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ORIGINAL RESEARCH

An efficient bi-objective approach for dynamic economic emission dispatch of renewable-integrated microgrids

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Abstract

To overcome the challenges of conventional power systems, such as increasing power demand, requirements of stability and reliability, and increasing integration of renewable energy sources, the concept of microgrids was introduced and is currently one of the most important solutions for solving the mentioned problems. Generally, microgrids have two operating modes, namely grid-connected and islanded modes. Based on the literature and its unique characteristics, the islanded mode is more challenging than the other one. In this paper, a new self-adaptive comprehensive differential evolution (SACDE) algorithm is proposed for solving economic load dispatch (ELD) and combined economic emission dispatch (CEED) problems, achieving optimal power consumption in isolated microgrids. Initially, SACDE is employed for solving the ELD problem as a single-objective function, meaning that the operational cost is just considered as the objective function, and thereby, the resources are scheduled accordingly. Then, a multi-objective platform based on SACDE is also proposed to solve the CEED problem. It means two objective functions, including operational cost and emission, are simultaneously optimized. For evaluating the performance of the proposed method, three different scenarios under various cases are considered. According to the results, when SACDE is employed to solve the single objective function (cost minimization) problem, it has better performance than other methods. In terms of the bi-objective scheme (cost and emission minimization), SACDE is significantly superior to the price penalty factor technique which is frequently used in previous studies.

Keywords Economic dispatch · Renewable energy sources · Differential evolution algorithm · Islanded microgrid

List of symbols

Sets

N_{of}	The total number of fitness functions
NG	The number of generators
NP	The number of population
nv	The number of variables
N_r	The number of solutions stored in the repository

Parameters

u_i	The cost coefficient ($\$/MW^2h$) of the ith generator
v_i	The cost coefficient ($/MWh) of the ith generator
w_i	The cost coefficient ($/h) of the ith generator
x_i	The emission coefficient of the ith generation unit in (kg/MW^2h)
y_i	The emission coefficient of the ith generation unit in (kg/MWh)
z_i	The emission coefficient of the ith generation unit in (kg/h)
a	Annuitization coefficient
r	The interest scale (0.09)
N	Investment duration (20 years)
I^{Sp}	The ratio of investment cost to unit power (5$/MWh)
G^S	The operational and maintenance costs considered as 0.000016$/MWh
I^{Wp}	The ratio of investment cost to unit power (1.4 $/MWh)
G^W	The operational and maintenance costs considered as 0.000016 $/MWh
$P_i^{\min}$	The minimum and maximum output power of the ith generator

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$P_i^{\max}$	The maximum output power of the *i*th generator
U_i	The weighting coefficient
C_r	A number between 0 and 1
UB	The upper bound of decision variables
LB	The lower bound of decision variables

Variables

E_T	Total emission value
P_i	Active power generation (MW)
P_{Solar}	Solar generation (MW)
F	The cost function
P_{Wind}	Wind generation (MW)
Q	The decision variables of the problem
$rand_1$	A uniform number between 0 and 1
R_n^{G+1}	A new solution generated in the mutation step
β_c	A constant number that is selected between 0 and 2
$Q_{r1}^G, Q_{r2}^G, Q_{r3}^G, Q_{r4}^G, Q_{r5}^G$	Randomly selected members of the population
Q_{best}^G	The best individual among all populations
S_n^{G+1}	A solution generated in crossover step
$rand_2$	A uniform random number between [0 1]
m_{rand}	A uniform random number between [0 1]
$fitness(\bullet)$	The fitness value of the underlying decision variable solution
$fitness_i^{min}$	The minimum fitness of the *i*th function
$fitness_i^{max}$	The maximum fitness of the *i*th function
μ_{fi}	The normalized fitness function for the *n*th solution
h_i	The ratio of the fuel cost to the emission of the corresponding generating unit
F_C	Total fuel cost

Abbreviations

ED	Emission Dispatch
SACDE	A new self-adaptive comprehensive differential evolution
ELD	Economic load dispatch
CEED	Combined economic emission dispatch
PPF	Price penalty factor
DE	Differential Evolution
PSO	Particle Swarm Optimizer
GSA	Gravitational Search Algorithm
RGM	Reduced gradient method
ACO	Ant colony optimization
CSA	Cuckoo search algorithm
ISA	Interior search algorithm
IHS	Improved harmony search
IAHS	Improved and adaptive harmony search
MHS	Modified harmony search

1 Introduction

1.1 Concept and motivation

Despite increasing power demand and numerous challenges of power systems, such as depletion of fossil fuels and global environmental concerns, utilities are obliged to provide high-quality and reliable power supplies with the least cost for their residential and industrial consumers. Due to these challenges, as one of the modern and most effective solutions, renewable energy sources such as solar and wind energy are increasingly integrated into the power systems these days (Abbasi et al. 2020; Shalchi et al. 2020). However, high integration of renewable energy sources causes serious challenges for power systems in different aspects, such as system stability, which in turn dramatically hinder high renewable energy sources penetration into the systems. For increasing renewable energy sources integration and controlling them optimally, several concepts have been developed and introduced so far. Microgrid concept can be named as one of the most well-known and effective solutions for overcoming the problems caused by the high penetration of renewable energy sources into power systems. Simply definition, a microgrid is a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid (Fu et al. 2013). A microgrid can connect to and disconnect from the grid to operate in grid-connected or islanded modes. Generally, a microgrid includes micro-sources, distributed energy resources, such as solar and wind units, energy storage systems, and controllable loads. As a rule, utilities should decrease the generation cost and the emission value as much as possible (Ghaedi et al. 2020; Abbasi et al. 2021). In contrast to the past decades when cost minimization was the only and most important objective for generating electric power, due to global concerns, such as environmental and human health concerns, caused by pollution of power generation, numerous regulations and solutions have recently been introduced to make the utilities able to decrease their harmful emissions, such as toxic gases exhalation, with possible least fuel cost (Krishnamurthy and Tzoneva 2012a). As mentioned above, a microgrid is developed as a small-scale power plant close to communities. It is also operated in two different modes, comprising islanded and grid-connected modes. In the islanded mode, microgrid may be more complicated than that in the grid-connected mode due to not having extra support from external resources (substation). Accordingly, microgrid operation under the islanded mode needs further investigations.

1.2 Literature review

As the economic load dispatch (ELD) implies, it is the scheduling of generation resources by considering an objective function (almost always operational cost) subject to several constraints. Therefore, it is an important problem associated with the optimal operation of microgrids. In terms of ELD, some efforts have been made so far on which a brief review is discussed here. To begin with, the authors of Al-Betar et al. (2022) developed a hybrid approach based on β-hill climbing optimizer and sine cosine algorithm to solve the ELD problem. As revealed from the results of Al-Betar et al. (2022), this hybridization helps to find superior results for some case studies compared with other state-of-the-art methods. Particle swarm optimization algorithm was also modified in Gholami and Dehnavi (2019) to effectively schedule both thermal and renewable resources in an islanded microgrid. From Gholami and Dehnavi (2019), it can be seen that better results can be obtained if an efficient algorithm is developed. ELD considering valve point effects has also been investigated in Gholamghasemi et al. (2019) on the basis of phasor particle swarm optimization. In Najibi and Niknam (2015), dolphin echolocation algorithm was utilized to schedule generation resources in grid-connected microgrids considering the uncertainties of renewable energies. Multi-area ELD was investigated in Qin et al. (2017) by an enhanced particle swarm optimization. As seen in Qin et al. (2017), the enhanced PSO has better performance in finding an optimum solution than other published works. Firefly algorithm is another evolutionary method employed to solve the ELD problem in Chen and Ding (2015).

On the other hand, the future trend toward the economic, environmental emission dispatch problem is to solve ELD as a multi-objective problem including different objectives like fuel cost, emission value and different gases exhalation to be fulfilled efficiently by finding the real operating point of power generation units. One of the key objective functions is emission reduction due to environmental concerns. Accordingly, the combined economic emission dispatch (CEED) is defined as a multi-objective problem which tends to minimize the operational cost and emissions emitted by thermal units. For solving the CEED, different computational methods and techniques have been introduced that are discussed as follows.

Initially, the price penalty factor (PPF) method is used to convert two objective functions into one objective function, meaning that the emission is converted to operational cost based on multiplying with coefficients obtained via thermal units' boundaries. This concept has different models and is frequently used for solving the CEED problem based on various evolutionary algorithms. For example, in Jacob Raglend et al. (2010), the 'Max–Max' PPF method is used for solving the CEED problem based on various Artificial Intelligence algorithms/techniques, including Differential Evolution (DE), Genetic Algorithm, Particle Swarm Optimizer (PSO), and Evolutionary Programming. Besides, the authors of Sharifi et al. (2017) used the Max-Max method and an improved artificial bee colony algorithm to solve the CEED problem. In addition, in Venkatesh et al. (2003), Güvenç et al. (2012), and Hamedi (2013), the authors employed this method, i.e., the 'Max–Max' PPF, for solving the problem by using Gravitational Search Algorithm (GSA), Parallelized PSO, and Evolutionary Programming. In Krishnamurthy and Tzoneva (2012b), a comparative study for solving the CEED problem with ''Min–Max'' PPF using PSO and Lagrange's Algorithm (LA) is presented. In addition, in Krishnamurthy and Tzoneva (2011) and Krishnamurthy and Tzoneva (2012c), LA and PSO algorithms are respectively employed by considering both ''Min–Max'' and ''Max–Max'' PPFs for solving the CEED problem. In Krishnamurthy and Tzoneva (2012d), the LA is used to solve the CEED problem by considering four penalty factors with a quadratic equation for obtaining the fuel cost and emission value. Moreover, the authors solved this problem by using six penalty factors with a cubic equation in Krishnamurthy and Tzoneva (2012e). Besides, the CEED problem is solved with consideration of the valve-point effect based on ''Min–Max'' and ''Max–Max'' PPF approach in Hemamalini and Simon (2009) and Shaw et al. (2012) where respectively, the Maclaurin series-based Lagrangian and the Opposition-based GSA approaches are used.

