

Optimal Charging Scheduling and Effective Generation Source Mobilization for Electric Vehicle Charging Stations

Minh Thien Vo¹, Thi Kieu Tien Doan², Quang Ai Nguyen², Van Phu Huynh², Ngoc Dieu Vo^{1*}

¹Ho Chi Minh City University of Technology, VNU-HCM, Vietnam

²Can Tho University of Technology, Vietnam

*Corresponding author. Email: vndieu@hcmut.edu.vn

ARTICLE INFO

Received: 14/01/2025
Revised: 01/02/2025
Accepted: 24/03/2026
Online First: 07/07/2026
Published:

KEYWORDS

Electric Vehicle Charging Station;
Vehicle-to-Grid;
Optimal Power Flow;
Gradient-Based Optimizer;
Distribution System.

ABSTRACT

Optimizing power generation sources, promoting the flexibility of consumption loads, effectively coordinating the electric vehicle charging station system (EVCS), integrating renewable energy, minimizing negative impacts on the system are always the desires of operators and investors. In this study, we proposed an optimal charging coordination model for EVCS that combines effective mobilization of power generation sources integrated with renewable energy, with the goal of minimizing power generation costs in two cases with and without considering emissions. The Gradient-Based Optimizer (GBO) algorithm was utilized to identify solutions, the search results were simulated using Matlab software and tested on IEEE 30 bus standard network, 7 charging stations, 3 charging levels in 24 hours according to the electricity price framework in Vietnam through 3 test cases and 2 scenarios considering Vehicle to Grid (V2G) technology. The solution results were compared with published studies, evaluating the proposed application.

Doi: <https://doi.org/10.54644/jte.2026.1766>

Copyright © JTE. This is an open access article distributed under the terms and conditions of the [Creative Commons Attribution-NonCommercial 4.0 International License](https://creativecommons.org/licenses/by-nc/4.0/) which permits unrestricted use, distribution, and reproduction in any medium for non-commercial purpose, provided the original work is properly cited.

1. Introduction

The rapid development of electric vehicles (EV) has resulted in fluctuating load infrastructure, creating pressure on the power grid, especially during load fluctuation scenarios, peak loads, power losses, and voltage instability [1]. Recently, many studies have proposed solutions to address these issues; however, a comprehensive and strategic evaluation is needed to ensure stability and sustainability. In this study, we proposed an optimal charging scheduling model for EVCS integrated with V2G [2], [3] operating in real-time under the current electricity pricing regulations in Vietnam, including peak hours, normal hours, and off-peak hours over a 24-hour period. The model incorporates different charging intensity factors and combines optimal power generation mobilization with renewable energy penetration to minimize operational costs under two conditions: with and without emission fees [4], [5]. The GBO algorithm was proposed to solve this problem [6], using MATLAB for simulation and the standard IEEE 30-bus distribution network for testing. The effectiveness of the model was demonstrated through three test cases and two EVCS integration scenarios, highlighting the superior advantages of applying the GBO algorithm to the EVCS problem [7]–[10].

Recent publications have highlighted power generation cost optimization in distribution networks by integrating thermal generators, solar, and wind energy. These methods include the Guided Artificial Bee Colony (GABC) for OPF [11], the Modified Bacteria Foraging Algorithm (MBFA) with the DFIG model [12], and the Bacteria Foraging Algorithm (BFA) [13], as well as power optimization using the Moth Swarm Algorithm (MSA) [14]. Some studies have also focused on wind energy cost models [15], power optimization considering emissions using non-smooth cost functions with the Backtracking Search Optimization Algorithm (BSOA) [16], and enhanced constraints. Additionally, proposals for integrating solar energy, hydropower, and hybrid multi-source systems into the grid emphasize challenges in economic efficiency [17], system limitations, and the variability of renewable energy sources, which have

been explored through various case studies. However, the emergence of integrated EVCS has introduced multiple constraints [18] and negative impacts that must be addressed from various perspectives. Technical strategies for application [19], including added values in terms of intensity, scale, timing, applied technology, and efficiency, require attention, as outlined in the proposed model.

The main contributions can be summarized as follows:

- Development of a scheduling model for EVCS integrating effective power mobilization with renewable energy integration.
- Demonstration of the effectiveness of the GBO algorithm for the problem.
- A dynamic multi-level power mobilization model for EVCS scheduling with V2G application.
- Proposal of practical solutions for the development of EVCS infrastructure.

2. Problem model

The problem of scheduling and optimizing power generation dispatch for the EVCS system involves determining the values of control variables to find the optimal solution for the desired objective function. Additionally, it must satisfy the physical constraints of the system, which are formulated through mathematical equations [4], The list of terms is presented in Table 1.

$$\text{Min } F(x,u) \quad (1)$$

Constraints:

$$y(x,u) = 0 \quad (2)$$

$$z(x,u) \leq 0 \quad (3)$$

Where $F(x,u)$ is the objective function; $y(x,u)$ representing equality constraints and $z(x,u)$ representing inequality constraints, x are state variables, and u are the corresponding control variables.

