Heuristic Enhanced Evolutionary Algorithm for Community Microgrid Scheduling

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ABSTRACT Scheduling of community microgrids (CMGs) is an important and challenging optimization problem. Generally, the optimization is performed to schedule resources of CMGs at minimum cost. In recent years, a number of algorithms have been proposed to solve such problems. However, the performance of these algorithms is far from ideal due to the presence of different complex equality and inequality constraints in CMGs. Furthermore, most of the current works ignore energy storage (ES) degradation costs in the optimization model, which has a significant impact on the life of ES. This paper develops both single and bi-objective optimization models by considering the life of ES along with the operating cost for scheduling a CMG. An efficient heuristic-enhanced Differential Evolution (DE) approach is proposed to solve these models; by exploiting the structure of equality constraints, the proposed heuristic is able to generate feasible solutions quickly. The significance of the proposed heuristic is that it can generate a high-quality solution with a considerably lower computational effort. Numerical simulations were performed to evaluate the performance of the proposed method, and obtained results were compared with the state-of-the-art algorithm. The simulation results corroborate the efficacy of the proposed method.

INDEX TERMS Community microgrid, energy scheduling, energy storage system, differential evolution, distributed generators, heuristic.

NOMENCLATURE

| ACRONYM | DESCRIPTION |
|---------|-------------|
| CMG | Community microgrid |
| CV | Constraint violation |
| DE | Differential evolution |
| DER | Distributed energy resources |
| DG | Distributed generators |
| ESS | Energy storage systems |
| FC | Fuel cell |
| MG | Microgrid |
| MT | Micro-turbine |
| PV | Photovoltaic |
| RES | Renewable energy resources |
| WT | Wind turbine |

| PARAMETER | DESCRIPTION |
|-----------|-------------|
| $\eta_{DG}$ | Generation efficiency of $i^{th}$ DG |
| $\Delta P_{\max DG} / \Delta P_{\min DG}$ | Ramp down/up rate of DG |
| $C_{\text{maint}}$ | Maintenance cost of $i^{th}$ DG |
| $C_{\text{run}}$ | Running cost of $i^{th}$ DG |
| $C_{\text{inv}}$ | Investment cost of ESS |
| $C_{\text{res}}$ | Residual value of ESS |
| $C_N$ | Number of constraints |
| $C_p$ | Crossover probability |
| $E_{\text{ess}}$ | Energy level of ESS |
| $E_{\text{min ess}} / E_{\text{max ess}}$ | Minimum/maximum energy level of ESS |
| $F$ | Scaling factor |
| $L_{\text{static}}$ | Static degradation of ESS |
| $N_{\text{cycle}}$ | Cycle life of ESS |
| $N_{DG}$ | Number of DGs |
| $N_p$ | Population size |
| $P_{\text{min DG}} / P_{\text{max DG}}$ | Minimum/maximum capacity of DG |
| $P_{\text{min ess}} / P_{\text{max ess}}$ | Minimum/maximum charging/discharging power of ESS |
| $T_{\text{shelf}}$ | Shelf life of ESS |
| $T$ | Schedule horizon |

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I. INTRODUCTION

The conventional electrical grid is a vast electric network comprising of energy consumers, long transmission and distribution systems, and large-scale fossil fuel-based power plants. While fossil fuel increases carbon footprint in the environment, power losses incurred in the long-distance transmission reduces energy efficiency. Environmental concerns have forced inclusion of clean renewable energy sources (RESs) into the grid [1]. However, the dynamics of the existing network does not allow high penetration of intermittent renewable energy sources [2]. To overcome these problems, the notion of microgrid (MG) came into existence. A microgrid is essentially a small-scale electric network. The community microgrid (CMG) is a type of MG designed to serve a particular community of energy consumers. It utilizes locally available distributed generators (DGs) such as micro-turbine, fuel cells, PV array and energy storage systems (ESSs) to meet the energy demand [3]. It can also operate in conjunction with the utility grid as a single controllable entity [4]. Consumers of the CMGs being in the vicinity of energy sources avoids power losses caused by long-distance energy transmission; this leads to improved energy efficiency [5].

Unlike the conventional grid, CMG possesses the capability of bidirectional flow of energy/information. This property enables CMGs to facilitate the integration of a high amount of renewable energy. CMGs not only reduce energy dependency on the utility grid but also can provide energy supply to the community during a grid blackout. Furthermore, it also enables end-users (consumers) to produce energy using renewable energy sources such as rooftop solar systems. In doing so, it turns the passive consumers into prosumers (consumer + producer). These prosumers can sell the excess energy to their neighbours/grid by participating in the electricity market [6]. As a results, they can save on their energy bills or make financial gains. Therefore, it might be possible to have flexible and reliable future electric grid with lower carbon emission through the implementation of CMGs.

Although CMGs offer numerous benefits, it face operational and economic challenges. Energy management optimization is performed to achieve optimal operation of CMGs. Generally, such optimization problems consider the reduction of operating cost, and environmental pollution, or maximization of profit as the objective function. These objectives of the CMG energy management problem can be obtained by optimal scheduling of different DGs, energy exchange with utility grid and ESSs while satisfying associated constraints [7]. Interaction among different stakeholders (e.g. DGs, utility grid, etc.) of the microgrid makes its’ operation complex and challenging. Also, the uncertainties associated with renewable generations [8] and controllable loads (e.g., electric vehicles) create power imbalance in the CMGs [9].

The power mismatch poses a threat to microgrid stability and may often lead to unprofitable operation. ESSs have been utilized to overcome the problem of load generation imbalance [10], [11]. Besides the constraints of different DGs and power balance, the constraint of the energy level of ESSs further complicates the problem. Moreover, due to the higher investment cost and the limited life cycle of ESSs, it is crucial to control their charge and discharge cycle; this will prolong the life span of ESSs. The amount of degradation of the ESS unit depends on the depth of its operating cycle. Hence, the ESS degradation cost need to be considered in the objective function of the energy management optimization problem. However, most of the related works did not adequately address the ESS degradation issue.

