



Optimizing Economic Dispatch and Energy Management in Micro Grids with Electric Transport Integration

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Abstract:- The surge in electricity demand has necessitated exploring alternative power generation sources, moving beyond the traditional reliance on fossil fuels. This transition is driven by dwindling fossil fuel reserves, energy shortages, and environmental issues, emphasizing the importance of electric transport as the future of transportation. Electric transport serves as distributed storage units and loads when connected to the grid, but their increasing use introduces new challenges for power quality and grid constancy. The fluctuating behavior of renewable energy and volatile load demands require effective energy storage solutions within the smart grid. Grid able vehicles offer a viable option as storage devices. The proposed model, tested using the Mother Optimization Algorithm (MOA), demonstrates substantial reductions in fuel costs, achieving a significant cost reduction of 19%.

Keywords: Electric Transport, Economic dispatch, Micro grids, Green sources, Energy management.

1. Introduction

The electrical power industry has experienced various financial challenges, leading governments to promote the utilization of alternative energy sources. This shift is driven by the increasing cost for fossil fuels, their declining reserves, and the rising emissions of greenhouse gases. Researchers are exploring diverse green sources of energy and effective measures to substitute the increasingly diminishing non-renewable sources. Plugged-in electric transport, which combines features of plugged-in hybrid electric transport and electric transport with vehicle to grid (V2G) capabilities, appears as a promising resolution to the issue of emissions. The integration of electric vehicles can substantially lower carbon emissions and mitigate reliance on conventional fuels [1]. The influence of plug-in electric vehicles on the overall economics and emissions of the electrical system is comprehensively analyzed in [2].

The author has detailed the impact of incorporating plugged-in electric transport to the grid for both auxiliary backup and charging functions [3]. The IEEE standards [4] provide an in-depth discussion on renewable sources and plugged-in hybrid electric automobile. The [5] examines the effects of plug-in electric vehicles and plug-in hybrid electric vehicles on electricity systems, and the insertion of renewable sources into these structures. Studies show a great deal of interest in and attention to the possible services that electric vehicles may provide to the present power system [6-7]. Although electrically powered automobiles might



offer several advantages, they can also add to the system's burden and put further stress on the grid.

The extensive uptake of electric vehicles has introduced various additional challenges with issues for the electrical grid, with security concerns being among the most prominent. These challenges also impact on the economic dynamics of the current electricity system [8].

The impact of electric automobile load to the grid has been examined across various domains, altering overall grid load capacity [9-10], impacting power quality upon integration [11], economic implications of EVs connecting to the grid, and environmental effects stemming from EV usage [12].

The shortcomings in the economic dispatch of electric vehicles primarily revolve around the integration challenges within existing grid frameworks. These gaps include the need for enhanced algorithms that can effectively manage the variable and unpredictable charging patterns of electric vehicles to optimize energy dispatch. Additionally, it is necessary for methodologies that can balance the economic benefits of using electric vehicles as flexible loads with the potential strain they might impose on the grid. Addressing these gaps requires innovative approaches in modeling, optimization techniques, and grid management strategies to ensure efficient and sustainable integration of electric vehicles into the broader energy ecosystem.

These gaps in economic dispatch for electric vehicles can be addressed through the MOA by leveraging its ability to handle complex, non-linear optimization problems. Mother's algorithm excels in optimizing systems with variable and unpredictable inputs. It can dynamically adjust strategies to balance economic benefits and grid stability, ensuring efficient dispatch of energy resources. By incorporating advanced modeling techniques and optimization strategies.

This work is novel in its approach to optimizing the economic dispatch of electric vehicles, focusing specifically on developing tailored methodologies. It introduces innovative strategies to handle the variability of electric vehicles charging and discharging patterns and their impact, aiming to maximize economic benefits while ensuring sustainable integration. The MOA technique has not been formerly applied to any dispatch problem. This study contributes a comprehensive analysis of the economic dispatch framework applied specifically to electric vehicles. We propose novel methodologies and algorithms tailored for minimizing amalgamation of electric vehicles into the power grid, addressing their unique implication patterns and impacts on grid stability. The research explores advanced modeling optimization strategies aimed at maximizing the economic benefits of electric vehicles as flexible loads while minimizing their strain on the grid. Additionally, we investigate the environmental and economic implications of electric vehicles integration, providing insights into sustainable energy management practices.

