Optimum Operation of Unbalanced AC Microgrid using PEVs and DERs Scheduling with Time-Varying Loads

YOUSAF, Zeeshan, NADEEM, Muhammad Faisal, AHMED, Ali, NOUMAN, Muhammad and AKMAL, Muhammad <http://orcid.org/0000-0002-3498-4146>

IET Smart Grid

WILEY

The Institution of Engineering and Technology

ORIGINAL RESEARCH OPEN ACCESS

Optimum Operation of Unbalanced AC Microgrid Using PEVs and DERs Scheduling With Time-Varying Loads

Zeeshan Yousaf[1] | Muhammad F. Nadeem[2] | Ali Ahmed[3] | Muhammad Nouman[2] | Muhammad Akmal[4]

[1]Faisalabad Electric Supply Company, Faisalabad, Punjab, Pakistan | [2]Department of Electrical Engineering, University of Engineering and Technology Taxila, Taxila, Punjab, Pakistan | [3]Department of Electrical Engineering, Australian National University, Canberra, Australia | [4]School of Engineering and Built Environment, Sheffield Hallam University, Sheffield, UK

Correspondence: Muhammad Akmal (m.akmal@shu.ac.uk)

Received: 9 January 2026 | **Revised:** 28 February 2026 | **Accepted:** 20 March 2026

Keywords: distributed power generation | electric vehicles | microgrid | nanogrid | optimisation | peer-to-peer energy trading

ABSTRACT

The studies pertaining to scheduling of plug-in electric vehicles (PEVs) and distributed energy resources (DERs) in unbalanced AC microgrids (MGs) usually consider time varying lumped load models. This may lead to unrealistic values and inappropriate system support as unbalanced MGs have different loading levels for each phase. Therefore, in this paper optimal scheduling of DERs and PEVs is performed in 3-phase unbalanced AC MG whilst considering different per-phase loading levels of time-varying voltage dependent (TVVD) load models. At first, the impact of lumped loading and per phase loading approach on DERs scheduling in unbalanced AC MG is investigated for TVVD load models. Then, PEVs are connected in presence of DERs whilst considering per phase loading in case of all TVVD loads to minimise the generation cost and system losses. Enhanced grasshopper optimization algorithm (EGOA) is utilised to evaluate the optimum performance of unbalanced AC MG. The results demonstrate that the values obtained through a per-phase loading approach are more realistic and PEVs integration has a significant impact on cost reduction.

1 | Introduction

Recently, Renewable Energy Resources (RERs) have attained much attention due to the limitations associated with fossil fuel-based power generation (i.e., depletion, increased cost and negative environmental impacts) [1, 2]. The global renewable energy installation has reached 3094 GW in 2021 [3] and it is expected that nearly 300 GW of renewable capacity will be added in 2022 [4]. Moreover, according to the market forecast report of the International Energy Agency (IEA), the global renewable energy-based electricity potential will rise up to 4800 GW by the year 2026 [5]. Besides many advantages posed by RERs, they are highly intermittent, unreliable and have large capital cost.

However, different types of DERs (Distributed Energy Resources), PHEVs (Plug-in Electric Vehicles) and ESSs (Energy Storage Systems) are installed in MG to handle load and source uncertainties. AC MGs may consist of 3-phase balanced or unbalanced networks (UBN). Unsymmetrical electrical loads and distribution lines that are not properly transposed may cause unbalancing in the MG network [6]. A balanced MG network can be investigated on a per phase basis but for unbalanced MG, there is a need to analyse each phase separately. In [7–9], Day-ahead scheduling of RERs has been presented with the aim of generation cost minimisation whilst considering RERs and demand uncertainty in balanced MG. In [10–14], DERs optimal scheduling in unbalanced AC MG is performed under generation and load uncertainty whilst considering constant power lumped load profile. It is not necessary that a lumped load profile depicts the actual scenario of a 3-phase unbalanced system.

Recently, time varying voltage dependent (TVVD) load models have been considered in a few studies [15–19] for performance assessment of balanced distribution systems (DS). However, practical distribution systems are usually unbalanced; therefore, the outcome of referred studies may be misleading and not realistic. Therefore, for effective planning of AC MG, there is a need to investigate the impact of TVVD load models in unbalanced DS.

The integration of Plug-in electric vehicles (PEVs) in presence of different DERs and time-varying loads is a promising solution for MG peak demand shaving [20, 21]. However, their integration in AC MGs is a challenging task, because their higher levels of penetration and inappropriate charging/discharging periods may negatively affect the MG operation and control [22, 23]. In [24], optimal scheduling of PEVs charging/discharging in presence of RERs in BDS is implemented for constant power loads. Congestion management strategy for DERs, PEVs and time-varying loads in BDS have been presented for cost-benefit and carbon reduction in [17]. The authors in [25], investigate the impact of high penetration of PEVs in presence of Distributed Generator (DG) in BDS whilst considering time-varying constant power loads.

The coordination approach of PEVs charging with DGs, ESSs and utility grid in distribution MG is proposed in [26], for cost-benefit analysis whilst considering constant voltage dependent load. The authors in [27], solved a multi-objective problem through optimal interaction of PEVs and PV to minimise cost and power losses in 3-phase UDN. In [28], two-stage volt-var optimisation strategy for integration PV and PEVs in UBN is presented to minimise generation cost. Optimal day-ahead scheduling of PEVs in UBN is presented in [29], for minimisation of power loss and generation cost. These studies [25–29], have considered either voltage-dependent or time varying lumped loads for optimal scheduling of DERs and PEVs in unbalanced 3-phase MGs, which may result in misleading computations [30, 31]. Moreover, the mentioned studies have not considered the TVVD load model for different types of loads (i.e., residential, commercial, industrial and mixed). Therefore, this study presents the optimal scheduling of DERs and PEVs in 3-phase unbalanced MG whilst considering TVVD load models. Furthermore, instead of adopting lumped loads, the time varying loading levels of each phase is considered independently. The comparative analysis of the proposed methodology with recent literature is summarised in Table 1. The originality of this research work is as under:

TABLE 1 | Comparative analysis of recent studies and the proposed work.

Paper	Unbalanced	EV scheduling	TVVD load	Per-phase
This paper	✔	✔	✔	✔
[32]	✔	✔	✖	✖
[33]	✔	✔	✖	✔
[34]	✔	✔	✖	✖
[35]	✔	✔	✖	✔

- Optimal scheduling of DERs and PEVs in unbalanced AC MG using time varying voltage dependent loads.
- Time varying loading levels of each phase is considered instead of adopting lumped load models for unbalanced AC MGs.
- Application of Enhanced Grasshopper (EG) algorithm for optimum scheduling of DERs and PEVs in unbalanced AC MGs.

2 | System Modelling

2.1 | Load Modelling

The power intake of AC MG largely depends upon the type of connected load, as its variation changes system operating conditions. The normalised daily load profile of TVVD (i.e., industrial, commercial and residential) loads is shown in Figure 1 [36]. The TVVD load models are dependent on both voltage and time as shown in the following equation [37].

$$P_a(t) = P_{la}(t) * V_a^{ni}(t) \tag{1}$$

$$Q_a(t) = Q_{la}(t) * V_a^{nj}(t) \tag{2}$$

Here P_a and Q_a are active and reactive power, P_{la} and Q_{la} are demands and V_a is the nominal voltage at node a. The voltage properties of connected load are described via ni and nj and their values are mentioned in Table 2 [38, 39].