Numerous optimization techniques, including both classical methods and computational intelligence techniques, have been employed to solve such energy management problems of CMGs. Classical methods such as dynamic programming (DP) [12], mixed-integer linear programming (MILP) [13], and non-linear programming [14], have been used for optimization of energy management problem. In [15], day-ahead scheduling of a MG is performed to reduce the operating cost. Approximate dynamic programming (ADP) based scheduling framework is proposed in this work. In [13], MILP is used for day-ahead scheduling of the combined heat and power (CHP) unit in a residential MG. These conventional techniques have been found to be effective in small-scale optimization problems. However, their performance degrades significantly when the dimensionality of the problem is increased i.e., in large scale MGs. Moreover, the problem formulation for these conventional methods requires to meet specific mathematical properties or needs simplifications.

Computational intelligence techniques have also been widely used for MG energy management and other applications [16], [17]. For example, meta-heuristic technique like memory-based genetic algorithm (GA) is proposed in [18] for cost minimization of a microgrid for 24 hours scheduling. The proposed GA is reported to demonstrate better performance. In [19], day-ahead scheduling considering

VARIABLE

| Variable | Description |
|----------|-------------|
| $C_t$    | Cost at hour $t$ |
| $C_{degr}$ | Degradation cost of ESS |
| $C_{grid}$ | Cost of power exchange with grid |
| $b_{buy}$ | Electricity buying price from the grid |
| $s_{sell}$ | Electricity selling price to the grid |
| $L_{degr}$ | Fraction of life degradation of ESS |
| $L_d$    | Dynamic degradation of ESS |
| $P_{ess}$ | Output power of ESS |
| $P_{fc}$ | Output power of FC |
| $P_{grid}$ | Power exchange with the grid |
| $P_{mt}$ | Output power of MT |
| $P_{RES}$ | Power output from renewable generation |
| $v_t$    | Load-generation mismatch at $t^{th}$ hour |

INDICES

- $k$: Index for charging/discharging cycle of ESS
- $m$: Index for a constraint
- $i$: Index of DGs/solution vectors
- $t$: Discrete time instant

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profit maximization of reconfigurable microgrid is presented. The authors solved the scheduling problem using time-varying acceleration coefficients particle swarm optimization (TVAC-PSO) algorithm. A multi-carrier energy microgrid is scheduled in [20] by optimizing operating cost of MG for a day. A wavelet theory based adaptive whale optimization algorithm is proposed to solve the optimization problem. Hourly scheduling of an islanded MG over 24 hour is presented in [21]. The authors used PSO algorithm for scheduling MG resources at minimum operating cost. A multi-objective day ahead scheduling of residential building MG with virtual energy storage is proposed in [22]. The operating cost, thermal comfort level, and pollutant emission are taken as objectives of the scheduling optimization and solved with non-dominated sorting genetic algorithm II (NSGA-II).

Although computational intelligence techniques have been employed successfully for solving a wide range of microgrid energy management problems, their performance is far from ideal due to the presence of complex constraints in the problem. In addition, as mentioned earlier, in most of the related works, degradation cost of ESSs have been either neglected completely or oversimplified. Consequently, the life of ESSs was not addressed properly during the optimization process. While some literature [23], [24] included degradation cost of ESS in single-objective small scale MG scheduling, bi-objective approach for larger MG systems having multiple ESS units were not investigated.

Therefore, in this work, ESS degradation cost is considered for the best scheduling of CMG components for a cycle of 24 hours. The problem is formulated and solved using two different approaches: i) single objective and ii) bi-objective optimization. In the former, the degradation cost is derived from the ESS operating cycle and incorporated with the operating cost. The later considers two different objective functions: one is to minimize the operating cost and second is to maximize the ESS life. To solve both optimization problems, heuristic enhanced differential evolution (DE) is introduced. It is well-known that satisfying the equality constraints in constrained optimization is a challenging task. As a consequence, the existing search approaches consume significant amount of computational effort to generate feasible solutions. However, because of the nature of equality constraints considered in this work, a simple heuristic is proposed in this paper which is able to generate feasible solutions quickly. The inclusion of this heuristic in the evolutionary search process helps to obtain high quality solutions with significantly lower computational effort. To make a link with the literature, this heuristic can be recognized as an in-feasibility repairing mechanism. Different simulation cases are considered to solve a CMG scheduling problem using proposed solution approaches. The obtained results are compared with ones obtained from the state-of-the-art algorithms. The results reveal that the proposed method has merits in terms of both solution quality and consistency.

The main contributions of this work are:
- CMG scheduling problem is formulated considering degradation cost of ESSs to account for its operational effect on long-term capital cost.
- An efficient heuristic is developed for equality constraint satisfaction which enhances the performance of proposed DE for solving CMG scheduling.
- Small scale CMG, as well as CMG of larger dimension, are scheduled to objectively assess the performance of the proposed method.
- Both single and bi-objective approaches are employed to solve the CMG scheduling problem.

This research considers a CMG with different DGs, consumer loads, grid connection, and multiple ES units with individual charging and discharging characteristics. Performance analysis of the proposed heuristic is the primary focus of this paper. While dynamic electricity price, load, and renewable generations over 24 hours are considered, the uncertainty of the parameters are left for the future work.

Rest of the paper is organized as follows. Section II describes the CMG system and mathematical problem formulation. The proposed algorithm and heuristic are elaborated in section III. Section IV presents and discusses the simulation results. Finally, conclusion and future work are presented in section V and section VI, respectively.

II. SYSTEM MODEL AND PROBLEM FORMULATION

In this section, the overview of a CMG and its optimization model formulation is presented.

A. OVERVIEW OF COMMUNITY MICROGRID

In this work, a representative model of a CMG is considered. It consists of different distributed generators (DGs) and residential loads. The DG units considered in the microgrid include photovoltaics (PVs), wind turbines (WTs), energy storage systems (ESSs), fuel cells (FCs) and micro-gas turbines (MTs). The CMG is connected to the utility grid can participate in the bidirectional energy exchange when required. The microgrid can sell and purchase electricity to and from the grid, respectively; this energy exchange depends on the electricity price obtained from the electricity market operator. Usually, the microgrid tends to buy power from the utility grid when the electricity price is low and sell when it is high. The power from renewable energy sources varies over time due to their intermittent nature. Renewable generators are non-dispatchable and utilized fully when available. The model of a community microgrid is presented in Fig. 1 showing the direction of energy flow of its different components.

