INTERNATIONAL JOURNAL of RENEWABLE ENERGY RESEARCH
M. Zakaria et al., Vol.12, No.3, September, 2022

Energy Management of MG Considering the Emission and Degradation Costs using A CAP-SA Optimization

Mohammad Zakaria *, Mohammed Sh. Seif *‡, Mohammed A. Mehanna *

*Department of Electrical Engineering, Al-Azhar University, Cairo, Egypt

(eng_m2011@azhar.edu.eg, eng.mseif@azhar.edu.eg, mehanna@azhar.edu.eg)

‡ Correspondence should be addressed to Mohammad Zakaria; Tel: +201554444225, eng_m2011@azhar.edu.eg.

Received: 07.08.2022 Accepted: 04.09.2022

Abstract- This paper addresses the problem of Micro-Grid (MG) Energy Management (EM) Control with considering a reduction in the overall cost of MG in a residential grid. The main motivation for this paper is to study the impact of Emissions from Distributed generators (DGs) and deterioration of energy storage devices (ESDs) on the overall operating cost of MG. One of the optimization targets to reduce the overall cost of MG operation is the emission of DGs and the deterioration of ESDs. This article offers a solution to the optimization issue while takes into account numerous constraints, utilizing of the Particle Swarm Optimization (PSO), Gravitational Search Algorithm (GSA), Hybrid Population-Based Algorithm (PSOGSA), and the suggested Capuchin Search Algorithm (Cap-SA). The usefulness and validity of the suggested method are shown using the simulation results by two scenarios without and with considering emission and degradation costs. Cap-SA has been contrasted with many effective optimization techniques. The results reveal that Cap-SA is an effective technique for reducing overall MG costs as compared with PSO by 29.5% and 25.5% in the first and second scenarios, respectively.

Keywords Microgrid, Capuchin search algorithm, Energy Management, Emission cost, Degradation cost.

1. Introduction

With the aged year of electricity transmission and distribution infrastructure, the need to significantly increase the power system's resilience has gained interest from academia on a worldwide scale [1]. Deploying MGs, with renewable energy resources is one realistic way to enhance the power system [2]. As a result, MGs improve the system by reducing the likelihood of load shedding and averting cascading blackouts [3]. MGs also provide a variety of uncommon options, like limiting carbon emissions [4], Peak demand reduction and load shaving have been addressed in [5] with BESS integration, and incorporating various renewable energy sources [6]. Under all these benefits, MGs have been widely deployed in recent years at industrial parks, military facilities, campuses of hospitals and universities, and utilities [7]. The advantages of the environment and economy of MG are the solution to the Economic Optimization Dispatch issue [8]. The multi-objective dispatchable optimization issue has so far been addressed by multiple methods [9]. The electrical sector is today faced with two significant yet seemingly incompatible challenges: maintaining a sufficient supply to fulfil the rising demand for power and reducing emissions [10]. The EM issue should include emissions as an optimization problem due to environmental concerns and emissions from traditional generating units [11]. Researchers' interest in developing efficient optimization approaches to address the EM problem has increased recently [12]. A rule-based real-time controller was combined to a predictive dynamic programming-based optimization technique to optimally manage the energy plan for a hybrid smart MG system [13]. If the Emission Cost of DG and the Degradation Costs for Charge - discharge Cyclical are not taken into account when formulating an EM issue, therefore the operational costs increase as a result of the effect of the battery lifetime [14], and thus the full power costs are not represented in the result.

1.1. Literature Review

To schedule the charge/discharge cycle of ESD in an isolated MG, a hybrid technique combining heuristic and analytical optimization has been proposed in [15]. To maintain a balance between supply and demand in the MG, the dynamic response is achieved using a real-time pricing scheme. The findings show that ESD effectively participates in the economic scheduling of an isolated MG. According to several published studies, optimization approaches are divided into three categories: conventional mathematical methods, intelligent optimization techniques, and hybrid methods.

conventional approaches such like dynamic programming is used in [16] to handle optimization issues on MG includes only photovoltaic (PV) systems, and ESD by finding the minimum of cash flow. In [17], the proposed approach with linear-programming-based multi-objective optimization has been used to minimize the operation cost and the environmental impact of a MG without considering deterioration of ESDs. Many intelligent approaches have been used to solve the optimization dispatch of a MG like the genetic algorithm, that used to minimize the shed load and maximize the lowest swing frequency [18]. Chaotic quantum genetic algorithm is proposed in [19] to solve the environmental economic dispatch problem for MG without considering degradation cost. PSO is used to minimize the total energy and operating cost of the MG without considering emission or degradation costs in [20]. Chaotic Binary PSO have been used to solve the optimization problem to maximize the economic benefits of MG and minimize the network loss [21]. A hybrid technique had been proposed to overcome these problems. PSO is a popular heuristic approach in methodologies because of its fast convergence, simplicity, and ability to search for optimal solution [22]. GSA was proposed in [23]; it based on gravitation's law of Newton and Although accuracy is not sacrificed it has high computational efficiency. GSA performances and advantages have already been demonstrated for optimization problems of MGs [24]. In recent research, a hybrid analysis-heuristic strategy to lower user and MG operational costs was built using the Jaya algorithm and the interior point method (IPM) [25]. The results indicate that by utilising demand response to reduce peak load while maintaining supply and demand balance, the suggested technique may balance the interests of the MG and consumers. Two-stage methodology for dynamic power dispatch in islanded MGs proposed in [26] a with Micro-turbines and ESD that takes demand side management into account. Dominance based evolutionary algorithm was employed in the first step to identify pareto-optimal solutions to the issue. In the second step, decision analysis was used to find the optimum answer.

Recently, Cap-SA was proposed in [27]; and it is a meta-heuristic technique employed by the food foraging behaviour of capuchin monkeys.

1.2. Contribution of Article

This paper's main contribution may be summed as follows:

- A novel optimization approach named "Capuchin Search Algorithm (Cap-SA)" has been introduced for lowering the power expenses of a MG.
- The proposed method has been successfully implemented to a MG system, and the robustness of the proposed Cap-SA optimization algorithm has been confirmed by comparing it with three of the existing powerful approaches "PSO, GSA, Hybrid PSOGSA".
- A case study is presented with the goal to minimize total cost considering startup/shutdown cost, running expenses of all DGs, and utility power purchase costs in two scenarios; without and with accounting for emission, and degradation costs.

1.3. Organization of This Paper

The following sections constitute this paper: Section 2 provides the MG model and the optimization issue in addition to the methodologies. Section 3 introduces the suggested algorithm for solving the issue, while Section 4 comprises the simulation and analysis of the results. Last, section 5 summarizes the conclusions.

2. Micro-Grid and Problem Formulation

2.1. Micro-Grid Model

Figure 1 shows the MG including the Wind turbine unit (WT), photovoltaic panel unit (PV), Micro-turbine (MT), Residential loads, and ESDs, which can operate in grid-connected or isolated modes. In order to fulfil load needs, the operators employ both powers from the utility and from DGs. Excess energy from the MG is either sold to the utility or saved in storage systems for future use.

