International Journal of Advanced Computer Technology
ISSN: 2319-7900 www.ijact.org Volume 13, Issue 2, April 2024

Optimized Scheduling of Plug-In Hybrid Electric Vehicles with Distributed Generation: Adapting to Various Vehicle Trip Models

Amit Kumar Kamat, Alka Thakur
Department of Electrical Engineering, SSSUTMS, Sehore, India

Abstract

This study presents a novel approach for optimizing the scheduling of plug-in hybrid electric vehicles (PHEVs) integrated with distributed generation systems. As PHEVs gain importance in the transition to sustainable transportation, effective energy management strategies are critical for maximizing their benefits. This research introduces an optimization model that considers various vehicle trip profiles, including daily commuting, long-distance travel, and variable trip frequencies. The model integrates distributed generation sources such as solar and wind energy to enhance charging efficiency and minimize operational costs. The performance of the proposed scheduling strategy was evaluated across different trip scenarios, focusing on key metrics such as energy utilization, cost savings, and emissions reduction using simulations. Results indicate that tailoring PHEV scheduling to specific trip profiles significantly enhances overall system efficiency, particularly when combined with renewable energy sources. This study contributes to the advancement of smart grid applications and highlights the importance of dynamic scheduling in fostering the adoption of PHEVs within sustainable energy systems.

Keywords: Plug-in Hybrid Electric Vehicles (PHEVs), Distributed Generation, Energy Management, Smart Grid, Renewable Energy Integration

1. Introduction

1.1 Background

Plug-in hybrid electric vehicles (PHEVs) represent a pivotal advancement in automotive technology, combining the features of traditional internal combustion engine (ICE) vehicles with electric propulsion systems. PHEVs are equipped with both an internal combustion engine and a rechargeable electric battery, allowing them to operate in either electric-only mode or hybrid mode, where the engine and electric motor work in tandem. This dual capability provides drivers with flexibility and a greater range of operational choices compared to fully electric vehicles (EVs).

One of the primary advantages of PHEVs is their potential to reduce greenhouse gas (GHG) emissions. Transportation is a significant contributor to global emissions, accounting for approximately 14% of all GHG emissions. By transitioning to PHEVs, which can run on electricity generated from renewable sources, the carbon footprint associated with personal transportation can be substantially diminished. When charged from renewable energy sources such as solar or wind, PHEVs can achieve near-zero emissions during operation, offering a cleaner alternative to conventional vehicles. Additionally, PHEVs can alleviate some of the challenges associated with fully electric vehicles, such as range anxiety and the fear of running out of battery power without access to charging stations. By providing an alternative fuel source, PHEVs ensure that drivers can complete longer trips without the need for frequent charging, making them a practical choice for a wider range of consumers.

Moreover, PHEVs can play a crucial role in the integration of renewable energy into the transportation sector. Their ability to charge during off-peak hours and respond to price signals from the grid allows for optimized energy usage. This not only supports grid stability but also contributes to lower electricity costs for consumers, particularly when paired with distributed generation systems. As cities and countries strive to meet ambitious emissions reduction targets and improve air quality, PHEVs stand out as a viable transitional technology. Their design and operational flexibility position them as an essential component of a sustainable transportation ecosystem, bridging the gap between traditional fuel sources and the future of fully electrified transportation. PHEVs are significant in the effort to reduce transportation-related emissions. Utilizing both electric and conventional powertrains provides a versatile solution that can lead to substantial environmental benefits while addressing consumer concerns about range and charging infrastructure. The integration of PHEVs with distributed generation further amplifies these benefits, fostering a cleaner, more sustainable energy landscape.

1.2 Overview of distributed generation and its role in energy systems

Distributed generation (DG) refers to the production of electricity from decentralized energy sources located close to the point of consumption rather than from large, centralized power plants. This approach includes a variety of technologies and sources, such as solar photovoltaic (PV) systems, wind turbines, combined heat and power (CHP) systems, biomass generators, and small-scale hydroelectric plants. As energy demands evolve and the need for sustainable practices increases, DG has emerged as a crucial component of modern energy systems.

1.2.1 Features of Distributed Generation

Distributed Generation (DG) offers several key features that contribute to a more efficient and resilient energy system. One of the primary advantages is its proximity to load; DG installations are often located close to the end-users they serve, which reduces transmission losses and improves the reliability of the power supply. This proximity also enables faster response times to changes in energy demand. Another important feature is the diversity of energy sources that DG encompasses. It includes both renewable and non-renewable sources, with a strong emphasis on renewable technologies. This variety enhances the resilience and adaptability of the energy system, making it less dependent on fossil fuels.

Additionally, DG systems are modular and scalable, meaning they can be deployed in smaller, incremental units that can be expanded as demand grows or as technology evolves. This flexibility is especially valuable when integrating new technologies into existing infrastructure. Finally, grid independence is another key feature, as DG can provide energy security and resilience, particularly in remote areas or during grid outages. Microgrids, which are localized energy systems that can operate autonomously, exemplify how DG enhances energy reliability and offers a more secure energy future.