2.2 | Wind Power

The characteristic of wind speed at a particular location modelled using Weibull distribution. The probability density of wind speed is given below [40].

$$f_{\varpi} = \frac{\kappa_{\varpi}}{\delta_{\varpi}}\left(\frac{\varpi}{\kappa_{\varpi}}\right) \times exp\left[\frac{\varpi^{\kappa_{\varpi}}}{\delta_{\varpi}}\right] \tag{3}$$

Where κ_{ϖ} and δ_{ϖ} are shape and scale index and ϖ represents the wind speed. The hourly generated power of WT based on wind speed data is computed as under:

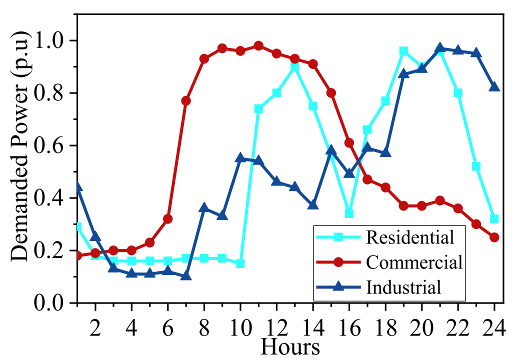

FIGURE 1 | TVVD hourly demand.

TABLE 2 | TVVD voltage exponent's values.

Demand	*ni*	*nj*
Residential	0.92	4.04
Commercial	1.51	3.4
Industrial	0.18	6
Constant	0	0

$$P_t(\varpi) = \begin{cases} 0 & 0 \le \varpi \le \varpi_{c\_in} \\ P_k \times \left(\dfrac{\varpi_{c\_out} - \varpi}{\varpi_{c\_in} - \varpi_k}\right) & \varpi_{c\_in} \le \varpi \le \varpi_k \\ P_k & \varpi_k\ \varpi \le \varpi_{c\_out} \\ 0 & \varpi \ge \varpi_{c\_out} \end{cases} \quad (4)$$

Where, $\varpi_{c\_out}, \varpi_{c\_in}$ and ϖ_k is cut-out, cut-in and rated wind speed of WT and $P_t(\varpi)$ is the output power.

2.3 | Photovoltaic Output

The output power of solar PV depends upon solar irradiance and environmental temperature. Therefore, in this paper the PV output is modelled using normal distribution. The rated power of a PV module is determined under standard test conditions (STC), but in actual scenario it is different. Hence, PV output is calculated using the following equation [40].

$$PV_P = PV_{STC} \times \frac{I_{\text{measured}}}{I_{STC}} \times (1 + \zeta(T_m - T_s)) \quad (5)$$

Where PV_P *and* PV_{STC} is the output and rated power of PV module, I_{measured} and I_{STC} are the measured and STC irradiance values, ζ is temperature coefficient and T_m and T_s are module cell and air temperature, respectively.

2.4 | Modelling of Plug-In Electric Vehicles

Electric vehicles play a critical role in pulling down environmental pollution. The PEVs act as a consumer in charging mode and they act as an electrical source in discharging mode. PEVs can join or leave the distribution system in $[x, y]$ time intervals depending upon the consumer behaviour. Mathematical modelling of PEV is as follows [41–43].

$$soc_t^{PEV} = \begin{cases} E_{Int}^{PEV} + \sum_{i=1}^{t}\left(\mu_{Ch}^{PEV} \times P_t^{PEV_{ch}} - \dfrac{P^{PEV_{dch}}}{\mu_{dCh}^{PEV}}\right), \forall t \le x-1 \\ E_{Int}^{PEV} + \sum_{i=1}^{t}\left(\mu_{Ch}^{PEV} \times P_t^{PEV_{ch}} - \dfrac{P^{PEV_{dch}}}{\mu_{dCh}^{PEV}}\right) - E_{\text{outside}}^{t}, \\ \forall t \ge y+1 \end{cases} \quad (6)$$

$$P_{PEV}^{\min} \le P_{PEV}^{ch/dch} \le P_{PEV}^{\max} \quad (7)$$

$$E_{24}^{PEV} = E_0^{PEV} \quad (8)$$

$$E_{x-1}^{PEV} = E_{\max}^{PEV} \quad (9)$$

3 | Problem Formulation

The objective function (OF) considered in this study comprises three sub-objective functions. These sub-objective functions include costs of utility, DERs generation and PEVs charging/discharging. The mathematical representation of combined OF is as follows:

$$min.\ OF = C^{DERs} + Cost^{PEV} + C^{\text{Utility}} \quad (10)$$

Where C^{DERs} is the operational cost of DERs, Cost^{PEV} is PEVs charging/discharging cost and C^{Utility} is cost of energy provided by the utility grid. The mathematical expressions of these are as follows:

$$C^{\text{Utility}} = \sum_{h=1}^{24} P_h^{\text{utility}} \times \xi_h \quad (11)$$

Where P_h^{utility} is the power purchased from the utility grid and ξ_h is the price of energy in corresponding operation hour.

$$Cost^{PEVs} = \left(\begin{aligned} &\sum_{m=1}^{NPEVs}\sum_{h=1}^{24}\Big[\beta \times PEV_{m,h}^{Ch/dCh} \\ &+\left(PEV_{m,h}^{Ch} \times R^{Ch} - PEV_{m,h}^{dCh} \times R^{dCh}\right)\Big]\end{aligned}\right) \quad (12)$$

Here, β and $R^{\text{dCh/CH}}$ are the coefficients of PEVs operation. DERs operation cost includes fuel cost, environment protection cost and operation & maintenance cost and is computed through following quadratic cost function [12, 13, 44].

$$\begin{aligned} C^{DERs} &= \sum_{h=1}^{24}\sum_{m=1}^{NDER} \alpha_m PDER_{m,h}^2 + \beta_m PDER_{m,h} + \gamma_m \\ m &= 1, 2.....NDERs \end{aligned} \quad (13)$$

Where α, β and γ are cost coefficients with constant values depending upon the type of DER [12]. The following constraints are considered for optimal operation of AC MG:

- The capacity of each DER must be within the upper and lower generation limits.

$$P_{min}^{KW} \le P^{PV} \le P_{max}^{KW} \quad (14)$$

$$P_{min}^{KW} \le P^{WIND} \le P_{max}^{KW} \quad (15)$$

$$P_{min}^{KW} \le P^{CHP} \le P_{max}^{KW} \quad (16)$$

- The generated power must be equal to summation of load demand and active power loss.

$$\begin{aligned} &\sum_{m=1}^{NDER} P_{m,t} + P_{\text{grid},t} + \sum\nolimits_{n=1}^{NPEV} P_{n,t}^{ch} \\ &= P_{\text{Load},t} + \sum_{n=1}^{NPEV} P_{n,t}^{dch} + P_{\text{Loss},t} \end{aligned} \quad (17)$$

- The SOC of PEVs must be limited to their minimum and maximum charging and discharging capacities:

$$0 \le E_t^{PEV_{ch}} \ge E_{\max,ch}^{PEV} \tag{18}$$

$$0 \le \mathrm{E_t^{PEV_{dch}}} \ge \mathrm{E_{max,dch}^{PEV}} \tag{19}$$

Penalty factor (pf) technique is used to handle power mismatch constraint [7]. After the introduction of pf, the objective function (OF) is as follows.

$$min.\ OF = \left(\begin{array}{l} C^{DERs} + C^{\mathrm{Utility}} + Cost^{PEVs} \\ +pf \left(\begin{array}{l} \sum\limits_{m=1}^{NDERs} \sum\limits_{n=1}^{NPEVs} \left(+ P_{PEVn} \right) \\ +P_{\mathrm{utility}} - P_{\mathrm{Load}} \ - P_{\mathrm{Loss}} \end{array} \right) \end{array} \right) \tag{20}$$

Where P_{LOSS} is power transmission and distribution loss (T&D) and calculated as.

$$P_{\mathrm{LOSS}} = P_{\mathrm{TLoss.}} + P_{Dis} \tag{21}$$

Where $\mathrm{P_{Dis}}$ is distribution loss in feeder lines and computed through three phase unbalance load flow analysis using forward backward sweep method [45]. The $\mathrm{P_{TLoss.}}$ is Power transmission loss and calculated using Kron's loss formula using below equation [46].

$$P_{TLOSS} = \sum_{m=1}^{NDERs} \sum_{n=1}^{NDERs} P_n P_m B_{mn} \tag{22}$$

Where $\mathrm{P_n}$ & $\mathrm{P_m}$ are power generated from main and corresponding DERs and B_{mn} is the power loss coefficient [46]. The Enhanced Grasshopper Optimization Algorithm (EGOA) is utilised to optimise the OF developed in the proposed methodology. The complete computational method using EGOA is presented in Figure 2.

