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Electric vehicle fast charging station energy management system for radial distribution network with a photo-voltaic distributed generator (PV-DG)

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ABSTRACT

As the demand for electric vehicles (EVs) increases in all countries, automobile companies are launching different types of EVs. Installation of EVCS in the present power system network without modification can cause an extra burden on the present network. However, this extra burden can be reduced if EVCS gets a supply of renewable energy resources. This paper proposes energy management schemes by installing a photo-voltaic distributed generator (PV-DG) and energy storage system (ESS) at an EVCS. An IEEE-33 bus system for the Saudi Arabia United Kingdom rural location has been selected to introduce real-time energy management schemes. In this radial distribution network (RDN), three EVCS of different capacities are installed at different locations to maintain the stability of the network. The power flow program is used in the MATLAB environment to check the stability of the network. Accurate solar data, traffic patterns, and EV charging patterns in Saudi Arabia are collected and used for energy management at EVCS. Three cases are used for comparison: EVCS annual charges, EVCS annual benefits, and grid annual fuel charges. All proposed cases are also simulated in MATLAB using MATPOWER6 to check the impact on voltage profile and power line flows.

1. Introduction

As the demand for electric vehicles (EVs) increases in all countries, automobile companies are launching different types of EVs. Installing electric vehicle charging systems (EVCSs) in the present power system network without modification can cause an extra burden on the present network. However, this additional power is a vital requirement for day-to-day existence. As a result, it began to develop and research new energy resources such as solar energy, wind energy, and other natural energy resources. Solar energy is mainly used in India and other countries among many other natural resources. Connecting a solar photovoltaic (PV)) system to the grid allows solar energy utilization. This study considered that natural resources do not emit any carbon particles into the atmosphere. To reduce the harmful carbon particles in the environment, EVs are the next best option. Using photovoltaic solar panels in conjunction with ESS coupled with a direct current (DC) bus and supported by the grid helps to improve the operation and efficiency of charging stations for electric vehicles. A decentralized energy management system (EMS) will be implemented to achieve effective charging of EVs and manage energy flow between the photovoltaic system, ESS, and the grid.

The purpose of the EMS is to control the storage and charging/discharging of battery energy and limit grid power usage. The control is based on integrating renewable energy sources (RES). It uses an optimization method to lower the cost of used energy in a stand-alone mode depending on the electrical grid while minimizing stress on existing power. The EMS must evaluate battery charge/discharge rates and grid power reduction methods. The control of ESS, PV, and load are all included in the proposed study of EMS. A powerful prediction model to explain a digital technology that aims to allocate dependable data connection between the charging station and the plugged Electric vehicle is mainly used nowadays. Aside from that, numerous characteristics are used in this technique to determine the optimal charging process and operating modes, such as the photovoltaic (PV) array's instantaneous power, the available energy in the battery storage buffer, and the grid's restricted power.

1.1. Literature review

In recent years, heightened awareness of the detrimental impacts of climate change has prompted urgent calls for action. A contemporary report from the United Nations has characterized climate change as a

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'code red for humanity,' emphasizing the severity of the situation [1]. Conversely, scientific studies have demonstrated that sustainable reductions in CO2 and other greenhouse gas (GHG) emissions could lead to improved air quality and stabilized global temperatures within the next two to three decades [2]. However, the challenge of decarbonizing distribution networks (DNs) is compounded by factors such as population growth and expanding industrial development. Projections indicate a nearly 50 % increase in electricity consumption over the next two decades, placing additional strain on existing power networks [3]. Moreover, concerns about energy security, supply reliability, and the environmental and human impacts of fossil fuels persist, particularly within the transportation sector [4]. In response, EVs have emerged as a viable solution, offering the potential to reduce dependency on fossil fuels and mitigate emissions [5].

In response to the imperative to curb air pollution from fossil fuel engines in the transportation sector, there has been a growing reliance on sustainable and renewable energy sources (RES). This trend has further accelerated the adoption of EVs and RESs within Distribution Networks [6,7]. However, the integration of EVs into electrical power grids has introduced significant technical, economic, and regulatory challenges [8]. Moreover, the increasing utilization of EVs presents additional financial and decarbonization hurdles in the operation of power and energy networks [9]. The environmental benefits of EVs can vary depending on factors such as charging and driving patterns, weather conditions, and the carbon intensity of the network [10]. Yet, while governments often incentivize EV adoption, their focus tends to center on the number and type of EVs adopted rather than considering charging behavior or the capacity of supporting RES to balance additional EV demand [11]. Furthermore, some regulations intended to encourage PEV ownership have inadvertently weakened carbon accounting by utilizing sales-averaged CO2 emissions, which are reduced through EV policy incentives, and by excluding charging emissions from the calculation [12].

Author [13] presented a review on PV-based charging stations in which the author has suggested Day-Ahead and Real-Time plans for EVCS so that maximum energy is used by PV sources. In [14] author uses EMS with state of charge constraints for a hybrid electric vehicle (HEV) on a bus route. Similarly, the author [15] presented a review on the EMS of HEV based on road conditions of the city. EMS for HEV is proposed by many researchers on the basis of deep reinforcement learning [16], artificial neural network (ANN) with ultra-capacitors [17], and an equivalent consumption minimization strategy [18].

An approach to real-time energy management (RTEM) Strategies design for an electric urban buses equipped with ESS composed of conventional batteries and super-capacitors is presented in [19]. Based on considerations of the battery's cycle life, total energy consumption, as well as the need to reduce battery consumption, a multi-objective optimization problem is presented by the author [20]. The uncertainties arising from roof-mounted solar PV panel power generation, household burden factor, and actual electricity pricing are integrated into the problem, and an appropriate logical battery deprivation price prototype is included by the author [21].

In this paper, RTEM strategy is proposed to reduce the EVCS load in RDN. The EVCS is connected with the grid, PV-DG, and ESS to get the rated power. Annual EVCS charges are calculated which include fuel charges, operation & maintenance charges, and installation charges, and compared with different cases. Grid annual fuel cost with EVCS is also calculated under different cases.

The main contribution of the proposed RTEM is as follows:

(i) The methodology is described to determine the optimal location of EVCS and size of EVCS in RDN.
(ii) The RTEM is proposed for EVCS by installing PV-DG and ESS.
(iii) To show the effectiveness of the proposed RTEM, real solar data, traffic, and charging pattern of Saudi Arabia is collected.
(iv) An Annual EVCS and RDN charges are evaluated and minimized by the proposed RTEM.
(v) Stability of the system for all proposed cases is also checked by voltage profile and line flow analysis.

The main framework of the proposed RTEM for RDN with EVCS is summarized in Fig. 1. The remainder of this article is organized as follows: Section 2 presents the methodology adopted to carry out the study. The case study and the discussion of the results are presented in Section 3. The conclusions end the paper in Section 4.

2. Methodology

In this section firstly, a methodology developed by [22,23] has been used to ascertain the ideal placement and capacity of EVCS within the RDN. Subsequently, the development of a (RTEM) system specifically tailored for EVCS is proposed, incorporating (PV-DG) systems and (ESS) to enhance efficiency. Real-world data pertaining to solar energy, traffic patterns, and charging behaviors in Saudi Arabia are collected to validate the effectiveness of the proposed RTEM. Further, the annual charges associated with EVCS and RDN operations are evaluated and minimized through the application of the proposed RTEM. Additionally, the stability of the system across all proposed scenarios is verified through voltage profile and line flow analyses to ensure optimal performance and reliability.

