An Optimal Energy Control System for Campus Microgrid Using Crow Search Algorithm Considering Economic Dispatch

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Abstract

This article presents an optimal energy control system that considers economic dispatch (ED) for a campus microgrid to reduce its operating cost. A newly developed crow search algorithm (CSA) is used to enforce the ED in this work. To achieve this purpose, an optimal size of distributed energy resources (DERs) in the campus microgrid is assumed. CSA is used to optimize the energy control system and find the minimum operating cost of the campus microgrid. To indicate the effectiveness of CSA, several scenarios under various load demand conditions in grid-connected and stand-alone microgrid modes are investigated in this work. According to the findings, the suggested model is capable of sufficient power supply in all scenarios and reduces the operating costs more effectively than the reference delineated in the same case. The outcomes confirm that the suggested model's performance is optimal for the energy control system of a campus microgrid.

Keywords: optimal energy control system, economic dispatch, operating cost, campus microgrid, crow search algorithm

1. Introduction

The worldwide renewable energy capacity is expected to increase rapidly over time [1]. This encourages researchers to develop microgrid systems capable of harnessing renewable energy's potential. Generally, the microgrid system can be operated in two modes [2-5]. It's a stand-alone mode for inaccessible utilities like remote areas or isolated islands [6], and a grid-connected mode that is suitable for supplying residential, urban, commercial, and central areas, up to educational facilities [7]. Among these, educational campuses are particularly well-suited for the implementation and development of microgrid systems. The availability of reliable human resources and regular administration in this area can be classified as a prosumer area that is very suitable for the implementation and development of microgrid systems [8-9].

A wide range of renewable energy sources (RES), including solar energy, wind, water, etc., can be used by microgrids [10]. However, the use of these RES like photovoltaic (PV) depends on stochastic climatic conditions and time resulting in varying electricity generation in the microgrid system [11-12]. Therefore, energy storage systems (ESS) such as battery energy storage systems (BESS), have been combined in microgrid systems to maintain power continuity in microgrids [13].

A diesel generator (DG) that is independent of time and weather generator also has been combined in microgrid to handle more complicated system conditions, such as power outages or when the renewable energy generation and storage systems are no longer able to handle load demand [14]. Although preventive attempts have been made through the combination of ESS and independent generation in microgrids, the complexity of microgrid operation is still a crucial issue that needs to be

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considered to make microgrids optimal and reliable. In this regard, the operation of microgrid systems needs to consider electricity storage systems, load devices, and generation units, while ensuring optimal and reliable operation of microgrid networks to handle the uncertainties in microgrids and minimize the operating costs [15].

To overcome the economic dispatch (ED) problem, which is based on the optimal power search of each distributed energy resources (DERs) to reduce the operation cost, several matters such as power continuity and various operating constraints are considered [16]. Various methods have been developed by several researchers in this field. Mellouk et al. [17] used the genetic algorithm (GA) to minimize grid charges and peak hours of energy consumption. Ali [18] has also used particle swarm optimization (PSO) and differential evolution (DE) to optimize energy management for microgrids in grid-connected and stand-alone modes. Nevertheless, renowned algorithms do have their restrictions. Examples of common issues include the slow convergence rate of GA, the instability of convergence in DE, and the tendency for both DE and PSO to easily fall into local optima, often requiring a substantial amount of time to converge [19].

One of the latest metaheuristic algorithms is the crow search algorithm (CSA) introduced by Askarzadeh [20], which adopts the memory-based nature of crows to hide and steal their food from other crows. CSA has only one equation and two tuning parameters, making it easy to implement while still being able to maintain the consistency and robustness of the algorithm by spending less computational time to achieve the best fitness value. Spea in [21] has used CSA to optimize the microgrid energy management with DERs consisting of PV/wind/DG systems in remote areas. Dey et al. [19] also used CSA to optimize it in microgrids with PV/wind turbine/DG configurations in grid-connected and stand-alone modes. The research results demonstrated that the algorithm excels in addressing energy management issues within the microgrid systems in terms of power continuity, economy, and emissions.

