Research Article – Vol. 01, Issue 03, No. 05

Advanced in Engineering and Intelligence Systems

Journal Web Page: https://aeis.bilijipub.com

Optimal commissioning of power plant units by including an energy storage system and demand-side program using a hybrid bacterial foraging and honey bee optimization method

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Highlights

- To cut expenses and environmental issues, smart grids are being studied
- "Ensuring safe operation" and "facilitating economic operation" are two main goals
- The optimum ESS charging and discharging are suggested in this article
- The proposed model is tested on a 4-unit system with ESS to verify its performance
- For optimization, a honeybee-mating algorithm with bacterial foraging were combined.

Article Info

Received: 28 August 2022
Received in revised: 28 September 2022
Accepted: 28 September 2022
Available online: 01 October 2022

Keywords

Unit commitment program,
Energy storage,
renewable energy resource,
smart grid,
demand side management

Abstract

Unit commitment (UC) programming is a critical task in power system operations, which faces problems such as uncertainty in generation and loads with the significant rise in the generation of electrical energy through renewable energy sources (RES) such as wind and responsive load programs. The problem of UC, or the unit commissioning problem, is a major optimization problem, the exact solution of which can lead to a significant reduction in costs. In this article, smart grids are considered which aim to reduce costs and environmental problems. Thus, this paper solves the UC problem in smart grids by considering the emission of generation units, resulting in a multi-objective function for minimization. With the introduction of smart grids, energy storage systems (ESS) have also been considered in the grid. This paper proposes the optimal charging and discharging of ESS. Another problem modeled in this article is that of demand response (DR) in smart grids. To validate the performance of the proposed model, it is tested on a 4-unit system with ESS and the results show its optimal performance. To solve the problem of UC programming, a hybrid honey bee mating and bacterial foraging algorithm are used to reduce the complexity of the problem and achieve optimal results.

Nomenclature

CHP	*Combined heat and power*	*PSO*	*Particle swarm optimization*
CP	*Center point*	*PV*	*Photovoltaic*
DR	*Demand response*	*PEV*	*Plug-in EV*
DRP	*DR program*	*P2G*	*Power-to-gas*
EVs	*Electric vehicles*	*RES*	*Renewable energy sources*

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HGSA	*Henry gas solubility optimization algorithm*	*SOC*	*State of charge*
HBMO	*Honey bee mating optimization*	*SOD*	*State of discharge*
MGWO	*Modified grey wolf optimization algorithm*	*SOE*	*State of energy*
MG	*Micro grid*	*UC*	*Unit commitment*

1. Introduction

The purpose of implementing the UC problem is to determine the ON units and the economic power flow to supply the load at the minimum cost. Due to uncertainties related to the load prediction error, unexpected generator decommissioning and transfer line outages during real-time operation, operators have to deviate from the pre-determined decisions by the unit commitment (UC) program and take costly modification measures, e.g., rapid generator commissioning or load disconnection to maintain system security [1].To overcome global warming and the environmental problems caused by fossil fuels, the industry has shifted its focus towards renewable energy sources (RES). Increased penetration of RESs that have fluctuating power generation, e.g., solar and wind energies, introduces more uncertainty to the system and poses new challenges for the grid manager and generation programming [2].In such conditions, there is a dire need for a UC process to manage system uncertainty [3].Currently, the electricity generation industry uses reserve constraints for the UC problem to deal with uncertainty [3].

Reduction of system operating costs is a key economic program in power systems. As such, programming for unit commissioning and decommissioning is of utmost importance [4].Generally, two objectives of “ensuring safe operation” and “facilitating economic operation” are of significance. In the traditional operation of power systems, the issue of entry and exit of units in the circuit is planned and implemented based on the principles of grid security.In such a case, the operation of the grid is not necessarily the most economical possible mode of operation. In the restructured environment, security can be facilitated by using various services available to the market and the electricity consumption price can be reduced by the economic use of the electricity market [5]. In [6], the authors introduced the use of electric ESSs as a proper strategy for reducing fluctuations and using renewable dispersed generators in the micro grid (MG). Among the various storage technologies, battery energy storage was introduced as a suitable option. In [7], considering the stochastic nature of wind power generation and electric vehicles (EVs), as well as the emission of thermal units, a model was formed in the presence of wind power and EVs. This model minimized the total cost and carbon emissions of the system by imposing operating constraints related to EVs and wind power. In [8], the authors considered energy management to reduce consumer energy costs, maximize user comfort and reduce carbon emissions. To this end, it introduced an efficient energy management model for an MG with the ant colony optimization algorithm for systematic load scheduling and charging/discharging of EVs. In [9], the authors dealt with the inability of governments to provide the necessary resources to invest in the electricity industry and the rise in the price of fossil fuels, as well as the tendency to study and pay attention to economic issues in power system research. Then, using a modified grey wolf optimization algorithm (MGWO), it solved the UC problem in a power system. It also considered system uncertainty, and finally, compared the results with those of the standard GWO and the particle swarm optimization (PSO) algorithms. In [10], the authors proposed a stochastic optimization framework for scheduling the commitment of dispersed generation (DG) units due to the high penetration of photovoltaic (PV) units. It also assessed the effect of flexible thermal and electrical loads on the overall operating cost of the system. In [11], the authors introduced a robust two-stage optimization model to solve UC problems by considering variable wind power generation. In [12], the authors proposed a robust optimization approach to adapt to wind output uncertainty. In [13], the authors analyzed the difference between multi-band robust optimization and Seng-Cheol robust optimization. This study also improved the multi-band robust optimization parameter setting method based on the wind power sample. The results were tested on an IEEE 39-bus power system with three wind farms. In [14], the authors examined UC scheduling on integrated fuel and natural gas systems. Natural gas storage was done by supporting the gas grid during peak hours of natural gas demand by reducing pipeline density.A hydrogen ESS was integrated with novel flexible technologies, including power-to-gas (P2G) and DR program (DRP), to reduce the RES costs of operation and transfer the peak load demand to peak hours. In [15], the authors performed a sensitivity analysis to evaluate the effect of increasing thermal load on the combined heat and power (CHP) unit operation as its thermal and electrical output. A plug-in EV (PEV) charging station was integrated to observe its effect on grid performance as PEVs impose on the system an unplanned and uncertain load. In [16], the authors examined the advantages of combining the stochastic programming framework with reserve constraints.