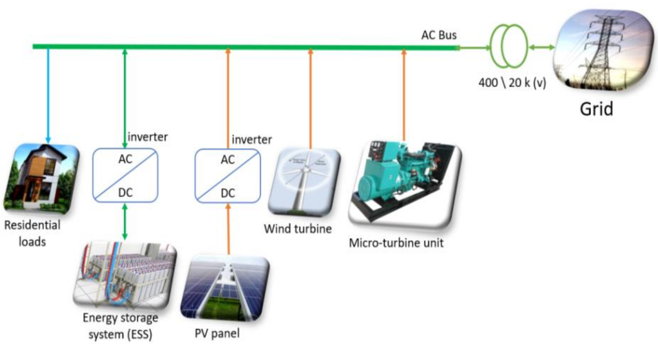

Fig. 1. The conceptual layout of the micro-Grid system.

2.2. The Formulation of Problem

The goal of the EM original problem solution is to meet several criteria while minimising the overall cost of the MG [28]. The expenses of various DG units and the cost of acquiring electricity from the utility are included in the MG's overall cost. The objective function may thus be expressed as [29]:

$$\min \{f_1(x_t), f_2(x_t), \dots, f_n(x_t)\} \tag{1}$$

$$g(x_t) = 0 \quad \& \qquad h(x_t) \leq 0 \tag{2}$$

Where: $f_n(x_t)$ is the vector of n optimization objectives, t is the various dispatch duration, $g(x_t)$ and $h(x_t)$ are the restrictions on equality and inequality respectively, and x_t is the set of decision values, which can be presented as [29]:

$$x_t = \{P_{x,t}, P_{utis,t}, P_{utim,t}, P_{bt,t}^{ch}, P_{bt,t}^{dis}, P_{load,t}\} \tag{3}$$

Where: $P_{x,t} = (P_{wt}, P_{pv} P_{mt})$ are the active power of the MG's WT, PV, and MT output respectively, $P_{utis,t}$ and $P_{utim,t}$ represents the active power purchased from the utility and the extra power that the MG sells to the utility respectively, $P_{bt,t}^{ch}$ and $P_{bt,t}^{dis}$ are the charge and discharge power of ESD and the load demand is represented by $P_{load,t}$.

2.3. Objective Function

The energy management system (EMS) regulates the output power parameters of DGs to match load demand while concurrently minimising operating costs, pollutant emission costs, and ESD degradation costs with meeting constraints. The following formulation represents the mathematical paradigm of the objective functions:

A. Operation Cost Function

The cost of running the MG is equal to the total of the power purchased from the utility and the costs associated with producing the power through the use of MT, PV, WT, and the cost of ESD, deducting the profit from selling extra energy to the grid. Therefore, [30] defines the operation cost function as:

$$f_1(x_t) = \sum_{t=1}^{H}\left[C_{uti}P_{uti,t} + F_{mt} + C_{pv}\sum_{n=1}^{N_{pv}}(P_{pv,t}^{n}) + C_{wt}\sum_{n=1}^{N_{wt}}P_{wt,t}^{n}\right] \quad (4)$$

Where: H, is total time taken, N_{pv}, N_{wt}, are the generator numbers of PV and WT respectively, C_{pv}, C_{wt} are the unit generation cost of PV and WT respectively ($/Wh), C_{uti}, is the price of acquiring power of the grid ($/Wh), and the F_{mt} is total operating cost of the MT ($) which can be written as :

$$\sum_{t=1}^{H}F_{mt} = \sum_{t=1}^{H}\left[C_{mt}\sum_{n=1}^{N_{mt}}P_{mt,t}^{n} + K_{oc}\sum_{n=1}^{N_{mt}}P_{mt,t}^{n} + SC_{mt,t}\right] \quad (5)$$

Where: C_{mt}, is the MT unit's fuel cost ($/Wh), K_{oc}, is operations and maintenance cost, $P_{mt,t}^{n}$, is the output power of the MT (W), and $SC_{mt,t}$ representing startup cost of the MT unit ($), it can be calculated as [30]:

$$\sum_{t=1}^{H}SC_{mt,t} = \sum_{t=1}^{H}\left[\left(\sigma_{mt} + \delta_{mt}(1 - e^{-\frac{\tau_{off,mt}}{\tau_{mt}}})\right).(1 - u_{(t-1),mt})\right] \quad (6)$$

Where: σ_{mt} and δ_{mt}, are hot startup time and cold startup time of MT, $\tau_{off,mt}$ and τ_{mt}, are the time which MT is turned off, and cooling time of MT, and $u_{(t-1),mt}$, is MT status at step $t-1$.

B. Emission Cost Function

The next optimization goal is to address environmental problems from polluting gases. The most noxious gases, CO2, SO2, and NOx, are included in the emission cost function. The objective function of emission cost is as [29]:

$$f_2(x_t) = \sum_{t=1}^{H}\left[\sum_{k=1}^{3}C_{emis,k}m_k(x_t)\right] = \sum_{t=1}^{H}\left[\sum_{k=1}^{3}C_{emis}u_k\sum_{n=1}^{N}(P_{mt,t}^{n} + P_{uti,t})\right] \quad (7)$$

Where: k is no. of the pollutant gas, $m_k(x_t)$, is the mass of the emission pollutant gas k, $C_{emis,k}$, is the polluting gas's cost coefficient, u_k, is the emission in g/wh.

C. Degradation Cost Function

The ESD life cycle may be used to represent the degrading cost of ESD. Detailed ESD degradation is a composite operation influenced by a number of variables, including temperature, charging/discharging rate, kind of ESD, and state of charge [31]. The charged and discharged power may be used to construct the degradation cost:

$$f_3(x_t) = \sum_{t=1}^{H}\left[\sum_{B=1}^{N_B}C_{bt}\left(P_{bt,t}^{ch} + P_{bt,t}^{dis}\right)\right] \quad (8)$$

Where: N_B represent the numbers of ESD, C_{bt} is the cost coefficient of battery cycles. The solution of Equation (1) identifies the most effective dispatch strategy for MG operating.

2.4. Constraints

The MG's operating status and the declaration of limited conditions are as follows [28]:

$$P_{mt}^{min} \le P_{mt,t} \le P_{mt}^{max} \quad (9)$$

$$0 \le P_{wt,t} \le P_{wt}^{max} \quad (10)$$

$$0 \le P_{pv,t} \le P_{pv}^{max} \quad (11)$$

$$\begin{Bmatrix} 0 \le \left|P_{bt}^{ch}\right| \le \left|P_{bt}^{ch,max}\right| \\ 0 \le P_{bt}^{dis} \le P_{bt}^{dis,max} \end{Bmatrix} \quad (12)$$

$$SOC_{min} \le SOC_t \le SOC_{max} \quad (13)$$

$$P_{uti,t} = P_{load,t} - [P_{mt,t} + P_{wt,t} + P_{pv,t} + P_{bt,t}] \quad (14)$$

Where: $P_{bt}^{ch,max}/P_{bt}^{dis,max}$ are the maximum power can be used to {charge / s to MG by} the battery, and $SOC_{min} = 50\ \%$, $SOC_{max} = 100\ \%$, are the battery's lowest and highest charge states.