B. PROBLEM FORMULATION

In this subsection, both single and bi-objective optimization models for a CMG are discussed. PVs and WTs being the non-dispatchable renewable energy sources are considered to have zero operating cost. However, their maintenance cost cannot be ignored. Therefore, the decision variables $x$ for
the optimization problem includes the power output of each dispatchable DG unit and power exchange with the utility grid as given in (1).

\[ x = \left[ p_{\text{MT}}, p_{\text{FC}}, p_{\text{ESS}}, p_{\text{grid}} \right] \] (1)

where \( p_{\text{MT}}, p_{\text{FC}}, p_{\text{ESS}}, \) and \( p_{\text{grid}} \) are the output power of MT, FC, ESS, and grid power exchange, respectively.

1) SINGLE OBJECTIVE FORMULATION

The aim of the single objective CMG optimization model is to produce a schedule of the microgrid components at minimum total cost. The objective function of the minimization problem can be formulated as in (2).

\[ \min x \quad F_1 = \sum_{i=1}^{T} C_i \] (2)

where \( F_1 \) is the total cost of CMG over the time horizon \( T \) and \( C_i \) is the cost at \( t^{th} \) hour. \( C_i \) comprises of operational and maintenance cost of all DGs (\( C_{\text{DG}_i} \)), and cost of power exchange with utility grid (\( C_{\text{grid},i} \)) and ESS degradation cost (\( C_{\text{ess},i} \)) as shown in (3).

\[ C_i = \sum_{i=1}^{N_{DG}} \left[ C_{\text{DG}_i} + C_{\text{grid},i} + C_{\text{ess},i} \right] \] (3)

\[ C_{\text{DG}_i} = \sum_{i=1}^{N_{DG}} \left\{ \frac{p_{\text{DG}_i} \cdot \text{run}}{\eta_{\text{DG}_i}} + p_{\text{DG}_i} \cdot \text{maint} \right\} \] (4)

\[ C_{\text{grid},i} = \begin{cases} p_{\text{grid}} \cdot \text{price}_{\text{buy}} & \text{if } p_{\text{grid}} > 0 \\ p_{\text{grid}} \cdot \text{price}_{\text{sell}} & \text{if } p_{\text{grid}} < 0 \\ 0 & \text{Else} \end{cases} \] (5)

\[ C_{\text{ess},i} = (C_{\text{inv}} - C_{\text{ess}}) \cdot L_{\text{degr}} \] (6)

The operational and maintenance cost of DGs at \( t^{th} \) time is equal to the sum of the cost of each DG at that instant. Here, \( p_{\text{DG}_i} \), is the active power generation of \( i^{th} \) DG at \( t^{th} \) instant; running cost, maintenance cost and generation efficiency of the \( i^{th} \) DG are denoted by \( C_{\text{DG}_i} \cdot \text{run}, C_{\text{DG}_i} \cdot \text{maint}, \) and \( \eta_{\text{DG}_i}, \) respectively. \( N_{DG} \) represents the number of DG units.

The cost of energy transaction with the grid is assumed positive if it is bought from the grid and negative when it is sold. \( p_{\text{grid}}, \text{price}_{\text{buy}}, \) and \( \text{price}_{\text{sell}} \) are the transacted power, per unit cost of electricity buying and selling respectively. In this work, electricity buying and selling price are considered to be the same. However, in real energy transaction, utility grid buys energy from CMG at a lower price. This assumption does not affect the proposed solution approach, and different rates can be easily incorporated.

\( C_{\text{inv}}, C_{\text{ess}} \) and \( L_{\text{degr}} \) represent the investment cost, residual value and fraction of life degradation of ESS, respectively, in (6). The residual value is the scrap value of the ESS unit at the end of its lifetime.

To calculate ESS degradation cost and its life, firstly, ESS life degradation is measured; this degradation consists of two-parts: static degradation \( (L_s) \) and dynamic degradation \( (L_d) \) as shown in (7). The static degradation refers to the deterioration of internal functional properties of the ESS unit. Such degradation increases the internal resistance of ESS, which eventually reduces ESS capacity [25].

\[ L_{\text{degr}} = L_s + L_d \] (7)

Static degradation occurs irrespective of the ESS operating modes and is related to its shelf life \( (T_{shelf}) \) as given below in (8).

\[ L_s = \frac{100\%}{T_{shelf}} \] (8)

On the other hand, dynamic degradation depends on ESS operation (charge-discharge cycle), specifically, depth of operating cycle. Higher the value of cycle depth, greater is the dynamic degradation and vice versa. For determination of dynamic degradation, rainflow cycle counting algorithm [26], initially used in metal fatigue estimation, has been applied successfully. It counts the irregular charge/discharge cycles of ESS along with the corresponding cycle depths [23], [27]. After determining charge/discharge cycles and their cycle depths, \( L_d \) can be calculated using (9).

\[ L_d = \sum_{k=1}^{N_{\text{cycle}}} \frac{n_k}{C_{\text{ess}}} \cdot C_{\text{ess}} \] (9)

where \( n_k \) is the number of full and half cycle counted using rainflow algorithm at the cycle depth of \( C_{\text{ess}}; s_p \) is the slope of ESS degradation curve. Total cycle life of the ESS is denoted by \( N_{\text{cycle}} \).

Having determined the ESS degradation, its expected life after one day simulation can be obtained using (10) [24]

\[ ESS_{life} = \frac{1}{L_{\text{degr}}} \] (10)
2) BI-OBJECTIVE FORMULATION

In the bi-objective approach, the operating cost is minimized while ESS life is maximized. ESS life is inversely proportional to its degradation cost as evident from (6) and (10). The bi-objective optimization problem can be formulated as in (11).

\[
\min_{x} \sum_{t=1}^{T} C_{DG_t} + C_{grid_t}
\]

\[
\max_{x} E_{SS_{life}}
\]

where \( F_1 \) represents the operating cost only ignoring ESS degradation part considered in single objective approach; the second objective \( F_2 \) considers ESS life presented in (10).

