IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 15 July 2024, accepted 1 September 2024, date of publication 11 September 2024, date of current version 23 September 2024.
Digital Object Identifier 10.1109/ACCESS.2024.3458410

RESEARCH ARTICLE

Impact Assessment of Electric Vehicles Integration and Optimal Charging Schemes Under Uncertainty: A Case Study of Qatar

SHEETAL DESHMUKH[1], **(Student Member, IEEE)**, **HANAN TARIQ**[2], **MOHAMMAD AMIR**[1], **(Member, IEEE)**, **ATIF IQBAL**[1], **(Fellow, IEEE)**, **MOUSA MARZBAND**[3], **(Senior Member, IEEE)**, **AND ABDULLAH M. A. B. AL-WAHEDI**[4]
[1]Department of Electrical Engineering, Qatar University, Doha, Qatar
[2]Faculty of Electrical and Control Engineering, Gdańsk University of Technology, 80-233 Gdańsk, Poland
[3]Center of Research Excellence in Renewable Energy and Power Systems, King Abdulaziz University, Jeddah 21589, Saudi Arabia
[4]KAHRAMAA, Doha, Qatar

Corresponding author: Sheetal Deshmukh (sd1912817@qu.edu.qa)

This publication was made possible by ‘‘Efficient Smart Home Energy Management with Emphasis on Electrical Vehicles' Charging/Discharging Strategy''- Graduate Research Assistant Fund. The statements made herein are solely the responsibility of the authors. The APC (Article Processing Charges) for this manuscript is funded by the Qatar National Library (QNL), Doha, Qatar.

ABSTRACT The integration of electric vehicles (EVs) is rapidly growing compared to conventional vehicles in Qatar. To assess how these electric vehicles will impact Qatar's distribution network, it is necessary to accurately model EV loads. However, EV loads exhibit uncertainties due to driving behaviour in charging time, state of charge (SOC), number of trips, and distance travelled. This necessitates the development of a probabilistic model. The Monte-Carlo method is employed to predict EV charging profiles probabilistically. The generated EV load profiles are assigned to different sectors and compared with the base case voltage profile curve. The IEEE-33 bus system is utilized to evaluate EV impacts considering the load pattern of Qatar. EV load profile generation is performed using MATLAB software, and impact assessment is conducted in DIgSILENT software. The results indicate that following EV integration, the system's voltage profile experiences drops in the early morning and afternoon. A proposed charging scheme (R2), coupled with the integration of solar PV into the system, can mitigate this voltage drop issue. The PV panels have a rating of 1503 kW and are connected to the 14th bus. In Qatar, the hot summer months span from June to September, so the average PV generation data for September is used. The implementation of the proposed reward charging scheme improves system performance in terms of the voltage profile, ensuring grid resilience.

INDEX TERMS Electric vehicles (EV) integration to power system, impact assessment, charging scheme.

NOMENCLATURE

EV	Electric vehicles.
RTP	Real-Time Pricing.
TOU	Time-of-Use.
CTP	Critical Peak Pricing.
PSO	Particle Swarm Optimization.
GA	Genetic Algorithm.
FL	Fuzzy Logic.
HVAC	Heating Ventailing Air conditioning.
BTM	Battery Thermal Management.
AC	Air Conditioner.
PTC	Positive Thermistor Heater.

The associate editor coordinating the review of this manuscript and approving it for publication was Tariq Masood.

THD	Total Harmonic Distortion.
MV	Medium Voltage.
LV	LV Voltage.
SOC, DOD	State of Charge, Depth of Discharge.
DTD	Daily Travelling Distance.
RS	Reward schemes.
RN, MN	Radial Network configuration, Mesh Network Configuration.
d	Distance.
C_{DT}, C_t	Charging Duration, Charging Time.

I. INTRODUCTION

The widespread adoption of electric vehicles (EVs) globally has given rise to a transformative shift in power systems, impacting generation, transmission, and distribution networks. The surge in EV charging introduces variations in load magnitude and alters timing patterns across distribution networks [1]. This phenomenon poses challenges such as transformer overloading, thermal limits of cables, and concerns about power quality and reliability, particularly amplified when high-power chargers are employed or EVs are charged in specific residential zones, catering to light vehicles or commercial fleets. The residential EV charging surge also raises the prospect of increased household electricity consumption, potentially necessitating electrical infrastructure upgrades. Studies indicate that the power demand and traffic flow curves peak during morning and evening hours, with reduced demand during the night [1]. Evening EV plug-ins can significantly heighten power draw, risking surpassing a distribution system's maximum supply capacity. Unmanaged demand spikes can overload distribution components, necessitating cable and transformer replacements, and may even require additional generation capability. Notably, 10% EV penetration in Germany resulted in bottlenecks, while Norway experienced a 5 kW increase in average residential load leading to a 30% overload of distributed transformers [2], [3]. The impact on utility grids extends to renewable energy sources, grid stability, and overall asset management [4]. Dynamic energy management methods and time-varying pricing schemes, as proposed in [5], present solutions to these challenges. For commercial EV or fast charging stations, the geographic and case-specific impacts are contingent on power levels, with public charging stations commonly featuring 50 kW power ratings and increasingly frequent installations of multiple charging plugs, elevating potential loads to the megawatt scale, especially in highway areas [1].

To address the escalating power demands and potential grid overloads arising from EV charging, several strategies have been proposed. Real-Time Pricing (RTP), Time-of-Use pricing (TOU), Critical Peak Pricing (CTP), and Peak Time Rebate (PTR) present scheduling-based solutions, optimizing charging times based on pricing structures. Alternative methods focus on minimizing power losses, voltage deviations, peak loads, and energy costs. Optimization techniques such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Fuzzy Logic (FL) aim to smartly manage EV charging [6]. Effective analysis of grid impacts and the implementation of dynamic pricing tier charging schemes hinge on the accurate development of EV charging demand models. Various methods, including Monte-Carlo, Markov chain theory, dynamic traffic flow, and agent-based approaches, have been proposed for modeling EV charging demand. Noteworthy contributions include individual EV load profiles generated based on real driving patterns and charging behaviours [7], [8]. The one method is Monte Carlo method for EV charging demand generation, another method that is widely employed in the agent-based modeling of EV charging demand [9], [10]. In alignment with these methodologies, this paper concentrates on generating EV charging demand profiles using the Monte Carlo method exclusively. A case study for Shenzhen, China, as presented in [11], predicts EV charging demand peaking at 21:30, reaching around 1760 MW and increasing the load by 11.08%. This underlines the critical importance of understanding and effectively managing EV charging demand for ensuring the resilience and sustainability of power distribution networks.

The comparison table assessing the impact of electric vehicles (EVs) utilizes the Monte Carlo method, presenting key findings from various papers, including uncertainties considered and the networks is discussed (Table 1). The impact assessments on EVs explore factors such as EV penetration, location, charging schemes, charging time, different states of charge (SOC), and various EV types. The parameters evaluated encompass voltage levels, as well as the overloading of transformers and cables. Notably, the majority of papers primarily focus on L1, L2 single-phase, and three-phase chargers, with power ratings ranging from 1.44 kW to 11 kW, emphasizing lower charger ratings. Additionally, the studies predominantly concentrate on radial networks, neglecting considerations for network reconfiguration (mesh). Assessing the impact of EVs on network reconfiguration could facilitate the integration of more electric vehicles and the efficient utilization of available resources. Furthermore, the objectives of network reconfiguration discussed in the literature include reducing active power losses, load balancing, service restoration, and enhancing system reliability. Some papers explore feeder reconfiguration concepts to integrate more EVs into the system, relying solely on optimization methods such as genetic algorithms and particle swarm optimization. However, these approaches involve intensive computational requirements and often fail to comprehensively consider the overall system impact of EVs. Additionally, they overlook the variability in EV load, such as changes in charging time, controlled and uncontrolled charging schemes, and the integration of renewable sources. Notably, these above studies overlook temperature uncertainties and their impact on energy consumption. The proposed work addresses these limitations by providing a more comprehensive analysis that

TABLE 1. Comparison between the proposed strategy and different research works on the resilience enhancement in DSs and microgrids.

No.	Objectives	Techniques	Key Findings	Uncertainty Consideration	Network	Research Gap
[12]	Proposes an energy consumption model and impact assessment; finds optimal DG system size and allocation.	Monte Carlo, genetic-based algorithm	DGs reduce line overloading.	AER range, number of trips, multiple charging events per day, low-power rating of EV charger, temperature variations.	38-node test system	Lower power rating of EV charger, Temp (Canada, northern USA, northern Europe).
[13]	Studies the impact on the LV network due to increased integration of EVs and non-linear loads.	Montecarlo	EV charging location affects voltage unbalance and harmonics; concentrated charging far from the substation increases voltage unbalance.	Charging time, SOC, battery size, power factor, low-power rating of EV charger.	IEEE European Low Voltage network and European network #7	Lower power rating of EV charger.
[14], [15]	Proposes smart distribution power flow for scheduling smart EV charging.	Monte Carlo	Uncontrolled charging results in increased peak demand, low node voltage levels, and increased feeder current magnitudes.	Distance, SOC, charging time, low-power rating of EV charger.	IEEE 13-Node Test, Real distribution feeder	Lower power rating of EV charger.
[16]	Generates EV demand profile and assesses impact on four charging strategies.	Monte Carlo	-	Energy consumption, battery capacity, type of EV, low-power rating of EV charger.	37-node IEEE test feeder	Lower power rating of EV charger.
[17]	Models EV charging load for private vehicles.	Monte Carlo	Different charging scenarios show varied impacts on peak load and SOC of EV battery.	Departure time, distance, battery, EV type, charging time, SOC, low-power rating of EV charger, impact analysis of charging profile, fixed battery capacity.	-	Lower power rating of EV charger, fixed battery capacity.
[7]	Generates individual EV load profiles and assesses their impact on the distribution grid.	Monte Carlo model with historical data	Simultaneous charging with single-phase chargers causes voltage unbalances; transformer/cable overloading with three-phase chargers.	Distance and SOC groups, charging time, low-power rating of EV charger.	Tejn LV grid	Fixed battery capacity, no public charging.
[18]	Proposes a centralized control algorithm to manage EV charging points in LV networks.	Monte Carlo for household and EV load	Control algorithm mitigates problems up to 20% EV penetration; successful for 100% penetration with control cycles up to 10 minutes.	-	Two real LV networks	Public charging, commercial and industrial, mixed chargers impact, communication-dependent.
[19]	Benchmarks the impact of uncontrolled EV charging on excess PV energy for different penetration levels.	Monte Carlo	Higher EV penetration decreases excessive PV energy; distribution of EV charger type plays a significant role.	Three-phase EV charger, rural, urban, and sub-urban grid.	Rural, urban, and sub-urban grid	Number of EVs used not enough to mitigate overvoltage.
[20]	Proposes a stochastic modeling and simulation technique to analyze EV charging impacts on the distribution network.	Monte Carlo	Average system loss increases with EV penetration; controlled charging by the stochastic method has a lower voltage drop.	Charging time, SOC, low-power rating of EV charger.	IEEE 13-Bus test system, TPC 25-bus distribution system	Lower power rating of EV charger.
[21]	Studies the impact of electric vehicles on power quality.	Monte Carlo	Battery electric vehicles cause more overload to distribution transformers; level 2 and level 1 chargers can be problematic.	SOC, distance, battery capacity, charging duration, low-power rating of EV charger, implementation of smart charging schemes.	IEEE 123-bus test distribution system	Lower power rating of EV charger, implementation of smart charging schemes.
[22]	Presents a probabilistic harmonic simulation method to study power-quality impact of EVs.	Monte Carlo simulation	PHEV chargers have negligible harmonic impact; Level 1 charger may cause the rise of neutral-to-earth voltage.	SOC, distance, battery capacity, charging duration, low-power rating of EV charger, implementation of smart charging schemes.	North America, MGN system	Lower power rating of EV charger, implementation of smart charging schemes.
[23]	Proposes a comprehensive model to study PHEV impacts on distribution system load demand.	Comprehensive model	Voltage deviation is not a sophisticated issue, but peak load and loss increment are concerns.	Battery capacity, SOC, distance, charging time, EV type, low-power rating of EV charger, implementation of smart charging schemes.	IEEE 34-node test feeder	Lower power rating of EV charger, implementation of smart charging schemes.
[24]	Develops a probabilistic benchmark for assessing impacts of uncontrolled charging of PHEVs on residential distribution networks.	Monte Carlo simulation	Uncontrolled charging can be detrimental to transformers; diversity effect not as clear at the primary levels.	SOC, distance, EV type, penetration, charging levels, implementation of smart charging schemes.	IEEE 123-node test feeder	Implementation of smart charging schemes.
[25]	Proposes a systematic co-modelling and simulation framework to investigate impacts of PEV charging facilities.	Systematic co-modeling	Uncontrolled charging can be detrimental to transformers; diversity effect not as clear at the primary levels.	Charging levels, implementation of smart charging schemes.	IEEE 34 Node Test Feeder	Considered single-player (PEV charging facility).
Proposed	Studies impact assessment of EV on both radial and mesh configurations; proposes reward charging schemes.	Monte Carlo	For base case, 30% operates in an unsafe region; 20% EV penetration in radial structure results in 39.3% of buses operating below 0.90p.u (radial), Mesh network has all buses in a safe region.	Distance, charging time as per Qatar office timing, temperature, SOC and battery size, different EV charger sizes for each group.	IEEE-33	Thermal and overloading of lines and THD not considered.

encompasses the impact of EVs on the overall system, considering the variability in EV load, temperature impact on energy consumption and the benefits of network reconfiguration for accommodating increased EV integration.

The impact assessment discussed above lacks applicability to the specific scenario in Qatar. Situated in a hot arid climate, Qatar experiences a significant influence on electricity demand due to air conditioning, closely tied to external temperatures. Research results [26], [27] highlight increased electricity demand on hot days (36.8 °C) and decreased demand on cold days (16.8 °C). For a comprehensive impact assessment of EVs in the Qatari context, considerations must include the unique charging times for EVs. Commonly scheduled for the evening, this timing may not align with Qatar's distinctive working hours. Moreover, the peak load in Qatar shows a peak demand at 15:00 hrs in September and a minimum demand at 15:30 hrs in February.

