Optimal Scheduling Scheme of an Autonomous Microgrid Considering the Operational and Maintenance Costs of the Micro-Sources

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ABSTRACT

The solution of the combined Economic-Emission Load Dispatch (EELD) problem of conventional or micro-grid (MG) system entails determination of the optimal power output of dispatchable generating units, to meet the system load, at the lowest possible cost and reduced greenhouse gases emission, subject to some constraints. In most studies, the installation, maintenance and operational costs of renewable energy sources are neglected while formulating the EELD of MG system. This significantly affect the accuracy of the scheme. Thus, this study developed the EELD of an MG system powered through conventional Diesel Engine Generators (DEG), photovoltaic (PV) and wind turbine (WT) systems dispatched for 24-hours. The EELD is formulated to minimize the fuel cost and emission of toxic gases taking into account the operational and maintenance costs of the RES. Meercat Optimization Algorithm (MOA) was employed for its robustness, rapid convergence, and global search capabilities. The performance of the MOA-based approach was evaluated by comparing fuel and emission costs of a 3-unit and 10-unit MG systems with those obtained using Salp Swarm Optimization (SSA) and African Vulture Optimization Algorithm (AVOA). The simulations results revealed that the MOA-based EELD achieves significant reductions in fuel costs of 13.08% compared to AVOA and 18.02% compared to SSA for the 3-DEG MG system, and 13.06% compared to AVOA and 17.98% compared to SSA for the 10-DEG MG system, while also lowering the emission costs. The MOA-based EELD method not only outperforms SSA and AVOA in terms of cost efficiency but also demonstrates superior convergence speed.

1. INTRODUCTION

The escalating and consistent surge in electrical energy consumption presents a pressing challenge, given the detrimental environmental impact and the finite nature of fossil fuel resources, which currently serve as the primary global energy source. Recognizing this imperative, Renewable Energy Sources (RES) have emerged as an enticing and widely embraced alternative. The compelling techno-economic and environmental advantages of RES have spurred its rapid integration to the grid (Alomoush, 2019; Cao, et al., 2019). This growing awareness of sustainability and the need for more resilient energy systems has spurred the adoption of grid-connected microgrid systems.

A microgrid (MG) is a localised power generation infrastructure designed to provide continuous and reliable power supply to a small and specific region. It consists of renewable and non-renewable distributed energy resources (DERs) known as micro-sources such as solar photovoltaic (PV), wind turbines (WT), and Diesel Engine Generator (DEG) and sometimes energy storage system (ESS). MGs can be operated independently of the traditional centralized grid (autonomous or islanded mode) or connect and interact with the larger grid as needed. In the former mode, the MG rely solely on their own micro-sources, while in the former, the MG draws power from or feed excess power into the main grid. Through this MG offers several benefits, including increased energy reliability and resilience, reduced energy costs, and the integration of RES and can provide backup power during grid outages (Wu, *et al*., 2014).

Recently, there has been remarkable increase in the integration of RES-based MGs into the existing grid (Basak, *et al*., 2023; Chen, *et al*., 2016). As such, their significance in shaping the economic dynamics of power generation cannot be overlooked. Despite their growing prominence, many research works tend to overlook the economic contributions of grid-tied MGs within the broader framework of Economic Dispatch (ED). This oversight undermines the potential benefits that grid-tied MGs could offer in optimizing the economic operation of the entire power system. Therefore, it is imperative to recognize the economic potential of grid-tied MGs and include them in ED studies to harness their capabilities fully (Güvenç, *et al*., 2012).

Economic dispatch (ED) is a crucial optimization process in power systems that determines the most cost-effective way to allocate generation resources to meet the load demand while satisfying operational constraints (Aluko, *et al.*, 2020). In the context of MG, ED aims to optimize the operation of the micro-sources to minimize operating costs of the non-RES while meeting demand.

As extension of ED, Economic Emission Load Dispatch (EELD) problem not only seeks to minimize costs but also aims to reduce emissions of toxic gases (CO_2 and NO_x) associated with power generation. This involves finding the optimal dispatch strategy for the available generation mix to achieve a balance between economic efficiency and environmental sustainability. By considering both cost and emissions objectives, the EELD problem reflects a bi-objective optimization problem (Aluko, *et al*., 2020; Kerdphol, *et al*., 2019).

In order to solve the ED or EELD as single or bi-objective optimization problems, conventional methods such as lagrange relaxation, dynamic programming, fast lambda iteration, quadratic programming, and the interior point technique have been applied extensively (Chen, *et al*., 2023). Even though these techniques are characterized by fixed structure but they suffer from high computational complexity and large running time which make them incompatible to handle large-scale optimization problems of power systems (Li, et al., 2022; Jiang, *et al.*, 2019). In addition, real dynamics of the system such as Valve Point Loading (VPL), Ramp Rate Limits (RRL), generation limits and transmission losses are difficult to be incorporated in the EELD using these conventional technique (Chen, *et al.*, 2016; Chhualsingh, *et al*., 2023). Thus, metaheuristic algorithms such as Genetic Algorithm (GA) (Nemati, *et al.*, 2018), African Vulture Optimization Algorithm (AVOA) (Mishra & Shaik, 2024), Harmony Search (HS) (Jordehi, 2021), Differential Evolution (DE) (Wang, *et al*., 2015), Harmony Search (Elattar, 2018), Teaching and Learning Based Optimization (TLBO), Grasshopper Optimization (GOA), Grey Wolf Optimizer (GWO) (Anil & Srikanth, 2018) and Ant Lion Optimizer (Alazemi & Hatata, 2019) have been applied for the EELD problem (Gad, 2022; Jiang, *et al*., 2019).