The weighted sum method is another method which sums both objective functions to convert them to a single objective function. In this regard, various investigations have been conducted. To illustrate those, in Aydin et al. (2014) and Chatterjee et al. (2012), the CEED problem with the weighted sum method is solved using the Artificial Bee Colony algorithm with Dynamic Population size algorithm and the opposition-based harmony search algorithm, respectively. For solving the CEED problem with consideration of the valve-point effect, the authors in Jiang et al. (2014) presented a hybrid approach including PSO and GSA techniques with the weighted sum method. Similarly, in Labbi and Ben Attous (2014), both objective functions, cost and emission, are summed based on the weighted sum method, and the associated problem is solved by Hybrid Big Bang–Big Crunch optimization algorithm.

Although the PPF and weighted sum method are much simpler and are used to solve multi-objective problems, they have some restrictions which may not be suitable to deal with current complex optimization problems. One of the problems is that they do not present a set of solutions (just one global solution is obtained). Another problem is that these methods decrease the flexibility for operators to make decisions fast, meaning that they need to solve the problem for different weighting factors, which is really time-consuming, particularly under real-time implementations. The summary of the literature review is outlined in Table 1.

To this end, a non-dominated sorting technique could be employed. This mechanism can be an alternative because it provides a set of solutions rather than a single solution. Then, the operators can select the compromised solution based on the fuzzy rules.

1.3 Novelties and contributions

In this paper, an efficient optimization algorithm, namely a new self-adaptive comprehensive differential evolution (SACDE) algorithm, is proposed for dealing with both problems of ELD and CEED, achieving optimal power consumption in the isolated microgrid. The proposed approach can be used for solving single- and multi-objective problems. Here, SACDE is utilized for solving the ELD problem as a single-objective function in the first stage. Moreover, a multi-objective platform is proposed to solve the CEED problem based on the proposed optimization algorithm (SACDE). To validate the performance of the proposed approach, thorough comparison and simulation results are presented based on three different scenarios, including various cases. These results show the superiority of the proposed method over other ones, such as the reduced gradient method (RGM) (Trivedi et al. 2015), ant colony optimization (ACO) method (Trivedi et al. 2015), cuckoo search algorithm (CSA) (Trivedi et al. 2018), interior search algorithm (ISA) (Trivedi et al. 2018), improved harmony search (IHS) algorithm (Lu et al. 2013; Elattar 2018), improved and adaptive harmony search (IAHS) algorithm (Ponz-Tienda et al. 2017).

The main contributions of this paper can be listed as follows:

- Providing an efficient algorithm to deal with scheduling of generation sources in the microgrid with high penetration of RESs such as solar and wind generation units.

Table 1 Summary of the literature review

Reference	Single-objective	Multi-objective	Thermal resources	Renewable energies	Non-dominated sorting	Price penalty factor	Weighted sum method	Fuzzy rules
Al-Betar et al. (2022)	Yes	No	Yes	No	No	No	No	No
Gholami and Dehnavi (2019)	Yes	No	Yes	Yes	No	No	No	No
Gholamghasemi et al. (2019)	Yes	No	Yes	Nos	No	No	No	No
Najibi and Niknam (2015)	Yes	No	Yes	Yes	No	No	No	No
Qin et al. (2017)	Yes	No	Yes	No	No	No	No	No
Chen and Ding (2015)	Yes	No	Yes	No	No	No	No	No
Jacob Raglend et al. (2010)	Yes	Yes	Yes	No	No	Yes	No	No
Sharifi et al. (2017)	Yes	Yes	Yes	No	No	Yes	No	No
Hamedi (2013)	Yes	Yes	Yes	No	No	Yes	No	No
Venkatesh et al. (2003)	Yes	Yes	Yes	No	No	Yes	No	No
Güvenç et al. (2012)	Yes	Yes	Yes	No	No	Yes	No	No
Krishnamurthy and Tzoneva (2012b)	Yes	Yes	Yes	No	No	Yes	No	No
Krishnamurthy and Tzoneva (2011)	Yes	Yes	Yes	No	No	Yes	No	No
Krishnamurthy and Tzoneva (2012c)	Yes	Yes	Yes	No	No	Yes	No	No
Krishnamurthy and Tzoneva (2012d)	Yes	Yes	Yes	No	No	Yes	No	No
Krishnamurthy and Tzoneva (2012e)	Yes	Yes	Yes	No	No	Yes	No	No
Hemamalini and Simon (2009)	Yes	Yes	Yes	No	No	Yes	No	No
Shaw et al. (2012)	Yes	Yes	Yes	No	No	Yes	No	No
Aydin et al. (2014)	Yes	Yes	Yes	No	No	No	Yes	No
Chatterjee et al. (2012)	Yes	Yes	Yes	No	No	No	Yes	No
Jiang et al. (2014)	Yes	Yes	Yes	No	No	No	Yes	No
Labbi and Ben Attous (2014)	Yes	Yes	Yes	No	No	Yes	Yes	No
Proposed method	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes

- Addressing a multi-objective framework leading to finding more optimum solutions (less cost and emission) compared with other existing techniques like PPF.
- Developing a new approach with better applicability to solve complicated problems. The proposed method is able to provide better solutions than the previously published ones, as proved by the comparison and simulation results.

1.4 Paper's structure

This paper is organized as follows. Section 2 presents the mathematical models and the problem formulation. In Sect. 3, the proposed optimization method is explained in detail. Besides, Sect. 4 presents the test microgrid data, simulation and comparison results, and discussions. Finally, the conclusion is given in Sect. 5.

2 Mathematical model

2.1 Fuel cost function of generators

As the main objectives of the ELD problem, the generation levels of all online units must be examined to reduce the total fuel cost of generators and the emission level of the system with consideration of the system constraints (Bhoye et al. 2016b). In this section, as the first objective of the ELD problem, minimizing the generation fuel cost is considered to be formulated. This objective should be realized with consideration of the power demand satisfaction and also the operating constraints of the system. According to Trivedi et al. (2016), the objective function of the fuel cost minimization of generation units can be expressed as follows:

$$Min\left(F_C\right) = \sum_{i=1}^{NG} \left(u_i P_i^2 + v_i P_i + w_i\right) \tag{1}$$

Due to the operation of various generation units, such as diesel, gas, and combined heat and power units, several harmful pollutants, such as carbon dioxide, nitrogen oxide, and sulfur dioxide, are released (Palanichamy and Babu 2008), which should be reduced according to the aforementioned reasons. For minimizing these toxic emissions in the Emission Dispatch (ED) problem, the following objective function is defined:

$$Min(E_T) = \sum_{i=1}^{NG} \left(x_i P_i^2 + y_i P_i + z_i\right) \tag{2}$$

2.2 Renewable energy sources

2.2.1 Solar energy

According to Bhoye et al. (2016a) and Trivedi et al. (2016), the cost function of solar generation unit can be written as follows:

$$F\left(P_{Solar}\right) = aI^{Sp} P_{Solar} + G^S P_{Solar} \tag{3}$$

In (3), the Annuitization coefficient, represented by a, is calculated as follows:

$$a = \frac{r}{\left(1 - (1 + r)^{-N}\right)} \tag{4}$$

In the above equations, P_{Solar}, r, N, I^{Sp} and G^S respectively denote the solar generation (MW), the interest scale (0.09), the investment duration (20 years), the ratio of investment cost to unit power (5$/MWh), and the operational and maintenance costs considered as 0.000016$/MWh.

Consequently, the cost function of the solar energy unit can be obtained by (5).

$$F\left(P_{Solar}\right) = 0.5477483 \times P_{Solar} \tag{5}$$

2.2.2 Wind generation

In (6), the general cost function of wind energy is written according to (Esmat et al. 2013).

$$F\left(P_{Wind}\right) = aI^{Wp} P_{Wind} + G^W P_{Wind} \tag{6}$$

where, P_{Wind}, I^{Wp}, and G^W respectively denote the wind generation (MW), the ratio of investment cost to unit power (1.4 $/MWh), and the operational and maintenance costs considered as 0.000016 $/MWh.

Accordingly, the cost function of the wind energy unit can be calculated as follows:

$$F\left(P_{Wind}\right) = 0.1533810 \times P_{Wind} \tag{7}$$

2.3 Final objective functions

In Sect. 2.1, the conventional model of the ED problem was presented without considering renewable energy sources. Here, this problem is formulated in the presence of renewable generation units, i.e., renewable energy sources.