The [28] showed how the electric vehicle range is affected by temperature. When the temperatures are optimal (21.5 °C), electric vehicles can operate at 115% of their rated range. For temperature 40 °C, the range drops down by 80% of the rated range. For cold conditions temperature −15 °C drops to 54% of the rated range. For the cold conditions, the impact of EV charging on the network for extreme cold conditions for temperatures (−5 °C, 0 °C, 5 °C, 10 °C, and 20 °C) is discussed in [29]. The key findings charging EV at lower temperatures increases harmonics and frequent charging of EVs leads to increased demand from the grid. The paper [29] lacks an impact assessment of EVs for hot conditions. In [30] for temperatures 30 °C and 40 °C charging time increases by 15-31% as compared to the optimal temperature due to an increase in HVAC (Heating Ventailing Air conditioning) and BTM (Battery Thermal Management) load during driving which compensated at charging. Moreover, the driving efficiency decreases at 40 °C by 25% which requires frequent charging. Another [31] paper showed the use of AC (Air Conditioner) and PTC (Positive, Thermistor Heater) increases per-mile energy consumption by 12% in Phoenix (which has a temperature like Qatar in summer) when compared to a vehicle with no HVAC. The increase in ambient temperature leads to an increase in use of HVAC while driving to cool the cabin cooling. While BTMS focus on maintaining optimal battery temperature during charging leading to an increase in energy consumption. The HVAC while driving impact increases by 10% and BTMS focus on maintaining optimal battery is 10% total energy consumption 20%. In this paper impact, assessment of EVs for Qatar's hot condition is carried out. Here it is assumed that energy consumption of electric vehicles increases by 20% in summer [26], [27]. This assumption is required for EV charging demand, implementation of charging schemes, and infrastructure development.

Some of the papers discussed the impact assessment of Qatar [32], [33]. In the paper [32], the author discussed the impact of total harmonic distortion (THD) on the distribution network. It was observed that for the medium voltage side (MV 11 kV) THD value was observed to be within limit for an increase in EV penetration while for low voltage side (LV 415 V) had a high value of THD that puts a limit on EVCS integration. The drawback of this paper is the lack of consideration of the impact of coordinated /smart charging schemes on EV integration on the distribution network. Another paper [33] discusses the impact of EVs on Qatar in which the worst scenario (10% EV penetration charged at the same time (14 hr) leading to an increase in the peak demand by 19.2% exceeding the generation limit. This can be avoided by using PV source generation and charging EVs from 5 am to 11 am would flatten the duck curve of EV demand. However, there is the chance of creating another peak from 5 am to 11 am. The problem further worsens if all the sectors (public, banks, commercial and private, and residential) charge their vehicles during the same period. Some of the existing research focuses on off-grid- EVCS along with the integration of solar, wind and energy storage batteries [34], [35], [36], [37], [38]. However, the study lacks smart charging implementation for grid-connected systems. Another work that is carried out is based on the placement of EV charging stations in Qatar University placement [39], [40]. The above work provides solutions from the utility point of does not encouraging customers to participate in EV charging to get compensation as rewards like incentives based, discounts on charging in non-peak hours. Therefore, there is a need to propose appropriate charging schemes to all sectors to integrate more EV integration that will not cause an increase will not affect grid stability and provide customer satisfaction. The unique reward charging schemes help to mitigate the impact of EV integration on the grid and make users participate in demand side response a win-win situation for the utility and EV users. Additionally, the focus of prior studies [27], [41] on Time-of-Use and incentive schemes for residential areas overlooks the potential implications in the commercial sector. Hence, the proposed paper introduces reward-based charging schemes targeting established government offices, banks, and private offices, providing a more holistic perspective on EV integration. Furthermore, the paper emphasizes the higher rating of L2 chargers and fast chargers in line with Kahrama's (state-owned electricity provider) guidelines. The overall system representation is illustrated in Fig. 1. The study primarily focuses on the bus voltages only without considering power quality issues.

The paper is distinguished by the following key contributions:

- **Comprehensive Impact Assessment**: The impact assessment is based on uncontrolled charging schemes, considering factors such as charging time, the level of EV penetration, and network reconfiguration.
- **Proposed Reward Charging Scheme**: The paper introduces five a novel reward-based charging scheme, contributing to the broader discourse on effective EV integration.

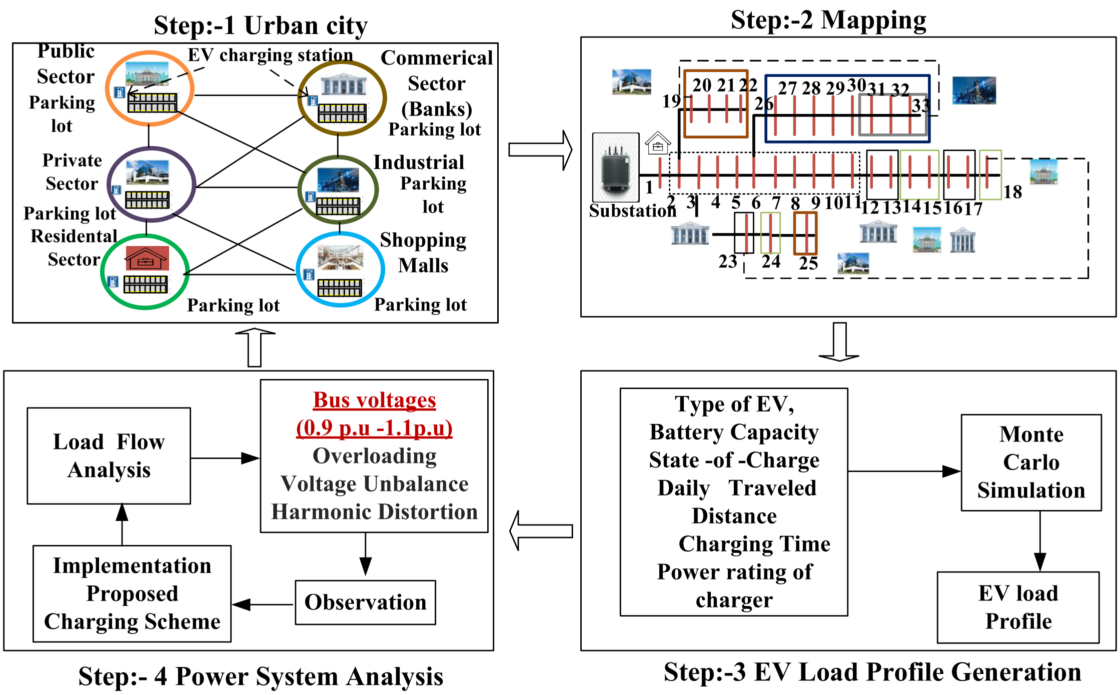


FIGURE 1. Overall system representation.

- **Integration of Renewable Sources**: The impact assessment of EVs is extended to include scenarios with the integration of renewable energy sources.

The paper's structure is organized to provide a clear understanding of the methodologies and findings:

- **Data Collection Methods (Section II)**: The paper begins by describing the methods employed for data collection.
- **Mathematical Modeling of EV Load Profile (Section III)**: Section III delves into the mathematical modeling involved in generating the EV load profile.
- **Reward-Based Charging Schemes (Section IV)**: Details regarding the proposed reward-based charging schemes are presented in Section IV.
- **Simulation Results (Section V)**: Section V comprehensively outlines the simulation results obtained from the study.
- **Conclusion (Section VI)**: The paper concludes with a summary of key findings and insights derived from the impact assessment and proposed charging schemes.

Fig 1 represents the steps for the overall impact assessment of EVs. Public, private, and bank sectors are first mapped to the electric network, then EV load profiles are generated considering uncertainties, and the last step is to integrate EV and base load and analyse load flow. For this overall system implementation, the data collected for the analysis is categorized into 5 types as shown in Fig 2.

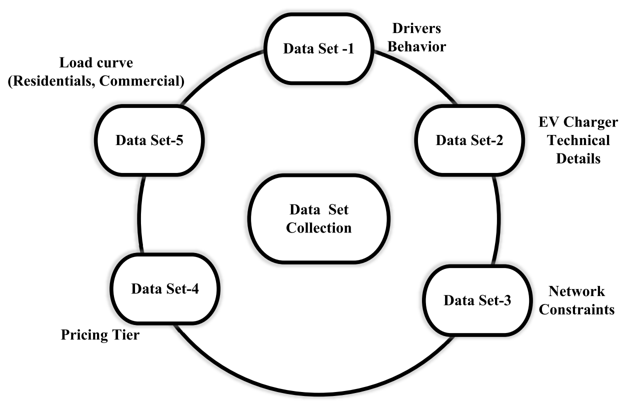


FIGURE 2. Data set types.

II. DATA COLLECTION

A. DATA-1 (DRIVERS BEHAVIOUR)

In this data-1, the data related to drivers' behaviour and EV specifications are considered. The average daily travelling distance (DTD) is around 40-100 km [26], [42]. 20 different electric vehicle specifications such as battery specifications and battery range kilometres were selected with mean, and standard deviation were calculated with maximum and minimum values. (Table 2) highlights the parameters.

1) UNCERTAINTY CONSIDERATIONS

The working hours in Qatar are classified into two categories; public sector and private sector. The public sector working

TABLE 2. Table of all parameters.

Sr.no	Uncertainties	Distribution	Mean, Std Deviation
1	Distance	Normal	(50 km, 20 km)
2	Battery Capacity	Normal	(78.77 kWh, 19.62 kWh)
3	Charging time G1	Normal	(6 hr, 1 hr)
	Charging Time G2-A	Normal	(7.30 hr, 1 hr)
	Charging Time G2-B	Normal	(15.30 hr, 1 hr)
	Charging Time G3	Normal	(9 hr, 1 hr)
	Charging Time G4	Normal	(8.30 hr, 1 hr)
	Charging Time G5	Normal	(18 hr, 1 hr)
4	Number of trips	Normal	(2.48, 1.16)
5	T_{Winter}	Normal	(16 °C, 10 °C)
6	T_{Summer}	Normal	(36 °C, 10 °C)
7	Energy Consumption T_{Winter}	-	Reduced (20%)
8	Energy Consumption T_{Summer}	-	Increased (20%)
9	Depth of discharge(DOD)	-	80%
10	State of Charge (SOC)	Normal	(50, 20)
11	Efficiency of charger	-	90%

hours are from 6 am to 2 pm and the private sector timing banks are 7.30 to 12 hrs and another shift from 15.30 hrs to 7.30 hrs and private offices timings 8.30 hrs or 9 hrs to 17.30 or 18 hrs. The arrival and departure time for various offices is depicted in Fig 3. Some of the other uncertainties considered are state-of-charge (SOC), charging time (C_t), energy consumption (E_C) and temperature of winter season (T_w) and summer season (T_s). The mean and standard deviation of the above uncertainties are given in (Table 2).

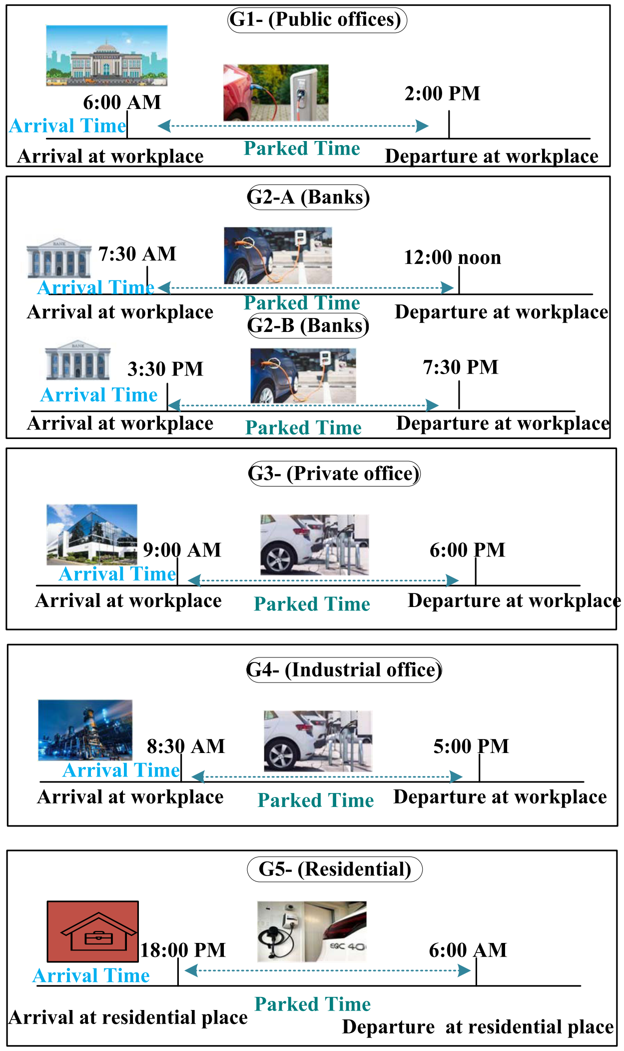


FIGURE 3. Arrival and parking time for group G1,G2-A,G2-B,G3,G4 and G5.

B. DATA-2 (EV CHARGER TECHNICAL DETAILS)

This data is related to EV charger technical details suggested by Kaharmaa the power rating of EV charger is given in (Table 3). The workplace and commercial groups are G1, G2-A, G2-B, and G3, G4. The residential sector as G5 with the level of charger recommended are three phase 11 kW and 22 kW EV chargers [42], [43].

TABLE 3. Power rating of EV charger [43].

Group Name	11 kW	22 kW	25 kW	50 kW DC	100 kW DC
G1 (Public)	YES	YES	-	-	-
G2-A,B (Banks)	YES	YES	-	-	-
G3 (Private)	-	-	YES	YES	-
G4 (Industrial/shopping)	-	-	-	YES	YES
G5 (Residential)	YES	YES	-	-	-

TABLE 4. Grid standard [45].

Sr.no	Parameters name	Parameters value
1	Voltage (IEC-Std 50160)	Between 0.90 p.u and 1.1 p.u
2	Total harmonic (THD)	$\leq 10\%$
3.	Transformer overload	$\leq 50\%$
4	Overloading of lines	According line specification

TABLE 5. Pricing tier of qatar (US Dollars).

kW	Residential (Villa/Flat)	Commercial	Industrial	Government Sector
(1-2000)	0.03	0.035	0.036	0.087
(2001-4000)	0.035	0.035	0.036	0.087
(4001-10,000)	0.05	0.06	0.036	0.087
(10,000-15,001)	0.05	0.06	0.036	0.087
15,001 and more	0.07	0.06	0.036	0.087

C. DATA-3 (NETWORK CONSTRAINTS)

This data considers the network constraints of the power system. Some of the constraints considered are given in (Table 4) under voltage level, total harmonic distortion (THD), transformer and line overloading [44], [45].