However, most researchers often overlook specific areas of microgrid application, especially those with unique energy consumption patterns like campus areas. On the other hand, the optimal size of the DER implemented is also a crucial factor that must be considered. In this work, the optimal size of DER in a grid-connected microgrid has been implemented in the campus area referred to [14] with the same site study while still being adjusted to the conventional market size. Therefore, this article presents an energy control for optimizing the energy management system in the grid-connected microgrid of campus areas with the ED problem to find the optimal power of each DER and minimize the total operational cost using CSA. In the proposed model, operating costs and the optimal unit capacity of each DER are considered. Furthermore, day-ahead control energy has been thoroughly explored concerning several constraints, such as power generation, electricity price, and various load conditions.

This paper is organized as follows: Section 2 presents the ED model of grid-connected campus microgrids, including the objective function, some constraints, and the case site profiles of the campus microgrid. CSA is the method used to solve the ED problem, and case studies are discussed in Section 3. The results of this study are presented in Section 4, and the conclusion is presented in Section 5.

2. ED Model of Grid-Connected Campus Microgrid

The ED problem essentially aims to find the lowest generation cost by finding the optimal output power of each DER. Nevertheless, in the ED problem, many aspects can be considered, such as power trading, scheduling, and demand side management (DSM) [16]. ED is a complex problem with large dimensions and many constraints to be considered. In grid-connected microgrids, especially in the campus area, the aspects of power trading, scheduling, and unusual load usage patterns need to be considered. Therefore, in this work, ED will be analyzed on a grid-connected microgrid in the campus area with PV, BESS, and DG configurations as shown in Fig. 1.

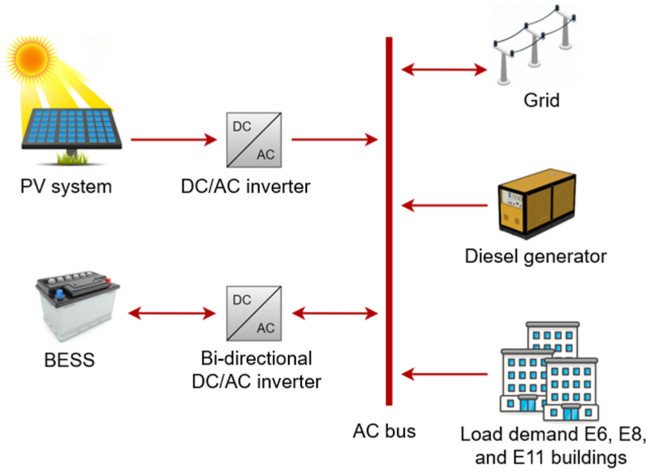

Fig. 1 University campus microgrid structure

2.1. Objective function

The main objective of ED in this work is to find the optimal power of each DER in a grid-connected campus microgrid to minimize the total operational cost using CSA. To achieve this purpose, the characteristics and optimal size of each DER must be considered. Furthermore, day-ahead control energy has been thoroughly explored regarding several constraints, such as power generation, electricity price, and various load conditions. In this case, a grid-connected microgrid that uses RES in the form of PV, ESS, and DG, is considered as follows [16]:

$$MinC_t = \sum_{t=1}^{T}\sum_{i=1}^{n} F_c\left[P(t)\right] + \sum_{i=1}^{n} C_{buy}(t)P_{buy}(t) - C_{sell}(t)P_{sell}(t) \tag{1}$$

where $MinC_t$ is the total cost function of the grid-connected microgrid, and $F_c(t)$ is the total operational cost of all DER units consisting of DG, BESS, and RES units in the form of PV in the time interval t. $C_{buy}(t)$, $C_{sell}(t)$, and $P_{buy}(t)$, $P_{sell}(t)$ are the powers and prices of electricity purchased and sold at t.