3) CONSTRAINTS

The individual component constraints, as well as the system constraints, must be satisfied in both single and bi-objective optimization. The active power of all dispatchable DG units are limited by their upper and lower limit given below in (12) [9].

\[
P_{DG_{min}} \leq P_{DG_t} \leq P_{DG_{max}}
\]

where \( P_{DG_{min}} \) and \( P_{DG_{max}} \) are the minimum and maximum power output of any DG unit. The ramp rate constraints of the DG units are expressed as in (13).

\[
\nabla P_{DG_{up}} \leq P_{DG_t} - P_{DG_{t-1}} \leq P_{DG_{down}}
\]

where \( \nabla P_{DG_{up}} \) and \( \nabla P_{DG_{down}} \) are the ramp up and ramp down limits of DG units per unit time, respectively.

The maximum charging/discharging rate limits the charging/discharging power of the energy storage device. The ESS power is considered positive when discharged and negative when charged. For longer ESS life, the energy level of the ESS due to charging/discharging is always maintained within a safe limit [28]. The constraints for ESS are presented below in (14) and (16).

\[
P_{ess_{max}} \leq P_{ess_t} \leq P_{ess_{max,Grid}}
\]

\[
E_{ess_{t+1}} = \begin{cases} 
E_{ess_t} + P_{ess, t} \eta^C \nabla t & \text{if } P_{ess_t} < 0 \\
E_{ess_t} + \frac{P_{ess, t}}{\eta^D} \nabla t & \text{if } P_{ess_t} > 0 \\
0 & \text{Else}
\end{cases}
\]

\[
E_{ess_{min}} \leq E_{ess_t} \leq E_{ess_{max}}
\]

where \( P_{ess_{max}} \) and \( P_{ess_{max,Grid}} \) are the maximum discharging and charging power; \( \eta^C \) and \( \eta^D \) are the charging and discharging efficiency. Energy level of the storage device \( E_{ess} \) is limited by its maximum \( (E_{ess_{max}}) \) and minimum \( (E_{ess_{min}}) \) level.

At any instant, the sum of power generation must be equal to the amount of power consumption in the CMG. The energy sources in the CMG includes the output of DGs, including RESs, energy bought from the utility grid and discharged from ESSs. On the other hand, the power consumption includes the power demand of residential load, electricity sold to the utility grid, and charging power of ESSs. The equality constraint of the power balance is shown in (17).

\[
N_{DG} \sum_{i=1}^{N_{DG}} P_{DG_t} + \sum_{t} P_{RES_t} + P_{grid_t} + P_{ess_t} - P_{load_t} = 0
\]

III. PROPOSED ALGORITHM

In this section, the proposed algorithm for solving both single and bi-objective CMG problems is discussed. Of many evolutionary algorithms (EAs), one of the most popular EAs, namely, Differential Evolution (DE) is considered. The primary motivation of using DE lies in its superior performance in solving problems with continuous variables, as shown in many real-world problems, including other power system problems [29]. The focus of this work is to develop an efficient algorithm for CMG optimization, for this, a useful heuristic is proposed to enhance the performance of DE. However, it is noted that the proposed heuristic is not limited to be used for DE only, it can be used for any other EAs. This heuristic is designed to obtain high-quality feasible solutions after repairing infeasible ones. The pseudocode of the proposed solution approach is given in Algorithm 1, with their steps, are discussed below. Furthermore, for better illustration of the steps the flowchart of the proposed method is shown in Fig. 2.

Algorithm 1 Proposed Method for Scheduling of CMG Energy Resources

Require: CMG data, algorithm parameters,
1: Initialization of \( x \) as in subsection III-A
2: for gen \( = 1 : genMax \) do
3: \( \) Repair \( x \) using subsection III-B
4: \( \) Fitness Evaluation according to subsection III-C
5: \( \) Selection as per subsection III-D
6: \( \) Evolution of \( x \) based on DE operators, as in subsection III-E
7: if termination criteria met then
8: \( \) STOP
9: \( \) end if
10: end for

The proposed solution approach initializes a population with randomly generated solutions in step 1. After that for each generation of the algorithm, the solution vectors are repaired with proposed heuristic, evaluated, selected and evolved according to step 3-6. These steps are repeated until termination criteria is met. Steps of Algorithm 1 are explained in the following subsections.

A. INITIALIZATION

The algorithm starts with the generation of the initial population of solutions, according to (18). The initial population is generated using Latin hypercube sampling (LHS).

\[
\tilde{x}_i = \tilde{x}_{min} + (\tilde{x}_{max} - \tilde{x}_{min}) LHS(NP) \quad \forall \in N_P
\]
where $N_P$ and $i$ denotes the population size and index of solution vector. $\bar{x}_{\text{min}}$ and $\bar{x}_{\text{max}}$ are the lower and upper bounds of decision variables.

### B. PROPOSED HEURISTIC

As CMG scheduling is a complex, constrained optimization problem, most of the initial (or new) solutions are infeasible. An EA would take significant amount of time to get feasible solutions via selection pressure and its search process. As a result, the convergence of the algorithm is likely to be slow. This problem becomes worse with the presence of equality constraints like (17). Intermittent generations from renewable sources and ESS energy level constraint further complicate the issue. Therefore, to enhance the convergence of the algorithm, an efficient but straightforward heuristic approach is proposed in this subsection. The pseudocode of the heuristic is discussed in Algorithm 2. All infeasible solutions having non-zero constraint violation ($CV$) are repaired using Algorithm 2 to make corresponding $CV = 0$ or at-least minimize the $CV$.

