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Optimal Operation of Standalone and Grid Connected Micro Grid Using Whale Optimization Algorithm

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ABSTRACT

Due to today's rapid socioeconomic expansion and environmental concerns, many modern civilizations are interested in researching alternate energy options, notably renewable ones. In this sense, a Micro-grid (MG) of multiple renewable energy sources can help achieve the intended goals while delivering electricity more efficiently, affordably, and safely. In this paper, an expert multi-objective Whale Optimization Algorithm (WOA) is proposed for optimal operation of a typical MG with Renewable Energy Sources (RESs) and a back-up Micro-Turbine/Fuel Cell/Battery hybrid power source to level power mismatch or store surplus energy when needed. The problem is a nonlinear constraint multi-objective optimization to minimize total operating cost and net emission. The proposed approach is tested on a typical MG and compared to WOA.
Keywords—Micro-grid, RESs, Whale Optimization Algorithm, Micro-Turbine and DG

I. INTRODUCTION

Wind, biomass, solar, and hydropower are just a few examples of alternative energy sources that have recently gained popularity due to their lower cost and less environmental impact. On the other hand, it has been proposed to combine these renewable energy sources with MG. Photovoltaic (PV), micro-turbines, fuel cells, and storage devices all have a role in the future of energy production.

However, when more DGs are integrated into the grid, new electrical system difficulties may emerge. An integrated distribution system and distributed generation can help alleviate this by using medium-sized generators (MGs). Regarding MGs in this context, approaches used for managing and monitoring their operation change with time, making it necessary to schedule energy sources more precisely in MGs to achieve various goals [1].

A slew of studies has been done on the best way to schedule processes in various types of environments. Economic scheduling was initially proposed to solve the optimization problem by looking for an outstanding collection of generators to meet power requirements and operational restrictions while being economically efficient. A multivariable optimization problem should be used in this case because of the environmental concerns and toxins released by typical fossil fuel units.

Strategies based on several objectives, including emission, have been developed in publications to determine a certain number of units for supplying the load while considering minimal cost levels and grid emissions. To produce distributed resources like renewable and fossil fuels, companies use distributed generation (DG). There are two basic types: those with and those without access to energy. Fuel-supplied forms may include microturbines and fuel cells. Scaled-down turbine engines include microturbines, which have integrated generators and energy electronics.

Using DG will save money on transmission and distribution resources and maintenance expenses while also reducing pollutants. Concentric transmission line losses will be reduced as well. Additionally, it can reduce the total grid capacity while increasing the quality of the peak and valley periods and the reliability of electricity delivery.

It has a powerful and efficient power supply for the network. As the DG spreads, it reveals more and more flaws. Because of the high costs and problems with control, only one person should have access. To begin with, because DG is a problematic source to manage, large systems are usually restrained and segregated to keep their impact on the power grid to a minimum. Distributed generation, on the other hand, has specific properties that make it function as a load [2], resulting in an extremely constrained structure for distributed generation.

The MG definition is recommended to integrate distributed generation into the net and maximize distributed generation's economic, energy, and environmental benefits. Small, self-sufficient, and decentralized, MG comprises batteries, turbines, and energy storage devices. It reduces feeder losses and improves the local electricity supply's dependability and efficiency, improving the stability of the power supply.

II. GLOBAL OPTIMIZATION TECHNIQUES

Typically, meta-heuristic products fall into two broad categories: solution-based and population-based. The search technique begins with one of the earlier class's possible solutions (Simulated Annealing, for example). This single candidate answer is then strengthened during the iterations. Nevertheless, population-based metaheuristics optimize the process by generating a succession of solutions (population). In this situation, the search process begins with a random population (many answers), which is gradually enhanced throughout the procedure [3].

Meta-heuristic algorithms in population have several advantages over single-solution algorithms: Multiple candidate solutions share search data, resulting in unexpected leaps into the promising search field. Multiple applicant solutions assist one another in avoiding locally optimal solutions. Meta-heuristics based on populations often perform better than single-solution algorithms in terms of analysis. Swarm Intelligence is an enthralling branch of population-based meta-heurism [4].

