Energy Management through Multi-Objective Optimization of Cost and Pollution in a Micro Grid

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Abstract: **Energy management and optimization have become an emerging necessity in microgrids, considering that in recent times, the integration of renewable energy resources has gained quite a lot of importance in reducing dependency on non-renewable resources. This paper focuses on optimizing the cost and level of pollution in the microgrid, which are two mostly contradictory elements, through an effective allocation of energy demands among DERs and the main grid. In this work, the Multi-objective Particle Swarm Optimization technique is employed to handle the financial implications and environmental impacts involved in microgrid operations. Indeed, it is expected that this work will provide ample information on how economic and ecological considerations can be traded off during energy management.**

Keywords: Microgrid, Renewable energy, Optimization, Energy management

I. INTRODUCTION

In today's world, as the distributed energy resources are growing significantly, the keen interest in optimizing the microgrid is putting on a spurt so that the clinging to non-renewable energy is turned down. Moreover, deep concern about global environmental pollution issues contradicts the accelerating power demands. Traditionally, irrespective of pollution, the cost of production is de-emphasized in the power generation industry. So, the rising energy demand, coupled with the finite nature of fossil fuel reserves and the pressing need to decrease pollution, necessitates creative ways to maximize energy utilization.

Optimization algorithms have emerged as important tools in this attempt, having the capacity to balance the complicated trade-offs between energy prices and environmental impact. Numerous optimization techniques, including simulated annealing, ant colony optimization, and genetic algorithms, have been used in energy management situations. When various factors and limitations are taken into account, these algorithms provide the capacity to locate optimal or nearly optimal solutions in complex energy consumption scenarios. However, these algorithms may suffer from slow convergence or high computational requirements. Nanda et al. [1] approached first for economic-emission load dispatch and multi-objective purpose through goal programming techniques. MOPSO (multi-objective particle swarm optimization) is used in various fields to optimize cost and pollution [2]. By the MINLP method, these objectives can be optimized [3]. But MINLP is not feasible for large-scale non-linear problems. A genetic algorithm optimization approach for smart energy management of microgrids can be used for such studies [4] [5]. Also, fuzzy logic is used for such energy allocation in microgrid [6].

In this study, we utilize key issues like cost and environmental impact through the application of the particle swarm optimization (PSO) technique. This paper focuses on optimizing energy consumption in microgrids by leveraging the capabilities of PSO to reduce costs and pollution levels.

The study provides a close look at how PSO has been used thus far to optimize energy usage and lays a foundation for more economically and ecologically suitable energy management systems.
The paper is well organized as follows: Section 2 outlines the methodology, based on modeling and implementing the PSO algorithm in order to optimize cost and pollution with the aim of eliciting energy management in a microgrid. Section 3 presents the formation of microgrid. Section 4 briefs the principles of particle swarm optimization. Section 5 elaborates the results of simulations with vital discussions. Section 6 concludes the paper.

II. SYSTEM MODELING

A. Objective Functions

Objective function for cost: The subsequent objective function is employed to minimize the expenses of microgrid operation [1].

$$min\, f_1(X) = \sum_{t=1}^{t=T}\Big[\sum_{i=1}^{i=N_G}\{P_{Gi}(t)B_{Gi}(t)\} - \sum_{j=1}^{j=N_S}\{P_{Sj}(t)B_{Sj}(t)\} - P_{Grid}(t)B_{Grid}(t)\Big] \quad (1)$$

Here, T represents the overall duration of the study, measured in hours. N_G and N_S denote the quantities of energy generation and storage units correspondingly. $P_{Gi}(t)$ and $P_{Sj}(t)$ stand for the power outputs of the i^{th} generation unit and j^{th} storage unit at specific time *t*. Similarly, $B_{Gi}(t)$ and $B_{Sj}(t)$ signify the energy prices presented for the i^{th} generation unit and j^{th} storage unit at time *t*. and $P_{Grid}(t)$ and $B_{Grid}(t)$ indicate the power quantities traded in the offered market at the given time *t.*

Objective function for pollution: The following objective function is employed to minimize the pollution content in microgrid [1].

$$\min f_2(X) = \sum_{t=1}^{t=T} Emission^t = \sum_{t=1}^{t=T}\Big[\sum_{i=1}^{i=N_G}\{P_{Gi}(t)E_{Gi}(t)\} + \sum_{j=1}^{j=N_S}\{P_{Sj}(t)E_{Sj}(t)\} + P_{Grid}(t)E_{Grid}(t)\Big] \quad (2)$$

In this context, $E_{Gi}(t)$, $E_{Sj}(t)$, and $E_{Grid}(t)$ stand for the quantities of pollution associated with the i^{th} generation unit, j^{th} storage unit, and the market at time *t*, measured in kilograms per megawatt-hour (kg/MWh) respectively.