2.1. Electric vehicle integration

In this section real selected rural radial distribution network details with a methodology to identify the optimal location of EVCS, size of EVCS, and PV-DG are described in detail. Real-time solar irradiation data, traffic, and EV charging behaviour of the selected network are also analysed in detail. For implementation of proposed methodology a LAPTOP- J8RF458, Intel(R) Core(TM) i5–8250 U CPU @ 1.60 GHz 1.80 GHz, Processor Installed RAM 8.00 GB (7.90 GB usable) and 64-bit operating system, x64-based processor is used.

2.1.1. Network selection and system description

To illustrate the proposed methodology and for implementation, an IEEE 33 bus radial distribution network which represents the Saudi Arabia United Kingdom rural location [27,24] is selected. The data of the bus system is taken from [28,25]. As shown in Fig. 2 the network has one slack bus, 32 load buses, 32 branches, one generator with a capacity of 10.0 MW and −10.0 to 10.0MVAr. In base case system active load is 3.7 MW, reactive load 2.3 MVAr, and active and reactive losses are 0.20 MW and 0.14MVAr. The active and reactive load profile of 32 load buses at the base case is represented in Fig. 3.

2.1.2. Optimal location and size of EVCS and PV-DG

The first step is to know the available power in a distribution network used for charging station installation. For this author [22] concept is used here, the EVCS capacity is determined by considering losses, reserve capacity, anda load of the network. The radial distribution network load is presented as [22]:

$$TP_{D,RDN} = P_D + P_{RDN,loss} + P_{res} \tag{1}$$

where$TD_{D,RDN}$ is the total demand of radial distribution network, P_D is the total power available in the RDN, $P_{RDN,loss}$Active loss of RDN and P_{res} is reserve power i.e. 10 % of the load.

The network capacity used for EVCS location can be determined by:

$$P_{EVCS} = TP_{RDN} - TP_{D,RDN} \tag{2}$$

Where P_{EVCS} *is* the power required by EVCS, TP_{RDN} is the total power available in the RDN, and $TP_{D,RDN}$ is the total power demand in the RDN.

Apply (1) and (2) in an IEEE 33 bus system the value of $TP_{D,RDN} =$

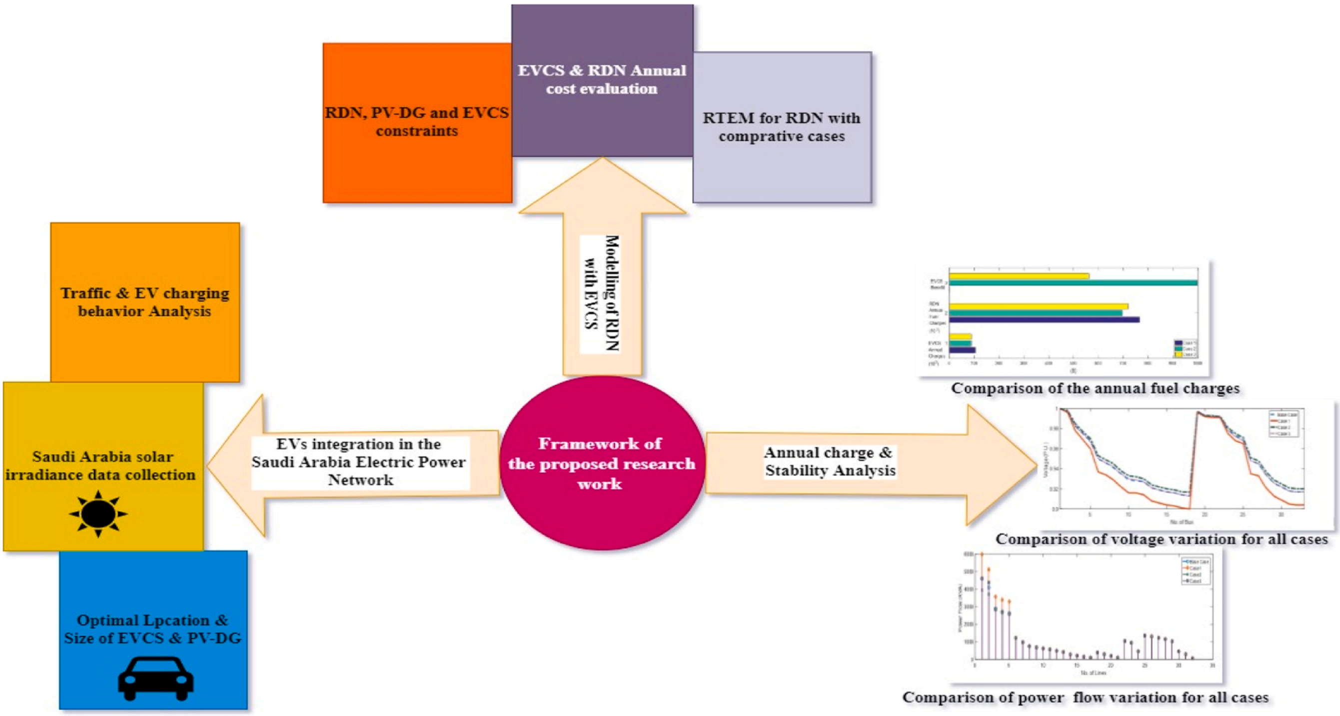

Fig. 1. Framework of the proposed RTEM for RDN with EVCS.

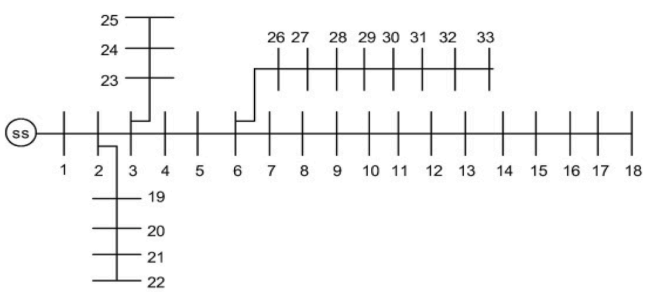

Fig. 2. An IEEE-33 bus radial distribution network.

$4.27MW$ and $P_{EVCS} = 5.73MW$ are obtained.

"It is assumed that 7.2KW energy is required to charge one electric vehicle then the total number of vehicles to be charged is approximately 690."

The second step is to know the optimal location of EVCS and size of each EVCS to be installed in the RDN. The flowchart in Fig. 4 explains the process for the selection of the optimal location of EVCS in RDN and size of each EVCS. By following the procedure shown in the flowchart the best combination is EVSC1 with 50 EVs (360KW) capacity at bus 2, EVCS2 with 50 EVs (360KW)capacity at bus 3, and EVCS3with 100EVs (720KW) at bus 6, is obtained taken from [22]. The detailed procedure to identify best location and size is explained in [22].

The installation of EVCS of total capacity of 1.44MW in distribution network without adding an extra power plant in the network can increases burden on the present system. To reduce this burden here PV power plant is installed as DG in the distribution network. The optimal location is at bus 2, 3 and 6 of capacity 0.5 MW each since it covers the full distribution network with EVCS as shown in Fig. 5.