The system's restriction boundaries are listed in table 1.

Table 1. Distributed generation data in the MG.

Unit	MaxPower (kW)	Min Power (kW)
WT	100	0
PV cell	100	0
Battery	60	-48
MT	60	12

2.5. Methodologies

The strategy for the proposed energy management, which accounts for multiple simultaneous objectives for the hybrid energy system, is described below. The battery has three states: charging, discharging, and inactive. The primary objectives of the EMS are as follows [30]:

- minimize the cost of energy generation.
- maximize battery life by controlling its state of charge (SOC) and process of charge/discharge.
- maximize the use of the available wind and PV power in a useful dump load when the battery is fully charged to increase system power utilization with the selection of the most appropriate conversion and control systems [32].

➢ when the MT is in operation, adjust its operating point between its limitation powers to increase its operational efficiency and reduce its environmental impact.

➢ maximize the available stored energy in the battery (i.e., higher battery SOC), and hence improving the reliability of the system, where ESD is one of the essential technological requirements of a smart grid [33].

3. Mathematical Model of Optimization Techniques

3.1. Particle Swarm Optimization

PSO is a heuristic optimization technique established by Kennedy and Eberhart [34]. The fundamental idea of the PSO algorithm is that a population swarm is randomly generated, be composed of individuals called particles. Each particle, representing a possible solution of the optimization problem, flies through a search space at a random velocity and updates its position based on its own best swarm experience, exploration, and the vector of previous velocity according to the equations [34]:

$$v_i^{k+1} = \omega v_i^k + c_1 r_1 (P_{besti}^k - x_i^k) + c_2 r_2 (g_{best}^k - x_i^k),\ x_i^{k+1} = x_i^k + v_i^{k+1} \quad (15)$$

where, ω is the inertia weight; $c1$ and $c2$ are acceleration constants; $r1$ and $r2$ are two random numbers in the range of {0, 1}; $P_{besti}^k$is the best position particle i, during each iteration, $Pbest$ and $Gbest$are updated and recorded based on the objective function [35].

3.2. Gravitational Search Algorithm

GSA is a heuristic optimization method based on Newton's gravity law [23]. The best location for the outcome is achieved by each agent drawing other agents into its gravitational field, to get the optimum solution. Position, inertial, and gravitational forces are some of the characteristics used to describe the agent. By using the following formulas, it is possible to determine the agent's position and velocity at time (t+1) [23]:

$$v_i^d(t+1) = rand_i v_i^d(t) + a_i^d(t) \quad (16)$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \quad (17)$$

Where: $$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \quad (18)$$

$$F_{ie}^d(t) = G(t)\frac{M_{pi}(t) * M_{ae}(t)}{\|x_i(t), x_e(t)\|_2 + \varepsilon}\left(X_e^d(t) - x_i^d(t)\right) \quad (19)$$

$$F_i^d(t) = \sum_{e \in Kbest, e \neq i} rand_e F_{ie}^d(t) \quad (20)$$

Where: M_{ae}, M_{pi} are the active and inactive gravitational mass for agents e and i, G(t) is the gravitational constant, ε is a tiny constant, and $\|x_i(t), x_e(t)\|_2$ is the Euclidian space between i and e agents, $M_{ii}(t)$ is i's inertial mass , $F_i^d(t)$ the force acting on it, and $a_i^d(t)$ represent the acceleration of agent i in a dimension d.

3.3. Hybrid population-based algorithm

The primary concept behind a hybrid PSOGSA is to combine PSO's social thinking (gbest) capacity with GSA's local search capabilities [22]. The velocity of any agent is computed as:

$$v_i^d(t+1) = c_3\left(rand_i v_i^d(t) + a_i^d\right) + (1 - c_3) * \left[c_1 rand_1\left(P_{best}^d - x_i^d(t)\right) + c_2 rand_2\left(g_{best}^d - x_i^d(t)\right)\right] \quad (21)$$

Agents' positions were specified as (17). Meeting an end condition will halt the process of updating velocities and locations [22].

3.4. Proposed algorithm (Capuchin Search Algorithm)

In order to improve search quality and avoid an early convergence to a local minimum, the article introduces for the first time in the energy management a devised method known as the Capuchin Search Algorithm (Cap-SA). It is a contemporary meta-heuristic search technique inspired by the foraging behaviours of capuchin monkeys in the wild. Essentially, Braik et al. offered the facts about capuchins when they were foraging [27], they navigate in three methods when looking for food sources: jumping, climbing, and swinging. The main assumptions of Cap-SA are based on these movement characteristics. The Cap-SA capuchin population is separated into two groups: "Alpha" (the leader) and "followers." Alpha's job is to locate food sources for the followers, which follow the leaders to update their locations. as presented in [27], while searching for food sources, Alpha uses the subsequent strategies: a. leaping on trees, b. jumping across riverbanks, c. swinging on trees, d. climbing on trees, and e. moving naturally on the ground.

The leaders continue use these mobility methods up until they find a desirable solution. To summarize, Cap-SA has been developed as in [27]. The existing velocity of ith capuchin in jth dimension in Cap-SA was specified as [27]:

$$v_j^i = \rho v_j^i + \tau a_1\left(X_{bestj}^i - x_j^i\right) r_1 + \tau a_2\left(F_j - x_j^i\right) r_2 \quad (22)$$

Where x_j^i denotes the current location of alpha ith in jth dimension, X_{bestj}^i is the location with the greatest fitness found so far, F_j is the best location of the food found so far, a_1 and a_2 are acceleration constants that regulate how X_{bestj}^i and F_j the affect velocity,τ is defined in Eq. 29, r_1 and r_2 are random numbers generated between 0 to 1, and the definition of the weight of inertia ρ is as [27]:

$$\rho = m_u - (m_u - m_l) * (k/K)^2 \quad (23)$$

where m_l and m_u are the inertia weight's minimum and maximum coefficient values. During each strategy, the location of alpha in Cap-SA is as follows [27]:

- *jumping on trees*

$$x_j^i = F_j + \frac{p_{bf}(v_j^i)^2 \sin(2\theta)}{g}$$

$$\theta = 1.5\ r;\ \ i < \frac{n}{2}\ \&\ \ 0.1 \le \epsilon_i \le 0.15 \quad (24)$$

where ϵ_i is a random distributed number within 0, 1, p_{bf} represents the probability of the capuchins' tails providing balance, θ is the capuchins' leaping angle.

- *jumping over riverbanks*

$$x_j^i = F_j + \frac{p_{ef} p_{bf} (v_j^i)^2 \sin(2\theta)}{g}$$

$$i < \frac{n}{2} \; \& \; 0.15 \le \epsilon_i \le 0.2 \qquad (25)$$

- *normal walking*

$$x_j^i = x_j^i + v_j^i$$

$$i < \frac{n}{2} \; \& \; 0.2 \le \epsilon_i \le 0.75 \qquad (26)$$

- *swinging on trees*

$$x_j^i = F_j + p_{bf} \sin(\theta)$$

$$i < \frac{n}{2} \; \& \; 0.75 \le \epsilon_i \le 0.9 \qquad (27)$$

- *climbing trees*

$$x_j^i = F_j + p_{bf}(v_j^i - v_{j-1}^i)$$

$$i < n/2; \;\; 0.9 \le \epsilon_i \le 1 \qquad (28)$$

where p_{ef} is the elastic possibility that a capuchin would move on the ground, and v_{j-1}^i is the capuchin's prior velocity.