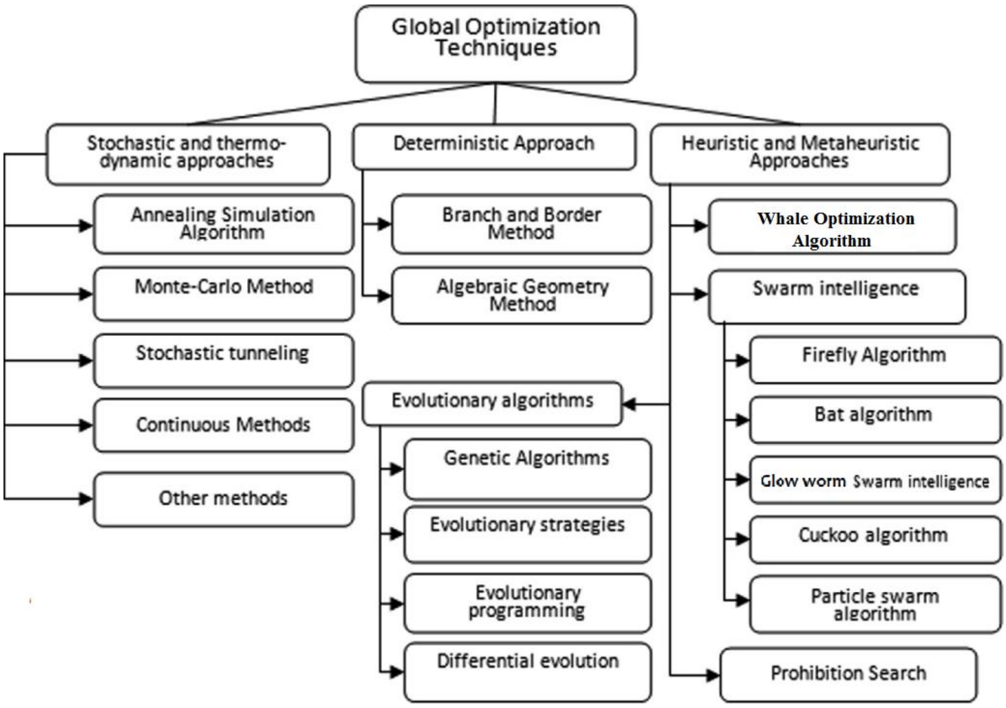


Fig. 1. Flow chart of Global Optimization Techniques.

Krishnanand K.N. and Ghose D. introduced the Glowworm Swarm Optimization Algorithm (GSO) in 2005 [5], a nature-inspired heuristic intelligence algorithm that mimics the behavior of a glowworm swarm while moving by employing luciferin to attract other glowworms nearby or looking for food. The more valuable luciferin is, the more desirable the glowworm will be since it is brighter. Numerous domains have benefited from the glowworm swarm optimization algorithm, including multimodal function and combinatorial optimization. The glowworm swarm optimization algorithm has been used in multiple disciplines, such as multimodal function and combination optimization, robotics applications, and wireless sensor networks.

III. COST-EFFECTIVE ECONOMIC DISPATCH OF MICROGRID

The total operating cost of the MG in $ includes the fuel costs of DGs, start-up/shut-down costs and the costs of power exchange between the MG and the utility [5]. The cost objective function aims to find OPFs from energy sources to load centres for a definite period economically. Such objective function can be formulated as below:

$$\begin{aligned} Min\ f_1(X) = \sum_{t=1}^{T} \Bigg\{ & \sum_{i=1}^{N_g} \big[u_i(t) P_{Gi}(t) B_{Gi}(t) + S_{Gi} \, | u_i(t) \\ & - u_i(t-1) | \big] + \sum_{j=1}^{N_s} \big[u_j(t) P_{sj}(t) B_{sj}(t) + S_{sj} \, | u_j(t) - u_j \\ & (t-1) | \big] + P_{Grid}(t) B_{Grid}(t) \Bigg\} \end{aligned} \quad (1)$$

Where ui(t) status of unit i at hour t, PGi(t) active power output of ith generator at time t, Psj(t) active power output of jth storage at time t, BGi(t) and BSj(t) are the bids of the DGs and storage devices at hour t, SGi and Ssj represent the start-up or shut-down costs for ith DG and jth storage respectively, PGrid(t) is the active power which is bought (sold) from (to) the utility at time t and BGrid(t) is the bid of utility at time t. X is the state variables vector which includes active power of units and their related states and is described as follows:

$$X = \left[P_g, U_g\right]_{1\times 2nT}$$
$$P_g = \left[P_G, P_S\right]$$
$$n = N_g + N_s + 1 \qquad (2)$$

where n is the number of state variables, Ng and Ns are the total numbers of generation and storage units; respectively, Pg is the power vector including active powers of all DGs, and Ug is the state vector denoting the ON or OFF states of all units during each hour of the day. These variables can be described as follows:

$$P_G = \left[P_{G1}, P_{G2}, \ldots, P_{G,Ng}\right]$$
$$P_G = \left[P_{Gi}(1), P_{Gi}(2), \ldots, P_{Gi}(t), \ldots, P_{Gi}(T)\right]; i = 1, 2, \ldots, N_g + 1$$
$$P_s = \left[P_{s1}, P_{s2}, \ldots P_{s,Ns}\right]$$
$$P_{sj} = \left[P_{sj}(1), P_{sj}(2), \ldots, P_{sj}(t), \ldots, P_{sj}(T)\right]; j = 1, 2 \ldots, N_s \qquad (3)$$