State variables:

$$u^T = [P_{TG,2}, \dots, P_{TG,N_{TG}}, P_{WS,1}, \dots, P_{WS,N_{WG}}, P_{SS,1}, \dots, P_{SS,N_{SG}}, P_{CS,1}, \dots, P_{CS,N_{EVCS}}, V_{G1}, \dots, V_{G,NG}] \quad (4)$$

Control variables:

$$x^T = [S_{TG,2}, \dots, S_{TG,N_{TG}}, S_{WS,1}, \dots, S_{WS,N_{WG}}, S_{SS,1}, \dots, S_{SS,N_{SG}}, S_{CS,1}, \dots, S_{CS,N_{CS}}] \quad (5)$$

2.1. Optimization objective function and system constraints

The objective of the problem is formulated as the sum of the cost functions of the power generation sources [4].

Objective function:

$$OF_1 = C_{T0}(P_{TG}) + TW + TS \quad (6)$$

Cost minimization with emissions:

$$OF_2 = OF_1 + C_{tax}E \quad (7)$$

The CS objectives must comply with the constraints.

Power balance:

$$P_{Gi} - P_{Di} - P_{CSi} - P_{lossi} = 0 \quad (8)$$

$$Q_{Gi} - Q_{Di} - Q_{CSi} - Q_{lossi} = 0 \quad (9)$$

Power limits:

$$P_{TG,i}^{min} \leq P_{TG,i} \leq P_{TG,i}^{max}, i = 1, \dots, N_{TG} \quad (10)$$

$$P_{ws,j}^{min} \leq P_{ws,j} \leq P_{ws,j}^{max}, j = 1, \dots, N_{WG} \quad (11)$$

$$P_{ss,k}^{min} \leq P_{ss,k} \leq P_{ss,k}^{max}, k = 1, \dots, N_{SG} \quad (12)$$

$$P_{CS,e}^{min} \leq P_{CS,e} \leq P_{CS,e}^{max}, e = 1, \dots, N_{CS} \quad (13)$$

$$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max}, i = 1, \dots, NG \quad (14)$$

Table 1. List of nomenclature.

Symbol	Description
$P_{TG}, P_{WS}, P_{SS}, P_{CS}$	Active power of thermal power plants, wind, solar and CS
P_{Di}, Q_{Di} and P_{lossi}, Q_{lossi} ,	Active, reactive power of at bus i and Active, reactive power loss at i
P_{Gi}, Q_{Gi}	Active, reactive power of the generation at bus i
P_{CSi}, Q_{CSi}	Active, reactive power of CS at bus i
$N_{TG}, N_{WG}, N_{SG}, N_{CS}$	The number of thermal power plants, wind, solar and CS
V_{Gi}, NB, N_L	Voltage generator i_{th} at bus i , number of buses, load buses
$C_{T0}(P_{TG}), TW$ and TS	Fuel cost of thermal, total costs of wind and solar power
E, C_{tax}	Emission cost, applicable carbon tax

2.2. Stochastic model for wind and solar energy

Thermal power generation at bus 5 and bus 11 is replaced by wind energy sources, while bus 13 generates solar energy to determine the penetration ratio of renewable energy. Weibull parameters with scale factor (c) and shape factor (k) are presented in [4]. Additionally, two wind speed distribution scenarios are described for 8,000 Monte Carlo simulations, with average wind speeds of 7.976 m/s and 8.862 m/s, consistent with the wind turbine design standards [14]. Solar energy depends on solar radiation (G), following a Lognormal distribution with a mean deviation and standard deviation σ and the distribution of solar radiation after running Monte Carlo simulations with 8000 scenarios in [5].

2.3. Application of GBO to the problem

An optimization problem includes decision variables, constraints, and an objective function. The GBO control parameters involve the transition between exploration and exploitation phases and the probability ratio. The iteration count and population size depend on problem complexity. In the algorithm, each population member is termed a "vector," with GBO comprising N vectors in a D-dimensional search space. A vector is represented as follows:

$$X_{n,d} = [X_{n,1}, X_{n,2}, \dots, X_{n,D}], \quad n = 1, 2, \dots, N, \quad d = 1, 2, \dots, D \quad (15)$$

The initial population vectors in GBO are created randomly, ensuring they are distributed within the boundaries of the D-dimensional search space, defined as follows:

$$X_n = X_{min} + rand(0, 1) \cdot (X_{max} - X_{min}) \quad (16)$$

Here, The bounds of the decision variable are X are defined by X_{min} and X_{max} , while $rand(0, 1)$ represents a randomly generated value within the interval $[0, 1]$.

The GBO algorithm takes inspiration from the Newton method, leveraging gradients and employing two core mechanisms: the Gradient Search Rule (GSR) and the Local Escaping Operator (LEO), alongside a vector set to navigate the search space. GSR uses gradient-based techniques to improve exploration and speed up convergence toward optimal points in the search space. Meanwhile, LEO allows the GBO to overcome local optima and continue searching for better solutions.

The effectiveness of the proposed algorithm is assessed through a two-phase process. Initially, 28 mathematical benchmark functions are utilized to analyze and measure various aspects of GBO's performance. Subsequently, GBO is applied to optimize 6 engineering problems, further demonstrating its capabilities [6], The program is presented in Table 2.

Table 2. Pseudo code of the GBO algorithm.

Step 1. Initialization

Assign values for parameters pr , ε and M .

Generate an initial population $X_0 = [x_{0,1}, x_{0,2}, \dots, x_{0,D}]$.

Evaluate the objective function value $f(X_0)$, $n = 1, \dots, N$.

Specify the best and worst solutions x_{best}^m and x_{worst}^m .