In this paper, we utilize the MOA algorithm to address the dispatch problem. Section 2 provides an overview of the MOA method. The formulation of the dispatch problem is detailed in Section 3, continued by a discussion of the numerical tests and results using the MOA in Section 4. Eventually, the conclusion is drawn in section 5.



2. Mothers Optimization Algorithm

The MOA [13] is a new metaheuristic method driven by the interaction between a female parent and her child, focusing on learning, guidance, and nurturing. The numerical prototype of the procedure is presented for search and exploration.

2.1 Mathematical description of MOA

The technique considered here is a population-oriented optimization method that addresses problems iteratively. The population created comprises of candidate explication and are vectors in the problem range. The initial population is created using Eq. (1) in the beginning of the procedure. Each component represents decision variable based on its search space position, leveraging the population's collective search ability to discover the optimal solution.

$$M_{I,J} = Lb_J + \text{Rand}(0,1) \times (Ub_J - Lb_J) \text{ Here } I = 1, 2, \dots, N \text{ and } J = 1, 2, \dots, K \quad (1)$$

In the proposed MOA, M illustrates the population matrix, N portrays population count, and K denotes the count for deciding parameters. Lb_J and Ub_J are the lower and upper confinements for deciding parameters, respectively.

The MOA updates its population in three phases, modeled on the interactions of a mother raising children, as detailed below.

2.1.1 Learning Level I: The first phase, called learning, in the MOA approach enhances global search and exploration by significantly altering population member positions. The best member, representing the mother, guides this phase. New positions are generated using Eq. (2), and if the target function value improves, the new positions are updated as per Eq. (3).

$$M_{I,J}^{p1} = M_{I,J} + (\text{Rand}(0,1)) * (MO_J - \text{Rand}(2) * M_{I,J}) \quad (2)$$

$$M_I = \begin{cases} M_I^{p1}, & F_I^{p1} < F_I \\ M_I, & \text{Else} \end{cases} \quad (3)$$

Where MO_J represents the J th attribute of the mother's location, M_I , J denotes, J th dimension for the I th population member's position M_I , M_I^{p1} is the renewed position in the first phase of the MOA. M_I , J^{p1} is the J th attribute, F_I^{p1} is its criterion function, $\text{Rand}(0,1)$ produces random numbers amidst 0 and 1, and $\text{Rand}(2)$ create numbers randomly in the set (1, 2).

2.1.2 Guidance Level II: The phase two of the MOA, inspired by a mother's role in counseling children to prevent misbehavior, the guidance phase enhances global search and exploration by significantly altering population members positions. Any member with a superior target function value than another is deemed to display undesirable behavior that should be avoided. The set of undesirable behaviors is identified using Eq. (4), and for each M_I , a member is randomly chosen from this arrangement. A new position is generated using Eq. (5) to avoid undesirable behavior, and if it enhances the objective function value, it replaces the previous position, as specified by Eq. (6).

$$\text{BadB}_I = \{M_K, F_K > F_I \Delta K \in \{1, 2, \dots, N\}\} \text{ Where } I = 1, 2, \dots, N \quad (4)$$

$$M_{I,J}^{p2} = M_{I,J} + (\text{Rand}(0,1)) * (M_{I,J} - \text{Rand}(2) * \text{SBadB}_{I,J}) \quad (5)$$



$$M_I = \begin{cases} M_I^{p2}, & F_I^{p2} \leq F_I \\ M_I, & \text{Else} \end{cases} \quad (6)$$

Where $BadB_I$ is the group of vile behaviors for the I th inhabitant, S_{BadB_I} is the choosen evil behavior for the I th member, and $S_{BadB_{I,J}}$ is its J th attribute, MI^{p2} is the new position evaluated for the I th member in step II. $MI, Jp2$ is the J th attribute, F_{Ip2} is its object function, $Rand(0,1)$ creates a random number amidst 0 and 1, and $Rand(2)$ yields random number from the set (1, 2).

