IET Generation, Transmission & Distribution

WILEY

The Institution of Engineering and Technology

ORIGINAL RESEARCH OPEN ACCESS

Deployment of GRN-PBIL Framework With Integrated DG-DRM in Electric Vehicle Charge Scheduling for Welfare Maximisation

Rajkumar Kasi[1] | Chandrasekaran Nayanatara[1] | Jeevarathinam Baskaran[2]

[1]Department of EEE, Sri Sai Ram Engineering College, Chennai, India | [2]Department of EEE, PSG Institute of Technology and Applied Research, Coimbatore, India

Correspondence: Chandrasekaran Nayanatara (Nayanathara.eee@sairam.edu.in)

Received: 27 February 2025 | **Revised:** 6 August 2025 | **Accepted:** 24 August 2025

Funding: The authors received no specific funding for this work.

ABSTRACT

The rapid adoption of electric vehicles (EVs) in recent years has led to a surge in power demand, presenting challenges in maintaining grid stability and efficiency. In response, service providers must integrate EVs with renewable energy sources while addressing the intermittent nature of distributed generation (DG) and fluctuating demand. Demand response management (DRM) offers a solution by aligning energy usage with renewable energy availability and optimising grid performance. Modern distribution systems advocate for the prediction of station usage and service availability to estimate charging demand. This research explores the use of a gated recurrent network (GRN) model for scheduling EV charging, with the goal of reducing peak demand. The integration of optimal DRM with DG further enhances the performance. The proposed scheduling algorithm incorporates DG-DRM to predict charging needs and alleviate peak load in the IEEE 33-bus system and the real-time utility network (RTUN)-17 bus test system. Consumer participation in DRM maximises the total social benefit by lowering generation costs and congestion indices. A heuristic GRN model, combined with a probability-based incremental learning algorithm, is introduced to tackle multi-objective optimisation. The algorithm is tested across various scenarios, with EV scheduling carried out in the first phase and DRM with DG parameters optimised in the second. The results show the algorithm's superior performance in achieving the objective function compared to other computational methods.

1 | Introduction

The accelerating integration of electric vehicles into modern transportation systems has significantly influenced the dynamics of power distribution networks. Also the surge in electric vehicle (EV) adoption poses challenges for grid operators and service providers, especially during peak load periods. The existing literature extensively documents the technical and operational issues associated with increased EV penetration. Research has highlighted significant challenges posed by EV charging infrastructures, including voltage instability, elevated peak demand, and increased energy losses [1]. Uncoordinated EV charging frequently creates simultaneous demand spikes, exacerbating congestion in distribution networks [2]. To counter these issues, diverse optimisation techniques have been explored, such as smart load management, time-of-use pricing, and bi-level particle swarm optimisation (PSO). These methodologies effectively manage peak loads, improve voltage regulation, and enhance load balancing [3–5]. Recent studies have further advanced EV charge scheduling optimisation through soft computational techniques for uncertainty modelling. The load uncertainty in EV charge scheduling was taken as a parameter in [6] and day ahead

This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

© 2025 The Author(s). *IET Generation, Transmission & Distribution* published by John Wiley & Sons Ltd on behalf of The Institution of Engineering and Technology.

optimisation was simulated in a typical micro grid. Thus the operation cost was considerable decreased by calculating the charging demand. As the charging level 1 and level 2 infrastructure mainly targets residential and commercial load hybrid optimisation which is proposed in [7] to predict the charging cost. For level 3 charging infrastructure Monte Carlo simulation methods is used to model the EV user behaviour. Hence the uncertainty nature was addressed by proper charge scheduling.

Fuzzy logic integrated with PSO addresses both user convenience and grid performance, though its efficacy is constrained by intermittent resource availability [8]. Additionally, leveraging vehicular communication networks has shown potential in simultaneously reducing traffic congestion and optimising energy consumption, providing multi-dimensional grid management benefits [9]. A two stage optimisation framework is proposed in [10] for electric vehicle scheduling in unbalanced distribution systems. The spatial and temporal data mining was integrated considering system constraints. Reduction in power losses, load balancing, and enhancement of voltage quality was achieved even under high EV penetration scenarios. However, these methods often oversimplify system constraints, potentially reducing their effectiveness in real-world scenarios. A deep recurrent model is developed in [11] to predict the charging behaviours and this algorithm required less training time and enhances the efficiency. The uncertainty of EV charging was taken into consideration in [12] and distributed generation (DG) penetration considering investment planning was taken into consideration. However, these methods often fall short in dealing with the stochastic variations like unpredictable user charging patterns or renewable power fluctuations. To bridge these gaps, researchers have proposed stochastic optimisation frameworks, including Lyapunov optimisation and mixed-integer programming (MIP). These allow dynamic and probabilistic adaptation of charging decisions based on real-time system conditions [13]. Multi-objective optimisation frameworks was proposed in [14] which commonly target the simultaneous minimisation of peak system demand, operational cost, power losses and CO_2 emissions. Recent studies have incorporated advanced optimisation techniques, such as genetic algorithm combined with adaptive neuro-fuzzy inference systems, for scheduling EV charging alongside DG integration. These methodologies minimise energy costs, decrease grid dependency, and enhance overall system efficiency. Such hybrid approaches are essential in formulating robust and adaptive energy management strategies suitable for modern smart-grid infrastructures in [15]. Metaheuristic-based EV scheduling with DG planning has been employed in [16] to manage supply demand uncertainties while active consumer participation is recognised as vital for minimising peak loads. The authors in [17, 18] used multi-objective optimisation for placement of DG devices and EV charging stations. Power loss and voltage deviation index were taken as an objective function.

A two-stage investment planning of DG was developed in [19] to reduce the negative impacts caused by EV charging demand. The operation feasibility was justified by taking IEEE 123 bus as the test system. The intermittent nature of renewable energy sources was addressed in [20] and an optimisation model was developed based on reinforcement learning. Computational time taken was less in this method. The authors in [21] optimises EV charge scheduling integrated with demand response management (DRM) using genetic algorithm that factor in price signals to manage load fluctuations more effectively. A day-ahead stochastic optimisation and coupon-based DR incentives aimed at increasing consumer participation and grid efficiency was analysed in [22]. The EV parking lot energy management approach for EV charge scheduling integrated with DRM focuses on maximising the load factor during daily operations. This method effectively accounts for the uncertain and stochastic behaviour of electric vehicles, enhancing energy utilisation and system reliability [23]. Methods like real-time pricing and time of use tariffs have successfully shifted EV charging to off-peak periods [24]. Temporal convolution network model was developed to forecast the demand data. However, DR alone is insufficient to address voltage regulation or loss minimisation unless integrated with coordinated scheduling. Studies [25] report that DR, when used alongside distributed generation (DG), can significantly reduce peak demand and improve load flexibility. Therefore, this research proposes a unified optimisation framework that integrates EV scheduling with DG and DRM parameter tuning, aiming to minimise peak load, reduce system losses, and achieve techno-economic benefits for both utilities and consumers.

It is observed that, scheduling EVs with the coordinated integration of DG-DRM may provide a trade-off solution to the power system network. However, scheduling with optimisation of the parameters is a significant concern in achieving techno-economic benefits. It is apparent that a unified optimisation framework for EV charging scheduling with concurrent tuning of DG and DRM parameters will reduce the peak load; thereby the customer and the utility benefit which is explored in this research.

The primary objective of this research is to propose a comprehensive, integrated optimisation framework for the scheduling and energy management of EVs in real-time distribution networks. This approach optimises EV charging schedules, to minimise peak loads, reduce operational costs, and enhance grid stability. By ensuring efficient energy distribution, the scheduling is designed to meet the dynamic demands of EV charging while maintaining the reliability of the distribution network. Through real-time optimisation, the proposed framework aims to integrate diversified load and charging patterns Thus, heuristic gated recurrent network (GRN)-probability-based incremental learning (PBIL) is performed to achieve the multi objective optimisation to facilitate sustainable grid management, and the effectiveness of the proposed method is validated by benchmarking its performance against varying proportions of capacity utilisation. A detailed analysis is provided through standard deviation that highlights the significance of the minimum and maximum values of the proposed technique.

The novelties of this research are as follows:

1. Gated recurrent network is formulated for EV charging scheduling and to predict the demand considering the intermittent nature of charging load patterns. By optimising, the approach guarantees a reduction in peak load, resulting in minimised congestion and generation cost benefiting both utilities and customers.
2. The prioritisation of these objectives is achieved through the simultaneous optimisation of DRM and DG parameters.

17518695, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/gtd2.70148, Wiley Online Library on [29/09/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

This methodology is applied to various load patterns using different scheduling techniques, which are challenging to handle with traditional computational methods.

3. Subsequently, multiple case studies were performed to justify the intermittent nature of the parameters using PBIL on the IEEE 33-bus and real-time utility network (RTUN)-17-bus systems.
4. Strategic scheduling and optimisation are developed to maximise the total social benefit (TSB), thus improving the overall performance of the distribution network. The results obtained are compared with individual optimisation techniques to validate the performance of the proposed approach.
5. The scalability of the proposed approach is also simulated in both test systems.

The rest of this paper is organised as follows: Section 2 introduces the modelling framework for the EV scheduling, DG, and DRM framework. Section 3 shows the formulation of the objective function. Section 4 introduces the development of a coordinated optimisation algorithm. Section 5 presents simulation results through various case studies and performance metrics. Section 6 concludes the research work by summarising the key findings and suggestions.