D. DATA-4 (PRICING TIER)

The (Table 5) highlights the different pricing tiers for each sector [43].

E. DATA-5 (LOAD CURVE)

As per the data collected from Kaharmaa, the summer season with the 30-minute interval that has the maximum peak

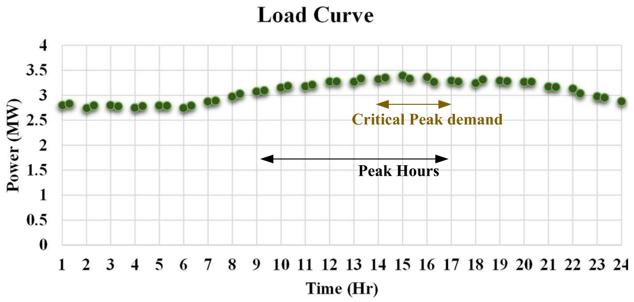


FIGURE 4. Load curve.

occurs in the afternoon at with P = 8475 MW [43]. This analysis considers 0.004% of peak load and derived a load curve as given in Fig 4. The highlighted peak period is marked in black from 9:00 to 17:00, with the critical peak occurring between 13:00 and 17:00.

III. MATHEMATICAL MODELLING AND METHODOLOGY

When the electric vehicle arrives at the residence or workplace to recharge, the amount of energy remaining is known as the state of charge (SOC). This SOC may vary it is a random number and its probability density function (pdf) depends on the daily travelling distance (DTD). The distribution for DTD is the normal type with zero probability for all negative distances as explained in Fig 5 a. The mean of the distribution is 50 km and the standard deviation is 20 km [25], [46], [47]. The probability function is given by the below equation. Where d is a random distance and μ, σ are for the mean and standard deviation, respectively.

$$f(d) = \frac{1}{d\sigma\sqrt{2\pi}} e^{-\frac{(ln(d)-\mu)^2}{2\sigma^2}}, d > 0 \tag{1}$$

The SOC of the battery is represented as in Fig 5 b [48].

The battery capacity and temperature mean values are 78.77 kWh, 36 ° C (summer), and 16 ° C (winter) are shown in Fig 5 c,d. The plug-in time of EVs for each group are shown in Fig 5 e. The Fig 5 f shows the block diagram for EV load profile generation. The charging duration for the electric vehicle is calculated considering battery capacity, level of the charger and initial SOC (C_{DT}). The normal distribution for the SOC is given in Fig 8b.

$$C_{DT} = \frac{B_{capacity} \times (1 - SOC) \times (DOD)}{P_{EVcharger} \times \eta} \tag{2}$$

In Eq. 2, the $B_{capacity}$ represents the battery capacity (kWh). The stored energy of the battery cannot be fully utilized without causing damage to the battery life. The is depth of discharge (DOD) defined as the fraction of power that can be utilized from the battery considered DOD is 60% which means that only 60% of battery capacity can be used by the load. $P_{EVcharger}$ represents the power rating of charger while η as the efficiency of charger.

The charging time (C_t) is considered as the mean and standard deviation for the public sector at 6 am mean standard deviation 1 hour (6,1) while for the private sector at 7 hrs, 9 hrs and 15 hrs mean standard deviation 1 hour (9,1), (7,1), (15,1). The charging time for each office is shown in Fig 5. The EV load profile generation block diagram representation is given in Fig 5. The algorithm of Monte Carlo is discussed below. This code was used to generate 100 EV load profiles for each sector as per the charger capacity assigned Table 3.

Algorithm

Start

- **Set the parameters:**
  - Set number of iterations value
  - Set number of EVs value
  - Set charging power level, battery capacity, distance and SOC, T_{summer} value
- **Create an array to store the load profiles values**
- **Start loop for iteration**
  - Initialize the load profile
- **Start loop for each EV**
  - Generate parameters of battery capacity, distance, and SOC using normal distribution
- **Calculate the energy consumption using above parameters**
  - Calculate the energy consumption based on temperature of season parameters
  - If $T_{summer} > 30$
  - Energy consumption = energy consumption $\times$ 1.2
  - End
- **Calculate the charging power level of charger**
- **Start Loop for number of trips**
  - Calculate for each trip charging duration and departure time
  - Calculate the start time and end time
  - Update the load profile
  - End loop for number of trips
- **End loop for each EV**
- **End loop for iteration**
- **Stop**

A. LOAD FLOW ANALYSIS

The load flow analysis can be implemented by different methods Newton-Raphson, Gauss-Seidel and Fast coupled method. The Newton-Raphson and Guass seidel were used for IEEE-5, IEEE-30, 33, 57 and 118 test buses [49]. Here the paper focuses on the netwon-raphson method is an iterative method that solves a set of non-linear simulatauus equations using Taylor's series expansion. In a n bus system that has n equations for active and reactive powers. the number of unknowns is 2(n-1) as the voltage magnitude and phase angle of slack and swing bus are known. The Newton-Raphson which works faster than the Gauss-seidel technique. Moreover, it saves time of computation and requires only fewer iterations.

Steps for implementation Newton-Raphson are given below [50] and [51]:

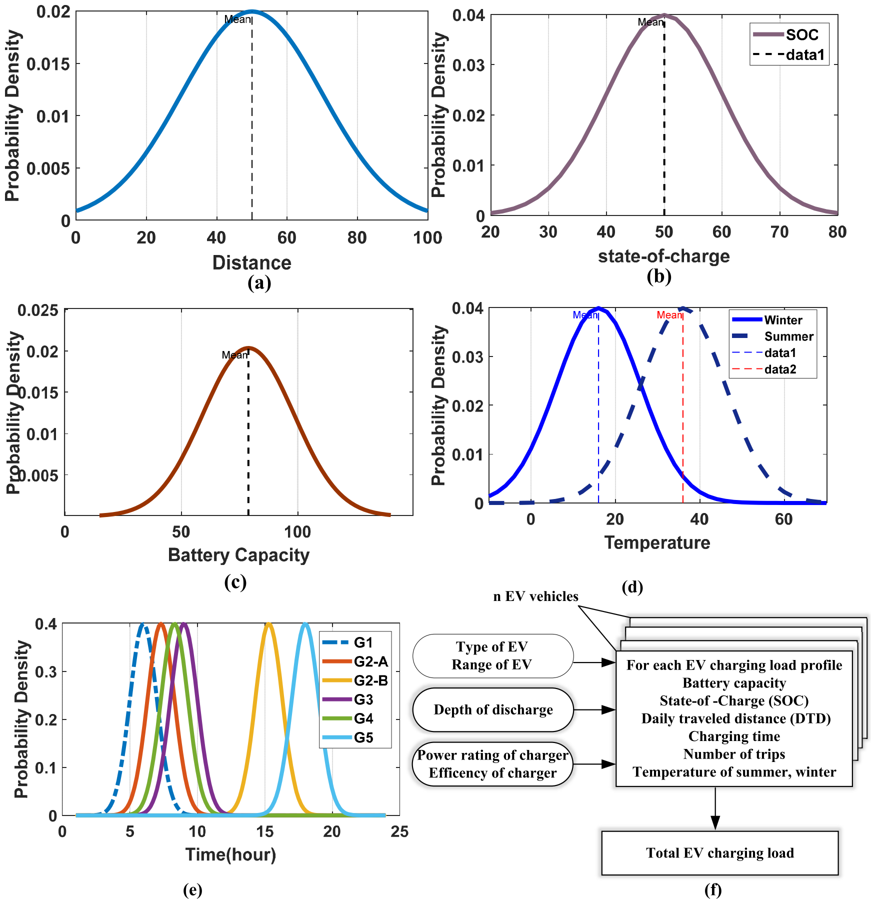


FIGURE 5. Probability distribution of (a) distance (b) state-of-charge (c) battery capacity (d) temperature (e) charging Time (f) EV charging load block diagram.

- Form the nodal admittance matrix ($Y_{i,j}$). Set initial bus voltage and reference bus.

$$\begin{aligned} \mathrm{V_i} &= \mathrm{V_{i,\,spec.}}\,\angle 0^\circ \text{ (at all PV buses)} \\ \theta_{\mathrm{i}} &= 1\angle 0^\circ \text{ (at all PQ buses)} \end{aligned} \tag{3}$$

where θ is the voltage angle and V_i is the magnitude of bus i.

- Calculate the real power P_i using below equation.

$$P_i = G_{ii}\,|V_i|^2 + \sum_{j=1}^{n} |V_i|\,\left|V_j\right|\left(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}\right) \tag{4}$$

- Calculate the reactive power Q_i using below equation.

$$Q_i = -B_{ii}\,|V_i|^2 + \sum_{j=1}^{n} |V_i|\,\left|V_j\right|\left(G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}\right) \tag{5}$$

- Form jacobian matrix H N' M L'.
- Calculate the errors.

$$\begin{aligned} \Delta P_i &= P_{i,\text{ specified.}} - P_{i,\text{ calculated}} \\ \Delta Q_i &= Q_{i,\text{ specified}} - Q_{i,\text{ calculated}} \end{aligned} \tag{6}$$

where ΔP_i = Active power errors
ΔQ_i = Reactive power errors
$P_{i,\text{ specified.}}$ = Active power at specific bus
$Q_{i,\text{ specified.}}$ = Reactive power at specific bus
$P_{i,\text{ calculated.}}$ = Calculated active power using voltage estimation
$Q_{i,\text{ calculated.}}$ = Calculated reactive power using voltage estimation

- Select tolerance value.
- Iteration stops if all the values are within the tolerance value.
- Update the values of V_i and θ_i.

IV. REWARD BASED CHARGING SCHEMES

The existing reward or incentives-based charging schemes are listed in the given (Table 6). They are broadly categorized as EV subsided, Tax benefits and charger incentives for Norway, Germany, France Spain Italy and the UK.

In these four different reward-based charging schemes are proposed for each sector and the results are analyzed for one of the reward schemes (RS). The proposed reward schemes are listed below:-

- RS1 - Tariff based.

TABLE 6. Comparison of existing reward charging schemes [52], [53].

Country	Number of Schemes	Details
Norway	3 (Subsidies, Tax Benefit, Charger Incentives)	• Subsidies: 50% fees on road toll and parking, funding for EV installation • Tax Benefit: No import and purchase tax. • Charger Incentives: Funding for EV charger installation.
Germany	3 (Subsidies, Tax Benefit, Charger Incentives)	• Subsidies: €9,000 discount on €40,000 EV purchase, 50% subsidy for commercial vehicles. • Tax Benefit: 10-year vehicle tax exemption. • Charger Incentives: Grants and incentives for public chargers and DC chargers.
France	3 (Subsidies, Tax Benefit, Charger Incentives)	• Subsidies: CO2 allowance, bonus for scrapping old cars. • Tax Benefit: 50% discount or full exemption on registration tax. • Charger Incentives: Credits for apartment building installations, grants for municipal charging points.
Spain	3 (Subsidies, Tax Benefit, Charger Incentives)	• Subsidies: Based on range, scrapping old vehicles. • Tax Benefit: Up to 75% reduction in purchasing cost, special tax exemption. • Charger Incentives: 30-40% reimbursement for installation.
Italy	3 (Subsidies, Tax Benefit, Charger Incentives)	• Subsidies: Bonus for EV purchasers with scrapping old vehicles. • Tax Benefit: Up to 75% reduction, exempted vehicle tax for 5 years. • Charger Incentives: 50% tax deduction on installation cost.
UK	3 (Subsidies, Tax Benefit, Charger Incentives)	• Subsidies: Reimbursement on EV purchase with scrapping old vehicles. • Tax Benefit: Exempted road tax, reimbursement on purchase cost. • Charger Incentives: 75% reimbursement for home and workplace installations.
UAE	4	• Registration fee reduction, free parking, toll exemption, free public charging or incentives.
India	6	• Incentives on purchase, loan interest rate discount, road tax and registration fee exemption, income tax benefit, scrapping old vehicle.

- RS2 - Bill Discount-based weekly/monthly/yearly
- RS3 - Free Public Charging Sessions
- RS4 - Reward as Vouchers
- RS5 - Environmental Impact

A peak hour and a non-peak hour pricing tier are used for the (RS1) charging scheme. From Fig 6, three peak hours are initial (6 hrs to 12.30 hrs) critical (12.30 hrs to 17.30 hrs) and final peak (17.30 to 18.30 hrs) hours. The non-peak hours are from 18.30 to 6 hrs. The pricing tier is highest for critical peak hours, followed by peak hours initial and peak hours final. The RS2 charging scheme deals with electricity bill discounts shown in Fig 7. Discounts will be available

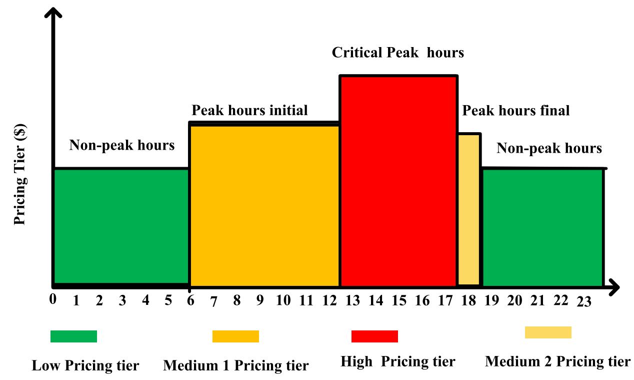


FIGURE 6. Reward scheme RS1.

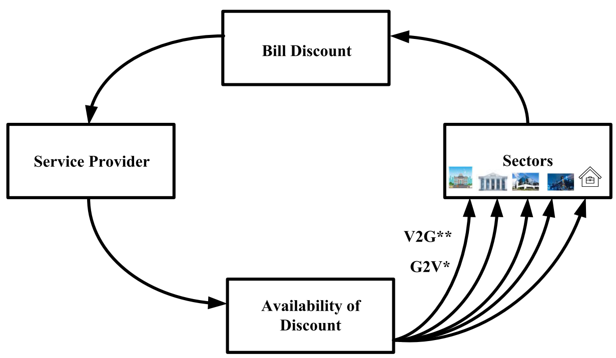
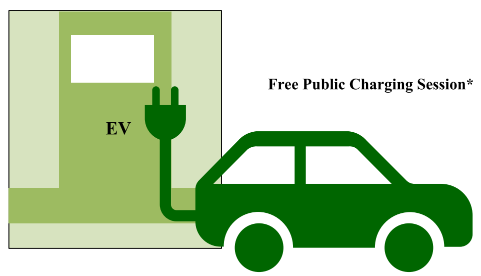


FIGURE 7. Reward scheme RS2.