Although these algorithms proved to be effective for ED and EELD in conventional power system, however Meercat Optimization Algorithm (MOA) is found to be more suitable for EELD in MG system. Firstly, MOA's fast convergence is particularly beneficial for time-sensitive operations in MGs, ensuring quick adjustment of generation schedules to meet fluctuating demand or renewable energy availability. Additionally, MOA's memoryless nature simplifies real-time decision-making, crucial for dynamic MG environments where rapid adjustments are necessary due to changes in generation or load conditions (Khatsu, *et al*., 2020). Its robustness to noise makes MOA suitable for handling uncertainties inherent in MG operations, such as variations in renewable energy output. Finally, MOA's scalability enables it to effectively optimize the dispatch of distributed energy resources in large-scale MGs. Hence MOA is chosen for this study.

In summary, this study developed the EELD scheme for an MG system powered through non-RES; DEG and RES; PV and WT systems dispatched for 24-hour. The EELD is formulated to minimize the fuel and emission costs taking into account the operational and maintenance costs of the RES (as functions of their power generation). The power generations from the non-RES conventional DEG is considered as the main decision variables, while the considering some set of equality and non-equality constraints (Khatsu, *et al*., 2020).

2. FORMULATION OF ELD IN MG

Optimal Economic Load Dispatch (ELD) refers to the process of determining the most cost-effective way to allocate the output of available generating units in MG or conventional system, to meet electricity demand while satisfying operational constraints. Micro-sources are not always operated at their full rated capacity due to economic, reliability and safety considerations (Cui, *et al.*, 2023). When considering the economic aspect, factors such as the operational costs of generators, greenhouse gas emissions, and the proximity of generation stations to load centres are pivotal considerations (Ghasemi, *et al*., 2016; Damisa, *et al*., 2019).

As an optimization problem, EELD is formulated to minimize the fuel and emission costs of the thermal generators. In some instances, the generators are sited close to the load centres and load density is very high, the transmission losses can be neglected (Zhang, *et al*., 2021), otherwise the losses are considered. The formulation involves the modelling of the objective function and the constraints.

2.1 Objective Function

Since the EELD is formulated to minimize both the fuel and emission costs of the non-RES micro-sources, thus, the EELD is formulated as bi-objective optimization problem, as

$$\min_{P_i^{DEG};\, i=1,2\ldots,n_{DEG}} C_{TOTAL}\left(C_{fuel}, C_{emission}, C_{WT}^{total}, C_{PV}^{total}\right)$$

$$C_{TOTAL} = wC_{fuel} + (1-w)C_{emission} + C_{WT}^{total} + C_{PV}^{total} \quad (1)$$

Where w is a predefined weighing factor ranging from 0 to 1. It is shows the priority of the fuel and emission costs in the objective function. $C_{emission}$ and C_{fuel} as functions of the DEG powers P_i^{DEG}, are the daily emission and fuel costs which expressed in (3.2) and (3.3), respectively.

$$C_{emission} = \sum_{t=1}^{24}\sum_{i=1}^{n}\left(\alpha_i + \beta_i P_{G_i} + \gamma_i P_{G_i}^2\right) + \tau_i e^{\xi_i P_{G_i}} \quad (2)$$

$$C_{fuel} = \sum_{t=1}^{24}\sum_{i=1}^{n}\left(a_i + b_i P_i^{DEG} + c_i {P_i^{DEG}}^2\right) \quad (3)$$

Where α_i, β_i, γ_i, $\xi_i$and τ_i are the emission coefficients and *a, b,* and *c* are the cost coefficients of the ith DEG unit. In some studies, valve point loading (VPL) effect considered which transforms the convex cost function (4) to non-convex, as shown in (5);

$$C_{fuel}(P_i^{DEG}) = \sum_{t=1}^{24}\sum_{i=1}^{n}\left(a_i + b_i P_i^{DEG} + c_i {P_i^{DEG}}^2\right) + \left|e_i.\sin\left(f_i\left(P_{min,i}^{DEG} - P_i^{DEG}\right)\right)\right|) \quad (5)$$

Where e_i and f_i represent cost coefficients that reflect the valve-point loading effects, and P_i^{DEG} is the minimum generation limit of ith DEG unit (Priya & Fuller, 2017).

Whereas C_{WT}^{total} and C_{PV}^{total} are the total costs of investment, maintenance and operation for the WT and PV. Due to the large integration of these sources to grid, the installation, maintenance and operational costs, C_{WT}^{total} are significant and therefore need to be considered while formulating EELD of MG. Equation (6) shows the C_{WT}^{total} as a function of the maintenance and operational cost, C_{WT}^{mo} expressed in $/kWh and the investment cost per unit kW generation of electricity, C_{WT}^{in} expressed in $/kW.

$$C_{WT}^{total} = P_{WT}\left(\mu C_{WT}^{in} + C_{WT}^{mo}\right) \quad (6)$$

Where P_{WT} represents the WT output power generation, while μ is the annualization coefficient of the MG system.