2.1.3 Nurture Level III: Mothers use encouragement to help children upgrade their skills. In MOA, the raising phase enhances localized search and exploitation by making little adjustments to positions. A new location is created for each component using Eq. (7), and if the goal function value enhances, it replaces previous location, as specified in Eq. (8).

$$M_{I,J}^{p3} = M_{I,J} + (1 - 2 * Rand(0,1)) * \frac{U_{bJ} - L_{bJ}}{T} \quad (7)$$

$$M_I = \begin{cases} M_I^{p3}, & F_I^{p3} \leq F_I \\ M_I, & \text{Else} \end{cases} \quad (8)$$

Where MI^{p3} is the latest position obtained for the I th member depending on third step of the MOA, $MI, Jp3$ is its J th dimension, F_{Ip3} is its goal function value, the function $rand(0, 1)$ produces random numbers in the interval (0, 1), and T is the count of iteration. After iterations, members are updated depending on steps from 1 to 3 using Eqs. (2) to (8) till the concluding iteration. The best solution is consistently updated and stored throughout the process. Upon completion, MOA provides the best candidate solution.

3. Problem Definition

Besides traditional thermal generators, the smart grid incorporates grid vehicles such as plug-in hybrid electric vehicles and electric vehicles, along with renewable sources like solar and wind power. Green energy sources are essential for lowering emissions and operational costs alongside thermal generators. The grid vehicles function as distributed storage devices to assist in load balancing. An optimization method integrates all these sources, including grid vehicles, to set an efficient schedule aimed at reducing expenses and emissions.

3.1 Modeling of Thermal Generators: The primary objective of economic load dispatch is to minimize the expense of generation. The generation cost of thermal generators is calculated using the following expression in Eq. (9).

$$FGC = \sum_{Tg=1}^{NTg} A P_{TG}^2 + B P_{TG} + C \quad (9)$$

Where FGC represents the final generation cost, NTg denotes the total number of thermal generators, and A, B, C are coefficient specification upsetting the generation cost. PTG is the active power generated by thermal generators.

3.2 Electrical Vehicle Modeling: In smart micro grid operations, electric vehicles serve multiple roles as energy sources, storage units, and loads. Balancing economic efficiency and



emissions reduction becomes challenging when managing the charging and discharging cycles of electric vehicles. This study models electric vehicles both as loads and energy

resources based on apex and off-peak hours. Considering power balance criteria and the effect of incorporating electric automobiles into the network, the following equations will represent electric automobile as both sources in Eq. (10) and loads in Eq. (11).

$$\sum_{Tg=1}^{NTg} P_{Tg}(t) + \sum_{Ev=1}^{NEv} P_K^{Ev}(t)(\phi_{pre} - \phi_{dep}) = LD(t) \quad (10)$$

$$\sum_{Tg=1}^{NTg} P_{Tg}(t) = LD(t) + \sum_{Ev=1}^{NEv} EvP_K^{Ev}(t)(\phi_{pre} - \phi_{dep}) \quad (11)$$

$$\sum_{K=1}^{Tt} NEv(t) = NEv^{max} \quad (12)$$

Where $NEv(t)$ represents the count of electric transport coupled to the grid at time t , $P_K^{Ev}(t)$ is the power of the K th vehicle, ϕ_{pre} / ϕ_{dep} denotes the charge/discharge state of the electric vehicles battery, η the efficiency of the system, and $NEvmax$, is the maximum number of electric transports utilized during the entire time.

3.3 Solar and Wind Energy System: In economic dispatch, the cost functions for solar and wind energy is typically defined differently from those of conventional thermal generators. Solar Energy Cost Function: The price of solar energy generation is often considered minimal because it primarily involves capital costs and very low operational costs. The cost function can be exhibited as a fixed cost per unit of energy generated.

$$C_{Solar} = C_{Fixed} \times P_{Solar} \quad (13)$$

Where C_{Solar} is the price of solar energy, C_{Fixed} is the fixed cost per unit of solar energy, and P_{Solar} is the power generated by solar panels.

Wind Energy Cost Function: Similar to solar, the price of wind energy is mainly composed of capital costs and low operational costs. The cost function can also be explicit as a fixed cost per unit of energy generated:

$$C_{Wind} = C_{Fixed} \times P_{Wind} \quad (14)$$

C_{Wind} depicts price of wind power, C_{Fixed} represents fixed cost per unit of wind power, and P_{Wind} is the power generated by wind turbines. In economic dispatch, green sources like sun and wind are often treated with zero or minimal marginal costs due to their negligible variable operating expenses. This makes them highly preferable for integration into the grid to reduce overall generation costs and emissions.



