OPTIMAL POWER MOBILIZATION FOR ELECTRIC VEHICLE CHARGING STATIONS IN DISTRIBUTION NETWORKS WITH DISTRIBUTED GENERATIONS AND BATTERY STORAGE SYSTEMS

Vo Minh Thien[1,2], Doan Thi Kieu Tien[2], Mai Phu Khai[2], Nguyen Phu Qui[2], Tran Minh Quyen[3], and Vo Ngoc Dieu[1,4]

[1]Department of Power Systems, Ho Chi Minh City University of Technology
[2]Can Tho University of Technology, Can Tho City, Vietnam
[3]Vinh Long University of Technology and Education
[4]National University Ho Chi Minh
Email: vmthien@ctuet.edu.vn

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ABSTRACT

The transition to clean energy in the transportation sector has driven a rapid increase in Electric Vehicles, necessitating effective solutions for Electric Vehicle Charging Stations (EVCS). This study proposes an improved optimization algorithm, combining a chaotic search function and the Runge Kutta optimizer, to address the optimal power dispatch problem for EVCS integrated with Vehicle-to-Grid technology in Distribution Networks featuring Distributed Generation and Battery Energy Storage Systems. Simulations on IEEE 33 and 69 bus systems under various scenarios reveal that Vehicle-to-Grid optimizes EVCS power allocation without requiring Battery Energy Storage Systems, ensuring economic and technical efficiency. Simulation results given show that, in the IEEE 33 bus network, peak charging power reaches 0.88 MW at 18:00, while maximum discharging power is 0.643 MW at 8:00, 11:00, and 14:00. Similarly, in the IEEE 69 bus network, discharging peaks at 0.877 MW at 10:00, with charging maxing out at 0.88 MW during late night hours. These findings highlight Vehicle-to-Grid flexibility in adapting to EVCS demands, optimizing costs and system operation.

1. INTRODUCTION

The development of renewable energy and green energy has always been a top priority for governments to achieve sustainable development. This trend has given rise to various models of efficient energy utilization, with the transportation sector serving as a notable example. Electric Vehicles (EVs) have gradually replaced traditional fossil fuel powered vehicles due to their significant advantages. However, the rapid increase in the number of EVs has posed numerous challenges, negatively impact in Distribution Networks (DN) (Nguyen, Tran, and Vo 2019). Issues such as voltage drops, localized overloading, load imbalances, and increased power losses were seriously threatening network stability (K. Kathiravan 2023). Additionally, the EV usage patterns created constraints, as EVs are typically not in continuous operation throughout the day but are concentrated during peak hours (Dai, Liu, and Wei 2019). This results in voltage fluctuations at load nodes, peak power demand, and undesirable reverse power flows at high size Electric Vehicle Charging Stations

(EVCS). These challenges not only presented complex problem for operators and investors but also attracted considerable attention from the scientific research community.

The recent studies have proposed solutions to mitigate the negative impacts of integrating EVCS into DN, such as determining the optimal location for EVCS installation to minimize installation and operational costs. These solutions have also demonstrated practical effectiveness when implemented on the standard IEEE 33 bus system using the JAYA algorithm (Mohanty and Babu 2021). The Arithmetic Optimization Algorithm (AOA) determines the optimal location of EVCS in the DN, aiming to minimize line power losses (K. Kathiravan 2023), the effectiveness of the solution has been demonstrated through various considered scenarios. Additionally, the optimal location of EVCS has been specifically analyzed in cases involving parking lots integrated with smart grids. The specific factors related to power demand have been effectively analyzed and addressed through the application of the Cuckoo Optimization Algorithm (COA) in combination with Monte Carlo simulation techniques (Bai and Qian 2023). The optimization of EVCS placement in a microgrid network has also been proposed using a hybrid algorithm of a Meta-heuristic optimization method based on an extended ant colony, called Mixed Integer Distributed Ant Colony Optimization (MIDACO), with the objective of minimizing generation power (Suresh et al. 2021). Several results demonstrated the superiority of the solution aimed at multi objective optimization, including minimizing active power losses, reactive power losses, and voltage deviation indices. These results have been implemented to achieve optimal power allocation for EVCS in a DN integrated with Distributed Generation (DG), using a hybrid technique that combines Genetic Algorithm and Particle Swarm Optimization (GA-PSO) (Rene, Tounsi Fokui, and Nembou Kouonchie 2023). The proposed solution introduced a dispatched technique for a more holistic approach to optimal power allocation for EVCS systems within a DN integrated with renewable energy and Battery Energy Storage Systems (BESS). This solution considers constraints related to convergence characteristics and load requirements through an improved algorithm, specifically the novel Chaotic Student Psychology Based Optimization (SPBO) and CSPBO algorithms.