* Receive Free 1 Public charging session if charged in non-peak hours for entire month/week

FIGURE 8. Reward scheme RS3.

depending on time (after 3 pm or non-peak hours) and the mode vehicles are operating in, such as grid-to-vehicle (G2V) and vehicle-to-grid (V2G). In peak hours, V2G mode offers a greater discount than G2V mode. There will be different discounts on electricity for residential, public offices, banks, and private and industrial areas.

The number of free charging sessions (RS3) will be available for different sectors. As shown in the Fig 8. The public sector has more free charging sessions Fig 8 if EVs are charged in non-peak hours for the entire month/week. The reward schemes (R4) will give vouchers for shopping, and grocery shops the vouchers will given if charged during non-peak hours and other vouchers if charged from solar plants installed in various sectors as shown Fig 9. This scheme

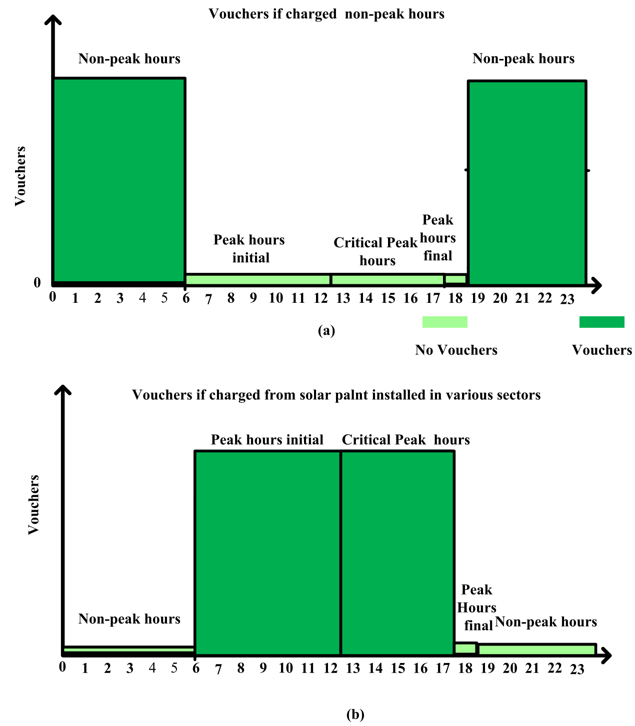


FIGURE 9. Reward scheme RS4.

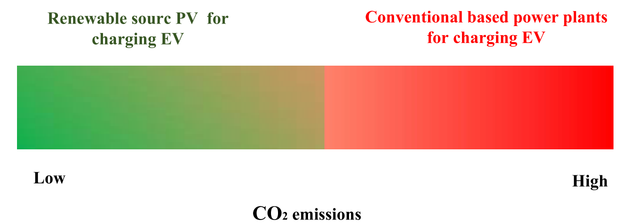


FIGURE 10. Reward scheme RS5.

can save monthly expenses of grocery. The last charging (RS5) scheme is shown in Fig 10. When EVs are charged by renewable sources that emit lower CO_2 emissions every week, they will get rewards as receive parking preferences in parks and malls.

V. SIMULATION RESULTS

The IEEE 33 bus system has been used for this study as shown in Fig 11. It has 33 buses with 32 fixed lines and 4 dotted branches (34, 35, 36 and 37) called tie lines. Initially, the system operates in the radial network. Tie lines highlighted in Fig 11 are connected later forming meshes to the radial system. EVs impact assessments are done for both network configurations from radial to mesh network. The grid source is connected to bus no 1 and other sources and reactive power compensation is absent. The safe operating range of the bus is considered as per [54], [55] 0.90 p.u and 1.1 p.u. In the modified system network only the voltage ratings are changed from 12.66 kV to 11 kV and the load as discussed in section II matches the Qatar Scenario.

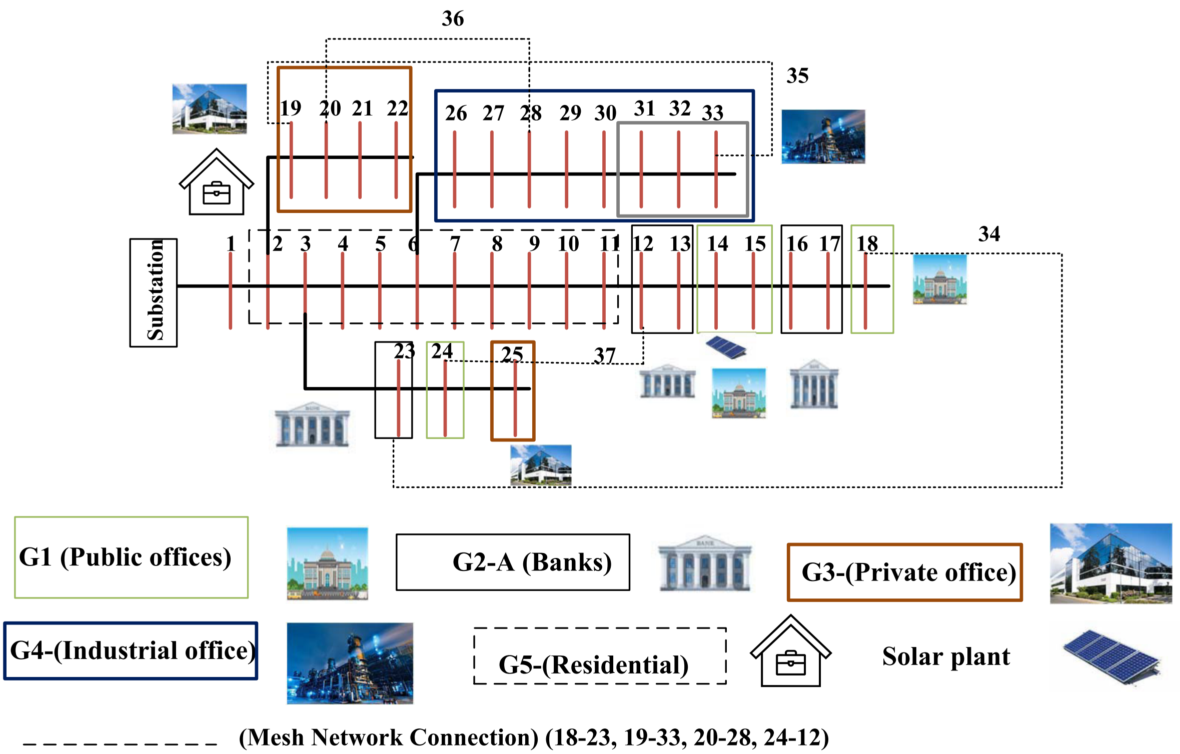


FIGURE 11. System under study.

The system is divided into 5 sectors with the following percentages 11% government (G1), banks (G2) and private office (G3) are 14.5% each while industrial (G4) is 27%, 33% residential (G5). Further, each sector load curve is derived from the base case shown in Fig.4 eg for the public sector (0.11% of base case load curve). Here Xn represents the R, B, P, Pr and I 'for' residential, bank, public, private, and industrial groups 'respectively' and n represents bus numbers 1 to 33. The list of buses for each sector is given below.

1) G1 (Public office) - P14, P15, P18, P24.
2) G2 (Banks)- B12, B13, B16, B17
3) G3 (Private office)- Pr19, Pr20, Pr21, Pr22, and Pr25.
4) G4 (Industrial office) - I26, I27, I28, I29, I30, I31, I32, I33.
5) G5 (Residential) - R2, R3, R4, R5, R6, R7, R8, R9, R10, R11.

The renewable sources are connected to bus number P14.

The system operates in two modes radial and mesh network. For both modes the study considers only on bus voltages. The two operation are discussed below:

1) RADIAL NETWORK CONFIGURATION (RN)

During this radial configuration, the switchable branches 34, 35, 36 and 37 are switched out. That is there is no loop formation.

2) MESH NETWORK CONFIGURATION (MN)

During this mesh configuration, the switchable branches 34, 35, 36 and 37 are switched on. Here the assessment is based on six factors as shown in Fig 12.

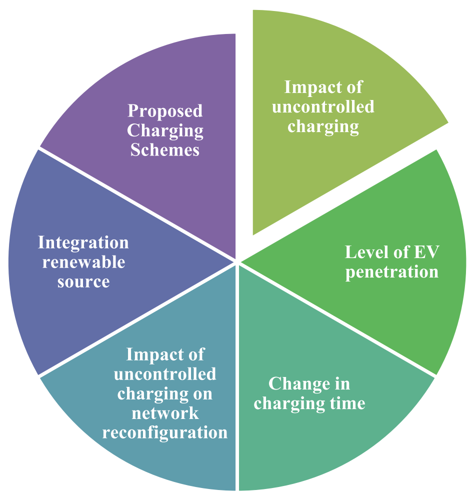


FIGURE 12. Impact assessment factors.

The analysis encompasses the following robust case studies (**CS**):

- **CS-A**: Baseline scenario with no EVs.
- **CS-B**: Significant impact scenario with 20% EVs in a radial network.

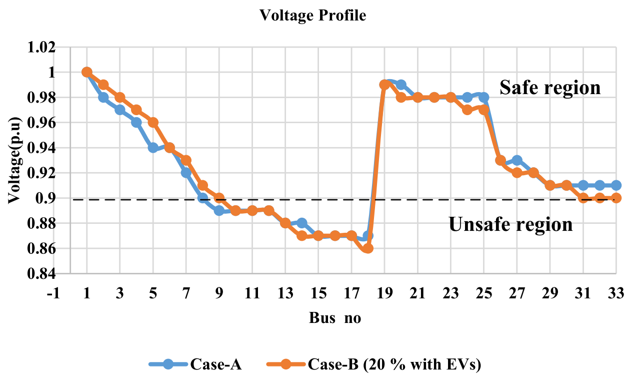


FIGURE 13. Base case bus voltages.

- **CS-C**: Enhanced scenario with 20% EVs and network reconfiguration.
- **CS-D**: Dynamic scenario involving 20% EV penetration in a mesh configuration, coupled with a shift in charging time.
- **CS-E**: Innovative scenario with 20% EV penetration in a mesh configuration, synergized with solar plants.
- **CS-F**: Outcome of the proposed reward charging schemes.

A. CS-A: BASE CASE WITH NO EVS

In the base case, a meticulous load flow analysis and quasi-dynamic simulations were executed using the DigSILENT PowerFactory software. The total active and reactive power recorded were 3.23 MW and 1.56 MVAR, respectively. The study focuses on the voltage profile only. The voltage profile following the load flow analysis is depicted in Fig 13. For the base case, it was observed that 30% of the system operates in the unsafe region. With a 20% EV penetration in a radial structure, this percentage increases to 39.3% in the unsafe region. The quasi-dynamic simulation provides detailed insights into the voltage profile changes across 24 hours for each sector. According to Table 4, the IEC standard 50160 specifies that the lower limit for the voltage parameter is 0.90 p.u., and the upper limit is 1.1 p.u. For the residential sector (R2 to R9), all operate in the safe region above 0.90 p.u, except for R10 to R11, which operate below 0.90 p.u. During the morning hours from 6 to 8, a general drop in voltage profile was noted, with buses R10 and R11 consistently operating in the unsafe region. Conversely, from 20 hrs onward, there is a rise in voltage profile in the base case (Fig 14a). In the G2 group, B23 operates in the safe mode at all times, while banks located in B12, B13, B16, and B17 enter the unsafe mode from 6 to 20 hrs (Fig 14c). In the public sector (G1 group), P24 is the only unit operating in the safe region, while P15, P18, and P24 are in the unsafe regions (Fig 14e). The private sector (G3 group) exhibits a consistent safe operation throughout the day for Pr19, Pr20, Pr21, Pr22, Pr23, Pr24, and Pr25 (Fig 14g). Finally, in the Industrial group (G4 group), all units (Ir26 to Ir33) operate in safe regions (Fig 15i).

B. CS-B: CASE WITH 20% EVS RADIAL NETWORK

To assess the impact of uncontrolled EV charging on the IEEE-33 bus system, EV load profiles were generated for each group using the Monte Carlo method, considering the charging times specified in Table 2. In this case (**CS-B**), EV loads were added to the base case of the system, with the charger level set as 60% of 11 kW and 40% of 22 kW. The charging time, with a mean and standard deviation of (14, 1), was considered. The average load profile for 100 EVs profiles was generated using Matlab in in Fig 16 and assigned to respective buses in the DigSILENT software.