Step 2. Main loop

While ($m < M$)

for $n = 1 : N$

for $i = 1 : D$

 Select randomly $r1 \neq r2 \neq r3 \neq r4 \neq n$ in the range of $[1, N]$

 Calculate the position $x_{n,i}^{m+1}$

end for

Local escaping operator

if $rand < pr$

 Calculate the position x_{LEO}^M

$$x_{n,i}^{m+1} = x_{LEO}^M$$

end

 update the position x_{best}^m and x_{worst}^m

end for

$m = m + 1$

end

Step 3: Results

 return x_{best}^m

3. Simulation results

Table 3. Wind and solar power generation capacity over 24-hour period.

Time		1	2	3	4	5	6	7	8	9	10	11	12
Wind power (MW)	Bus 5	6.25	5.875	5.75	5.875	5.5	5.625	4.75	4.25	6.25	9.25	11.75	15.5
	Bus 11	5	4.7	4.6	4.7	4.4	4.5	3.8	3.4	5	7.4	9.4	12.4
Solar power (MW)	Bus 13	0	0	0	0	0	2.5	5	13.5	25	35	45	47.5
Time		13	14	15	16	17	18	19	20	21	22	23	24
Wind power (MW)	Bus 5	17.75	20.125	22.75	24	21.5	20.25	17.5	14.625	10.375	8.125	7.25	6.625
	Bus 11	14.2	16.1	18.2	19.2	17.2	16.2	14	11.7	8.3	6.5	5.8	5.3
Solar power (MW)	Bus 13	50	47.5	41.5	36	27.5	15	6.5	2.5	0	0	0	0

The problem model is implemented and simulated to find the solution on the IEEE 30-bus standard power grid model. Thermal power generation is replaced at bus 1, 2, and 8; wind power at bus 5 and bus 11; and solar power at bus 13. The total load power is 283.4 MW and 126.2 Mvar, with 25 control variables, including power dispatch, coordination, and voltage at different generator bus.

The wind power parameters follow a Weibull distribution, and the Lognormal distribution represents the factors for renewable energy sources [5], the power generation capacity is presented in Table 3.

Simulation parameters applied: $Max_age = 200$, $pr = 0.5$, $nP = 100$. The power value of P_{TG2} at bus 2 is $20 \div 80$ MW, P_{TG3} at bus 8 is $10 \div 35$ MW, and the voltage limits at the bus are $0.95 \div 1.1$ pu. The simulation integrates the testing of 7 EVCS locations on the IEEE 30-bus network, with EVCS capacities at two levels [20], a total rated power of 3.124 MW, 53 charging connection ports, tested through 2 test cases and 2 scenarios, with charging power intensity enhancement factors of (1.6), (1.0), and (0.5) [21], evaluated through a 24-hour electricity buy-sell cost framework. The objective function considers emission costs to enhance evaluation with more complex constraints. The total operating cost, including emissions, is minimized using a multi-objective cost function with an emission tax of 20 \$/ton [4]. This tax encourages greater use of renewable energy sources.

3.1. Case 1: Simulation test

To demonstrate that GBO is an effective and reliable proposed solution, the model is simulated and tested for comparison with 8 algorithms such as: An augmentation of Grey Wolf Optimizer - Cuckoo Search (AGWOCS) [22], Wild horse optimizer (WHO) [23], Runge Kutta optimizer (RUN) [24], Mountain Gazelle Optimizer (MGO) [25], Grasshopper Optimisation Algorithm (GOA) [6], Slime Mould Algorithm (SMA) [26], Atomic Orbital Search (AOS) [27], Coronavirus herd immunity optimizer (CHIO) [28] through 50 runs, with the independent results presented in Figure 1.

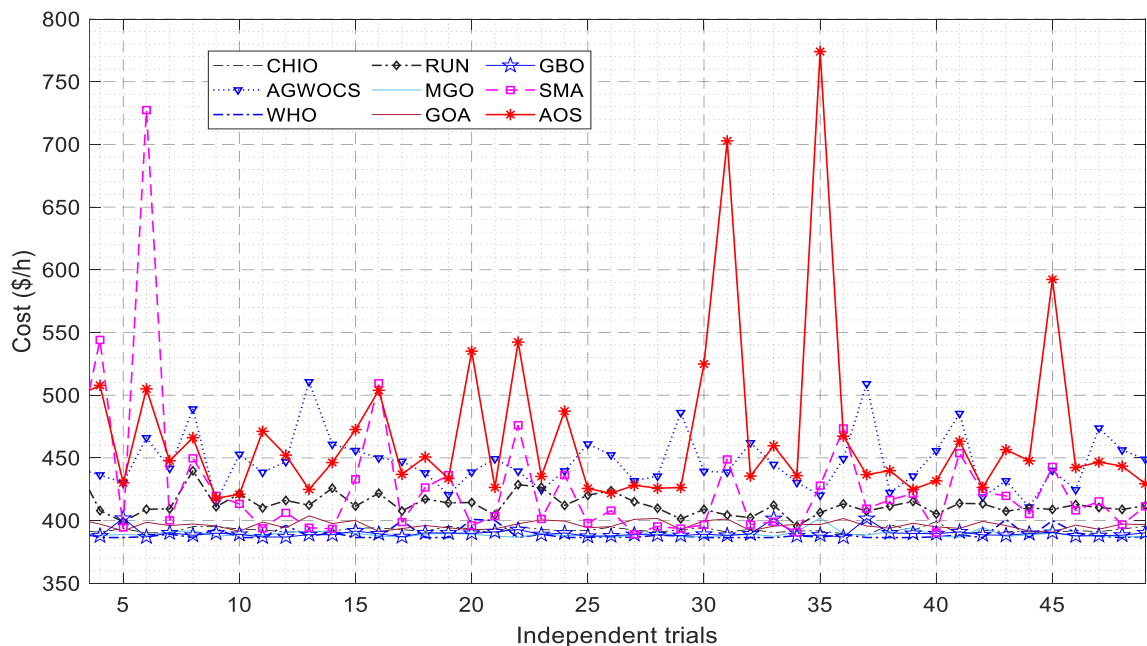


Figure 1. Comparison results of the search capabilities of the algorithms.