Implemented on the IEEE 33 bus system and a real 136 bus distribution network in Brazil, this solution has demonstrated its superiority when addressing the problem with more comprehensive constraints in overcoming the limitations of integrating EVCS.

In addition to location determination and power balancing issues, there have also been proposals for integrating Vehicle-to-Grid (V2G) dispatch techniques to enhance the efficiency of EVCS. For example, the optimization of the location of Electric Vehicle Rapid Charging Stations (EVRCS) in a DN integrated with V2G strategy, aimed at minimizing installation costs and power losses, has been demonstrated as effective when applying the Grey Wolf Optimization (GWO) algorithm in solving the problem (Ahmad et al. 2021).

An advanced study enhancing practicality, an optimization technique based on artificial intelligence for integrating EVCS with the random dispatch of solar energy, has considered installation location constraints through the application of an artificial intelligence based Hybrid Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) approach known as hybrid GA - PSO. This has proposed practical solutions for the distribution and development of EV rollout (Rene and Fokui 2024). The V2G technique has also been considered in scheduling combined with wind energy sources to serve EVCS, with the objective of optimizing the used of renewable energy to minimize power losses. Its effectiveness has been demonstrated through the application of an improved Adaptive Particle Swarm Optimization (APSO) to solve the issues in the study (Shang et al. 2023). The V2G continues to be examined and its impact is evaluated in grids integrated with BESS to demonstrate its effectiveness, considering the constraints related to its influence when applied (Mojumder et al. 2022). The proposed solution with high practical applicability remained the optimal dispatch strategy for EVs in V2G applications. This strategy has shown its superiority when applying an improved hybrid method based on the gradual reduction of swarm size with the Grey Wolf Optimization (GRSS-GWO) algorithm. The study focuses on optimizing operational costs, applying (Eltamaly 2023), and supports voltage regulation in the DN when integrating EVCS (Mazumder and Debbarma 2021).

Although many solutions have been proposed for location determination involving the integration of DG sources, BESS, and V2G techniques, they have yet to explore dynamic DG sources, constrained V2G (within a 24-hour framework), and high voltage stability maintenance to minimize the impact of peak load phenomena. These existing issues must be addressed when developing EVCS systems in practice.

In this study, we proposed a solution to address the aforementioned issues, which includes: optimal power dispatch for EVCS applying V2G with constraints in a DN integrated with DG and BESS, within the 24-hour framework (peak, normal, and off peak hours) as regulated in Vietnam. An improved chaotic Runge Kutta optimizer (CRUN) algorithm, combining chaotic search functions and the RUN algorithm, proposed to enhance the solution search results. The results are simulated using MATLAB R2022a software, with two standard IEEE 33 bus and 69 bus DN used for testing through two scenarios: charging intensity dispatch and V2G dispatch with constraint. These scenarios are compared, analyzed, and proposed for practical implementation.

The main contributions of the study include the following:

- The V2G dispatch problem model with constraints within a 24-hour framework.
- The improvement of the new CRUN algorithm applied to enhance solution efficiency.
- The technique applied to the EVCS problem combined with simulation for result retrieval.
- The proposed solution for the development of EVCS infrastructure.

2. THE PROBLEM MODEL

2.1. The objective function

The proposed solution to address the EVCS dispatch problem in the DN, with voltage constraints ranging from 0.95÷1.05, considers the integration of DG and BESS to minimize power losses during peak hours with parameters such as:

$$F = \min(P_{loss}) \tag{1}$$

Where P_{loss} the power loss of the system.

2.2. Constraints

The conditions and constraints for the problem as follows (Thien Vo Minh, Long Diep, Hoan Van Pham and Ngoc 2025):

\+ *Power balance*

$$P_{SUB} + \sum_{j=1}^{N_{DG,EVCS}} P_{DG,EVCS} = \sum_{j=1}^{N_b} P_L + \sum_{j=1}^{N_{BESS}} P_{BESS} \tag{2}$$

$$Q_{SUB} + \sum_{j=1}^{N_{DG,EVCS}} Q_{DG,EVCS} = \sum_{j=1}^{N_b} Q_L + \sum_{j=1}^{N_{BESS}} Q_{BESS} \tag{3}$$

Where, N_b nodes voltage;

P_{SUB}, Q_{SUB} represent the active power and reactive power supplied by the electrical grid.