The quasi-dynamic results for this case (**CS-B**) are presented in Fig 14 (b). In this scenario, 20% of the buses are EVs, connected to buses (R3, R4, B23, P14, Pr19, I27, I28). The voltage profiles for the residential sector (G5) indicate that buses R2 to R5 operate in a safe mode throughout the day, while R6 to R11 are in an unsafe mode. Voltage drops were observed twice: first from 3 to 6 hrs and then at t = 11 to 13 hours, compared to the base case voltage profile. The voltage profile improves from 14.30 hrs. Buses R8 to R11 experience higher voltage drops as they are farther from the substation. The bank sector EV, connected to bus B23, operates in a safe region all day, with voltage drops observed for bank buses B12, B13, B16, and B17 at periods 3.30 to 6 hrs and the second drop at t = 11 to 13 hrs in Fig 14 (d). The voltage drop at t = 13 hrs decreases by 0.45 % for B12,B13,B16 and B17 while 0.20% decrease for B23. In Fig 14 (f), voltage drops in the public sector occur in the early morning and afternoon. For the other two sectors, voltage drops were observed at 8 am for the private office, and at time t = 3.30 to 7 hrs for the industrial sector. Public office P24 has a small voltage drop and operates above 0.90 throughout the day, being near the source. Offices P14, P15, and P18, situated farther from the substation, experience larger voltage drops, especially P14, which is connected to an EV. The voltage drop occurs at two intervals during the day: one in the morning and another small drop at t = 11 to 13 hrs. In the private sector (Fig 14h), all offices at Pr19, Pr20, Pr21, Pr22, and Pr25 operate in a safe region for 24 hours. However, voltage drops occur during two intervals. The voltage drop is smaller in Pr19, being closer to the source, while Pr25, connected to the B23 bus with bank sector EV load, experiences a higher voltage drop. In the industrial sector, EV load is connected to I27 and I28. Fig 15(j) shows that all buses in this sector experience a larger voltage drop due to the higher-rated EV charger size. The impact of 40% EV penetration on all sectors is shown in Fig 17. The EVs are connected to buses R4, R5, R6, R7, B12, B23, P14, P24, Pr19, Pr20, I26 to I29. Residential, banks, public, private offices, and industrial sectors exhibit a larger first voltage drop compared to the second voltage drop. Despite this,

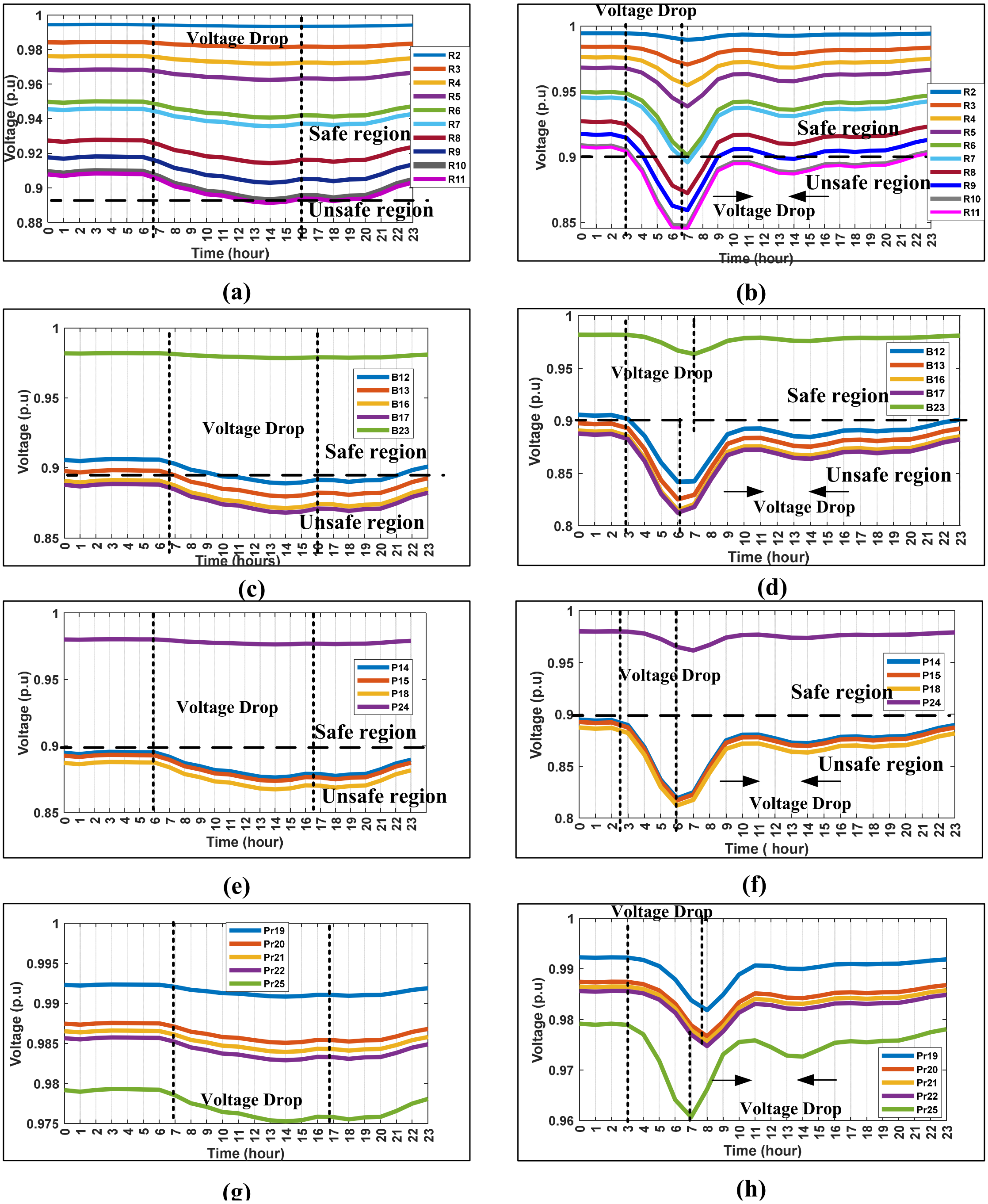
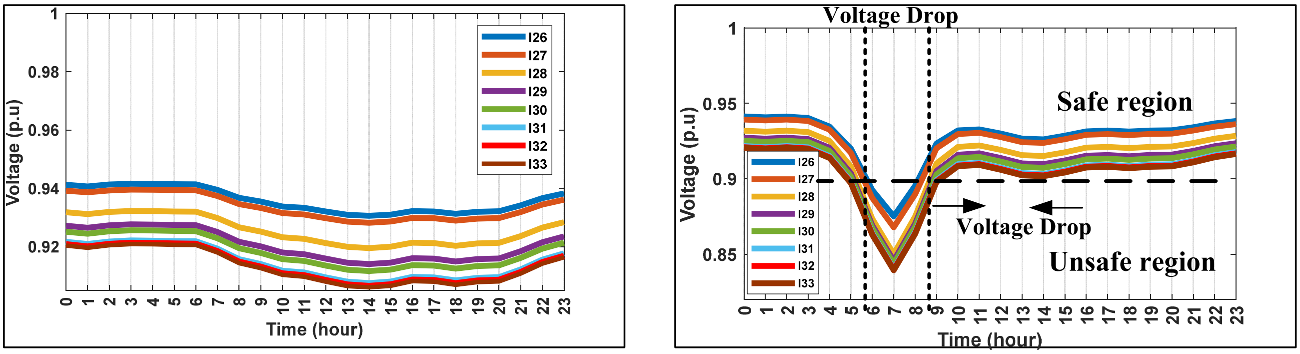


FIGURE 14. CS-A(a),(c),(e) and (g) and CS-B results 20% EV penetration (b),(d),(f),(g).

private offices continue to operate in safe regions throughout the day.

C. CS-C: 20% EVS PENETRATION WITH NETWORK RECONFIGURATION

In this scenario, the impact of uncontrolled charging on network reconfiguration is observed. After adding EV load profiles to the base case, switchable branches or tie lines 34, 35, 36, and 37 are activated for the mesh network. The results for this case are presented in Fig 18. All sectors operate within a safe voltage range compared to the scenarios in Fig 14 (b), (d), (f), and (h), and Fig 15 (j). Additionally, the voltage profile waveform pattern for the radial network is similar to that of the mesh network, as depicted in Fig 18. Despite the resemblance in the waveform patterns, the voltage drop for the residential, banks, public, and industrial sectors



(i)

(j)

FIGURE 15. CS-A (i) and CS-B results (j).

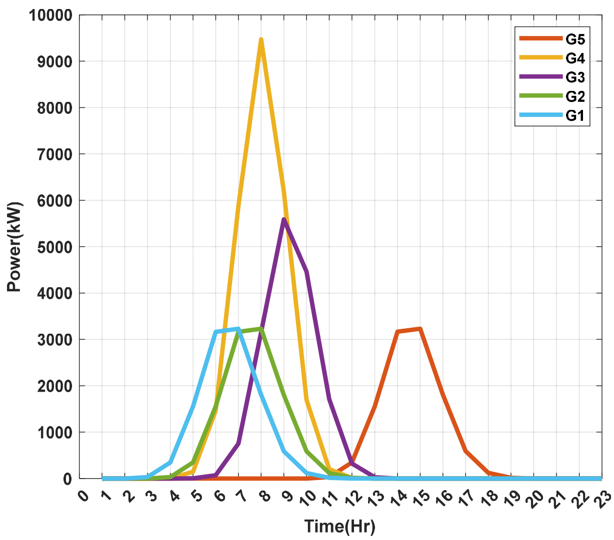


FIGURE 16. Average charging profile for 100 EVs for group G1, G2-A, and G3, G4, G5.

shows improvement in the mesh network by 11.70% (bus R11) in Fig 18(a), 16.99% (B17), 17.77% (P18), and 15.37% (I33) respectively at 7 hrs. Notably, Pr25 exhibits a reduced voltage drop by 1.5625%. For the bank, public-private, and industrial sectors, significant voltage drops are observed for B13, P14, Pr22, and I27. (Table 7) provides a comparison of load flow analysis between different EV penetrations and configurations. The table clearly indicates that the mesh configuration yields a better voltage profile and lower load losses compared to the radial network. The voltage profile improvement in mesh configuration is due to connection strong bus to the weak bus.

D. CS-D: 20 % EVS PENETRATION IN A MESH CONFIGURATION WITH A CHANGE IN CHARGING TIME

The impact of uncontrolled EV charging with change in charging time is considered in this case for residential (18,2) and banks (15,1). For this case, the results are shown in Fig 19. Two voltage drops occurred during 24 hours in Fig 19. The first drop in voltage in all sectors in the early morning time and the second drop in the afternoon. The second voltage drop for the sectors residential, banks, public, and private is sharper as compared to the first voltage drop. In addition, goes below 0.96p.u (R11, B13, P14, and Pr25) in Fig 19 as compared to in Fig 18. The industrial sector buses are unchanged. The voltage drop becomes larger as the penetration of EV increases to 40%.

E. CS-E: 20% EVS PENETRATION IN A MESH CONFIGURATION WITH SOLAR PV PLANT

In this case, the impact of integrating PV sources and EVs is analyzed. For this scenario (**CS-E**), PV integration is considered at bus P14. The rating of the PV panels is 1503 kW for the 14th bus. In Qatar, the hot summer months extend from June to September, and therefore, the average PV generation data for September is taken into account. (location - 25.239727°, 51.613770° (25°14'23'', 051°36'50''), obtained from the website [56], was used for analysis. Large-scale commercial photovoltaic systems mounted with tilt of PV panels 24 degrees are selected. The results indicate an improvement in the voltage profile, as illustrated in Fig 20. In this case, all sector buses are operating in safe regions above 0.90 p.u. Furthermore, there is an increase in the voltage profile for residential, banks, public, and private sectors during the period from 6 to 13 hours, compared to the case other cases. For the industrial sector, the voltage profile improves from 10 to 13 hours. Specific increases in voltage are observed in bus P14 (5.26%), bus B13 (4.21%), buses Pr25 and R11 (2.08%), and bus Ir33 (1.04%) at 10 hrs.

F. CS-F: PROPOSED REWARD CHARGING SCHEMES RESULTS

In this case, the impact of controlled charging is analysed with mesh and radial network reconfiguration. To do this

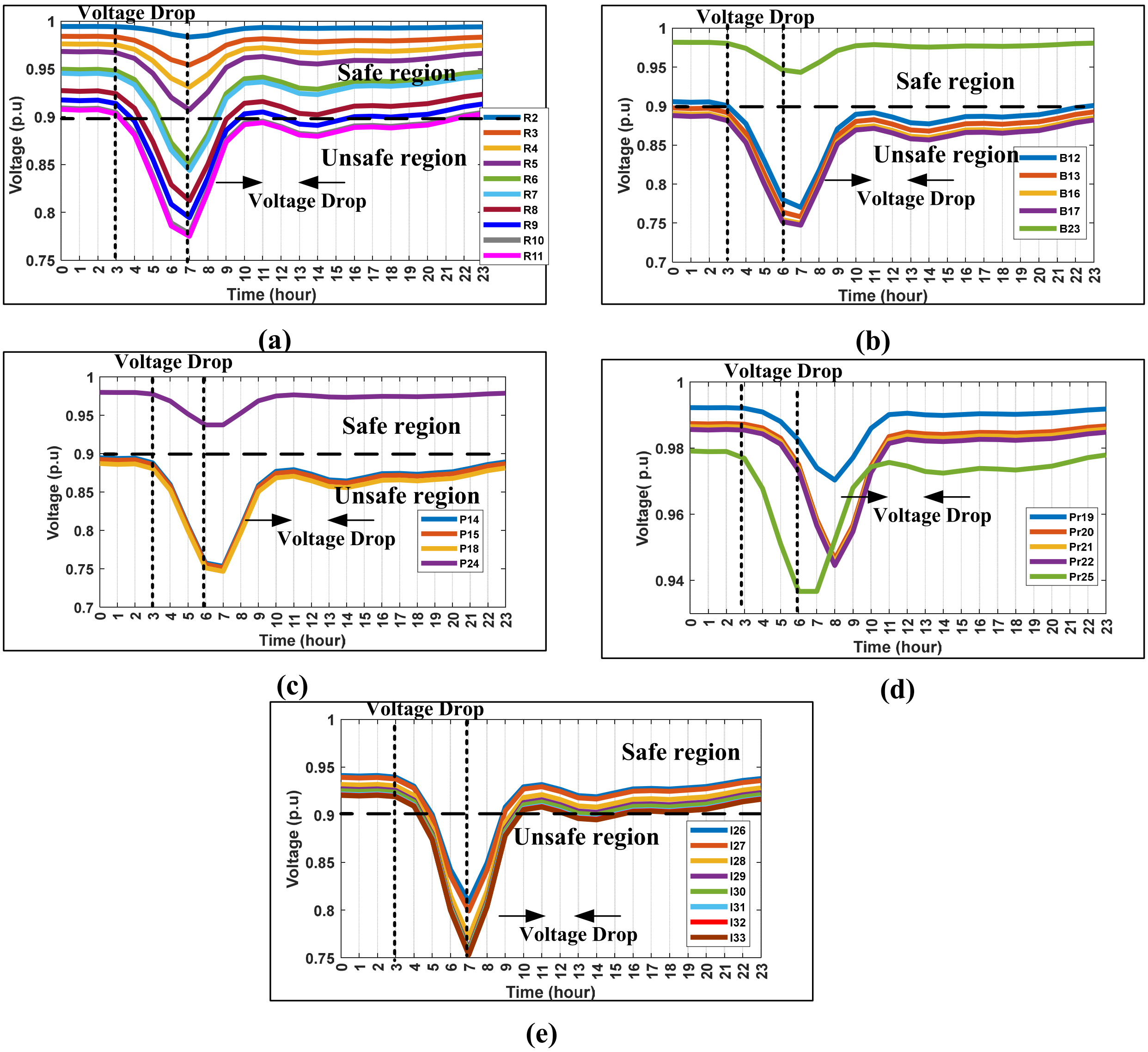


FIGURE 17. **CS-B results 40 % EV penetration (a) Residential (b) Banks (c) Public (d) Private (e) Industrial.**