Similarly, (7) shows the C_{PV}^{total} as a function of the maintenance and operational cost, C_{PV}^{mo} expressed in $/kWh and the investment cost per unit kW generation of electricity, C_{PV}^{in} expressed in $/kW.

$$C_{PV}^{total} = P_{PV}\left(\mu C_{PV}^{in} + C_{PV}^{mo}\right) \qquad (7)$$

Where μ is the annualization coefficient of the MG system. The annualization coefficient μ expressed in (8) is a financial metric used to convert costs occurring over multiple years into an equivalent annual value. It is commonly used in cost-benefit analysis and economic evaluation of projects (such as MG installation) to compare the financial impacts of different investment options over their expected lifetimes.

$$\mu = \frac{r}{1 + (1 + r)^{-yrs}} \qquad (8)$$

Where *r* is the interest rate of the MG investment and *yrs* is its investment duration in years.

2.2 Constraints in EELD of MG

In the EELD of MG, there are several constraints that need to be considered to ensure optimal operation while adhering to technical, environmental regulations and economic objectives. Constraints are put in place to avoid violating these objectives. These constraints considered are:–

2.2.1 Active generation-demand balance:

To maintain the stability of the MG, the total demand, P_D and the transmission losses, P_{loss} in the MG must be equal to the total generation from all the micro-sources, P_G^{total} while accounting for the variability RES. In the case of grid-tied, the power supply from the main grid, P_{grid} is also considered from the generation side, as defined in (9),

$$P_D + P_{loss} = \sum P_G^{total} + P_{grid} \qquad (9)$$

Unlike ED in conventional system with wide geographical area making the transmission losses significant, in this study, the MG system are assumed to be clustered in a small area and close to the load centres, hence the transmission losses are relatively insignificant, hence neglected.

2.2.2 Generation limits of the micro-sources

In the context of MGs, the generation limits of micro-sources refer to the maximum and minimum generation capacities of individual distributed sources within the MG. These limits are determined by various factors such as the size and capability of the micro-source. To avoid damaging the component parts of the micro-sources, the output power of each of the sources are constrained within certain minimum and maximum limits as expressed in (10):

$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max} \qquad \forall\, i = 1, 2, .., n \quad (10)$$

Where P_G^{min} and P_G^{max} are the lower and upper generation limits of the ith micro-sources. Tables 3.4 and 3.5 show the DEGs generation limits considered in this study for the two test systems.

2.3 Implementation of Meercat Optimization Algorithm for the Developed ED

EELD are highly complex, constrained and combinatorial multi-objective optimization problems (Abdelaziz, *et al.,* 2016). As such, it requires robust optimization for its solution. In this study, Meercat Optimization Algorithm (MOA) is used.

Meerkat Optimization Algorithm (MOA) is a metaheuristic optimization technique inspired by simulating the behavior pattern of meerkats in nature. MOA is mainly inspired by the survival strategies of meerkat populations, whose sentinel mechanism controls meerkats to switch between different behavior patterns.

The initial population of the Meerkat, X as formulated in the MOA is expressed in (10), generated as a normal distribution between the upper boundary u_b and the lower boundary l_b, simulating the distribution of meerkats in the search space.

$$X = [X_1 \quad X_2 \quad \cdots \quad X_i \quad \cdots \quad X_N] \qquad (10)$$

$$= \begin{Bmatrix} x_1^1 & x_2^1 & \cdots & x_j^1 & \cdots & x_D^1 \\ x_2^1 & x_2^2 & \cdots & x_j^2 & \cdots & x_D^2 \\ \vdots & \vdots & \cdots & \vdots & \ddots & \vdots \\ x_1^N & x_2^N & \cdots & x_j^N & \cdots & x_D^N \end{Bmatrix} \qquad (11)$$

Where X_i represents a current candidate solution, N represents the total number of individuals, and D is the problem's dimension size.

Meerkat individuals hunt or search for food with the same probability and conduct the global search in the following.

$$X_i^{t+1} = X_i^t + h_i X_i^{t-1} \qquad (12)$$

The parameter h_i is the step size decreasing with the increase of the number of iterations, which plays a vital role in global search and later convergence.

3. TEST SYSTEMS DESCRIPTION

The developed EELD is implemented on a two test systems consisting of 3-unit and 10-unit MG systems.

3.1 Three-DEG MG

The first system considered in this study is a DEG-PV-WT autonomous MG. The DEG units are primary energy sources since they are not effected by whether and easily dispatchable. In addition, the DEG have relatively low ramp limits, as such they can withstand the changing hourly loads. Table 1 shows fuel and emission cost coefficients of the DEG units, as well as their generation limits.

Table 1: 3-unit system cost coefficients and generation limits (Mishra & Shaik, 2024)

DEG Unit	Fuel coefficients			Emission coefficients		
	a_i (\$/hr)	b_i (\$/MWhr)	c_i (\$/MW^{2}hr)	α_i (\$/hr)	β_i (rad/MW)	γ_i (rad/MW)
DEG$_1$	1530	21	0.0024	60	-1.355	0.0105
DEG$_2$	992	20.16	0.0029	45	-0.6	0.008
DEG$_3$	600	20.4	0.021	90	-0.555	0.012

Table 2: 10-unit system cost coefficients (Basu, 2011).