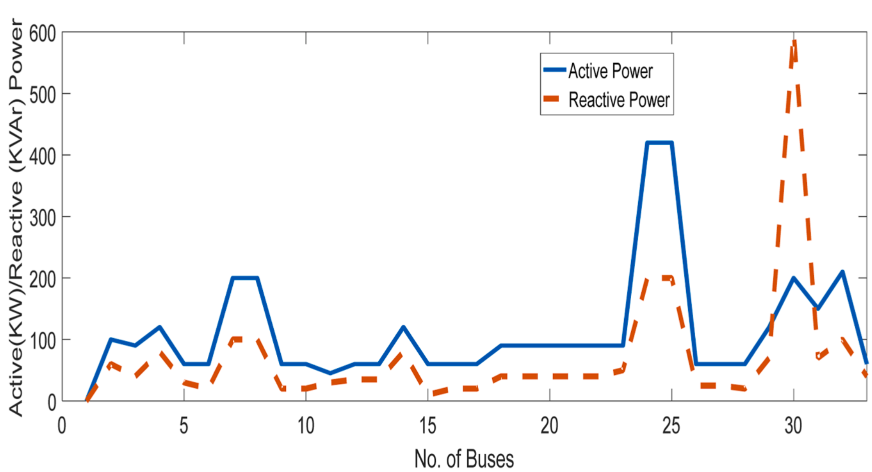

Fig. 3. Base case active and reactive load profile.

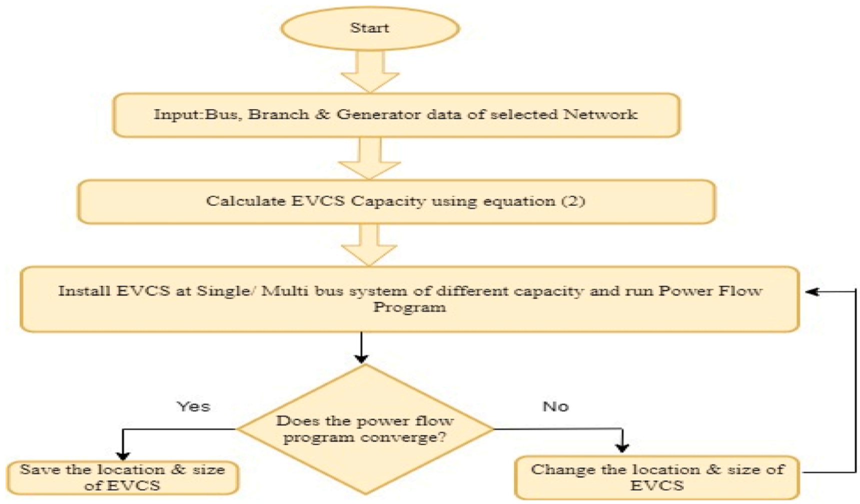

Fig. 4. Flowchart for optimal size and location of EVCS.

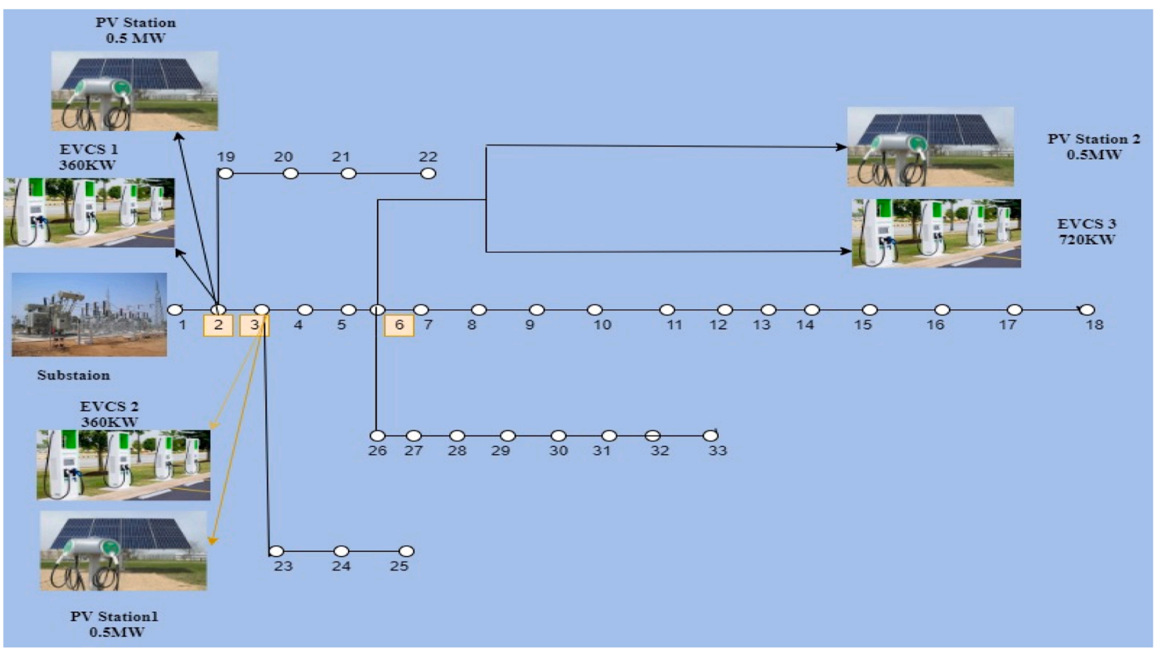

Fig. 5. 33 bus distribution network with EVCS and PV-DG.

2.2. *Saudi Arabia Solar irradiance analysis*

Solar data of Saudi Arabia is collected from [26], the whole year 2019 is divided in four seasons according to SaudiArabia's weather [27]. From each season two days with maximum temperature and minimum temperature are selected. More details of season and temperature are given in Table 1.

On the basis of Table 1, total eight days solar irradiation data of 10 h are collected from [26] and plotted in Fig. 6.

The relation between solar irradiation and PV active power output can be expressed as [28]:

$$P_{ir} = \begin{cases} P_{ir-rated} \cdot \dfrac{ir}{ir_{rated}} & 0 \le ir \le ir_{rated} \\ P_{ir-rated} ir_{rated} < ir \end{cases} \tag{3}$$

Table 1
Saudi Arabia Season Detail with temperature.