Where T represents the total number of hours, PGi(t) and Psj(t) are the real power outputs of ith generator and jth storage at time t, respectively.

$$U_g = \left[u_1, u_2, \ldots, u_n\right] = \{u_i\}_{1\times n} \in \{0,1\};$$
$$u_k = \left[u_k(1), u_k(2), \ldots, u_k(t), \ldots, u_k(T)\right]; k = 1, 2, \ldots, n \qquad (4)$$

where uk(t) is the status of unit k at hour t.

A. Power balance Constraints

The total power generation from DGs in the MG must cover the entire demand inside the grid. Since a small 3-feeder radial L.V system is proposed in work, there is no urgent need to consider transmission losses which are low numerically. Hence,

$$\sum_{i=1}^{N_g} P_{Gi}(t) + \sum_{J=1}^{N_s} P_{sj}(t) + P_{Gird}(t) = \sum_{k=1}^{N_k} P_{LK}(t) \qquad (5)$$

where PLk is the amount of kth load level and Nk is the total number of load levels.

B. Real power generation capacity

For a stable operation, the active power output of each DG is limited by lower and upper bounds as follows:

$$P_{Gi,\min}(t) \le P_{Gi}(t) \le P_{Gi,\max}(t)$$
$$P_{sj,\min}(t) \le P_{sj}(t) \le P_{sj,\max}(t)$$
$$P_{grid,\min}(t) \le P_{Grid}(t) \le P_{grid,\max}(t) \qquad (6)$$

where PG,min(t), Ps,min(t) and Pgrid,min(t) are the minimum active powers of ith DG, jth storage and the utility at the time t. Similarly, PG,max(t), Ps,max(t) and Pgrid,max(t) are the maximum power generations of corresponding units at hour t.

Since there are some limitations on the charge and discharge rate of storage devices during each time interval, the following equation and constraints can be expressed for a typical battery[6]:

$$W_{ess,\min} = W_{ess,t-1} + \eta_{charge} P_{charge} \Delta t - \frac{1}{\eta_{discharge}} P_{discharge} \Delta t \quad (7)$$

$$\begin{cases} W_{ess,\min} \le W_{ess,t} \le W_{ess,\max} \\ P_{charge,t} \le P_{charge,\max} ; P_{discharge,t} \le P_{discharge,\max} \end{cases} \quad (8)$$

Where Wess,t and Wess,t 1 are the amount of energy storage inside the battery at hour t and t-1 respectively, Pcharge(Pdischarge) is the permitted rate of charge(discharge) during a definite period (Δt), ηcharge(ηdischarge) is the efficiency of the battery during charge(discharge) process. Wess,min and Wess,max are the lower and upper limits on the amount of energy storage inside the battery and Pcharge,max(Pdischarge,max) is the maximum rate of battery charge(discharge) during each time interval Δt.

IV. WHALE OPTIMIZATION ALGORITHM

The Whale Optimization Algorithm (WOA) is a metaheuristic, nature-inspired optimization algorithm that is based on the social (bubble net) behaviour of whales, or the encircling mechanism, in the summer sky in the tropical temperature regions [8, 9]. The WOA was developed by researchers at the University of California, Santa Cruz. It was invented in 2016 by Indrajit N. Trivedi at the Government Engineering College in Gandhinager (Gujarat), and it is based on the encircling behaviour that is seen in natural settings, such as fish schools; see inserts for more information. Although the WOA algorithm shares many similarities with other algorithms that are based on the so-called swarm intelligence, such as the well-known Particle Swarm Optimization (PSO), Artificial Bee Colony optimization (ABC), and Bacterial Foraging (BFA) algorithms, it is in fact much simpler both in terms of its concept and its implementation. In particular, this is because the WOA algorithm has many similarities with other algorithms that are based on the so-called swarm intelligence.