The proposed heuristic starts with the equality constraint as it is very challenging to satisfy in generating the feasible solutions. Here, the violation in equality constraint (load-generation imbalance) $v_t$ is enumerated first, as shown in Algorithm 2. Then, any inequality constraint violations are corrected in such a way that minimize or eliminate deviation from equality constraint, while satisfying other constraints. For example, consider a CMG having three DGs, where DG1 and DG3 are the costliest and the cheapest units respectively. At any particular hour, suppose, due to the randomly generated solutions the aggregated production from DGs is 50 kW (DG1 = 10 kW, DG2 = 18 kW, DG3 = 22 kW) to meet the load of 40 kW. The deviation in power balance due to the excess generation (10 kW) can be removed by reducing production from the costliest unit, which is DG1 in this case. If DG1 only partially eliminates deviation due to its minimum generation constraint, then rest of the excess power will be reduced from next costlier unit, i.e. DG2 and so on. To minimize the ESS degradation cost (or maximize ESS

#### Algorithm 2 Proposed Heuristic

1. calculate load-generation imbalance $v_t$ for all $t$
2. $v_t = \text{total generation-load}$
3. for $t = 1 : \text{simulation period}$ do
4. sort per unit energy cost of each dispatchable DGs and grid
5. if $v_t \neq 0$ then
6. while $v_t > 0$ do
7. Reduce output of costlier DG units sequentially until $v_t = 0$ or minimum. start with costliest unit
8. if costlier unit under consideration is an ESS then
9. Reduce ESS output by the amount that does not violate ESS constraints and update $\bar{x}$
else
10. reduce output by maximum possible amount that required for minimum $v_t$ and satisfy unit’s constraints. update $\bar{x}$
end if
11. end while
12. end if
13. while $v_t < 0$ do
14. In similar way of steps 7-10, increase output of cheaper DG units sequentially until $v_t = 0$ or minimum. start with cheapest unit
15. end while
16. end for

- Fig. 2. Flowchart of the proposed method.
life), the proposed heuristic tracks the ESS energy level and regulates its charging/discharging for possible minimum cost.

**C. FITNESS EVALUATION**

Each solution is evaluated to determine its fitness corresponding to the objective function and the system constraints. The objective value corresponding to a solution vector \( \mathbf{x}_i \) is denoted as \( f_i \) and corresponding constraint violation is evaluated as in (19).

\[
CV_i = \sum_{m=1}^{C_N} g_m(\mathbf{x}_i) \quad (19)
\]

where \( g_m \) and \( C_N \) represent any particular constraint and number of constraints, respectively. Total constraint violation corresponding to \( i^{th} \) solution is \( CV_i \). Any solution vector \( \mathbf{x}_i \) is considered feasible if \( CV_i = 0 \), otherwise it is considered infeasible.

**D. SELECTION**

After evaluating all the solutions of a generation, they are sorted based on the well-known principle of non-dominated sorting and crowding distance [30]. In the selection process, individual solutions are ranked according to their value of \( f \) and \( CV \). Solutions with a minimum amount of \( CV \) are always preferred. If the value of \( CV \) for all solutions are zero, then the solution with minimum \( f \) is chosen as the minimization problem is considered in this work. If there exist solutions with the same value of \( f \), then solutions having less crowding distance with the neighbouring solutions are selected. Following this process, the best solution vectors are passed to the next generation.

**E. EVOLUTION**

The solutions of a generation are sorted based on the selection operator (subsection III-D). Then, new solutions are generated using two DE operators, namely mutation, and crossover.

Among different variants of mutation operator, ‘DE/rand/1’ is considered in this work for simplicity. This operator generates a new parameter vector known as the mutant vector from the parent vector of the population using (20).

\[
\mathbf{v}_{i,k+1} = \mathbf{x}_{r_1,k} + F(\mathbf{x}_{r_2,k} - \mathbf{x}_{r_3,k}) \quad (20)
\]

where \( r_1, r_2, \) and \( r_3 \) are three mutually different random integers and distinct from \( i \). \( F \) is the mutant vector and \( F \) is the scaling factor \( \in [0, 2] \) which controls the differential variation. For maintaining diversity in the perturbed population vector, crossover operator is applied on the mutant vector and offspring/trial vector is generated as shown in (21)

\[
\mathbf{u}_{ji,k+1} = \begin{cases} 
\mathbf{v}_{ji,k+1} & \text{if } rand \leq C_{rp} \\
\mathbf{x}_{ji,k} & \text{if } rand > C_{rp} 
\end{cases} \quad (21)
\]

where \( j \) and \( C_{rp} \) are the index of decision variable and crossover probability respectively. \( rand \) is used to generated uniform random number \( \in [0, 1] \).

**IV. RESULTS AND DISCUSSION**

The proposed heuristic-based DE is applied for scheduling a community microgrid. The day-ahead hourly predicted data of CMG is shown in Table 1. The rating of different DGs and their per-unit costs are presented in Table 2. The power exchange with the utility grid is limited between -50 kW and 100 kW. The minimum, maximum, and rated capacity of ESS is set to 40 kWh, 200 kWh, and 222 kWh, respectively. The data used in this work are extracted from literature [9], [31].

In this work, both (i) single objective and (ii) bi-objective solution approaches have been simulated to investigate the performance of the proposed heuristic based method. Following three different cases have been considered to simulate the single objective approach.

- Case-1: minimize CMG operating cost only without considering ESS degradation cost in the objective function.
- Case-2: add ESS degradation cost with objective function as in (3) and solve as single-objective problem.
- Case-3: increase the CMG dimension by adding more DGs and loads. Then, solve as in case-2.