2 | Modelling of EV Scheduling and DG With DRM

This section presents a direct approach for optimal scheduling of EV, mathematical modelling of DG and DRM for reducing the peak demand by rescheduling the customer's forecasted load to manage the deficit power without increasing the generation units.

2.1 | Modelling EV Scheduling

Efficient management of EV charging networks necessitates advanced scheduling strategies. The proposed model optimises capacity utilisation and enhances customer satisfaction by reducing waiting times and offering more responsive and efficient services.

The generalised scheduling model is characterised by arrival rates and service rates as shown in Equation (1),

$$\lambda_n = \begin{cases} \lambda, & 0 \le n \le N \\ 0, & n > N \end{cases}, \quad \mu_n = \begin{cases} n\mu, & 0 \le n < c \\ c\mu, & c \le n \le N \end{cases} \tag{1}$$

The probability distribution of EVs in the system is computed to optimise operational efficiency and ensure adequate service levels for users. The utilisation factor of the charging system indicates how effectively the charging stations are utilised.

$$P_n = \begin{cases} \frac{(\lambda/\mu)^n}{n!} P_0, & 0 \le n < c \\ \frac{(\lambda/\mu)^n}{c!\, c^{n-c}} P_0, & c \le n \le N \end{cases} \tag{2}$$

When $1 \le n < c$, all n EVs are actively receiving charging services. However, when $n \ge c$, only c vehicles are being charged simultaneously, while the remaining n-c EVs are queued and waiting for an available charging pile. Once the system reaches a steady state, Equation (2) can be solved using a recursive approach. This yields the probabilities of different service states, which are expressed in Equation (3).

$\rho = \left(\frac{\lambda}{\mu}\right)$, assuming $\frac{\rho}{c} < 1$, the value of P_0 is determined from $\sum_{n=0}^{\infty} P_n = 1$.

For a multi-channel queuing system, the probability of charging station can be calculated using the following formula:

$$P_0 = \begin{cases} \left[\sum_{n=0}^{c-1} \frac{(\rho)^n}{n!} + \frac{(\rho)^c}{c!} \frac{\left(1 - \left(\frac{\rho}{c}\right)^{N-c+1}\right)}{(1-\frac{\rho}{c})} \right]^{-1}, & \frac{\rho}{c} \ne 1 \\ [15pt] \left[\sum_{n=0}^{c-1} \frac{(\rho)^n}{n!} + \frac{(\rho)^c}{c!}(N-c+1) \right]^{-1}, & \frac{\rho}{c} = 1 \end{cases} \tag{3}$$

Thus the above probability P_0 indicates the likelihood that all charging stations are idle at a given time. It is a key parameter in queuing model and serves as a normalisation constant used to determine the probability distribution of system states P_n, which further enables the calculation of average queue length and expected waiting time.

The expected number of EVs in the waiting line to be charged is given by Equation (4),

$$L_q = \sum_{n=c}^{N} (n-c) P_n$$
$$L_q = \begin{cases} \frac{(\rho)^{c+1}}{(c-1)!(c-\rho)^2} \left\{ 1 - \left(\frac{\rho}{c}\right)^{N-c+1} \right\} - (N-c+1)\left(1-\frac{\rho}{c}\right)\left(\frac{\rho}{c}\right)^{N-c} P_0, & \frac{\rho}{c} \ne 1 \\ \frac{(\rho)^c (N-c)(N-c+1)}{2c!} P_0, & \frac{\rho}{c} = 1 \end{cases} \tag{4}$$

The mathematical equation as derived above provides the operations at EV charging stations, considering service rates and charging pile availability. Therefore, the scheduling parameters are formulated as:

17518695, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/gtd2.70148, Wiley Online Library on [29/09/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

2.1.1 | Total Number of EVs in the System

$$L_s = L_q + \frac{\lambda_{eff}}{\mu} = L_q + \frac{\lambda(1-P_k)}{\mu} = L_q + r(1-P_k) \tag{5}$$

$r\,(1-P_k) < c$ ensures the effective arrival rate Equation (5). Thus the probability of EVs not joining the queue is Equation (6):

$$\lambda_{eff} = \mu\left[c - \sum_{n=0}^{c-1}(C-n)P_n\right] \tag{6}$$

2.1.2 | Expected Waiting Time in the System (W_S)

The average waiting time for an EV in the system considering both charging and queuing is given by,

$$\left.\begin{aligned} W_s &= \frac{L_s}{\lambda_{eff}} = \frac{L_q}{\lambda(1-P_k)} \\ W_q &= W_s - \frac{1}{\mu} = \frac{L_q}{\lambda_{eff}} \end{aligned}\right\} \tag{7}$$

The total charging power demand is interpreted in terms of waiting time parameters Equation (7). It describes the dynamics of an EV charging station, capturing the interplay between arrival rates, service rates, and queue management to enhance operational efficiency and customer satisfaction.

The charging time $t_{c,i}$ for each EV is calculated by Equation (8) where $i = 1, 2, 3\ldots, N_{min}$.

$$t_{c,i} = \begin{cases} t_{max}, & r[0,1] < \mu n_{max} e^{-\mu n_{max} t_{max}} \\ -\frac{1}{\mu n_{max}} \ln\left(\frac{r[0,1]}{\mu n_{max}}\right), & r[0,1] \geq \mu n_{max} e^{-\mu n_{max} t_{max}} \end{cases} \tag{8}$$

The charging power for the m^{th} type of EVs is integrated by Equation (9)

$$P_{ch}(m) = P_{EV,max}\left(N_m - \sum_{i=1}^{N_{min}} e^{-\frac{at_{c,i}}{t_{max}}}\right) \tag{9}$$

Thus, the total charging power demand for EVs is given by Equation (10)

$$P_D = \sum_{N=1}^{N_{max}} P_{ch}(m) \tag{10}$$

2.2 | DG Modelling

The modelling of different types of DG is as follows:

Type 1-DG: These DG sources are designed to deliver real power at unity power factors. The power output from solar PV systems is influenced by the hourly irradiance and ambient temperature. The relationship is detailed in the specified Equation (11).

$$P_t^{pv} = \sum_{i=1}^{n} P_{rated,i}(1 + k_i(T_t - 25)) \tag{11}$$

Type 2-DG: These DG sources, including wind turbines, are designed to deliver real power and consume reactive power as part of their operation. The power output from wind turbines is determined by Equations (12)–(14):

$$P_{wind} = 0.5 \times m \times A \times C_p(\beta, N_r) \times V^3, \tag{12}$$

$$N_r = \frac{\omega_r \times R_r}{V} \tag{13}$$

$$P_{wind}(t) = \begin{cases} 0, & V(t) < V_{ci},\ V(t) > V_{co} \\ P_{wind} \times \frac{V(t)-V_{ci}}{V_r - V_{ci}}, & V_{ci} \leq V(t) \leq V_r \\ P_{wind}, & V_r \leq V(t) \leq V_{co} \end{cases} \tag{14}$$

2.3 | DRM Modelling

The strategy for altering the customer demand curve to better align with the available generation from renewable energy sources is DRM. By creating the following mathematical problem, the network under investigation, DRM capability data, and load profile levelling are determined in the Equations (15) and (16) below:

Minimise

$$\sum_t \left(\text{Load}_{active}^t - \text{Load}_{active}^{mean}\right)^2 \tag{15}$$

$$\text{Load}_{active}^t = \text{Load}_{active\text{-}Non\ Responsive}^t + \text{Load}_{active\text{-}Res}^t + \text{Load}_{load}^t \tag{16}$$

where, Load_{active}^t, $\text{Load}_{active}^{mean}$, $\text{Load}_{active\text{-}Non\ Responsive}^t$, $\text{Load}_{active\text{-}Res}^t$ and Load_{load}^t are the active, mean, non-responsive and responsive loads, respectively.

In reality, each bus may have a variety of loads, that is, a combination of commercial, residential and industrial loads. The consumption patterns of these loads are rescheduled using DRM that performs load shifting from peak to off-peak periods.

2.4 | Total Generation Cost Index

The electricity generation within the studied power system originates from two main sources: distributed generators and the utility grid. The total energy cost for a day is calculated using the Equations (17)–(19) as given below:

$$\text{GCI}_{G,m} = C_{dg} + C_{grid} \tag{17}$$

$$C_{dg} = \sum_{t=1}^{t}\left[\sum_{i=1}^{n_{DG}} P_j(t) * C_j(t)\right] \tag{18}$$

$$C_{grid} = \sum_{t=1}^{24}\left[P_{grid}(t) * M_p(t)\right] \ldots. \tag{19}$$

17518695, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/gtd2.70148, Wiley Online Library on [29/09/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Therefore, the fitness function generation cost index (GCI) Equation (20) is given as:

$$\text{Minimise}F1 = \left\{ \sum_{m=1}^{\text{ND}} \sum_{m=1}^{\text{NG}} \sum_{m=1}^{\text{NDG}} \in \left(\text{GCI}_{G,m}\right) \right\} \tag{20}$$

3 | Model Formulation

The proposed heuristic optimisation technique aims at optimising the utility system by maximising the objective function under all possible comprehensive cases. This is achieved by determining the optimal operation and scheduling of the charging stations based on arrival, waiting, and departure times with the optimal DRM-DG penetration.