P_{DG}, Q_{DG} represent the active power and reactive power generated by the DG.

P_L, Q_L represent the total active and reactive power losses in the entire system.

P_{CS}, Q_{CS} represent the total active and reactive power demand at the EVCS.

P_{BESS}, Q_{BESS} correspond to the active and reactive power supplied by the BESS.

+ *Voltage constraints*

The voltage limits at the load buses are presented as follows:

$$V_i^{\min} \le V_i \le V_i^{\max} \qquad i = 1,2,3...,N_b \qquad (4)$$

$V_i^{\min}$, $V_i^{\max}$ represent the voltage levels below the lower threshold and above the upper threshold, respectively.

+ *Power constraints.*

The power limits are applied to the minimum and maximum values of active power at bus i^{th} as follows:

$$P_{EVCS,i}^{\min} \le P_{EVCS,i} \le P_{EVCS,i}^{\max} \qquad i = 1,2,3...,n \qquad (5)$$

$$P_{DG,i}^{\min} \le P_{DG,i} \le P_{DG,i}^{\max} \qquad i = 1,2,3...,n \qquad (6)$$

$$P_{BESS,i}^{\min} \le P_{BESS,i} \le P_{BESS,i}^{\max} \qquad i = 1,2,3...,n \qquad (7)$$

Where,

$P_{EVCS,i}^{\min}$, $P_{DG,i}^{\min}$, $P_{BESS,i}^{\min}$, are the minimum power required for EVCS, DG, and BESS in the i^{th} buses;

$P_{EVCS,i}^{\max}$, $P_{DG,i}^{\max}$, $P_{BESS,i}^{\max}$, are the maximum power required for EVCS, DG, and BESS in the i^{th} buses;

N, is the number of EVCS, DG, and BESS in the DN.

2.3. The CRUN Algorithm for the EVCS problems

2.3.1. The RUN Algorithm

The RUN algorithm, proposed by Dalia Yousri and colleagues, is inspired by the Runge Kutta method (RKM), which is used to solve ordinary differential equations (Ahmadianfar et al. 2021). The mathematical formula of the RUN algorithm consists of a set of stages, which are detailed as follows:

Initialization stage:

The number of initialization points is based on the limits [LB, UB] within the search space. This process is performed according to the following equation:

$$Z_{i,j} = LB_j + r_1 \times \left(UB_j - LB_j\right), \quad i = 1,2,...,N, \quad j = 1,2,...,D \qquad (8)$$

Where, D represents the range of the given problem. LB and UB are the lower and upper limits of the j^{th} variable in the value set $z_{i,j}; i = 1,2,....N$, N represents the search agent.

Solution update stage:

The RUN algorithm uses a Search Mechanism (SM) based on the Runge Kutta method to adjust the position of the current solution in each iteration, as described below:

$$Z_i = \begin{cases} Z_{CF} + S_{FM} + \mu \times randn \times Z_{mc} & \text{if } rand \le 0.5 \\ Z_{mF} + S_{FM} + \mu \times randn \times Z_{ra} & \text{otherwise} \end{cases} \qquad (9)$$

Where:

$Z_{CF} = \left(Z_c + r \times SF \times g \times Z_c\right)$ and $S_{FM} = SF \times SM \times Z_{mF} = \left(Z_m + r \times SF \times g \times z_m\right) \times Z_{ra} = \left(Z_{r1} - Z_{r2}\right)$ and $Z_{mc} = \left(Z_m - Z_c \times r \in \left[-1,1\right]\right.$ it is an integer used to adjust the direction of the search process. The symbols $g \in \left[0,2\right]$ and $\mu \in \left[0,1\right]$ represent random values. SF denotes the adaptive adjustment factor, which is defined as follows:

$$SF = 2.(0.5 - rand) \times f \qquad (10)$$

Where

$$f = a \times \exp\left(-b \times rand \times \left(\frac{t}{Maxt}\right)\right) \qquad (11)$$

Where *Maxt* is the number of iterations, in the equation (9) Z_c and Z_m has been represented.

$$Z_c = \varphi \times Z_i + (1-\varphi)\times Z_{r1} \quad (12)$$

$$Z_m = \varphi \times Z_b + (1-\varphi)\times Z_{pb} \quad (13)$$

In equation (21), [0,1] represents a random value within the range from 0 to 1. The symbols Z_b and Z_{pb} represent the best performing agent up to the current point and the optimal agent at each iteration, respectively.