RES, such as PV is a source of clean energy that does not require fuel costs. Although there are still installation, maintenance, and operation costs that can be calculated to determine the cost function of RES [21]. In this study, the investment cost of RES is not considered as described by:

$$F_c\left(P_{pv}\right) = \left[\frac{r}{1-(1+r)^{-N}} + O_p\right]P_{pv} \tag{2}$$

where $F_c(P_{pv})$ is the operating cost of the PV, P_{pv} is the PV output power, r and N are the interest rate and lifetime of the unit in years, and O_p is the ratio of operating and maintenance costs to installed unit power. In [22], the value of r is set to 0.09 and N = 20 years, the value of O_p is 0.016 \$/kW used in this study and some previous studies [21, 23-24]. The PV cost function in Eq. (2) can be replaced by:

$$F_c\left(P_{pv}\right) = 0.12554647 \times P_{pv} \tag{3}$$

2.2. Constraint

Total power production from each DER should be equal to the electricity load demand, as represented by:

$$P_g(t) + P_{DG}(t) + P_{BESS}(t) + P_{pv}(t) = P_{load}(t) \tag{4}$$

$$P_g(t) = P_{but}(t) - P_{sell}(t) \tag{5}$$

On the other hand, to ascertain system operation stability, each DER should have maximum and minimum limits according to,

$$P_{\min} \le P_i \le P_i^{\max} \tag{6}$$

In a grid-connected microgrid, it can be ensured that power buying and selling transactions to and from the grid as represented in:

$$C_t^p(t) = \begin{cases} Cbuy(t)Pg(t) \;\; if \;\; Pg \ge 0 \\ Csell(t)Pg(t) \;\; if \;\; Pg \le 0 \end{cases} \forall t\{0,1,\ldots,T\} \tag{7}$$

where $P_{DG}(t)$, $P_{BESS}(t)$, and $P_{PV}(t)$ are the output power of DG, BESS, and PV at t, while $P_{Load}(t)$ denotes the power demand at t. P_i^{min} and P_i^{max} represent the minimum and maximum output power limits of unit i. (t) is the total electricity cost at t. A positive value for grid power means the system is buying power from the grid. Whereas, if the value is negative, it means the system is selling power to the grid.

Restrictions and patterns of BESS usage are also important to be considered in the microgrid system's operation. The output and input power capacities of the BESS, state of charge (SOC) limitations, and changes in the BESS are represented by the following equations [16]:

$$\begin{aligned} & P_{BESS}(t) \in \left[\left(-P_{dis}^{\max}, -P_{dis}^{\min}\right), \left(-P_{ch}^{\max}, -P_{ch}^{\min}\right)\right] \\ & if \;\; P_{BESS}(t) > 0 \rightarrow BESS_{charges}; \\ & if \;\; P_{BESS}(t) < 0 \rightarrow BESS_{discharges}; \\ & if \;\; P_{BESS}(t) = 0 \rightarrow BESS_{idle} \end{aligned} \tag{8}$$

$$SOC_{BESS-\min}(t) = \frac{e_{critical}}{e_{BESS-cap}} \le SOC_{BESS}(t) \le 1 \tag{9}$$

$$SOC_{BESS}(t+1) = SOC_{BESS}(t) + \frac{P_{BESS}(t)\tau}{e_{BESS-cap}} \tag{10}$$

where P_{ch}^{max} and P_{ch}^{min} are the maximum and minimum BESS charges, respectively. Whereas P_{dis}^{max} dan P_{dis}^{min} is the maximum and minimum BESS discharges. $SOC_{BESS\text{-}min}(t)$ is the minimum SOC limit, $SOC_{BESS}(t)$ is the SOC of BESS, $e_{critical}$ is the energy consumed during critical load, τ is the time period, and $e_{BESS\text{-}cap}$ is the capacity of BESS.

2.3. Case site profiles

As has been explained in the previous section, the campus area is the most suitable place for the implementation and development of microgrid systems. The focus of this site study is the campus areas, specifically the university buildings in the Electrical Engineering Department of the Faculty of Engineering at Universitas Negeri Semarang. These buildings are E6, E8, and E11 as shown in Fig. 2. It's located in Sekaran, Gunungpati, Semarang City, Indonesia, with coordinates of 7.05° south latitude, 110.40° east longitude, and an altitude of 187 meters above sea level [25]. As a result, the climate can be classified as tropical, featuring two distinct seasons: the dry season and the rainy season, which occur throughout the year. The daily load pattern in the site study has an unusual pattern where peak hours occur during the day, with the main load consisting of lighting, air conditioning, and campus electrical equipment such as computers, projectors, and electrical trainers set in the laboratory. The total daily load profile is 246.5 kWh and the annual average load is 68,204.1 kWh/year [14].