- *The random position of alpha while looking for food sources* [27]:

$$x_j^i = \tau(lb_j + (ub_j - lb_j)rand())$$

$$i < \frac{n}{2} \; \& \; \epsilon_i \le pr \; \& \quad \tau = 2e^{-21(k/K)^2} \qquad (29)$$

where pr indicates, with a value of 0.1, the probability of walk search randomly, lb_j and ub_j are the jth dimension of the lower and upper limits in the search space, τ is demarcated as a function of iterations, K stands for the maximum iteration value and k for the current iteration. The location of the leaders' followers in Cap-SA is updated as follows [27]:

$$x_j^i = 0.5\left(\acute{x}_j^i + x_j^{i-1}\right) \; \& \; n/2 \le i \le n \qquad (30)$$

where x_j^i and x_j^{i-1} reflect the followers' current and prior locations respectively, but $\acute{x}_j^i$ represent the leaders' current position.

The capuchins' new positions are appraised and updated as part of the optimization process, which is carried out using an iterative loop practice. These procedures are performed at each iterative loop until it reaches convergence. When the criterion has been met, the hunt for convergence is over. The proposed CapSA flowchart is introduced in Figure 2 [36].

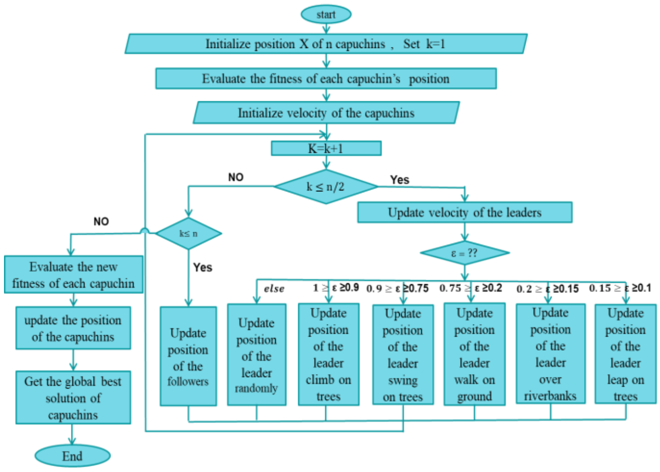

Fig. 2. Flowchart of the proposed method Cap-SA.

As Cap-SA has underlined its dependability and convergence performance in adopting several benchmark test functions [27], Hence, we came to the conclusion that the Cap-SA is an appropriate substitute way to minimize the operating cost of the MG.

The development of energy from renewable sources as an electricity generator is necessary because the rising power demand is currently not directly proportionate to the availability of conventional sources of energy for electricity generation [37]. so the traditional Grid should be converted to smart grid by inserting DGs in the Grid, sectionalizing the network to multi-zones (MGs), and do optimal planning, operation and energy management of the system. Microgrids are gaining popularity as a promising technology in order to include renewable energy sources in the distribution system [38].

4. Results and Discussion

All the simulations are implemented in MatlabR2020a.

The MG system is connected to the utility grid in the MG structure represented in Figure 1, which comprises of a WT, PV, ESD, MT, and residential load. The load demand diagram is similar to that in [39], and its size is multiplied by 300 Watthours, as shown in figure 3, and Table 2 displays several coefficients of contaminants emission [6].

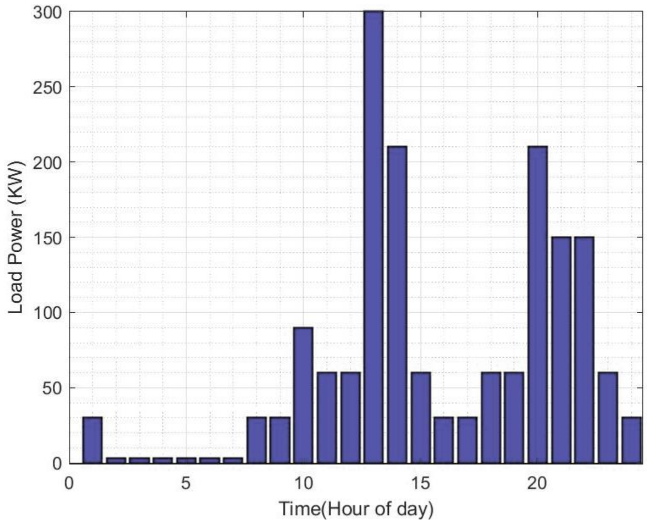

Fig. 3. The load power profiles of micro-Grid under study.

The energy management issue covered in Section 3 is applied using PSO, GSA, PSOGSA, and Cap-SA optimization approaches, and the simulation outcomes were compared with one another. It should be emphasized that the suggested (PSO, GSA, PSOGSA, and Cap-SA) has precisely the identical wind power, PV power, and load power profiles.

The parameter settings for the proposed Cap-SA are given in Table 3 [36], and maximum iteration number for any algorithm is set to 400. The best outcomes are indicated based on an average of more than 30 runs. Figure 4 shows the WT's output power expressed as a proportion of its maximum power output, where the percentage of PV output power is shown in Figure 5. for all case studies.

Table 2. Emission coefficient of pollutants for MT

Type	Emission Factors for DEG (kg/kWh)
NOx	0.00052
SO2	3.63*10^-6
CO2	0.5025

Table 3. Parameter settings of the Cap-SA

Parameter	Value
Population size	50
Number of Generations	400 (max)
a1, a2	1.10, 1.25
ml ,mu	0.1, 0.9
Ppf	0.7
Pef	19

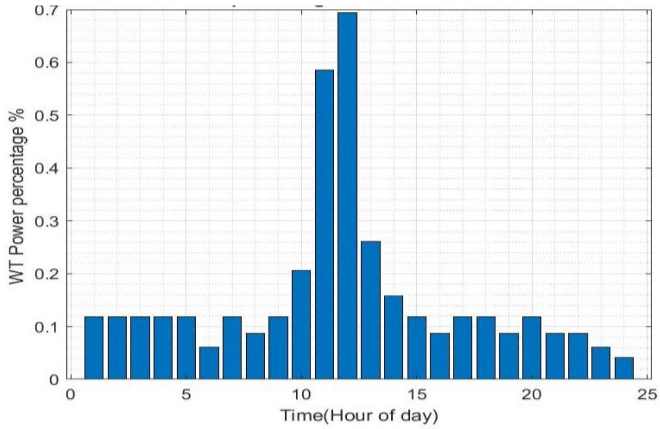

Fig. 4. The power generated from WT.