In [17], the authors discussed the UC problem by including ESSs (ESS). In this paper, the authors proposed a meta-heuristic algorithm called the Henry gas solubility optimization algorithm (HGSA) to solve the problem. This algorithm seems to behave similarly to the PSO algorithm to some extent, but due to more accurate modeling, the update function can be superior to the PSO algorithm. In [18], the authors presented the UC problem by considering the natural gas grid. In this article, the objectives of minimizing the operating cost of the units and the cost of gas units were considered. In [19], the authors proposed the UC problem to reduce generation costs. In this paper, the constraint of the units' slope change was studied and several heuristic algorithms were used to solve the proposed problem. It was shown that the differential evolution algorithm had better performance than other evolutionary algorithms in terms of UC. In [20], a novel global optimization algorithm was proposed to solve the UC problem. The center point (CP) algorithm was modeled to solve the UC problem, which was ultimately compared to the solution by CPLEX. The results showed this algorithm outperformed CPLEX.

The reduction of unit costs along with the cost of charging and discharging the EVs is considered in this paper and the Benders optimization algorithm is chosen to solve the proposed problem. We attempt to consider the UC problem in smart grids and ESSs in modeling. The reduction of environmental pollution is also considered in this problem and its related constraints, including the slope constraint, the minimum / maximum ON/OFF time of the units and the reserve constraint, are also taken into account to propose a complete model of the UC problem.

2. The proposed modeling

In this section, the modeling (the multi-objective function model, constraints governing the optimization and power flow) are presented and, at the end, the evolutionary algorithm is described. The goal is to reduce power losses, improve the voltage profile and balance the load index, presented as a multi-objective function.

2.1. Objective function of the problem

In this section, the mathematical model and the proposed method for solving the problem are presented. First, problem modeling, including the objective function and problem constraints, are introduced and, finally, the proposed problem-solving method is described

$$\begin{aligned}\min F = &\left(\sum_{j\in N}\sum_{t\in T} c_i^{fix} v_{i,t} + c_i^{\mathrm{var}} g_{i,t} + c_i^{fule} g_{i,t} + c_i^{su} s_{i,t} + c_i^{sd} u_{i,t}\right)\\ &+\left(\sum_{i\in N}\sum_{t\in T} c_i^{sox} g_{i,t} + c_i^{nox} g_{i,t} + c_i^{co2} g_{i,t}\right)\\ &+\left(\sum_{i\in M}\sum_{t\in T} c_i^{ess}\left[p_{i,t}^{cha}\times\eta_i - p_{i,t}^{dis}\times 1/\eta_i\right]\right)\end{aligned} \tag{1}$$

Equation (1) represents the multi-objective function considered in this paper. This function consists of three parentheses; the first parentheses include unit operating costs, the second include unit emission costs and the third include the cost of charging and discharging the ESS. In the first parenthesis of the objective function, N is equal to the sum of generation units and T is equal to the set of operating time. c_i^{fix} is the fixed cost of the i-th generation unit, $v_{i,t}$ is the binary variable of unit i and $v_{i,t}$ is the binary variable of the i unit at time t to indicate the on / off status of the generation unit; c_i^{var} is the variable cost of the variable unit i, $g_{i,t}$ is the power generated by the i unit at time t, c_i^{fule} is the fuel cost of i unit and c_i^{su} is the cost of turning the i unit on; $s_{i,t}$ is the binary variable of the i unit at time t in order to indicate the ON hours of generation units, c_i^{sd} is the cost of turning off the ith unit at the th-th time in order to indicate the ON hours of generation units; c_i^{sd} is equal to the cost of turning off the i unit; $u_{i,t}$ is the binary variable of unit i at time t in order to indicate the OFF hours of generation units. In the second parenthesis of the function, c_i^{sox}, c_i^{nox} and c_i^{co2} denote the ith generation units. In the third parenthesis, c_i^{ess} is the cost of operating the ith storage system, $p_{i,t}^{cha}$ is the charge capacity of the ith storage at hour t, η_i indicates the efficiency of the ith storage system and M represents the total number of ESSs in the system.

2.2. Objective function of the problem

This section presents the constraints of the problem. The proposed UC problem constraints are briefly equal to the constraints of operating the generation units, the power balance in the system, power slope, maximum and minimum on / off time of the units, reserve in the system, optimal charge and discharge constraints of the ESS and the energy remaining in the storage system, which are presented below, respectively. Constraint (2) ensures that generation units are operated between the minimum and maximum allowable capacities.

$$v_{i,t}g_{i,t}^{\min} \le g_{i,t} \le v_{i,t}g_{i,t}^{\max} \tag{2}$$

Eq. (3) shows the constraint of the upward and downward power slope of power generation units.