DG units have been combined in a microgrid system to handle more complicated system conditions, such as power outages or when the renewable energy generation and storage systems are no longer able to handle load demand. Therefore, in this work, the optimal capacity of DG was considered. The cost characteristics of DG units are described in Table 1.

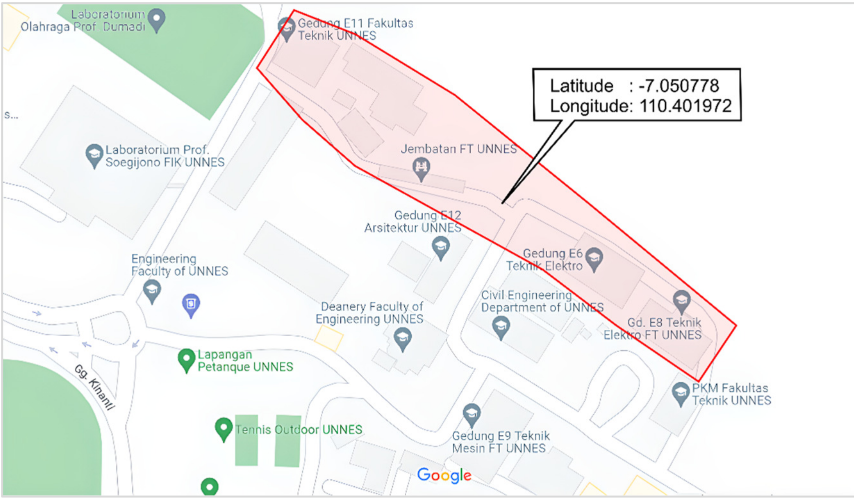

Fig. 2 E6, E8, and E11 buildings location [25]

Table 1 DG generation cost characteristics

DG	State	Generation capacity (kW)	Cost ($/kW)
DG1 (28 kW)	Low	7-14	0.185
	Medium	15-21	0.16
	High	22-28	0.156
DG2 (48 kW)	Low	12-24	0.171
	Medium	25-36	0.143
	High	37-48	0.132

3. Crow Search Algorithm

One of the latest metaheuristic algorithms for solving energy management problems, specifically the ED problem, is CSA. However, in its implementation, CSA also has several tuning parameters that need to be adjusted. In this section, an overview of CSA and its implementation in ED problems is addressed.

3.1. Overview of CSA

CSA is one of the latest metaheuristic algorithms introduced by Askarzadeh in 2016 [20], which adopts the memory-based nature of crows to hide and steal their food from other crows. This algorithm adapts the intelligent behavior of crows in a flock to find the best food source based on the objective function. In the optimization perspective, the crow acts as the searcher, the environment serves as the search space, every food source hiding place is a feasible solution, the quality of the food source is the objective function (fitness), and the best food source in the environment is the problem's global solution [20]. Furthermore, it can be assumed that we have a *d-dimensional* search space in an environment occupied by several crows, then the position of Crow i at iteration time in the search space can be expressed by $x^{i,iter} = (x_1^{i,iter}, x_2^{i,iter}, x_3^{i,iter},\ldots, x_d^{i,iter})$ [21]. Where (i = 1, 2, 3,…, N), (iter = 1, 2, 3,…, $iter_{\max}$); d is the number of decision variables, N is flock size, and $iter_{\max}$ is the maximum number of iterations.

The crow's current position, represented by $m^{i,iter}$ is stored in the memory of crow as the current best position. To update the crow's position, it can be assumed that at an iteration, there is a Crow j going to its hiding place $m^{j,iter}$. Then Crow i decides to follow Crow j to its hiding place. In this case, two possible circumstances will change the crow's position.