1.2.2 Role in Energy Systems

Distributed Generation (DG) offers several benefits that contribute to a more sustainable, reliable, and efficient energy system. One of the key advantages is its role in enhancing energy security. By diversifying energy sources and reducing dependence on centralized power plants, DG strengthens the energy supply, mitigating the risks associated with fuel supply disruptions and improving grid stability. DG also plays a crucial role in supporting renewable energy integration. It helps facilitate the incorporation of renewable sources into the energy mix by generating electricity closer to the point of use, which helps balance supply and demand, particularly during peak periods when renewable generation is high. Another significant benefit of DG is its ability to reduce transmission losses. Since DG sources are often located near consumers, less energy is lost during transmission, leading to increased efficiency. This reduction in losses contributes to lower overall energy costs and decreases the environmental impacts associated with electricity transmission. DG also empowers consumers by allowing them to become active participants in the energy market. Technologies like rooftop solar panels enable consumers to generate their electricity, potentially lowering energy bills and enhancing energy independence. DG systems also support demand response initiatives, where advanced technologies allow for real-time adjustments to energy generation based on demand signals. This flexibility helps improve overall grid efficiency and reliability. Lastly, DG has notable environmental benefits. By prioritizing renewable energy sources, it reduces greenhouse gas emissions. It lowers local air pollutants, which is particularly significant in urban areas, where air quality is a pressing public health concern.

1.3 Research contribution

This research aims to address the existing gaps by simultaneously analyzing mobility patterns achieved through the introduction of a multi-zonal distribution system. Additionally, the correlation among the elements of driving patterns is examined. The study investigates the optimal placement and utilization of renewable energy sources, followed by the implementation of the proposed Two-layer Particle Swarm Optimization (TPSO) algorithm. This approach aims to minimize the total operational cost and reduce system losses in less computational time. The specific objectives of this research are as follows:

1. To propose a simple, non-iterative solution, called the Loss Reduction Index (LRI), for optimally selecting locations that minimize system losses when placing units.
2. To implement an optimization algorithm to minimize the total operational cost of scheduling Plug-in Hybrid Electric Vehicles (PHEVs) at charging stations.
3. To analyze the system's performance by considering variations in PHEV types, the percentage of miles driven in all-electric range, travel distances, and customer charging preferences.
4. To optimally place and utilize renewable energy sources for the scheduling of PHEVs.

2. Related Work

Mahmud et al. [19] discuss all of the aspects related to EV charging, energy transfer, and grid integration with distributed energy resources in the Internet of Energy (IoE). More recently, Das et al. [20] presented an evaluation of how future-connected EVs and autonomous driving would affect EV charging and grid integration. Other important EV charging issues are those that are related to battery management, as well as battery health and lifetime estimations since they are key factors in increasing the battery lifetime. Li et al. [21] review recent advancements in Big Data analytics to allow for data-driven battery health estimation. More specifically, they classify them in terms of feasibility and cost-effectiveness and discuss their advantages and limitations.

Liu et al. [22] go one step further and propose a machine learning-enabled system that is based on Gaussian process regression (GPR) to predict lithium-ion battery ageing. Finally, other approaches instead explore advanced fault diagnosis techniques since battery faults can potentially cause performance degradation [23]. The authors Huang et al. (2015) assumed a distribution network with high penetration of PHEVs. They stated that the PHEV charging scheduled during the night results in less operational cost. The results are interesting and show different kinds of expected charging schedules. However, scheduling all the PHEVs during the night may result in peak load at night. Also, this study focuses on locating the charging stations that differ from the locations already assigned to their work.

Alonso et al. (2014) analyzed the effect of smart charging in the distribution system. The authors also analyzed the base case scenario. The smart charging schedule is applied based on the genetic algorithm. However, this model does not take electricity prices into account. Rahman et al. (2015) to intelligently optimize the charging of plug-in hybrid electric vehicles. A game theory analysis was done by Malandrino et al. (2015) to analyze the charging stations selected by electric vehicle drivers. Yang et al. (2015) adopted Ant Colony Optimization (ACO) to model the load and identify electric vehicle charging stations. However, these methods require a large number of iterations to ensure algorithm convergence, which may reduce the algorithm's computational efficiency. Rahman et al. (2015) and hybrid optimization methods are increasing in order to optimize dissimilar charging infrastructure parameters. An optimization approach defined with the aim of curtailing the cost of charging enhances the charging of electric vehicle behaviour. The results show that linear programming is good enough to solve the problem of electric vehicle charging optimization. An optimum approach based on Discrete Particle Swarm Optimization (DPSO) to find the appropriate charging and discharging times for electric vehicle fleet. Suitable charging infrastructure development and management can pledge a larger penetration of PHEV. Thus, from the past literature regarding the optimization area, it seems that the application of various optimization methods is still in the premature stage. Pallonetto et al. (2016) determine the optimal location of CS by taking into account the high penetration of photovoltaic panels. Stochastic loads and stochastic generation of the photovoltaic panels are used. The model focuses on minimizing the objective function of power loss and voltage deviation. However, the author aims to install only one charging station in the distribution network, and the behaviour of drivers is also not taken into account.