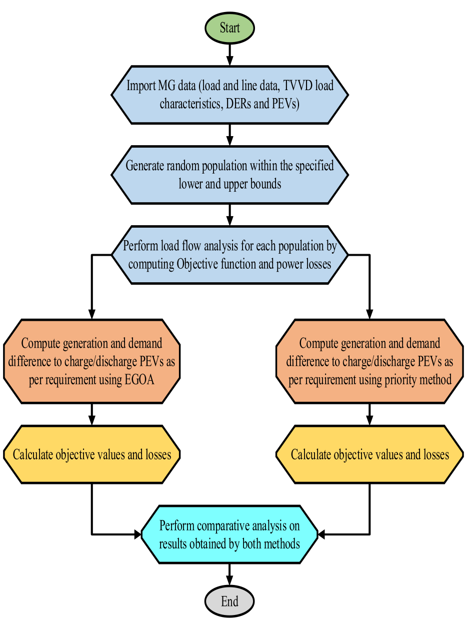

FIGURE 2 | Flow chart of proposed methodology.

4 | Case Study

The proposed AC MG consists of 200 PEVs, 02 units of PV-based DER, 03 units of wind energy-based DER and 01 CHP power plant as shown in Figure 3 [12]. Hourly prices of electricity utility are shown in Figure 4 [47], whereas the cost coefficients and maximum capacity of DERs are taken from [13]. The maximum hourly capacity of renewable energy-based DERs is computed through wind speed and irradiance data [12], as shown in Figure 5. The proposed scheme is implemented on an unbalanced IEEE 37 node feeder [48].

The maximum active and reactive power demand of IEEE 37 feeders is 2.457 MW and 1.201 MVAr respectively. It is supposed that AC MG parking has a PEVs charging station facility where working staff and others can park their PEVs for active power charging/discharging purposes. The type of PEVs, their appearance in the MG and operating coefficient, are selected from [17]. The maximum charging and discharging of PEVs batteries are restricted to 0.9 of their maximum capacity.

It is supposed that in case of all TVVD loads, the load connected to each bus of MG is of the same type that is, whilst studying residential TVVD load model, the load connected to each bus is of residential type and same for the rest of load models except in mixed model where node 701-718 are residential, 720-731 commercial and 732-744 are industrial types.

5 | Results and Discussion

Two case studies are developed in this paper to evaluate proposed methodology. The results obtained for each of the case studies by applying EGOA are discussed in this section.

5.1 | Case Study I

In this case, comparison of lumped load and each phase loading (without considering PEVs) for DERs scheduling to reduce power losses and cost of generation with all TVVD loads is discussed. Recent literature pertaining to scheduling of DERs in unbalanced AC MG considered lumped loading [10–14], which leads to inappropriate outcomes of generation cost, T&D power losses and system loading. The comparison of lumped load with each phase loading of unbalanced AC MG for all TVVD models is shown in Table 3. It depicts that the overall generation cost, T&D power losses and total system loading increases for each phase loading as compared to lumped loading. The maximum increase in generation cost is obtained for the constant load model (6.80%) followed by mixed (4.65%), residential (4.93%), commercial (3.82%) and industrial load (2.67%).

Although the system losses and loading in residential model is highest (22.3%) followed by mixed (21.75%), industrial (21.7%), commercial (21.02%) and constant (18.28%) load model, respectively. This shows that for realistic scenarios of generation cost, T&D power losses and total system loading of unbalanced AC MG each phase loading have significant importance and must be considered for better outcomes of the integration of RERs and PEVs.

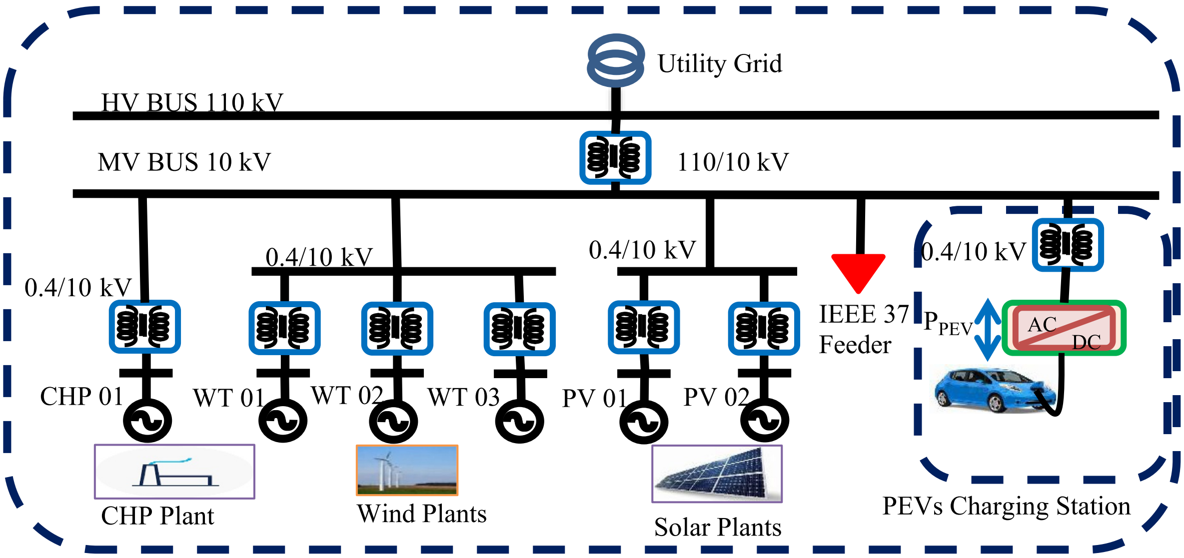

FIGURE 3 | Micro grid structure.

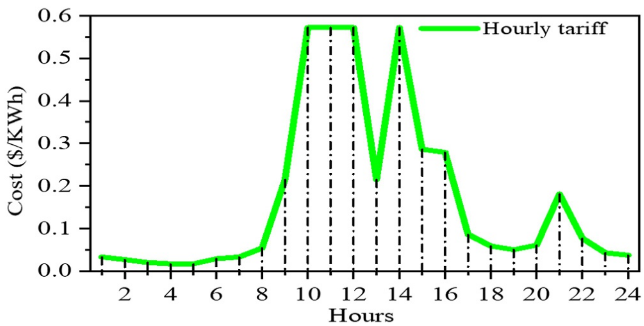

FIGURE 4 | Hourly utility price.

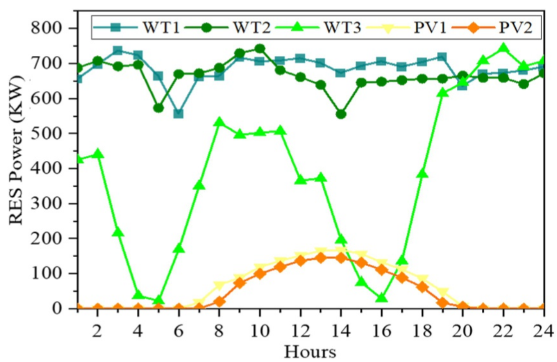

FIGURE 5 | RES hourly generating capacity.

5.2 | Case Study-II

The optimal scheduling of DERs with PEVs for each phase loading of all TVVD load models is presented in this case study.