TABLE 7. **Comparison with with base case.**

Case	Vmin (bus no)	Vmax (bus no)	P (MW)	Q(MVAR)	Load (MW, MVAR) Load Losses (MW, MVAR)
A (RN)- No EVs	0.86 18)	0.99 (20)	3.23	1.56	(3.42, 1.77),(0.19, 0.21)
B (RN)- 20% EV	0.87 (18)	0.98 (20)	4.01	1.95	(3.80, 1.70) (0.21, 0.25)
B(MN) - 20% EV	0.94(11)	0.98 (20)	4.18	2.02	(4.08, 1.88) (0.10,0.15)
B (RN) - 40% EV	0.85 (24)	0.98 (21)	4.00	1.94	(3.76, 1.67) (0.24, 0.28)
B (MN) - 40% EV	0.96 (14)	0.98 (19, 33)	4.24	1.98	(4.14, 1.84) (0.10, 0.14)

10 driver ratings from (1 to 5) are taken for reward charging schemes RS1 to RS5. Further, using ANOVA p values are calculated to compare the mean values across different groups to if there is a significant difference. The p-values of RS1, RS2, RS4 and RS5 as given in (Table 8). values less than 0.05 concluding that there is a significant difference from the other drivers [57]. The schemes RS1, RS2, RS4, and RS5 are having values less

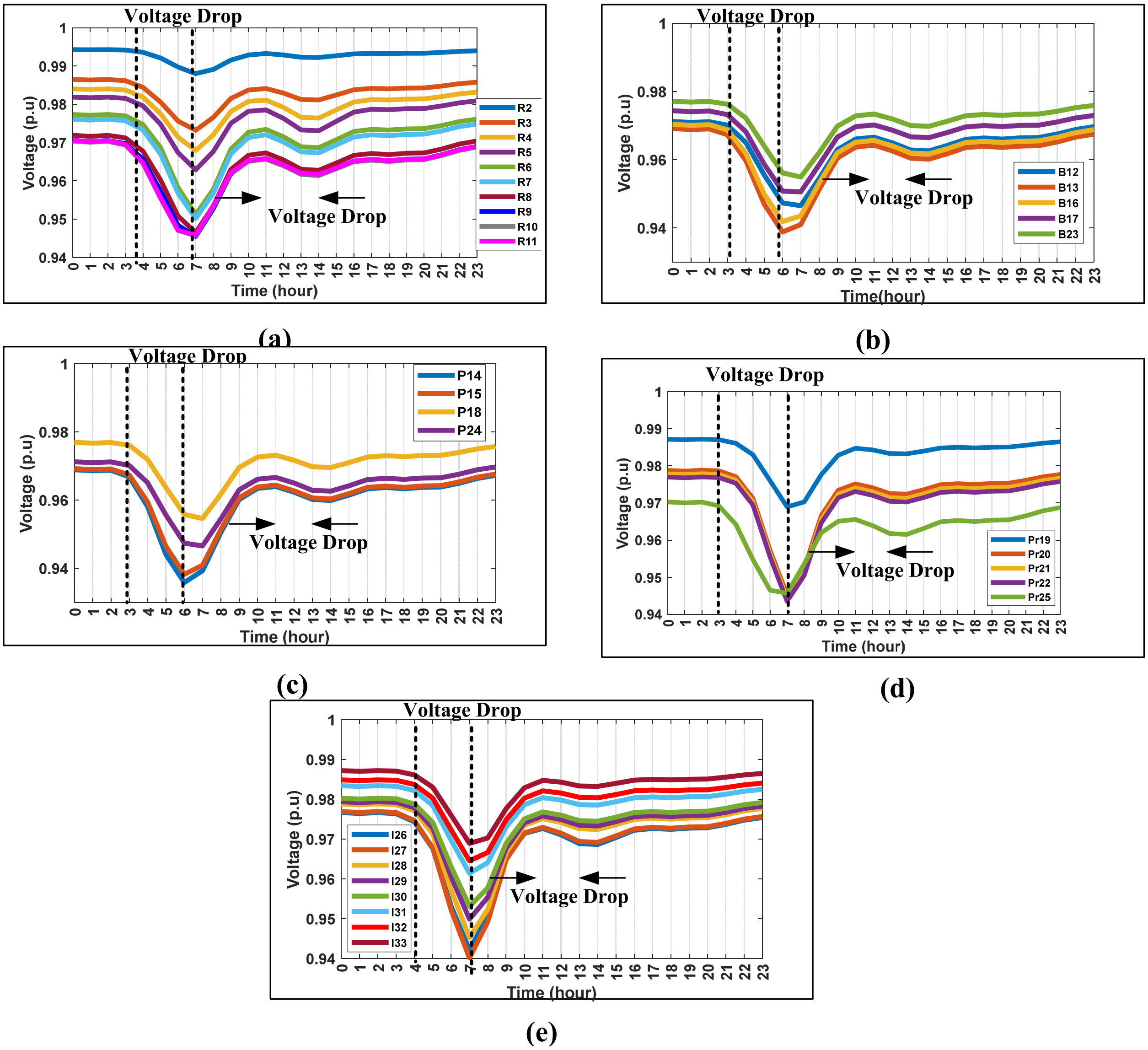


FIGURE 18. CS-C results ((a) Residential (b) Banks (c) Public (d) Private (e) Industrial.

TABLE 8. Comparision with TOU.

Schmes	P-Value
RS1	0.011736
RS2	0.008735
RS3	0.083819
RS4	0.016265
RS5	0.011629

than 0.05. Furthermore,the Pearson correlations analysis are used to find relationships between schemes. If near to 1 positive linear relationship between two schemes If near to -1 strong negative linear relationship between schemes If near to weak or no linear relationship between schemes.

The results of 40% EV penetration for the mesh network with reward charging RS2 is shown in Fig 21. Now to implement a reward charging scheme residential sector the service provider discounts on tariff rates as a reward to the residential sector if charged after 15 hrs onwards. The tariff rate for non-peak hours (15 to 24) is considered as lesser as compared to peak hours. Comparing results within Fig 18 the following are observations.

- The first observation was that the voltage drop that was occurring earlier between 11 to 14 hrs is no more for all sectors.
- Secondly, it was observed that a voltage drop occurs for 15 to 24 the service provider assigned a discount for this duration for the residential sector.

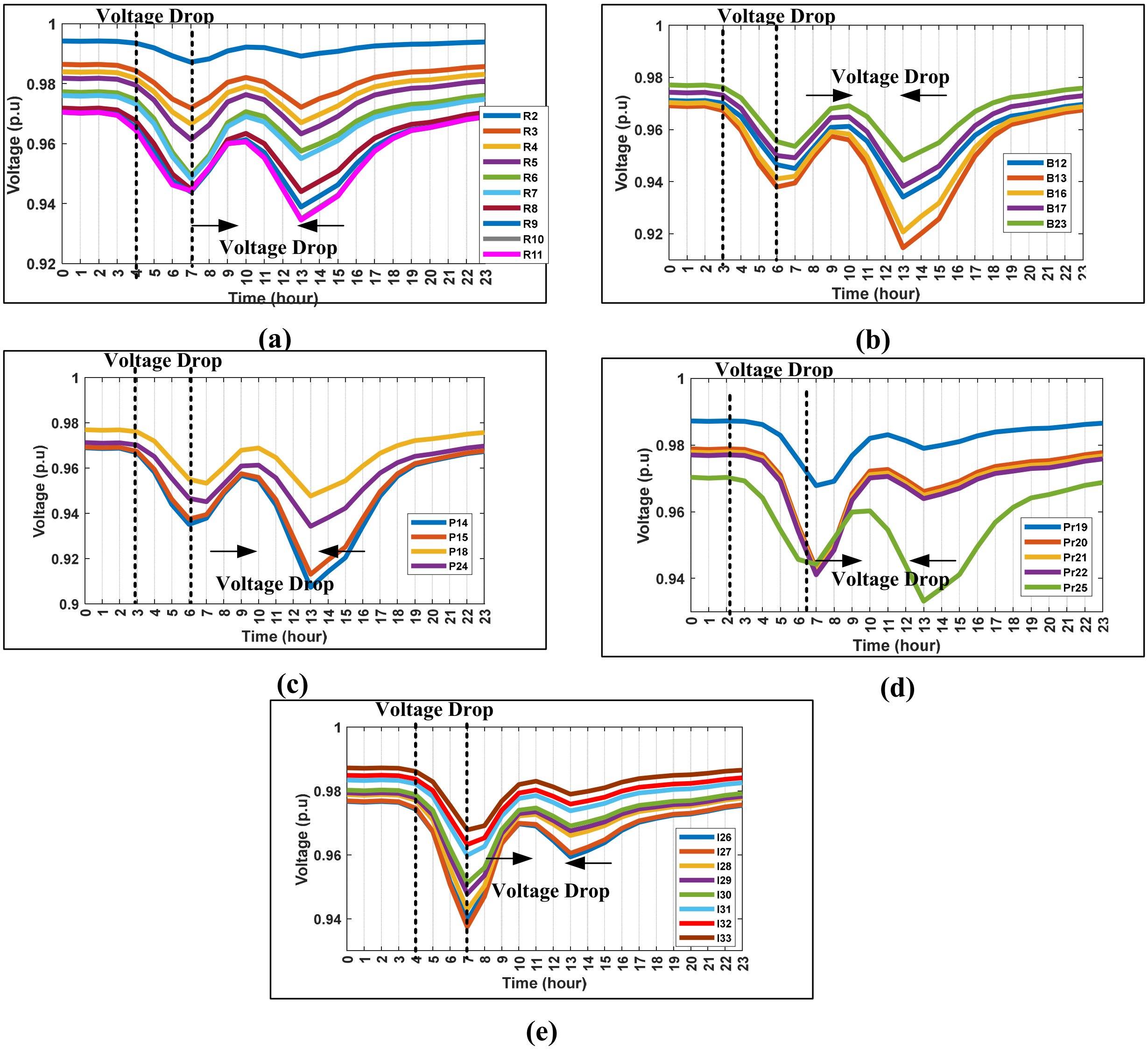


FIGURE 19. **CS-D results (a) Residential (b) Banks (c) Public (d) Private (e) Industrial.**

TABLE 9. **Comparison with TOU results.**

Cases	P (MW)	Q(MVAR)	Load (MW, MVAR) Load Losses (MW, MVAR)
UNC A (RN)- No EVs	3.23	1.56	(3.42, 1.77), (0.19, 0.21)
UNC B (RN)- 20% EV	4.01	1.95	(3.80, 1.70), (0.21, 0.25)
UNC B (MN) - 20% EV	4.18	2.02	(4.08, 1.88), (0.10, 0.15)
UNC B (RN) - 40% EV	4.00	1.94	(3.76, 1.67), (0.24, 0.28)
UNC B (MN) - 40% EV	4.24	1.98	(4.14, 1.84), (0.10, 0.14)
TOUC (RN)- 20% EV	3.71	1.88	(3.51, 1.65), (0.20, 0.23)
TOUC (MN)- 20% EV	3.89	1.91	(3.80, 1.579), (0.09, 0.12)
TOUC (RN)- 40% EV	4.23	2.00	(3.83, 1.75), (0.21, 0.24)
TOUC (MN)- 40% EV	4.00	1.94	(3.91, 1.81), (0.09, 0.13)

Uncontrolled Charging (UNC) and Time-of-Use Charging (TOUC), RN (Radial Network) and MN (Mesh Network)

That improves the overall performance of the other buses.

- The third observation is that the first voltage drop that occurred early in the morning is still visible because

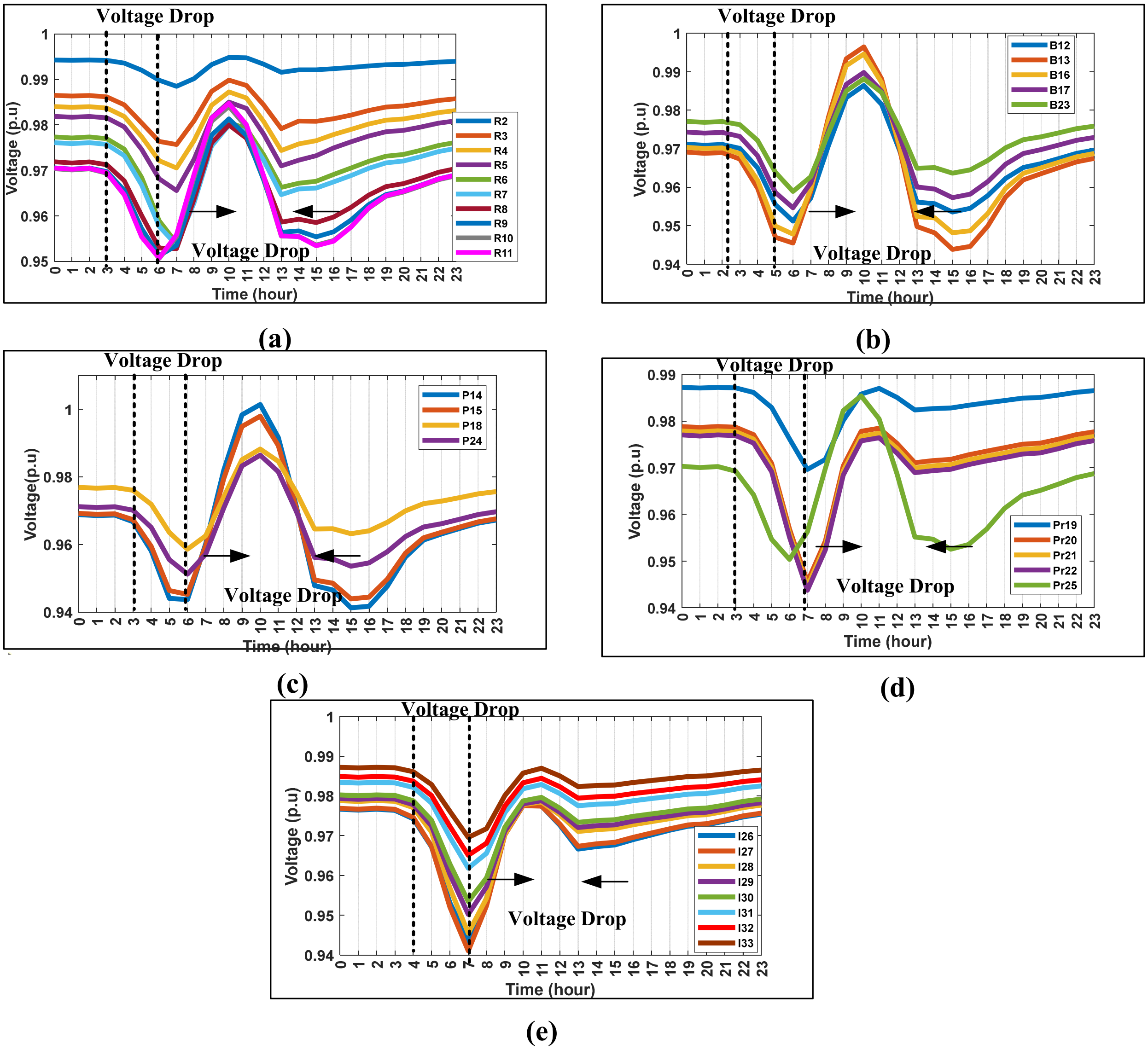


FIGURE 20. CS-E results with EVs and PVs (a) Residential (b) Banks (c) Public (d) Private (e) Industrial.