DEG Unit	Fuel coefficients			Emission coefficients			Generation limits	
	a_i (\$/hr)	b_i (\$/MWhr)	c_i (\$/MW^{2}hr)	α_i (\$/hr)	β_i (rad/MW)	γ_i (rad/MW)	$P_{min,i}^G$ (MW)	$P_{max,i}^G$ (MW)
DEG$_1$	1000.403	40.5407	0.12951	360.0012	-3.9864	0.04702	10	55
DEG$_2$	950.606	39.5804	0.10908	350.0056	-0.9524	0.04652	20	80
DEG$_3$	900.705	36.5104	0.12511	330.0056	-3.9023	0.04652	47	120
DEG$_4$	800.705	39.5104	0.12111	330.0056	-3.9023	0.04652	20	130
DEG$_5$	756.799	38.539	0.15247	13.8593	0.3277	0.0042	50	160
DEG$_6$	451.325	46.1592	0.10587	13.8593	0.3277	0.0042	70	240
DEG$_7$	1243.531	38.3055	0.03546	40.2669	-0.5455	0.0068	60	300
DEG$_8$	1049.998	40.3965	0.02803	40.2669	-0.5455	0.0068	70	340
DEG$_9$	1658.569	36.3278	0.02111	42.8955	-0.5112	0.0046	135	470
DEG$_{10}$	1356.659	38.2704	0.01799	42.8955	-0.5112	0.0046	150	470

3.2 10-DEG MG

The second system considered in this study is a relatively larger with 12 micro sources comprising of 10 DEG units, a PV and a WT systems. The system operated with all the sources online. The DEG units are primary energy sources and are complimented with energy generated from the PV and the WT systems. Table 2 shows fuel and emission cost coefficients of the DEG units, as well as their generation limits

In this study, the RES are powers modelled with the assumptions that

i. All the output powers of the RESs are fully dispatched and are therefore not part of the sources optimized. Only the DEGs power (non-renewable energy) are considered as the optimization variables,

ii. The uncertainties associated with the RESs and demand are not considered,

The output power of the WT depends on the cut-in speed, V_{in}, as expressed in (13).

$$P_{WT} = \begin{cases} 0, & 0 \le V_{in} \le V_{in} \\ P_{WT}\left(\frac{V^3 - V_{in}^3}{V_{rated}^3 - V_{in}^3}\right), & V_{in} \le V \le V_{rated} \\ P_{WT}, & V_{in} \le V \le V_{out} \end{cases} \quad (13)$$

Where V_{rated}, V_{in} and V_{out} are the rated, cut-in, and cut-out wind velocities respectively.

Once the wind speed exceeds the cut-in speed, the turbine's blades begin to turn, and electricity generation gradually increases as the wind speed increases further.

Moreover, the output power generation of PV system, P_{PV} is modelled as a function of the sun irradiances, solar cell temperature, and PV array zone, as shown in (14)

$$P_{PV} = P_{PV}^{rated}\frac{G}{G_{STC}}\{1 - k(T_c - T_t)\} \quad (14)$$

Where P_{PV}^{rated} is the rated PV power under normal test conditions (G_{STC} = 1000W/m^2, T_r = 25^{0}C), and G, k and T_c are the light radiation intensity, power temperature coefficient, and atmospheric temperature, respectively.

Table 3 shows the average daily wind speed and solar irradiance data used in this study.

Table 3: daily wind speed and solar irradiance (Mishra & Shaik, 2024)

Time (Hour)	**Wind speed (m/s)**	**Solar Irradiance (w/m^2)**
1	9.3	0
2	9.4	0
3	7.7	0
4	8.2	99
5	8.2	295
6	8.1	498
7	7.8	592
8	7.6	733
9	7.3	905
10	7.2	924
11	7	880
12	6.8	782
13	6.5	625
14	6.3	433
15	5.8	227
16	5.4	42
17	6	0
18	7	0
19	7.9	0
20	8.9	0
21	9.8	0
22	10.3	0
23	10.2	0
24	9.8	0

4. RESULTS AND DISCUSSION

The two systems described in the previous sections are simulated with a daily load, WT and PV generations profiles in MATLAB. The EELD is applied to the fuel and emission costs as formulated in (1) – (3). In either scenario, the performance of the MOA is compared with that of SSA and AVOA.

4.1 3-DEG MG

The first system with 3 DEG units, PV and WT systems is studied with the daily load demand, and generation profiles as shown in Figure 1 and 2 respectively.