Case i: Crow j did not realize that Crow i was following it. Therefore, Crow i will find out the hiding place of Crow j.

Case ii: Crow j realizes that Crow i is following it. Therefore, Crow j will try to trick Crow i into protecting its hiding place by randomly moving to other locations in the search space.

According to the possibility of both cases above, the next position of Crow i can be expressed by:

$$X^{i,iter+1} = \begin{cases} X^{i,iter} + r^{i} \times fl^{i,iter} \times \left(m^{j,iter} - X^{i,iter}\right) & r^{j} \geq AP^{j,iter} \\ a\ random\ position & otherwise \end{cases} \tag{11}$$

where r_i and r_j are randomly distributed numbers between 0 and 1. $fl^{i,iter}$ is the flight length of Crow i at iteration iter, and $AP^{j,iter}$ represents the awareness probability of Crow j at iteration iter. Furthermore, the crow's memory will be updated by:

$$mi, iter+1 = \begin{cases} X^{i,iter+1} f\left(x^{i,iter+1}\right), & is\ better\ than\ f\left(m^{i,iter}\right) \\ m^{i,iter}, & otherwise \end{cases} \tag{12}$$

where $f(...)$ represents the objective function value.

In this algorithm, diversification and intensification are controlled by *fl* and *AP*. The value of *fl* will be directly proportionate to the similarity value of the crow position, and the *AP* value will be proportionate to the crow position diversity level. Therefore, setting a small value for *fl* ($fl < 1$) generates a local search close to $X^{i,iter}$, whereas setting a large value for *fl* ($fl > 1$) will cause a global search far from $X^{i,iter}$. On the other hand, increasing the value of *AP* decreases the probability of finding a solution around the current best location and the algorithm will tend to explore solutions in the global search space. Rather than decreasing the value of *AP*, the algorithm will tend to search around the location where the current best solution is found [15, 17, 22].