B. Constraints and Limitations

Power balance: The power balance is maintained according to the following equation:

$$\sum_{k=1}^{N_k} P_{LK}(t) = \sum_{i=1}^{N_G} P_{Gi}(t) + \sum_{j=1}^{N_S} P_{Sj}(t) + P_{Grid}(t) \quad (3)$$

here, $P_{LK}(t)$ represents the quantity of K at the load level, and N_K stands for the overall count of load levels existing within the grid.

Power limit of units: The power handling capabilities of the generation units, storage units, and the market need to be constrained by certain limits. The limits are as follows:

$$P_{Gi(min)}(t) \leq P_{Gi}(t) \leq P_{Gi(max)}(t) \quad (4)$$

$$P_{Sj(min)}(t) \leq P_{Sj}(t) \leq P_{Sj(max)}(t) \quad (5)$$

$$P_{Grid(min)}(t) \leq P_{Grid}(t) \leq P_{Grid(max)}(t) \quad (6)$$

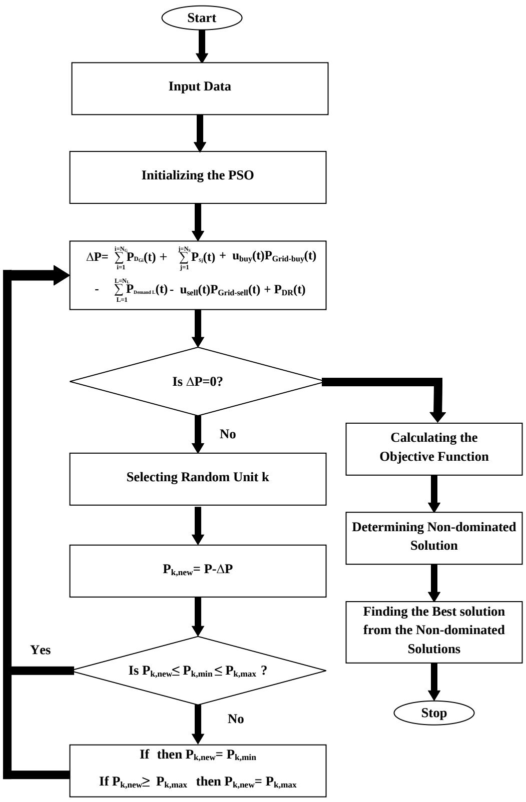

Fig. 1. Flowchart of the proposed methodology.

III. FORMATION OF MICRO-GRID

Micro grids are an integration of different types of distributed generators (DGs) such as micro turbines, wind turbines, solar cells, fuel cells, batteries and diesel generators. These units are able to connect and trade both power and energy with the main power grid. This configuration allows all the available resources to have the say and come up with plans with respect to how power is generated. These control measures are executed in the micro-grid system by both local and central controllers.

The system under this study is represented in Figure 1 and is said to be a systems approach. Different generation resources are combined in a micro grid configuration such as micro turbines, wind turbines, solar cells, fuel cells, and battery units. Also the micro grid has an interface to the main power grid exporting and importing energy.

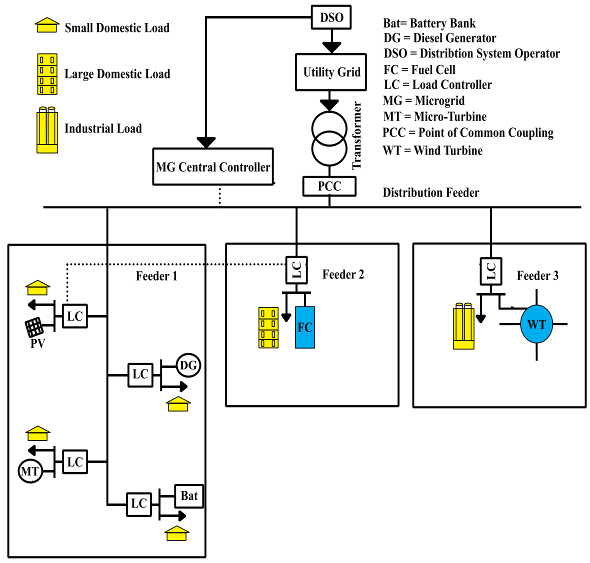

Fig. 2. Schematic diagram of the arrangement of the microgrid under study.