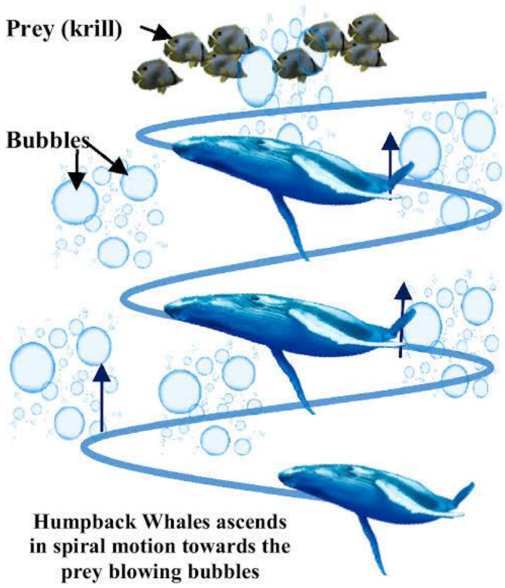


Fig. 4.1 Tropical Whales

WOA has three rules.

1. All whales catch surface fish.
2. This searching is concluded near the surface to provide a bubble net to collect little fish.
3. A problem's goal function determines the whale's bubble net surrounding. Bubble net is proportional to the objective function for maximising problems.

According to recent bibliography, the algorithm is very efficient and can outperform other conventional algorithms, such as genetic algorithms, for solving many optimization problems. This fact has been justified in a recent study, where the statistical performance of the whales algorithm was measured against other well-known optimization algorithms using various standard stochastic test functions [8,9]. Its key benefit is that it employs real random numbers and is based on global communication among swarming particles (whales). As a result, it seems more effective in multi objective optimization, such as the economic load dispatch problem in our case.

The whales algorithm has three rules based on real whales' bubble nets [8,9]. These:

(1) All whales catch surface fish.

(2) Then, it was watched that this searching was accomplished near the surface to provide a bubble net to collect small fish.

(3) A problem's goal function determines the whale's bubble net surrounding. Bubble net is proportional to the objective function for maximising problems.

Prey Equation

The whales algorithm uses a monotonically declining attractiveness function [8,9].

First, whales circle prey. WOA estimates if the best candidate solution is objective prey or near ideal. After the best search agent is determined, the other hunt operators will try to catch up. Equations explain this behaviour:

$$D = | C. X (t) - X (t) | \text{ ....(9)}$$

$$X (t + 1) = X (t) - A .D \text{ ....(10)}$$

where t is the iteration, A and C are coefficient vectors, and X is the best solution's position vector. If there's a better approach, X should be adjusted every iteration. Determine A and C as follows:

$$A = 2a \cdot r - a \text{ ....(11)}$$

$$C = 2 \cdot r \quad \text{........(12)}$$

Bubble-Net Attacking Method

Two strategies are utilized to figure the feeding conduct of humpback whales as follows.

Shrinking encircling mechanism:

This is achieved by reducing the estimate of an in the equation (11). Notate that the variation range of A is also lowered by a. As a result, A will be a random value during the interval [a, a], where a decreases from 2 to 0 across all emphasis. Setting A at random within [1,1], the new position of an inquiry operator can be defined anywhere between the specialist's first position and the position of the current best specialist. This tendency is illustrated quantitatively in Figure 2 (a).

Spiral updating position:

This approach initially determines the whale's (X, Y) and prey's (X, Z) distance (X , Y). A winding condition is formed between whale and prey to replicate humpback whales' helix-shaped development.

$X(t+1) = X^*(t)-A. D$ if $p<0.5$ ….(11)

$X(t+1)=D'..\cos(2\pi l)+X^*(t)$if $p\geq 0.5$ ….(12)