2.3.1 First objective function

By considering the two terms of solar and wind generation units, the ELD problem given in (1) can be re-written as an integrated equation as described in the following:

$$Min(F_C) = \sum_{i=1}^{NG} \left(u_i P_i^2 + v_i P_i + w_i\right) + 0.1533810 \times P_{Wind} + 0.5477483 \times P_{Solar} \tag{8}$$

2.3.2 Second objective function

As another critical objective in the operation of power systems, emission minimization is defined as the second objective function as given below:

$$Min(E_T) = \sum_{i=1}^{NG} \left(x_i P_i^2 + y_i P_i + z_i\right) \tag{9}$$

In (8) and (9), two objective functions are defined, which must be simultaneously minimized. For solving these objective functions, a multi-objective platform is required, which can be achieved by means of a dominant concept. It is noteworthy that the advantage of multi-objective planning is that a set of solutions, namely Pareto-optimum solutions, will be obtained rather than a single solution, which in turn enable the system operator to make an efficient decision based on the system's preference.

2.4 Constraints

2.4.1 Isolated microgrid

By definition, an islanded (isolated) microgrid is disconnected from the main grid, which means that there is not any energy exchange between the microgrid and the main grid (Ramabhotla et al. 2014).

2.4.2 Power balance constraint

The power balance constraint can be written as follows, demonstrating that the load demand should be equal to the power generated by all available generation units.

$$P_{Load} = \sum_{i=1}^{NG} \left(P_i\right) + P_{Solar} + P_{Wind} \tag{10}$$

2.4.3 Power generation constraint

As presented in (11), the output power of each generation unit has a given minimum and maximum values as its constraints (Ramabhotla et al. 2014).

$$P_i^{\min} \le P_i \le P_i^{\max} \tag{11}$$

3 Proposed optimization approach

In this section, the conventional differential evolution (DE) algorithm and the proposed optimization approach, along with the proposed multi-objective planning approach, are presented.

3.1 Conventional differential evolution algorithm

As an evolutionary algorithm, the DE algorithm can solve non-deterministic polynomial-time (NP)-hard problems (Wang et al. 2018). This algorithm has been introduced to tackle the main drawback of the genetic algorithm, i.e., its lack of local search. For better understanding, Fig. 1 shows the workflow of the DE algorithm's operators. As seen, this algorithm generates the population between the upper and lower bounds of problems. Then, the mutation operator is used for making a new individual based on selecting some members of the population. After that, by using the crossover operator, the mutated individual is combined with the ith member of the population. By obtaining the mentioned operators, a new individual is made which is evaluated based on the objective function. The obtained fitness for this individual is compared with the fitness of the ith individual, and the best one (lowest and highest fitness values for minimization and maximization, respectively) is selected for the next generation. It should be noted that these steps are repeated until reaching the stopping criteria.

In the following sub-sections, the above-mentioned process is mathematically presented.

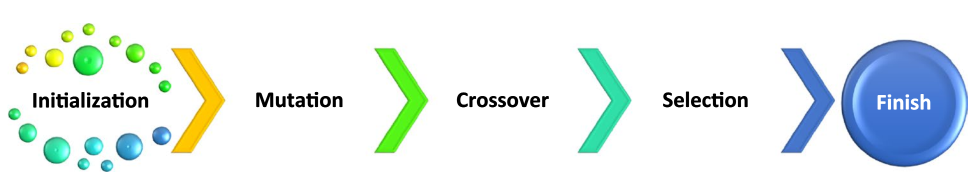


Fig. 1 Workflow of the operators of DE algorithm

3.1.1 Initialization

After defining the upper and lower bounds of the problem, the population is stochastically generated as follows:

$$Q_{n,m} = LB_{n,m} + \left(UB_{n,m} - LB_{n,m}\right) * rand_1 forn = 1, 2, \dots, NP\&m = 1, 2, \dots, nv \tag{12}$$

3.1.2 Mutation operator

In this step, three vectors of the population are randomly selected, and a new solution) R_n^{G+1}) is created by using (13).

$$R_n^{G+1} = Q_{r1}^G + \beta_c * \left(Q_{r2}^G - Q_{r3}^G\right) \tag{13}$$

3.1.3 Crossover operator

According to the vector obtained from the mutation operator and the nth member of the population, a solution is made as follows:

$$S_{n,m}^{G+1} = \left\{ \begin{array}{ll} R_{n,m}^{G+1} & ifrand_2 \le C_r \ or \ m = m_{rand} \\ Q_{n,m}^G & otherwise \end{array} \right\} \tag{14}$$

By using this solution, a diverse individual can be obtained, making it possible to escape from local minima.

3.1.4 Selection operator

In this step, the best solution is achieved by comparing the Q_n^G and S_n^{G+1} vectors. As described in (15), if the fitness of the created vector, i.e., S_n^{G+1}, is less than that of the nth member of the population, it will be kept for the next generation; otherwise, the previous individual will be saved for the next generation.

$$Q_n^{G+1} = \left\{ \begin{array}{ll} S_n^{G+1} & iffitness\left(S_n^{G+1}\right) \le fitness\left(Q_n^G\right) \\ Q_n^G & otherwise \end{array} \right\} \tag{15}$$

3.2 Proposed optimization approach (algorithm)

In fact, the mutation operator plays a central role in the proposed algorithm. Accordingly, the purpose of this investigation is to use multiple mutations to improve both efficiency and search capability. Unlike the original method presented in Wang et al. (2018), and Gholami and Jazebi (2020a, b) where one mutation is used, multiple mutations are used in the proposed optimization approach. The proposed mutation operator is explained in detail in the following, while other steps are the same as the conventional approach in Sect. 3.1.

3.2.1 Mutation operator

For achieving improved performance in the proposed approach, a new mutation operator is developed. Unlike the conventional DE algorithm, different mutations are used in the proposed approach rather than using only one mutation. In (16) to (20), these mutation operators are described. For generating a new vector, one of these mutation operators is selected and used which in turn not only provides more diversity but also improves the efficiency of the proposed algorithm. In Algorithm 1, the pseudocode of the proposed approach is represented.

$$\left(R_n^{G+1}\right)_1 = Q_{r1}^G + \beta_c * \left(Q_{r2}^G - Q_{r3}^G\right) \tag{16}$$

$$\left(R_n^{G+1}\right)_2 = Q_{best}^G + \beta_c * \left(Q_{r1}^G - Q_{r2}^G\right) \tag{17}$$

$$\left(R_n^{G+1}\right)_3 = Q_n^G + \beta_c * \left(Q_{best}^G - Q_n^G\right) + \beta_c * \left(Q_{r1}^G - Q_{r2}^G\right) \tag{18}$$

$$\left(R_n^{G+1}\right)_4 = Q_{r1}^G + \beta_c * \left(Q_{r2,j}^G - Q_{r3,j}^G\right) + \beta_c * \left(Q_{r4}^G - Q_{r5}^G\right) \tag{19}$$

$$\left(R_n^{G+1}\right)_5 = Q_{best}^G + \beta_c * \left(Q_{r1}^G - Q_{r2}^G\right) + \beta_c * \left(Q_{r3}^G - Q_{r4}^G\right) \tag{20}$$

Effective mutation not only helps to strengthen an algorithm's efficiency to escape from the local optima, but it also pushes the solution towards the global optimum. If the population diversity increases, the chance of escaping from the local optima increases. The proposed method can generate the population based on different mutation mechanisms, which in turn results in better search capability and escaping from local minima. In the suggested optimization approach, 5 different mutations are utilized which are described as follows. To commence with, mutation 1 in (16) tries to update the *nth* member based on a stochastic manner, which makes a new member based on the three random individuals. On the other hand, mutation 2 in (17) tends to push the current member towards the best solution. In mutation 3 in (18), some solutions are randomly selected and mixed with the global best solution to make a solution near the current global best solution. Mutation 4 in (19) is similar to mutation 2, while a random solution is used rather than the global best member, meaning that a new solution on the search space is generated which may be far away from the global best solution. Finally, in mutation 5 in (20), the *nth* member is oriented to the global best member with considering more random members, which helps to have further distance from the current global best member. To sum up, when these mutations are randomly applied, more different populations are obtained, which in turn enhances the ability of the algorithm to have better search space exploration.

Algorithm 1 Pseudocode of the proposed optimization algorithm

Initialize the population within LB and UB bounds
while itr < maxim number of iteration
  for each member
------------------------------- apply mutation -----------------------------
    IndexMutation= randomly generate an integer number within [1 5]
    switch IndexMutation
      case 1
        $\left(R_n^{G+1}\right)_1 = Q_{r1}^G + \beta_c * \left(Q_{r2}^G - Q_{r3}^G\right)$
      case 2
        $\left(R_n^{G+1}\right)_2 = Q_{best}^G + \beta_c * \left(Q_{r1}^G - Q_{r2}^G\right)$
      case 3
        $\left(R_n^{G+1}\right)_3 = Q_n^G + \beta_c * \left(Q_{best}^G - Q_n^G\right) + \beta_c * \left(Q_{r1}^G - Q_{r2}^G\right)$
      case 4
        $\left(R_n^{G+1}\right)_4 = Q_{r1}^G + \beta_c * \left(Q_{r2,j}^G - Q_{r3,j}^G\right) + \beta_c * \left(Q_{r4}^G - Q_{r5}^G\right)$
      case 5
        $\left(R_n^{G+1}\right)_5 = Q_{best}^G + \beta_c * \left(Q_{r1}^G - Q_{r2}^G\right) + \beta_c * \left(Q_{r3}^G - Q_{r4}^G\right)$
    endswitch
------------------------------- apply crossover -----------------------------

$$S_{n,m}^{G+1} = \begin{cases} R_{n,m}^{G+1} & if\ rand_2 \le C_r\ or\ m = m_{rand} \\ Q_{n,m}^G & otherwise \end{cases}$$

---------------------------------- evaluation --------------------------------
    amend solution, $S_{n,m}^{G+1}$, between UB and LB;
    evaluate the fitness of $S_{n,m}^{G+1}$ via the objective function
------------------------------- apply selection -----------------------------

$$Q_n^{G+1} = \begin{cases} S_n^{G+1} & if\ fitness\left(S_n^{G+1}\right) \le fitness\left(Q_n^G\right) \\ Q_n^G & otherwise \end{cases}$$

  endfor
endwhile
return results

As seen in the pseudocode, the mutation of DE algorithm has several options. It means a random integer number is generated in [1, 5] and saved in IndexMutation. Following this, one mutation is applied based on this index. For example, if IndexMutation = 3, the mutation which is shown in (18) is applied. This mechanism is executed stochastically to generate new solutions. This is an excellent way for increasing the population diversity, resulting in escaping from local minima.