5.2.1 | Optimum Scheduling of DERs and PEVs

The sudden variations in power demand and uncertainties associated with DERs in MGs may affect the optimum performance of the system. Therefore, the charging/discharging pattern of PEVs should follow the time varying characteristics of MG demand and generation. The PEVs in the presence of different DERs are integrated into AC MG to store low price energy in off-peak hours and curtailment of expensive power share in peak intervals.

TABLE 3 | Comparison of lumped and each phase loading.

	Cost ($)		Losses (kW)	
Demand type	Lumped load	Non lumped	Lumped load	Non lumped
Constant	2724	2923	6091	7454
Residential	983	1034	2192	2820
Commercial	1208	1256	2708	3429
Industrial	986	1013	2137	2729
Mixed	1435	1505	3259	4165

5.2.2 | Comparative Study Between Priority and EGOA Based Scheduling

The hourly PEVs charging/discharging patterns depend upon equality constraints (Equation 17) between available generation and power demand. Firstly, the PEVs integrated into the power system without optimisation technique using priority-based generation scenarios of different DERs and in the second case, the EGOA scheduled the DERs optimally in the presence of PEVs. The results obtained are depicted in Figures 6–10. The analysis of results reveals that in simple priority-based case, the DERs and PEVs charging/discharging are random in nature and the share of CHP is more in peak hours as shown in Figures 6a and 7a which increases the total cost, whereas in EGOA scheduled case, the EGOA optimally allocate DERs and PEVs charging/discharging whilst fulfiling the system demand in terms of available generation as shown in Figures 6b and 7b, respectively.

Hence, the hourly and overall generation cost reduces from 1054$ to 957$ and system losses from 2.69 to 2.56 MW and this

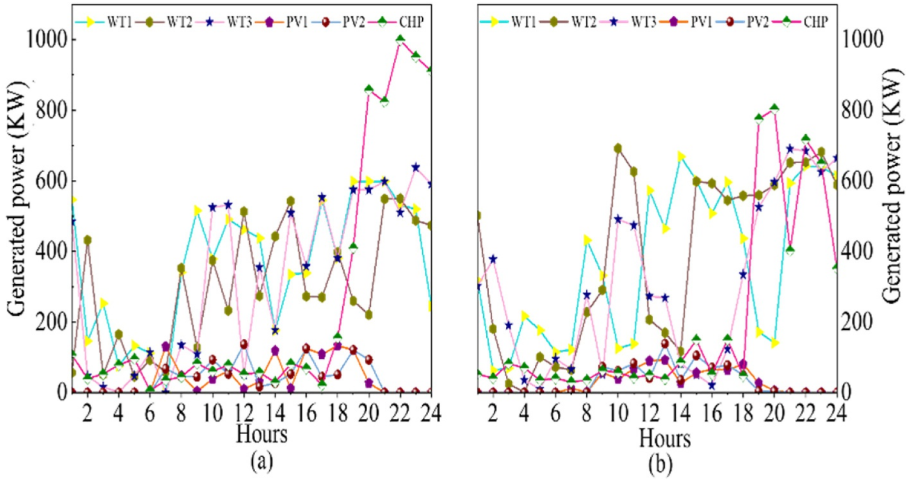

FIGURE 6 | DERs generation (a) with priority and (b) with EGOA for a mixed TVVD load model.

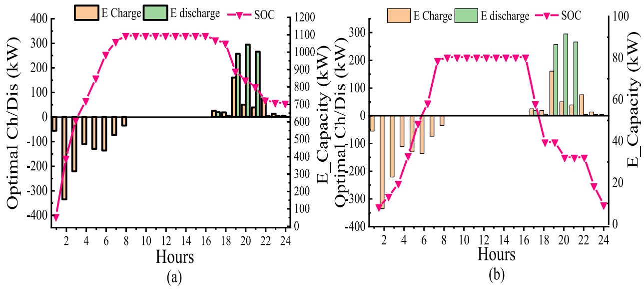

FIGURE 7 | PEVs charging/discharging (a) with priority and (b) with EGOA for a mixed TVVD load model.

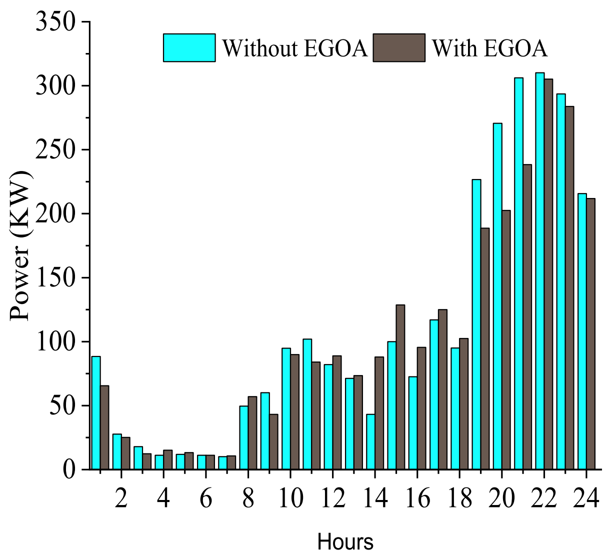

FIGURE 8 | Hourly power losses using both methods for a mixed TVVD load model.

decreasing trend is significant in peak hours as can be observed from Figures 8 and 9, respectively. This intensifies that optimal scheduling of DERs and PEVs is an essential element of power system operation to obtain maximum benefits. Furthermore, it is evident from Figure 10a,b that the power mismatch is more in the priority case, especially during peak hours in comparison with EGOA.

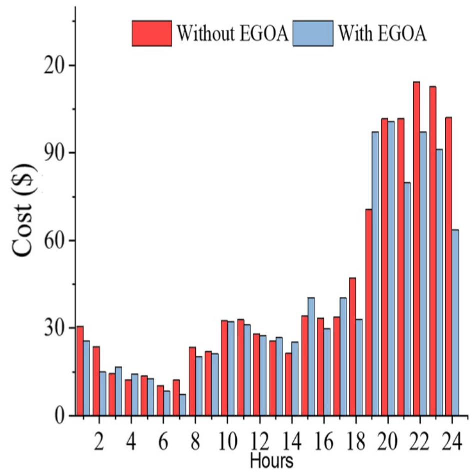

FIGURE 9 | Hourly operation cost using both methods for a mixed TVVD load model.

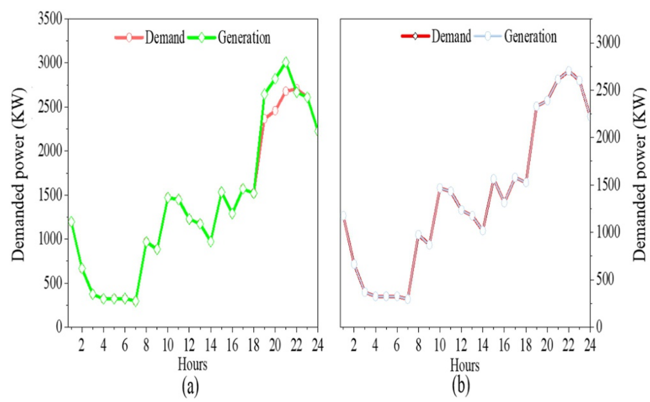

FIGURE 10 | Power mismatch (a) with priority and (b) with EGOA for a mixed TVVD load model.

Furthermore, the PEVs charging/discharging patterns in both cases are shown in Figure 7a,b, which depicts that in priority case only 25% of PEVs storage is used in discharging whereas the EGOA optimally scheduled the charging/discharging of PEVs. Therefore, the EGOA is used for optimal scheduling of DERs and PEVs.