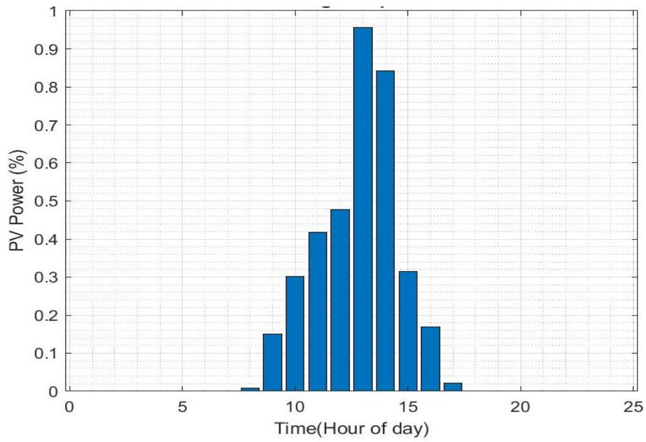

Fig. 5. The PV Panel's output power.

Scope of Work:

The proposed energy flow management strategy is tested on a real-time system according to different scenarios [40] to minimize operating cost in two scenarios:

- Scenario 1 represents the base case "Total operating cost without considering (emission cost, degradation cost),
- Scenario 2 is the same as the base case but with considering all costs (emission cost, degradation cost, startup and shut-down cost, operating costs of all DGs, and the costs of purchased power from the utility)

i. Scenario 1:

Scenario 1 was simulated without considering emission cost, or degradation cost. The power in kw shown in Table 4, is the difference of the load demand between load power and the WT and PV powers which is shared by DGs, the storage batteries, and the Utility.

The comparative convergence of the total cost (best solutions) of four different algorithms is shown in Fig. 6. It is shown clearly that all algorithms converged smoothly to the optimum value in the optimization process but the proposed CapSA optimization outperforms the PSO, GSA and PSOGSA methods as a whole; it has the advantage of reducing cost. Figure 7 presents the resource energy scheduling (scenario A) for the 24 periods under study according to CapSA.

Table 4. Output Powers from Battery, MT and Utility per hour for 4-algorithms in Scenario 1

Hours	PSO			GSA			PSOGSA			Cap-SA		
	BT	MT	UT	BT	MT	UT	BT	MT	UT	BT	MT	UT
1	24	12	-18	-48	12	54	0	12	6	11	12	-4
2	10	12	-31	60	12	-81	-43	13	21	-30	12	9
3	7	12	-28	60	12	-81	-4	14	-19	13	12	-34
4	11	12	-32	-48	12	27	60	12	-81	-25	12	4
5	-18	12	-4	60	60	-129	60	13	-82	-30	16	5
6	12	12	-28	60	12	-75	58	35	-96	60	12	-75
7	-29	12	8	60	12	-81	-47	35	4	-25	12	4
8	0	12	8	60	41	-81	59	52	-90	60	12	-52
9	31	12	-41	-48	12	39	-19	12	10	-30	55	-22
10	-26	12	53	-48	12	75	-48	12	75	-25	12	53
11	31	12	-84	60	12	-112	58	19	-118	58	12	-110
12	-6	12	-64	60	60	-177	-4	12	-66	-30	29	-56
13	-35	12	201	-48	12	214	-48	12	214	60	12	106
14	7	12	90	60	60	-10	60	12	38	60	12	38
15	22	12	-17	-48	12	53	14	12	-10	-30	12	35
16	7	12	-15	-48	12	40	38	18	-52	-30	12	22
17	-39	13	42	60	12	-56	-48	12	52	60	12	-56
18	40	12	-4	-48	12	84	9	18	21	-30	60	18
19	-30	12	70	60	12	-21	-17	46	22	60	12	-21
20	30	12	156	60	12	126	25	12	161	-16	12	202
21	-9	12	139	-48	12	177	-48	12	177	-30	12	159
22	15	12	115	60	12	69	60	12	69	60	12	69
23	-11	13	53	60	12	-18	60	12	-18	60	12	-18
24	14	12	-1	60	60	-94	-27	12	41	-30	12	44

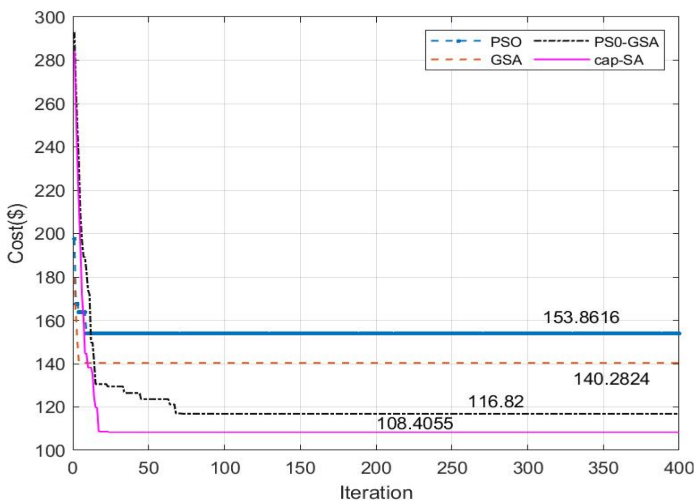

Fig. 6. Comparison between the convergence characteristics of the four algorithms in scenario A.

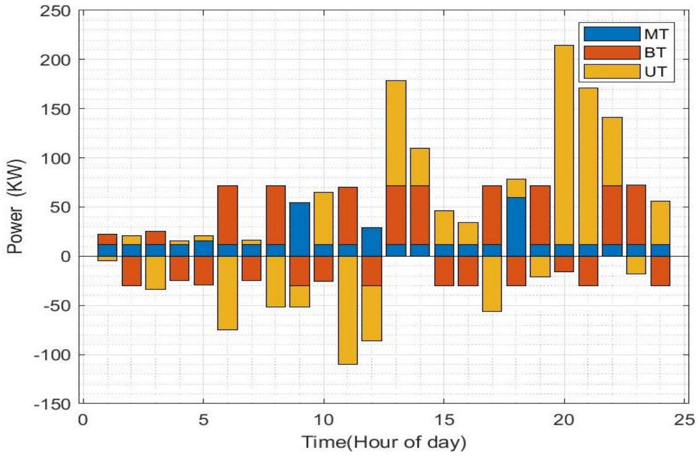

Fig. 7. Best solutions obtained EM problem using CapSA in scenario A.

The hourly cost of all algorithms was mentioned in Table 5. And it can be seen that the best parentage saved cost per day is related to CapSA optimization, and it was 29.54%, considering PSO as a base.

i. Scenario 2:

This case is the same as the base case but with considering all costs (emission cost, degradation cost, start-up and shut-down cost, operating costs of all DGs, and the costs of purchased power from the utility). Table 6 present Output Powers from Battery and MT beside the power of the main grid according to the four algorithms for the total 24 hours of the day.

Table 5. The Best hourly cost of all algorithms in the two scenarios, and savings.