3.2. *Implementation of CSA to ED problem*

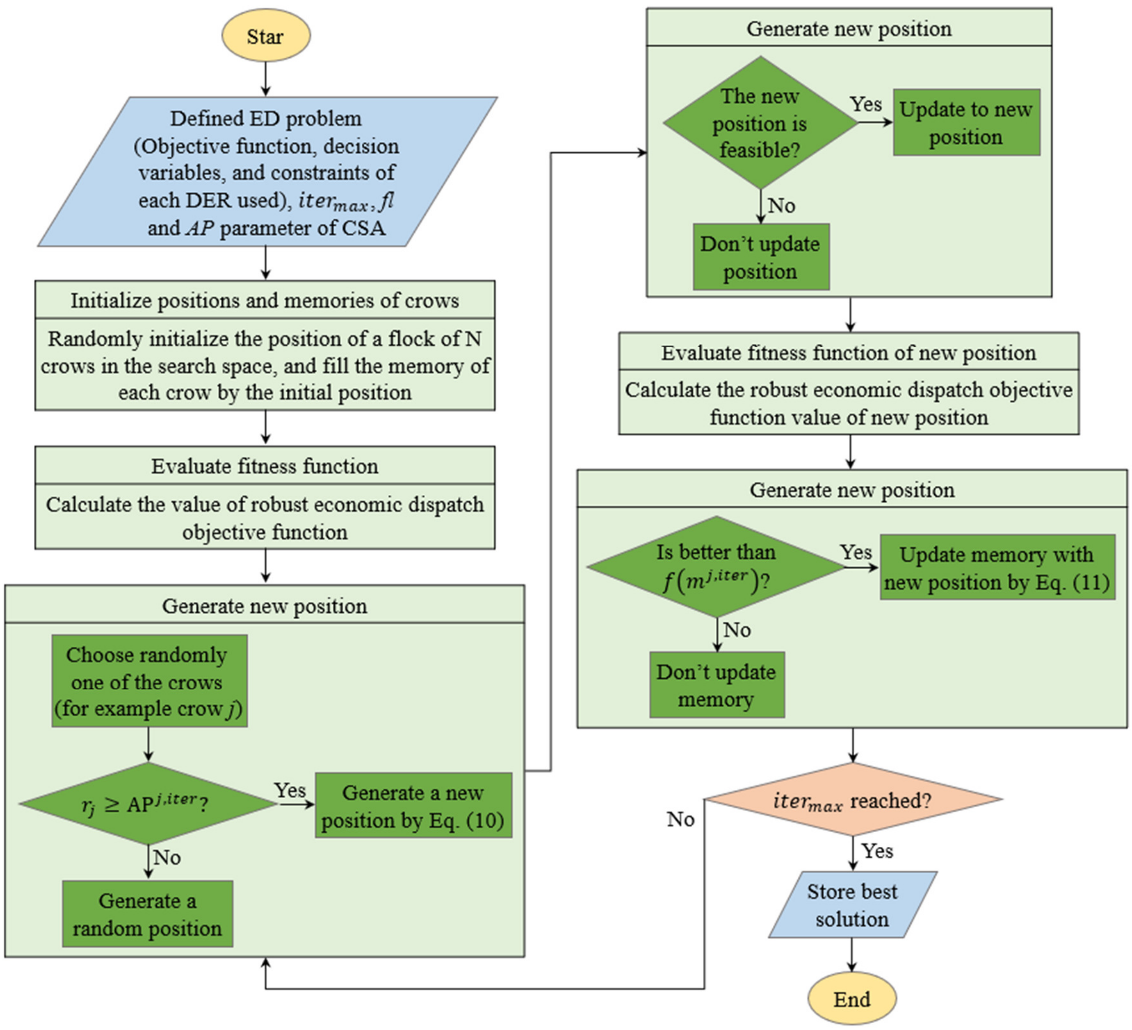

Fig. 3 Flowchart of CSA for solving ED

In the previous section, it was mentioned that the ED problem aims to minimize the total generation cost of all microgrid DER units while considering the power availability and optimal capacity selection of the installed DERs. In this problem, CSA plays a role in finding the most optimal combination of power output from each DER of the campus microgrid to minimize its generation cost while considering power availability.

Before presenting the CSA, it must be remembered that to solve the ED problem, it is necessary to meet some equality and inequality constraints as introduced in Eqs. (1)-(10). On the other hand, memory-based algorithms such as CSA essentially have different optimization solutions for each running instance. The settling of the algorithm relies on the initial position and the random movement of the population to find optimal solutions in the search space.

Therefore, assessing memory-based algorithms in a single run is not an appropriate comparison. To assess the robustness of the algorithm, multiple test runs are required. The algorithm is considered reliable when it consistently produces results across all runs [26]. The tuning parameters directly affect the final result of the algorithm. Prior studies [21, 26-28] have established and demonstrated the optimal values of *fl* and *AP*, which are adopted in this work. Table 2 provides details of CSA tuning parameters. Finally, the detailed steps of CSA implementation for the ED problem are described in the flowchart presented in Fig. 3.

Table 2 Details of CSA tuning parameters

$iter_{max}$	Flock size	fl	AP
200	40	2	0.1

4. Results and Discussion

In this section, CSA has been used to optimize the ED problem on the grid-connected campus microgrid that uses PV as a renewable energy source and is supported by BESS and DG. To provide a comprehensive investigation of the ED problem in this work, the microgrid was tested under various load demands in grid-connected and stand-alone modes to prove the feasibility of the microgrid system for solving the various possible conditions, as detailed in Table 3.

Table 3 Detailed profile of scenarios

Scenarios	Grid	Load demand
1	On	< PV generation
2	On	> PV generation
3	Off	< BESS capacity
4	Off	> BESS capacity
5	Off	< DG capacity
6	Off	> DG capacity
7	Off	> DG + BESS capacity

As discussed in the previous section, the algorithm tuning parameters greatly affect the final result of the algorithm. The best values of the *fl* and *AP* parameters in CSA have also been determined as 2 and 0.1 [17, 22-24]. Nevertheless, population-based algorithms such as CSA also depend on the flock size parameter. Therefore, in this section, various flock size values are compared to find the best flock size parameter value for the CSA to find the minimum operating cost with the lowest error value in the 24-hour simulation period.