As already mentioned, the proposed optimization algorithm can be employed to solve both single- and multi-objective problems. For single-objective problems, the approach explained in this section is used. However, for multi-objective problems, a different selection operator is introduced as presented in Sect. 3.3.

3.3 Proposed multi-objective approach

As already mentioned, it is required to minimize two different functions at the same time. A dominant principle could also be used to handle multi-objective problems. In contrast to a single-objective plan, a multi-objective plan can acquire a set of solutions known as Pareto-optimal solutions instead of just a single solution. If the following conditions are satisfied, vector Q_1 dominates Q_2 (Azizivahed et al. 2018, 2019)

$$\forall i \in \{1, 2, ..., N_{of}\}, \quad fitness_i(Q_1) \le fitness_i(Q_2) \tag{21}$$

$$\exists i \in \{1, 2, ..., N_{of}\}, \quad fitness_i(Q_1) < fitness_i(Q_2) \tag{22}$$

where N_{of} denotes the total number of fitness functions.

Now, the set of solutions should be normalized into the values between [0, 1] by using a Fuzzy method as expressed below. In other words, the trapezoidal fuzzy model shown in Fig. 2 is used to normalize the objective functions.

$$\mu_{fi}(Q) = \begin{cases} 1 & fitness_i(Q) \le fitness_i^{\min} \\ \frac{fitness_i^{\max} - fitness_i(Q)}{fitness_i^{\max} - fitness_i^{\min}} & fitness_i^{\min} < fitness_i(Q) < fitness_i^{\max} \\ 0 & fitness_i(Q) \ge fitness_i^{\max} \end{cases} \tag{23}$$

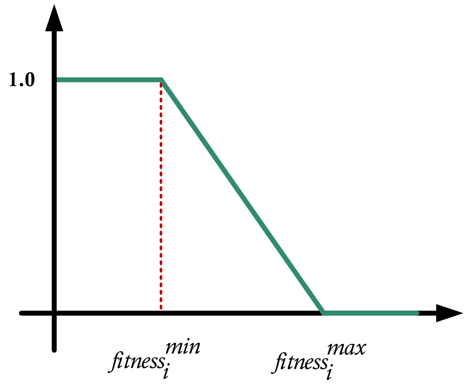


Fig. 2 Membership function for both objective functions

In (23), the minimum and maximum fitnesses of the ith function are denoted by $fitness_i^{min}$ and $fitness_i^{max}$, respectively. The final solution is chosen among the normalized solutions by using the following criteria:

$$\gamma_\mu(n) = \frac{\sum_{i=1}^{N_{of}} U_i \times \mu_{fi}(x_m)}{\sum_{m=1}^{N_r} \sum_{i=1}^{N_{of}} U_i \times \mu_{fi}(x_m)} \tag{24}$$

To provide a fair comparison with previous works, i.e., Elattar (2018) and Trivedi et al. (2018), the final solution selected by (24) is converted into total cost based on the PPF. The PPF is responsible for transferring the physical sense of emission to the fuel cost and is described as follows.

$$h_i = \frac{u_i\left(P_i^{\min}\right)^2 + v_i\left(P_i^{\min}\right) + w_i}{x_i\left(P_i^{\max}\right)^2 + y_i\left(P_i^{\max}\right) + z_i} \tag{25}$$

$$\begin{aligned} TotalCost = &\sum_{i=1}^{NG} [(u_i P_i^2 + v_i P_i + w_i) + h_i(x_i P_i^2 + y_i P_i + z_i)] \\ &+0.1533810 \times P_{Wind} + 0.5477483 \times P_{Solar} \end{aligned} \tag{26}$$

Figure 3 shows the simple flowchart of the proposed optimization approach for solving the CEED problem.

4 Simulation results and discussion

In this section, simulation results along with comprehensive discussion and comparisons are presented for proving the proposed solution's performance. Initially, the

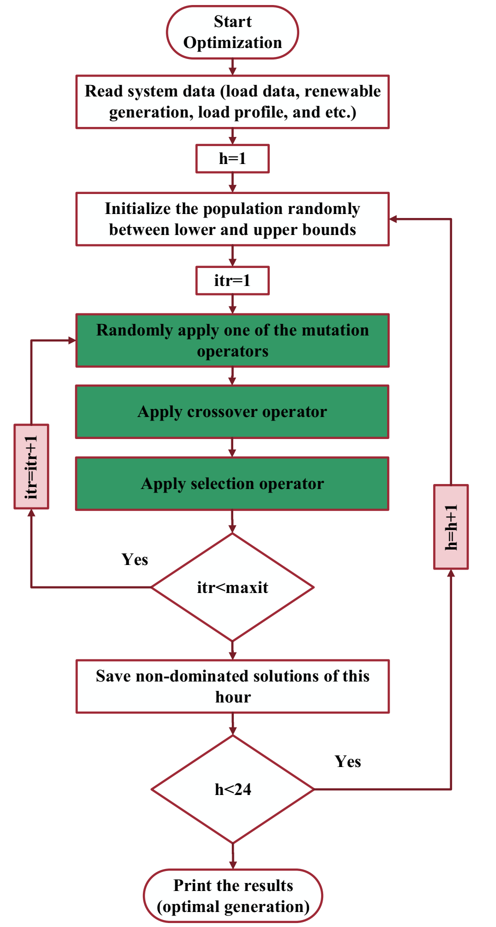


Fig. 3 Flowchart of the proposed algorithm (SACDE)

test microgrid's data are presented. Then, three scenarios, including different cases, are defined, and their results are presented and discussed. These scenarios and their cases are depicted in Fig. 4 and are listed in the following:

A.Scenario 1 (Single-objective scheduling): •Case 1: All sources included •Case 2: All sources without wind energy •Case 3: All sources without solar energy •Case 4: All sources without solar and wind energy	B.Scenario 2 (Bi-objective operation, i.e., CEED): •Case 1: All sources included •Case 2: All sources without wind energy •Case 3: All sources without solar energy •Case 4: All sources without solar and wind energy	C.Scenario 3 (Other evaluations): •Case 1: Sensitivity analysis of algorithm's parameters •Case 2: ED with considering power loss •Case 3: Comparison with non-dominated sorting genetic algorithm II (NSGA-II)

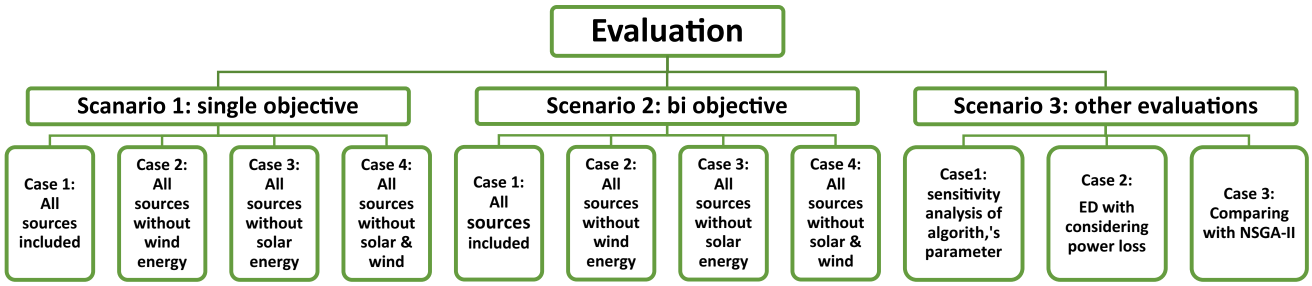


Fig. 4 An overview of the scenarios and their cases to evaluate the proposed method

Table 2 Solar and wind generation data for 24 h

Time (h)	Generation (MW)		Time (h)	Generation (MW)		Time (h)	Generation (MW)	
	Solar	Wind		Solar	Wind		Solar	Wind
1	0	1.7	9	24.05	20.58	17	9.57	3.44
2	0	8.5	10	39.37	17.85	18	2.31	1.87
3	0	9.27	11	7.41	12.80	19	0	0.75
4	0	16.66	12	3.65	18.65	20	0	0.17
5	0	7.22	13	31.94	14.35	21	0	0.15
6	0.03	4.91	14	26.81	10.35	22	0	0.31
7	6.27	14.66	15	10.08	8.26	23	0	1.07
8	16.18	26.56	16	5.30	13.71	24	0	0.58

