RES output. Additionally, the optimum value of the minimum DoD for the BESS was found to be 43.5% for the high-RES scenario and 43.1% for the low-RES scenario. This suggests that maintaining the DoD within the range of 40%–45% in standalone DC microgrids will enhance the life of BESS and reduce lifecycle costs.

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