$$-R_i^{dw} \le g_{i,t+1} - g_{i,t} \le R_i^{up} \tag{3}$$

In Eq (3), R_i^{up} and R_i^{dw} are the upward and downward slope of the ith generation unit, respectively. Eqs. (4) and (5) represent the minimum on and off times of generation units, respectively, which are defined as follows:

$$\sum_{k=t-UP_i+1}^{t} s_{i,k} \le v_{i,t} \tag{4}$$

$$\sum_{k=t-DT_i+1}^{t} u_{i,k} \le 1 - v_{i,t} \tag{5}$$

In (4), UP_i is the minimum time on time and, in (5), DT_i is the minimum off time of the ith unit. Eq. (6) shows the relationship between the off and on binary variables and the status of the units, introduced as follows:

$$S_{i,t+1} - u_{i,t+1} = v_{i,t+1} - v_{i,t} \tag{6}$$

Eq. (7) also shows the energy remaining at hour t in the ith storage system, which is defined as follows:

$$e_{i,t+1} = e_{i,t} + p_{i,t}^{cha} \times \eta_i - p_{i,t}^{dis} \times 1/\eta_i \tag{7}$$

In (7), $e_{i,t}$ is the energy remaining in the ith storage at time t. Equations (8) and (9) indicate the constraint on the charge and discharge capacity of storage systems, respectively. $z_{i,t}$ is a binary variable that shows the charge and discharge status of the storage system; if 1, it indicates the battery charge. $p_{i,t}^{-cha}$ is the maximum charging power and $p_{i,t}^{-dis}$ is the maximum discharge power.

$$0 \le p_{i,t}^{cha} \le p_{i,t}^{-cha} z_{i,t} \tag{8}$$

$$0 \le p_{i,t}^{dis} \le p_{i,t}^{-dis}\left(1 - z_{i,t}\right) \tag{9}$$

Eq. (10) indicates the intended reserve limit, which is defined as follows. Moreover, r_t is the amount of load reserve at hour t.

$$\sum_{i\in N}\sum_{t\in T} g_{i,t}^{\max} - g_{i,t} \ge r_t \tag{10}$$

Eq. (11) shows the power balance in the system; the output power in the grid should be equal to the power consumption. Here, the power of the units and the discharge power of the storage system are viewed as the generated power, while the system load and charging power of the ESS are regarded as consumed power. On this, p_t^d is the load power of the system at hour t.

$$\sum_{i\in N} g_{i,t} + \sum_{i\in M} p_{i,t}^{dis} = p_t^{dsm} + p_{i,t}^{dis} \tag{11}$$

The DR (DR) program is given in Eqs. (12) to (14).

$$\beta_t = \sigma p_t^d \tag{12}$$

$$p_t^d - \beta_t \le p_t^{dsm} \le p_t^d + \beta_t \tag{13}$$

$$\sum_{t\in T} p_t^{dsm} = \sum_{t\in T} p_t^d \tag{14}$$

In (12), σ is the percentage to be shifted in the DR program, p_t^d is the load at hour t and β_t is the amount of power that is to be shifted from hour t. Eq (13) shows that load shifts or load changes. p_t^{dsm} must be between the difference between the minimum and maximum allowable values. Eq (14) ensures that the sum of the changed loads in the DR is equal to the sum of the initial loads of the system; in other words, no load must be removed in the DR for us to add its cost to the objective function.

Optimization problems must be solved such that the power flow Eqs (15-16) constantly hold:

$$P_i = \sum_{i=1}^{N_{Bus}} V_i V_j Y_{ij} \cos\left(\theta_{ij} - \delta_i + \delta_j\right) \tag{15}$$

$$Q_i = \sum_{i=1}^{N_{Bus}} V_i V_j Y_{ij} \sin\left(\theta_{ij} - \delta_i + \delta_j\right) \tag{16}$$

Here, P_i and Q_i are the active and reactive power injected into the grid's ith bus, respectively. V_i and δ_i are respectively the voltage amplitude and angle of the ith node. Y_{ij} and θ_{ij} are the admittance amplitude and angle between nodes i and j of the grid, respectively. Herein, the Newton-Raphson method is adopted for load dispatch.

2.3. Problem solving method

In this section, the problem-solving method is presented. As discussed in the objective function and problem constraints sections, the proposed model for the UC problem is a linear integer programming model. In general, an optimization problem is solved as follows:

$$\min f\left(x\right) \tag{17}$$

$$s.t\ A.x \le b \tag{18}$$

$$Aeq.x = beq \tag{19}$$

$$lb \le x \le ub \tag{20}$$

$$x = \text{int}\,eger \tag{21}$$

Therefore, if the optimization problem is converted into the problem (17) to (21), provided that function f is linear and variable x is binary and continuous, with the constraints of equality and inequality, the problem can be solved using powerful mathematical software programs recently presented by great mathematicians; it can be ensured that the obtained solutions are the global optima.

To solve the above problem, we use the hybrid algorithm of honey bee mating and bacterial foraging. The hybrid algorithm is described below.

2.4. HBMO algorithm

The honey bee mating optimization (HBMO) is a novel optimization algorithm inspired by the actual mating process of honey bees. As a general optimization method based on the inset behavior, this algorithm relies on the mating behavior of male bees with the queen bee. Honey bees' behavior is an interaction of genetics, the physiological and ecological environment, the social conditions of the hive or a combination of these factors [21].

A beehive often houses a queen with a long life to lay eggs, from 0 to several hundreds of male bees (drones), and about 10000-60000 workers. The queen(s) play the main role of reproduction in some species of honey bees and are responsible for laying eggs. The queen lays about 1500 eggs in 24 hours. Drones are the fathers of the beehive. They are exclusively male and must mate with the queen. The brood from fertilized eggs grow to be queens or workers and the brood from non-fertilized eggs grow to be drones. Most of the tasks in each hive are delegated to the workers, including raising the offspring, taking care of the queen and male bees, cleaning the hive, adjusting the temperature of the hive, collecting nectar, pollination, etc.