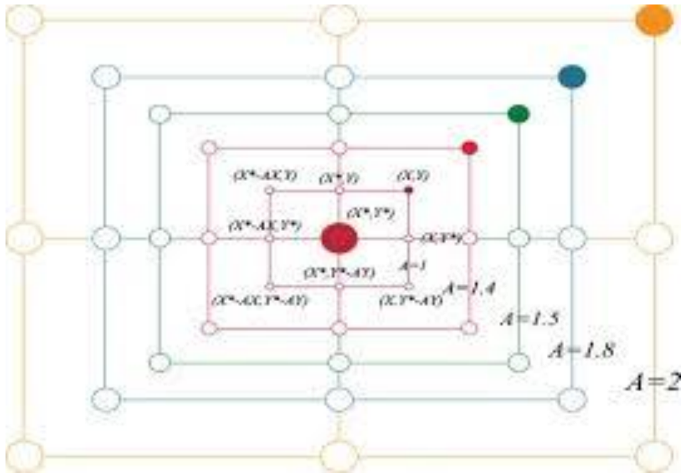


Fig.4.2(a) shrinking encircling mechanism

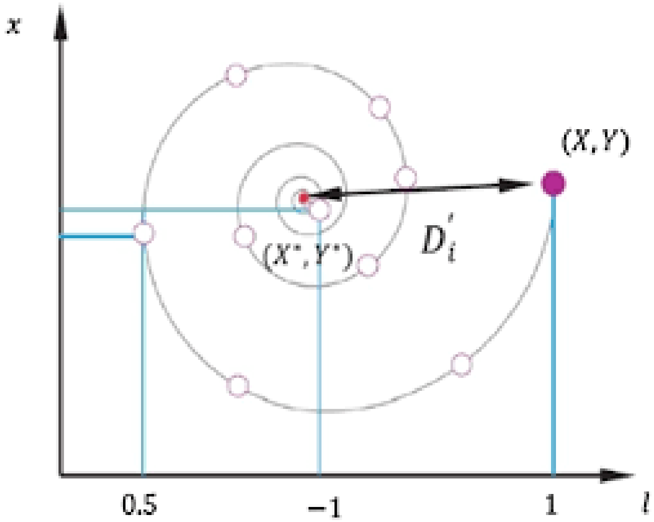


Fig.4.2(b) spiral updating position

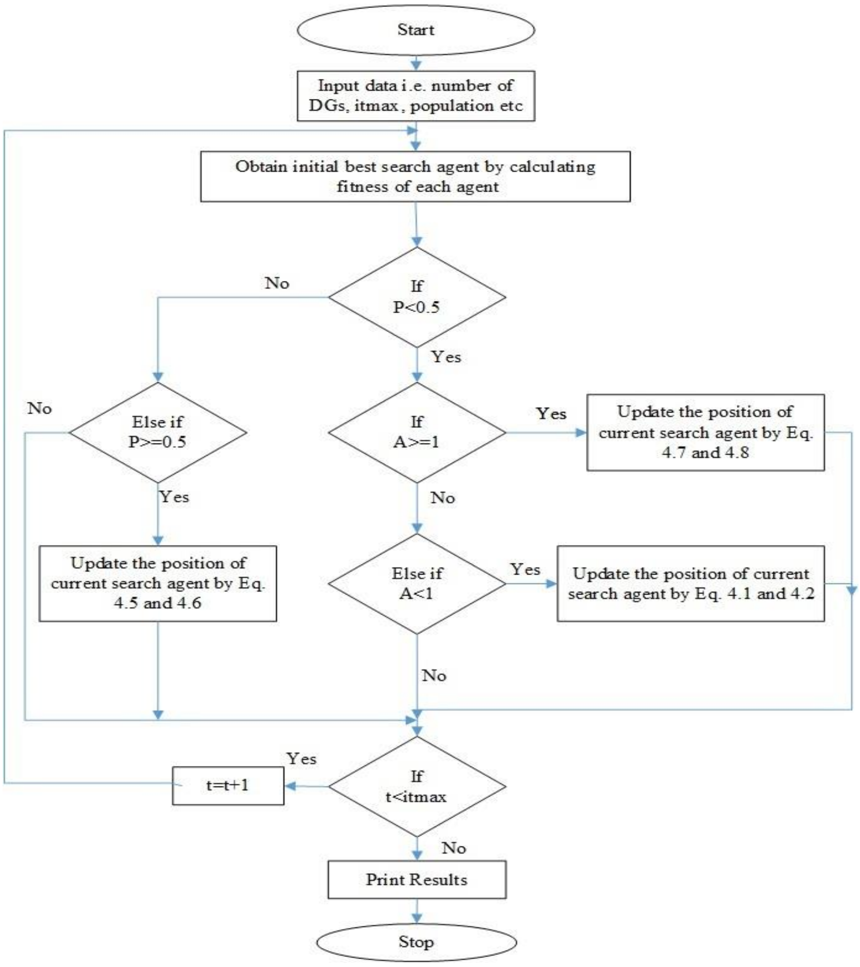
where p is in [0,1]. Despite using bubble nets, humpback whales hunt indiscriminately.

Search for pray:

Humpback whales seek randomly according on position. A with irregular qualities greater than 1 or less than 1 is used to shift the search agent away from a reference whale. The position of an inquiry operator has been updated in the investigation stage based on a randomly chosen search agent, not the best pursuit operator determined this manner. This approach and |A| > 1 emphasise research and allow WOA calculation for global pursue. Mathematical model:

$D = | C . \; - X |$ ……….(13)

$X (t + 1) = \; - A . D$ ………(14)



V. RESULT AND DISCUSSION

In this part of the work the proposed WOA algorithm is implemented to solve the multi-operation management problem for a typical MG as shown in Fig. 5.1.