Season	*Spring (Mid-March –Mid June)*	*Summer (Mid-June to Mid-September)*	*Autumn (Mid-September to Mid-December)*	*Winter (Mid-December to Mid-March)*
Date	15/06/2019	30/06/2019	18/09/2019	14/03/2019
Maximum Temperature	45.6 ^{O}C	46.5 ^{O}C	42.4 ^{O}C	31.9 ^{O}C
Date	18/03/2019	14/09/2019	21/11/2019	18/01/2019
Minimum Temperature	8 ^{O}C	24.5 ^{O}C	5.7 ^{O}C	3.7 °C

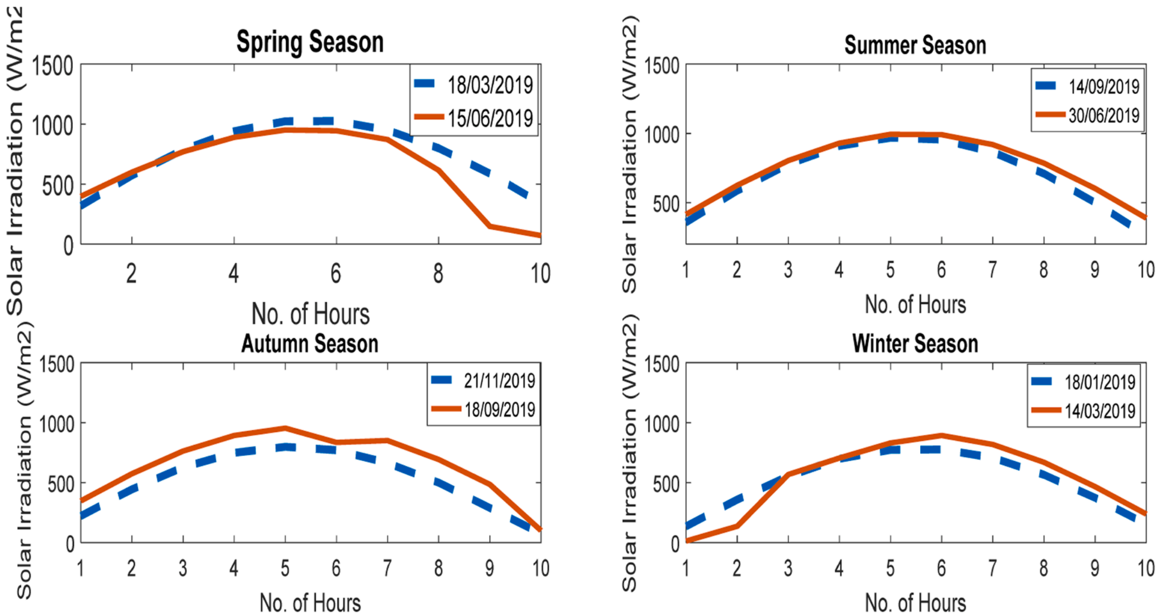

Fig. 6. Season-wise solar irradiation variation.

In which ir_{rated} is PV- rated solar irradiance (W/m^2), $P_{ir-rated}$ is rated PV active power output (KW), ir is solar irradiance (W/m^2).

The reactive power output range can be given as [29]:

$$\sqrt{S_{PV-rated}^2 - P_{ir}^2} \leq Q_{ir} \leq \sqrt{S_{PV-rated}^2 - P_{ir}^2} \tag{4}$$

From Eq. (4), $S_{PV-rated}$ is PV-rated capacity (kVA) and P_{ir}/Q_{ir} is PV active/reactive power output (kW/kVar).

2.3. Traffic and EV charging behavior analysis

For the deployment of EVs in the RDN it is necessary to understand the traffic behavior in Saudi Arabia. Fig. 7 shows the traffic behavior of Riyadh city for both working (Sunday- Thursday) and non-working day (Friday- Saturday) [30]. On working day peak traffic occurs mainly at 7:00 a.m. and 5:00pm. The second peak duration is remaining longer as shops, private businesses are closed in the afternoon and reopen at 4:00p.m. At night after 8:00 p.m. people start moving towards their destination. On Friday and Saturday, people start moving after noon time for prayer and for shopping respectively.

The deployment of EVs in Saudi Arabia according to population is summarized by the author [31]. According to author charging of EVs are divided in three categories as shown in Fig. 8(i) Peak charging (9:00a.m. to 1:00p.m.) (ii) Off-peak charging (9:00p.m. to 1:00a.m.) and (iii) Random charging (unpredictable). The figure also shows that at some instant no charging is also possible

EVs charging nature depends on many different parameters such as (i) size and type of battery (ii) type of charger (slow or fast charger) (iii) SOC at the time of plugged in for charging.

In this paper, a fast charger with a capacity of 7.2 KW is used, and to improve the battery life maximum and minimum state of charge (SOC) reference values are set at 90 % and 30 % [32].The charging time required by each EV will depend on SOC value and is given by [29]:

$$T_t^{ch} = \begin{cases} 0, \ if SOC_t \geq SOC_{ref} \\ Cap_t.(1 - SOC_t)/P_{EV}^{rated}, & \text{if } Cap_t.(1 - SOC_t) \Big/ P_{EV}^{rated} \\ T_t^{park}, \ if \ Cap_t.(1 - SOC_t)/P_{EV}^{rated} > T_t^{park} \end{cases} \leq T_t^{park} \tag{5}$$

In which, SOC_t State of charge of EV at time t, SOC_{ref} is the threshold SOC value, Cap_t is battery capacity of EV at time t (kWh), P_{EV}^{rated} is the EV rated charging power (kW) and T_t^{park} parking time of EV in EVCS.

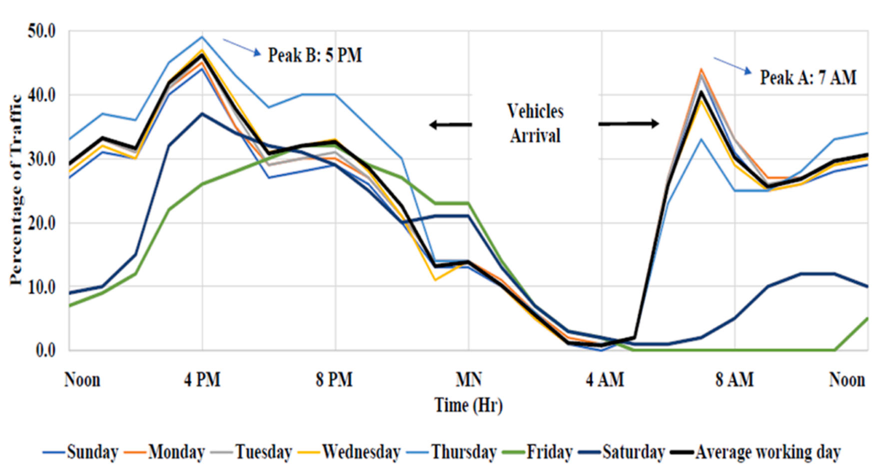

Fig. 7. Traffic and EV Charging behavior analysis [30].

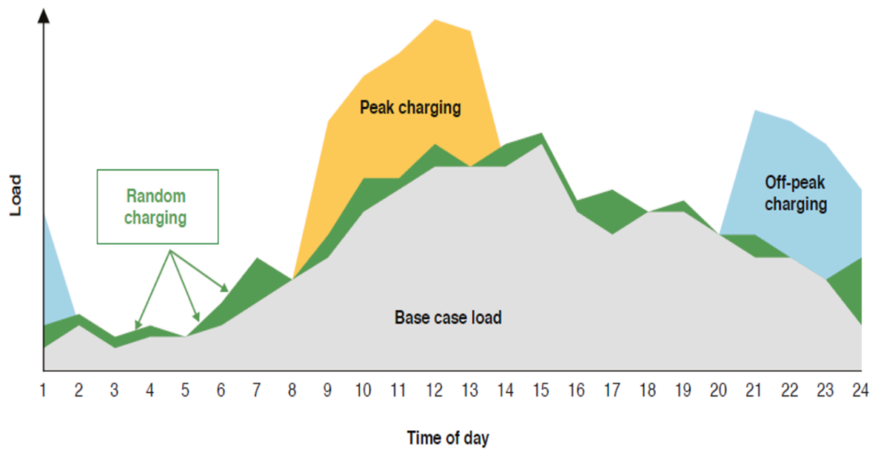

Fig. 8. Charging Scenarios [31].