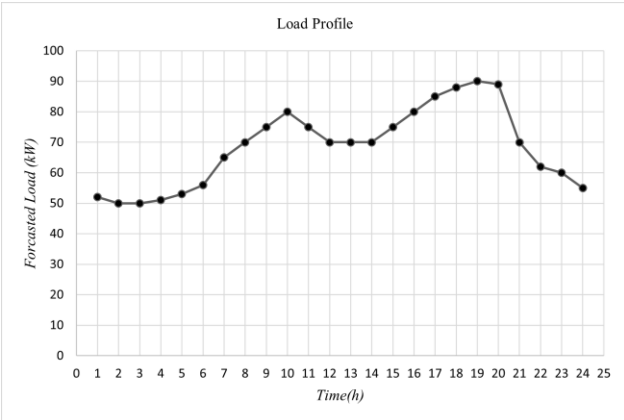

Fig. 3. Forcasted Daily Load Profile of the Microgrid

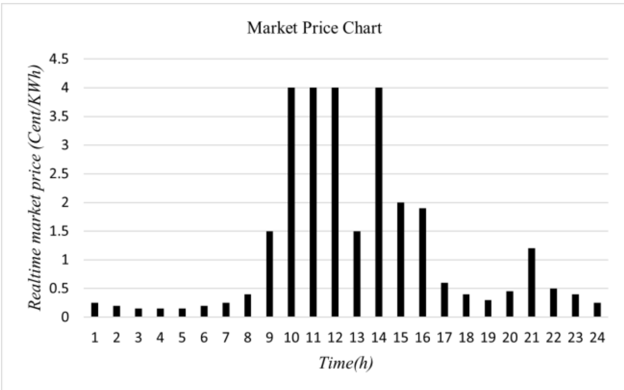

Fig.4. Real Time Hourly Price of the Microgrid

Unit	DERs	Bid (Cent/kWh)	P_{min}(kW)	P_{max}(kW)
1	MT	0.457	6	30
2	PAFC	0.294	3	30
3	Batt	0.38	-30	30
4	PV	2.584	0	0
5	WT	1.073	-30	30
6	Grid	_	-30	30

Table 1: Bids and Limitation for DERs

Unit	DERs	CO_2(kg/kWh)	SO_2(kg/kWh)	NO_x(kg/kWh)
1	MT	0.72	00000036	0.0001
2	PAFC	0.46	0.000003	0.0000075
3	Batt	0.01	0.0000002	0.000001
4	PV	0	0	0
5	WT	0	0	0
6	Grid	0.95	0.005	0.0021

Table 2: Emission Rate for DERs

IV. PRINCIPLES OF PSO ALGORITHM:

The Particle Swarm Optimization algorithm is a population-based optimization methods that have been derived from social behaviors of birds and fish schooling [7]. Its main aim is to accomplish an optimum solution within complicated search spaces through interactions of different individuals moving in a swarm of particles [8]. The PSO algorithm has proven effective in finding optimum solutions for most well-known benchmark functions. Each particle in this context represents every potential solution in the search space, where the position of every particle is mapped out to a candidate solution, and the velocity of the particle determines its flight through the search space

Initialization: Initialize a population of particles by randomly placing the particles in the search space. Each particle then represents a possible solution to the problem at hand. The positions are usually initialized randomly, whereas the velocities are often initialized to zero or to a small random value in order to give an initial movement to particles.

Particle Update Equations: The position and the velocity are updated on each iteration. The velocity update equation for particle I at iteration t+1 is given by:

$$V_i(t+1) = w * V_i(t) + c_1 * rand() * (Pbest_i(t) - X_i(t)) + c_2 * rand() * (Gbest_i(t) - X_i(t))$$

where, w is the inertia weight controlling the impact of previous velocities, c_1 and c_2 are acceleration constants, $rand()$ generates a random number between 0 and 1 to introduce stochasticity. $Pbest_i(t)$ is the personal best position it has achieved so far, $Gbest_i(t)$ is the global best position found among all particles up to iteration i, $X_i(t))$ is the current position of particle i at iteration t.

The new position of the particle is then updated by:

$$X_i(t+1) = X_i(t) + V_i(t+1)$$

Termination: The PSO algorithm continues to iterate until a termination condition is met, such as reaching a maximum number of iterations or achieving a desired level of convergence. The algorithm aims to converge to the optimal solution by updating the positions and velocities of the particles based on their own best-known positions and the best-known positions of the entire population.

In summary, the PSO algorithm is a population-based optimization algorithm that iteratively updates the positions and velocities of particles to search for optimal regions in complex search spaces. The algorithm is based on the social behavior of particles and has been shown to perform well in finding optima of various test functions. The update equations for the position and velocity of each particle in the PSO algorithm can be mathematically represented, and the algorithm continues to iterate until a termination condition is met.