The results in Figure 1 demonstrate the superiority of GBO over other algorithms, including WHO, GOA, and MGO. While GBO also shows very strong performance, its stability is not as high. This confirms that the proposed GBO is suitable for the problem model.

3.2. Case 2: Power generation cost optimization test

The superiority of the GBO algorithm over GWO in the optimization of operational costs for power generation sources, with the determination of renewable energy penetration rates, has been compared. The

results in Table 4 demonstrate the superior solution of GBO with a cost of 628.98 \$/h, 429 (s) for CPU time and 629.04 \$/h, 535 (s) compared to 781.4 \$/h and 809.93 \$/h for GWO in the two cases of excluding and including emission costs, respectively. Additionally, the voltage values at the generator buses still ensure stability within the permissible constraint limits $0.95 \div 1.10$ pu.

Table 4. Comparison results of the power generation dispatch cost optimization problem.

Parameter	Without considering emissions		Considering emissions costs	
	GWO [4]	GBO	GWO [4]	GBO
Optimal costs (\$/h)	781.4	628.98	809.9	629.04
CPU time (s)	429	390	535	416

3.3. Scenario 1: Integration of EVCS with V2G application under constraints

In this case, the model survey of the integrated problem into the power grid in section (3.2) was further investigated by adding 7 EVCS with 3 level-1 stations and 4 level-2 stations, with a total power of 3.124 MW. The EVCS locations are randomly placed at buses 19, 21, 23, 2, 19, 20, and 23 [29]. The charging intensity factors are (1.6), (1.0), and (0.5) [21]. All EVCSs apply V2G technology, and the renewable energy power generation sources provided over 24 hour period. Constraints are set to improve operational efficiency as well as optimize the economics due to the buy-sell electricity cost differences according to the specified hourly frameworks for both the operator and the EV owner, as detailed in Table 5 and according to the unit cost [30].

Table 5. Scenario of optimal EVCS charging and discharging power distribution over a 24-hour period.

Establishing EVCS coordination constraints applying V2G technology (MW)							
Time frame	Low	Normal	High	Normal	High	Normal	Low
	1÷3	4÷9	10÷11	12÷16	17÷19	20÷22	23÷24
EVCS 1 ÷ EVCS 3	0.308	0.308	0.308	0.308	0.308	0.308	0.308
EVCS 4 ÷ EVCS 7	0.550	0.550	0.550	0.550	0.550	0.550	0.550
V2G intensity with charging/discharging constraints (%)	160/0	100/100	50/160	100/100	50/160	100/100	160/0
V2G intensity without charging/discharging constraints (%)	160/160	100/100	50/50	100/100	50/50	100/100	160/160

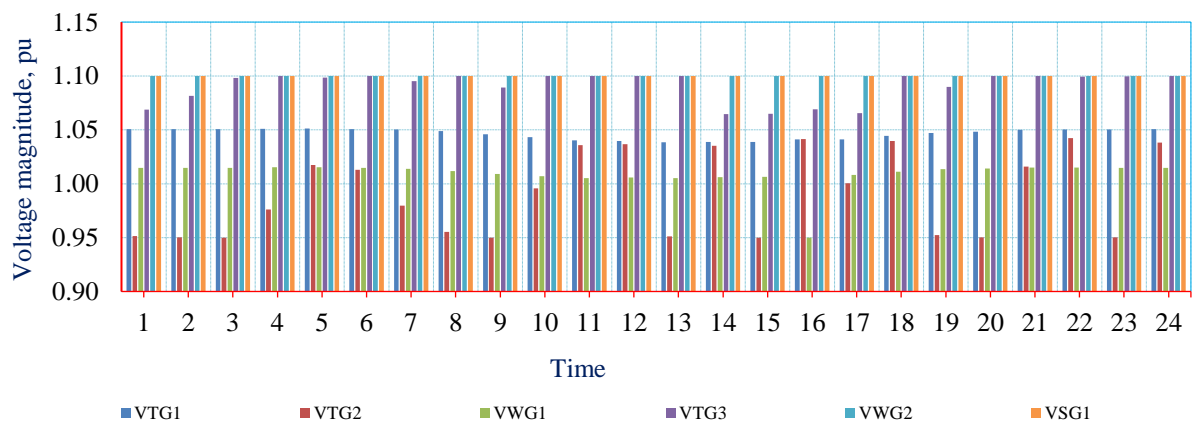


Figure 2. Voltage curve of Scenario 1 surveyed over 24 hours.

The voltage intensity curve at the generator buses in Figure 2 shows stability and good compliance with the set constraints. The slight fluctuations at VTG1 and VTG3 are not concerning, especially since the voltage

at VWG2 and VSG1 remains almost unchanged, reflecting high stability, always within the high threshold limit of 0.95 to 1.1 pu, ensuring power quality.