2.4. Modelling of radial distribution network with EVCS

In this section mathematical modelling of the RDN with EVCS are described in detail. The mathematical modelling consists of various constraints of the network which must be satisfied at any load with EV charging uncertainty. Here optimized cost of charging station and fuel are also formulated.

2.4.1. Radial distribution network, PV-DG, and EVCS constraints

EVs load and consumer load both are uncertain in the RDN. To remain the system stable at any load variation, power flow, voltage, active power, reactive power, and generator constraints must be remain satisfied.

Active and reactive power flow constraints:

$$P^{eq}_{RDN,j} = P^{Load}_{RDN,j} - P^{PV-DG}_{RDN,j} + P^{EV}_{RDN,j} \forall_{RDN}, \ \forall_j \in \Omega_N \tag{6}$$

$$Q^{eq}_{RDN,j} = Q^{Load}_{RDN,j} - Q^{PV-DG}_{RDN,j} \forall_{RDN}, \ \forall_j \in \Omega_N \tag{7}$$

$P_{RDN,ij}/Q_{RDN,ij}$ is the active/reactive power flow in branch ij in RDN (kW/kVar) and R_{ij}/X_{ij} resistance/reactance of branch ij (Ω) and Ω_N represent number of buses in the RDN. The $U_{RDN,\ j}$ is the Voltage magnitude at bus j (kV), .Ω_L is branches in the RDN and $I_{RDN,ij}$ current in branch ij (A).

Voltage constraints:

$$U_{min} \le U_{RDN,i} \le U_{max} \forall_{RDN,t}, \ \forall_i \in \Omega_N \tag{8}$$

Where U_{min}/U_{max} is the lower /upper limit of voltage magnitude (kV).

Transmission line current constraints:

$$|I_{RDN,ij}| \le I_{ij,max} \forall_{RDN,t}, \ \forall_{ij} \in \Omega_L \tag{9}$$

From Eq. (9), $I_{ij,max}$is maximum current value in branch ij (A).

PV-DGs size constraints:

$$S^{rated}_{PV-DG,i} = N^{PV-DG}_i * S^{unit}_{PV-DG} \forall_i \in \Omega_{PV-DG} \tag{10}$$

where $S^{rated}_{PV-DG,i}$ rated capacity of PV-DG installed at bus i(kVA), N^{PV-DG}_i number of PV-DG installed at bus i, S^{unit}_{PV-DG} unit rated capacity of PV-DG (kVA), Ω_{PV-DG} set of RND buses for PV-DG installation.

Regulations on PV-DG reactive outputs:

$$N^{PV-DG}_i * Q^{unit}_{PV-DG,lim} \le Q^{PV-DG}_{RDN,t,i} \le N^{PV-DG}_i * Q^{unit}_{PV-DG,lim} \forall_{RDN,t}, \ \forall_i \in \Omega_{PV-DG} \tag{11}$$

$Q^{unit}_{PV-DG,lim}$ is the reactive power output of each PV-DG unit (KVAr) and $Q^{PV-DG}_{RDN,t,i}$ is the PV-DG reactive power output at RDN bus i at any time t (KVAr).

EVs dispatches regulation constraints:

$$\sum_{j\in\Omega_{CF}} B_{RDN,k,j} = 1 \ \forall_{RDN,k}, \ \forall_i \in \Omega_N \tag{12}$$

Ω_N Buses in the distribution system, $B_{RDN,k,j}$ is unified representation of $B^{WD}_{RDN,j,k}$ and $B^{NWD}_{RDN,j,k}$

$$B_{RDN,k,j} = 0 \forall_{RDN,t}, \ \forall_{RDN,k,} \forall(\text{I},\text{j}) \in \{(\text{I},\text{j}) \left[d_{ij} > d_{lim} \right. \tag{13}$$

i/j is the bus index, d_{ij} is the distance from bus i to bus j(km), d_{lim} is the maximum extra traffic distance accepted by EV owners in charging dispatches (km).

When EV need charging, EV must be parked at EVCS where EV charging slot is booked then EVCS slot is marked by1. However due to traffic EV distance is greater then d_{lim}, EVCS slot is marked by 0. Here d_{lim} value is set at 0.6Km [29].

Power requirement for EV charging:

$$P^{EV}_{RDN} = P^{EV}_{EV,rated} * \left(\sum_{i=1}^{N_{bus}} \sum_{k\in\Omega^{EV}_{RDN,t}} B_{RDN,k,j} \right) \forall_{RDN}, \ \forall_i \in \Omega_{CF} \tag{14}$$

This constraint shows the availability of power after satisfying the consumer base load of RDN.

Availability of EV charging facilities:

$$N^{CF}_J \ge \sum_{i=1}^{N_{bus}} \sum_{k\in\Omega^{EV}_{RDN}} B_{RDN,k,j} \ \forall_{RDN}, \ \forall_j \in \Omega_{CF} \tag{15}$$

N^{CF}_j is number of charging facility installed at bus j, Ω_{CF} number of buses where EVCS are installed.

The installed EVCS must satisfy the charging facility for N number of vehicles at any season at any time.

2.5. Energy management technique

In this section mathematical formulation of energy management technique for annual expenditure of EVCS and RDN is presented. The EVCS expenditure consists of installation, operation, maintenance and fuel cost. The RDN expenditure consists of power cost taken by different distributed generators and grid to supply the demand. Both EVCS and RDN expenditures are formulated in four seasons. In [29,33] only EVCS and PV-DG annual cost are calculated, here annual RDN expenditures are also calculated.

EVCS annual charges $C_{A,EVCS}$ is given as:

$$C_{A,EVCS} = C^I + C_{O\&M} + C_{A,F,EVCS} \tag{16}$$

Investment annual cost $C^I$of EVCSs:

$$C^I = R_d \cdot \sum_{i=1}^{N_{bus}} \left(C^I_{FCF} * N_i^{FCF}\right) + C^I_{PV-DG} \tag{17}$$

where R_d is an auxiliary variable in annual cost, N_{bus} is the number of buses in RDN and $C^I_{FCF/PV-DG}$ is investment cost for each FCF and PV-DG ($) and C^I is the annual investment cost of EVCS($), N_i^{FCF} iindicates the number of FCF installed at bus i.

Where the auxiliary variable $R_d = \frac{d(1+d)^{y}CF}{(1+d)^{y}CF-1}$ and d is the discount rate, y_{CF} the economic life of the charging facility (year).

Operation and maintenance annual cost $C_{O\&M}$ of EVCSs:

$$C_{O\&M} = \sum_{i=1}^{N_{bus}} \left(c^{O\&M}_{FCF} * N_i^{FCF}\right) + C^{O\&M}_{PV-DG} \tag{18}$$

where N_{bus} is the number of buses in the RDN and N_i^{FCF} is an integer variable that indices the installation number of FCF at bus i and $C^{O\&M}_{FCF/PV-DG}$ operation and maintenance annual cost of each FCF/PV-DG.