The queen commences the special mating dance. In this flight, drones follow the queen to mate with her in space. In each mating flight, the queen mates with 7-20 drones on average. In each mating, sperms enter and are collected in the spermatheca. In fact, the mating flight can be likened to a set of displacements in space and time (the environment), wherein the queen flies at different points and with variable speed, hits drones that are at that point at that moment and randomly mates with them. Evidently, the queen has a certain level of energy at the outset of the mating flight, which is reduced and approximates zero at the end of the path, i.e., when the queen returns to the hive [22].

Therefore, the HBMO algorithm can be summarized in the following basic steps:

1) Queen's mating: The algorithm begins with the mating flight, wherein the queen (best solution) randomly selects its mates among the drones to fill her spermatheca and, eventually, produce the new brood. In this stage, the queen (the best solution) mates with any drone based on the following rolling probabilistic function:

$$prob(Q,D) = e^{\frac{-\Delta(f)}{S(t)}} \ge q_0 \tag{22}$$

where *Prb* (*Q, D*) is the probability of the addition of the sperm of drone *D* to the spermatheca volume of queen Q with the probability of successful mating. $\Delta(f)$ is the difference between the queen's and drone's fitness function, S(t) is the queen's speed at time t and q_0 is a random value (0,1). The queen's speed and energy are reduced after each mating based on the following Eqs. (23) and (24):

$$S(t+1) = \alpha \times S(t) \tag{23}$$

$$E(t+1) = E(t) - \gamma \tag{24}$$

where α is a coefficient between 0.1 and 1 for the queen's speed reduction and γ is a coefficient between 0 and 0.1 for the queen's energy reduction following each mating. At the end of the mating flight, the queen's energy and speed decrease to such an extent that they can be assumed zero.

2) Production of a new generation of children (new solutions): The new brood (test solution) is generated by replacing the drones' genes with the queen's genes based on the following:

$$child = parent1 + \beta(parent2 - parent1) \qquad (25)$$

Here, β is a random value (0,1).

3) Nurturing and promoting the brood's generation: In this stage, workers nurture and promote the brood's generation based on the following:

$$\begin{aligned} Brood_i^k &= Brood_i^k \pm (\delta + \varepsilon) Brood_i^k \\ \delta &\in [0,1], 0 < \varepsilon < 1 \end{aligned} \qquad (26)$$

where δ is generated randomly between 0 and 1, while ε is a constant number.

4) Queen selectivity: After arranging the brood as the new solutions on the basis of the degree of promotion in the generation based on the workers' fitness function, the best ones are selected to replace the queen in the next mating flight if they have better fitness than the current queen. Otherwise, the current queen (the best solution) once again starts mating to produce the new brood (new solutions).

5) Stopping the algorithm: If the conditions of the algorithm are met, the current queen is selected as the final solution. Otherwise, a new generation of drones is generated and the stages before satisfying the stop condition are iterated.

In the following, to improve the performance of this algorithm, the local search method will be applied.

2.5. Bacterial foraging algorithm

This algorithm is based on the idea that, in nature, animals with poor foraging methods run a higher risk of extinction than those with successful foraging strategies. After many generations, animals and weak foraging methods are eliminated or transformed into better forms. *E. coli* that lives in the human intestine has a four-stage foraging method. These four stages are chemotactic, swarming, reproduction, elimination and dispersal [23].

1) Chemotactic

Bacteria begin to move and swim in this stage. In fact, depending on their tail rotation, they hop and begin moving in a certain direction (tumble). If the amount of food is higher in the new path, the bacterium begins swimming in the same direction (swimming).

Suppose we aim to find the minimum value of $J(\theta), \theta \in \Re^p$. Let θ be the bacterium's location and J(θ) the amount of food in location θ. Assume that $J(\theta) > 0, J(\theta) = 0, J(\theta) < 0$ respectively denote that the bacterium has good, neutral or bad food in location θ. To perform tumbling, a vector with unit length known as $\phi(i)$ is generated. This vector is used to define the new direction for bacterium's post-tumbling chemotactic. The new location of the bacterium is defined as:

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\phi(i) \qquad (27)$$

where $\theta^i(j,k,l)$ indicates the location of the ith bacterium in the jth chemotactic stage, kth reproduction and ith elimination and dispersal. $C(i)$ is the bacterium's chemotactic size in the direction of chemotactic $\phi(i)$. If the size of $J(i,j,k,l)$ in $\theta^i(j+1,k,l)$ is less than its size in $\theta^i(j,k,l)$, another chemotactic step with size $C(i)$ is taken in the direction $\phi(i)$ and the bacterium begins to swim in direction $\phi(i)$. This swimming continues until the size of J(θ) is reduced and to the maximum permissible number of swimming stages Ns. This indicates that the bacterium will continue moving in the same direction until it finds a better food environment.

2) Swarming

When a bacterium finds a better path for food, it attracts the other bacteria and they reach the main source of food more quickly. Swarming leads to the bacteria's mass movement towards the food.

It $P(j,k,l) = \left\{\theta^i(j,k,l) i = 1,2,\ldots,s\right\}$ is assumed as the set of bacteria's locations, swarming is modeled as:

$$\begin{aligned} j_{cc}(\theta, P(i,j,l)) &= \sum_{i=1}^{s} j_{cc}^{i}(\theta, \theta^i(j,k,l)) \\ &= \sum_{i=1}^{s}\left[-d_{attract}\exp(-\omega_{attract}\sum_{m=1}^{p}(\theta_m - \theta_m^i)^2)\right] \\ &+ \sum_{i=1}^{s}\left[-d_{repellant}\exp(-\omega_{repellant}\sum_{m=1}^{p}(\theta_m - \theta_m^i)^2)\right] \end{aligned} \qquad (28)$$

where $j_{cc}(\theta, P(i,j,l))$ is a time-dependent function depending on the movement of all the bacteria and is added to the value of the cost function, $J(i,j,k,l)$. Therefore, bacteria try to find food, escape places without food, attract each other and, at the same time, do not get too close to each other; s is the total number of bacteria and p is the number of parameters that must be optimized and regarded as the bacterium's location coordinates in the p-dimensional space. Moreover, ωattract, dattract, ωrepellant and hrepellant are the coefficients, for which proper values must be selected depending on the problem.