The error value is intended as the value of the equality constraints of generation power and demand. Table 3 shows the results of system testing with a variety of different flock size values. It can be seen that the flock size value also affects the performance of the algorithm to overcome the ED problems. Based on Table 4, it can be concluded that the best flock size parameter is 40. It is proven that the system with this parameter value gets the minimum value both in the error value and the total operating cost for the 24-hour simulation period.

Table 4 CSA performance under various flock size values

Flock size	Error			Std. Div	Total cost
	Best	Mean	Worst		
10	0	0.0822397	0.84183	0.177009574	98.198854
20	0	0.0441478	0.635726	0.129478714	95.801322
30	0	0.0346462	0.320607	0.073146489	95.635962
40	**0**	**0.0107046**	**0.056599**	**0.015878668**	**94.498001**
50	0	0.0306957	0.640118	0.127186635	94.835849
60	0	0.0273400	0.478794	0.095874636	95.141849

To prove the effectiveness of the CSA algorithm in handling the ED problem, the hourly operation of the microgrid during the 24-hour simulation period is shown in Fig. 4. Based on the figure, it can be seen that during the peak load after 08:00, the proposed system can meet the load demand, even able to charge the BESS and sell the excess power to the grid. On the other hand, when the PV system is unable to meet the load demand, the system combines BESS, grid, and DG to meet the load demand while still keeping the objective of finding the lowest cost and considering the equality constraints of generation and demand.

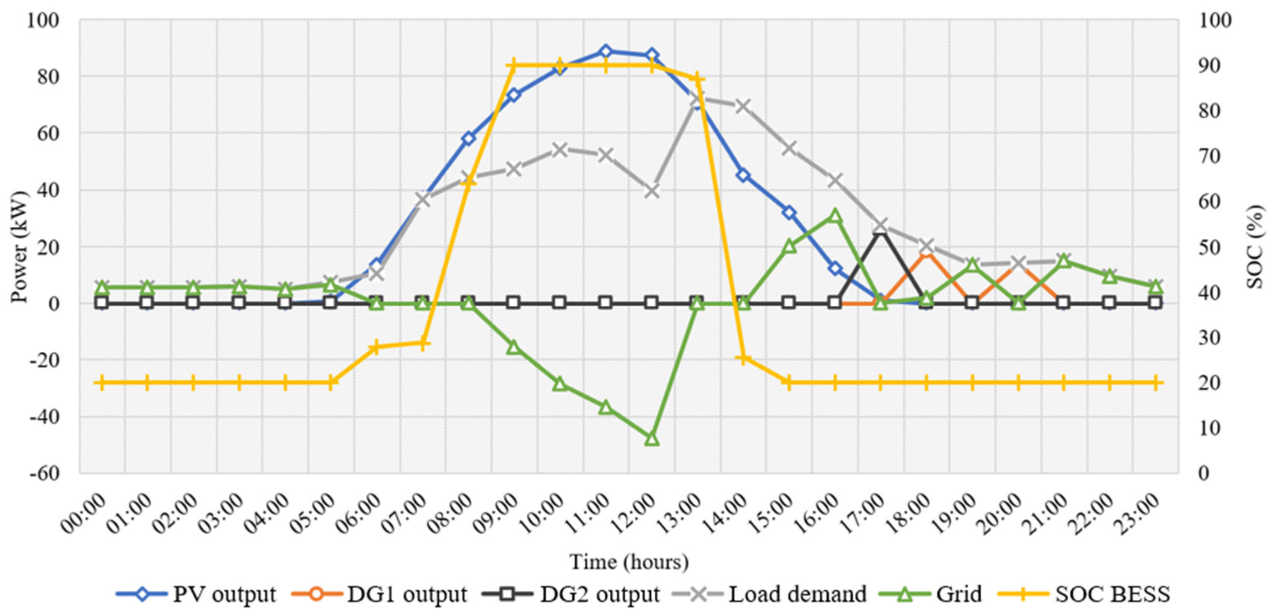

Fig. 4 The hourly output energy pattern of campus microgrid using CSA considering ED