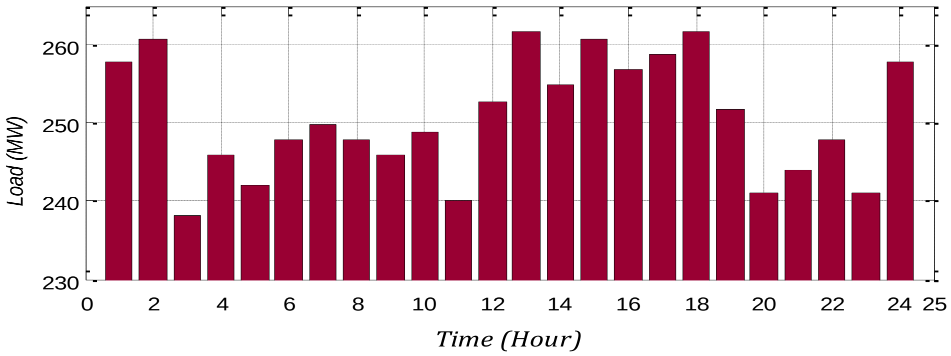

Figure 1: Daily load profile for 3-DEG system

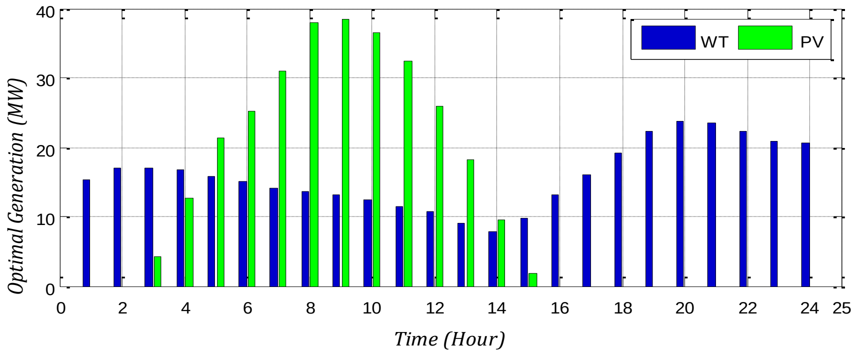

Figure 2: WT and PV profiles for 3-DEG system

The developed EELD algorithm is applied to optimize the generation from the DEGs in order to minimize the fuel and emission costs. The DEGs are used in an optimal manner to complement the generation from the two RESs in order to meet the hourly demand. By carefully balancing the power output from each DEG, the EELD algorithm reduces operational costs and environmental impact.

Figure 3 illustrates the optimal hourly generation from the DEGs, showing that at each hour, the load demand is precisely met by the combined generation from the PV, WT, and the optimized DEG outputs. This alignment is achieved because transmission losses are considered negligible in this study, and the hard constraints on the generation limits of the DEGs were not violated.

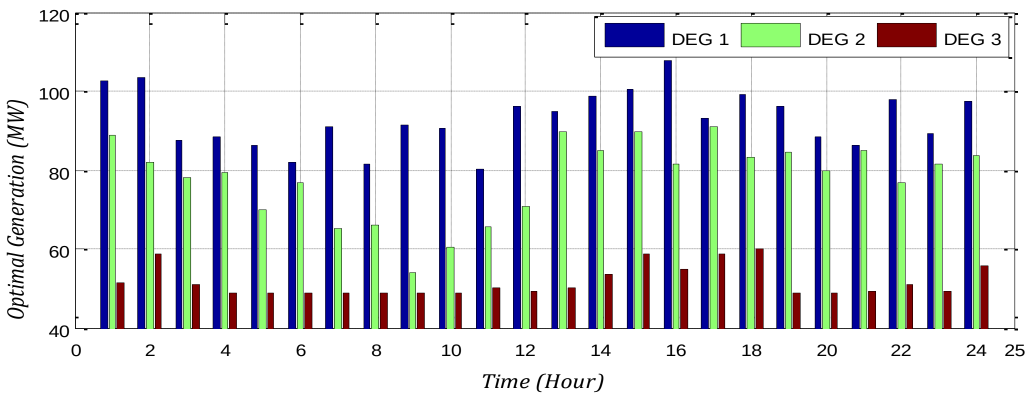

Figure 3: Optimal Generation for 3-DEG system

From the optimal generation summarized in Table 4, it is observed that DEG_1 produces the most power, while DEG_2 generates less, and DEG_3 contributes the least.

This generation dispatch shown in Figure 4, indicates that DEG_3 has the lowest fuel cost, making it the most economical to operate, followed by DEG_2, with DEG_1 having the highest fuel cost. The generation outputs are aligned with the cost coefficients of the DEGs, confirming that the optimization process correctly prioritized the use of the less expensive units, thereby minimizing overall fuel costs.

Table 4.1: Optimal EELD for 3-DEG System

Hour	Load (MW)	Optimal generation (MW)			RES generation (MW)	
		P_{DEG1}	P_{DEG2}	P_{DEG3}	WT	PV
1	257.74	102.52	88.65	51.22	15.356	0
2	260.68	103.23	81.81	58.65	16.983	0
3	238.14	87.74	77.95	51.14	16.983	4.3218
4	245.98	88.18	79.36	49.02	16.66	12.769
5	242.06	86.31	69.72	49	15.68	21.344
6	247.94	81.82	76.96	49	15.023	25.137
7	249.9	90.87	65.12	49	14.043	30.860
8	247.94	81.39	65.98	49.01	13.72	37.837
9	245.98	91.46	54.02	49	13.063	38.435
10	248.92	90.53	60.45	49.03	12.416	36.505
11	240.1	80.18	65.74	50.31	11.436	32.438
12	252.84	96.13	70.82	49.12	10.78	25.989
13	261.66	95.01	89.5	49.9	9.143	18.100
14	254.8	98.7	84.95	53.75	7.84	9.5648
15	260.68	100.55	89.75	58.79	9.8	1.7836
16	256.76	107.7	81.32	54.68	13.063	0
17	258.72	93.31	90.79	58.61	16.003	0
18	261.66	99.01	83.21	60.17	19.276	0
19	251.86	95.97	84.68	49	22.216	0
20	241.08	88.39	79.84	49	23.843	0
21	244.02	86.24	85.15	49.1	23.52	0
22	247.94	97.97	76.97	50.79	22.216	0
23	241.08	89.45	81.65	49.07	20.903	0
24	257.74	97.61	83.85	55.7	20.58	0

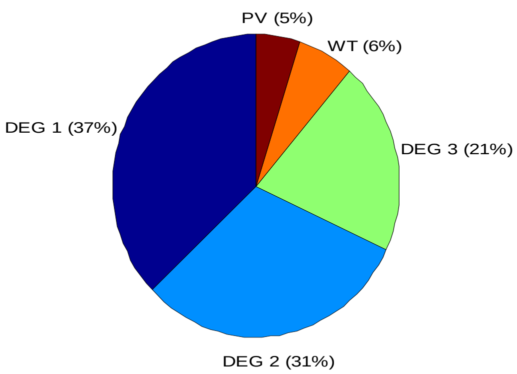

Figure 4: Overall generation dispatch for 3-DEG system

Figure 4.5 and 4.6 show the fuel and emission costs obtained with these optimized generation.