3) Reproduction

A half of the bacteria that fail to find proper food are eliminated; in the other half consisting of healthy bacteria, each bacterium is divided into two which are located in the bacterium's previous place. This keeps the population of bacteria constant.

4) Elimination and dispersal

The life of the bacterium population changes gradually as they consume food, or suddenly due to other factors. Events can kill or disperse the bacteria. This may initially disrupt the chemotactic towards food, but can also positively affect it, because the dispersal of bacteria may put them in places close to good food sources. Elimination and dispersal prevent the bacteria from entrapment in local optima. In each state of elimination and dispersal, any bacterium in the population runs the ped risk of elimination and dispersal. To keep the number of bacteria constants, if one bacterium is eliminated, a new bacterium is randomly placed in the search space.

5) The hybrid method

To promote efficiency, a combination of these two algorithms is used. The procedure of the hybrid method is as follows:

Stage 1: The HBMO algorithm searches the search space and presents the best solution.

Stage 2: The best solution obtained in Stage 1 is sent to the bacterial foraging algorithm.

Stage 3: The bacterial foraging algorithm begins to optimize around the best solution sent from Stage 1.

Sage 4: The best solution obtained from the previous stage is sent to the HBMO to once again find the best solution with more precision.

Stage 5: If the stop condition is met, the algorithm converges, the iteration of these stages ends and the best solution is proposed. This hybrid method covers both the search space and the exploration space.

3. Simulation results

Simulation results are presented in this section. To this end, a 4-unit system is selected for analysis, which is introduced and presented in separate sections.

3.1. The four-unit system

This section presents the results of the four-unit system simulation. In this system, four generator units are considered, along with an ESS. Table (1) presents the parameters related to generation units and Table (2) shows the parameters of the ESS.

Table 1. Specification of studied DGs.

	Unit 1	Unit 2	Unit 3	Unit 4
Minimum power (kW)	75	60	25	20
Maximum power (kW)	300	250	80	60
High power slope (kW)	40	36	30	30
Low power slope (kW)	40	36	30	30
Minimum OFF time (h)	0	1	0	1
Minimum ON time (h)	1	0	0	1
Fixed cost ($)	0/0021	0/0042	0/0018	0/0034
	Unit 1	**Unit 2**	**Unit 3**	**Unit 4**
Variable cost ($)	16.83	16.95	20.47	23.6
Fuel cost ($)	648/74	585/62	213	252
Cost of commissioning ($)	500	170	150	2300
Cost of decommissioning ($)	1100	400	350	5000
Sox emission cost ($)	0/001	0/0021	0/0009	0/0017
Nox emission cost ($)	8/4150	8/4750	10/37	11/8
CO2 emission cost ($)	324/37	292/81	106/5	126

Table 2. ESS parameters

	ESS
Maximum charging power (MW)	100
Maximum discharging power (MW)	80
Capacity (kWh)	250
Cost of operation ($)	2000
Efficiency (%)	85

Figure (1) displays a comparison between the load in the initial state and after the DR in the four-unit system in 24 hours. The amount of load shift per hour is equal to 1% of the total load in the same hour.

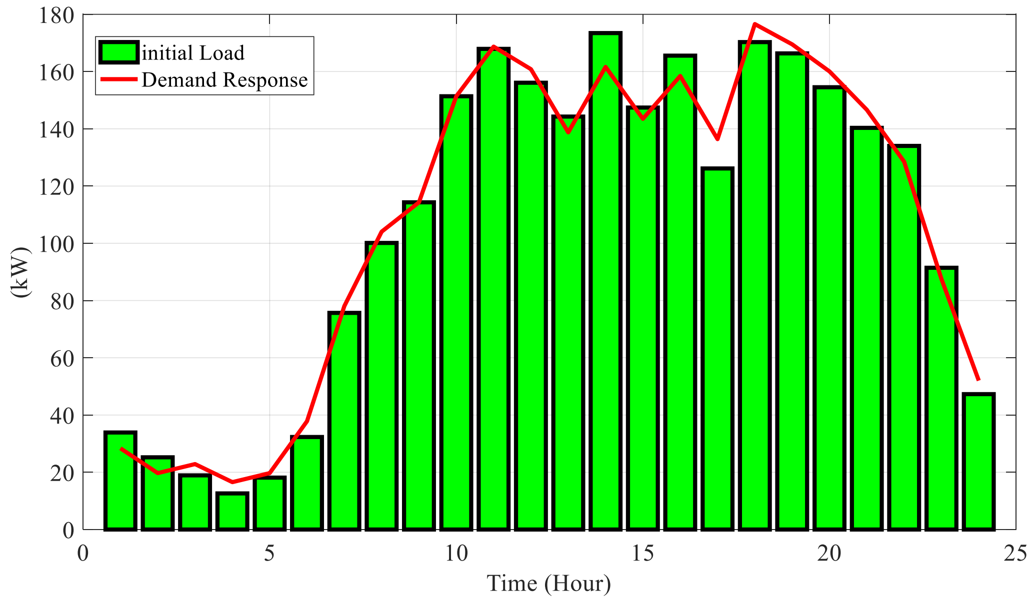

Fig. 1. Comparison of 24-hour load in the four-unit system.