Table 5 The total CSA results for the ED problem in each scenario for several hours

Scenarios	Load (kW)	PV (kW)	BESS charge (kW)	BESS discharge (kW)	DG1 (kW)	DG2 (kW)	Grid purchase (kW)	Grid sell (kW)	Cost ($)
1	238.230	390.931	24.243	0	0	0	0	128.457	43.019871
2	267.514	161.881	0	27.720	0	26.278	51.635	0	29.295997
3	275.43	265.213	0	10.217	0	0	-	-	33.500997
4	319.914	334.133	21.219	0	7	0	-	-	44.517511
5	336.470	355.329	18.859	0	0	0	-	-	45.741956
6	401.850	279.964	2.796	16.795	71.532	36.355	-	-	41.904463
7	544.477	402.278	10.958	10.983	105.185	36.987	-	-	70.292881

Finally, the total CSA results for the ED problem in each scenario for several hours are described in Table 5. It should be noted that the scenarios were tested under various load demand conditions on different days for several hours in each scenario, resulting in different amounts of PV generations and load demand. From the table, it can be seen that the proposed system could handle different load demand conditions in both grid-connected and off-grid modes in all scenarios. In grid-connected mode, especially in Scenario 1, the system is even able to sell excess generation back to the grid. In addition, in the worst-case scenario (Scenario 7) when load demand exceeds the capacity of BESS and DG, the system can meet the load demand and charge BESS. Fig. 5 presents the comparison of the total operational cost using the proposed method with the conventional method that optimizes the usage pattern of RES as the main source [29]. The results obtained show that the implemented CSA can reduce operating costs by 0.677% with a generation cost of $94.498001.

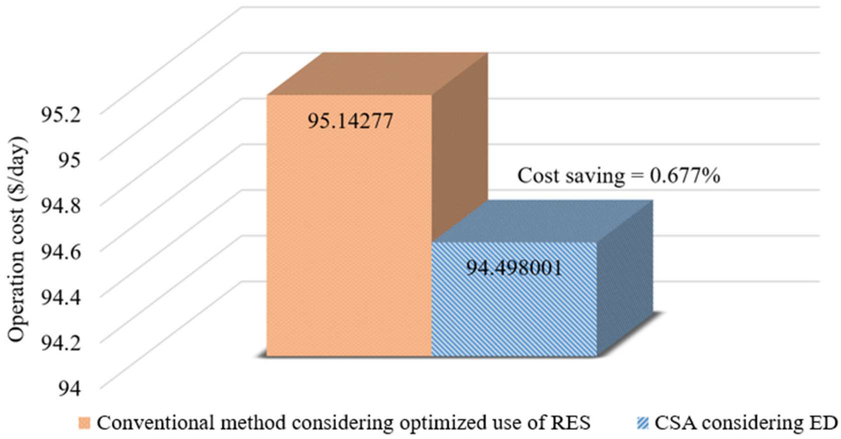

Fig. 5 Cost comparison between energy control system using CSA and conventional method considering optimized use of RES [29]

5. Conclusions

This paper presents an optimal energy control system using CSA that considers ED on a university campus microgrid using a DER configuration consisting of PV, BESS, and DG. The optimal capacity of the DER is assumed to support optimal generation within the microgrid system. The overall control energy is optimized by CSA to obtain the least operating cost while still considering the load demand. The optimal flock size parameter that can obtain a minimum value, considering both error and total operating costs, during a 24-hour CSA simulation period, is 40. Furthermore, the proposed system was tested in seven different scenarios under various load demands. In all scenarios, CSA proves sufficient to meet the load demand. In addition, the proposed method has been compared with conventional methods considering the optimized use of RES, and it has been proven that the proposed method can reduce operating costs better. The results of this study validate that the energy control model with CSA, considering ED, offers optimal performance for the operation of the university campus microgrid.

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Conflicts of Interest

The authors declare no conflict of interest.

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