**TABLE 1. Day-ahead hourly predicted data of CMG.**

| Time (hour) | PV (kW) | WT (kW) | Load (kW) | Electricity price (€/kWh) |
|------------|---------|---------|-----------|--------------------------|
| 1          | 0       | 1.785   | 52        | 0.23                     |
| 2          | 0       | 1.785   | 50        | 0.19                     |
| 3          | 0       | 1.785   | 50        | 0.14                     |
| 4          | 0       | 1.785   | 50        | 0.12                     |
| 5          | 0       | 1.785   | 56        | 0.12                     |
| 6          | 0       | 0.915   | 63        | 0.20                     |
| 7          | 0       | 1.785   | 70        | 0.23                     |
| 8          | 0.2     | 1.305   | 75        | 0.38                     |
| 9          | 3.75    | 1.785   | 76        | 1.5                      |
| 10         | 7.525   | 3.09    | 80        | 4                       |
| 11         | 10.45   | 8.775   | 78        | 4                       |
| 12         | 11.95   | 10.41   | 74        | 4                       |
| 13         | 23.9    | 3.915   | 72        | 1.5                     |
| 14         | 21.05   | 2.37    | 72        | 4                       |
| 15         | 7.875   | 1.785   | 76        | 2                       |
| 16         | 4.225   | 1.305   | 80        | 1.95                    |
| 17         | 0.55    | 1.785   | 85        | 0.60                    |
| 18         | 0       | 1.785   | 88        | 0.41                    |
| 19         | 0       | 1.302   | 90        | 0.35                    |
| 20         | 0       | 1.785   | 87        | 0.43                    |
| 21         | 0       | 1.3005  | 78        | 1.17                    |
| 22         | 0       | 1.3005  | 71        | 0.54                    |
| 23         | 0       | 0.915   | 65        | 0.30                    |
| 24         | 0       | 0.615   | 56        | 0.26                    |

**TABLE 2. DG specifications.**

| DG | Min (kW) | Max (kW) | Running cost (€/kWh) | Maintenance cost (€/kWh) |
|----|----------|----------|----------------------|--------------------------|
| FC | 3        | 30       | 0.2                  | 0.04                     |
| MT | 6        | 30       | 0.4                  | 0.12                     |
| ESS| -30      | 30       | -                    | 0.02                     |
| PV | 0        | 25       | -                    | 0.08                     |
| WT | 0        | 15       | -                    | 0.11                     |
Among the three cases mentioned above, case-1 (without ESS degradation cost) is a benchmark problem that was taken from [9]. Therefore, the performance of the proposed method is directly compared with the state-of-the-art algorithm for the case-1 [9]. In cases 1 and 2, ESS was assumed to be exhausted at the beginning of the day ahead scheduling, therefore an initial energy level was set to its lower bound. However, in case-3, having multiple ESS units, different initial energy levels were set. Furthermore, a bi-objective simulation was considered, which is the larger CMG instance of case-3 with an additional objective function to maximize ESS life.

All of the above simulation cases were solved using two variants of the proposed method: (i) DE with heuristics (DE-H) and (ii) DE without heuristics (DE-NH), under the same computational budget and problem’s data. For each case, both variants of the algorithm were run independently for 31 different times, to carry out statistical analysis and verify the robustness of the proposed method. For each run, the number of generation was set to 1200, and population size was considered to be four times the number of decision variables (i.e., 384) in case-1 and case-2 of single-objective approach. The stopping criteria of the algorithm was set to the maximum number of generations. The population size for case-3 (single-objective) and bi-objective problem was chosen to be 400. The proposed algorithms were implemented on a computer with a 3.20 GHz Intel Core i7 processor with 16 GB of RAM in the MATLAB (R2018a) environment.

In the following subsections, results of all the simulation cases are presented.

A. SINGLE OBJECTIVE APPROACH

1) CASE-1

This case aims to schedule CMG components for the duration of 24 hours with minimum possible operating cost. The operating cost includes running and maintenance cost of DG units as well as energy exchange cost with utility grid. For a fair comparison with [9], the degradation cost of ESS is not considered in this case.

The convergence plot of the median run of the proposed algorithms for the case-1 is shown in Fig. 3. Although DE-NH reached close to the same final fitness value as DE-H, it took much longer compared to DE-H. Furthermore, DE-H, by virtue of repair, obtained feasible solutions at the beginning, whereas DE-NH found the first feasible solution after 25 generations.

The simulation results obtained from the proposed method are presented in Table 4 and Table 5. The findings presented indicate that DE-H produced a better result with lower standard deviation. Furthermore, for the sake of comparison with literature, the best, worst, average and standard deviation (STD) of the electricity production cost of microgrid is presented in Table 3. The production cost is calculated by deducting the revenue (negative cost) earned from energy selling to the grid from operating cost. The obtained results were compared with the case one presented in [9] where the electricity production cost was optimized. The electricity production cost includes the operating cost of DGs and energy purchase cost from the utility grid. Results show that the proposed DE-H had an electricity production cost of €1160.60; which is lower than the value reported in [9] that employed comprehensive learning particle swarm optimization (CLPSO) algorithm. This comparison confirms that the proposed method is superior to [9], which is due to the effectiveness of the proposed heuristic.

Active power generation of energy resources for 24 hours using DE-H is shown in Fig. 4. For the minimum operating
cost of CMG, cheaper units should produce more while satisfying all the constraints. Among all units, ESS is the cheapest units. Therefore, ESS should discharge at the instants of higher grid price as well as other instants if its energy level lies within the bounds. It should charge at lower grid prices. Since initial energy level of ESS was set to lower bound, it was charged (negative power) at the hours of lower grid energy prices, which are between 02:00-07:00, 18:00 and 19:00. As expected, due to higher grid prices, the ESS discharged (positive power) at 10:00-12:00, 14:00-16:00 and 21:00 to minimize the cost.

At the initial hours 01:00 to 07:00, the cost of FC and MT are higher than ESS and grid. Therefore, the algorithm set the generation of FC and MT to their minimum limits. CMG imported energy from the utility grid due to its cheaper energy prices at those instants. FC and MT produced close to their maximum capacity during 09:00 to 16:00 due to the higher grid prices. At the same periods, energy was exported from CMG to the grid to counter balance the overall cost. It is seen from Fig. 4, at the instants of higher grid prices, the proposed algorithm reduced energy import from grid to zero.

As discussed above, the proposed heuristic-based technique (DE-H) exhibits its capability to produce the most economical combinations of DG outputs for overall cost minimization.

The degradation cost of ESS has an impact on the overall cost of the CMG as discussed in section I. Case-2 is introduced below to investigate the impact of ESS degradation.