TABLE 10. Impact of RS.

Schemes	Advantage	Parameter	Parameter Effect
RS1	Financial Benefit for consumers, Utility	Voltage Drop reduces, overall improves in system performance	Time and Revenue
RS2	Financial Benefits for consumers, Utility	Voltage Drop reduces overall improve in system performance	Revenue
RS3	Increase in EV adoption, Financial Benefits for consumers	Voltage Drop reduces,overall improves overall system performance	Time (non-peak hours)
RS4	Environmental Benefit, Public Awareness	Voltage Drop reduces, overall improve in system performance	Load Variation (With/without PV consideration)
RS5	Environmental Benefit, Public Awareness and Increase in EV adoption	Voltage Drop reduce, overall improve in system performance	Co2 Emission

of reward charging scheme is not implemented in other sectors. The other reason is the, EV charging for banks, public, private and industrial sectors as shown in Fig 16.

- The fourth observation is that the voltage profile improved after 8pm onwards because the base **CS-A** and EV load is lower as seen in Fig.14,15,16. However, all buses are operating above 0.90 p.u and they are in safe regions all day.

The below comparison (load flow analysis) (Table 9) of the impact of uncontrolled and TOU charging impact on generation, load and load losses for 20 % and 40% EV penetration for radial and mesh network analysis. It was observed that TOU charging reduced load with lesser load losses for both RNs and MNs. The (Table 10) give details about the impact of RS (advantage, parameters and parameters effect for RS 1 to 5).

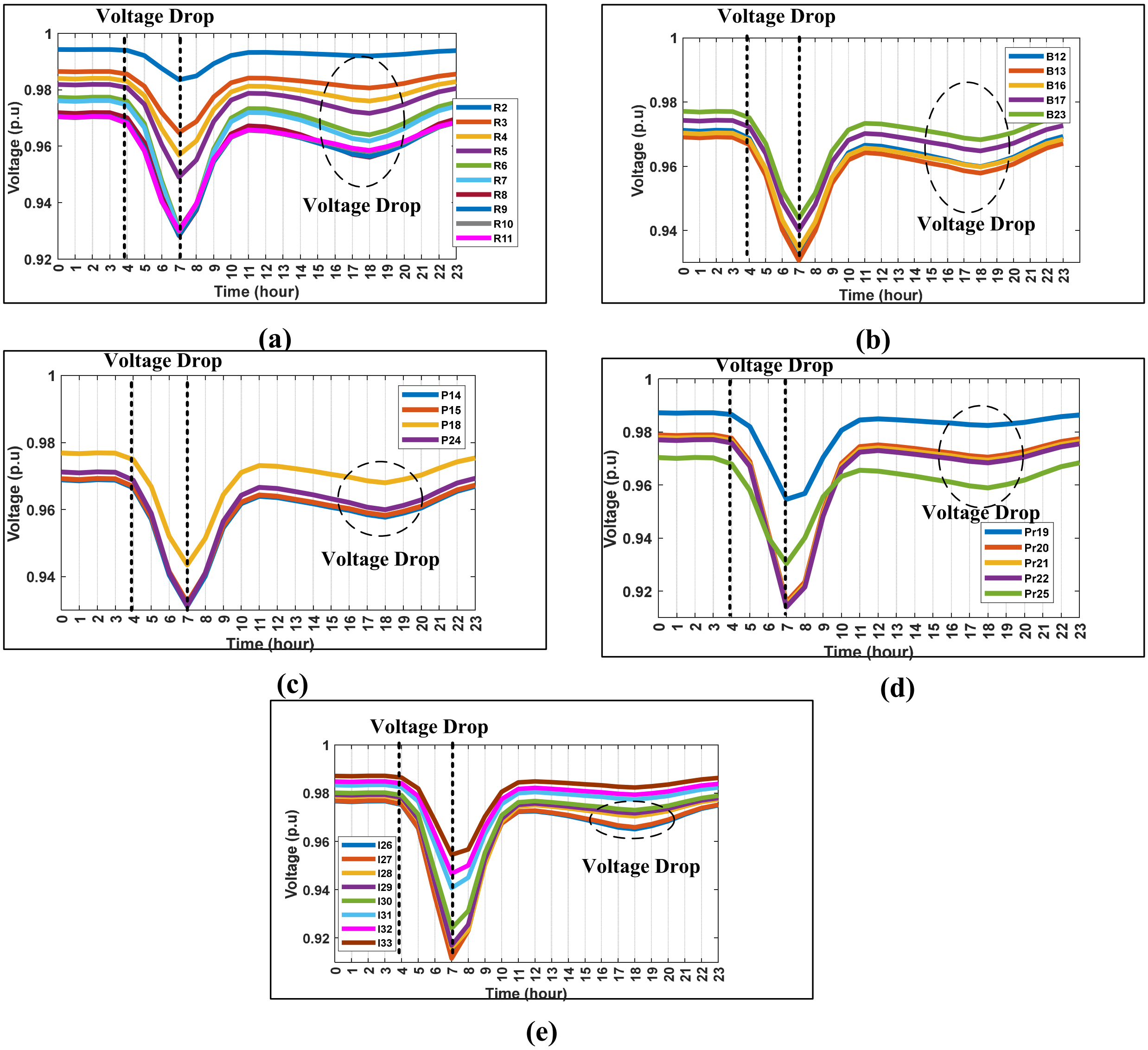


FIGURE 21. **CS-F Proposed reward charging schemes RS2 results with EVs and PVs(a) Residential (b) Banks (c) Public (d) Private (e) Industrial.**

VI. CONCLUSION

In conclusion, the impact assessment of Electric Vehicles (EVs) is influenced by several key factors. This study identifies seven crucial elements that determine the impact:

- Network load curve pattern.
- Type of network (radial, mesh).
- Schedule of charging time.
- Power rating of EV charger.
- Charging schemes (uncontrolled, reward charging schemes).
- Location of EV integration.
- Integration of solar PV plants.

The paper investigates the impact of both uncontrolled and controlled EV charging in distribution systems with radial and mesh configurations. Additionally, it proposes four reward charging schemes applicable to public, private, bank offices, industrial, and residential sectors. The key conclusions drawn from the study include:

- For 20% EV penetration, specific sectors such as residential (R1 to R8), bank (B23), and public (P24), as well as private offices (Pr19 to Pr25), operate in the safe region throughout the day. However, other sectors experience unsafe conditions, and further increases in EV penetration worsen the voltage drop.
- Mesh configuration with 20% EV penetration results in all sector buses operating in safe regions, indicating a reduction in load losses compared to radial networks.
- Altering charging times and introducing additional EVs (shopping load) to mesh configurations leads to a sharper voltage drop during specific hours (11 to 13 hrs).
- The integration of solar PV in mesh configurations improves the voltage profile during the period from 8 to 13 hrs, with all bus voltages above 0.90 p.u.

- Implementation of the R2 scheme in the residential sector helps avoid voltage drops during specific time intervals. Implementing specific schemes for one sector also enhances the voltage profile of other sectors.

The findings emphasize the importance of implementing reward charging schemes and network reconfiguration during specific time intervals, such as early morning and early afternoon, to alleviate network stress and equipment wear. These strategies can aid in sustainable, green energy management, acting as additional sources during peak demand. The study underscores that implementing reward charging schemes and network reconfiguration facilitates the integration of more EVs into distribution networks without violating operational limits.

The future scope involves implementing Vehicle-to-Grid (V2G) grid analysis across all sectors. It is essential to acknowledge the study's limitation, as it did not consider other parameters like lines overloading, thermal limits, and Total Harmonic Distortion (THD),etc.

ACKNOWLEDGMENT

This publication was made possible by "Efficient Smart Home Energy Management with Emphasis on Electrical Vehicles' Charging/ Discharging Strategy"- Graduate Research Assistant Fund. The statements made herein are solely the responsibility of the authors. The APC (Article Processing Charges) for this manuscript is funded by the Qatar National Library (QNL), Doha, Qatar.

REFERENCES

[1] (2000). *GLobal EV Outlook 2*. Accessed: Sep. 27, 2023. [Online]. Available: https://www.iea.org/reports/global-ev-outlook-2022/executive-summary

[2] P. Jochem, A. Märtz, and Z. Wang, "How might the German distribution grid cope with 100% market share of pev," in *Proc. 31th Int. Electr. Vehicle Symp.*, vol. 30, 2018, pp. 1–23.

[3] (2016). *What Do Electric Cars Mean for Power Lines*. [Online]. Available: https://www.nve.no/Media/4720/

[4] M. Muratori, "Impact of uncoordinated plug-in electric vehicle charging on residential power demand," *Nature Energy*, vol. 3, no. 3, pp. 193–201, Jan. 2018.

[5] M. Muratori and G. Rizzoni, "Residential demand response: Dynamic energy management and time-varying electricity pricing," *IEEE Trans. Power Syst.*, vol. 31, no. 2, pp. 1108–1117, Mar. 2016.

[6] A. Amin, W. U. K. Tareen, M. Usman, H. Ali, I. Bari, B. Horan, S. Mekhilef, M. Asif, S. Ahmed, and A. Mahmood, "A review of optimal charging strategy for electric vehicles under dynamic pricing schemes in the distribution charging network," *Sustainability*, vol. 12, no. 23, pp. 1–24, 2020.

[7] L. Calearo, A. Thingvad, K. Suzuki, and M. Marinelli, "Grid loading due to EV charging profiles based on pseudo-real driving pattern and user behavior," *IEEE Trans. Transport. Electrific.*, vol. 5, no. 3, pp. 683–694, Sep. 2019.

[8] S. Shahidinejad, S. Filizadeh, and E. Bibeau, "Profile of charging load on the grid due to plug-in vehicles," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 135–141, Mar. 2012.

[9] W. Yang, Y. Xiang, J. Liu, and C. Gu, "Agent-based modeling for scale evolution of plug-in electric vehicles and charging demand," *IEEE Trans. Power Syst.*, vol. 33, no. 2, pp. 1915–1925, Mar. 2018.

[10] K. Chaudhari, N. K. Kandasamy, A. Krishnan, A. Ukil, and H. B. Gooi, "Agent-based aggregated behavior modeling for electric vehicle charging load," *IEEE Trans. Ind. Informat.*, vol. 15, no. 2, pp. 856–868, Feb. 2019.

[11] Y. Zheng, Z. Shao, Y. Zhang, and L. Jian, "A systematic methodology for mid-and-long term electric vehicle charging load forecasting: The case study of Shenzhen, China," *Sustain. Cities Soc.*, vol. 56, May 2020, Art. no. 102084.

[12] M. F. Shaaban, Y. M. Atwa, and E. F. El-Saadany, "PEVs modeling and impacts mitigation in distribution networks," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 1122–1131, May 2013.

[13] P. Rodríguez-Pajarón, A. Hernández, and J. V. Milanović, "Probabilistic assessment of the impact of electric vehicles and nonlinear loads on power quality in residential networks," *Int. J. Electr. Power Energy Syst.*, vol. 129, Jul. 2021, Art. no. 106807.

[14] I. Sharma, C. Cañizares, and K. Bhattacharya, "Smart charging of PEVs penetrating into residential distribution systems," *IEEE Trans. Smart Grid*, vol. 5, no. 3, pp. 1196–1209, May 2014.

[15] M. Tavakoli, F. Shokridehaki, M. Funsho Akorede, M. Marzband, I. Vechiu, and E. Pouresmaeil, "CVaR-based energy management scheme for optimal resilience and operational cost in commercial building microgrids," *Int. J. Electr. Power Energy Syst.*, vol. 100, pp. 1–9, Sep. 2018.

[16] P. Olivella-Rosell, R. Villafafila-Robles, A. Sumper, and J. Bergas-Jané, "Probabilistic agent-based model of electric vehicle charging demand to analyse the impact on distribution networks," *Energies*, vol. 8, no. 5, pp. 4160–4187, May 2015.

[17] H. Qiang, Y. Gu, J. Zheng, X. Zhou, and X. Li, "Modeling and simulating of private EVs charging load," *Open Electr. Electron. Eng. J.*, vol. 9, no. 1, pp. 231–237, Jul. 2015.

[18] J. Quirós-Tortós, L. F. Ochoa, S. W. Alnaser, and T. Butler, "Control of EV charging points for thermal and voltage management of LV networks," *IEEE Trans. Power Syst.*, vol. 31, no. 4, pp. 3028–3039, Jul. 2016.

[19] S. Wagh, Y. Yu, A. Shekhar, G. R. C. Mouli, and P. Bauer, "Aggregated impact of EV charger type and EV penetration level in improving PV integration in distribution grids," in *Proc. IEEE Transp. Electrific. Conf. Expo. (ITEC)*, Jun. 2021, pp. 595–600.

[20] R.-C. Leou, C.-L. Su, and C.-N. Lu, "Stochastic analyses of electric vehicle charging impacts on distribution network," *IEEE Trans. Power Syst.*, vol. 29, no. 3, pp. 1055–1063, May 2014.

[21] M. K. Gray and W. G. Morsi, "Power quality assessment in distribution systems embedded with plug-in hybrid and battery electric vehicles," *IEEE Trans. Power Syst.*, vol. 30, no. 2, pp. 663–671, Mar. 2015.

[22] C. Jiang, R. Torquato, D. Salles, and W. Xu, "Method to assess the power-quality impact of plug-in electric vehicles," *IEEE Trans. Power Del.*, vol. 29, no. 2, pp. 958–965, Apr. 2014.

[23] S. Shafiee, M. Fotuhi-Firuzabad, and M. Rastegar, "Investigating the impacts of plug-in hybrid electric vehicles on power distribution systems," *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1351–1360, Sep. 2013.