Table 3 Load profile for 24-h period

Time (h)	Load (MW)	Time (h)	Load (MW)	Time (h)	Load (MW)
1	140	9	210	17	170
2	150	10	230	18	185
3	155	11	240	19	200
4	160	12	250	20	240
5	165	13	240	21	225
6	170	14	220	22	190
7	175	15	200	23	160
8	180	16	180	24	145

Table 4 Characteristic of the generators

Characteristic		Generators		
		1	2	3
Power generation limits	Minimum	37	40	50
	Maximum	150	160	190
Fuel cost coefficients	u ($/MW^{2}h)	0.024	0.029	0.021
	v ($/MWh)	21	20.16	20.4
	w ($/h)	1530	992	600
Emission coefficient	x (kg/MW^{2}h)	0.0105	0.008	0.012
	y (kg /MWh)	− 1.355	− 0.6	− 0.555
	z (kg /h)	60	45	30

4.1 Test microgrid data

Here, data of the test microgrid are given (Elattar 2018; Trivedi et al. 2018). Table 2 lists the data of solar and wind generations for a 24-h period which belong to a location on the east coast of the United States of America (USA). The demand throughout the time horizon is shown in Table 3 (Elattar 2018; Trivedi et al. 2018). Moreover, Table 4 presents the generators' characteristics, including their generation limits and fuel cost and emission coefficients (Elattar 2018; Trivedi et al. 2018).

4.2 The results of Scenario 1 (single-objective scheduling)

Here, only the ED is considered and solved as a single-objective function. To prove the performance of the proposed method, its results (hourly and daily costs of the generation units) are compared with those of previously published methods/approaches, including RGM (Trivedi et al. 2015), ACO (Trivedi et al. 2015), CSA (Trivedi et al. 2018), and ISA (Trivedi et al. 2018). As already mentioned, this scenario includes 4 cases whose results are presented in the following subsections.

Table 5 Results of Case 1 (all sources included) of Scenario 1

Time	RGM ($/h)	ACO ($/h)	CSA ($/h)	ISA ($/h)	Proposed approach ($/h)
1	6297	6134	6117	6117	6113.350
2	6474	6312	6192	6192	6188.205
3	6565	6439	6291	6292	6285.583
4	6650	6512	6235	6234	6230.801
5	6759	6682	6573	6575	6560.708
6	6867	6807	6742	6735	6728.862
7	7209	6837	6487	6488	6479.810
8	7762	6780	6093	6093	6102.521
9	8649	7457	6758	6750	6751.723
10	9713	7852	6930	6936	6931.916
11	8722	8358	8026	8026	8028.953
12	8794	8594	8216	8213	8218.940
13	9654	8146	7425	7408	7419.068
14	9013	7760	7154	7154	7160.281
15	7905	7424	7126	7129	7122.418
16	7268	6943	6648	6649	6639.498
17	7276	6756	6555	6553	6547.099
18	7288	7146	7107	7107	7098.672
19	7544	7538	7530	7525	7530.902
20	8567	8517	8510	8510	8508.714
21	8167	8153	8150	8148	8145.102
22	7314	7316	7313	7313	7306.453
23	6674	6605	6599	6599	6587.643
24	6389	6275	6267	6266	6252.836
Total	183,520	173,343	167,044	167,012	**166,940.1**

Table 6 Results of Case 2 of Scenario 1

Time	RGM ($/h)	ACO ($/h)	CSA ($/h)	ISA ($/h)	Proposed approach ($/h)
1	6298	6152	6157	6122	6152.459
2	6483	6380	6393	6392	6380.427
3	6579	6496	6509	6539	6496.518
4	6677	6611	6624	6623	6611.169
5	6778	6727	6741	6741	6726.762
6	6881	6844	6856	6849	6842.277
7	6950	6924	6827	6827	6817.636
8	7020	6972	6714	6713	6708.416
9	7626	7616	7226	7204	7234.326
10	8001	7987	7336	7286	7349.333
11	8498	8469	8334	8346	8336.193
12	8808	8719	8669	8669	8670.182
13	8277	8272	7747	7746	7758.753
14	7831	7827	7396	7396	7402.468
15	7485	7479	7319	7319	7316.131
16	7074	7048	6963	6964	6955.745
17	6833	6769	6635	6635	6626.012
18	7202	7187	7150	7151	7141.725
19	7548	7549	7556	7555	7550.999
20	8569	8513	8514	8513	8513.155
21	8168	8148	8151	8161	8153.242
22	7316	7313	7321	7321	7313.277
23	6677	6611	6625	6625	6611.051
24	6387	6266	6275	6311	6266.341
Total	175,966	174,879	172,038	172,008	**171,934.59**

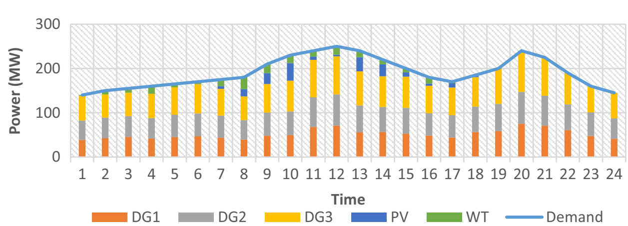


Fig. 5 Generated power of different generation units in Case 1 of Scenario 1

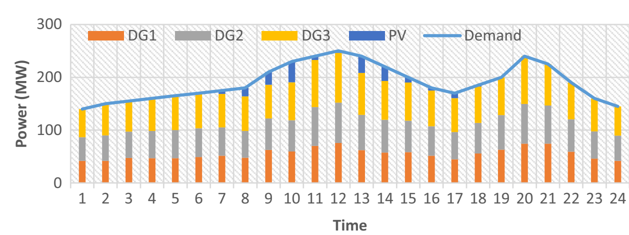


Fig. 6 Generated power of different generation units in Case 2 of Scenario 1

4.2.1 Case 1 (all sources)

In this case, the microgrid contains all energy sources (generation units). The results of Case 1, which are the hourly cost of the generation units, are presented in Table 5. As seen, the proposed approach outperforms other methods by scheduling generations with the least expenditure. In Fig. 5, the generated powers of different generation units in Case 1 for the proposed approach are presented.

4.2.2 Case 2 (all sources excluding wind generation unit)

In this case, the microgrid contains all energy sources, excluding wind energy. The results of different methods including the proposed method for Case 2 are listed in Table 6. As seen, the least generation cost, i.e., 171934.59 ($/day), belongs to the proposed approach among all of the compared methods. In Fig. 6, generated powers of different units in Case 2 for the proposed method are shown.

4.2.3 Case 3 (all sources with no solar generation unit)

In this case, the microgrid includes no solar energy source. Table 7 presents the results of diverse approaches for this case, demonstrating that the proposed one shows the best performance by providing the least generation cost (171163.856 ($/day)). Besides, Fig. 7 shows the hourly generated powers of different units in Case 3 obtained by the proposed approach.

Table 7 Results of Case 3 of Scenario 1

Time	CSA ($/h)	ISA ($/h)	Proposed approach ($/h)
1	6117	6117	6114.916
2	6192	6187	6187.308
3	6292	6292	6284.435
4	6236	6236	6230.605
5	6573	6572	6560.995
6	6743	6742	6729.882
7	6633	6632	6621.039
8	6473	6472	6463.633
9	7307	7307	7301.786
10	7844	7844	7841.422
11	8205	8209	8203.986
12	8305	8304	8305.738
13	8167	8167	8165.968
14	7785	7783	7782.090
15	7362	7362	7354.861
16	6771	6776	6758.698
17	6777	6777	6765.157
18	7161	7161	7150.532
19	7538	7545	7530.957
20	8510	8508	8512.094
21	8148	8148	8144.722
22	7314	7272	7312.996
23	6600	6600	6586.688
24	6261	6261	6253.347
Total	171,314	171,274	**171,163.856**

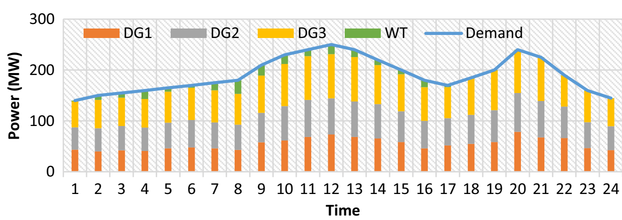


Fig. 7 Generated powers of different generation units in Case 3 of Scenario 1

4.2.4 Case 4 (no renewable energy sources)

In Table 8, the hourly and total generation costs of different approaches for Case 4 of Scenario 1, where microgrid includes only fuel-based generation units (no renewable energy sources). Based on these results, the proposed approach is ranked as the best algorithm for obtaining the least generation cost (176197.27 ($/day)) among all methods. In addition, Fig. 8 presents different units' generations acquired by the proposed approach.