3. Types of Vehicles

In this section, three different types of vehicles are discussed in detail.

3.1 Conventional Vehicle

Conventional vehicles typically operate with an efficiency of only 30%, meaning that 70% of the energy is lost during the conversion process. However, with the introduction of hybrid vehicles, these energy losses have been significantly reduced.

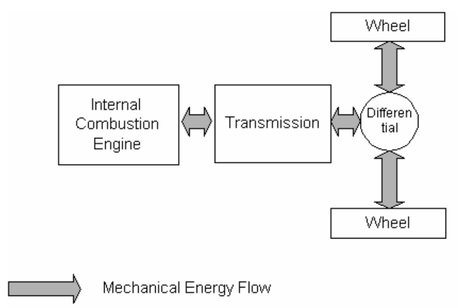

Fig.1 Conventional vehicle block diagram

3.2 Hybrid Electric Vehicle

By means of the regenerative braking system, the braking energy is saved in the battery. When lower torque or velocity is needed, the excess energy produced by the ICE is stored in the battery. In contrast, the additional required energy can be extracted from the battery. This will lead to more efficient operation of ICE with reduced emissions.

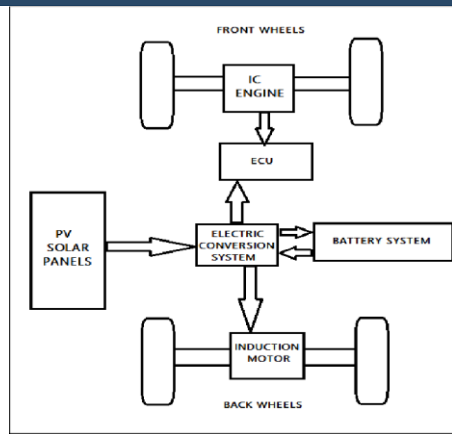

Fig. 2 Block diagram of hybrid vehicle

3.3 Plug-in Hybrid Electric Vehicles (PHEVs)

A Plug-in Hybrid Electric Vehicle (PHEV) combines an internal combustion engine with an electric drive system. PHEVs are equipped with large-capacity batteries that an external power source can charge. An increase in the All-Electric Range (AER) of PHEVs leads to improved efficiency. While PHEVs share a similar structure with hybrid electric vehicles, they offer the added benefit of grid charging capability. As a result, PHEVs can help reduce emissions in both residential and commercial areas. However, major challenges remain, including high fossil fuel consumption and the depletion of fossil fuel resources. The transition from fossil fuel-powered vehicles to PHEVs is not only beneficial for the automotive sector but also has significant implications for the grid sector.

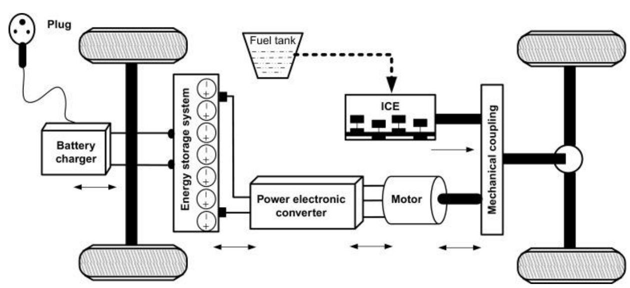

Fig 3 Block diagram Plug-in Hybrid Electric Vehicles

4. Charging Methods

The PHEVs can be charged from the electricity grid by plugging into an electrical outlet. A suitable infrastructure is essential for introducing any new technology. Fortunately, the existing grid infrastructure can be used depending on the charging rate. However, an additional investment is probably necessary when fast charging is preferred or when the penetration of PHEVs is high.

4.1 Slow Charging

Slow charging is charging at a lower power rating. The vehicles are connected to the low-voltage grid. The slow charging could occur in small or medium enterprises or at the parking lot of large companies during the day. The slow charging method comprises three charging levels. A standard outlet has a voltage level of 230 V, a maximum current of 20 A, and a maximum output of 4.6 kW.

4.2 Normal Charging

The electric outlet with a maximum current of 32A, which has a maximum power output of 7.4kW, is involved in normal charging. Some parking lots are equipped with a phase connection with a line voltage of 230 V or 400V. The 230 V connections have a rating of 32A and 6kW, and the 400V connection has a rating of 20A and a power output of 13.8 kW. Higher charging levels are also possible, and thus, the preference for charging level depends on the customer.