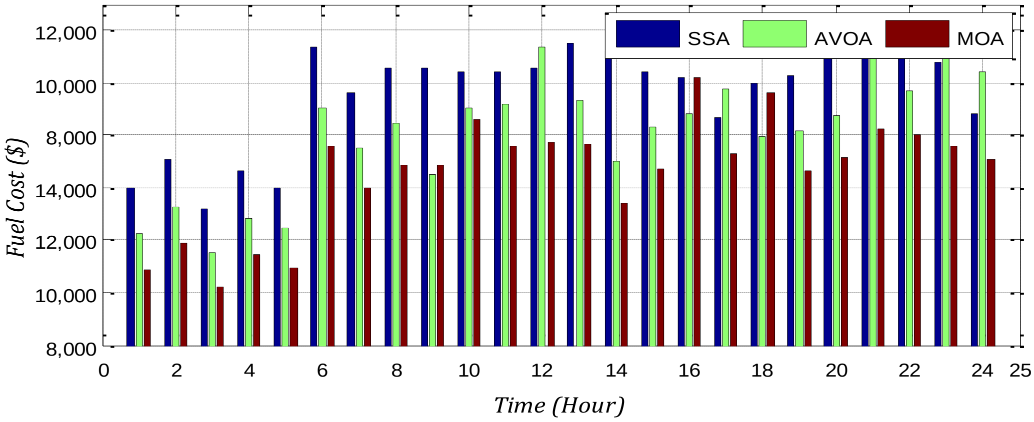

Figure 5: Fuel Cost in 3-DEG system

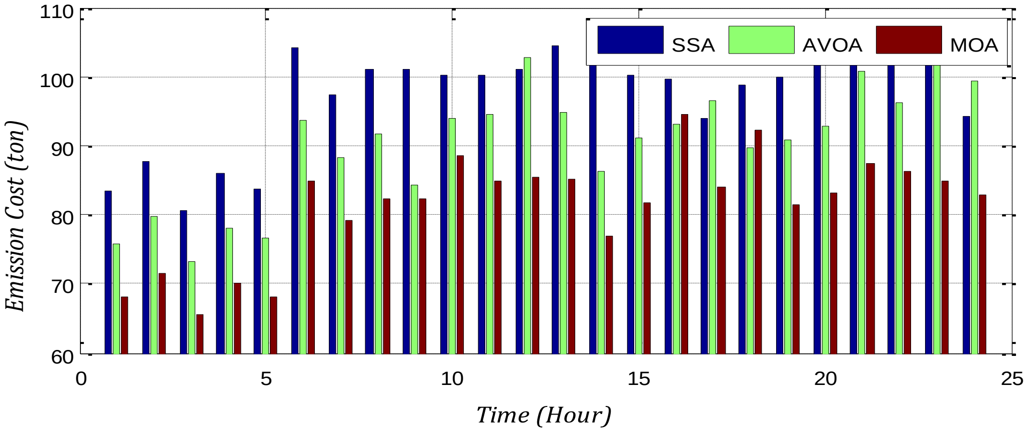

Figure 6: Emission Cost in 3-DEG system

When comparing the performance of the developed MOA-based EELD with other optimization methods; SSA and AVOA, it is clear that the MOA-based achieves superior results in terms of both fuel and emission costs. Table 4.2 highlights these differences, showing that while AVOA performs better than SSA, the MOA-based EELD surpasses both.

Table 4: Performance Evaluation of MOA-based EELD on 3-DEG System

Costs	SSA	AVOA	MOA
Fuel cost ($/day)	306860	288827	251047
Emission cost (*ton*/day)	2332.1	2166.2	1951.5
Total costs ($/day)	309192.1	290993.2	252999

Specifically, the fuel costs obtained by the SSA, AVOA, and MOA-EELD are $306,860/day, $288,827/day, and $251,047/day, respectively. This demonstrates the MOA's exceptional capability in minimizing operational expenses. Moreover, the MOA-EELD not only reduces fuel costs significantly but also achieves notable improvements over the other algorithms. The MOA outperforms the AVOA with a 13.08% reduction in fuel costs and exceeds the SSA with an 18.2% reduction. In addition to these cost savings, the MOA-based EELD also achieves lower emission costs, making it the most efficient and environmentally friendly option among the three approaches. This performance underscores the effectiveness of the MOA in optimizing power generation systems by balancing cost and environmental considerations.

Furthermore, the MOA not only delivers superior cost savings and emission reductions but also demonstrates faster convergence compared to the other algorithms.

4.2 10-DEG MG

The second system considered in this study is a relatively larger with 12 micro sources comprising of 10 DEG units, a PV and a WT systems. The system operated with all the sources online. Figure 8 and 9 shows the daily load demand, and generation profiles used in the study.