It should be noted here that based on Figs. 5, 6, 7, 8, presenting the hourly generation of each unit of Scenario 1, the generation units can perfectly cover the whole load, and also the constraints are perfectly satisfied. Besides, Figs. 9 and 10 respectively compare the hourly and total generation costs of Scenario 1 obtained by the proposed method. According to these figures, utilization of renewable energy sources can remarkably decrease both hourly and total operational costs of the system. If PV and WT engage in power generation alongside thermal units (Case 1), larger cost savings are observed. There is a slight cost rise in Case 2 due to the exclusion of WT. Likewise, in Case 3, where PV does not participate in the microgrid, the cost is higher than that in Case 1. Nevertheless, the cost reaches its peak in Case 4 as the thermal units only feed consumption and the renewable sources are entirely ignored. Through this comparison, it can be seen that more renewable energy integration results in greater cost and emission minimization.

Table 8 Results of Case 4 of Scenario 1

Time	RGM ($/h)	ACO ($/h)	CSA ($/h)	ISA ($/h)	Proposed approach ($/h)
1	6298	6152	6157	6157	6152.155
2	6483	6380	6393	6395	6381.719
3	6579	6496	6509	6531	6495.561
4	6677	6611	6625	6635	6611.172
5	6778	6727	6741	6742	6727.319
6	6881	6844	6856	6858	6847.733
7	6986	6969	6973	6971	6960.835
8	7094	7078	7088	7087	7077.144
9	7795	7788	7793	7793	7787.495
10	8300	8284	8272	8272	8269.342
11	8569	8513	8514	8514	8512.979
12	8848	8760	8758	8758	8758.343
13	8569	8513	8514	8433	8519.312
14	8040	8031	8032	8026	8029.449
15	7548	7549	7556	7571	7548.870
16	7094	7078	7088	7086	7076.606
17	6881	6844	6856	6856	6842.947
18	7204	7194	7204	7203	7196.408
19	7548	7549	7556	7555	7550.118
20	8569	8513	8514	8511	8512.582
21	8168	8149	8152	8151	8150.121
22	7316	7313	7319	7322	7311.897
23	6677	6611	6625	6625	6611.063
24	6389	6266	6275	6268	6266.105
Total	177,291	176,212	176,370	176,320	**176,197.27**

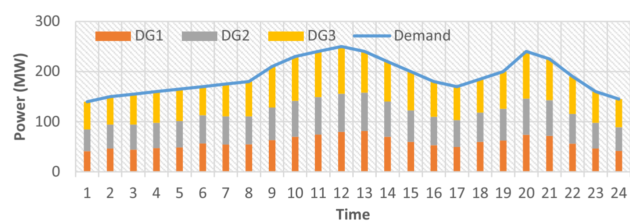


Fig. 8 Generated powers of different generation units in Case 4 of Scenario 1

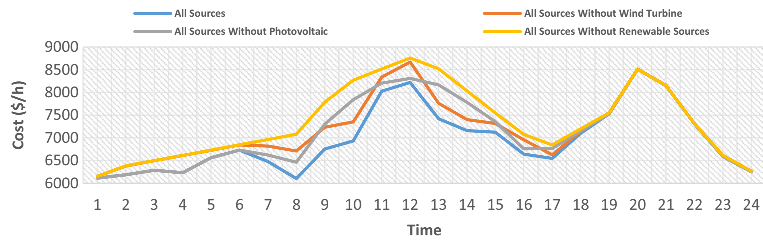


Fig. 9 Hourly generation costs of Scenario 1 over a day obtained by the proposed approach

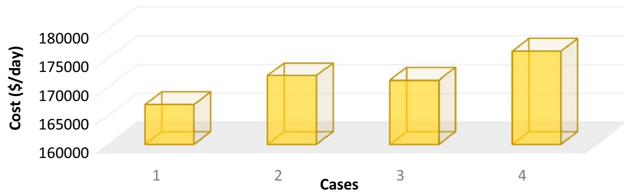


Fig. 10 Total generation costs of Scenario 1 over a day obtained by the proposed approach

4.3 The results of Scenario 2 (bi-objective scheduling)

Unlike Scenario 1, the economic and emission are simultaneously solved as a bi-objective function (CEED problem) in Scenario 2. The results of the proposed approach are compared with those of other methods, such as RGM (Trivedi et al. 2015), ACO (Trivedi et al. 2015), CSA (Trivedi et al. 2018), ISA (Trivedi et al. 2018), IHS (Elattar 2018), IAHS (Elattar 2018), and MHS (Elattar 2018) for validating the superior performance of the proposed one. As already mentioned, four cases are defined in this scenario too. In Fig. 11, some of the Pareto Front examples obtained by the proposed approach for different hours are shown.

As seen in this figure, a Pareto solution has two different values (cost and emission). Therefore, the results in Tables 9, 10, 11, 12 are the combination of these two items obtained based on the PPF to have a fair comparison with other published works. In other words, the PPF is responsible for transferring the physical sense of emission to the fuel cost.

4.3.1 Case 1 (all sources)

In this case, all generation units are employed in the microgrid whose results (hourly and daily generation costs) for different algorithms are listed in Table 9. As seen, SACDE (the proposed approach) can outperform the others by providing the least total generation cost (177936.6 ($/day)). Fig. 12 shows the generated powers of the generation units obtained by the proposed approach.

Fig. 11 Some Pareto-Front examples obtained by the proposed approach in Scenario 2 for **a** Case 1 at hour = 1 **b** Case 2 at hour = 8 **c** Case3 at hour = 18 **d** Case 4 at hour = 22

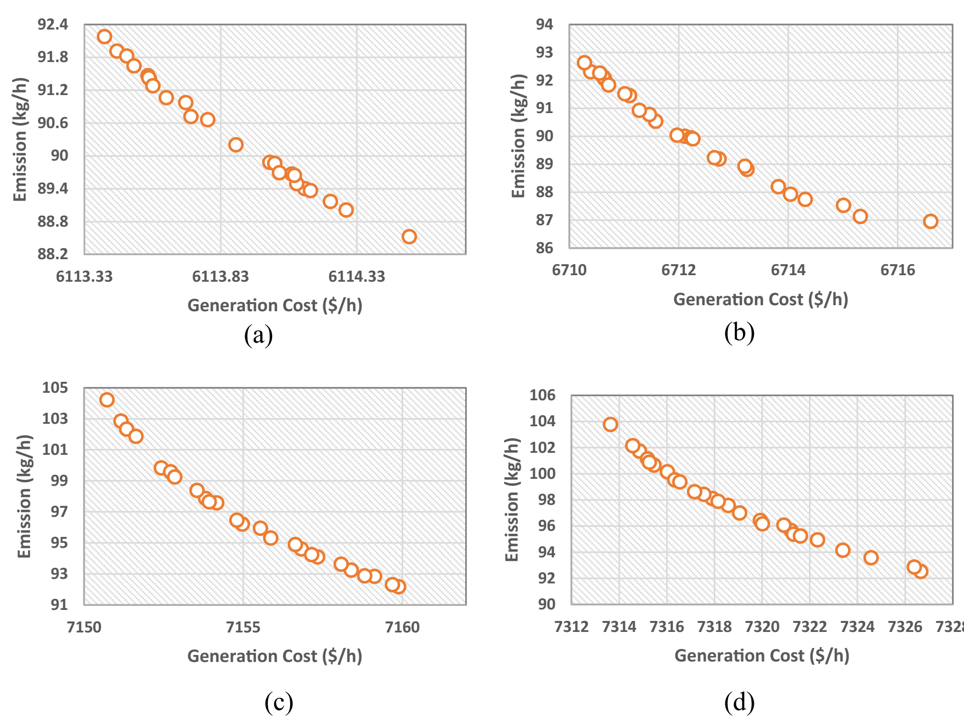


Table 9 Results of Case 1 of Scenario 2

Time	RGM cost ($/h)	ACO cost ($/h)	CSA cost ($/h)	ISA cost ($/h)	IHS cost ($/h)	IAHS cost($/h)	MHS cost($/h)	Proposed approach($/h)
1	8529	7250	7153	7153	7090.50	7058.00	6942.80	6537.83
2	8648	7511	7203	7203	7151.10	7130.20	7010.30	6604.19
3	8675	7704	7278	7278	7170.80	7151.50	7100.70	6699.52
4	8795	7742	7280	7285	7159.60	7130.80	7049.60	6647.80
5	8758	8211	7545	7545	7528.20	7450.10	7377.20	7002.35
6	8848	8459	7723	7679	7600.10	7572.20	7553.30	7163.50
7	8964	8406	7457	7457	7444.20	7423.80	7294.10	6892.11
8	9308	7923	7138	7138	7051.00	7050.30	6935.60	6523.33
9	9609	9040	7731	7731	7660.30	7640.90	7576.40	7182.27
10	10,049	9599	7920	7937	7851.50	7845.40	7770.80	7381.70
11	11,520	11,184	9231	9231	9152.00	9150.00	9073.40	8563.23
12	12,098	11,616	9470	9470	9394.30	9381.30	9314.30	8773.12
13	10,676	10,320	8482	8482	8400.30	8374.40	8326.20	7900.93
14	9982	9707	8186	8186	8135.40	8119.90	8025.40	7614.23
15	9569	9351	8154	8159	8100.60	8090.50	7984.40	7565.17
16	9030	8469	7622	7626	7550.50	7539.60	7457.90	7064.31
17	8872	8189	7526	7525	7470.60	7440.20	7362.60	6970.26
18	9273	9061	8132	8131	8050.80	8040.40	7956.60	7528.83
19	9990	9852	8652	8636	8549.60	8511.00	8462.30	8011.77
20	12,646	11,897	9846	9811	9760.60	9710.00	9690.90	9138.38
21	11,496	11,101	9383	9383	9249.90	9219.70	9221.60	8718.55
22	9534	9488	8371	8370	8300.80	8281.40	8194.50	7775.98
23	8667	8077	7572	7572	7463.70	7440.10	7403.10	7020.84
24	8517	7498	7254	7262	7225.80	7195.70	7070.80	6656.48
Total	232,053	217,655	192,309	192,250	190,512.3	189,947.5	188,154.4	**177,936.6**