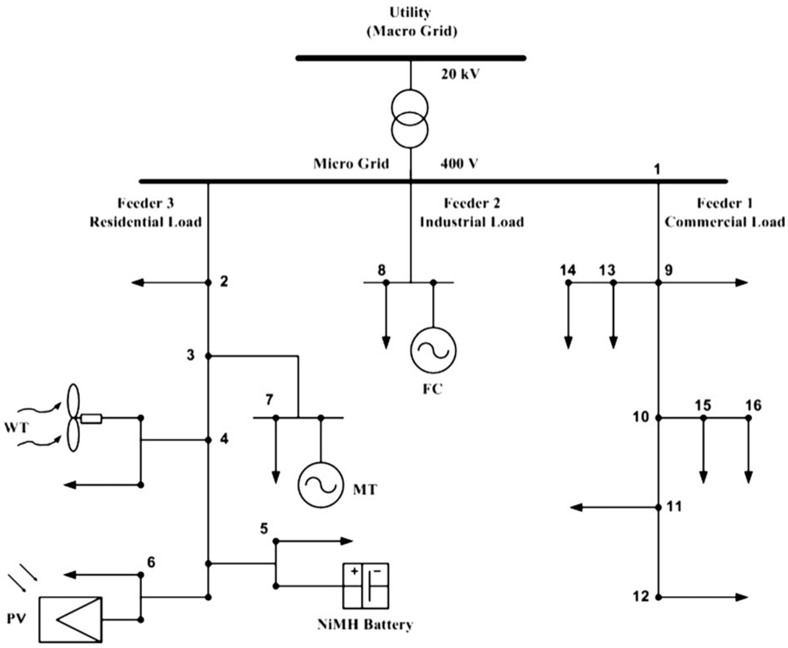


Fig. 5.1 A typical L.V micro-grid

Table 1 shows the optimal PV, FC, MT and WT schedule in a microgrid for a day in grid-connected mode. For allocation of optimal set points to the units through the entire case studies, all DGs are considered"ON" or in state "1", thus there will be no start-up or shut-down cost for the mentioned units.

TABLE I. TYPICAL MICRO GRID INPUT DATA

Type	Pmin (kW)	Pmax (kW)	Bid ($/kWh)	OM ($/kWh)	Startup/shut down ($/kWh)
MT	6	30	0.457	0.0446	0.96
FC	3	30	0.294	0.08618	1.65
PV	0	25	2.584	0.2082	0
WT	0	15	1.073	0.525	0
BES	-30	30	0.38	0	0
Utility	-30	30	0	0	0

The bid coefficients in $ per kilo-Watt hour (kWh) and Pmin and Pmax for DGs are given in Table 2. To simplify our analysis, all units in this paper are assumed to be operating in electricity mode only and no heat is required for the examined period.

Table I shows optimal schedule of PV, FC, MT and WT in microgrid for a day in grid connected mode. The total cost of DGs in microgrid and power cost to the grid for the proposed method for a day is 1141.41566 $ and -94.43061 $ respectively as shown in Table 5.2. Suppose if the total generated power from the FC and MT is not sufficient to meet the load demand, then the remaining required power is imported from the main grid to satisfy the total load demand. The convergence characteristic of firefly algorithm for grid connected mode is shown in Fig. 5.4. From Fig. 5.4, it is clearly seen that the optimal result is achieved within 48thiterations, hence the proposed approach is much faster in obtaining the results

Fig. 5 A Cost of DG in $ over 24 Hours

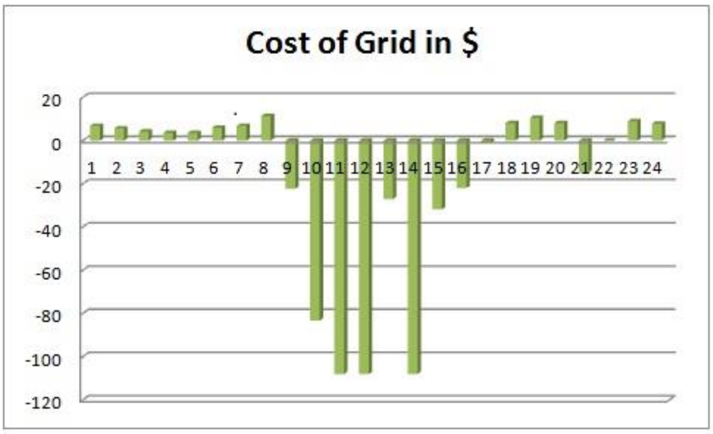


Fig. 5 B Cost of Grid in $ over 24 Hours

TABLE II OOPTIMAL COST – GRID MODE

Cost of Grid	112.99930$
Cost of DG	669.01588$
Startup/Shutdown cost	0.00000$
Maintenance Cost of DG	86.10477$
Operation cost MG	868.11994$