4.3 Fast Charging

Increasing the power of the charger outlet reduces the charging time. For a battery pack of 15 kWh in 5 minutes, a charging power of 180 kW is required. Thus, a charging station (CS) of 15 PHEVs that can be charged in 30 minutes requires a charging rate of 30 kW. Possibly, the fast charging stations are connected directly to the medium-voltage level. Furthermore, this connection requires large investments and heavy disaster. The main advantage of fast charging is that it lowers the range anxiety and the barrier to purchasing a PHEV. With the PHEVs with ICE and plugging-in capability, it is possible to drive a longer distance, which makes them more attractive.

5. Proposed Methodology

The goal of finding the optimal location for DG and CS in the distribution system is implemented by using the power loss calculated using the backwards-forward sweep method based on optimal load flow. The flow chart is shown in Figure 4. The smart charging strategy to minimize the TOC is implemented using the Two-layer Particle Swarm Optimization (TPSO). The dominant solution matrix is mapped to the search space. Each PHEV is viewed as a dimension in the search space, and the sequence starting point is the coordinates of the specific dimension.

5.1 Two-layer Particle Swarm Optimization (TPSO)

In terms of problem description, in optimization-based scheduling, it is necessary to take into account accurate information about PHEVs, available resources, location of charging station, and available battery capacity. This information enables us to determine the required battery charge for each period to guarantee the final desired SOC. Due to the network size and huge elements, the optimization turns into a large combinational problem with different specifications and requirements. This fact makes these two layers of PSO essential. The charging and discharging patterns of PHEVs can be classified into different patterns. For example, if a PHEV requires 7 hours for charging and 2 hours of discharging, then one possible sequence could be "11-1-111111", and the total possible sequence for a PHEV is $C\ 2 = 36$. The thirty-six sequences form the feasible solution of a particular PHEV. The search space of the optimization problem includes a feasible solution with all possible strategy vectors for each PHEV, and it is very large. Thus, adopting random initialization as in standard PSO would fail to find the optimal solution.