The parameter SM, defined in equation (9), is updated according to the following formula.

$$SM = \frac{1}{6}(Z_{RK})\Delta Z; \quad (14)$$

Where:

$$\begin{aligned}
Z_{RK} &= K_1 + 2\times K_2 + 2\times k_3 + k_4\\
k_1 &= \frac{1}{2\Delta Z}(rand\times Z_w - u\times Z_b),\\
k_2 &= \frac{1}{2\Delta Z}(rand\times(Z_w + rand_1\times k_1\times\Delta Z) - U_a\\
k_3 &= \frac{1}{2\Delta Z}\left(rand\times\left(Z_w + rand_1\times\left(\frac{1}{2}k_2\right)\times\Delta Z\right) - U_b\right.\\
k_4 &= \frac{1}{2\Delta Z}(rand\times(Z_w + rand_1\times k_3\times\Delta Z) - U_c\\
U_a &= (u.Z_b + rand_2\times k_1\times\Delta Z))\\
U_b &= \left(u.Z_b + rand_2\times\left(\frac{1}{2}k_2\right)\times\Delta Z\right))\\
U_c &= (u\times Z_b + rand_2\times k_3\times\Delta Z))
\end{aligned} \quad (15)$$

$$\Delta Z = 2\times rand\times|Stp|;$$

Where

$$Stp = rand\times((Z_b - rand\times Z_{avg}) + \gamma) + rand\times (Z_n - rand\times(u-l))\times\exp\left(-4\times\frac{t}{Maxt}\right)$$

Where the value of z_b and z_w are updated as:

If $f(Z_i) < f(Z_{pb})$	$z_b = z_i$ $Z_w = z_{pb}$
else	$z_b = z_{pb}$ $Z_w = z_i$
end	

Solution quality improvement stage:

To enhance the quality of solutions in this stage, various operators are applied to improve convergence speed and reduce the risk of getting stuck in local optimal. This process is described as follows:

$$Z_{new2} = \left\{ Z_{new1} + r\times\left|(Z_{new1} - Z_{avg}) + rand\right| \; if\,\omega < 1 \quad (Z_{new1} - Z_{avg}) + r\times\omega\times Z_{na} \quad otherwise \right. \quad (16)$$

$$\begin{aligned}
Z_{na} &= \left|(u\times Z_{new1} - Z_{avg}) + rand\right|\\
\omega &= rand(0,2)\times\exp\left(-c\left(\frac{t}{\max t}\right)\right),\\
c &= 5\times rand\\
Z_{avg} &= \frac{Z_{r1} + Z_{r2} + Z_{r3}}{3}\\
Z_{new1} &= \beta\times Z_{avg} + (1-\beta)\times Z_b
\end{aligned} \quad (17)$$

In equation (17), $\beta \in [0,1]$ represents a random number and is an integer.

$$\begin{aligned}
Z_{new3} &= (Z_{new2} - r_1\times Z_{new2}) + SF\times D_z,\\
D_z &= (r_2\times Z_{RK} + (v\times Z_b - Z_{new2}))
\end{aligned} \quad (18)$$

Where $V = 2\times r_3$ and r_1, r_2 and r_3 represent random numbers.

2.3.2. The CRUN algorithm

To enhance search efficiency, the algorithm incorporates a chaotic function to adjust positions, expand exploration capabilities, and avoid local optima. The CRUN method operates in two stages: RUN updates the positions of the search agents, followed by CLS examining the neighboring regions to refine potential solutions. From a high-quality solution, CLS generates a better solution using a chaotic map based on the Iterative map, as follows (Thien Vo Minh, 2025):

$$X_{best,k}^{new} = X_{best,k} + (Y_k - 0.5)\times(X_{i,k} - X_{j,k}) \quad (19)$$

In which, $X_{best,k}$ and $X_{best,k}^{new}$ are the positions of the good and best solutions found by CLS in the k^{th} iteration, respectively. Meanwhile $X_{i,k}$ and $X_{j,k}$ are two randomly selected solutions from the population. If the new solution is better, it will replace the current one.