4. Result Analysis

In this study, 50000 electric automobiles are integrated into a 6-unit thermal generator system as detailed in [14]. The generator constants and dynamic load dataset are sourced with [14], provided in Table I. Each 50000 electric automobiles charges and discharges once per day, within a 24-hour period. The electric vehicle specification is referred from [14]. Three

different cases have been analyzed to review the impact of electric vehicles and renewable energy on the system and to evaluate the versatility of the algorithm. These cases incorporate various combinations to provide a comprehensive analysis.

Table 1: Techno Economical Specification of Thermal Generators

Parameters/TG	TG1	TG2	TG3	TG4	TG5	TG6
A (\$)	240.0	200	220	200	220	190
B(\$/MW)	7.00	10.00	8.50	11.00	10.50	12.00
C(\$/MW ²)	0.007	0.0095	0.009	0.009	0.008	0.0075
Power Min.	100.0	50.0	80.0	50.0	50.0	50.0
Power Max.	500.0	200.0	300.0	150.0	200.0	120.0

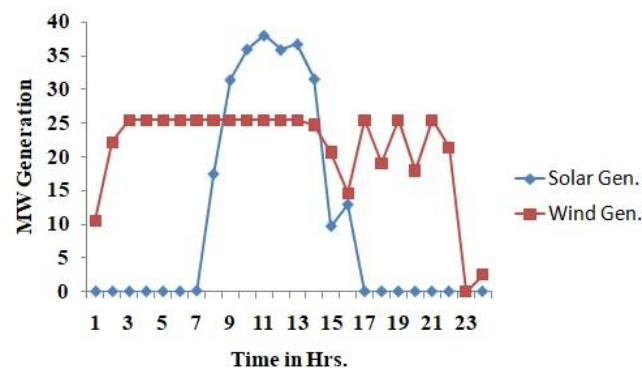


Fig. 1 Solar and Wind power generation throughout a day

4.1 Case type I: In this scenario, thermal generators and renewable energy sources collaborate to match the required load demand. The MOA is applied to a 6-unit thermal system, and its performance is equated to that of the Chimp Optimization Algorithm. The evaluation shows that the fuel consumption cost using MOA is \$296,489.63 per day. Figure 2 illustrates the distribution of power generation among the six generators, highlighting the effectiveness of MOA in balancing the power output across the system.

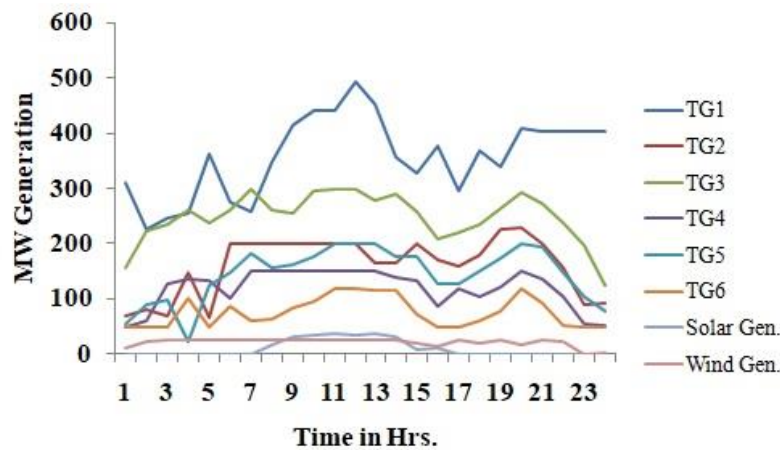


Fig. 2 Economic Dispatch of generators and renewable sources

4.2 Case type II: In the second case, the system consists of thermal generators and electric vehicles, with the electric vehicles acting solely as loads. No renewable energy sources are included in this scenario. Here, electric vehicles contribute to the overall requirement of the network. The fuel combustion cost for this setup is \$332,551.50 per day. Figure 3 provides a detailed view of how power is distributed among the generators and the electric vehicles, demonstrating the strike of incorporating electric automobiles as loads on the microgrid performance and cost.