3.1 | Formulation of the Objective Function

To enhance the benefits of EV customers, the objective of the Stage 1 framework is to optimise the scheduling of EVs. This aims to minimise the overall generation cost while meeting their charging requirements thereby reducing the peak load. The network under study and the data on DRM capability is gathered and the levelling in load profile is established by calculating the active old and new load data. The objective function for peak load reduction with DRM is summarised as Equation (21).

$$\text{Minimise } F_2 = \text{PLR} = \frac{\text{Load}^t_{\text{active}}\text{ old} - \text{Load}^t_{\text{active}}\text{ new}}{\text{Load}^t_{\text{active}}\text{ old}} \tag{21}$$

This fitness function aims to minimise the total energy generation cost while incorporating the effects of the DRM.

3.2 | Congestion Index

The maximum benefit to the customer can be guaranteed through effective congestion management. The distribution system becomes more congested with the penetration of EVs which leads to unexpected rise in power demand. The congestion index is used to identify the allowable power flow in the line, using which the DG placement can be fixed. The congestion index (CI) is given by the following Equation (22):

$$\text{Minimise } CI = \sum\nolimits_{i \in Nl} \beta_k \left(\frac{P_{\text{act}}}{P_{\text{max}}}\right)^2 \tag{22}$$

where β_k is used as the weighing factor for the line which varies between 0 and 1.

3.3 | Total Social Benefit

TSB quantifies the net societal benefit derived from efficiently scheduling vehicles and reducing congestion. By incorporating quadratic cost functions related to scheduling and EV parameters, optimising TSB ensures a coordinated approach that enhances societal benefits while achieving economic and environmental sustainability. The comprehensive TSB objective function is expressed in Equation (23).

$$F3 = \text{Max TSB}_{\text{CI}} = \sum_{i=1}^{\text{ND}} \left(x_{di} P_{di}^2 + y_{di} P_{di} + z_{di}\right) - \sum_{i=1}^{\text{NG}} \left(x_{gi} P_{gi}^2 + y_{gi} P_{gi} + z_{gi}\right) - \sum_{i=1}^{\text{NDG}} \left(x_{dgi} P_{dgi}^2 + y_{dgi} P_{dgi} + z_{dgi}\right) \tag{23}$$

3.3.1 | Scheduling Constraints

When EVs arrive at the charging station, they require specific charging piles. The constraints ensuring proper allocation are as follows:

$\rho = \frac{\lambda}{c\mu} < 1$: Charging station—idle mode

$\rho = \frac{\lambda}{c\mu} = 1$: Charging station—operates at full capacity

$\rho = \frac{\lambda}{c\mu} > 1$: Charging station—exceeds the full capacity

$$\sum_{m=1}^{M} \delta_{(m,n)} = 1, \quad \text{for all } n \in N \tag{24}$$

$$\delta_{(m,n)} P_{\text{CH}}(m,t) = 0, \forall t \in [t_n^{\text{start}}, t_n^{\text{end}}], \forall t \in T, \forall n \in N \tag{25}$$

Here, $\delta_{m,n}$ is a binary variable indicating whether the n^{th} EV is assigned to the m^{th} charging pile of Equations (24) and (25).

3.3.2 | Power Balance Constraints

The real power and reactive power are essential to ensure that the power generation meets the load demand, thereby maintaining system stability Equation (26) and power quality Equation (27).

$$P_i = \sum_{n=1}^{\text{NB}} V_i V_j Y_{ij} \cos(\theta_{ij} - \delta_j + \delta_i), \quad i = 2, 3, \ldots\ldots, \text{NB} \tag{26}$$

$$Q_i = \sum_{n=1}^{\text{NB}} V_i V_j Y_{ij} \sin(\theta_{ij} - \delta_j + \delta_i), \quad i = 2, 3, \ldots\ldots, \text{NB} \tag{27}$$

3.3.3 | Inequality Constraints

To ensure stable and safe voltage levels across the network, the voltage at each bus must remain within the specified limits Equation (28).

$$V_{\min} \le V_i(t) \le V_{\max} \tag{28}$$

Distributed generation units have operational limits that must be incorporated into DRM to ensure whether they function within their technical and safety capabilities Equation (29):

$$P_{\text{PV}}^{\text{total}} + P_{\text{wind}}^{\text{total}} \le P_{\text{demand}}^{\text{base}} \tag{29}$$

In the base case scenario of power flow model, with no DG units connected, the net power output from the DG units and the power

17518695, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/gtd2.70148, Wiley Online Library on [29/09/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

generation at the load buses are assumed to be zero, as indicated by the following Equations (30) and (31).

$$\begin{cases} P_{\mathrm{dg}} = 0 \\ P_{\mathrm{G}} = 0 \end{cases} \tag{30}$$

The aim of this research is to schedule EVs optimally to minimise generation costs and peak loads while maximising TSB. Thus, the fitness is given as

$$\text{Fitness function} = F(\max) = \left\{ W_1 \times \left(\frac{1}{F_1}\right) + W_2 \times \left(\frac{1}{F_2}\right) + W_3 \times F_3 \right\} \tag{31}$$

Where W_1, W_2 and W_3 represent the weighting factors for the fitness function 1, 2, and 3, respectively. Thus, $\sum_{s=1}^{3} W_t = 1$,

The proposed formulation ensures that EVs are scheduling, DRM and DG to achieve the desired fitness function. It aims at balancing multiple objectives: maximising customer benefit, minimising power loss, and supporting high EV penetration and sustainable energy use in modern power networks

4 | GRN-PBIL for EV Scheduling With Optimal DRM–DG Parameters

The algorithm simulated considers two important aspects. The GRN used for EV scheduling is employed to predict the EV charging demand and grid loads and the implementation of PBIL aims at guaranteed social benefit to both utility and consumers.

1. Input the time series data set on EV charging patterns as derived from Equations (1)–(10) and from line data and bus data.
2. Normalise the data set and split into train, test and validation. Fix learning rate = 0.001 and epochs = 100.
3. Initialise the GRN model and loss function to compute the predicted and the actual values.
4. Evaluate the model and use the trained model to predict the demand.
5. Compute the charging power demand and ensure fairness in scheduling. Perform forward backward sweep load flow algorithm and integrate DRM to reduce the peak load.
6. Generate population using PBIL and fix the learning rate as 0.01. For each solution calculate the fitness function.
7. Update the probability vector and perform crossover and mutation.
8. Stop the iteration if maximum possible solution is arrived.

GRN-PBIL strategy is employed to address the EV optimised scheduling for maximisation of total social benefit through a series of steps, as illustrated in Figure 1.

5 | Simulation Results

The test systems considered are used for solving the multi-objective optimisation problem using the GRN-genetic algorithm

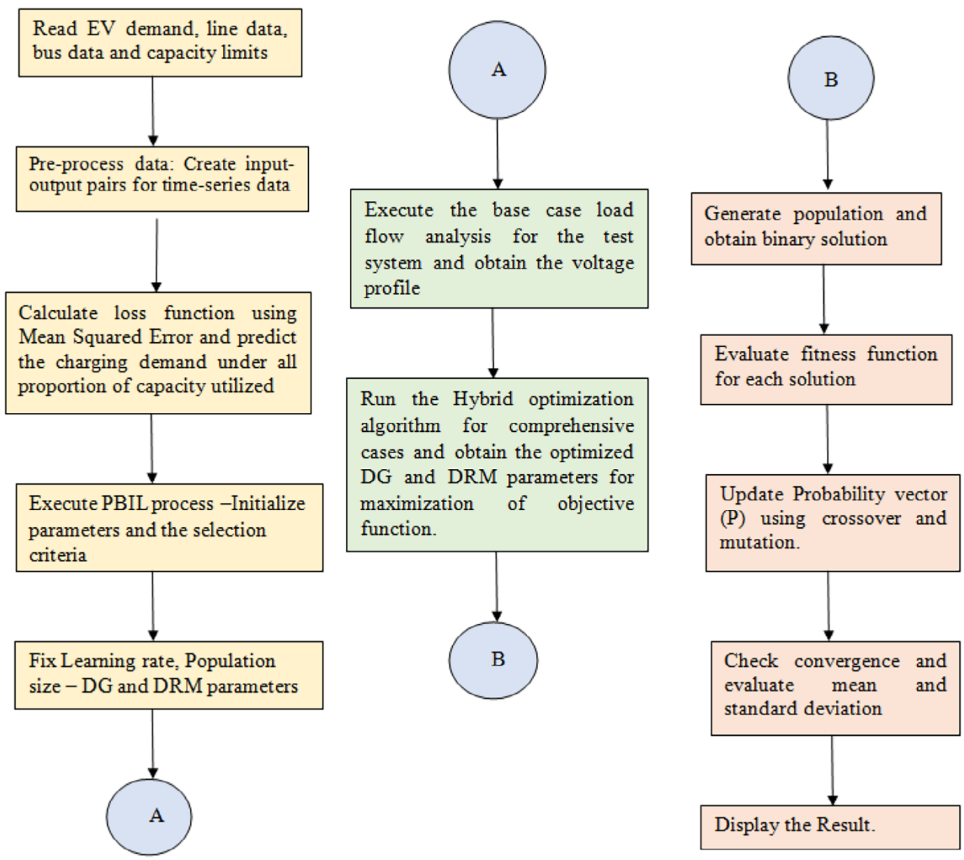


FIGURE 1 | Working methodology for intelligent coordinated algorithm.