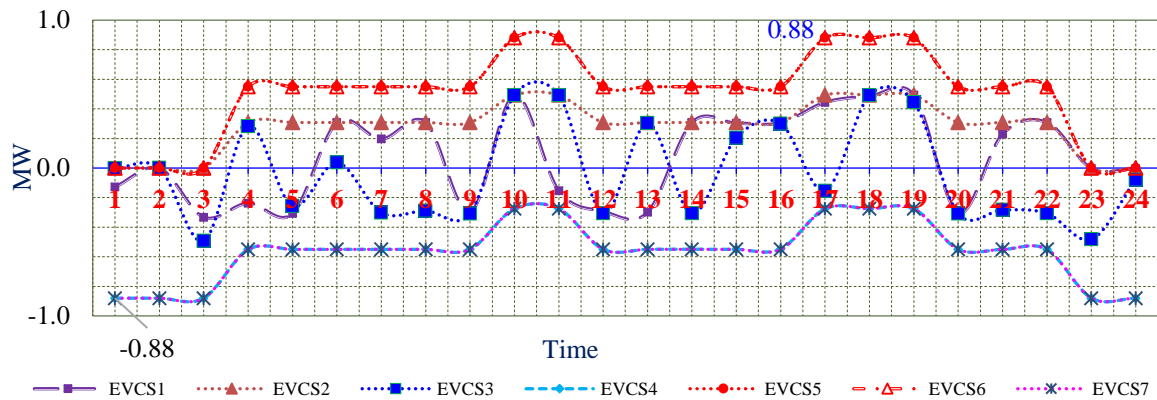


Figure 3. Charging and discharging diagram of EVCS in the 24-hour survey frame of Scenario 1.

Figure 3 illustrates the charging and discharging power of EVCS when applying V2G technology with constraints over 24 hour period. Based on the results of the power flow in the surveyed time frames, it can be concluded that the power constraint settings of V2G technology meet the requirements well. During the off-peak hours 23, 24, 1, 2, and 3, no discharging occurs to the grid, and charging is prioritized during this time. For the peak hours, discharging to the grid is prioritized during hours 10, 11, 17, 18, and 19, where the discharging power exceeds the charging power, reaching a maximum discharging peak of 0.88 MW. Meanwhile, during the remaining regular hours, the charging and discharging capacity fluctuates based on the power supply difference and the demand from the load. Overall, the time frames meet the set constraints well. This affirms that V2G technology can proactively establish constraints and coordinate power according to the requirements of each time point, mobilizing renewable energy sources effectively for both users and investors. This trend demonstrates the potential for optimization and the efficiency of the entire system.

3.4. Scenario 2: Integration of EVCS with V2G technology without constraints

In this scenario, the location and parameters of the EVCS are the same as in Scenario 1, and the V2G technology is still applied over the 24 hour period. However, the objective of the problem is to apply V2G intensity without charging constraints Table 5 and discharging, in order to assess the ability and transmission speed of the generation sources when the integrated EVCS power changes.

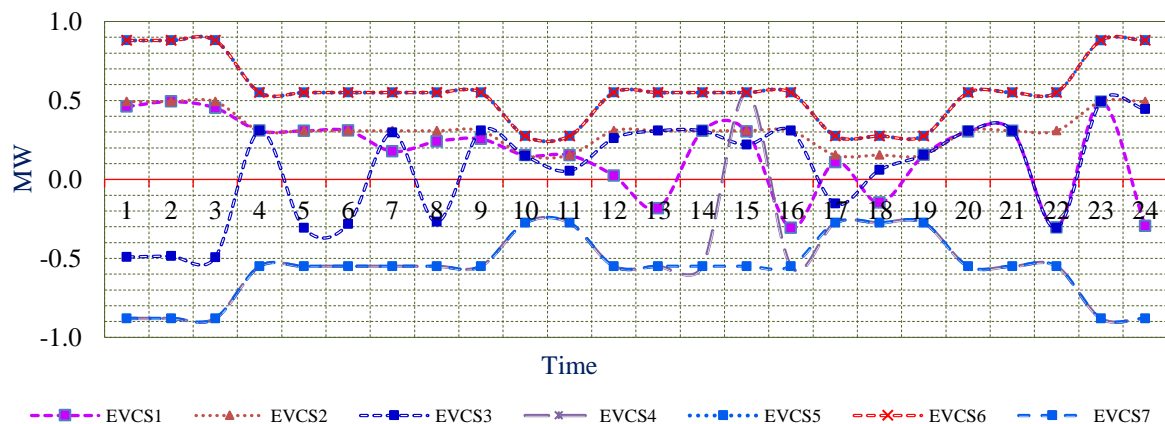


Figure 4. Charging and discharging power of EVCS in the 24-hour survey period of Scenario 2.

The results presented in Figure 4 show stable performance across many EVCS when no constraints are applied. Specifically, EVCS2 maintains a stable voltage around 0.493 MW and 0.308 MW,

indicating stable charging. EVCS5 and EVCS6 fluctuate slightly between 0.88 MW and 0.55 MW, reflecting the V2G coordination process that closely follows changes in the power supply from renewable energy sources. Although EVCS1 and EVCS3 experience significant fluctuations from 0.461 MW to -0.295 MW and from -0.493 MW to 0.493 MW, this signals the need for further improvement in the charging/discharging process and the impact of installation locations. The EVCS system effectively meets the power balance constraints of the problem, ensuring efficient and stable energy supply.