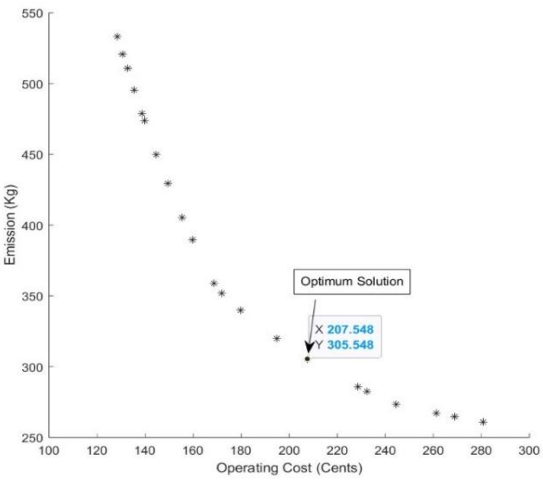

Fig.5. Pareto Front of Emission vs. Operating Cost for Limited Grid Exchange Operation

V. SIMULATION RESULTS

This section presents the results of simulation for two operation modes—namely, Normal Operation and Unlimited Grid Exchange Operation. Each mode has different advantages and trade-offs regarding cost optimization and emission reduction.

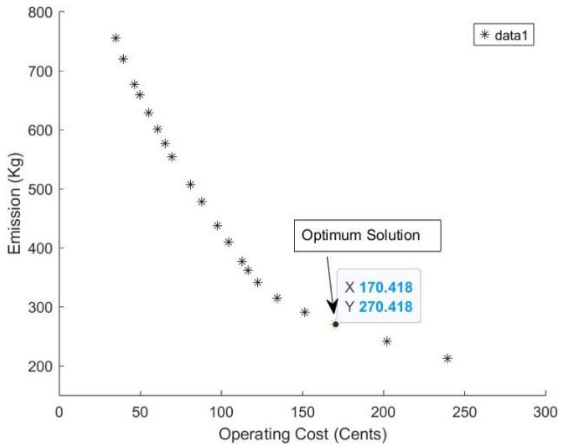

Fig.6. Pareto Front of Emission vs. Operating Cost for Unlimited Grid Exchange Operation

Limited Grid Exchange Operation:

Under Limited Grid Exchange Operation (Fig. 5), the main source within the microgrid is DERs and has limited interaction with the main grid. This approach focuses more on operating cost versus levels of pollution for sustainability using locally available renewable resources, such as solar and wind with energy storage. The system manages demand very well while reducing reliance on external grid resources. The best compromise solution obtained in this mode corresponds to an operating cost of 207.5 cents at an emission level of 305.5 kg (Table 3), proving efficient and eco-friendly energy management of the microgrid with minimum reliance on the grid.

Case	**Operation Cost (cents)**	**Emission (kg)**
Limited Grid Exchange	207.5	305.5
Unlimited Grid Exchange	170	270.4

Table 3: Comparison of Best Compromise Solution

Unlimited Grid Exchange Operation:

As it shows in Fig. 6, in this operation, the microgrid accesses unlimitedly to the main grid, then it can be more flexible to react on the real-time pricing. As the present mode makes use of low-cost energy periods to decrease the overall cost of operation, it is reflected by the lower operating cost of 170 cents (Table 3). However, this comes at the expense of higher emissions-increase to 270.4 kg-what constitutes higher utilization of grid energy which generally contains non-renewable sources. Although this operating mode has great savings in cost, it also displays a large compromise regarding environmental impact in view, whereby economic efficiency is favored at the expense of higher pollution levels.

Hour	**PV(KW)**	**MT(KW)**	**PAFC(KW)**	**WT(KW)**	**Batt(KW)**	**Grid(KW)**
1	0	20.215	30	1.785	30	-30
2	0	6	30	0.6696	30	-16.6696
3	0	6	30	0	30	-16
4	0	6	30	0	30	-15
5	0	6	30	0	30	-13
6	0	6	30	0.8906	30	-10.8906
7	0	30	30	1.785	30	-26.785
8	0	30	30	1.305	30	-21.785
9	0	30	30	1.785	30	-16.785
10	7.525	30	30	3.09	30	-20.615
11	6.225	30	30	8.775	30	-30
12	0	29.59	30	10.41	30	-30
13	0	30	30	3.915	30	-23.915
14	7.63	30	30	2.37	30	-30
15	7.875	30	30	1.785	30	-24.66
16	4.225	30	30	1.305	30	-15.53
17	0	30	30	1.785	30	-6.785
18	0	30	30	1.785	30	-3.785
19	0	30	30	1.302	30	-1.302
20	0	30	30	1.785	30	-11.785
21	0	30	30	1.3005	30	-21.3005
22	0	30	30	1.3005	30	-29.3005
23	0	29.085	30	0.915	30	-30
24	0	24.385	30	0.615	30	-30