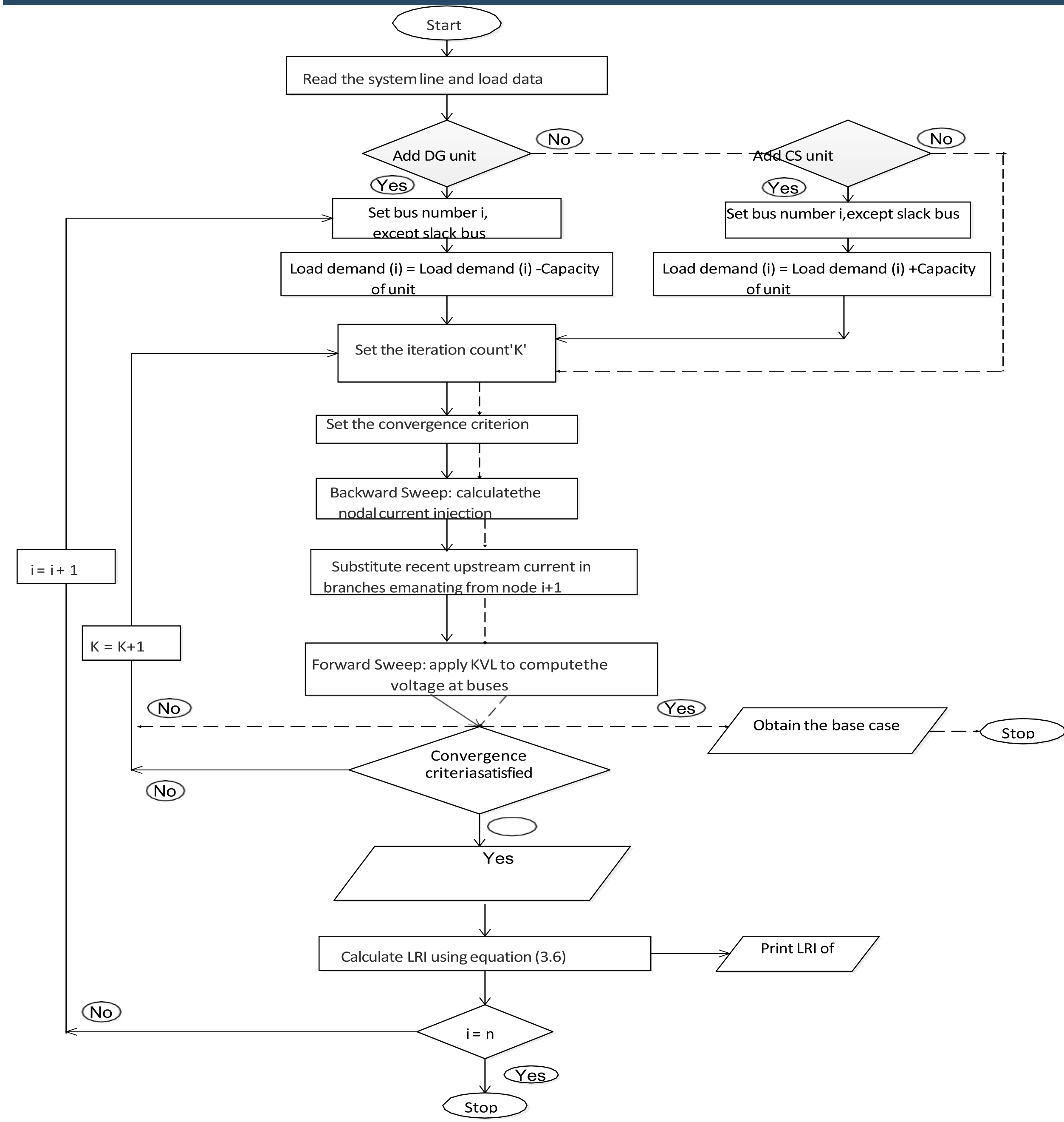

Fig. 4 Flowchart of implementing proposed LRI.

As frequent switching between the charging and discharging modes greatly affects the battery life span, the strategy with minimum switching forms the dominant solution. In the upper layer of TPSO, such dominant solutions are extracted from the feasible solution. Thus, in the dominant solution matrix, a new Sv vector of each PHEV is created by eliminating the rows in a feasible solution that involves frequent switching. Based on this dominant solution, the proposed TPSO algorithm finds the optimal charging sequence in the lower layer.

The computational procedure of the TPSO algorithm is elaborated as follows

step 1. Initialize all the particles in the search space. The position and velocity of the particles are set randomly within the dominant search space.

step 2. Evaluate the fitness of each particle with respect to the objective function.

step 3. If it is the better solution for this particle, then store its position as Pbest for this specific particle. Then, update the velocity and position and compute the fitness value. If it is better than the current Pbest, store its position as a new particle unchanged. Pbest position; otherwise, keep the original

step 4. Check the fitness value of each particle. If it is the best solution of all the particles, then store its position as the Gbest position.

step 5. If the stopping criterion is satisfied, then go to step 6; otherwise, go to step 2.

step 6. Output the optimal solution.

6. Result and Discussion

The first test system under study is the IEEE 33-bus radial distribution network, which consists of thirty-three buses with a total active load of 3715 kW and a reactive load of 2300 kVAR. The second test system is the IEEE 69-bus radial distribution feeder, which includes one main branch and seven laterals. This system has a total active load of 3801.9 kW and a reactive load of 2694.1 kVAR. In the baseline scenario, it is assumed that there are no Plug-in Hybrid Electric Vehicles (PHEVs) or Distributed Generation (DG) units in the system. The power loss and voltage profile values obtained in the base case represent the system's conditions before adding any units to the IEEE 33-bus and IEEE 69-bus distribution systems. This base case scenario is then compared with the system after adding the new units. For both test systems, the analysis includes power loss, voltage profile, energy cost, and peak-to-average energy ratios. The key difference between the two systems is that the first test system is used to analyze PHEVs with the same battery capacity. In contrast, the second system analyzes PHEVs with batteries of different capacities.

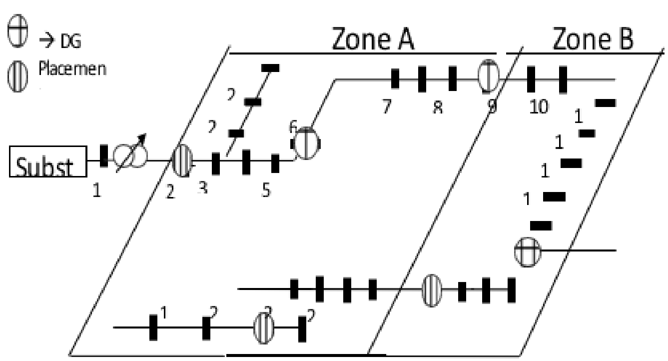

Fig. 5 Multi-zone 33-bus distribution system

6.1 IEEE 33-bus radial distribution system

The proposed multi-zone 33-bus radial distribution system is shown in Figure 5. Each node is considered to be a customer node point. From Figure 5.5, it can be observed that the distribution network consists of three zones: A, B, and C respectively. The optimal location for adding the DG and CS units is evaluated using the proposed LRI calculation.

6.1.1 Power loss reduction in 33-bus microgrid system

Selecting a suitable location for integrating DG and CS units is of utmost importance. With the proposed approach, the LRI is calculated using equation (5.9). The LRI value of each load bus for selecting a suitable location for the CS and DG unit is shown in Table 1.

Table 1 LRI for placing the CS and DG units.