5.2.3 | EGOA Based Scheduling

The maximum obtained generation in MW of RERs-based DGs using EGOA are 2.01, 1.94, 1.98, 1.949 and 2.14 at 21, 11, 22, 22 and 11 h of the day for residential, commercial, industrial, mixed and constant load models, respectively. The hourly generation of DERs for all TVVD loads without considering PEVs is presented in Figure 11. The CHP-based generation in MW without considering PEVs is 0.93, 0.031, 0.94, 0.94, 0.77 whereas with PEVs integration, the CHP-based generations in MW are 0.49, 0, 0.40, 0.61 and 0.44 at 20, 17, 21, 21 and 19 h of the day for residential, commercial, industrial, mixed and constant load models, respectively.

This demonstrates that costly generation through CHP-based DGs is curtailed which enables maximum usage of cost-effective RERs and PEVs in all TVVD loads. The curtailment in CHP-based generation is minimum in the commercial load model as peak demand in this load model occurred between 09:00a.m. to 04:00p.m. and PEVs are not available at this time for discharging.

The utility grid is only required for a constant load model whereas in all others TVVD load models have sufficient generation to meet the load demand. The PEVs are in charging mode from 01:00 a.m. to 08:00 a.m. when low price energy is available in bulk and in discharging mode in peak hours from 16:00 p.m. to 24:00 p.m. in all TVVD models. The maximum charging in MW of PEVs are 0.89, 0.88, 0.86, 0.84 and 0.08 for constant, mixed, residential, industrial and commercial load, respectively for 24 h of the day. Furthermore, the maximum discharging patterns of PEVs occurred in different hours of the day as per the AC MG time-varying demand requirements for all TVVD models as shown in Figure 12.

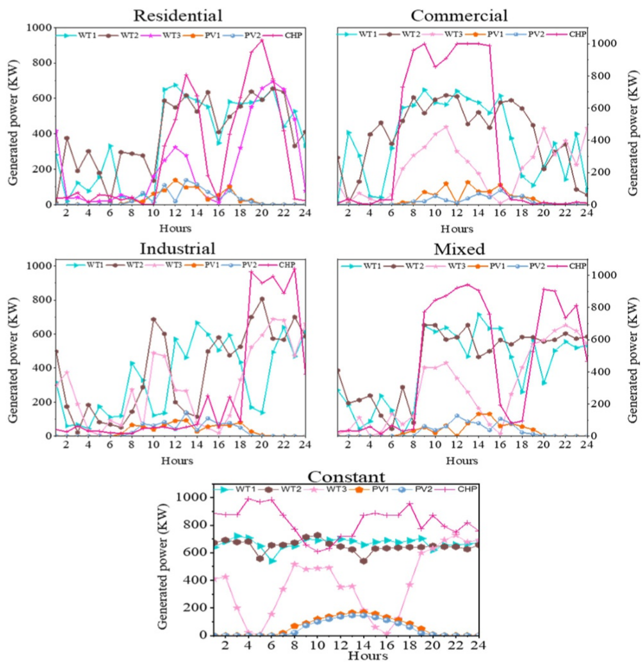

FIGURE 11 | DERs generation in all TVVD without PEVs.

The PEVs have the least charging/discharging in the commercial model because of low demand when PEVs are available whereas the PEVs have peak hours when PEVs are absent. Although the PEVs have the least charging/discharging capacity in commercial demand, their capacities are enough to curtail CHP-based generation to zero from 5:00 p.m. to 12:00 a.m. as shown in Figure 13. This demonstrate that proposed PEVs integration strategy has significant cost reduction through shifting of peak demand (16–24 h) to off-peak intervals (01–08 h) of the day for all TVVD models except commercial

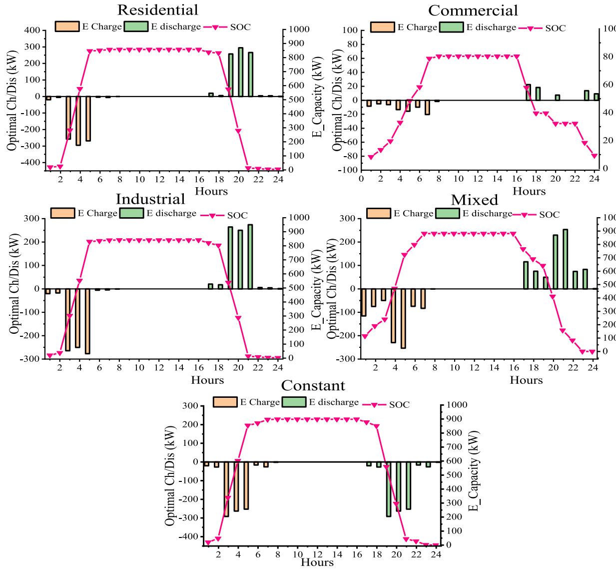

FIGURE 12 | PEVs charging/discharging.

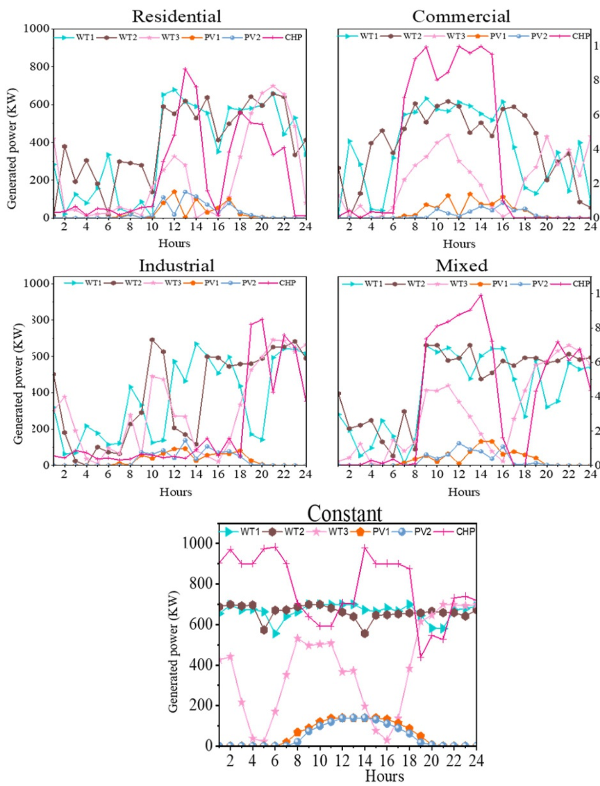

FIGURE 13 | DERs generation in all TVVD with PEVs.

demand which enable the MG operator as well as the customer to achieve significant cost benefits and peak system load reduction.

5.2.4 | Generation Costs and Power Losses

The hourly generation cost for each TVVD load model with and without PEVs is presented on Figure 14. It is evident from Figure 1, that the power demand starts increasing at hour-7 and is maximum till hour-24. Similarly, the share of CHP is also increasing in the same time duration, which leads to hourly cost increment for all TVVD models as shown in Figure 14. Similarly, the hourly variation in T&D losses with and without PEVs is presented in Figure 15. It is clear from this figure that in the presence of PEVs T&D losses are reduced significantly for industrial and mixed load models in hours 17–24 when PEVs discharging capacity is maximum. Although in other hours of the day and load models a considerable reduction in T&D losses are also observed.

It is clear from Table 4 that a significant reduction in total generation cost and T&D power losses obtained with the optimal scheduling and integration of PEVs in the presence of DERs for all TVVD models.