Table 4: Allocation of Optimal Power considering Cost and Emission Objective for Limited Grid Exchange

Hour	PV(KW)	MT(KW)	PAFC(KW)	WT(KW)	Batt(KW)	Grid(KW)
1	0	30	30	1.785	30	-39.785
2	0	6	30	1.785	30	-17.785
3	0	6	30	0.6848	30	-16.6848
4	0	6	30	0.6881	30	-15.6881
5	0	6	30	0.6884	30	-13.6884
6	0	6	30	0.915	30	-10.915
7	0	30	30	1.785	30	-26.785
8	0	30	30	1.305	30	-21.785
9	0	30	30	1.785	30	-16.785
10	7.525	30	30	3.09	30	-20.615
11	10.45	30	30	8.775	30	-34.225
12	11.95	30	30	10.41	30	-42.36
13	0	30	30	3.915	30	-23.915
14	21.05	30	30	2.37	30	-43.42
15	7.875	30	30	1.785	30	-24.66
16	4.225	30	30	1.305	30	-15.53
17	0	30	30	1.785	30	-6.785
18	0	30	30	1.785	30	-3.785
19	0	30	30	1.302	30	-1.302
20	0	30	30	1.785	30	-11.785
21	0	30	30	1.3005	30	-21.3005
22	0	30	30	1.3005	30	-29.3005
23	0	30	30	0.915	30	-30
24	0	30	30	0.615	30	-30

Table 5: Allocation of Optimal Power considering Cost and Emission Objective for Unlimited Grid Exchange

VI. CONCLUSION

This study presents PSO for optimizing microgrid energy management in order to achieve cost reduction and emissions minimization. The obtained results, from simulations of mode Limited Grid Exchange and Unlimited Grid Exchange, prove that to maintain the minimal values of emissions, local DERs are prioritized by the Limited Exchange mode, but the Unlimited Exchange mode provides a minimum operating cost by taking advantage of flexible interactions with the grid but with a slight increase in emissions. This underlines the need to bring in a balance between the economic objective and the environmental objective when operating the microgrid. Other directions for future research concern the development of adaptive controls and real-time integration of data in order to achieve better optimization in dynamic environments.

References:

1. Nanda, J., Khotari, D. P. and Lingamurthy, K. S. 1988. Economic-emission load dispatch through goal programming techniques. IEEE Trans. Energy Conv., 3(1): 26–32.

2. M. A. Abido, Multi-objective particle swarm optimization for optimal power flow problem, Handbook of Swarm Intelligence, adaptation, learning and optimization, Springer, (2010) 241-268.

3. H. Akulker, E. Aydin, "Optimal design and operation of a multi-energy microgrid using mixed-integer nonlinear programming: Impact of carbon cap and trade system and taxing on equipment selections," *Applied Energy*, Volume 330, Part A, (2023) 120313.

3. Kamboj, A., & Chanana, S., "Optimization of cost and emission in a Renewable Energy micro-grid," 2016 IEEE 1st International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES), IEEE, (2016).

4. Mohsenian-Rad, A.-H., Wong, V. W., Jatskevich, J., Schober, R., & Leon-Garcia, A. (2010). Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid. IEEE Transactions on Smart Grid, 1(3), 320-33.

5. Guo, W., Li, G., Zhang, X., & Yang, Z. (2016). 46 multi-objective energy management of microgrid using improved NSGA-II algorithm. Applied Energy, 162, 944-955.

6. A. B. G. V. L. R. Kumar, S. K. M. Barik, "Optimization of energy management in a renewable energy-based microgrid using fuzzy logic," *Journal of Cleaner Production*, Volume 241, (2019) 118397.

7. H. Moazen, S. Molaei, L. Farzinvash, and M. Sabaei, PSO-ELPM: PSO with elite learning, enhanced parameter updating, and exponential mutation operator, Information Sciences, Elsevier, (2023) 70-91.

8. M. Clerc and J. Kennedy, The Particle Swarm: Explosion, Stability, and Convergence in a Multi-Dimensional Complex Space, IEEE Transactions on Evolutionary Computation, IEEE, (2002) 58-73.