Annual fuel cost required by EVCSs:

$$C_{A,F,EVCS} = \sum_{S=1}^{4} S_{WD} * \sum_{EVCS=1}^{N,EVCS} EV_{N,CF} * C_{F,G} * C_{F,PV-DG} * \Delta t + \sum_{S=1}^{4} S_{NWD} * \sum_{EVCS=1}^{N,EVCS} EV_{N,CF} * C_{F,G} * C_{F,PV-DG} * \Delta t \tag{19}$$

$EV_{N,CF}$ = Number of EVs connected to EVCS charger
$C_{A,F,EVCS}$= Annual fuel cost required for EVCS ($/ MWh)

The annual fuel cost for RDN is divided into working and non-working day of four seasons:

$$C_{A,F,RDN} = \sum_{S=1}^{4} S_{WD} * \sum_{i=1}^{Nbus} P_D * C_{F,G} * C_{F,PV-DG} * 24 + \sum_{S=1}^{4} S_{NWD} * \sum_{i=1}^{N} P_D * C_{F,G} * C_{F,PV-DG} * 24 \tag{20}$$

Δt = time segment span required for EV charging
$C_{A,F,RDN}$- Annual fuel charges required for RDN ($/ MWh)
S_{WD}/S_{NWD}= Season working/non working day
P_D = load of RDN
$C_{F,G}$= Fuel cost of power taken from conventional generator ($/MWh)
$C_{F,PV-DG}$= Fuel cost of power taken from PV-DG ($/MWh)

3. Case study

A real RDN 33 bus system which is a part of urban areaof United Kingdom of Saudi Arabia [24] is selected for proposed RTEM and annual cost evaluation. The 33 bus system network is proposed by [25], all line, branch, generator data is taken from [34].Modified RDN with three EVCS and three PV-DG is shown in Fig. 8. In RDN if energy is managed in a proper manner network dependability on main grid will reduces same time carbon emission also decreases. To manage the energy in RDN with EVCS and PV-DG here different cases are considered.

Case1: RDN with three EVCS without PV-DG
Case2: RDN with three EVCS with three PV-DG and ESS
Case3: RDN with three EVCS with two PV-DG and ESS

3.1. Real parameter estimation for RDN

To show the effectiveness of the RTEM real solar irradiation data is collected [26] and real PV active power generation is calculated from Eq. (3).The peak value of solar irradiation is fixed to 1000 W/m2 [29]. The solar irradiation data is collected for ten hours from 8:00am to 6:00pm.The economic life of PV-DG is 25 years, the investment cost is 1200$/KVA, O & M cost is 2$/MWh, while fuel cost, CO_2 emission is Zero [35].Practically it is very difficult to calculate PV active power generation for throughout the year since it is out of the scope of this paper. However solar irradiation is almost remain similar in a season, therefore here a year (2019) is divided into four seasons as described in section(2.2).The spring season had a non-working day (NWD) 27, working day (WD) 65, summer had NWD 26, WD 66, Autumn had NWD 26, WD 65, and Winter had NWD 25, WD 65 in 2019. From each season one working and one non-working day with maximum solar irradiation are selected and active power generated by PV-DG is shown in Fig. 9 and Fig. 10 for Case-2and Case-3 respectively.

According to real traffic pattern [30] and EV charging pattern [31] of Saudi Arabia EVs distribution for each EVCS is presented in table 2. Here three type of charging hour's peak charging (8:00am-1:00pm), off peak charging (9:00pm-1:00am) and random charging (1:00pm-9:00pm and 1:00am-8:00am) hours are selected.

The RTEM strategy proposed here is based on charging schedule and PV output used for EVCS. In this paper three type of charging strategies are proposed.

The RTEM for peak charging: In this duration most of the EVs reached to their destination such as offices, schools and other working places and they park their EVs at EVCS for charging. During this period all EVCS are filled with 80 % for WD and 20 % for NWD of capacity. In this period as per the solar irradiation data collected for Saudi Arabia sufficient PV power remains available in all season to charge the EVs. Extra power is stored in ESS to charge EVs in night.

The RTEM for random charging: All EVCS are installed with fast charging so most of the EVs are charged in the morning time. In random charging, it is assumed that only 20 % of EVs are parked in WD and 10 % in NWD at EVCS for charging. During this period EVCS can take power directly from PV-DG or from ESS.

The RTEM for off-peak charging: In this charging interval consumer load is low and most of the people are returning to home after shopping or closing their shops and they park their EVs at EVCS for charging. In off-peak charging it is assumed that only 60 % EVs are parked in both WD and NWD at EVCS for charging and power is taken from ESS.

3.2. Annual charge estimation for RDN and EVCS

The power consumed by RDN and EVCS for WD and NWD for four seasons for three cases are calculated and represented in table 3. The RDN is paying maximum fuel charges in case-1 since in case-2 and case-3 RDN taking some power from PV-DG installed in EVCS. The cost of power taken by grid by cconventional generator is taken as 20$/MWh and cost of power taken by PV-DG is taken as 0.378$/MWh. Both power cost are calculated by running optimal power flow program using [34] in modified RDN. The EVCS is taking power from grid only in case-1 however in case-2 and case-3 not taking any power from grid since PV-DG installed at EVCS is enough to charge the EVs in all three proposed RTEM strategies and in all seasons.

The annual fuel charges of PV-DG based EVCS and RDN is calculated by using equ.(16). The investment cost, operation & maintenance cost of PV-DG is taken from [35] as1200$/KVA and 2$/MWh. The EVCS investment cost is taken as $400 per unit and 10 % of the investment cost is taken as annual operation& maintenance cost for charging power of 7.2KW. The EVCS is getting benefit of 997.65$ and 561.65$in case-2 and case-3 respectively by selling its power to RDN as shown in Fig. 11. The EVCS annual charges almost remain same in Case-2 and Case-3, for

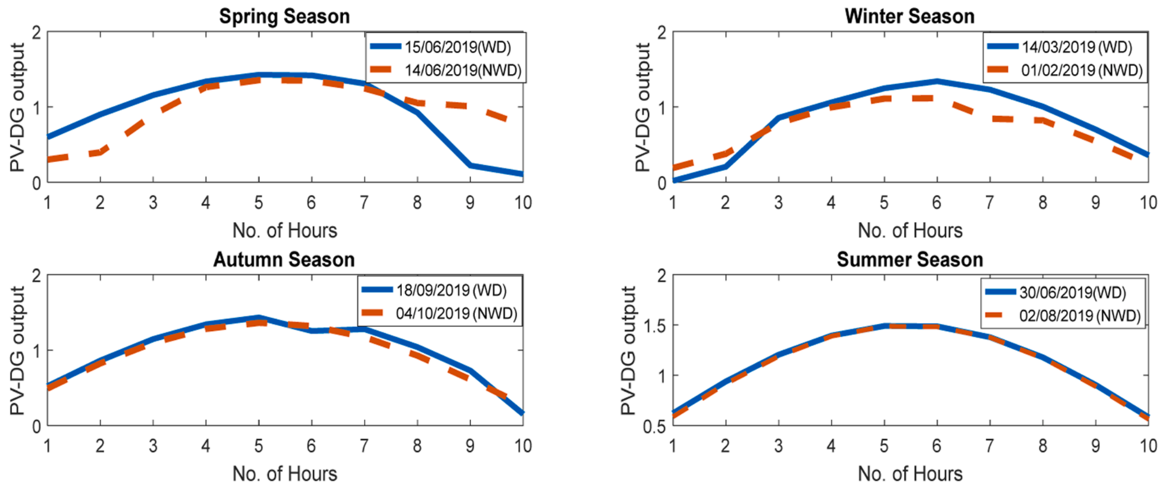

Fig. 9. PV-DG Active Power Generation (Case2).