Cost of Grid	0.00000$
Cost of DG	726.13250$
Start –Up /Shutdown Cost	0.00000$
Maintenance Cost of DG	100.39985$
Operation Cost of MG	826.53235$

TABLE III OPTIMAL COST – ISLAND MODE

Time (h)	Demand, DG sources and outputs (kW)					Status					Cost ($)		SC
	MT	FC	PV	WT	Grid	MT	FC	PV	WT	Grid	Grid	DG	
1	30	3.02	0	0	-13.02	1	1	1	1	1	6.9	9.65	0
2	6.38	30	0	0	-18.88	1	1	1	1	1	5.7	4.563	0
3	30	3.04	0	0	-15.54	1	1	0	0	1	4.2	8.699	0
4	30	30	0.01	0.01	-6.99	1	1	1	1	1	-0.489	19.9	0
5	29.44	3	0	0	-8.92	1	1	1	1	1	3.597	10.95	0
6	28.1	27.98	0	0	-22.24	1	1	0	0	1	5.531	12.62	0
7	12.93	3.22	23.87	0	-2.52	1	1	1	0	1	6.9	67.57	0
8	28.07	28.44	0	0	29.29	1	1	0	0	1	-4.549	32.32	0
9	28.95	28.94	0	0	-13.39	1	1	0	0	1	43.51	16.65	0
10	6.43	30	24.48	0	30	1	1	1	1	1	-48.29	86.42	0
11	7.38	3	6.12	0	30	1	1	1	1	1	114	31.48	0
12	30	30	0	0	30	1	1	0	0	1	-62.97	33.93	0
13	12.94	28.9	0	0	30	1	1	1	1	1	-2.494	25.81	0
14	30	30	0.01	9.43	30	1	1	1	1	1	-106	44.06	0
15	30	3	21.26	0	27.68	1	1	1	0	1	-15.2	80.06	0
16	15.41	3	0	0	29.48	1	1	0	0	1	57.74	19.13	0
17	30	29.41	0	0	-5.91	1	1	1	1	1	18	20.11	0
18	30	30	0.01	6.87	-10.87	1	1	1	1	1	12.3	25.79	0
19	6.18	26.83	0	0	27.25	1	1	0	0	1	9.356	21.07	0
20	30	29.76	0	0	-4.76	1	1	1	1	1	12.9	20.65	0
21	13.23	3	0	0	29.77	1	1	1	1	1	35.1	18.24	0
22	7.92	3.01	0	0	30	1	1	1	1	1	15.7	15.91	0
23	30	3.08	0	0.01	30	1	1	1	1	1	-0.298	26.06	0
24	30	30	0	0	-13.54	1	1	1	1	1	1.831	17.39	0

Table IV Optimal output power and corresponding status of each DG and Utility

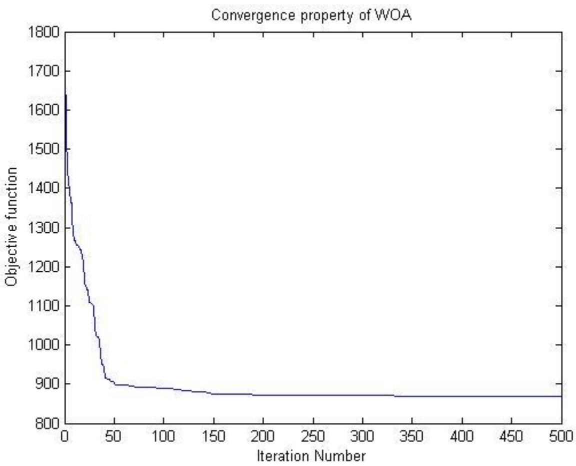


Fig. 5.2 Convergence property of whale algorithm – Grid Connected Mode

ISLAND MODE

Table 5.3 shows optimal schedule of PV, FC, MT and WT in microgrid for a day in island mode. The total cost of DGs in microgrid for the proposed method for a day is 1186.25457 $ as shown in table 5.4. Suppose if the total generated power from the FC and MT is not sufficient to meet the load demand, then the remaining required power is imported from the main grid to satisfy the total load demand. The convergence characteristic of firefly algorithm for island mode is shown FIg.5.4.From Fig. 5.4, it is clearly seen that the optimal result is achieved within 50th iterations, hence the proposed approach is much faster in obtaining the results