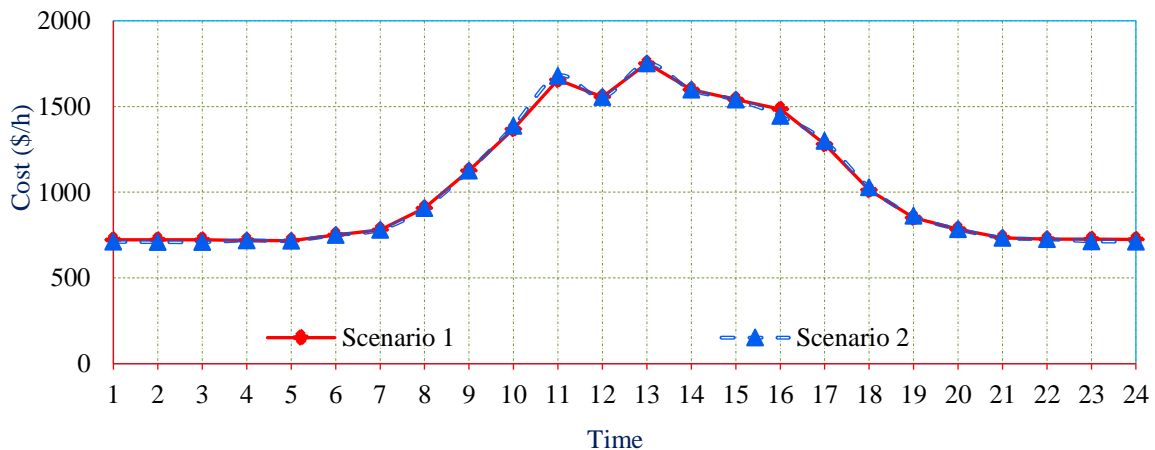


Figure 5. Comparison of optimal cost between two scenarios.

The results of the optimal operation cost for sourcing power in both scenarios, presented in Figure 5, show that both cases have a stable trend with cost changes over time, and the differences are minimal, demonstrating the effective mobilization and coordination of EVCS and generation sources in meeting the power balance constraints of the problem. Specifically, Scenario 1 has a cost range from 717.396 \$/h to 1,751.802 \$/h, with the lowest cost at 05:00 being 717.396 \$/h, and the highest at 13:00 being 1,751.802 \$/h. Afterward, the cost gradually decreases, especially toward the end of the survey cycle. Scenario 2 has a cost range from 709.179 \$/h to 1,751.791 \$/h, lower than Scenario 1, with the lowest cost at 03:00 being 709.179 \$/h, but the highest cost still occurs at 13:00, at 1,751.791 \$/h, similar to Scenario 1. This indicates that Scenario 2 may provide a more optimal long-term cost efficiency, with lower costs and more stability during the survey period. The cost increases between the 8:00 and 19:00 time slots, reflecting the objective of mobilizing power from renewable energy sources according to the given penetration rate.

Clearly, the survey results of the 2 scenarios that the cost of mobilizing power sources was equivalent. However, the scenario with constraint 1, the difference in charging and discharging costs was higher, bringing better efficiency to investors and EV owners when applying the difference in electricity purchase and sale prices applying V2G and this was also the solution we propose to support effective investment decisions.

4. Conclusion

Based on the simulation results, comparisons, and evaluation of different scenarios, it can be concluded that GBO is a powerful algorithm that outperforms several other algorithms in finding the optimal solution for the operational cost of coordinating power generation sources with renewable energy penetration in systems integrated with EVCS using V2G technology. The problem model, through various case studies, demonstrates the proactive nature of V2G technology in establishing priority constraints regarding mobilized power sources and charging/discharging power throughout the operational process. Additionally, the EVCS coordination technique brings significant benefits to both investors and EV owners. Furthermore, the problem model showcases the robustness and multi-level capacity dispatch, and coordination of charging based on practical electricity buying and selling cost frameworks in Vietnam, considering peak, off-peak, and normal hours. This is of great significance in proposing effective calculation models for developing EVCS infrastructure in practice.

Acknowledgments

We acknowledge Ho Chi Minh City University of Technology (HCMUT), VNU-HCM for supporting this study.

Conflict of Interest

The authors declare no conflict of interest.