Bus No.	LRI	Rank	Location Identification	Bus No.	LRI	Rank	Location Identification
2	0.0054	1	CS – Zone A	18	0.324	32	DG –Zone C
3	0.0321	6	-	19	0.0072	2	-
4	0.0474	8	-	20	0.0224	3	-
5	0.0631	10	-	21	0.0262	4	CS –Zone B
6	0.0984	12	DG –Zone A	22	0.032	5	-
7	0.1042	14	-	23	0.0411	7	-
8	0.1477	17	-	24	0.0586	9	-
9	0.1722	20	-	25	0.0711	11	-
10	0.1973	24	DG –Zone B	26	0.1034	13	-
11	0.2018	25	-	27	0.1101	15	-
12	0.2101	26	-	28	0.1359	16	-
13	0.244	27	-	29	0.1558	18	-
14	0.257	28	-	30	0.1673	16	CS – Zone C
15	0.2693	29	-	31	0.187	21	-
16	0.2841	30	-	32	0.1926	22	-
17	0.3103	31	-	33	0.1972	23	-

As loss reduction is one of the most broadly accepted indexes in power systems, it is involved in evaluating the suitable location. The minimum value of LRI shows the suitable location for placement. A DG and a CS are located in each zone, as shown in Figure 6. The optimal location of DGs and CSs in each zone is evaluated, and the results are tabulated as shown in Table 2. From Table 2, it can be observed that the base case network loss is 210.9991 kW, whereas the loss increases to 257.1981 kW with the addition of CS; this negatively affects the performance of the system. Upon installing DG units of suitable size, the network loss is considerably reduced by 54.04%, though CS persists in the same location as earlier. This shows that integrating both the DGs and CSs in each zone improves the system's performance.

6.1.2 Peak to average energy ratio (PAR) evaluation in 33-bus microgrid system

The load curve is flattened to the maximum extent as the Distributed Generations (DGs) contribute to both the system and vehicular loads. The optimally scheduled power curves, showing the contributions of wind, solar, and fuel cell energy in zones A, B, and C, respectively, are illustrated separately in Figures 6(a), 6(b), and 6(c). By calculating the peak and average vehicular and system load, the PAR is derived. To better see its significant impact, the PAR in the DG integrated system is compared with the one without it. It is shown in Table 5.4 and compared with the Ant Colony Optimization (ACO) algorithm in the existing literature.

Table 2 Power loss with suitable location of DG and CS

Parameters	**Zone A**	**Zone B**	**Zone C**
DG type	Wind (AC output)	Solar (DC output)	Fuel cell (DC output)
DGs' capacity range (kW)	200 – 1000	200 – 1000	1– 300
Location	@6	@10	@18
CS type	Level 2: AC charging	Level 3: DC charging	Level 3: DC charging
CSs' capacity range (kW)	200 – 1000	200 – 1000	200 – 1000
Location	@2	@21	@30
Power loss (kW) Loss reduction	Base case: 210.9991 w/o DG and w/ CS: 118.8308 w/ DG and CS: 257.1981 54.04 %		