According to formula (18), Y_k is a convergence variable generated using 10 chaotic maps as follows:

$$Y_{k+1} = \mu \times Y_k \times (1 - Y_k) \quad (20)$$

In which, $Y_k \in (0,1)\ \forall k \in \{0,1,2,...\}$ and $\mu \in (0, 4]$.

2.3.3. Applying CRUN to the EVCS problem

Step 1: Initialize the parameters *nP, Max_iter*.

Step 2: Initialize the initial population Z for the CRUN algorithm.

Step 3: Evaluate the fitness of each individual Z_i.

Step 4: Find the optimal value in the population Z_{CF}, Z_{mF}, Z_{mc}.

Step 5: Update individuals Z_i.

If $\omega < 1$ Use the first row of equation (16).

Otherwise $\omega > 1$ Use the second rowof equation (16).

Step 6: Update the parameter ω and adjust based on the chaotic function equation (19).

Step 7: Apply random conditions and update:

If rand < 0.5 update Z_i using equation (17).

If rand $\leq \omega$ update Z_i using equation (18).

Step 8: Check the stopping condition**:**

If $t \leq maxt$, increment t, and repeat from step 3. Otherwise, terminate the algorithm.

Step 9: Display the results and terminate.

3. The simulation results

3.1. The simulation testing

In this section, the improved CRUN algorithm is tested using simulations with 10 different chaotic search functions over a total of 1000 iterations. The objective of this simulation is to minimize power losses, with the IEEE 33 and 69 bus networks used for testing. The results compare and identify the best improved algorithm for application to the problem model. Simulation results clearly indicates that CRUN4 achieves the best convergence characteristic Fig. 1. Therefore, CRUN4 is proposed as a method for solving the EVCS problem.

To further demonstrate the effectiveness of the improved CRUN4 compared to RUN in the EVCS problem, the problem model is implemented in four cases as follows:

- Case 1: Charging intensity dispatch in the 33 bus network.
- Case 2: Charging intensity dispatch in the 69 bus network.
- Case 3: V2G dispatch with constraints in the 33 bus network.
- Case 4: V2G dispatch with constraints in the 69 bus network.

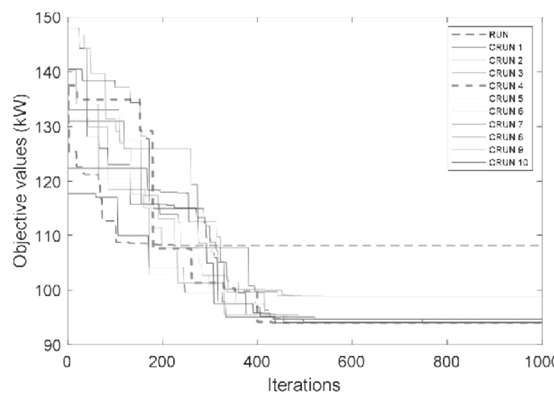

Figure 1. Convergence characteristics of CRUN

Simulation input parameters

The power capacity of 7 EVCS is fixed at nodes 4, 8, 16, 22, 24, 29, and 30 along with 3 DGs at nodes 24, 14, and 30, and BESS at nodes 8 and 27 in the IEEE 33 bus system. For the IEEE 69 bus system, EVCS are placed at nodes 10, 48, 49, 36, 44, 45, and 48, with 3 DGs at nodes 66, 61, and 18, and BESS at nodes 18 and 61 (Rene and Fokui 2024), (Rene et al. 2023), (Mohamed and Kowsalya 2014). This configuration aims to minimize losses, maintain high power quality, optimize energy utilization from DGs, and enhance overall system performance.

The power output profiles of Photovoltaic (PV) and Wind Turbine (WT) sources over a 24-hour period are presented in Table 1 to simulate the dispatchable power capacity. WT and PV sources are referenced based on the following parameter set (Hung and Mithulananthan 2012).