REFERENCES

- [1] F. Ahmad, A. Iqbal, I. Ashraf, M. Marzband, and I. Khan, "Optimal location of electric vehicle charging station and its impact on distribution network: A review," *Energy Rep.*, vol. 8, pp. 2314–2333, 2022, doi: 10.1016/j.egy.2022.01.180.
- [2] M. Mazumder and S. Debbarma, "EV charging stations with a provision of V2G and voltage support in a distribution network," *IEEE Syst. J.*, vol. 15, no. 1, pp. 662–671, Mar. 2021, doi: 10.1109/JSYST.2020.3002769.
- [3] M. R. H. Mojumder, F. A. Antara, M. Hasanuzzaman, B. Alamri, and M. Alsharaf, "Electric vehicle-to-grid (V2G) technologies: Impact on the power grid and battery," *Sustainability*, 2022, doi: 10.3390/su142113856.
- [4] I. U. Khan, N. Javaid, K. A. A. Gamage, C. J. Taylor, S. Baig, and X. Ma, "Heuristic algorithm based optimal power flow model incorporating stochastic renewable energy sources," *IEEE Access*, vol. 8, pp. 148622–148643, 2020, doi: 10.1109/ACCESS.2020.3015473.
- [5] P. P. Biswas, P. N. Suganthan, and G. A. J. Amaratunga, "Optimal power flow solutions incorporating stochastic wind and solar power," *Energy Convers. Manag.*, vol. 148, pp. 1194–1207, 2017, doi: 10.1016/j.enconman.2017.06.071.
- [6] S. Saremi, S. Mirjalili, and A. Lewis, "Grasshopper optimisation algorithm: Theory and application," *Adv. Eng. Softw.*, vol. 105, pp. 30–47, 2017, doi: 10.1016/j.advengsoft.2017.01.004.
- [7] K. Balu and V. Mukherjee, "Optimal allocation of electric vehicle charging stations and renewable distributed generation with battery energy storage in radial distribution system considering time sequence characteristics of generation and load demand," *J. Energy Storage*, vol. 59, p. 106533, 2023, doi: 10.1016/j.est.2022.106533.
- [8] A. Mohammad, R. Zamora, and T. T. Lie, "Integration of electric vehicles in the distribution network: A review of PV-based electric vehicle modelling," *Energies*, vol. 13, no. 17, 2020, doi: 10.3390/en13174541.
- [9] F. G. Venegas, "Electric vehicle integration into distribution systems: Considerations of user behavior and frameworks for flexibility implementation," Ph.D. dissertation, Univ. Paris-Saclay, 2021. [Online]. Available: <https://theses.hal.science/tel-03338497>
- [10] G. A. Salvatti, E. G. Carati, J. P. D. Costa, R. Cardoso, and C. M. O. Stein, "Integration of electric vehicles in smart grids for optimization and support to distributed generation," in *Proc. IEEE Int. Conf. Ind. Appl. (INDUSCON)*, 2018, pp. 963–970, doi: 10.1109/INDUSCON.2018.8627290.
- [11] M. R. Adaryani and A. Karami, "Artificial bee colony algorithm for solving multi-objective optimal power flow problem," *Int. J. Electr. Power Energy Syst.*, vol. 53, no. 1, pp. 219–230, 2013, doi: 10.1016/j.ijepes.2013.04.021.
- [12] A. Panda and M. Tripathy, "Security constrained optimal power flow solution of wind-thermal generation system using modified bacteria foraging algorithm," *Energy*, vol. 93, pp. 816–827, 2015, doi: 10.1016/j.energy.2015.09.083.
- [13] D. Dike, "Economic dispatch of generated power using modified lambda-iteration method," *IOSR J. Electr. Electron. Eng.*, vol. 7, no. 1, pp. 49–54, 2013, doi: 10.9790/1676-0714954.
- [14] A. A. A. Mohamed, Y. S. Mohamed, A. A. M. El-Gaafary, and A. M. Hemeida, "Optimal power flow using moth swarm algorithm," *Electr. Power Syst. Res.*, vol. 142, pp. 190–206, 2017, doi: 10.1016/j.epsr.2016.09.025.
- [15] G. P. Granelli and M. Montagna, "Security-constrained economic dispatch using dual quadratic programming," *Electr. Power Syst. Res.*, vol. 56, no. 1, pp. 71–80, 2000, doi: 10.1016/S0378-7796(00)00097-3.
- [16] A. E. Chaib, H. R. E. H. Boucekara, R. Mehasni, and M. A. Abido, "Optimal power flow with emission and non-smooth cost functions using backtracking search optimization algorithm," *Int. J. Electr. Power Energy Syst.*, vol. 81, pp. 64–77, 2016, doi: 10.1016/j.ijepes.2016.02.004.
- [17] H. M. Dubey, M. Pandit, and B. K. Panigrahi, "Hybrid flower pollination algorithm with time-varying fuzzy selection mechanism for wind integrated multi-objective dynamic economic dispatch," *Renew. Energy*, vol. 83, pp. 188–202, 2015, doi: 10.1016/j.renene.2015.04.034.
- [18] B. Shang *et al.*, "V2G scheduling of electric vehicles considering wind power consumption," *IET Renew. Power Gener.*, vol. 14, 2023, doi: 10.1049/rpg2.12916.
- [19] A. M. Eltamaly, "Optimal dispatch strategy for electric vehicles in V2G applications," *Smart Cities*, vol. 6, no. 6, pp. 3161–3191, 2023, doi: 10.3390/smartcities6060141.
- [20] E. A. Rene, W. S. T. Fokui, and P. K. N. Kouonchie, "Optimal allocation of plug-in electric vehicle charging stations in the distribution network with distributed generation," *Green Energy and Intelligent Transportation*, 2023, doi: 10.1016/j.geits.2023.100094.
- [21] W. S. T. Fokui, M. J. Saulo, and L. Ngoo, "Optimal placement of electric vehicle charging stations in a distribution network with randomly distributed rooftop photovoltaic systems," *IEEE Access*, vol. 9, pp. 132397–132411, 2021, doi: 10.1109/ACCESS.2021.3112847.
- [22] S. Sharma, R. Kapoor, and S. Dhiman, "A novel hybrid metaheuristic based on augmented grey wolf optimizer and cuckoo search for global optimization," in *Proc. Int. Conf. Secur. Cyber Comput. Commun. (ICSCCC)*, 2021, pp. 376–381, doi: 10.1109/ICSCCC51823.2021.9478142.
- [23] I. Naruei and F. Keynia, "Wild horse optimizer: A new meta-heuristic algorithm for solving engineering optimization problems," *Struct. Multidiscip. Optim.*, 2022, doi: 10.1007/s00366-021-01438-z.
- [24] I. Ahmadianfar, H. Chen, A. A. Heidari, and A. H. Gandomi, "RUN beyond the metaphor: An efficient optimization algorithm based on Runge–Kutta method," *Expert Syst. Appl.*, 2021, doi: 10.1016/j.eswa.2021.115079.
- [25] B. Abdollahzadeh, F. S. Gharehchopogh, N. Khodadadi, and S. Mirjalili, "Mountain gazelle optimizer: A new nature-inspired metaheuristic algorithm for global optimization problems," *Adv. Eng. Softw.*, vol. 174, p. 103282, 2022, doi: 10.1016/j.advengsoft.2022.103282.
- [26] S. Li, H. Chen, M. Wang, A. A. Heidari, and S. Mirjalili, "Slime mould algorithm: A new method for stochastic optimization," *Future Gener. Comput. Syst.*, vol. 111, pp. 300–323, 2020, doi: 10.1016/j.future.2020.03.055.