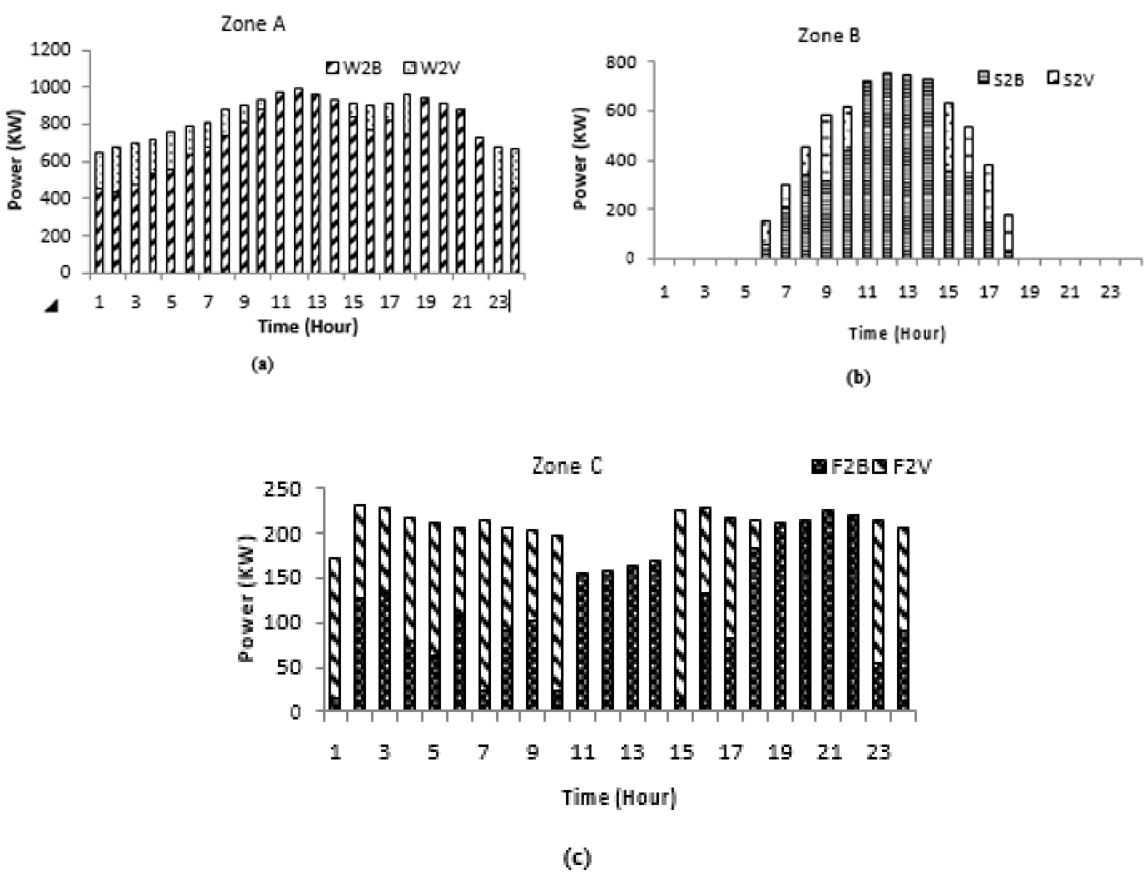

Figure 6 Contribution of DG in energy exchange (a) Zone A, (b) Zone B and (c) Zone C

Table 3 PAR minimization in 33-bus multi-zone

	Scenario 1			Scenario 2		
	TPSO	PSO	ACO*	TPSO	PSO	ACO*

PAR	1.9859	1.9928	1.9962	0.6837	0.6837	0.9683
Convergence iteration	43	47	39	40	43	38
Computational time	10.79	10.76	14.79	9.83	10.67	13.43

Table 3 depicts that an integrated DG source minimizes the peak load of the multi-zone distribution system. The maximum DG power is allowed in scenario two; consequently, the total power demand is greatly decreased, resulting in PAR minimization.

7. Conclusion

This research investigates the optimal integration of renewable energy in charging Plug-in Hybrid Electric Vehicles (PHEVs). Due to the increased power demand for charging PHEVs at charging stations (CS), the network experiences higher power losses compared to the base case. This indicates that adding a CS unit to an existing distribution system increases system losses. However, by incorporating suitable Distributed Generation (DG) units along with the CS unit, it is possible to reduce the losses in the network. The proposed approach is also shown to improve the voltage profile, enhancing the stability of the system to a considerable extent. The smart scheduling scheme, using the Two-layer Particle Swarm Optimization (TPSO) algorithm, demonstrates powerful optimization capabilities by achieving the minimum Total Operational Cost (TOC) while ensuring the satisfaction of new constraints such as battery capacity, mobility patterns, and charging infrastructure. The Peak-to-Average Ratio (PAR) values are significantly reduced with the integration of DG sources, showcasing the effectiveness of the smart scheduling scheme in utilizing renewable energy sources efficiently. The study also investigates the optimal location selection for CS and DG units using the Loss Reduction Index (LRI). The integration of renewable sources in the distribution system leads to a reduction in both total operational costs and system power loss. Therefore, it is recommended that renewable energy sources for PHEV scheduling be integrated into charging stations. Future work could explore the integration of renewable energy forecasting techniques, such as solar irradiance and wind speed forecasting, into the first layer of PSO. Accurate forecasting would enable better planning for renewable energy dispatch. Additionally, future studies could focus on large-scale simulations involving thousands of PHEVs and various renewable energy sources to assess the scalability and efficiency of the two-layer PSO approach in real-world conditions.

Reference

[1] Rahman, I, Vasant, PM, Singh, BS and Abdullah-Al-Wadud, M 2015, ‘On the performance of accelerated particle swarm optimization for charging plug-in hybrid electric vehicles’, Alexandria Engineering Journal, vol. 55, no. 1, pp. 419-426.

[2] Rahman, I, Vasant, PM, Singh, BS, Abdullah-Al-Wadud, M and Nadia, A 2016, ‘Review of recent trends in optimization techniques for plug-in hybrid, and electric vehicle charging infrastructures’, Renewable and Sustainable Energy Reviews, vol. 58, pp. 1039-1047.

[3] Chan, C.C. The state of the art of electric, hybrid, and fuel cell vehicles. Proc. IEEE 2007, 95, 704–718. [CrossRef]

[4] Albatayneh, A.; Assaf, M.N.; Alterman, D.; Jaradat, M. Comparison of the Overall Energy Efficiency for Internal Combustion Engine Vehicles and Electric Vehicles. Environ. Clim. Technol. 2020, 24, 669–680.

[5] OECD iLibrary. Non-Exhaust Particulate Emissions from Road Transport: An Ignored Environmental Policy Challenge; Technical Report; OECD Publishing: Paris, France, 2020. Available online: https://doi.org/10.1787/4a4dc6ca-en (accessed on 22 February 2021).

[6] Blázquez Lidoy, J.; Martín Moreno, J.M. Eficiencia energética en la automoción, el vehículo eléctrico, un reto del presente. Econ. Ind. 2010, 377, 76–85.

[7] Nissan. Nissan Leaf. Available online: https://www.nissan.co.uk/vehicles/new-vehicles/leaf/range-charging.html (accessed on 20 February 2021).