For the 10 DEG units, the developed EELD algorithm is utilized to optimize their generation, aiming to minimize both fuel consumption and emissions. The DEGs are strategically operated to complement the generation from the two RESs, ensuring that the hourly demand is consistently met. By precisely balancing the power output of each DEG, the EELD algorithm effectively reduces both operational costs and environmental impact.

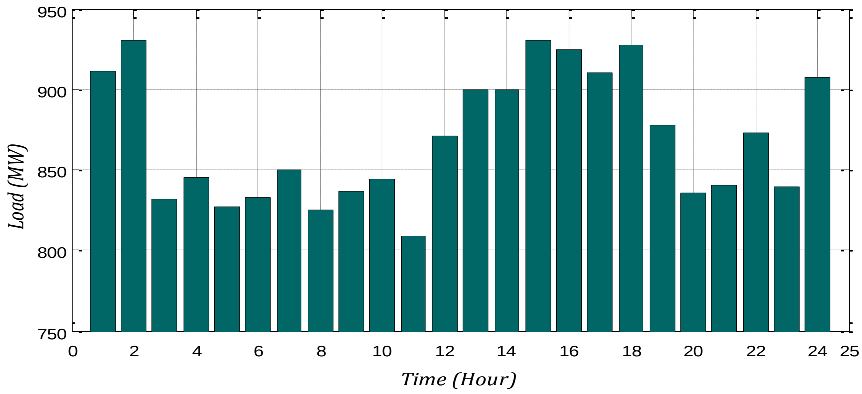

Figure 7: Daily load profile for 10-DEG system

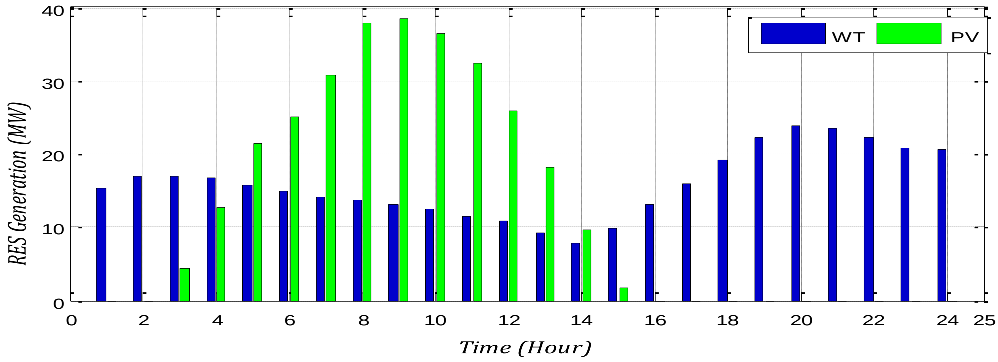

Figure 8: WT and PV profiles for 10-DEG system

Figure 10 illustrates the optimized hourly generation from the DEGs, highlighting how the combined output from the PV, WT, and optimized DEGs consistently meets the load demand.