- [27] M. Azizi, "Atomic orbital search: A novel metaheuristic algorithm," *Appl. Math. Model.*, vol. 93, pp. 657–683, 2021, doi: 10.1016/j.apm.2020.12.021.
- [28] M. Alweshah, S. Alkhalaiheh, M. A. Al-Betar, and A. A. Bakar, "Coronavirus herd immunity optimizer with greedy crossover for feature selection in medical diagnosis," *Knowl.-Based Syst.*, vol. 235, p. 107629, 2022, doi: 10.1016/j.knsys.2021.107629.
- [29] E. A. Rene, W. S. Tounsi Fokui, and P. K. N. Kouonchie, "Optimal allocation of plug-in electric vehicle charging stations in the distribution network with distributed generation," *Green Energy Intell. Transp.*, vol. 2, no. 3, p. 100094, 2023, doi: 10.1016/j.geits.2023.100094.
- [30] D. X. Tien, N. T. H. Thanh, and N. X. Truong, "Study and Designing Remote Electrical Load Monitoring and Control System for Electricity Demand Management Programs," *Vietnam J. Agri. Sci.*, vol. 22, no. 6, pp. 778–788, 2024.

Minh Thien Vo received his B.Eng. degrees in Electrical Engineering from Department of Electrical Engineering, College of Engineering Technology, Can Tho University (CTU), Can Tho City, Vietnam and M.Eng. in Electrical Equipment, Network and Machine from Ho Chi Minh City University of Technology (HCMUT), VNU-HCM, Ho Chi Minh city, Vietnam, in 2007 and 2012, respectively. He is currently a lecturer at Department of Electrical - Electronic - Telecommunication, Can Tho University of Technology (CTUT), Can Tho City, Vietnam. His research interests are power system optimization and new energy integrated in power systems.

Email: ymthien.sdh222@hcmut.edu.vn. ORCID:  <https://orcid.org/0009-0006-6254-8508>

Thi Kieu Tien Doan received her B.Eng. and M.Eng degrees in Biotech of Food Area from Institute of Food and Biotechnology, Can Tho University, Can Tho City, Vietnam, in 2001 and 2005, respectively and her D.Eng. degree in Biotech from CTU. Her is currently a lecturer at Department of Biotech - Chemical tech - Foodtech and Research Space for New Energy Development, Can Tho University of Technology (CTUT), Can Tho City, Vietnam. Her research interests are biotech and new energy for sustainable biotech development.

Email: dtktien12@gmail.com. ORCID:  <https://orcid.org/0009-0009-5888-3962>

Quang Ai Nguyen is currently a student majoring in Electrical-Electronic-Semiconductor Engineering and a member of Research Space for New Energy Development (CTUT). His research interests are power system optimization and new energy integrated in power systems.

Email: nqai2000002@gmail.com. ORCID:  <https://orcid.org/0009-0000-8095-0687>

Van Phu Huynh received the degree of Engineer in Electrical and Electronics Engineering Technology from Can Tho University of Technology (CTUT), Can Tho city, in 2018 and his M.Eng. degree in Power Management from Ho Chi Minh City University of Technology (HCMUT), Ho Chi Minh city, Vietnam, in 2024. He is currently a Lecturer at Department Electrical - Electronic – Telecommunication, Can Tho University of Technology (CTUT), Can Tho, Vietnam. His research interests are power system optimization and new energy integrated in power system.

Email: hvphu@ctu.edu.vn. ORCID:  <https://orcid.org/0009-0004-1533-6890>

Ngoc Dieu Vo received his B.Eng. and M.Eng. degrees in Electrical Engineering from Ho Chi Minh City University of Technology (HCMUT), VNU-HCM, Ho Chi Minh city, Vietnam, in 1995 and 2000, respectively and his D.Eng. degree in Energy from Asian Institute of Technology (AIT), Pathumthani, Thailand in 2007. He is currently a lecturer at Department of Power Systems, Faculty of Electrical and Electronic Engineering, HCMUT. His interests are applications of AI in power system optimization, power system operation and control, power system analysis, and power systems under deregulation.

Email: vndieu@hcmut.edu.vn. ORCID:  <https://orcid.org/0000-0001-8653-5724>