17518695, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/gtd2.70148, Wiley Online Library on [29/09/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

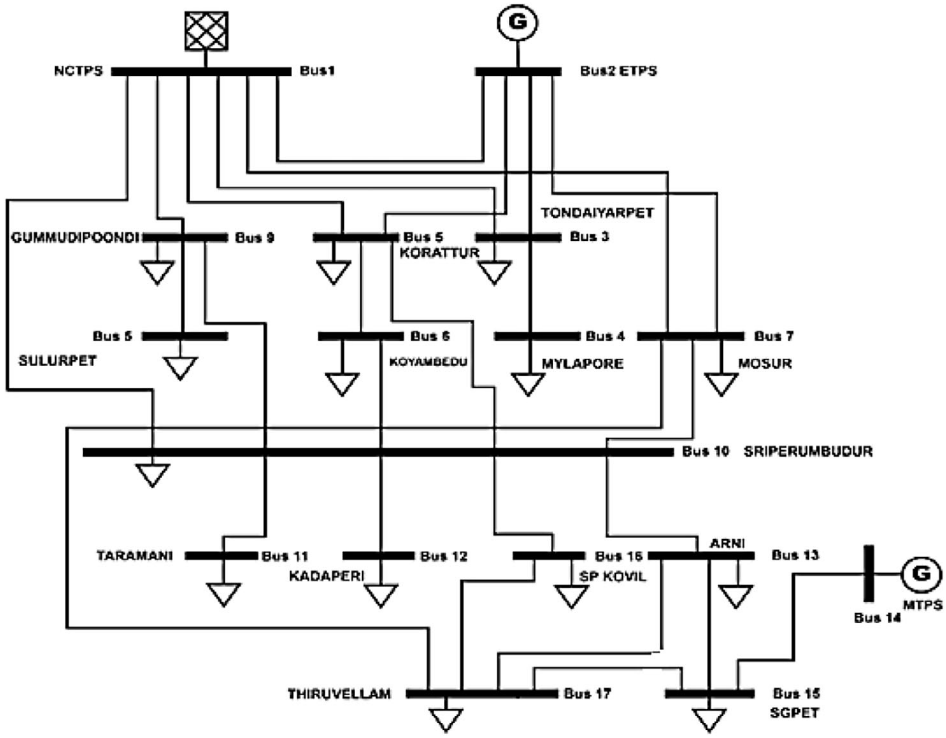


FIGURE 2 | Real time utility network-17 bus system.

TABLE 1 | Enhancement in voltage level IEEE 33 bus system.

Voltage level (p.u)	Existing number of buses (Bus No)		
	Without scheduling	**With scheduling alone**	**Scheduling with DG+DRM**
0.47–0.64	1 (9)	Nil	Nil
0.65–0.72	2 (12, 21)	Nil	Nil
0.73–0.84	5 (3, 8, 13, 20, 25)	Nil	Nil
0.85–0.94	12 (2, 4, 5, 6, 7, 11, 16, 17, 19, 22, 28, 30)	3 (5, 9, 23)	Nil
0.95–1.05	12 (10, 14, 15, 18, 23, 24, 26, 27, 29, 31, 32, 33)	26 (2, 3, 4, 6, 7, 8, 10, 12, 13, 14, 15, 16, 17, 18, 20, 21, 22, 24, 25, 26, 27, 29, 30, 31, 32, 33)	28 (2.3, 4, 5, 7, 8, 9, 10, 12, 13, 14, 15, 16, 17, 18, 20, 21, 22, 23, 24, 25, 26, 27, 29, 30, 31, 32, 33)
1.06–1.1	Nil	3 (11, 19, 28)	4 (6, 11, 19, 28)

(GA), GRN-micro genetic algorithm (MGA), and GRN-PBIL. A comparative study is made between discrete and hybrid optimisation methods to show the efficacy of the proposed algorithm.

The real-time test system data [26] considered is given in Figure 2. The improvement in bus voltage level with all possible scenarios in IEEE and in real time bus systems is illustrated in Tables 1 and 2.

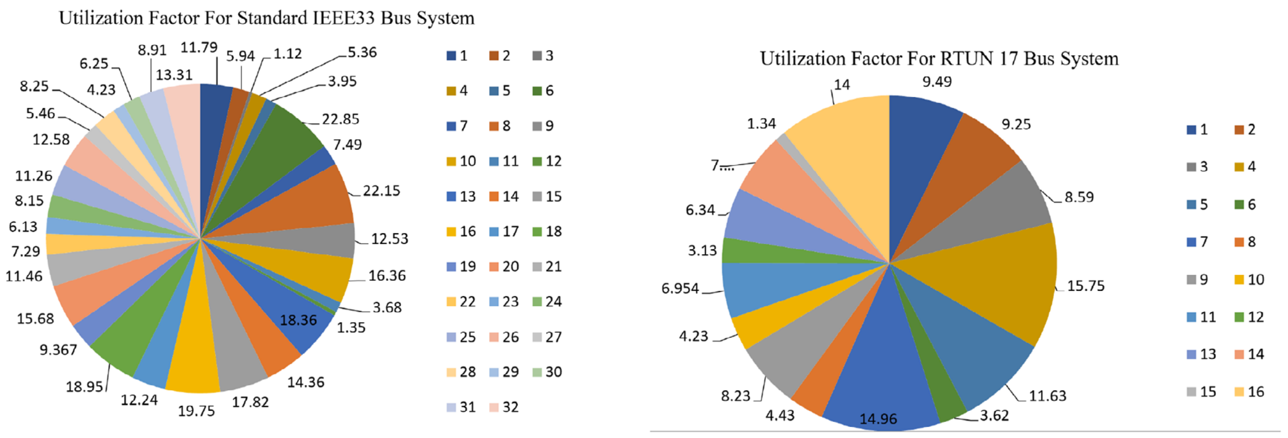
To expand the investigation, the utilisation factor is calculated to its respective threshold point and the convergence ability is also examined. The scalability of the proposed approach as indicated in Figure 3a,b is justified by checking the utilisation factor. Therefore, a trade-off solution is obtained by taking the utilisation factor as the scalable parameter.

The algorithm categorises the load into peak, intermittent, and low load clusters, assigning priority to the scheduling of EVs. The congestion of the real-time system, both with and without scheduling is examined to analyse the successful penetration of predicted data. It is evident that the congestion index is notably decreased after GRN optimisation, as shown in Figure 4. The peak load reduction for the charging station at idle mode, full capacity and exceeding the full capacity in the IEEE 33 bus system is given in Figure 5a–c. Such optimisation facilitated proper DG planning which resulted in generation cost minimisation with an increase in TSB. The PLR for the three utilisation test cases was simulated in the RTUN system and the results indicate a considerable decrease in peak load under all comprehensive scenarios, which are shown in Figure 6a–c.

17518695, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/gtd2.70148, Wiley Online Library on [29/09/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 2 | Enhancement in voltage level RTUN-17 bus system.

Voltage level (p.u)	Existing number of buses		
	Without scheduling	With scheduling alone	Scheduling with DG+DRM
0.47–0.64	2 (11, 13)	Nil	Nil
0.65–0.72	3 (7, 12, 16)	Nil	Nil
0.73–0.84	5 (2, 5, 6, 9, 17)	Nil	Nil
0.85–0.94	3 (3, 10, 14)	5 (3, 5, 8, 10, 15)	Nil
0.95–1.05	4 (4, 8, 15, 16)	9 (4, 7, 9, 11, 12, 13, 14, 16, 17)	14 (2, 3, 4, 5, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17)
1.06–1.1	Nil	2 (2, 6)	2 (6, 13)



(a) Utilization Factor For Standard IEEE 33 Bus System

(b) Utilization Factor For real time utility network (RTUN) 17 Bus System

FIGURE 3 | Utilisation factor.

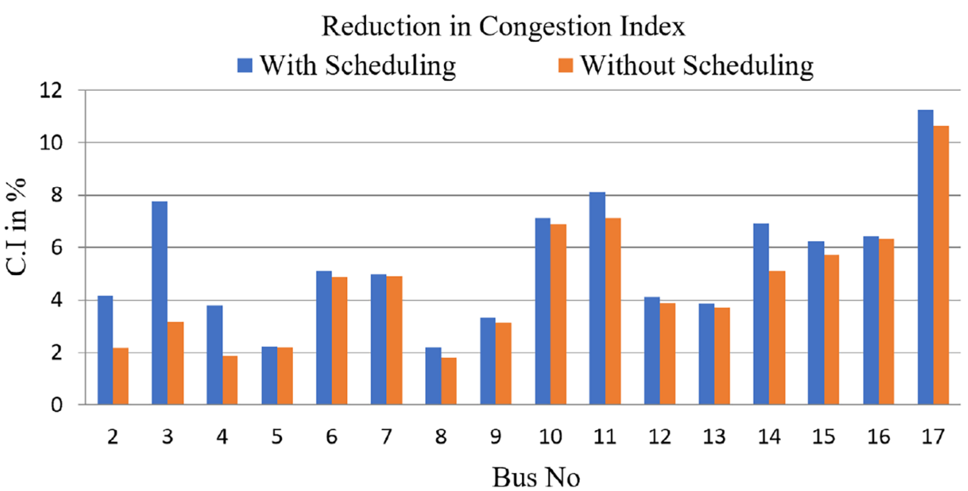


FIGURE 4 | Reduction in congestion index.