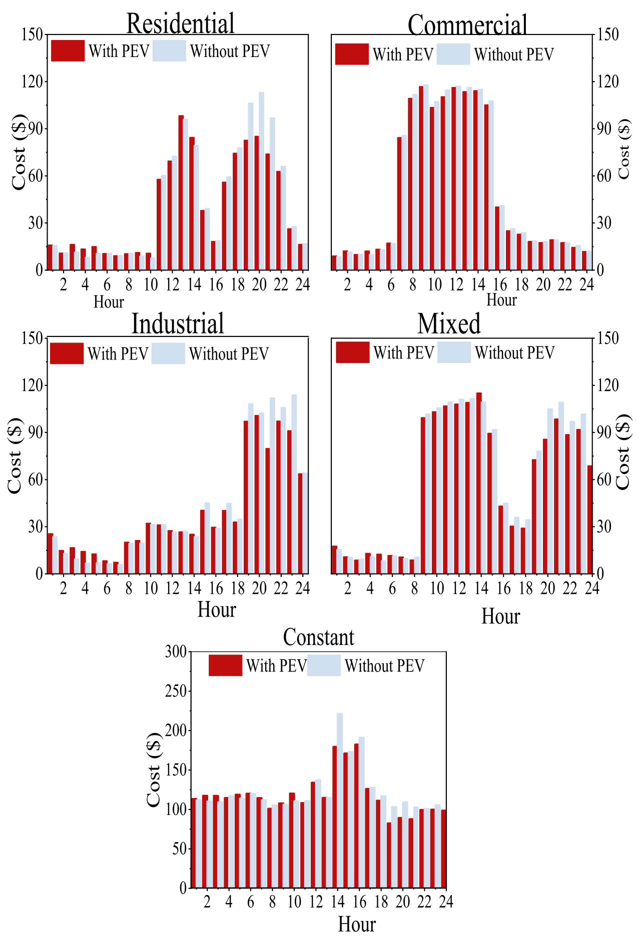

FIGURE 14 | Hourly cost in all TVVD.

Also, the CHP generation is curtailed with the integration of PEVs in peak hours of residential, industrial and mixed demand from hour 17–24, which significantly reduces cost and T&D losses. The maximum cost benefit ($) is obtained in residential model (6.38%) followed by industrial (5.53%), mixed (4.72%), constant (3.11%) and commercial (1.75%) whereas maximum decrease in T&D power losses in residential demand (7.87%) followed by industrial (6.19%), mixed (4.87%), constant (2.25%) and commercial demand (2.71%), respectively.

In terms of commercial demand with PEVs integration, the reduction in total cost and T&D losses is low compared to other models due to the low MG demand pattern in hours 17–24. At this time of the day PEVs are not available for discharge and maximum demand is shared by RERs whereas CHP has the least share. The maximum cost benefit ($) and T&D loss reduction occurred in residential demand because the residential demand has peak load when PEVs have maximum discharging capacities. The constant demand has maximum cost benefits in terms of maximum saving ($) because CHP-based expensive power generation is maximum due to maximum load throughout the day and RERs generation is varying.

5.2.5 | Voltage Profile Improvement

The integration of DERs in a MG also poses a technical benefit which includes improvement in voltage profile of each phase. The proposed methodology also improves the voltage profile of each phase for all TVVD loads as shown in Figure 16. It can be observed from this figure that maximum pu voltage at each node is obtained for the commercial TVVD load model followed by residential, mixed, industrial and constant TVVD load models.

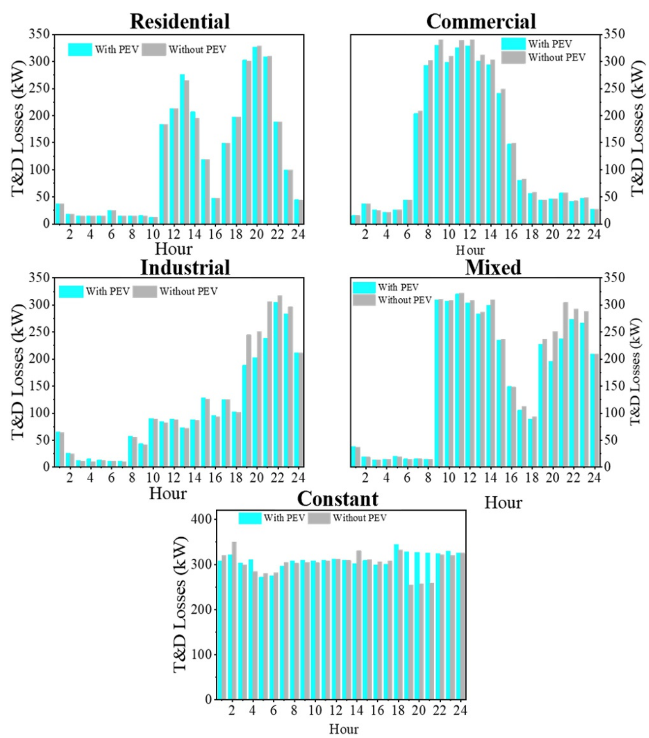

FIGURE 15 | Power losses in all TVV.

TABLE 4 | Generation cost and T&D losses in all TVVD.

	Cost ($)			T&D losses (kW)		
Demand type	**No PEVs**	**With PEVs**	**% Reduction**	**No PEVs**	**With PEVs**	**% Reduction**
Constant	2923	2832	3.11	7454	7286	2.25
Residential	1034	962	6.38	2820	2598	7.87
Commercial	1256	1234	1.75	3429	3336	2.71
Industrial	1013	957	5.53	2729	2560	6.19
Mixed	1505	1434	4.72	4165	3962	4.87

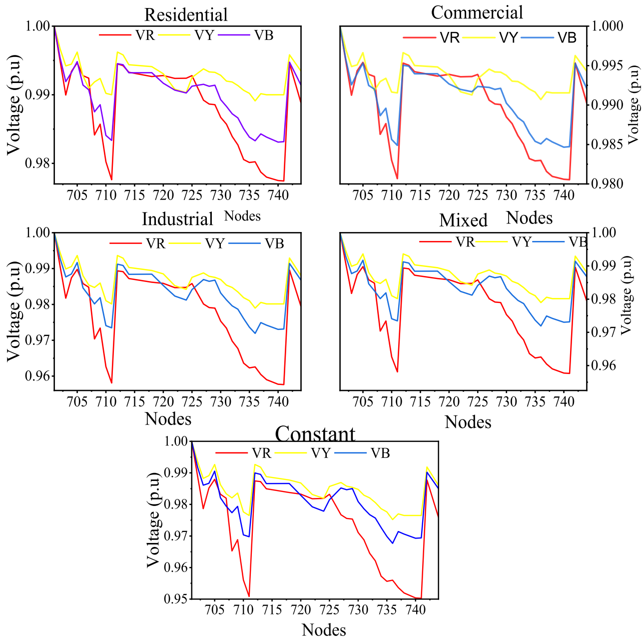

FIGURE 16 | Voltage profile.

Figure 17 shows the convergence comparisons between EGOA and PSO and it can be seen that EGOA will have a lower final cost of $1434/day than PSO with a final cost of $1506/day. In addition, EGOA is converging more quickly (15 iterations vs. 25 iterations) and is more regular and stable, which also proves its better optimisation results.

6 | Conclusion

In this paper, optimal scheduling of DERs and PEVs is performed in 3-phase unbalanced AC MG whilst considering dissimilar per phase loading levels of time-varying voltage dependent (TVVD) load models. Initially, impact of lumped loading and per phase loading approach on DERs scheduling in unbalanced AC MG is investigated for TVVD models and then, PEVs are connected in presence of DERs to minimise the generation cost and system losses using EGOA. The obtained results demonstrate that per phase loading approach produced more realistic results as compared to lumped loading and generation through CHP-based DGs is curtailed; resulting in maximum utilisation of cost-effective RERs and PEVs for all TVVD loads. The highest value of cost and T&D losses are obtained for residential load (7.87%) whereas the least value of cost and T&D losses are obtained for commercial demand (1.75%) in the absence of PEVs. The maximum benefit of PEVs introduction is obtained for residential load as its peak demand occurs during maximum discharging capacities of PEVs. The integration of PEVs has less impact on the reduction of total cost and T&D losses for commercial demand as compared to other load models due to dissimilarity between hourly charging/discharging patterns of PEVs and load demand. Hence, integration of PEVs is a viable option for economic operation of MG in case of all TVVD load models.