Table 1. Typical power of WT and PV

Hour	PVs	WTs	Hour	PVs	WTs
24-1	0	0.25	12-13	1	0.71
1-2	0	0.235	13-14	0.95	0.805
2-3	0	0.23	14-15	0.83	0.91
3-4	0	0.235	15-16	0.72	0.96
4-5	0	0.22	16-17	0.55	0.86
5-6	0.05	0.225	17-18	0.3	0.81
6-7	0.1	0.19	18-19	0.13	0.7
7-8	0.27	0.17	19-20	0.05	0.585
8-9	0.5	0.25	20-21	0	0.415
9-10	0.7	0.37	21-22	0	0.325
10-11	0.9	0.47	22-23	0	0.29
11-12	0.95	0.62	23-24	0	0.265

3.2. Case 1: Charging intensity dispatch in the 33 bus network

In this case, the EVCS power is fixed according to 3 charging levels, and the DG output is fixed to determine the dispatch power of the BESS in the system (Thien Vo Minh, 2025).

The simulation results in Table 2 show that when the EVCS power intensity changes, the dispatch power of the BESS also fluctuates accordingly. Specifically, as the EVCS power increases, the BESS discharges power to the grid to meet the EVCS load demand, and vice versa. Additionally, the power loss objective value also increases, which demonstrates that the power balance constraints of the problem are effectively met. The three cases also confirm that the improved CRUN4 algorithm performs better than RUN in the search process. The voltage stability constraints at the bus nodes, shown in Figure 2, indicate that in all three cases, the voltage remains within the 0.95÷1.05 pu, range across the entire system.

Table 2. Results across 3 dispatch levels

Charging level	EVCS (MW)	DG (MW)	BESS (MW)				Power loss (kW)	
			RUN		CRUN		RUN	CRUN
Low charging	1.562	0.61	-0.4420	0.1037	-0.4426	0.1038	78.1594	78.1594
Average charging	3.124	0.61	-0.0890	0.5	-0.0895	0.5	101.3493	101.3491
Heavy charging	4.9984	0.61	-0.5	-0.5	-0.5	-0.5	75.7536	75.7536

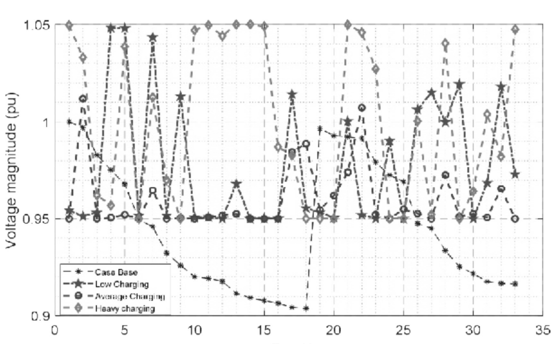

Figure 2. Bus voltage via 3 studied cases

3.3. Case 2: Charging intensity dispatch in the 69 bus network

The EVCS, BESS, and DG parameters are the same as in Case 1; however, the installation node locations change according to the scale of the IEEE 69 bus network, in order to compare the BESS power response in the larger system and check the voltage stability constraints at the bus nodes.

Table 3. Results across 3 dispatch levels

Charging level	EVCS (MW)	DG (MW)	BESS (MW)				Power loss (kW)	
			RUN		CRUN		RUN	CRUN
Low charging	1.562	0.61	-0.2929	-0.3320	0.0241	0.2508	106.1970	106.1966
Average charging	3.124	0.61	0.2033	0.4728	-0.0774	0.3734	107.9950	107.9948
Heavy charging	4.9984	0.61	0.4857	0.4930	0.4516	0.4911	116.9387	116.9385

The same EVCS dispatch power, the larger system shows a significantly lower power loss compared to the 33 bus case. However, the power constraints are still well met, with values at low, medium, and high charging levels of 106.1966, 107.9948, and 116.9385 kW, respectively. Additionally, the BESS system effectively maintains and fulfills the power dispatch task for the EVCS system. The voltage intensity studied meets the constraint values within the range of 0.95 ÷1.05 pu. In this case, the voltage remains stable at the high threshold of 1.05 for most instances, with only a few cases fluctuating at 0.95 pu. This indicates that the constraints of the problem are effectively meeting the objective.