Time	**Demand, DG sources and outputs (kW)**					**Status**					**Cost ($)**		
(h)	**MT**	**FC**	**PV**	**WT**	**Grid**	**MT**	**FC**	**PV**	**WT**	**Grid**	**Grid**	**DG**	sc
1	6.23	3	1077	0	30	1	1		0	0	0	42.95	0
2	14.4	3.16	0	0	29.94	1	1	0	0	0	0	18.89	0
3	6.21	12.29	0	0	30	1	1	0	0	0	0	18.89	0
4	6021	12.29	0	0	30	1	1	0	0	0	0	17.85	0
5	29.92	29.92	0	0	-6.34	1	1	0	0	0	0	20.06	0
6	6	25.56	0	0	29.94	1	1	1	1	0	0	21.63	0
7	8.33	29.18	0	0	29.99	1	1	0	0	0	0	23.78	0
8	29.97	29.97	0	13.92	-1.37	1	1	0	1	0	0	36.93	0
9	13.51	29.99	0	0	29.99	1	1	0	0	0	0	26.39	0
10	29.03	18.67	0	0	29.79	1	1	0	0	0	0	30.08	0
11	29.98	29.98	0	0	15.04	1	1	0	0	0	0	28.23	0
12	29.99	12.51	0	0	29.99	1	1	0	0	0	0	28.78	0
13	29.91	10.18	0	0	29.91	1	1	0	0	0	0	28.03	0
14	10.18	29.91	0	0	29.91	1	1	0	0	0	0	24.81	0
15	13.53	29.99	0	0	29.99	1	1	0	0	0	0	26.39	0
17	30	30	24.89	1.77	-3.16	1	1	0	0	0	0	87.55	0
18	28.7	28.7	0	0	28.6	1	1	0	0	0	0	32.42	0
19	29.01	29.02	0	0	0	1	1	0	0	0	0	32.8	0
20	30	30	0	13.74	0	1	1	0	1	0	0	41.55	0
21	30	30	1.18	14.69	0.13	1	1	1	1	0	0	41.4	0
22	10.8	29.91	0	0	29.91	1	1	0	0	0	0	24.811	0
23	6	28.23	0	0	27.77	1	1	1	1	0	0	21.595	0
24	29.92	29.92	0	0	-6.34	1	1	0	0	0	0	20.061	0

Table V Optimal output power and corresponding status of each DG and Utility power grid – Island Mode

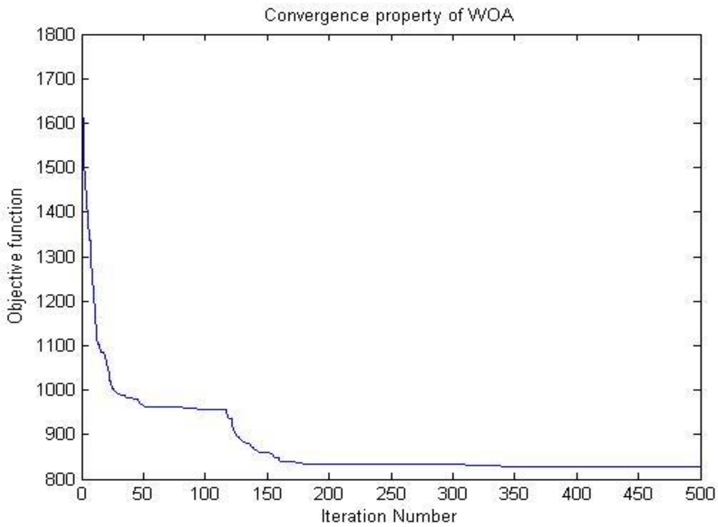


Fig5.3 Convergence property of whale algorithm – Island Mode

Algorithm	Worst solution($)/Day	Average($)/Day	Best solution($)/Day
WAO	1426.4098	956.5511	826.5323
PSO	1141.745	1071.8351	958.019
GA	1261.243	1096.3251	986.83
BA	1106.986	989.3718	923.814

5.3 Result Comparison

VI. CONCLUSION

In this project, a WOA algorithm is proposed and implemented to solve the multi-operation management problem in a typical MG with RESs. To evaluate the performance of the proposed algorithm several test cases are introduced and the simulation results are gathered subsequently. The numerical results indicate that the proposed method not only demonstrates superior performances but also shows dynamic stability and excellent convergence of the swarms. The proposed method also yields a true and well distributed set of optimal solutions giving the system operators various options to select an appropriate power dispatch plan according to economical considerations.

VII. ACKNOWLEDGMENT

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VIII. REFERENCES

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