Figure (2) illustrates the simulation results belonging to the state of charge and discharge (SOC/SOD) of the ESS in solving the proposed UC problem. The hours when the storage system is charged are on the negative y-axis and the hours when the storage system delivers power or discharges it into the system are shown on the positive y-axis.

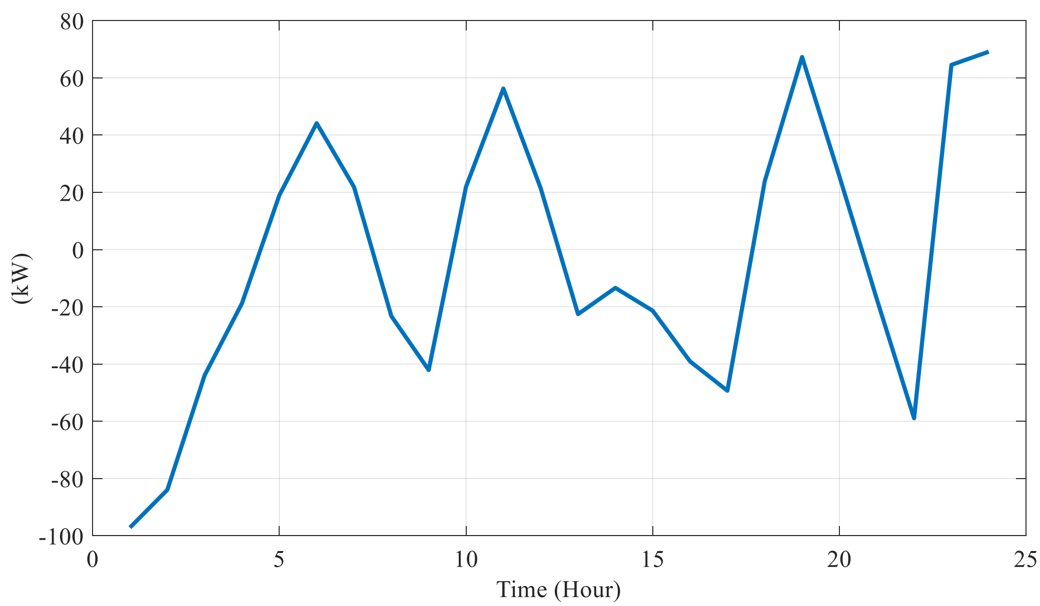

Fig. 2. SOC/SOD of the ESS

Figure (3) also shows the state of energy (SOE) in the storage after simulation. As an example, by 4 o'clock, the energy capacity remaining in the storage has increased, which means that the storage is charged (Fig (2)). From 5 to 7, according to Figure (3), the energy capacity in the storage is reduced, meaning that the storage is discharged (Fig (2)).

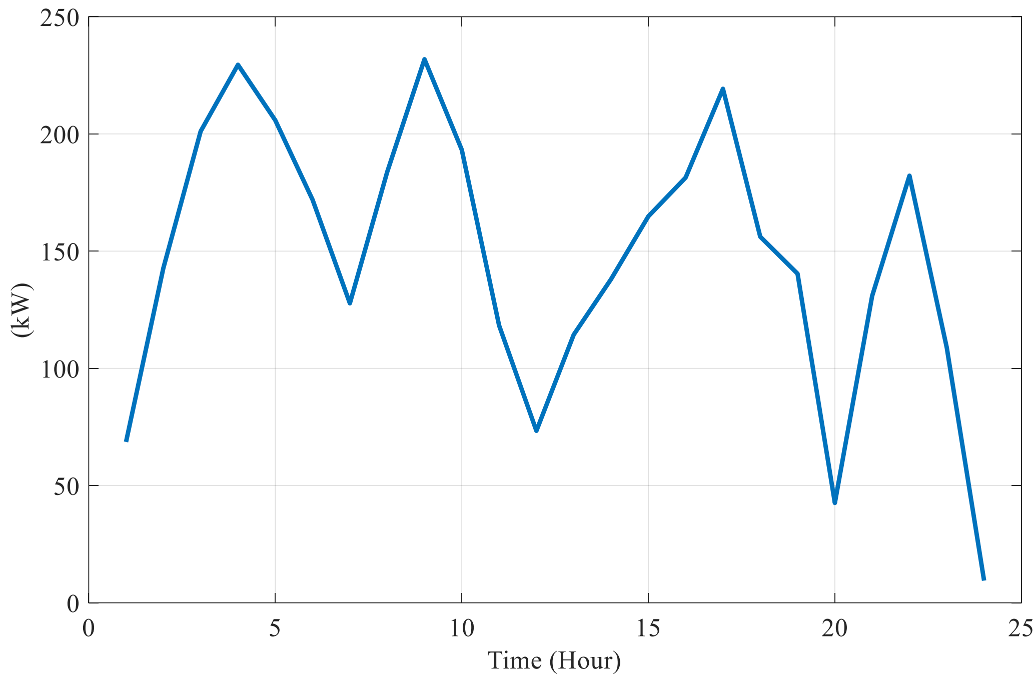

Fig. 3. SOE of the storage system

Figure (4) also shows the optimal output power of generation units in the next 24 hours. In this figure, it is well shown how much each unit should generate per hour to supply the grid load and obtain the minimum value of the objective function.