Table 10 Results of Case 2 of Scenario 2

Time	RGM cost ($/h)	ACO cost ($/h)	CSA cost ($/h)	ISA cost ($/h)	MHS cost ($/h)	Proposed approach ($/h)
1	8490.00	7317.00	7179.00	7156.00	6977.40	6564.61
2	8528.00	7694.00	7365.00	7364.00	7194.40	6789.66
3	8592.00	7922.00	7479.00	7508.00	7310.30	6908.16
4	8675.00	8117.00	7598.00	7599.00	7429.50	7064.11
5	8756.00	8318.00	7721.00	7721.00	7550.80	7185.20
6	8878.00	8600.00	7848.00	7841.00	7675.30	7277.93
7	8849.00	8589.00	7816.00	7816.00	7647.20	7248.53
8	8969.00	8559.00	7692.00	7692.00	7530.90	7129.81
9	9788.00	9630.00	8269.00	8244.00	8105.90	7696.62
10	10,235.00	10,139.00	8397.00	8337.00	8242.20	7834.17
11	12,153.00	11,648.00	9620.00	9634.00	9465.90	8932.64
12	13,327.00	12,336.00	10,052.00	10,053.00	9903.00	9334.05
13	10,957.00	10,788.00	8887.00	8887.00	8734.90	8268.22
14	10,153.00	10,012.00	8467.00	8467.00	8305.80	7882.97
15	9707.00	9617.00	8377.00	8378.00	8206.80	7784.50
16	9093.00	8829.00	7974.00	7970.00	7797.90	7390.77
17	8810.00	8279.00	7608.00	7608.00	7444.40	7057.02
18	9340.00	9137.00	8182.00	8182.00	8006.60	7579.49
19	10,009.00	9937.00	8657.00	8657.00	8483.50	8047.97
20	12,664.00	12,032.00	9851.00	9849.00	9696.60	9480.87
21	11,495.00	11,197.00	9388.00	9400.00	9226.10	8702.54
22	9540.00	9479.00	8379.00	8379.00	8203.00	7784.37
23	8675.00	8117.00	7598.00	7596.00	7429.50	7055.20
24	8515.00	7491.00	7264.00	7263.00	7082.80	6677.05
Total	234,198	223,784	197,668	197,601	193,650.8	**183,676.4**

Table 11 Results of Case 3 of Scenario 2

Time	CSA cost ($/h)	ISA cost ($/h)	MHS cost($/h)	Proposed approach ($/h)
1	7153.00	7152.00	6943.40	6525.48
2	7203.00	7199.00	7010.50	6602.32
3	7279.00	7279.00	7099.60	6703.52
4	7235.00	7235.00	7050.20	6650.98
5	7544.00	7545.00	7377.20	6966.28
6	7724.00	7724.00	7553.40	7153.10
7	7606.00	7606.00	7439.40	7053.18
8	7443.00	7443.00	7278.50	6884.91
9	8364.00	8364.00	8190.10	7770.00
10	9006.00	9006.00	8840.70	8362.65
11	9454.00	9461.00	9295.80	8771.53
12	9581.00	9581.00	9425.90	8904.99
13	9408.00	9407.00	9248.70	8725.14
14	8933.00	8933.00	8766.30	8320.77
15	8427.00	8427.00	8252.30	7816.37
16	7756.00	7758.00	7584.20	7191.79
17	7761.00	7761.00	7590.10	7179.05
18	8194.00	8193.00	8017.20	7604.62
19	8636.00	8644.00	8461.90	8009.29
20	9845.00	9842.00	9690.70	9131.69
21	9383.00	9383.00	9221.80	8702.38
22	8371.00	8325.00	8194.70	7771.34
23	7572.00	7571.00	7403.70	7012.31
24	7254.00	7254.00	7070.80	6681.92
Total	197,132	197,093	193,006.9	**182,495.6**

4.3.2 Case 2 (no wind generation unit)

In this case, only wind energy is not employed in the microgrid. The hourly and total operational costs obtained by different approaches for this case are given in Table 10. As seen, the least total cost, i.e., 183,676.4 ($/day), is provided by the proposed approach. In Fig. 13, generated powers of different generators while employing the proposed method are shown.

4.3.3 Case 3 (no solar generation unit)

Here, the microgrid has no solar generation unit. In Table 11, the results (generation costs) of the compared approaches for this case are given where the proposed approach has the superior performance by giving the total cost of 182495.6 ($/day). Additionally, the hourly generated powers of different generation units obtained by the proposed approach are shown in Fig. 14.

4.3.4 Case 4 (no renewable energy resources)

In Table 12, the hourly and total operational costs of different methods for Case 4 of Scenario 2, where the microgrid includes no renewable energy sources, are listed. According to the results, the proposed algorithm is the superior one by providing the least cost (187935.12 ($/day)) among

Table 12 Results of Case 4 of Scenario 2

Time	RGM cost ($/h)	ACO cost ($/h)	CSA cost ($/h)	ISA cost ($/h)	MHS cost ($/h)	Proposed approach ($/h)
1	8490.00	7317.00	7179.00	7179.00	6977.40	6560.18
2	8528.00	7694.00	7365.00	7367.00	7194.40	6803.19
3	8592.00	7922.00	7479.00	7499.00	7310.30	6921.50
4	8675.00	8117.00	7598.00	7608.00	7429.50	7041.87
5	8756.00	8318.00	7721.00	7722.00	7550.80	7155.64
6	8878.00	8600.00	7849.00	7851.00	7675.40	7295.47
7	9005.00	8768.00	7978.00	7978.00	7802.50	7415.95
8	9167.00	8998.00	8110.00	8110.00	7933.70	7527.76
9	10,527.00	10,406.00	8943.00	8943.00	8774.30	8307.12
10	11,867.00	11,347.00	9540.00	9540.00	9380.90	8843.60
11	12,664.00	12,032.00	9851.00	9850.00	9696.60	9114.53
12	13,511.00	12,476.00	10,170.00	10,170.00	10,020.00	9412.21
13	12,664.00	12,032.00	9850.00	9746.00	9696.60	9115.96
14	11,160.00	10,889.00	9238.00	9230.00	9074.40	8560.57
15	10,009.00	9936.00	8657.00	8675.00	8483.50	8024.32
16	9167.00	8998.00	8110.00	8109.00	7933.70	7531.09
17	8875.00	8599.00	7849.00	7849.00	7675.60	7282.98
18	9347.00	9186.00	8244.00	8244.00	8067.50	7641.68
19	10,009.00	9936.00	8657.00	8657.00	8483.50	8021.98
20	12,664.00	12,032.00	9851.00	9847.00	9696.60	9139.83
21	11,495.00	11,197.00	9388.00	9388.00	9226.10	8716.82
22	9540.00	9479.00	8377.00	8379.00	8203.00	7778.18
23	8675.00	8117.00	7598.00	7598.00	7429.50	7026.77
24	8515.00	7491.00	7265.00	7260.00	7082.80	6695.92
Total	240,780	229,887	202,867	202,799	198,798.4	**187,935.12**

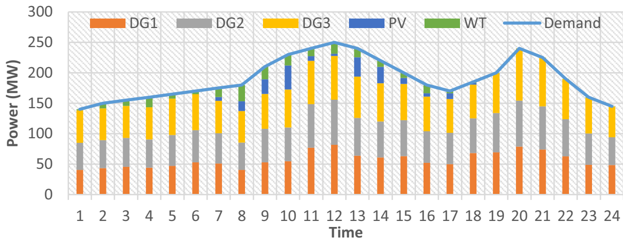


Fig. 12 Generated powers of different generation units in Case 1 of Scenario 2

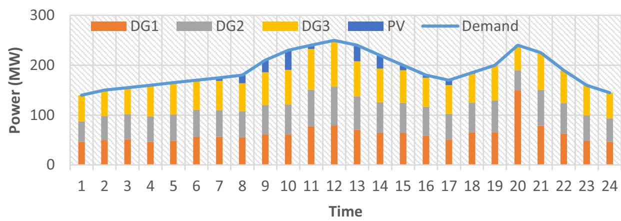


Fig. 13 Generated powers of different generation units in Case 2 of Scenario 2

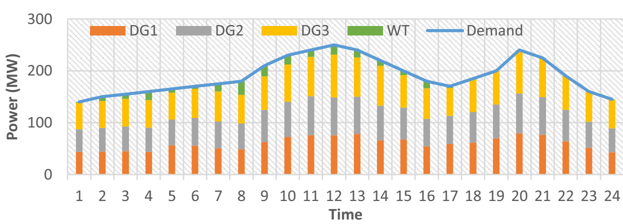


Fig. 14 Generated powers of different generation units in Case 3 of Scenario 2

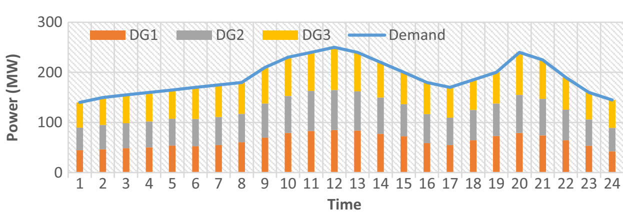


Fig. 15 Generated powers of different generation units in Case 4 of Scenario 2

all compared methods. Besides, Fig. 15 shows different units' generated powers which are obtained by the proposed approach.