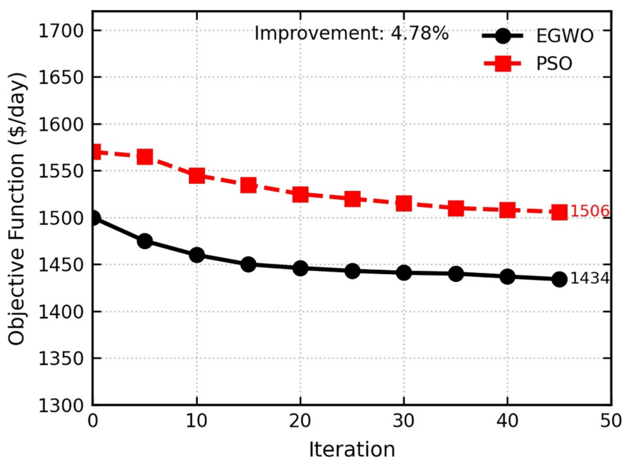

FIGURE 17 | Iterative cost convergence of EGOA and PSO.

Author Contributions

Zeeshan Yousaf: conceptualisation, investigation, writing – original draft. **Muhammad F. Nadeem:** supervision, writing – review and editing, methodology. **Ali Ahmed:** formal analysis, investigation, writing – review and editing. **Muhammad Nouman:** data curation, software, validation. **Muhammad Akmal:** supervision, writing – review and editing.

Funding

The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data are available from the first or corresponding author upon reasonable request.

Rights Retention Statement

References

1. R. C. Rial, "Biofuels Versus Climate Change: Exploring Potentials and Challenges in the Energy Transition," *Renewable and Sustainable Energy Reviews* 196 (2024): 114369, https://doi.org/10.1016/j.rser.2024.114369.

2. B. Nemati, M. Kamali, T. M. Aminabhavi, R. Dewil, M. E. V. Costa and I. Capela, "Sustainability Assessment of Carbonaceous Nano-structured Materials for Efficient Hydrogen Storage," *International Journal of Hydrogen Energy* 135 (2025): 477–498, https://doi.org/10.1016/j.ijhydene.2025.04.307.

3. I. R. E. Agency, Renewable Capacity Statistics 2021, (March 2021), https://www.irena.org/publications/2021/March/Renewable-Capacity-Statistics-2021.

4. Iea, Renewable Energy Market Update—May 2022, (May 2022), https://www.iea.org/reports/renewable-energy-market-update-may-2022/renewable-electricity.

5. I. E. Agency, Renewables 2021, (December 2021), https://www.iea.org/reports/renewables-2021.

6. M. R. Nayak, D. Behura and S. Nayak, "Performance Analysis of Unbalanced Radial Feeder for Integrating Energy Storage System With Wind Generator Using Inherited Competitive Swarm Optimization Algorithm," *Journal of Energy Storage* 38 (2021): 102574, https://doi.org/10.1016/j.est.2021.102574.

7. K. M. R. Pothireddy and S. Vuddanti, "Novel Demand Response-Based Stochastic Optimisation in a Grid-Connected Microgrid Considering Outlier Detection and Imputation," *International Journal of Ambient Energy* 46, no. 1 (2025): 2442602, https://doi.org/10.1080/01430750.2024.2442602.

8. H. Chen, L. Gao and Z. Zhang, "Multi-Objective Optimal Scheduling of a Microgrid With Uncertainties of Renewable Power Generation Considering User Satisfaction," *International Journal of Electrical Power & Energy Systems* 131 (2021): 107142, https://doi.org/10.1016/j.ijepes.2021.107142.

9. A. M. Shotorbani, S. Zeinal-Kheiri, G. Chhipi-Shrestha, B. Mohammadi-Ivatloo, R. Sadiq and K. Hewage, "Enhanced Real-Time Scheduling Algorithm for Energy Management in a Renewable-Integrated Microgrid," *Applied Energy* 304 (2021): 117658, https://doi.org/10.1016/j.apenergy.2021.117658.

10. Q. Yang, N. Dong and J. Zhang, "An Enhanced Adaptive Bat Algorithm for Microgrid Energy Scheduling," *Energy* 232 (2021): 121014, https://doi.org/10.1016/j.energy.2021.121014.

11. K. Gholami and E. Dehnavi, "A Modified Particle Swarm Optimization Algorithm for Scheduling Renewable Generation in a Micro-Grid Under Load Uncertainty," *Applied Soft Computing* 78 (2019): 496–514, https://doi.org/10.1016/j.asoc.2019.02.042.

12. E. A. Mahdiraji and M. K. Zarini, "Application of Distributed Algorithm in a Microgrid for Optimal Energy Management and Rapid Convergence," *Quantum Journal of Engineering, Science and Technology* 6, no. 1 (2025): 55–70, https://doi.org/10.55197/qjoest.v6i1.190.

13. A. Askarzadeh, "A Memory-Based Genetic Algorithm for Optimization of Power Generation in a Microgrid," *IEEE Transactions on Sustainable Energy* 9, no. 3 (2017): 1081–1089, https://doi.org/10.1109/tste.2017.2765483.

14. A. Tabares and P. Cortés, "Using Stochastic Dual Dynamic Programming to Solve the Multi-Stage Energy Management Problem in Microgrids," *Energies* 17, no. 11 (2024): 2628, https://doi.org/10.3390/en17112628.

15. A. Ahmed, M. F. N. Khan, I. Khan, H. Alquhayz, M. A. Khan and A. T. Kiani, "A Novel Framework to Determine the Impact of Time Varying Load Models on Wind DG Planning," *IEEE Access* 9 (2021): 11342–11357, https://doi.org/10.1109/access.2021.3050307.

16. M. S. Sajini, S. Suja and M. G. Raj, "Impact Analysis of Time-Varying Voltage-Dependent Load Models on Hybrid DG Planning in a Radial Distribution System Using Analytical Approach," *IET Renewable Power Generation* 15, no. 1 (2021): 153–172, https://doi.org/10.1049/rpg2.12013.

17. J. Salehi and A. Abdolahi, "Optimal Scheduling of Active Distribution Networks With Penetration of PHEV Considering Congestion and Air Pollution Using DR Program," *Sustainable Cities and Society* 51 (2019): 101709, https://doi.org/10.1016/j.scs.2019.101709.

18. A. Ahmed, M. F. Nadeem, I. A. Sajjad, R. Bo, I. A. Khan and A. Raza, "Probabilistic Generation Model for Optimal Allocation of Wind DG in Distribution Systems With Time Varying Load Models," *Sustainable Energy, Grids and Networks* 22 (2020): 100358, https://doi.org/10.1016/j.segan.2020.100358.

19. C. Wang, Z. Zhang, O. Abedinia and S. G. Farkoush, "Modeling and Analysis of a Microgrid Considering the Uncertainty in Renewable Energy Resources, Energy Storage Systems and Demand Management in Electrical Retail Market," *Journal of Energy Storage* 33 (2021): 102111, https://doi.org/10.1016/j.est.2020.102111.

20. J. Menyhart, "Electric Vehicles and Energy Communities: Vehicle-to-Grid Opportunities and a Sustainable Future," *Energies* 18, no. 4 (2025): 854, https://doi.org/10.3390/en18040854.

21. A. Boubaris, A. Kyritsis, K. Babouras, et al., "Study on the Effectiveness of Commercial Anti-Islanding Algorithms in the Prospect of Mass Penetration of PVs in Low-Voltage Distribution Networks," *IET Energy Systems Integration* 3, no. 1 (2021): 39–59, https://doi.org/10.1049/esi2.12007.

22. F. Freschi, M. Mitolo and R. Tommasini, "Electrical Safety of Electric Vehicles," in *Proceddings 2017 IEEE/IAS 53rd Industrial and Commercial Power Systems Technical Conference (I&CPS)*, (2017), 1–5.