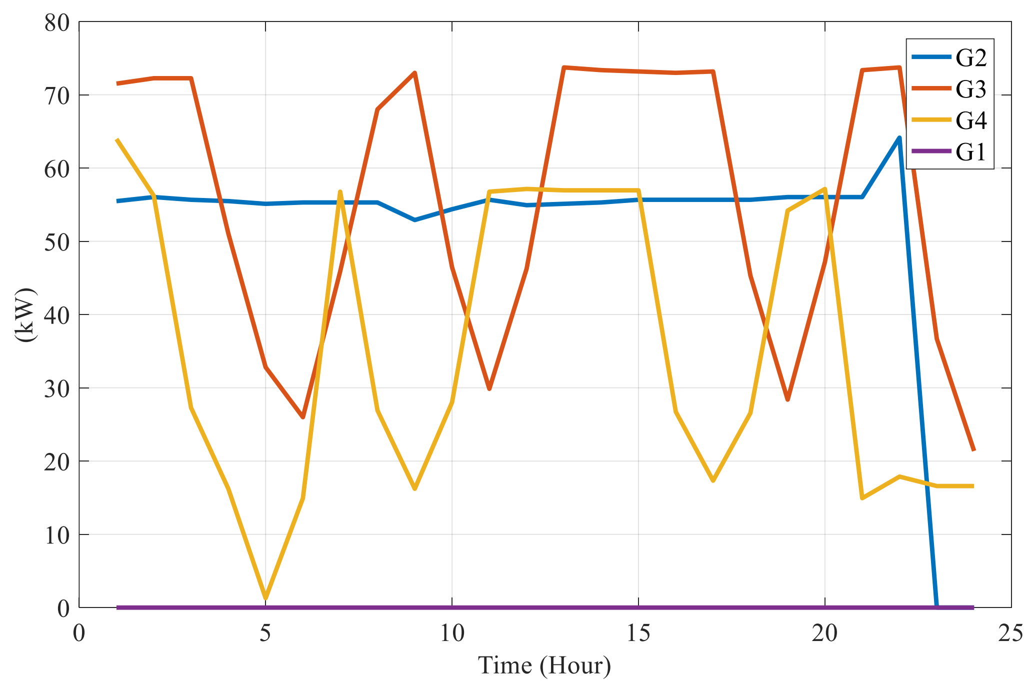

Fig. 4. Output power of generation units in the four-unit system

Figure (5) also shows all the power variables in the system. In this figure, the power of generation units, charging and discharging power of ESS and the grid load power within 24 hours after simulation are presented in the four-unit system.

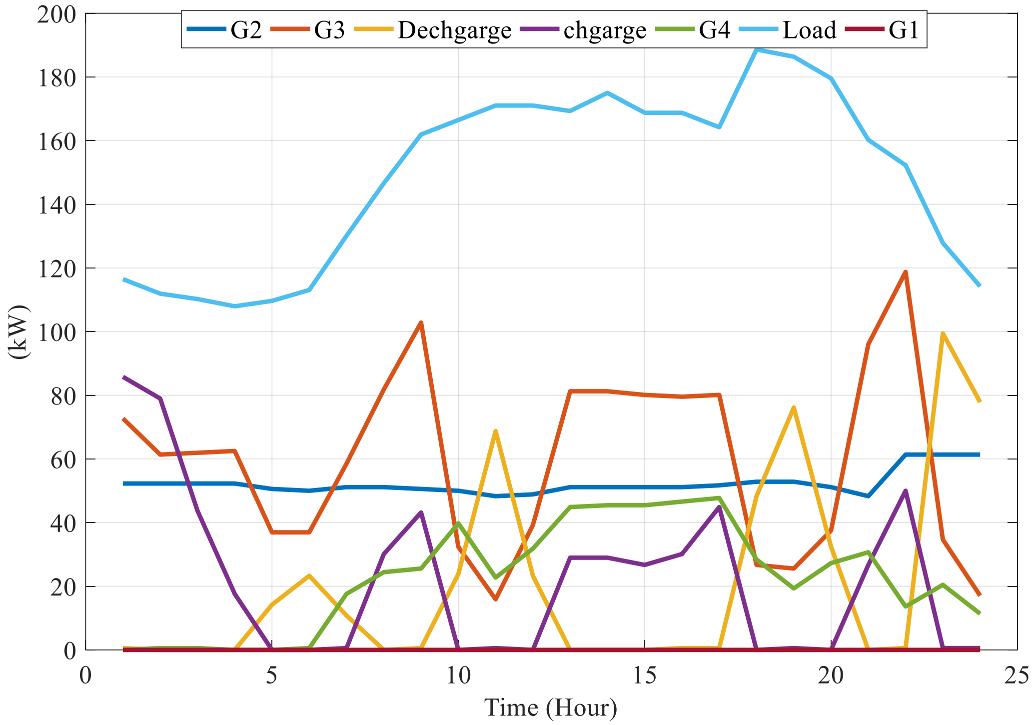

Fig. 5. Output power of generation units along with load and charge and discharge of the ESS in the four-unit system

Table (3) lists the multi-objective function of the problem for the next 24 hours. In this table, the effect of the ESS on the objective function of the problem is well shown. The cost function is $ 1727278 in the case of the storage system and DR system, $ 173743838 in the case of a storage system only and $ 2083293 in the case of no storage and no DR system.

Table 3. Four-unit system simulation results

	No ESS	With ESS	With ESS and DR
Cost objective function ($)	2083293	1737438	1727278

Figure (6) shows the power output results without the ESS. Table (4) shows the power of generation units, charge and discharge capacity of the ESS, along with the value of the objective function. For example, at 1 o'clock when the grid load is 115.8 kW, unit 1 is off, units 2, 3 and 4 generate 60, 80 and 60 kW, respectively, and the battery is charged by 84.2 kW. In this way, for the next 24 hours, the optimal values of each of the decision variables are presented.