[24] M. S. ElNozahy and M. M. A. Salama, "A comprehensive study of the impacts of PHEVs on residential distribution networks," *IEEE Trans. Sustain. Energy*, vol. 5, no. 1, pp. 332–342, Jan. 2014.

[25] J. Xiong, K. Zhang, Y. Guo, and W. Su, "Investigate the impacts of PEV charging facilities on integrated electric distribution system and electrified transportation system," *IEEE Trans. Transport. Electrific.*, vol. 1, no. 2, pp. 178–187, Aug. 2015.

[26] K. Clement-Nyns, E. Haesen, and J. Driesen, "The impact of charging plug-in hybrid electric vehicles on a residential distribution grid," *IEEE Trans. Power Syst.*, vol. 25, no. 1, pp. 371–380, Feb. 2010.

[27] L. Gurriaran, K. Tanaka, I. S. Bayram, Y. Proestos, J. Lelieveld, and P. Ciais, "Warming-induced increase in power demand and CO_2 emissions in Qatar and the middle east," *J. Cleaner Prod.*, vol. 382, Jan. 2023, Art. no. 135359.

[28] (2024). *To What Degree Does Temperature Impact EV Range*. Accessed: Jun. 27, 2024. [Online]. Available: https://www.geotab.com/blog/ev-range/

[29] I. S. Bayram, "Impacts of electric vehicle charging under cold weather on power networks," in *Proc. 56th Int. Universities Power Eng. Conf. (UPEC)*, Aug. 2021, pp. 1–6.

[30] J. Lindgren and P. D. Lund, "Effect of extreme temperatures on battery charging and performance of electric vehicles," *J. Power Soures*, vol. 328, pp. 37–45, Oct. 2016.

[31] J. Neubauer and E. Wood, "Thru-life impacts of driver aggression, climate, cabin thermal management, and battery thermal management on battery electric vehicle utility," *J. Power Sources*, vol. 259, no. 1, pp. 262–275, 2014.

[32] A. Ahmed, A. Iqbal, I. Khan, A. Al-Wahedi, H. Mehrjerdi, and S. Rahman, ''Impact of EV charging station penetration on harmonic distortion level in utility distribution network: A case study of Qatar,'' in *Proc. IEEE Texas Power Energy Conf. (TPEC)*, Feb. 2021, pp. 1–6.

[33] I. Safak Bayram, ''A stochastic simulation model to assess the impacts of electric vehicle charging on power generation: A case study for Qatar,'' in *Proc. IEEE Transp. Electrific. Conf. Expo. (ITEC)*, Jun. 2019, pp. 1–5.

[34] T. S. Uyar, *Accelerating the Transition to a 100% Renewable Energy Era*. Cham, Switzerland: Springer, 2020.

[35] A. Al Wahedi and Y. Bicer, ''A case study in Qatar for optimal energy management of an autonomous electric vehicle fast charging station with multiple renewable energy and storage systems,'' *Energies*, vol. 13, no. 19, p. 5095, Sep. 2020.

[36] A. Al Wahedi and Y. Bicer, ''Development of an off-grid electrical vehicle charging station hybridized with renewables including battery cooling system and multiple energy storage units,'' *Energy Rep.*, vol. 6, pp. 2006–2021, Nov. 2020.

[37] A. A. Wahedi and Y. Bicer, ''Techno-economic assessment of a renewable energy-based electric vehicle fast-charging station in Qatar,'' in *Computer Aided Chemical Engineering*. Amsterdam, The Netherlands: Elsevier, 2021, pp. 1629–1634.

[38] A. Al Wahedi and Y. Bicer, ''Techno-economic optimization of novel stand-alone renewables-based electric vehicle charging stations in Qatar,'' *Energy*, vol. 243, Mar. 2022, Art. no. 123008.

[39] F. Angizeh, A. Ghofrani, E. Zaidan, and M. A. Jafari, ''Adaptable scheduling of smart building communities with thermal mapping and demand flexibility,'' *Appl. Energy*, vol. 310, Mar. 2022, Art. no. 118445.

[40] H. M. Abdullah, A. Gastli, L. Ben-Brahim, and S. O. Mohammed, ''Integrated multi-criteria model for long-term placement of electric vehicle chargers,'' *IEEE Access*, vol. 10, pp. 123452–123473, 2022.

[41] A. Gastli, Y. Charabi, R. A. Alammari, and A. M. Al-Ali, ''Correlation between climate data and maximum electricity demand in Qatar,'' in *Proc. 7th IEEE GCC Conf. Exhibition (GCC)*, Nov. 2013, pp. 565–570.

[42] H. M. Abdullah, A. Gastli, L. Ben-Brahim, and S. O. Mohammed, ''Planning and optimizing electric-vehicle charging infrastructure through system dynamics,'' *IEEE Access*, vol. 10, pp. 17495–17514, 2022.

[43] *KAHRAMAA*. Accessed: Oct. 31, 2023. [Online]. Available: https://www.km.qa/CustomerService/Pages/ServicesRegulations.aspx

[44] (2021). *Power Qaulity*. Accessed: Oct. 31, 2023. [Online]. Available: https://powerquality.blog/2021/07/22/standard-en-50160-voltage-characteristics-of-public-distribution-systems/

[45] B. E. Carmelito and J. M. D. C. Filho, ''Hosting capacity of electric vehicles on LV/MV distribution grids—A new methodology assessment,'' *Energies*, vol. 16, no. 3, p. 1509, Feb. 2023.

[46] F. J. Soares, J. A. Peças Lopes, and P. M. Rocha Almeida, ''A Monte Carlo method to evaluate electric vehicles impacts in distribution networks,'' in *Proc. IEEE Conf. Innov. Technol. Efficient Reliable Electr. Supply*, Sep. 2010, pp. 365–372.

[47] Y. Xing, F. Li, K. Sun, D. Wang, T. Chen, and Z. Zhang, ''Multi-type electric vehicle load prediction based on Monte Carlo simulation,'' *Energy Rep.*, vol. 8, pp. 966–972, Nov. 2022.

[48] K. Qian, C. Zhou, M. Allan, and Y. Yuan, ''Modeling of load demand due to EV battery charging in distribution systems,'' *IEEE Trans. Power Syst.*, vol. 26, no. 2, pp. 802–810, May 2011.

[49] S. Mishra and Y. S. Brar, ''Load flow analysis using MATLAB,'' in *Proc. IEEE Int. Students' Conf. Electr., Electron. Comput. Sci. (SCEECS)*, Feb. 2022, pp. 1–4.

[50] P. Sharma and N. Batish, ''Computational analysis of IEEE 57 bus system using NR method,'' *Int. J. Adv. Res. Elect., Electron. Instrum. Eng.*, vol. 4, no. 11, pp. 1–19, 2015.

[51] A. Nur and A. Kaygusuz, ''Load flow analysis with Newton-raphson and Gauss–Seidel methods in a hybrid AC/DC system,'' *IEEE Can. J. Electr. Comput. Eng.*, vol. 44, no. 4, pp. 529–536, Jun. 2021.

[52] (2023). *Incentives*. Accessed: Nov. 27, 2023. [Online]. Available: https://dubaievhub.ae/government-framework/incentives/

[53] (2023). *EV Incentives*. Accessed: Nov. 27, 2023. [Online]. Available: https://www.panion.org/ev-incentives-2023-these-6-countries-promote-e-mobility-the-most/

[54] M. E. Baran and F. F. Wu, ''Network reconfiguration in distribution systems for loss reduction and load balancing,'' *IEEE Trans. Power Del.*, vol. 4, no. 2, pp. 1401–1407, Apr. 1989.

[55] (2023). *Global Solar Atlas*. Accessed: Nov. 27, 2023. [Online]. Available: https://globalsolaratlas.info/detail?c=25.458155

[56] S. H. Dolatabadi, M. Ghorbanian, P. Siano, and N. D. Hatziargyriou, ''An enhanced IEEE 33 bus benchmark test system for distribution system studies,'' *IEEE Trans. Power Syst.*, vol. 36, no. 3, pp. 2565–2572, May 2021.

[57] H. S. K. S. Albadr, ''Drivers of electric vehicle adoption in new markets: The case of Qatar,'' Ph.D. dissertation, College Sci. Eng., Hamad Bin Khalifa Univ., Middle East, Qatar, 2023.

SHEETAL DESHMUKH (Student Member, IEEE) received the bachelor's degree in instrumentation engineering and the master's degree in electrical engineering from Mumbai University, India, in 2010 and 2013, respectively. Currently, she is pursuing the Ph.D. degree with Qatar University. Her research interests include the impact assessment of electric vehicles on the power system electric vehicle charging schemes, dc–dc converters, multilevel inverters, and the application of power electronics in renewable energy systems. She received the Best Paper Award: 2021 IEEE 4th International Conference on Computing, Power, and Communication Technologies (GUCON).

HANAN TARIQ received the B.S. degree in electrical (power) engineering from the COMSATS University Islamabad, Abbottabad Campus, Pakistan, in 2016, and the M.Sc. degree in electrical engineering from the Imperial College of Business Studies (ICBS), Lahore, Pakistan, in 2018. He is currently pursuing the Ph.D. degree with the Department of Electrical Power Engineering, Gdańsk University of Technology, Poland. He has been associated with research and teaching at multiple universities, since 2017. His research interests include power system safety, power system stability, and dynamics and simulative studies of power systems.

MOHAMMAD AMIR (Member, IEEE) received the B.Tech. degree in electrical engineering from Integral University, Lucknow, India, in 2015, the M.Tech. degree from the Department of Electrical Engineering, Madan Mohan Malaviya University of Technology (MMMUT), Gorakhpur, India, in 2018, and the Ph.D. degree (Hons.) from the Department of Electrical Engineering, Jamia Millia Islamia University, Delhi, New Delhi, India, in 2023. He is currently a Senior Researcher with the Department of Electrical Engineering, Indian Institute of Technology Delhi (IIT), India. Additionally, he is leading a research project as the Principal Investigator (PI) funded by the Science and Engineering Research Board with a grant of 3.03 million INR. He engaged as a Visiting Research Associate with the Department of Electrical Engineering, Qatar University, and contributed to the National Priorities Research Program Project. He was a Research Assistant with the Advanced Power Electronics Research Laboratory, Department of Electrical Engineering, JMI, from January 2021 to February 2023, working under the SPARC Project of MHRD, Government of India, in collaboration with Aalborg University, Denmark. His research interests include renewable energy, intelligent energy management, energy storage, electric vehicles, power system optimization, and smart microgrids.

ATIF IQBAL (Fellow, IEEE) received the B.Sc. and M.Sc. degrees in electrical engineering from Aligarh Muslim University (AMU), Aligarh, India, in 1991 and 1996, respectively, the Ph.D. degree from Liverpool John Moores University, Liverpool, U.K., in 2006, and the D.Sc. degree (Habilitation) in control, informatics, and electrical engineering from Gdańsk University of Technology, Gdańsk, Poland, in 2019. He is currently a Full Professor with the Department of Electrical Engineering, Qatar University, Doha, Qatar, and a former Full Professor with the Department of Electrical Engineering, AMU. He is a Honorary Adjunct Professor with M. A. American University, Nigeria, and Bharath University, India. He is also an Adjunct Faculty Member with the Community College, Doha. He has been listed in the Top 2% Highly Cited Scientists of the World (Stanford University, USA), since 2019. He has published widely in international journals and conferences on his research findings related to power electronics, variable speed drives, e-mobility, smart grids, complex energy transitions, micro and nano grids, and renewable energy sources. He has authored or co-authored more than 580 research articles, eight patents, four books, and several chapters in edited books. He has supervised several large research and development projects worth several million USD. He has supervised 21 Ph.D. students. He is a fellow of IET (U.K.), IE (India), and AIAA (Asia Pacific). He was a recipient of the Outstanding Faculty Merit Award, from 2014 to 2015, and the Research Excellence Awards at Qatar University, in 2015 and 2022. He has received a Research Excellence Award from the College of Engineering, Qatar University, in 2019. He has received several best research papers awards at top international conferences. He is serving as the Vice-Chair of the IEEE Qatar Section. He is an Associate Editor of IEEE Transaction on Industrial Electronics and a Senior Editor of IEEE Access.

MOUSA MARZBAND (Senior Member, IEEE) is currently with the Center of Research Excellence in Renewable Energy and Power Systems, King Abdulaziz University, Jeddah, Saudi Arabia. He has been listed among the Top 1% of Highly Cited Researchers in Engineering, as reported by Thomson Reuters, from 2019 to 2021, and has been recognized among the Top 2% of Highly Cited Scientists in the world by Stanford University, USA, since 2022. He has published extensively in international journals and conferences on topics related to power systems, renewable energy integration, e-mobility, smart grids, complex energy transitions, microgrids, and renewable energy sources. He has authored or co-authored more than 200 research articles, holds one patent, and has written two books and several chapters in edited volumes. His research contributions have been pivotal in leading and supervising several large-scale research and development projects, with a total funding amounting to several million Pounds. One of his notable projects, funded by the British Council (£186k), with a focus on the design of power electronic topologies and smart controllers for energy storage and electric vehicles in home microgrids. He also received funding from the QNRF-National Priority Research Program (NPRP13S-108-200028) for the Project "Impact Assessment of EV Charging Stations and Regulation Policies for the Upcoming Active Distribution Network of Qatar Utility Grid," from 2021 to 2024, amounting to approximately $600k. In addition, his proposal "Electric Vehicles Point Location Optimization via Vehicular Communications (EVOLVE)" has been funded by the Marie Skłodowska-Curie Actions Staff Exchange, from 2022 to 2026, with a total funding of £620k. He serves as the Principal Investigator on the Project "Optimal Scheduling of Electric Vehicle-Integrated Multi-Energy Systems with High Renewable Generation," funded by EPSRC (EP/S032053/1) through DTE Network+, and also leads the "Bi-Directional MIMO DC/DC Converter for V2G/X Infrastructures," funded by Innovate U.K. (£300k). He has supervised six Ph.D. students, contributing to the next generation of researchers in the field of energy systems, and renewable energy technologies.

ABDULLAH M. A. B. AL-WAHEDI received the B.Sc. degree in electrical engineering and applied physics from Case Western Reserve University, USA, in 1996, the master's degree in business administration (MBA) from Qatar University, in 2007, and the Ph.D. degree in sustainable energy from Hamad Bin Khalifa University, in 2022. He has joined Qatar General Electricity and Water Corporation (KAHRAMAA), since 2001. He is currently the Shared Services Director responsible for IT, HR, and facility management services.