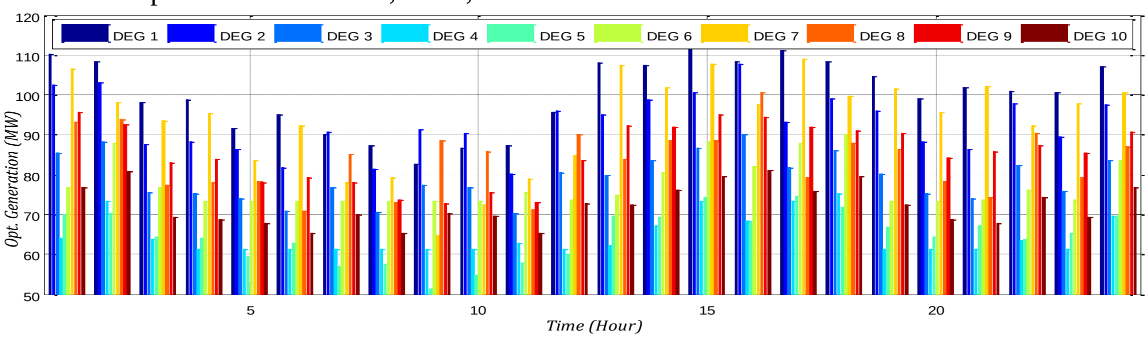

Figure 9: Optimal Generation for 10-DEG system

Table 2: Optimal EELD for 10-DEG System

Hour	Optimal DEG generation (MW)									
	P_{DEG1}	P_{DEG2}	P_{DEG3}	P_{DEG4}	P_{DEG5}	P_{DEG6}	P_{DEG7}	P_{DEG8}	P_{DEG9}	P_{DEG10}
1	110.35	102.52	85.42	64.03	69.93	76.83	106.38	93.18	95.58	76.87
2	108.5	103.23	88.37	73.31	70.23	87.98	98.18	93.92	92.52	80.94
3	98.26	87.74	75.54	63.93	64.55	76.71	93.54	77.4	82.85	69.44
4	98.64	88.18	75.13	61.27	64.19	73.53	95.23	78.13	83.77	68.6
5	91.59	86.31	73.88	61.25	59.36	73.5	83.67	78.21	78.02	67.66
6	94.91	81.82	70.88	61.25	62.98	73.5	92.35	70.79	79.39	65.41
7	90.04	90.87	76.91	61.25	57.06	73.5	78.14	85.06	78	69.94
8	87.45	81.39	70.6	61.26	57.49	73.51	79.18	72.99	73.69	65.2
9	82.83	91.46	77.31	61.25	51.51	73.5	64.82	88.57	72.74	70.23
10	86.82	90.53	76.69	61.28	54.74	73.54	72.54	85.79	75.49	69.78
11	87.32	80.18	70.22	62.89	58.02	75.46	78.89	71.21	72.96	65.25
12	95.63	96.13	80.46	61.4	59.97	73.68	84.99	90.18	83.48	72.63
13	107.97	95.01	79.97	62.37	69.7	74.85	107.4	83.91	92.26	72.45
14	107.45	98.7	83.71	67.19	69.35	80.62	101.94	88.69	91.82	76.22
15	112.95	100.55	86.63	73.49	74.27	88.19	107.7	88.56	95.15	79.67
16	108.34	107.7	90.02	68.35	68	82.02	97.58	100.62	94.51	81.19
17	111.17	93.31	81.75	73.26	74.7	87.91	108.95	79.29	92.05	75.96
18	108.53	99.01	86.06	75.21	71.69	90.25	99.85	87.92	91.11	79.59
19	104.77	95.97	80.31	61.25	66.84	73.5	101.61	86.54	90.32	72.48
20	99.02	88.39	75.26	61.25	64.42	73.5	95.81	78.28	84.12	68.7
21	101.88	86.24	73.86	61.38	67.13	73.65	102.19	74.24	85.7	67.67
22	100.9	97.97	82.24	63.48	63.88	76.18	92.36	90.52	87.47	74.38
23	100.61	89.45	75.99	61.33	65.36	73.6	97.99	79.13	85.55	69.26
24	107	97.61	83.64	69.62	69.78	83.55	100.62	87.12	90.73	76.65

The optimal generation data summarized in Table 4.2 reveals that DEG1, DEG2, and DEG7 generate the most power, while DEG4 and DEG5 contribute the least. The generation dispatch illustrated in Figure 4.11 shows that DEG_1, DEG_2, and DEG_7 have the lowest fuel costs, making them the most economical to operate. This dispatch pattern aligns with the DEGs' cost coefficients, confirming that the optimization process effectively prioritized the use of the less expensive units, thereby minimizing overall fuel costs.

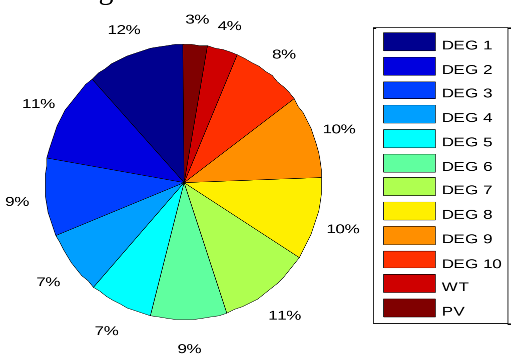

Figure 10: Overall generation dispatch for 10-DEG system

When evaluating the performance of the developed MOA-based EELD against other optimization methods such as SSA and AVOA, it is evident that the MOA-based approach outperforms both in terms of fuel and emission costs. Table 4 summarizes these performance improvements.

Table 3: Performance Evaluation on 10-DEG System

Costs	SSA	AVOA	MOA
Fuel cost	1064935.79	1002355.06	871238.43
Emission cost	8155.37	7574.46	6825.58
Total fuel cost	1073091.16	1009929.53	878064.02

The fuel costs obtained using SSA, AVOA, and MOA-EELD are $1,064,935.79/day, $1,002,355.06/day, and $871,238.43/day, respectively, underscoring the MOA's exceptional ability to minimize operational costs. The MOA-EELD significantly lowers fuel expenses, with a 13.06% reduction compared to

AVOA and a 17.98% reduction compared to SSA. In addition to these cost savings, the MOA-based EELD also achieves lower emission costs, making it the most efficient and environmentally sustainable option among the three approaches. This performance highlights the MOA's effectiveness in optimizing power generation systems by balancing cost efficiency with environmental considerations.

Moreover, the MOA not only provides superior cost and emission reductions but also demonstrates faster convergence than the other algorithms.

5.0 CONCLUSION

In conclusion, this study successfully developed the EELD scheme to determine the optimal power output from dispatchable DEG units, aiming to meet the system's load at the lowest possible cost while minimizing emissions, all within the constraints of the system's operation. The study uniquely integrates the costs associated with the installation, maintenance, and operation of Renewable Energy Sources (RES), which is a significant contribution to the field.

The MOA, known for its robustness, rapid convergence, and global search capabilities, was employed to solve the EELD problem. The performance of the MOA-based approach was rigorously evaluated by comparing its results to those obtained from the SSA and AVOA. The study, conducted in MATLAB 2022(b), tested the developed EELD on two systems: a 3-unit DEG-PV-WT autonomous MG and a larger 12-source MG comprising 10 DEG units, a PV system, and a WT system. The results demonstrate that the MOA-based EELD approach not only significantly reduces fuel costs achieving a 13.06% reduction compared to AVOA and a 17.98% reduction compared to SSA, but also lowers emission costs, making it the most efficient and environmentally sustainable option among the methods tested. Moreover, the MOA-based EELD method outperforms both SSA and AVOA in terms of convergence speed, as evidenced by the convergence curves over 100 iterations.

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