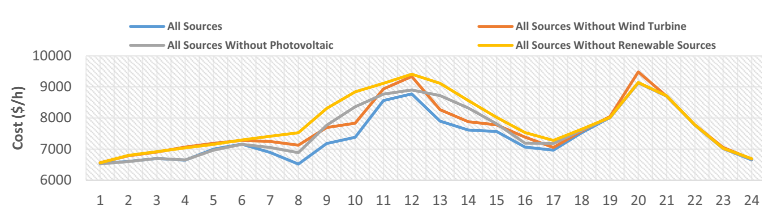
According to Figs. 12, 13, 14, 15, by using the proposed method, the whole load is supplied by the generation units, and the constraints are perfectly satisfied. Moreover, Figs. 16 and 17 respectively compare the hourly and total costs acquired by the proposed approach in Scenario 2. As seen, both hourly and total costs can be considerably reduced by employing renewable energy sources in the system. In detail, when both renewable energy sources, including PV and WT, participate in power generation in the presence of thermal units (Case 1), a lower cost is obtained. Besides, there is a little increase in the cost of Case 2 where no WT exists. Similarly, in Case 3 (no PV in the microgrid), the cost is more than that in Case 1. Moreover, in Case 4, the cost has the highest value because the demand is merely supplied by the thermal units. Consequently, it is clear that the more renewable energies are integrated into the microgrid, the more reduction in the cost and emission can be achieved. The total emission emitted from thermal units is also depicted in Fig. 18 where it is obvious that the microgrid experiences a higher emission if there is no renewable energy integration. While, the cost significantly decreases by employing solar energy and wind turbine.

4.4 The results of Scenario 3

4.4.1 Case 1: sensitivity analysis on the algorithm's parameters

For optimum tuning of the algorithm's parameters, the parameter Cr is set to 0.1 initially, and thereby, the parameter β_c is changed from 0.1 to 0.9. The results of the tuning of β_c are shown in Fig. 19a. As seen, the best range of β_c is between 0.2 to 0.4. After acquiring the optimal value of the parameter β_c, the optimum value of the parameter Cr is obtained. Hence, the parameter β_c is considered to be equal to 0.3, and then the parameter Cr is changed from 0.1 to 0.9 to extract its best value. According to Fig. 19b. the parameter Cr should have a value between 0.3 and 0.4 to achieve desirable performance.

Fig. 16 Hourly costs of Scenario 2 over a day obtained by the proposed approach



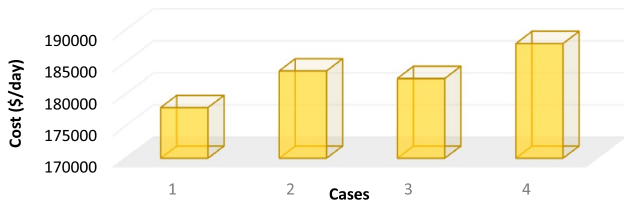


Fig. 17 Total costs of Scenario 2 over a day obtained by the proposed approach

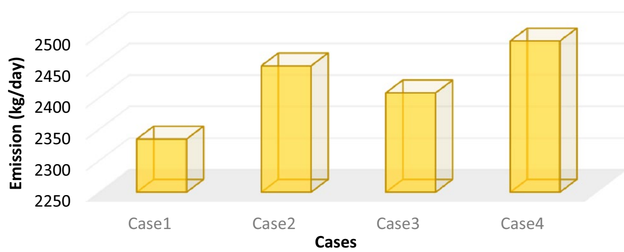
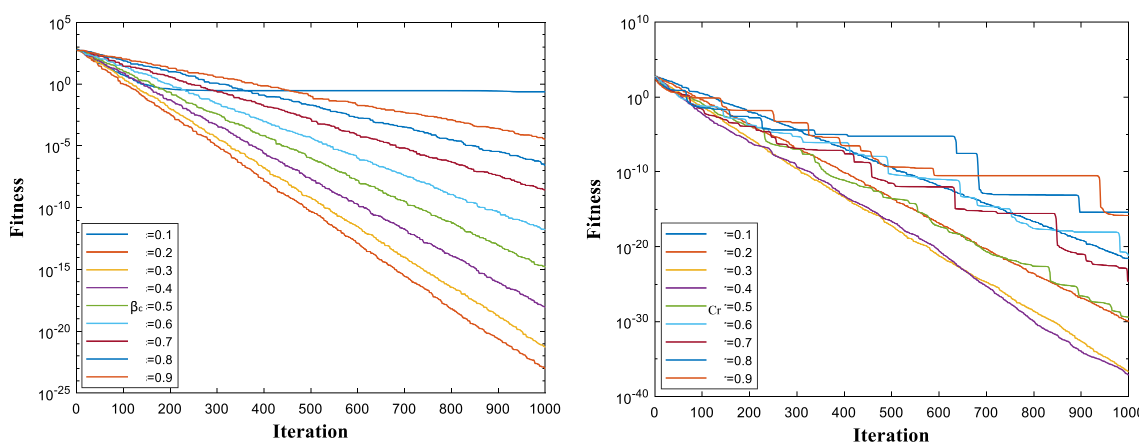


Fig. 18 Total emission of Scenario 2 over a day obtained by the proposed approach



(a) Effect of β_c on the performance of the algorithm

(b) Effect of Cr on the performance of the algorithm

Fig. 19 Parameter tuning of the proposed approach

Table 13 Results of all cases of Scenario 1 considering the power loss

Cases	Total cost ($/day)
Case1	172,306.8
Case2	177,324.5
Case3	176,550.9
Case4	181,614.0

4.4.2 Solving ED in the presence of power loss

During the operation of power systems, some of the generated power is wasted as losses. Generally, 5–10% of the generated power is wasted as losses (Asrari et al. 2016; Gholami and Parvaneh 2019). Accordingly, the power balance constraint in (10), including power loss, is modified to $P_{Load} + P_{loss} = \sum_{i=1}^{NG} (P_i) + P_{Solar} + P_{Wind}$. Here, it is assumed that 5 percent of generated power which is equal to 5% of the load is wasted. The results for all cases of Scenario1 by considering the power loss are obtained and listed in Table 13; it is shown that the amount of operational cost is increased since the power loss is considered in the calculations.

4.4.3 Comparison with NSGA-II

Here, the efficiency of the proposed approach is compared with NSGA-II (Deb et al. 2000) whose results are shown in Fig. 20. As seen, the proposed approach is the superior one compared to the NSGA-II since it can provide high-quality solutions.

5 Conclusion

These days, the demand for renewable energies integration has increased sharply due to environmental concerns. Thus, proposing efficient operational optimization schemes to cope with such emerging technologies is necessary. This article proposes a new optimization algorithm to deal with both problems of ELD and CEED, leading to optimal power consumption in an islanded microgrid. For this aim, a new modified version of differential evolution algorithm, named

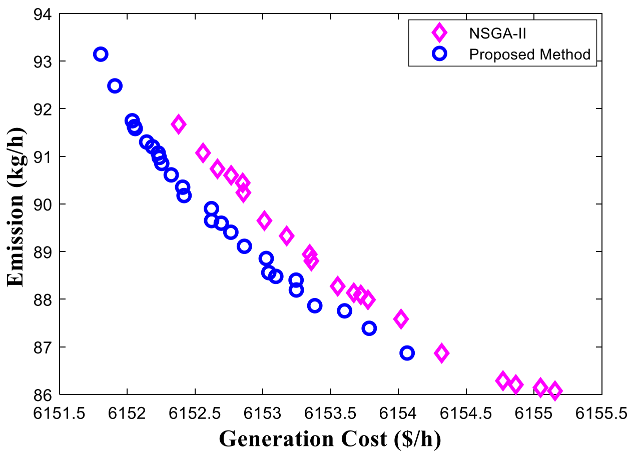


Fig. 20 Comparison between NSGA-II and the proposed method

self-adaptive comprehensive differential evolution algorithm (SACDE) is proposed. The proposed algorithm is assessed under two conditions, including single- and multi-objective operations. Regarding single-objective scheduling, this algorithm is employed to solve the ELD problem. In terms of the multi-objective operation, the CEED problem with two objective functions of cost and emission is solved. According to the comprehensive results presented in the previous sections, the proposed approach by providing the optimal solution (giving the lowest cost) outperforms the other similar methods such as RGM, ACO, and CSA. The sensitivity analysis of the parameters associated with the algorithm was also investigated to determine their best values. In addition to comparing the proposed algorithm with other similar ones such RGM, ACO, CSA, a separate comparison between the proposed approach and the NSGA-II, a well-known algorithm, was also performed, proving the superiority of the proposed algorithm over NSGA-II. For future works, considering electric vehicle charging stations in reconfigurable microgrids suffering from renewables' uncertainties and performing a comprehensive comparison between all existing algorithms to schedule microgrids' resources can be suggested.

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