The peak load reduction under different utilisation factor and various allocations of DG units is analysed for three conditions across the two test systems. With utilisation factor variations, different optimal solutions for the siting and sizing of DG units can be determined, as depicted in Tables 3 and 4.

The plotted data reflect the charging needs for EV users which is influenced by level 1, level 2 and level 3 charging stations, respectively. The charging needs refers the instantaneous time-varying power demand required by EV during its charging process. The discrete optimisation shown in Figure 7, provides 24 h load cycle for the targeted, forecasted and optimised load. This representation highlights the systematic management of demand through optimised GRN-PBIL scheduling. The result shows that generated power is considerably reduced during peak hours, lowering generation costs and increasing overall social welfare thus facilitating in achieving multi-objective optimised output.

17518695, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/gtd2.70148, Wiley Online Library on [29/09/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

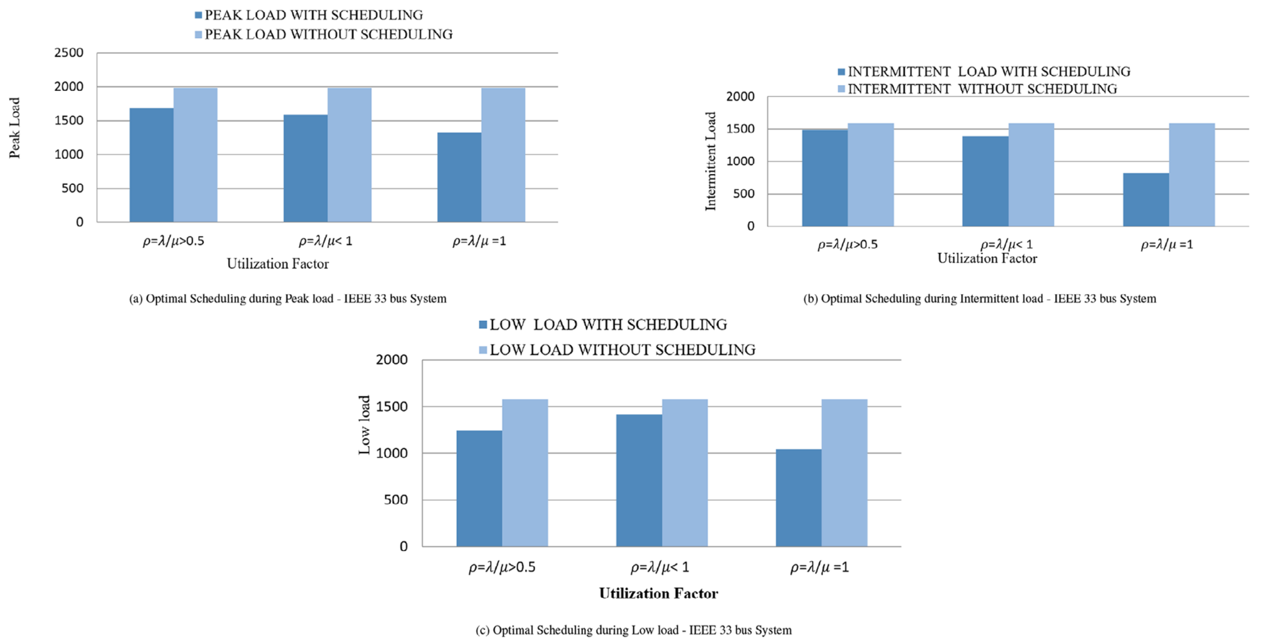


FIGURE 5 | Optimal scheduling for IEEE 33 bus system under different load conditions.

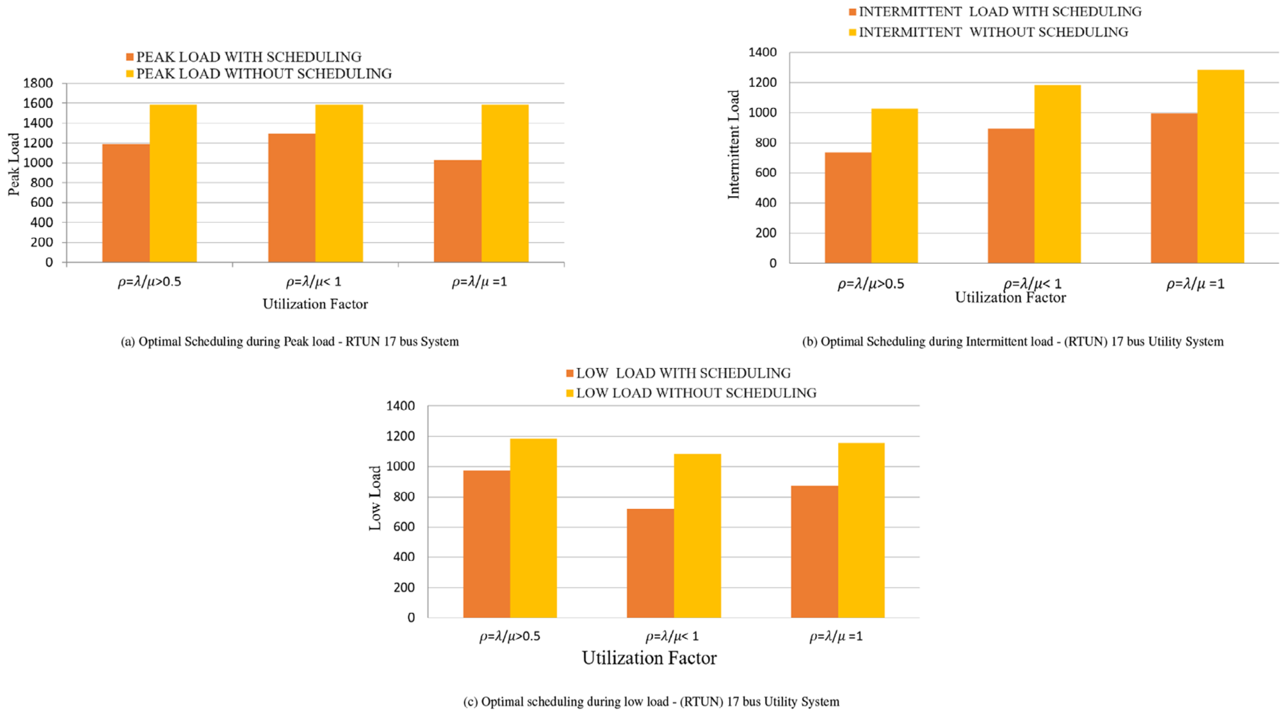


FIGURE 6 | Optimal scheduling for RTUN-17 bus system under different load conditions.

TABLE 3 | Impact of scheduling on PLR IEEE 33 bus system.

Scenario	Bus location	DG size (p.u)	With scheduling-PLR (%)	Without scheduling-PLR (%)
$\rho = \frac{\lambda}{\mu} > 0.5$ (Exceeding mode)	21	1.42	12.23	23.4
$\rho = \frac{\lambda}{\mu} = 1$ (Full capacity mode)	5	0.69	5.53	12.65
$\rho = \frac{\lambda}{\mu} < 1$ (Idle mode)	15	0.32	4.15	18.45

17518695, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/gtd2.70148, Wiley Online Library on [29/09/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 4 | Impact of scheduling on PLR RTUN-17 bus system.

Scenario	Bus location	DG size (p.u)	With scheduling-PLR (%)	Without scheduling-PLR (%)
$rho = \frac{\lambda}{\mu} > 0.5$ (Exceeding mode)	14	1.03	11.3	25.4
$\rho = \frac{\lambda}{\mu} = 1$ (Full capacity mode)	5	0.58	7.53	14.35
$\rho = \frac{\lambda}{\mu} < 1$ (Idle mode)	12	0.42	6.15	16.75

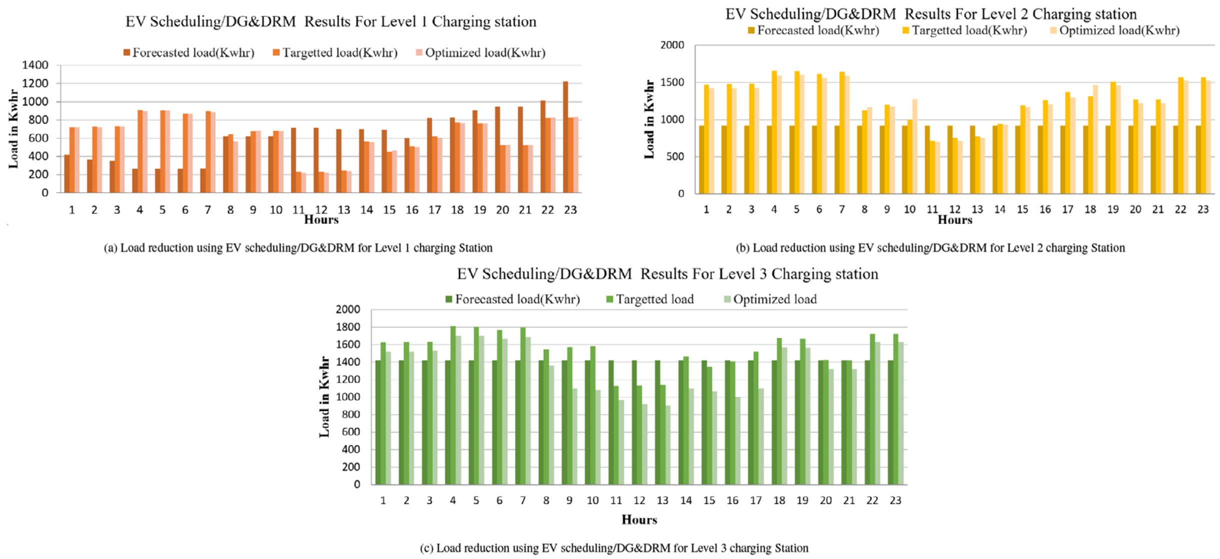


FIGURE 7 | Load reduction using EV scheduling/DG&DRM for charging station.