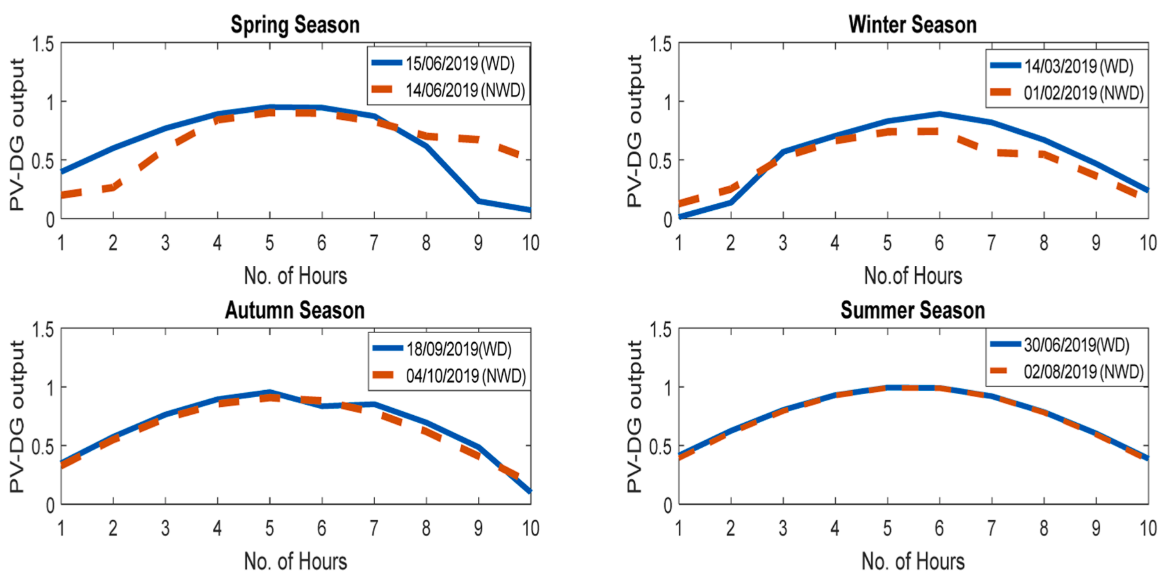

Fig. 10. PV-DG Active Power Generation (Case3).

Table 2
Charging schedule.

	Peak Charging		Random Charging		off- Peak Charging		Random Charging	
Time	8:00am-1:00pm		1:00pm-9:00pm		9:00pm-1:00am		1:00am-8:00am	
Day	WD	NWD	WD	NWD	WD	NWD	WD	NWD
EVCS 1(50)	40	10	10	5	30	30	10	5
EVCS 2(50)	40	10	10	5	30	30	10	5
EVCS 3(100)	80	20	20	10	60	60	20	10

Case-1, 16 % more annual charges are charged. Annual fuel charges of RDN is lowest in Case-2 where three PV-DG of 1.5MW capacity is installed and higher in Case-1where RDN taking power only from grid.

3.3. Discussion

The table 4 presents a comparative study of various research references focusing on different aspects related to energy management with EVCS and PVDG installed at 33 bus system. It's evident from the table that there's a diversity in the approaches taken by different studies. For instance, while some studies prioritize minimizing fuel costs, others focus on EVCS charges or address issues related to voltage and power flow violations. Moreover, the inclusion of real solar data collection and the presence of an ESS are also significant factors considered across these studies.

Interestingly, the comparison highlights that the current study encompasses all the evaluated aspects, making it comprehensive in its approach to energy management and optimization. By incorporating strategies to minimize fuel costs and EVCS charges, utilizing real solar data, addressing voltage and power flow violations, and integrating an ESS, this study offers a holistic solution to the challenges in energy management, reflecting a robust and multi-faceted approach towards sustainable energy practices.

In [29,33] authors only calculated annual charges for charging station but have not checked the feasibility of network. To check the feasibility of proposed cases all cases are simulated using [34] in MATLAB by modifying the RDN for RTEM. To check the feasibility and stability here voltage magnitude at each bus and power flow through each line for all proposed cases are compared with base case as shown in Fig. 12 and Fig. 13 respectively.

The greatest voltage variation is observed in Case 1, where EVCS

Table 3
Comparative analysis of different cases.

Case-1(Without PVDG)									
Working Day					Non-Working Day				
PV-DG output (MW)	Power consumed by EVCS (MW)	ESS to RDN (MW)	Power from Grid to RDN (MW)	Fuel Charge paid by RDN ($)	PV-DG output (MW)	Power consumed by EVCS (MW)	ESS to RDN (MW)	Power from Grid to RDN (MW)	Fuel Charge paid by RDN ($)
0	2.592MW	0	105.072	2101.44	0	1.44MW	0	103.92	2078.4
Summer Season									
Case-2(With PV-DG and 1.5MW Capacity)									
11.175	2.592MW	8.583	93.897	1877.94	11.050	1.44MW	9.610	92.87	1857.4
Case-3(WithPV-DG and 1MW Capacity)									
7.45	2.592MW	4.858	97.622	1952.44	7.367	1.44MW	5.927	96.553	1931.06
Spring Season									
Case-2(With PVDG and 1.5MW Capacity)									
9.393	2.592MW	6.801	95.679	1913.58	9.618	1.44MW	8.178	94.302	1886.04
Case-3(With PVDG and 1MW Capacity)									
6.2620	2.592MW	3.67	98.81	1976.2	6.412	1.44MW	4.972	97.508	1950.16
Autumn Season									
Case-2(With PVDG and 1.5MW Capacity)									
9.751	2.592MW	7.159	95.321	1906.42	9.360	1.44MW	7.92	94.56	1891.2
Case-3(With PVDG and 1MW Capacity)									
6.501	2.592MW	3.909	98.571	1971.42	6.24	1.44MW	4.800	97.68	1953.6
Winter Season									
Case-2(With PVDG and 1.5MW Capacity)									
8.013	2.592MW	5.421	97.059	1941.18	7.0170	1.44MW	5.577	96.903	1938.06
Case-3(With PVDG and 1MW Capacity)									
5.3420	2.592MW	2.750	99.73	1994.6	4.678	1.44MW	3.238	99.242	1984.84

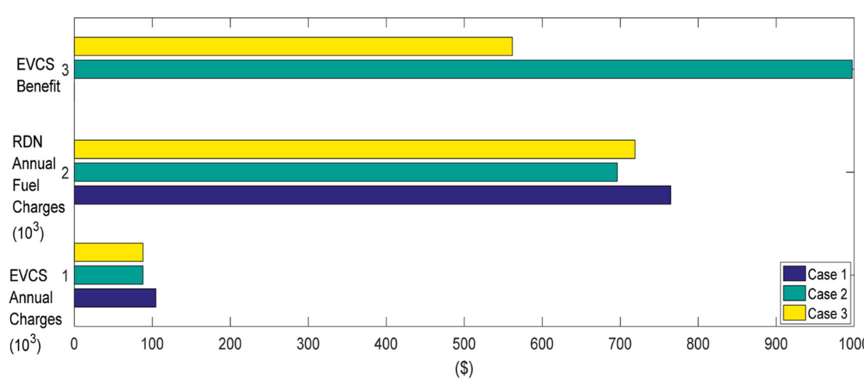

Fig. 11. Comparison of the annual fuel charges.