[8] Tesla. Tesla Official Website. 2019. Available online: https://www.tesla.com/en_EU/supercharger (accessed on 21 February 2021).

[9] Berjoza, D.; Jurgena, I. Effects of change in the weight of electric vehicles on their performance characteristics. Agron. Res. 2017, 15, 952–963.

[10] Yong, J.Y.; Ramachandaramurthy, V.K.; Tan, K.M.; Mithulananthan, N. A review of the state-of-the-art technologies of electric vehicles, its impacts and prospects. Renew. Sustain. Energy Rev. 2015, 49, 365–385. [CrossRef]

[11] Habib, S.; Kamran, M.; Rashid, U. Impact analysis of vehicle-to-grid technology and charging strategies of electric vehicles on distribution networks—A review. J. Power Sources 2015, 277, 205–214. [CrossRef]

[12] Liu, L.; Kong, F.; Liu, X.; Peng, Y.; Wang, Q. A review on electric vehicles interacting with renewable energy in smart grid. Renew. Sustain. Energy Rev. 2015, 51, 648–661. [CrossRef]

[13] Vasant, P.; Marmolejo, J.A.; Litvinchev, I.; Aguilar, R.R. Nature-inspired meta-heuristics approaches for charging the plug-in hybrid electric vehicle. Wirel. Netw. 2019, 26, 4753–4766. [CrossRef]

[14] Shuai, W.; Maillé, P.; Pelov, A. Charging electric vehicles in the smart city: A survey of economy-driven approaches. IEEE Trans. Intell. Transp. Syst. 2016, 17, 2089–2106. [CrossRef]

[15] Tan, K.M.; Ramachandaramurthy, V.K.; Yong, J.Y. Integration of electric vehicles in smart grid: A review on vehicle to grid technologies and optimization techniques. Renew. Sustain. Energy Rev. 2016, 53, 720–732. [CrossRef]

[16] Hu, J.; Morais, H.; Sousa, T.; Lind, M. Electric vehicle fleet management in smart grids: A review of services, optimization and control aspects. Renew. Sustain. Energy Rev. 2016, 56, 1207–1226. [CrossRef]

[17] Mahmud, K.; Town, G.E.; Morsalin, S.; Hossain, M. Integration of electric vehicles and management in the internet of energy. Renew. Sustain. Energy Rev. 2018, 82, 4179–4203. [CrossRef]

[18] Das, H.; Rahman, M.; Li, S.; Tan, C. Electric vehicles standards, charging infrastructure, and impact on grid integration: A technological review. Renew. Sustain. Energy Rev. 2020, 120, 109618. [CrossRef]

[19] Li, Y.; Liu, K.; Foley, A.M.; Zülke, A.; Berecibar, M.; Nanini-Maury, E.; Van Mierlo, J.; Hoster, H.E. Data-driven health estimation and lifetime prediction of lithium-ion batteries: A review. Renew. Sustain. Energy Rev. 2019, 113, 109254. [CrossRef]

[20] Liu, K.; Li, Y.; Hu, X.; Lucu, M.; Widanage, W.D. Gaussian Process Regression With Automatic Relevance Determination Kernel for Calendar Aging Prediction of Lithium-Ion Batteries. IEEE Trans. Ind. Inform. 2020, 16, 3767–3777. [CrossRef].

[21] Thakur, Alka, S. Wadhwani, and A. K. Wadhwani. Motor current signature analysis as a tool for induction machine fault diagnosis. International Journal of Computer Science and Information Technology Research 3.3 (2015): 309-313.

[22] Parsai, Neha, Alka Thakur, and M. dan Tech. , PV Curve-Approach for Voltage Stability Analysis., International Journal of Information Technology and Electrical Engineering 4.2 (2015):

a. 46-52.

[23] Thakur, Alka, Sulochana Wadhwani, and Vandana Sondhiya. Health monitoring of rotating electrical machine using soft computing techniques: A Review., International Journal of Scientific and Research Publications 3.11 (2013): 1-3.

[24] Alka Thakur, S. Wadhwani and A.K. Wadhwani A Review On Induction Motor Fault Diagnostic Techniques Elixir International Journal 93C (2016) 39829-39833 Accepted: 25 April 2016;.

[25] Alonso, M, Amaris, H, Germain, J.G, and Galan, JM 2014, 'Optimal charging scheduling of electric vehicles in smart grids by heuristic algorithms', Energies, vol. 7, no.4, pp. 2449

[26] Yang, S, Wu, M, Yao, X and Jiang, J 2015, 'Load modelling and identification based on ant colony algorithms for EV charging stations', IEEE Transactions on Power System, vol. 30, no. 4, pp. 1997-2003.

[27] Pallonetto, F, Oxizidis, S, Milano, F and Finn, D 2016, 'The effect of time-of-use tariffs on the demand response flexibility of an all-electric smart- grid-ready dwelling', Energy Building, vol. 128, pp. 56-67.