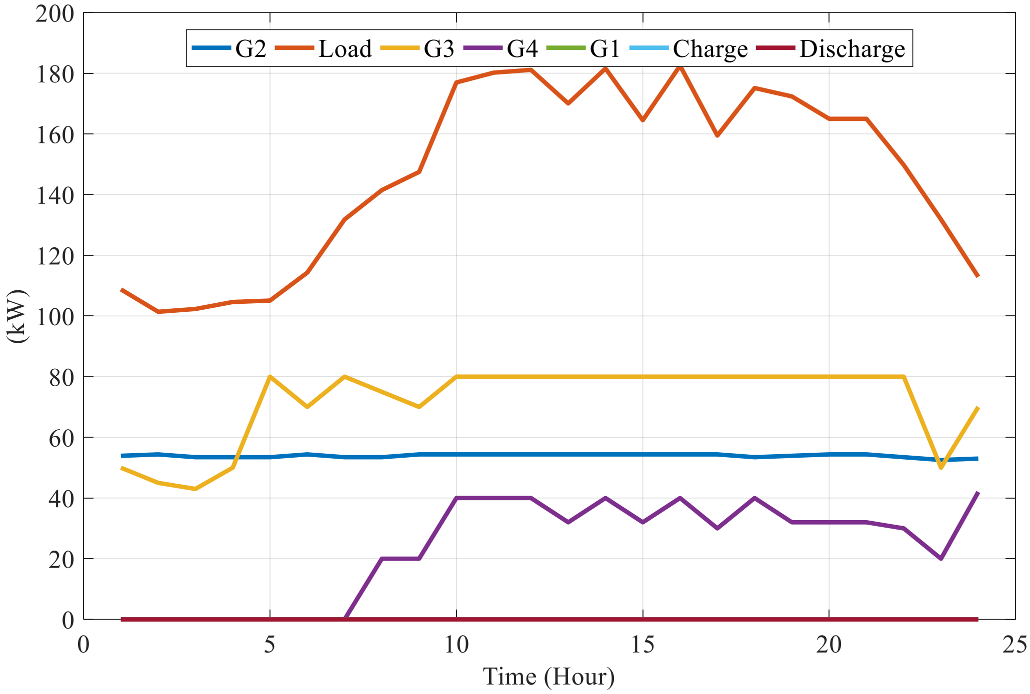

Fig. 6. Power output of units without considering the ESS unit in the 4-unit system

Figure 7 illustrates the power of the generation units, the charging and discharging capacity of the ESS and the value of the objective function. For example, at 1 o'clock when the grid load is 115.8 kW, unit 1 is off, units 2, 3 and 4 generate 60, 72 and 50 kW, respectively, and the battery is charged by 68.4 kW. In this way, for the next 24 hours, the optimal values of each of the decision variables are given.

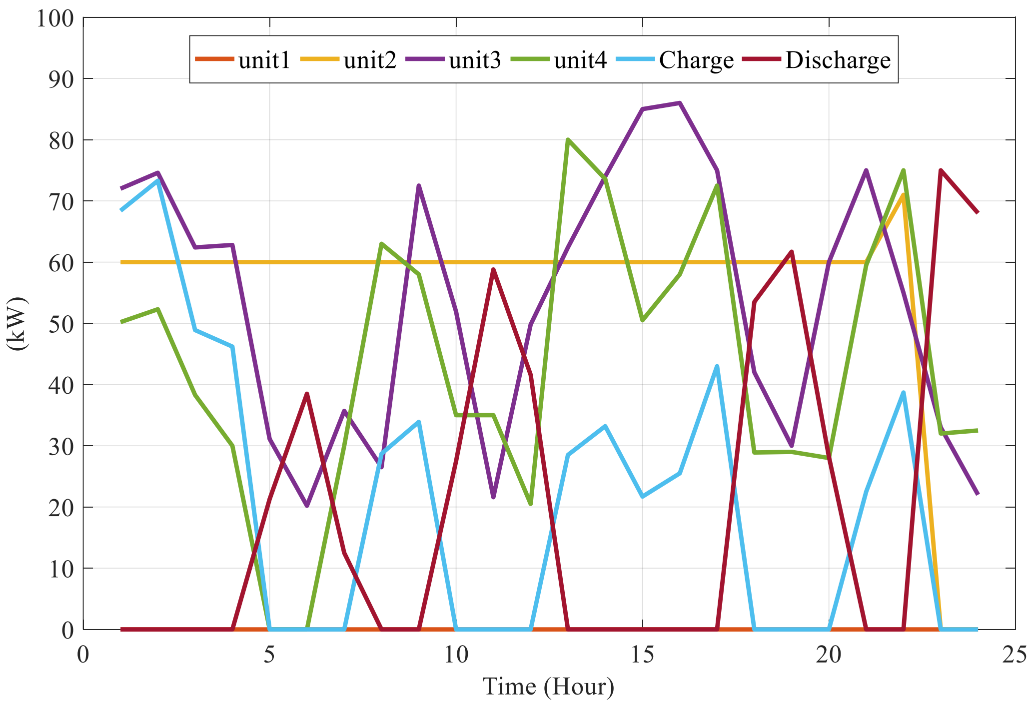

Fig. 7. Four-unit system simulation results

4. Conclusions

Reduction of system operating costs is a key economic program in power systems. As such, programming for unit commissioning and decommissioning is of utmost importance. In general, the two objectives of "ensuring safe operation" and "facilitating economic operation" are of great importance. This paper proposed, modeled and solved the UC problem in smart grids by considering the reduction of economic costs and environmental problems. In this study, the UC problem in smart grids was solved by modeling a multi-objective function and considering ESS and load management. The proposed method was applied to a 4-unit system and the results showed the optimal performance of the proposed model. Herein, we used a hybrid algorithm of honey bee mating and bacterial foraging for optimization. The proposed method could provide suitable results in comparison with old models i.e., in Table 3, the proposed approach could provide the cost function value as $ 1727278 in the case of the storage system and DR system, $ 173743838 in the case of a storage system only and $ 2083293 in the case of no storage and no DR system.

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