TABLE 5 | Scheduling with DG/DRM levels 1 and 2—IEEE 33 bus system.

Level 1 charging station					Level 2 charging station				
Bus	Device	Rated value (MW)	Max TSB (%)	PLR (%)	Bus	Device	Rated value (MW)	Max TSB (%)	PLR (%)
2	1	4.32	3.15	3.47	3	1	3.91	3.47	7.78
3	2	1.72	5.94	2.93	5	2	2.77	4.72	9.34
4	1	0.81	5.15	5.12	7	1	1.65	10.32	12.79
5	1	1.92	9.32	3.72	9	2	2.24	19.13	10.73
6	2	3.94	11.66	11.54	10	1	3.77	10.65	16.52
9	1	2.55	15.26	7.45	15	2	0.12	3.24	8.99
10	1	3.46	10.47	7.24	17	1	1.64	17.33	9.265
11	2	5.27	15.73	16.73	30	1	2.93	10.80	9.934
13	1	0.58	16.32	14.62					
15	2	3.64	8.47	11.63					
17	1	4.12	19.46	15.71					
19	1	4.64	10.42	9.21					
32	2	4.18	9.44	6.81					

5.1 | Comprehensive Optimisation

A comprehensive trade-off solution is performed to prove the efficiency and to arrive a global optimal output, which is less possible using the individual computational technique. DG parameters that is, size, location and rating are concurrently optimised and their fitness function is evaluated for the two test system. Tables 5–8 prove the effectiveness of the optimisation techniques which are evaluated for levels 1, 2 and 3 charging stations. The simulated results give a trade-off solution in both the test systems.

17518695, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/gtd2.70148, Wiley Online Library on [29/09/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 6 | Scheduling with DG/DRM levels 1 and 2—RTUN-17 bus system.

Level 1 charging station					Level 2 charging station				
Bus	Device	Rated value (MW)	Max TSB (%)	PLR (%)	Bus	Device	Rated value (MW)	Max TSB (%)	PLR (%)
2	1	4.67	12.78	2.44	3	1	2.23	2.34	3.56
3	2	1.52	4.90	3.95	4	1	1.49	3.23	7.38
5	2	0.94	9.57	4.12	5	2	0.64	16.38	16.04
7	1	3.79	11.37	1.06	6	1	3.24	18.37	14.04
10	1	4.67	13.16	11.62	10	2	2.79	22.31	6.437
11	1	3.68	17.36	8.38	15	2	3.14	4.23	7.99
14	2	2.89	12.37	9.29					
15	1	4.11	19.83	6.734					

TABLE 7 | Scheduling with DG/DRM level 3—IEEE 33 bus system.

Level 3 charging station				
Bus	Device	Rated value (MW)	Max TSB (%)	PLR (%)
2	2	5.64	5.44	9.43
3	1	4.20	5.32	4.58
4	2	0.72	10.43	9.11
5	2	1.44	12.36	7.012
6	2	3.26	18.66	11.25
7	1	2.55	19.54	16.56
9	1	1.42	4.26	7.11
10	2	2.14	12.54	3.75
11	1	3.83	17.56	13.54
13	2	4.02	1133	11.54
15	1	3.45	3.51	4.32
17	1	3.16	19.54	14.7
19	2	2.28	16.37	2.35
25	1	3.25	27.43	7.56
26	2	3.14	7.88	11.32
28	1	3.29	19.44	3.84
32	2	3.48	20.53	5.85

TABLE 8 | Scheduling with DG/DRM level 3—RTUN-17 bus system.

Level 3 charging station				
Bus	Device	Rated value (MW)	Max TSB (%)	PLR (%)
2	2	4.68	4.24	9.48
3	1	3.24	1.74	7.48
4	1	4.82	9.42	11.52
7	1	3.54	11.74	10.49
9	2	0.23	13.52	7.38
11	1	3.25	15.66	8.87
14	1	2.58	7.32	7.27
16	2	3.12	3.62	4.50
17	2	2.78	14.754	13.63

EVs scheduling with DG/DRM optimisation is much effective when loadability case studies are considered. The results from the base and comprehensive cases confirm that it is possible to prioritise multi-objective optimisation without fully compromising other objectives. The efficiency of the suggested approach is shown by its linear convergence characteristics. Figure 8a,b displays the number of iterations with the variation in the customer benefits and the iterations with the fitness value, respectively. It is evident that the algorithm starts reaching the optimum solution in 10 iterations, which shows the fast convergence performance of the proposed optimisation technique.

Case (i): Coordinate optimisation—idle mode.

Case (ii): Coordinate optimisation—full capacity.

Case (iii): Coordinate optimisation—exceeding full capacity.

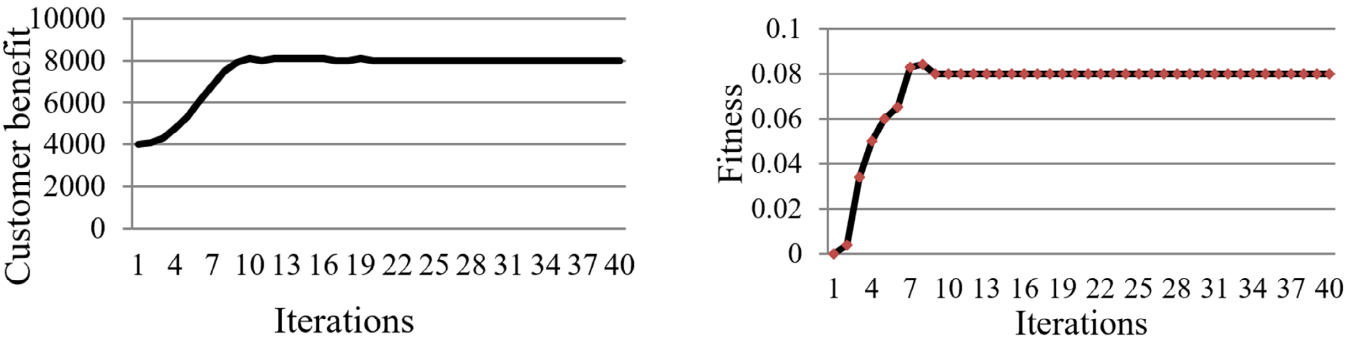
Case (iv): Coordinate optimisation—exceeding full capacity but needs servicing.

To prove the effectiveness of the optimisation program, the results of individual and hybrid optimisation are investigated. It is noted that significant locations are identified, but in some cases, the GA and MGA techniques reach local optima, which proves that GRN-PBIL surpasses traditional computational approaches in all respects as shown in Table 9.

Performance comparison of different scenarios is shown in Tables 10–13. To ensure reliable outcomes from the proposed optimisation algorithm; the solution is selected based on its performance in multiple independent trials with random starts. The fitness function is arrived with variable load and generation parameters.

Tables 14–17 show the approach to identify a plan for optimal distribution network operation in the RTUN test system. The comprehensive cases are used to evaluate the effectiveness of the proposed GRN-PBIL. These strategies are expected to aid in

17518695, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/gtd2.70148, Wiley Online Library on [29/09/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License



(a) Customer benefit along with iterations

(b) Fitness along with iterations

FIGURE 8 | Convergence trends of the proposed algorithm over 40 iterations.

TABLE 9 | Concurrent case study optimisation.

Case study	Load increase	Generation cost in ($/h)			Power load reduction (%)		
		GA	MGA	GRN-PBIL	GA	MGA	GRN-PBIL
I	30%	987.56	981.46	821.69	13.28	20.49	33.34
II	40%	971.67	1000.47	873.48	22.64	22.89	24.76
III	45%	952.23	959.23	838.27	15.53	18.44	25.21
IV	45%	969.68	964.62	846.44	21.41	26.23	23.39

TABLE 10 | Case (i): Coordinate optimisation—idle mode—IEEE 33 bus system.

Computation parameter	Scheduling	DG/DRM	Scheduling, DG/DRM
Total generation (MW)	252.84	286.35	277.53
Total load (MW)	248.37	285.48	273.62
Objective function ($/h)	**968.52**	**982.36**	**1058.91**

TABLE 11 | Case (ii): Coordinate optimisation—full capacity—IEEE 33 bus system.