2) CASE-2
For case-2, the objective function in (2) is considered by incorporating the degradation cost of ESS. The data regarding per-unit investment cost of ESS and its scrap value are extracted from [32]. The shelf life of the ESS is assumed to be 20 years, and cycle life equals to 3500. Convergence plot of median run for case-2 is shown in Fig. 5. Similar to the previous case, the convergence plot shows that DE-H converged faster than DE-NH.

Results obtained after simulating case-2 are summarized in Table 4 and Table 5. Although DE-NH provided lower best cost, DE-H produced better results in all other respects. The results in Table 5 also show that without considering degradation cost (case-1) ESS life diminished at a faster rate due to the higher degradation. On the contrary, when degradation cost was taken into consideration (case-2), ESS degradation cost dropped by 71.31% and ESS life increased about threefold. For better clarity of impacts of considering ESS degradation cost, cycle count versus cycle depth of ESS charging/discharging operation for both cases is presented in Fig. 6. It is evident from Fig. 6 that CMG schedule considering ESS degradation significantly reduced the cycle depth of ESS operation. The lower cycle depth in case-2 resulted in prolonged ESS life. Although case-2 produced higher operating cost than case-1, the longevity of ESS life outweighs the effect in the long run due to the saving in the higher replacement cost of ESS. The schedule of CMG obtained in case-2 is shown in Fig. 7.

Reflecting the related works on CMG scheduling, a single ESS unit was considered in case-1 and case-2. However, having multiple energy storage units in CMG increases reliability and is more practical, especially when CMG operates in islanded mode. Therefore, case-3 is introduced below to further investigate the performance of the proposed method for larger CMG having multiple ESS units.

3) CASE-3
In this case, the dimension of the CMG scheduling problem is doubled compared to the case-1 and 2. The CMG size is increased by replicating the same DG units mentioned in the previous cases. The capacity of renewable generators and demand of CMG are increased proportionately to keep in line with the increased generation capacity. Two ESS, two microturbine and three fuel cell units were included in the larger CMG. Unlike case-1 and 2, the initial energy levels of each ESS unit were assumed to be different. Because, in a practical...
system having multiple ESS unit, it is unlikely that all the ESSs will be charged/discharged in a similar fashion.

The convergence plot of median run for case-3 is presented in Fig. 8. Similar to previous cases, the proposed heuristic-based approach converged faster than that of without heuristic. Results presented in Table 4 and Table 5 shows that compared to DE-NH, DE-H produced a lower value of total cost as well ESS degradation cost. The best cost obtained using DE-H is €1988.10 whereas it is €1023 with DE-NH. The obtained values of the cost function implies that DE-H consistently outperforms DE-NH even for increased problem dimension.

Generation schedule of MT, FC and ESS along with their aggregated output obtained using DE-H is shown in Fig. 9 (a)-(c). From Fig. 9 (c), it can be seen that ESSs charged during the lower energy prices from grid such as at 01:00-08:00 hours. On the contrary, ESSs discharged during the higher grid prices. Evolution of energy level for both ESS over 24 hours is shown in Fig. 11. The energy level of both ESS varied between its lower and upper bounds.

Between MT and FC, overall, FC was committed more than MT due to its cheaper energy compared to MT. During the beginning hours (01:00-07:00), the production of both MT and FC were limited to their minimum capacity owing to lower energy cost from the grid. The generation of MT and FC varied accordingly based on the price signal and load demand. For a better understanding of the overall scenario, aggregated generation from DGs, load, and power exchange with the utility grid is presented in Fig. 10. This shows that during the hours of higher grid energy prices energy was exported from CMG to utility grid, rather than importing; while energy was imported from the grid at the lower grid price instants.

The total degradation cost for two ESS units obtained in case-3 with DE-H was €79.20 (ESS1 = €39.02, ESS2 = €40.18), which is relatively higher compared to the single ESS unit considered in case-2. Since the purpose of including degradation cost is to prolong the ESS life, it might be fair to solve case-3 using a bi-objective approach. This
B. BI-OBJECTIVE APPROACH

In this case, the CMG scheduling problem is formulated as a bi-objective optimization presented in (11). Instead of giving a particular solution, bi-objective optimization provides a set of non-dominated solutions. This gives the CMG operator more freedom to choose the desired solution. So, the bi-objective problem is formulated considering CMG operating cost and ESS life as two objectives which are conflicting in nature. The first objective is the operating cost which is needed to be minimized; whereas, ESS life is the aggregated life of all ESS units, which is to be maximized.

The non-dominated solutions of the median run obtained using the bi-objective approach are presented in Fig. 12. This shows that the proposed DE-H produced a better non-dominated set of solutions compared to DE-NH. As shown in Fig. 12, the best solution obtained using the single-objective approach had an operating cost of $908.90 with corresponding ESS life of 13.83 years. For the same value of...
FIGURE 12. Non-dominated solutions of median run for bi-objective approach.

operating cost/ESS life obtained in the single-objective case, bi-objective approach generated a better corresponding ESS life/operating cost. Hence, it is evident that the bi-objective model can provide a set of high quality solutions than single-objective one in terms of both operating cost and ESS life. To further assess the performance of DE-H and DE-NH in the bi-objective approach, hyper-volume (HV) indicator is calculated. For HV computation, the obtained non-dominated fitness values were normalized based on their ideal and nadir points as in (22) [33].

\[
f_{\text{norm}} = \frac{f_{\text{actual}} - f_{\text{ideal}}}{f_{\text{nadir}} - f_{\text{ideal}}}
\]

where \(f_{\text{norm}}\) and \(f_{\text{actual}}\) are the normalized and actual fitness values, respectively. The ideal and nadir points of the fitness values are denoted by \(f_{\text{ideal}}\) and \(f_{\text{nadir}}\) respectively.

The obtained HV indicator from non-dominated solutions of 31 different runs is presented in Table 6. The higher HV values of DE-H confirms its dominance over DE-NH. Furthermore, the convergence plot of HV for the median run shown in Fig. 13 proves the superiority of the proposed heuristic-based approach.