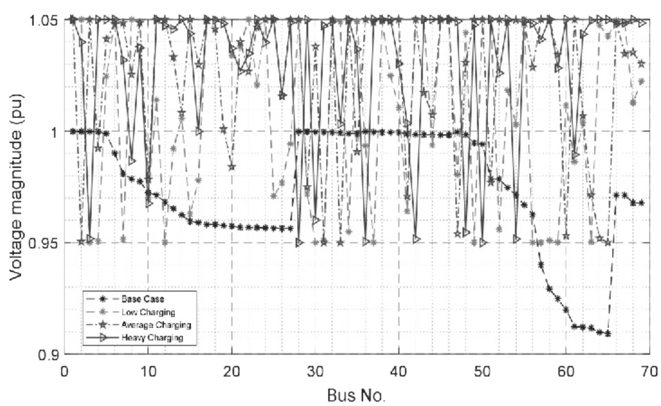

Figure 3. Simulated voltage via 3 cases

3.4. V2G dispatch with constraints in the 33 bus network

Table 4. Constraints for V2G over a 24-hour

Establishing constraints for V2G (MW)							
Time	Low	Normal	High	Normal	High	Normal	Low
	24 1÷3	4÷9	10÷11	12÷16	17÷19	20÷22	23
EVCS 1÷3	0.308	0.308	0.308	0.308	0.308	0.308	0.308
EVCS 4÷7	0.550	0.550	0.550	0.550	0.550	0.550	0.550
V2G intensity with constraints (%)	160/0	100/100	50/160	100/100	50/160	100/100	160/0

In this case, the EVCS power applying V2G dispatches according to the required power, similar to the BESS, with constraints set in Table 4 (during off peak hours, only 160/0% charging is prioritized, during peak hours, 50/160% discharging is prioritized, and during normal hours, charging and discharging are balanced at 100/100%), the simulation searched for optimal values within the 24-hour time frame based on electricity buy and sell costs in Vietnam (Remote and Load 2024). In this case, the DG power is dispatched from Table 1, and BESS is not used.

The simulation results for the 24-hour frame with constraints when applying V2G in the 33 bus network are presented in Figure 4, clearly showed the dispatch capability of the EVCS when V2G is applied. In this case, the DG dispatch capacity primarily covers the EVCS's charging state in all hours. Only during some peak hours, when the EVCS power recharges a significant amount such as 0.88 MW at 18:00, 0.643 MW at 8:00, 11:00, and 14:00, does the system charge. During other hours, no power is discharged to the grid due to the charging priority constraints.

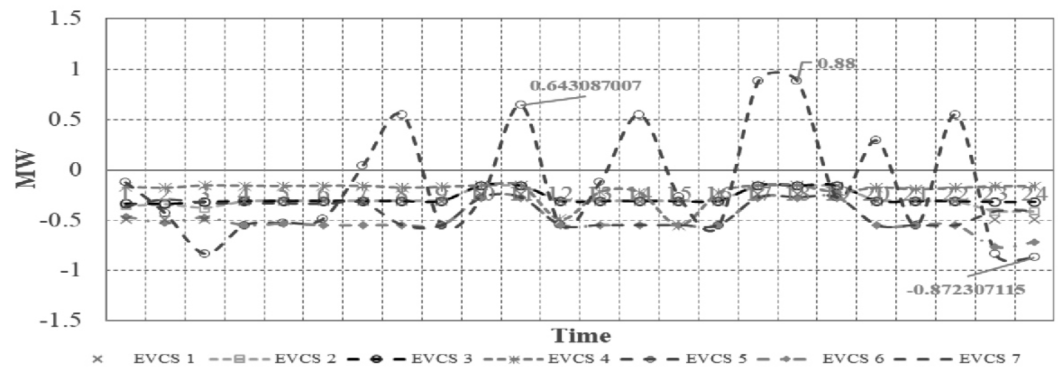

Figure 4. Simulation results of V2G dispatch with constraints on the IEEE 33 bus

3.5. V2G Dispatch with Constraints on the 69 Bus Network

In this case, the constraints are set as in Case 3, with the DG parameters presented in Table 1. The EVCS and DG node locations are the same as in Case 2.