Table 4
Comparative study at 33 bus system with EVCS and PVDG.

Ref.No.	Year	Minimize Fuel cost	Minimize EVCS charge	Real solar data collection	Voltage Violations	Power flow violations	ESS
36	2023	Yes	No	No	Yes	Yes	Yes
37	2023	No	No	No	Yes	Yes	No
38	2023	Yes	No	No	Yes	Yes	No
39	2023	No	No	No	Yes	Yes	No
40	2020	Yes	Yes	No	Yes	Yes	No
41	2023	No	Yes	No	Yes	Yes	No
42	2023	No	No	No	Yes	Yes	Yes
43	2023	No	No	No	Yes	Yes	No
44	2022	Yes	Yes	No	Yes	Yes	No
This study		Yes	Yes	Yes	Yes	Yes	Yes

solely draw power from the grid. This increased variation likely stems from the direct reliance on grid electricity, which can introduce fluctuations in voltage levels due to demand variability and network constraints. In contrast, Case 3 exhibits voltage variations similar to the base case, suggesting that the integration of renewable energy sources and energy storage systems at EVCS helps stabilize the voltage profile within the distribution network.

The power flow through lines varies mostly from line one to line five in case-1 since all EVCS installed at buses connected to these lines. From line number six to line number thirty two the power flows through the lines are almost equal. However the network is remain stable in all cases since the network is converged and no contingency or other faults are observed.

Overall, the comparison between Case 1 and Case 3 highlights the importance of integrating renewable energy and energy storage technologies into EVCS to minimize voltage variations and enhance grid

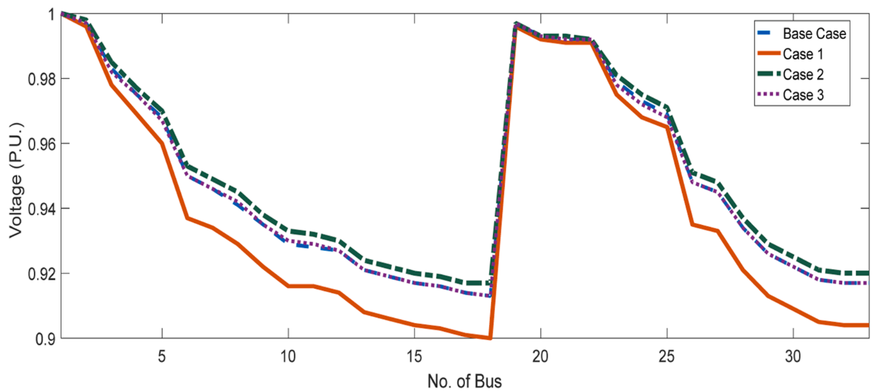

Fig. 12. Comparison of voltage variation for all cases.

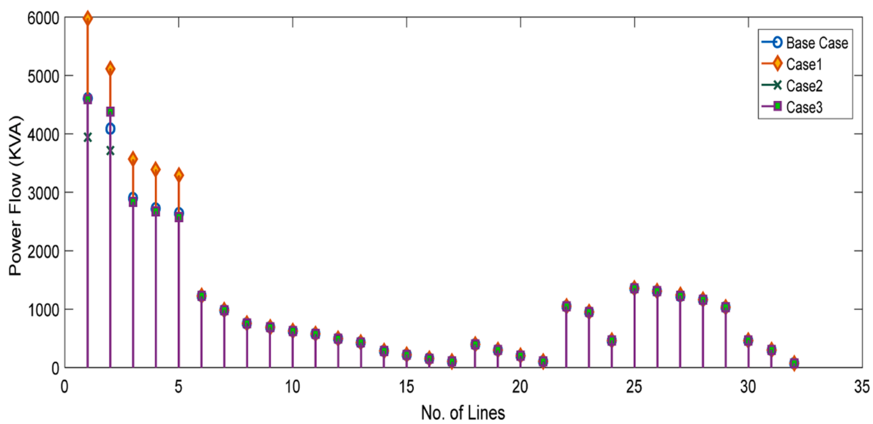

Fig. 13. Comparison of power flow variation for all cases.

stability. By reducing reliance on grid power and incorporating locally generated renewable energy, Case 2 demonstrates a more resilient and sustainable approach to electric vehicle charging within the distribution network.

The primary beneficiaries of the devised approach include electric vehicle owners, energy consumers, utility companies, and policymakers involved in energy and transportation sectors. Electric vehicle owners stand to benefit from more accessible and efficient charging infrastructure, potentially reducing their overall costs and carbon footprint. Energy consumers, including residential, commercial, and industrial users, may experience improved grid stability and reliability, as well as reduced dependence on conventional fossil fuel-based energy sources. Utility companies can optimize grid operations, better manage demand fluctuations, and potentially integrate more renewable energy into their portfolios, contributing to sustainability goals. Policymakers gain insights into effective strategies for promoting electric vehicle adoption and renewable energy integration, informing future regulations and initiatives.

4. Conclusion and future scope

In this study, a comprehensive approach utilizing RDN has been proposed to strategically determine the capacity and locations for installing EVCS equipped with PV-DG. The methodology presented here offers a scalable framework applicable to various distribution networks, enabling the effective planning and deployment of multiple EVCSs integrated with renewable energy sources.

Through the formulation of annual PV-DG-based EVCS fuel charges, RDN fuel charges, and EVCS benefits with Real-Time Energy Management (RTEM), this study highlights the economic viability and environmental benefits of the proposed approach. The results indicate that EVCSs equipped with PV-DG systems can operate independently of the grid, generating revenue by supplying excess power to the RDN while simultaneously reducing the grid's dependency on conventional fuel sources.

Moreover, the proposed RTEM significantly minimizes RDN fuel charges, further underscoring the cost-effectiveness and sustainability of integrating renewable energy into EV charging infrastructure. The stability analysis conducted on a modified RDN with EVCSs confirms the robustness and reliability of the proposed approach, demonstrating its feasibility and effectiveness in real-world applications.

Future research endeavors in this domain could delve deeper into the optimization of Real-Time Energy Management strategies, leveraging advancements in optimization algorithms and smart grid technologies. Additionally, further exploration of policy frameworks and regulatory mechanisms could facilitate the seamless integration of renewable energy-based EVCSs into existing infrastructure, fostering a more sustainable and resilient transportation ecosystem.

CRediT authorship contribution statement

Kirti Pal: Methodology, Writing – original draft, Writing – review & editing. **Tripti Kunj:** Methodology, Validation, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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