23. R. A. Walling, R. Saint, R. C. Dugan, J. Burke and L. A. Kojovic, "Summary of Distributed Resources Impact on Power Delivery Systems," *IEEE Transactions on Power Delivery* 23, no. 3 (2008): 1636–1644, https://doi.org/10.1109/tpwrd.2007.909115.

24. M. Kajanova, P. Bracinik and M. Tkac, "Charging Power Control Based on Electric Vehicle Owners' Requests for Delivered Energy and Charging Time," in *Proceedings 2024 ELEKTRO (ELEKTRO)*, (2024), 1–4.

25. A. Rajapandiyan and S. Thangavel, "Energy Management in Distribution System Due to the Integration of Renewable Energy Powered EV Charging Infrastructures," in *Power Systems Operation with 100\% Renewable Energy Sources* (Elsevier, 2024), 281–297.

26. Z. Luo, H. Ren, G. Xin, M. Xu, F. Wang and Y. Zhang, "Optimal Operation of Microgrid With Consideration of V2G's Uncertainty," *IET Generation, Transmission & Distribution* 18, no. 2 (2024): 289–302, https://doi.org/10.1049/gtd2.13033.

27. M. Esmaili and A. Goldoust, "Multi-Objective Optimal Charging of Plug-In Electric Vehicles in Unbalanced Distribution Networks," *International Journal of Electrical Power & Energy Systems* 73 (2015): 644–652, https://doi.org/10.1016/j.ijepes.2015.06.001.

28. T. M. Aljohani, A. Saad and O. A. Mohammed, "Two-Stage Optimization Strategy for Solving the VVO Problem Considering High Penetration of Plug-In Electric Vehicles to Unbalanced Distribution Networks," *IEEE Transactions on Industry Applications* 57, no. 4 (2021): 3425–3440, https://doi.org/10.1109/tia.2021.3077547.

29. K. Knezović, A. Soroudi, A. Keane and M. Marinelli, "Robust Multi-Objective PQ Scheduling for Electric Vehicles in Flexible Unbalanced Distribution Grids," *IET Generation, Transmission & Distribution* 11, no. 16 (2017): 4031–4040, https://doi.org/10.1049/iet-gtd.2017.0309.

30. P. Fortenbacher, A. Ulbig and G. Andersson, "Optimal Placement and Sizing of Distributed Battery Storage in Low Voltage Grids Using Receding Horizon Control Strategies," *IEEE Transactions on Power Systems* 33, no. 3 (2017): 2383–2394, https://doi.org/10.1109/tpwrs.2017.2746261.

31. Y. Gilasi, S. H. Hosseini and H. Ranjbar, "Resilience-Oriented Planning and Management of Battery Storage Systems in Distribution Networks," *IET Renewable Power Generation* 17, no. 10 (2023): 2575–2591, https://doi.org/10.1049/rpg2.12770.

32. C. Ruiyang, W. Dong, C. Lu and Z. Jingchen, "An Optimization Method for Distribution Network Voltage Stability Based on Dynamic Partitioning and Coordinated Electric Vehicle Scheduling," *Energies* 19, no. 2 (2026): 571, https://doi.org/10.3390/en19020571.

33. M. A. Ebrahim, E. E. Ahmed, M. M. Salama and M. M. R. Ahmed, "Enhancing Electrical Distribution Network Performance amidst Rising Electric Vehicle Integration," *Energy Reports* 14 (2025): 4540–4559, https://doi.org/10.1016/j.egyr.2025.11.055.

34. B. V. Kumar and A. Farhan, "Optimal Integration of EV Charging Stations and Capacitors for Net Present Value Maximization in Distribution Network," *IEEE Latin America Transactions* 23, no. 3 (2025): 239–250, https://doi.org/10.1109/tla.2025.10879176.

35. T. Li, M. Zhang, Z. Hu, X. Wang, Y. Zhou and M. Yan, "Distributed Cooperative Scheduling for Distribution Network and Smart Charging Hubs Driven by Unbalanced Distribution Locational Marginal Price," *Applied Energy* 401 (2025): 126668, https://doi.org/10.1016/j.apenergy.2025.126668.

36. M. F. Nadeem Khan, T. N. Malik and I. A. Sajjad, "Impact of Time Varying Load Models on PV DG Planning," *Journal of Renewable and Sustainable Energy* 10, no. 3 (2018): 035501, https://doi.org/10.1063/1.5028170.

37. E. Lopez, H. Opazo, L. Garcia and P. Bastard, "Online Reconfiguration Considering Variability Demand: Applications to Real Networks," *IEEE Transactions on Power Systems* 19, no. 1 (2004): 549–553, https://doi.org/10.1109/tpwrs.2003.821447.

38. W. W. Price, "Bibliography on Load Models for Power Flow and Dynamic Performance Simulation," *IEEE Transactions on Power Systems* 10, no. 1 (1995): 523–538, https://doi.org/10.1109/59.373979.

39. O. Khoubseresht and H. Shayanfar, "The Role of Demand Response in Optimal Sizing and Siting of Distribution Energy Resources in Distribution Network With Time-Varying Load: An Analytical Approach," *Electric Power Systems Research* 180 (2020): 106100, https://doi.org/10.1016/j.epsr.2019.106100.

40. N. Nikmehr and S. N. Ravadanegh, "Optimal Power Dispatch of Multi-Microgrids at Future Smart Distribution Grids," *IEEE Transactions on Smart Grid* 6, no. 4 (2015): 1648–1657, https://doi.org/10.1109/tsg.2015.2396992.

41. M. H. Amini, M. P. Moghaddam and O. Karabasoglu, "Simultaneous Allocation of Electric Vehicles' Parking Lots and Distributed Renewable Resources in Smart Power Distribution Networks," *Sustainable Cities and Society* 28 (2017): 332–342, https://doi.org/10.1016/j.scs.2016.10.006.

42. S. Sachan and N. Adnan, "Stochastic Charging of Electric Vehicles in Smart Power Distribution Grids," *Sustainable Cities and Society* 40 (2018): 91–100, https://doi.org/10.1016/j.scs.2018.03.031.

43. A. Mousaei, Y. Naderi, S. M. Arif and I. S. Bayram, "Voltage Stability Enhancement in IEEE 14-Bus System Using Deep Deterministic Policy Gradient for EV Charging Management," in *2025 10th IEEE Workshop on the Electronic Grid (eGRID)* (IEEE, September 2025), 1–6.

44. A. Rezvani, M. Gandomkar, M. Izadbakhsh and A. Ahmadi, "Environmental/economic Scheduling of a Micro-Grid With Renewable Energy Resources," *Journal of Cleaner Production* 87 (2015): 216–226, https://doi.org/10.1016/j.jclepro.2014.09.088.

45. D. H. M. W. Thukaram, H. M. W. Banda and J. Jerome, "A Robust Three Phase Power Flow Algorithm for Radial Distribution Systems," *Electric Power Systems Research* 50, no. 3 (1999): 227–236, https://doi.org/10.1016/s0378-7796(98)00150-3.

46. E. Dehnavi and H. Abdi, "Optimal Pricing in Time of Use Demand Response by Integrating With Dynamic Economic Dispatch Problem," *Energy* 109 (2016): 1086–1094, https://doi.org/10.1016/j.energy.2016.05.024.

47. C. Chen, S. Duan, T. Cai, B. Liu and G. Hu, "Smart Energy Management System for Optimal Microgrid Economic Operation," *IET Renewable Power Generation* 5, no. 3 (2011): 258–267, https://doi.org/10.1049/iet-rpg.2010.0052.

48. W. H. Kersting, "Radial Distribution Test Feeders," *IEEE Transactions on Power Systems* 6, no. 3 (1991): 975–985, https://doi.org/10.1109/59.119237.