Computation parameter	Scheduling	DG/DRM	Scheduling, DG/DRM
Total generation (MW)	279.72	263.52	251.77
Total load (MW)	252.46	251.64	237.29
Objective function ($/h)	**975.34**	**963.10**	**1010.34**

TABLE 12 | Case (iii): Coordinate optimisation—exceeding full capacity—IEEE 33 bus system.

Computation parameter	Scheduling	DG/DRM	Scheduling, DG/DRM
Total generation (MW)	274.52	280.36	270.73
Total load (MW)	266.71	272.32	267.92
Objective function ($/h)	**987.32**	**972.81**	**1052.56**

TABLE 13 | Case (iv): Coordinate optimisation—exceeding full capacity but need servicing—IEEE 33 bus system.

Computation parameter	Scheduling	DG/DRM	Scheduling, DG/DRM
Total generation (MW)	284.57	291.79	289.95
Total load (MW)	279.99	289.89	288.84
Objective function ($/h)	**992.57**	**999.342**	**1012.56**

17518695, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/gtd2.70148, Wiley Online Library on [29/09/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 14 | Case (i): Coordinate optimisation—idle mode—RTUN-17 bus system.

Computation parameter	Scheduling	DG/DRM	Scheduling, DG/DRM
Total generation (MW)	232.84	236.35	267.53
Total load (MW)	228.37	267.48	253.62
Objective function ($/h)	**948.52**	**962.36**	**1038.91**

TABLE 15 | Case (ii): Coordinate optimisation—full capacity—RTUN-17 bus system.

Computation parameter	Scheduling	DG/DRM	Scheduling, DG/DRM
Total generation (MW)	249.72	243.52	231.77
Total load (MW)	222.46	231.64	227.29
Objective function ($/h)	**945.34**	**943.10**	**1007.34**

TABLE 16 | Case (iii): Coordinate optimisation—exceeding full capacity—RTUN-17 bus system.

Computation parameter	Scheduling	DG/DRM	Scheduling, DG/DRM
Total generation (MW)	275.52	279.36	268.73
Total load (MW)	265.71	271.32	265.92
Objective function ($/h)	**986.32**	**971.81**	**991.86**

effective operational planning in spite of the intermittent nature of the parameters.

The best solution and the worst solution for maximising the welfare objective are treated as ($F3_{max,2}$) ($F3_{min,2}$). The same pattern is followed for other fitness functions and is tabulated in Table 18.

The computational performance of our proposed method and other computational techniques is tabulated in Table 19. The results prove that EV scheduling and by coordinated DG DRM approach, play a vital role in achieving the maximum TSB.

The average value for the fitness function taken with respect to the case studies is tabulated in Table 20. The results show that with proper knowledge of the system, the utility and the customer benefit under all possible comprehensive scenarios.

6 | Conclusion

This research investigated the performance of the power system by scheduling EVs with the penetration of DG and DRM. The work provides a heuristic GRN-PBIL optimisation to evaluate the comprehensive cases for achieving desirable solutions. The inferences from the proposed strategy are as follows:

1. The TSB maximisation with peak load reduction and generation cost minimisation are taken as fitness functions. Congestion index and the utilisation factor are considered a scalable factor to justify the intermittent nature of the parameters. The proposed algorithm is compared with different computational techniques to identify the global optimum output.
2. The research begins with the GRN by relevantly extracting the information from the data set. The charging demand is identified and the peak load reduction is achieved.
3. Distribution load flow is simulated and power injection modelling is formulated using PBIL. DRM with DG coordination is performed and the consumption pattern of consumers is determined.
4. Concurrent optimisation of the fitness function for multiple utilisation factors is explored thereby achieving the desired objective function. Standard IEEE 33 bus system and a real time Indian utility system are taken as test system to validate the research.

TABLE 17 | Case (iv): Coordinate optimisation—exceeding full capacity but need servicing—RTUN-17 bus system.

Computation parameter	Scheduling	DG/DRM	Scheduling, DG/DRM
Total generation (MW)	279.45	284.47	285.72
Total load (MW)	278.04	279.79	272.58
Objective function ($/h)	**937.45**	**943.95**	**947.47**

17518695, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/gtd2.70148, Wiley Online Library on [29/09/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 18 | Scalability evaluation of objective function.

Scenario	F1 ($/h)			F2 ($/h)			F3 (%)		
	Min $F1_{m1}$	Max $F1_{n1}$	Standard deviation	Min $F2_{m2}$	Max $F2_{n2}$	Standard deviation	Min $F3_{m3}$	Max $F3_{n3}$	Standard deviation
33 bus system—IEEE	613	789	22.768	884	1044	11.2	35	47	5.34
Indian utility system	542	988	17.074	708	1023	7.32	26	39	13.37

TABLE 19 | Computational performance.

Method	Objective functions (Scheduling, DG with DRM)		
	Cost minimisation (%)	Congestion minimisations (%)	TSB maximisation (%)
GRN-PBIL	7.34	20.78	23.65
GA	4.12	14.45	18.43
MGA	3.95	11.23	13.66

TABLE 20 | Evaluated functions for different scenarios.

Evaluated functions	Case study (i)		Case study (ii)		Case study (iii)	
	Avg. of discrete optimisation	GRN-PBIL	Avg. of discrete optimisation	GRN-PBIL	Avg. of discrete optimisation	GRN-PBIL
Total generation (MW)	221.64	262.46	242.47	261.75	289.64	293.32
Total load (MW)	224.43	234.78	238.41	267.01	287.02	292.49
Peak load reduction (%)	11.38	8.02	37.04	25.78	18.07	14.24
Generation cost reduction (%)	5.69	10.23	6.314	6.986	9.17	17.01
Computational time (s)	0.19	0.11	0.47	0.32	0.44	0.08
Objective function ($/h)	**1032.56**	**1149.31**	**1229.23**	**1893.74**	**1041.32**	**1051.79**

5. The results illustrate the necessity for scheduling and the integration of DRM with DG to achieve the desired trade-off solution under all possible comprehensive cases. It is also proved that with proper expert knowledge, this multi objective optimisation will be more effective which is not possible with individual computational techniques.
6. The proposed optimisation is a reliable method for the proper planning of power system networks.

Nomenclature

Variables

λ	Vehicle arrival rate at charging station
μ	Service rate for charging vehicles
N	Capacity of charging station
n	Number of vehicle in the charging station
ρ	System utilisation rate
L_q	Number of vehicles waiting in queue
L_s	Total number of vehicles in system
W_q	Average waiting time in queue
W_s	Average time a vehicle spends in system
λ_{eff}	Effective arrival rate
r	Random arrival rate of vehicles
t_{wait}	Waiting time
μ_{avg}	Average service rate
$t_{c,i}$	Charging time
μn_{max}	Maximum charging rate parameter
T_t	Current temperature of PV panel
P_{wind}	Power generated by the wind turbine
V_{ci}	Cut-in wind speed
V_{co}	Cut-out wind speed
$P_i(t)$	Powers of i^{th} DG and grid at time t
$C_i(t)$	Operating cost of i^{th} DG at time t
$M_p(t)$	Market price at time

17518695, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/gtd2.70148, Wiley Online Library on [29/09/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

λ_n	Total arrival rate at charging station
μ_n	Total arrival rate at charging station
ω_r	Rotor rotational speed
R_r	Rotor radius wind turbine parameter
$V(t)$	Wind speed at time
$t_{\max}$	Maximum charging time

Parameters

P_k	Probability of exceeding capacity
P_n	Probability of having n vehicles in the charging station
P_0	Probability of having idle charging state
$P_{EV,\max}$	Maximum power for each electric vehicle
α	Tuning parameter
$GCI_{g,i}$	Generation cost index
n_{DG}	Number of buses containing loads and DG units
P_{act}	Actual power
M	Air density
$P_{\max}$	Maximum power
t_n^{start}, t_n^{end}	Time interval when the n^{th} EV is scheduled for charging
P_i, P_{dg}, P_{ch}, P_D	Real power generation, charging and demand
θ_{ij}	Phase angle of admittance
δ_i, δ_j	Voltage angle
P_{pv}^{total}	Total power generated from photovoltaic (PV) sources
P_{wind}^{total}	Total power generated from wind turbine
P_{demand}^{base}	Total base power demand
Q_i	Reactive power injection
P_g	Power purchased from the grid
$x_{di}, y_{di}, z_{di}, x_{gi}, y_{gi}, z_{gi}, x_{dgi}, y_{dgi}, z_{gi}$	Cost coefficients
$P_{rated,i}$	Rated power
P_t^{pv}	Power output of photovoltaic
P_{wind}	Power generated by the wind turbine
V_i, V_j	Voltage at i^{th} and j^{th} bus
$N_{\min}$	Minimum number of vehicles considered in calculations
$V_{\max}, V_{\min}$	Minimum and maximum voltage limit
Y_{ij}	Admittance matrix
C_p	Power coefficient as a function of wind turbine parameters

Sets and Indices

m	Set of all EV vehicles
c	Number of charging piles
m, n	Indices for charging piles and electric vehicles
k_i	Temperature coefficient of PV panel
N_r	Rotor speed
V	Volume
V_r	Rated wind speed of wind turbine
A	Swept area of the wind turbine blades
i, j, k	Indices for buses, lines, loads
T	Time period
ND	Number of load buses
NG	Number of generation buses
NDG	Number of buses containing loads and DG units
NB	Number of buses
W_t	Total weightage factor
F_1, F_2, F_3	Fitness functions: generation cost, power loss, total social benefit
W_1, W_2, W_3	Weightage functions: generation cost, power loss, total social benefit
d, g, ch, and dgm	Demand, generation, charging and distributed generation

Author Contributions

Rajkumar Kasi: conceptualisation, data curation, formal analysis, investigation, methodology, resources, software, validation, writing original draft. **Chandrasekaran Nayanatara:** conceptualisation, data curation, formal analysis, investigation, methodology, software, supervision, visualisation, validation, writing – original draft, writing – review and editing. **Jeevarathinam Baskaran:** data curation, methodology, software, validation, writing – review and editing.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

References

1. M. Haghani, F. Sprei, K. Kazemzadeh, Z. Shahhoseini, and J. Aghaei, “Trends in Electric Vehicles Research,” *Transportation Research Part D: Transport and Environment* 123 (2023): 103881, https://doi.org/10.1016/j.trd.2023.103881.