Hours	cost/ hour ($/h)							
	Scenario 1				Scenario 2			
	PSO	GSA	PSOGSA	CapSA	PSO	GSA	PSOGSA	CapSA
1	4.77	3.09	2.58	1.39	4.77	3.09	2.58	1.39
2	-0.06	-2.68	-3.67	2.34	-0.06	-2.68	-3.67	2.34
3	1.46	8.60	-0.55	-0.88	1.46	8.60	-0.55	-0.88
4	1.56	2.25	0.67	0.36	1.56	2.25	0.67	0.36
5	4.60	-0.47	0.66	-1.36	4.60	-0.47	0.66	-1.36
6	2.88	4.17	-0.04	1.50	2.88	4.17	-0.04	1.50
7	1.62	-0.83	0.49	-2.33	1.62	-0.83	0.49	-2.33
8	5.10	4.51	-0.08	7.05	5.10	4.51	-0.08	7.05
9	3.25	9.46	10.03	0.33	3.25	9.46	10.03	0.33
10	6.86	6.44	-1.61	4.89	6.86	6.44	-1.61	4.89
11	-1.63	-3.92	0.01	-2.64	-1.63	-3.92	0.01	-2.64
12	-0.19	2.65	0.63	-3.12	-0.19	2.65	0.63	-3.12
13	20.95	18.70	16.15	17.18	20.95	18.70	16.15	17.18
14	12.49	20.30	21.06	8.86	12.49	20.30	21.06	8.86
15	5.29	4.49	2.12	6.82	5.29	4.49	2.12	6.82
16	4.47	0.61	0.02	-0.23	4.47	0.61	0.02	-0.23
17	4.54	3.28	7.17	2.22	4.54	3.28	7.17	2.22

18	7.86	6.33	6.55	5.84	7.86	6.33	6.55	5.84
19	8.99	13.59	6.75	6.75	8.99	13.59	6.75	6.75
20	22.88	21.92	19.80	19.99	22.88	21.92	19.80	19.99
21	16.48	11.95	12.20	13.09	16.48	11.95	12.20	13.09
22	21.92	22.62	14.33	16.91	21.92	22.62	14.33	16.91
23	6.85	3.51	12.47	12.06	6.85	3.51	12.47	12.06
24	4.54	3.18	8.22	7.77	4.54	3.18	8.22	7.77
Total Cost/Day	153.9	140.3	116.8	**108.4**	167.49	163.77	135.96	**124.8**
SAVING	Base	8.83%	24.07%	**29.54%**	Base	2.22%	18.82%	**25.5%**
Simulation Time (s)	24.2	29.1	22.7	**21.6**	26.7	33.3	27.2	**22.5**

Figure 8 compares the convergence of the total costs for the four different strategies, and shows that all algorithms smoothly arrived at the best value during the optimization process, however the recommended Cap-SA method outperforms the combined PSO, GSA, and PSOGSA techniques and has the advantage of cost minimization. Figure 9 presents the resource energy scheduling (scenario B) for the 24 periods under study according to CapSA.

According to table 5, the target values of the objective optimization of different methods are compared. As can be observed, the suggested algorithm (Cap-SA) shows better performance than the other techniques. With an increase in test function dimension, the suggested Cap-SA's performance becomes more effective.

Table 6. Output Powers from Battery, MT and Utility per hour for 4-algorithms in Scenario 2

Hours	PSO			GSA			PSOGSA			Cap-SA		
	BT	MT	UT	BT	MT	UT	BT	MT	UT	BT	MT	UT
1	2	12	4	60	12	-54	-48	12	54	-30	19	29
2	29	12	-50	60	12	-81	-9	12	-12	-18	30	-21
3	9	12	-30	-48	12	27	60	15	-84	60	12	-81
4	9	12	-30	60	12	-81	5	12	-25	-30	12	9
5	-19	12	-2	60	12	-81	53	12	-74	44	12	-65
6	0	12	-16	60	60	-123	-48	12	33	-30	12	15
7	8	12	-29	60	60	-129	10	12	-31	44	12	-65
8	1	12	7	60	12	-52	60	12	-52	-14	24	10
9	3	12	-12	-48	12	39	60	18	-75	-19	14	8
10	2	12	25	-48	12	75	-5	12	32	60	12	-33
11	9	12	-62	60	16	-116	-47	12	-5	-30	13	-23
12	-19	13	-51	-48	12	-21	-42	29	-44	60	12	-129
13	0	12	166	60	12	106	60	12	106	-7	12	174
14	21	12	76	-48	12	146	60	24	26	-7	12	105
15	-4	12	8	-48	12	53	55	12	-51	-22	17	21
16	-7	12	-1	60	60	-116	60	12	-68	-9	13	0
17	3	12	1	60	12	-56	-48	12	52	38	12	-34
18	1	12	35	60	60	-72	34	12	2	-30	12	66
19	-6	12	45	-48	12	87	-13	12	52	60	12	-21
20	1	12	185	52	12	134	38	12	148	-30	12	216
21	11	13	118	60	12	69	7	12	122	60	12	69
22	-38	12	167	-48	12	177	60	13	69	60	13	68
23	22	13	19	60	12	-18	-48	23	79	-28	30	52
24	16	12	-2	60	60	-94	60	12	-46	60	32	-67

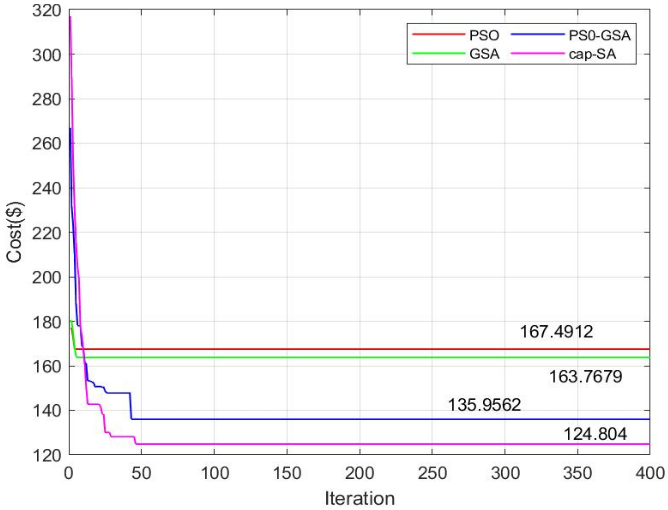

Fig. 8. Comparison between the convergence characteristics of the four algorithms.

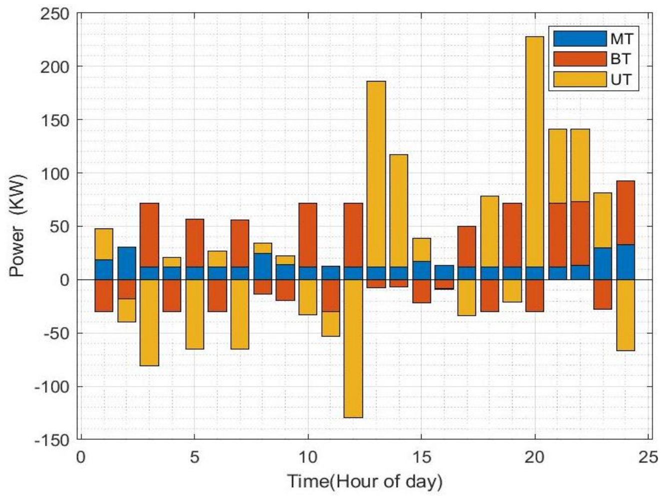

Fig. 9. Best solutions obtained EM problem using CapSA in scenario 2.

Table 7. Emission quantity according to CapSA in the two scenarios, and savings.