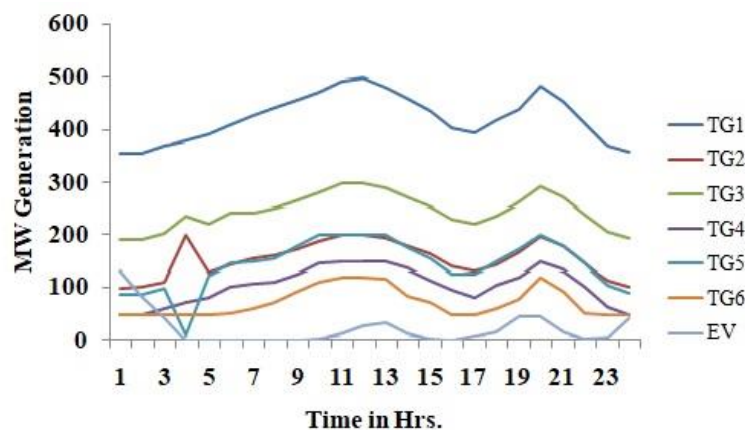


Fig. 3 Economic Dispatch of Generators and Renewable Sources

4.3 Case type III: In the third case, thermal generators, renewable energy sources, and electric automobiles collectively meet the total demand. Here, electric vehicles function as both loads and sources. As demonstrated in Figure 4, electric vehicles act as sources during peak periods and as loads during off-peak periods. The combustion cost in this scenario is \$30,4324.34 per day. Although plugged-in electric automobiles are seen as a viable answer to emissions, the study demonstrates that total cost of operation increases with plugged-in



electric automobiles in the system due to their energy consumption, which leads to higher fossil fuel use. However, the inclusion of V2G technology provides only marginal benefits compared to systems without plugged-in electric automobiles. The overall cost also rises with increased power generation.

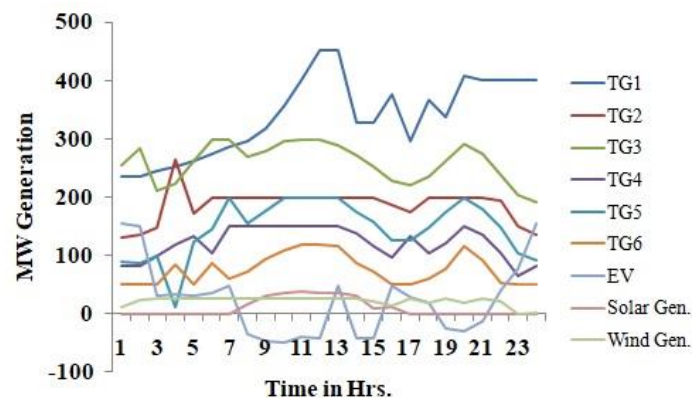


Fig. 4 Economic Dispatch of generators, electric vehicle and renewable sources

All the above three cases evaluated through MOA, are analyzed with the outcomes of Chimp optimization algorithm and are depicted in Table 2. It can be observed that the results obtained from MOA have outperformed in comparison to chimp optimization algorithm.

Table 2. Comparative Cost Analysis of Algorithms

Technique Used	Thermal Gen.+ Electric Veh.	Thermal Gen. + Ren. Sources	Thermal Gen.+ Electric Veh. + Ren. Sources
Chimp OA	397294.10	316498.35	326625.6
Mothers OA (Proposed)	332551.5	296489.63	304324.34

5. Conclusion

In this investigation, the dynamic load dispatch issue has been effectively addressed using the MOA. The proposed algorithm was tested on 6-unit generator systems integrated with electric vehicles, renewable sources, and a combination of both. The results demonstrated that the MOA significantly reduced generation costs compared to scenarios without EVs and renewable sources. Furthermore, the MOA outperformed the Chimp Optimization Algorithm in terms of cost efficiency, achieving cost reductions of 19.46%, 7.328%, and 6.74%. The findings indicated that the MOA successfully achieved efficient load distribution at a cost-effective rate.

The primary limitations of these studies stem from the assumptions that grid vehicles will always discharge when required by the grid and that the lifespan of a grid able vehicle battery follows a simple linear relationship with its charging/discharging cycles. Although these assumptions might be plausible in an ideal scenario, they are impractical for several reasons as grid able vehicle performance depends on battery quality, with longevity determined by its



left-over capability after recurrent use as both a contributor and user. The battery maintenance cost is very high and is affected by the rate at which its capacity degrades.

The proposed MOA approach facilitates various research opportunities for future investigations. A particularly promising area of research comes to the expansion of binary and multi-faceted versions of the proposed method. Additionally, this powerful algorithm can be applied to solve multi-dimensional dynamic dispatch problems in electrical grids, highlighting its versatility and effectiveness.

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