TABLE 6. Hyper-volume indicator of algorithms (ref.: [1.1,1.1]).

| Case | Algorithm | Best | Median | Average | Worst | STD  |
|------|-----------|------|--------|---------|-------|------|
| 1    | DE-H      | 559.82 | 573.98 | 579.73  | 605.28 | 14.35|
|      | DE-NH     | 581.18 | 608.50 | 611.67  | 646.90 | 15.71|
| 2    | DE-H      | 603.13 | 622.99 | 622.24  | 645.20 | 11.37|
|      | DE-NH     | 647.77 | 701.62 | 701.75  | 761.34 | 23.62|
| 3    | DE-H      | 1023.94| 1044.59| 1048.04 | 1079.34| 16.92|
|      | DE-NH     | 1106.87| 1199.89| 1204.06 | 1285.42| 47.53|

D. PARAMETRIC TESTS

In this subsection, the impacts of different parameters of the algorithm on the fitness value are investigated.

1) EFFECT OF POPULATION SIZE

The results presented in Table 4 and Table 5 are based on stopping criteria of the maximum number of generations. Results show that the average computation time for DE-H was slightly higher than that of DE-NH. This result is expected due to the additional computation needed in repairing solutions by the proposed heuristic. However, from the convergence plot, it appears that the proposed DE-H can give better results within a smaller number of generations.

To further investigate the computational efficacy of the proposed heuristic, a second stopping criterion of equal computation time for both DE-H and DE-NH was applied. The maximum computation time was chosen arbitrarily to be 75% of the average time needed for DE-NH with first stopping criteria. The allocated maximum computation time for case-1, case-2 and case-3 were 78.66, 185.22 and 456.65 seconds, respectively. The obtained results from 31 different runs are shown in Table 7. The results confirm that proposed DE-H can give better fitness value than DE-NH with the same computational budget, which indicates faster convergence of DE-H toward optimal/near-optimal solution. These results prove the computational efficiency of the proposed method.
2) EFFECT OF F AND CRp

It is well known that achieving the proper combination of scaling factor (F) and crossover probability (C_r) for DE is a difficult task. In this work, these values were set to 0.3 and 0.9, respectively. The variation of median fitness value for 31 runs with respect to different values of F and C_r are shown in Fig. 14 (b)-(c), respectively. It is seen that variation in the fitness values is less with DE-H compared to the DE-NH. Furthermore, the proposed DE-H gives fitness value with lower standard deviation. These results indicate that the proposed heuristic helps the algorithm to be less sensitive to the parameter variations.

E. STATISTICAL TESTS

In this subsection, the performance of the proposed algorithm is evaluated using different statistical tests. Although there are several statistical tests available in literature, widely acceptable Wilcoxon and Friedman tests were used in this work. Such a choice is inspired from the application of these tests in different recent literature [33], [34] in the field of computational intelligence. However, it is worth to mention that the comprehensive results reported in this work will allow anyone to use other statistical tests to compare the performance of their own algorithm against the proposed algorithm in this paper. Additionally, the performance of the algorithms were evaluated using box plot analysis.

1) WILCOXON TEST

For the single objective cases, a Wilcoxon sign test was performed to investigate the effect of the individual algorithms. The objective values obtained from 31 different runs of the algorithms were taken as the sample for the test. The test was performed using the 5% significance level of the samples. The obtained results are presented in Table 8, which shows that p values for the case-1 and 3 are less than 0.05; this indicates a significant difference between the results of DE-H and DE-NH. Although results in case-2 were not significantly different, DE-H excelled DE-NH in most of the runs.

| Comparison   | Case | Better | Similar | Worse | p-value   |
|--------------|------|--------|---------|-------|-----------|
| DE-H vs. DE-NH | 1    | 23     | 0       | 8     | 0.00116   |
| DE-H vs. DE-NH | 2    | 19     | 0       | 12    | 0.18300   |
| DE-H vs. DE-NH | 3    | 31     | 0       | 0     | <0.00001  |

2) FRIEDMAN TEST

Friedman test was performed to rank the overall performance of the algorithms. For this, the median values of the objective function obtained in case 1-3 were used. From the test result given in Table 9, it is clear that the heuristic-based method (DE-H) achieved the higher rank compared to that of without heuristic (DE-NH); this higher rank indicates superior performance.
DE-H outperformed DE-NH in terms of best, median, worst and outlier solution. Although DE-NH produced the best value in case-2, it underperformed DE-H in all other respect. Furthermore, the box plot also shows that the spreading of fitness values are less with DE-H. The lower dispersion of fitness values indicates a smaller standard deviation (also shown in Table 4); this confirms the robustness of the proposed heuristic-based method.

V. CONCLUSION

In this work, both single and bi-objective constrained optimization problems were formulated for scheduling a CMG. An evolutionary framework based on a DE and a new heuristic was employed to solve both optimization models. In the single-objective approach, three different simulation cases were solved to evaluate the performance of the proposed algorithm. Furthermore, in the bi-objective approach, along with operating cost reduction of CMG, an additional objective was considered to maximize the life of ESS.

Result analysis shows that the proposed heuristic-based method (DE-H) exhibits consistently superior performance than without heuristic (DE-NH) and the state of the art algorithm for single-objective problems. The proposed DE-H was able to produce better solutions compared to DE-NH with the same computational budget. However, the single-objective approach forces the CMG operator to schedule CMG based on a unique solution. Such a solution fails to extend the life of ESSs satisfactorily. To overcome these problems, the CMG scheduling problem was solved using the bi-objective approach. The simulation results reveal that the bi-objective model was able to produce a set of better solutions compared to the corresponding single objective one. The proposed heuristic based solutions again outperform those without heuristic. The parametric tests show that the proposed heuristic-based approach is less sensitive to parameter variation than that of without heuristic. Furthermore, the statistical analysis validates the robustness and effectiveness of the proposed method.

VI. FUTURE WORK

Due to the proliferation of renewable-based CMGs, there is an increasing research trend in this area. In order to contribute to the body of knowledge, this research will be extended further incorporating uncertainty of the parameters, environmental factors and real-life test networks. Another research aspect could be energy trading among CMGs in the electricity market environment. Also, self-adaptive algorithms will be developed for future works.
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