2. P. P. Singh, F. Wen, I. Palu, S. Sachan, and S. Deb, “Electric Vehicles Charging Infrastructure Demand and Deployment: Challenges and Solutions,” *Energies* 16, no. 1 (2022): 7, https://doi.org/10.3390/en16010007.

3. A. Masoum, S. Deilami, P. Moses, M. Masoum, and A. Abu-Siada, “Smart Load Management of Plug-in Electric Vehicles in Distribution and Residential Networks with Charging Stations for Peak Shaving and

17518695, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/gtd2.70148, Wiley Online Library on [29/09/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Loss Minimisation Considering Voltage Regulation," *IET Generation, Transmission & Distribution* 5, no. 8 (2011): 877–888, https://doi.org/10.1049/iet-gtd.2010.0574.

4. F. Marzbani, A. H. Osman, and M. S. Hassan, "Electric Vehicle Energy Demand Prediction Techniques: An In-Depth and Critical Systematic Review," *IEEE Access* 11 (2023): 96242–96255, https://doi.org/10.1109/access.2023.3308928.

5. K. Prakash, M. Ali, M. Siddique, et al., "Bi-Level Planning and Scheduling of Electric Vehicle Charging Stations for Peak Shaving and Congestion Management in Low Voltage Distribution Networks," *Computers and Electrical Engineering* 102 (2022): 108235, https://doi.org/10.1016/j.compeleceng.2022.108235.

6. J. C. Vinitha, G. Ramadas, and P. U. Rani, "PSO-Based Fuzzy Logic Controller for Load Frequency Control in EV Charging Station," *Journal of Electrical Engineering & Technology* 19, no. 1 (2023): 193–208, https://doi.org/10.1007/s42835-023-01568-y.

7. N. Aung, W. Zhang, K. Sultan, S. Dhelim, and Y. Ai, "Dynamic Traffic Congestion Pricing and Electric Vehicle Charging Management System for the Internet of Vehicles in Smart Cities," *Digital Communications and Networks* 7, no. 4 (2021): 492–504, https://doi.org/10.1016/j.dcan.2021.01.002.

8. R. Yasmin, B. M. R. Amin, R. Shah, and A. Barton, "A Survey of Commercial and Industrial Demand Response Flexibility With Energy Storage Systems and Renewable Energy," *Sustainability* 16, no. 2 (2024): 731, https://doi.org/10.3390/su16020731.

9. B. Rasouli, M. J. Salehpour, J. Wang, and G. J. Kim, "Optimal Day-Ahead Scheduling of a Smart Micro-Grid via a Probabilistic Model for Considering the Uncertainty of Electric Vehicles' Load," *Applied Sciences* 9, no. 22 (2019): 4872, https://doi.org/10.3390/app9224872.

10. O. Elma, "A Dynamic Charging Strategy With Hybrid Fast Charging Station for Electric Vehicles," *Energy* 202 (2020): 117680, https://doi.org/10.1016/j.energy.2020.117680.

11. H. W. Pandey, R. Kumar, and R. K. Mandal, "Transformation of Indian Distribution Sector: Opportunity and Challenges for Unlocking the Demand Response Potential," *Renewable Energy Focus* 42 (2022): 221–235, https://doi.org/10.1016/j.ref.2022.06.008.

12. P. Zare, A. Dejamkhooy, and I. F. Davoudkhani, "Efficient Expansion Planning of Modern Multi-Energy Distribution Networks With Electric Vehicle Charging Stations: A Stochastic MILP Model," *Sustainable Energy Grids and Networks* 38 (2023): 101225, https://doi.org/10.1016/j.segan.2023.101225.

13. B. Kandpal, P. Pareek, and A. Verma, "A Robust Day-Ahead Scheduling Strategy for EV Charging Stations in Unbalanced Distribution Grid," *Energy* 249 (2022): 123737, https://doi.org/10.1016/j.energy.2022.123737.

14. A. Singh, B. K. Jha, D. Singh, and R. K. Misra, "Optimal Scheduling of PHEVs and D-BESSs in the Presence of DGs in a Distribution System," *IET Generation, Transmission & Distribution* 13, no. 22 (2019): 5019–5032, https://doi.org/10.1049/iet-gtd.2019.0428.

15. K. R. Reddy, C. H. H. Basha, V. Prashanth, C. Dhanamjayulu, S. Shivashimpiger, and R. Likhitha, "A Novel on Energy Management Strategy with Maximum Exploitation of Renewables and EV Storage in Distribution Networks," *International Transactions on Electrical Energy Systems* 2023 (2023): 1–18, https://doi.org/10.1155/2023/1365608.

16. V. V. V. S. N. Murty and A. Kumar, "Optimal DG Integration and Network Reconfiguration in Microgrid System With Realistic Time Varying Load Model Using Hybrid Optimisation," *IET Smart Grid* 2, no. 2 (2019): 192–202, https://doi.org/10.1049/iet-stg.2018.0146.

17. K. E. Adetunji, I. W. Hofsajer, A. M. Abu-Mahfouz, and L. Cheng, "An Optimization Planning Framework for Allocating Multiple Distributed Energy Resources and Electric Vehicle Charging Stations in Distribution Networks," *Applied Energy* 322 (2022): 119513, https://doi.org/10.1016/j.apenergy.2022.119513.

18. J. Zhao, Z. Xu, J. Wang, C. Wang, and J. Li, "Robust Distributed Generation Investment Accommodating Electric Vehicle Charging in a Distribution Network," *IEEE Transactions on Power Systems* 33, no. 5 (2018): 4654–4666, https://doi.org/10.1109/tpwrs.2018.2796645.

19. M. Z. Zeb, K. Imran, A. Khattak, et al., "Optimal Placement of Electric Vehicle Charging Stations in the Active Distribution Network," *IEEE Access* 8 (2020): 68124–68134, https://doi.org/10.1109/access.2020.2984127.

20. K. Zhou, K. Zhou, and S. Yang, "Reinforcement Learning-Based Scheduling Strategy for Energy Storage in Microgrid," *Journal of Energy Storage* 51 (2022): 104379, https://doi.org/10.1016/j.est.2022.104379.

21. P. Sharmila, S. Mahadevan, J. Baskaran, and C. Nayanatara, "Heuristic DRP-DG Optimization Strategy Adopted for Maximizing Total Social Welfare in the Real Time Indian Utility Network," *IET Renewable Power Generation* 16, no. 14 (2022): 3092–3107, https://doi.org/10.1049/rpg2.12560.

22. B. Alinia, M. H. Hajiesmaili, and N. Crespi, "Online EV Charging Scheduling With On-Arrival Commitment," *IEEE Transactions on Intelligent Transportation Systems* 20, no. 12 (2019): 4524–4537, https://doi.org/10.1109/tits.2018.2887194.

23. I. Sengor, O. Erdinc, B. Yener, A. Tascikaraoglu, and J. P. S. Catalao, "Optimal Energy Management of EV Parking Lots Under Peak Load Reduction Based DR Programs Considering Uncertainty," *IEEE Transactions on Sustainable Energy* 10, no. 3 (2019): 1034–1043, https://doi.org/10.1109/tste.2018.2859186.

24. P. Zare, A. Dejamkhooy, and I. F. Davoudkhani, "Efficient Expansion Planning of Modern Multi-Energy Distribution Networks With Electric Vehicle Charging Stations: A Stochastic MILP Model," *Sustainable Energy Grids and Networks* 38 (2023): 101225, https://doi.org/10.1016/j.segan.2023.101225.

25. C. Nayanatara, J. Baskaran, and D. Kothari, "Hybrid Optimization Implemented for Distributed Generation Parameters in a Power System Network," *International Journal of Electrical Power & Energy Systems* 78 (2016): 690–699, https://doi.org/10.1016/j.ijepes.2015.11.117.

26. C. Venkatesan, R. Kannadasan, M. H. Alsharif, M. K. Kim, and J. Nebhen, "Assessment and Integration of Renewable Energy Resources Installations With Reactive Power Compensator in Indian Utility Power System Network," *Electronics* 10, no. 8 (2021): 912, https://doi.org/10.3390/electronics10080912.

17518695, 2025, 1, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/gtd2.70148, Wiley Online Library on [29/09/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License