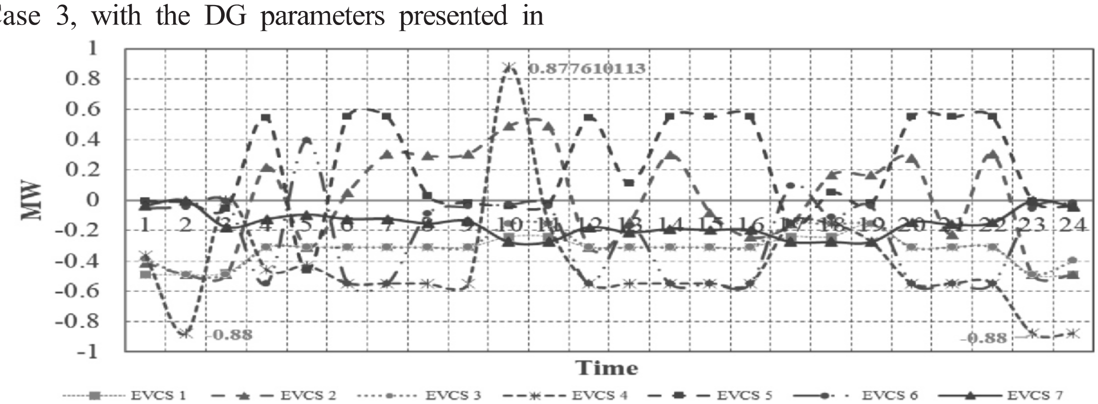

Figure 5. Simulation results of V2G dispatch with constraints on the IEEE 69 bus

The V2G results were more evident when applied to a larger system with high power fluctuation. Therefore, the power fluctuation was more noticeable, with the maximum discharge rate reaching 0.877 MW at 10:00 and the maximum charging rate of 0.88 MW at 2:00, 23:00, and 24:00, in line with the established constraint values. This demonstrated that the V2G technique can be proactively set according to the EVCS system's power scale, providing optimal benefits for investors, operators, and vehicle owners. With this solution, the system does not require the integration of BESS since the V2G technique utilizes the EV battery size for dispatch, resulting in more direct and cost effective benefits. Therefore, we proposed this solution for the development of EVCS systems in practice.

4. CONCLUSION

The simulation results confirm that the improved CRUN4 algorithm outperforms the original RUN when applied to the optimal EVCS dispatch problem with V2G, combined with constraints for DG dispatch and BESS power dispatch. Across four simulation cases, the results demonstrated superior performance and excellent achievement of the problem's objectives and constraints. In Case 4, when V2G dispatch with constraints is applied without BESS, it provides high technical efficiency and optimal investment cost. This solution is also recommended for practical application in planning and developing EVCS infrastructure.

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ĐIỀU ĐỘNG CÔNG SUẤT TỐI ƯU CHO TRẠM SẠC XE ĐIỆN TRONG MẠNG PHÂN PHỐI VỚI HỆ THỐNG PHÁT ĐIỆN PHÂN TÁN VÀ HỆ THỐNG LƯU TRỮ PIN

TÓM TẮT

Sự chuyển đổi năng lượng sạch trong lĩnh vực giao thông đã thúc đẩy sự tăng nhanh xe điện, đòi hỏi phải có những giải pháp hiệu quả cho những trạm sạc xe điện. Nghiên cứu này đề xuất một thuật toán tối ưu được cải tiến, kết hợp hàm tìm kiếm hỗn loạn và thuật toán tối ưu Runge-Kutta, để giải quyết bài toán phân bổ công suất tối ưu cho các trạm sạc xe điện tích hợp công nghệ phương tiện kết nối lưới điện trong mạng điện phân phối có hệ thống phát điện phân tán và hệ thống lưu trữ pin. Những mô phỏng trên hệ thống 33 nút và 69 nút dưới nhiều kịch bản khác nhau cho thấy công nghệ phương tiện kết nối lưới điện có thể tối ưu hóa việc phân bổ công suất cho các trạm sạc xe điện mà không cần sử dụng hệ thống lưu trữ pin, đảm bảo tính hiệu quả về kinh tế và kỹ thuật. Kết quả mô phỏng chỉ ra rằng, trong mạng lưới 33 nút, công suất sạc đỉnh đạt mức 0,88MW vào lúc 18 giờ, trong khi công suất xả tối đa là 0,643MW vào các thời điểm 8 giờ, 11 giờ và 14 giờ. Tương tự, trong mạng lưới 69 nút, công suất xả đỉnh đạt mức 0,877MW vào lúc 10 giờ, với công suất sạc tối đa là 0,88MW vào các giờ đêm muộn. Những kết quả này nhấn mạnh tính linh hoạt của công nghệ xe đến lưới điện trong việc đáp ứng nhu cầu của các trạm sạc xe điện, đồng thời tối ưu hóa chi phí và vận hành hệ thống.

Từ khóa: *BESS, DG, EVCS lập lịch, V2G cho EV, tối ưu Runge Kutta*