Case Study	Total Emission (Kg)	Saving
Scenario 1	287.5	Base
Scenario 2	269.7	6.2 %

In Table 5, when compared to existing population-based optimization algorithms, the suggested approach seems to have the greatest performance and saved cost by 25.5% parentage than the PSO algorithm in scenario 2. Despite a 15.1% rise in total daily cost in scenario 2 over the prior scenario based on the proposed algorithm that offered best cost reduction, the value of hazardous emissions was lowered by 6% as shown in table 7.

5. Conclusions

This study proposes an optimum design technique of an MG based on an innovative computational intelligence methodology called Cap-SA. It depicts a real-time EMS of a MG as a cost function in two scenarios including both degradation cost of ESD due to charge/discharge periods, and the most harmful gases emissions cost: CO2, SO2 and NOx in second scenario. Real-time GSA, PSO, Hybrid PSOGSA, and Cap-SA based EMS of a MG that is connected to the main grid and composed of (MT, WT, PV, and ESD) was presented. The results indicate that the objective function was reduced more effectively using a Cap-SA based EMS, demonstrating Cap-SA's adaptability and superiority to alternative optimization methods. Simulation results were also obtained for the same system using the PSO, GSA, and Hybrid PSOGSA optimization, and show the benefits of the proposed approach in increasing the overall system energy sustainability, and its effectiveness to solve this problem for a MG. This article may be summed up as below:

- An optimization algorithm called Cap-SA had been presented for minimizing the electricity costs for a MG.
- A case study was presented in two different scenarios for MG taking into account the costs of degradation, emissions, starting up and shutting down, operating of all DGs, and purchasing electricity from the grid.
- The robustness of the proposed Cap-SA optimization algorithm had been confirmed by comparing it with three other powerful algorithms "PSO, GSA, Hybrid PSOGSA" in the two different scenarios.
- Albeit rise in total daily cost when considering emission in scenario 2 over those without the consideration in scenario 1 based on the proposed algorithm that offered best cost reduction, the value of emission pollutants was reduced by 6%.

Finally, in the future, Cap-SA optimization algorithm can be modified or mixed with other metaheuristic algorithms to tackle an extremely dynamic MG network with large integration of unpredictable energy sources and a range of scenarios. EMS can be solved in a probabilistic manner with consideration of the uncertainty of input random variables, like PV, WT, Demand load, and market prices.

References

[1] Y. Wang, C. Chen, J. Wang, and R. Baldick, "Research on Resilience of Power Systems under Natural Disasters - A Review," IEEE Transactions on Power Systems, vol. 31, no. 2, pp. 1604–1613, Mar. 2016, doi: 10.1109/TPWRS.2015.2429656.

[2] G. Liu, T. ben Ollis, Y. Zhang, T. Jiang, and K. Tomsovic, "Robust Microgrid Scheduling with Resiliency Considerations," IEEE Access, vol. 8, pp. 153169–153182, 2020, doi: 10.1109/ACCESS.2020.3018071.

[3] G. Liu, T. Jiang, T. B. Ollis, X. Li, F. Li, and K. Tomsovic, "Resilient distribution system leveraging distributed generation and microgrids: A review," IET Energy Systems Integration, vol. 2, no. 4, pp. 289–304, Dec. 2020, doi: 10.1049/iet-esi.2019.0134.

[4] X. Li, R. Zhang, L. Bai, G. Li, T. Jiang, and H. Chen, "Stochastic low-carbon scheduling with carbon capture power plants and coupon-based demand response," Appl Energy, vol. 210, pp. 1219–1228, Jan. 2018, doi: 10.1016/j.apenergy.2017.08.119.

[5] G. Liu, T. B. Ollis, B. Xiao, X. Zhang, and K. Tomsovic, "Distributed energy management for community microgrids considering phase balancing and peak shaving," IET Generation, Transmission and Distribution, vol. 13, no. 9, pp. 1612–1620, 2019, doi: 10.1049/iet-gtd.2018.5881.

[6] E. E. Elattar, and S. K. Elsayed, "Optimal Location and Sizing of Distributed Generators Based on Renewable Energy Sources Using Modified Moth Flame Optimization Technique" IEEE Access, vol. 8, pp. 109625–109638, 2020, doi: 10.1109/ACCESS.2020.3001758.

[7] A. Hirsch, Y. Parag, and J. Guerrero, "Microgrids: A review of technologies, key drivers, and outstanding issues," Renewable and Sustainable Energy Reviews, vol. 90. Elsevier Ltd, pp. 402–411, Jul. 01, 2018. doi: 10.1016/j.rser.2018.03.040.

[8] J. Zeng, Q. Wang, J. Liu, J. Chen, and H. Chen, "A Potential Game Approach to Distributed Operational Optimization for Microgrid Energy Management with Renewable Energy and Demand Response," IEEE Transactions on Industrial Electronics, vol. 66, no. 6, pp. 4479–4489, Jun. 2019, doi: 10.1109/TIE.2018.2864714.

[9] H. Shuai, J. Fang, X. Ai, Y. Tang, J. Wen, and H. He, "Stochastic optimization of economic dispatch for microgrid based on approximate dynamic programming," IEEE Trans Smart Grid, vol. 10, no. 3, pp. 2440–2452, May 2019, doi: 10.1109/TSG.2018.2798039.

[10] E. Mengelkamp, J. Gärttner, K. Rock, S. Kessler, L. Orsini, and C. Weinhardt, "Designing microgrid energy markets: A case study: The Brooklyn Microgrid," Appl Energy, vol. 210, pp. 870–880, Jan. 2018, doi: 10.1016/j.apenergy.2017.06.054.

[11] G. Aghajani and N. Ghadimi, "Multi-objective energy management in a micro-grid," Energy Reports, vol. 4, pp. 218–225, Nov. 2018, doi: 10.1016/j.egyr.2017.10.002.

[12] L. Mellouk, M. Ghazi, A. Aaroud, M. Boulmalf, D. Benhaddou, and K. Zine-Dine, "Design and energy management optimization for hybrid renewable energy system- case study: Laayoune region," Renew Energy, vol. 139, pp. 621–634, Aug. 2019, doi: 10.1016/j.renene.2019.02.066.

[13] M. Jafari and Z. Malekjamshidi, "Optimal Energy Management of a Residential-based Hybrid Renewable Energy System Using Rule-based Real-time control and 2D Dynamic Programming Optimization Method" Renewable Energy 146, pp: 254-266, 2020.

[14] B. Xu, J. Zhao, T. Zheng, E. Litvinov, and D. S. Kirschen, "Factoring the cycle aging cost of batteries participating in electricity markets." IEEE Transactions on Power Systems 33, no. 2 pp: 2248-2259, 2017.

[15] Li, Yang, Z Yang, Li Guoqing, Mu Yunfei, Dongbo Zhao, Chen Chen, and Bo Shen. "Optimal scheduling of isolated microgrid with an electric vehicle battery swapping station in multi-stakeholder scenarios: A bi-level programming approach via real-time pricing" Applied energy, 232, pp: 54-68, 2018.

[16] An, Luu Ngoc, and Tran Quoc-Tuan, "Optimal energy management for grid connected microgrid by using dynamic programming method," IEEE Power & Energy Society General Meeting, Denver, pp. 1-5, USA, 2015.

[17] A. Chaouachi, R. M. Kamel, R. Andoulsi, and K. Nagasaka, "Multiobjective intelligent energy management for a microgrid," IEEE Transactions on Industrial Electronics, vol. 60, no. 4, pp. 1688–1699, 2013, doi: 10.1109/TIE.2012.2188873.

[18] Y. Y. Hong, M. C. Hsiao, Y. R. Chang, Y. der Lee, and H. C. Huang, "Multiscenario underfrequency load shedding in m Microgrid consisting of intermittent renewables," IEEE Transactions on Power Delivery, vol. 28, no. 3, pp. 1610–1617, 2013, doi: 10.1109/TPWRD.2013.2254502.

[19] G. C. Liao, "Solve environmental economic dispatch of Smart MicroGrid containing distributed generation system - Using chaotic quantum genetic algorithm," International Journal of Electrical Power and Energy Systems, vol. 43, no. 1, pp. 779–787, Dec. 2012, doi: 10.1016/j.ijepes.2012.06.040.

[20] J. Radosavljević, M. Jevtić, and D. Klimenta, "Energy and operation management of a microgrid using particle swarm optimization," Engineering Optimization, vol. 48, no. 5, pp. 811–830, May 2016, doi: 10.1080/0305215X.2015.1057135.

[21] P. Li, D. Xu, Z. Zhou, W. J. Lee, and B. Zhao, "Stochastic optimal operation of microgrid based on chaotic binary particle swarm optimization," IEEE Trans Smart Grid, vol. 7, no. 1, pp. 66–73, Jan. 2016, doi: 10.1109/TSG.2015.2431072.

[22] S. Z. M. H. Seyedali Mirjalili, "A New Hybrid PSOGSA Algorithm for Function Optimization," International Conference on Computer and Information Application., pp. 374–377, 2010.

[23] E. Rashedi, H. Nezamabadi-pour, and S. Saryazdi, "GSA: A Gravitational Search Algorithm," Inf Sci (N Y), vol. 179, no. 13, pp. 2232–2248, Jun. 2009, doi: 10.1016/j.ins.2009.03.004.

[24] S. Duman, U. Güvenç, Y. Sönmez, and N. Yörükeren, "Optimal power flow using gravitational search algorithm," Energy conversion and management, vol. 59, pp. 86–95, Jul. 2012, doi: 10.1016/j.enconman.2012.02.024.

[25] Li, Yang, Li Kang, Z Yang, Yu Yang, Xu Runnan, and M Yang. "Stochastic optimal scheduling of demand response-enabled microgrids with renewable generations: An analytical-heuristic approach." Journal of Cleaner Production 330 p: 129840, 2022.

[26] Y. Li, Z. Yang, D. Zhao, H. Lei, B. Cui, and S. Li, "Incorporating energy storage and user experience in isolated microgrid dispatch using a multi-objective model," IET Renewable Power Generation, vol. 13, no. 6, pp. 973–981, Apr. 2019, doi: 10.1049/iet-rpg.2018.5862.

[27] M. Braik, A. Sheta, and H. Al-Hiary, "A novel meta-heuristic search algorithm for solving optimization problems: capuchin search algorithm," Neural Comput Appl, vol. 33, no. 7, pp. 2515–2547, Apr. 2020, doi: 10.1007/s00521-020-05145-6.

[28] M. H. Mostafa, S. H. E. A. Aleem, S. G. Ali, A. Y. Abdelaziz, P. F. Ribeiro, and Z. M. Ali, "Robust energy management and economic analysis of microgrids considering different battery characteristics," IEEE Access, vol. 8, pp. 54751–54775, 2020, doi: 10.1109/ACCESS.2020.2981697.

[29] X. Wu, W. Cao, D. Wang, and M. Ding, "A multi-objective optimization dispatch method for microgrid energy management considering the power loss of converters", Energies, vol. 12, no. 11, p: 2160, Jun. 2019, doi: 10.3390/en12112160.

[30] S. A. Pourmousavi, M. H. Nehrir, C. M. Colson, and C. Wang, "Real-time energy management of a stand-alone hybrid wind-microturbine energy system using particle swarm optimization", IEEE Transactions on Sustainable Energy, vol. 1, no. 3, pp: 193–201, Oct. 2010, doi:10.1109/TSTE.2010.2061881.

[31] M. F. Zia, E. Elbouchikhi, and M. Benbouzid, "Optimal operational planning of scalable DC microgrid with demand response, islanding, and battery degradation cost considerations," Appl Energy, vol. 237, pp. 695–707, Mar. 2019, doi: 10.1016/j.apenergy.2019.01.040.

[32] E. Aydin, A. Polat, And L. T. Ergene, "Vector control of DFIG in wind power applications,". 5th International Conference on Renewable Energy Research and Applications (ICRERA) IEEE, pp. 478–483 Nov. 2016.

[33] S. N. Saxena, "Smart Distribution Grid–and How to Reach the Goal." International Journal of Smart Grid 3, no. 4, pp. 188-200, Dec. 2019.

[34] D. Wang, D. Tan, and L. Liu, “Particle swarm optimization algorithm: an overview,” Soft computing, vol. 22, no. 2, pp. 387–408, Jan. 2018, doi: 10.1007/s00500-016-2474-6.

[35] I. I. Atteya, H. A. Ashour, N. Fahmi, and D. Strickland. "Distribution network reconfiguration in smart grid system using modified particle swarm optimization" International Conference on Renewable Energy Research and Applications (ICRERA) IEEE, pp. 305-313. Nov, 2016.

[36] M. Braik, “A Hybrid Multi-gene Genetic Programming with Capuchin Search Algorithm for Modeling a Nonlinear Challenge Problem: Modeling Industrial Winding Process, Case Study,” Neural Processing Letters, vol. 53, no. 4, pp. 2873–2916, Aug. 2021, doi: 10.1007/s11063-021-10530-w.

[37] I. M. Opedare, T. M. Adekoya, and A. E. Longe, “Optimal Sizing of Hybrid Renewable Energy System for Off-Grid Electrification: A Case Study of University of Ibadan Abdusalam Abubakar Post Graduate Hall of Residence,” International Journal of Smart Grid (ijSmartGrid), vol. 4, no. 4, pp. 176–189, 2020, doi: 10.20508/.v4i4.135.g110.

[38] E. Is El-sayed, M. M. Al-Gazzar, and M. Sh Seif, “Energy Management of Renewable Energy Sources Based on Support Vector Machine,” INTERNATIONAL JOURNAL of RENEWABLE ENERGY RESEARCH vol. 12, no. 2, 2022.

[39] C. Wang, “Modeling and control of hybrid wind/photovoltaic/fuel cell distributed generation systems”. Montana State University, 2006.

[40] N. Z. Bako, A. M. Tankari, and S. A. Maiga, "Design Methodology of a Multi-village Microgrid." International Journal of Smart Grid-(ijSmartGrid), pp: 67-76. vol. 2, no. 1, March, 2018.