Optimal sizing and allocation of Solar based Distributed Generation and Wireless Charging Station for Transportation Electrification

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Abstract: **Decarbonizing the grid unlocks Electric Vehicles (EVs') environmental benefits by leveraging renewable energy. Distributed Generation Units (DGs) like solar minimize losses and defer network upgrades. Additionally, challenges associated with EVs, such as charging infrastructure and range anxiety, can be conveniently addressed through Wireless Charging Stations (WCS). This manuscript introduces a novel planning model for the allocation of WCSs based on DGs with an aggressor-based approach. A Mixed-Integer Non-Linear Program (MINLP) is formulated to optimize the allocation process. Probabilistic models are developed to accurately represent the stochastic behaviour of WCSs, residential loads, and DGs. The proposed model considers the cost and revenue components of both WCSs and solar-based DGs. Furthermore, a distinct distribution network is depicted on a geographical map to illustrate the connectivity of the network within the urban area while considering practical constraints for the installation of WCSs and solar-based DGs at each bus location. A new scoring scheme incorporating geographical aspects is presented to estimate the demand for WCS locations for EV riders. This scoring scheme aims to maximize revenue for investors by ensuring the installation of solar-based WCSs. The results demonstrate the financial viability and effectiveness of solar-based WCSs from a revenue perspective.**

Keywords: Electric Vehicles, Wireless Charging, Charging Station Allocation, Optimization, Distributed Generations

Nomenclature

EVs	Electric Vehicles
CS	Charging Station
DGs	Distributed generation units
WCS	Wireless Charging Station
MINLP	Mixed-integer non-linear program
DNs	Distribution networks
DERM	Distributed Energy Resource Management
DER	Distributed Energy Resources
SOC	State-of-Charge
BESSs	Battery Energy Storage Systems
RESs	Renewable Energy Sources
LDCs	Local Distribution companies
FCSs	Fast Charging Stations
RTS	reliability test system
PDF	probability distribution function
NPV	net present value
FIT	feed-in-tariff
O&M	operation & maintenance

AADT	annual average daily traffic
PV	Photovoltaic
GA	Genetic Algorithm
PVF	Present Value Function
FIT	Feed in Tariff

1. Introduction

The EV demand is increasing, resulting in the growth of the global EV stock by 20 crore vehicles, accomplishing a total of 51 crores globally in 2018 [1]. Some new environmental concerns and social trends are attributed to the growing number of EVs. Further, the sudden connectivity of numerous EVs may disbalance the grid stability. Hence, charging EVs through decarbonized grid could be the key to eliminating the carbon footprint of transportation and the grid sector. Consider a futuristic aspect of EV charging that all EV owner have their residential wireless chargers. However, they might depend on WCSs on the highways or in the city to increase the range [2]. The WCSs installation is still in the primitive stage. The EVs adoption could be faster by solving the refuelling problem, posing a challenge in the Distributed Network (DNs) operation. Whereas DNs mandate the upgradation of infrastructure to encounter the huge EV and WCS demands. [3] For such demand, the electric utility must forecast precisely and build more DGs. This challenge can be tackled differently, such as modelling of EV demand may use traditional EV travel information to model EV holders driving behaviour as shown in [4]. Assuming people charging time from earlier literature that they charge EVs at the end of the day [5]. This assumption is widespread among earlier research studies, as seen in [5], where models are introduced considering single and multiple charging per day. Zhou et al. have estimated when the EVs would require charging through DN using Monte Carlo simulation [6]. The authors in [7] developed a new model for EV coordinated demand and compared it to the uncoordinated charging model. Fang He et al. have adopted a game theoretical approach and developed a model for the equilibrium interactions among electricity prices, traffic, and power flow. However, they have not considered DERM in their model [8]. With recently available EV charging data [9], a shift is taking place where researchers are relying on real EV data in building more accurate models to site and size WCSs. The problem of WCS allocation is similar to shortlisting candidate positions, hence selecting the most suitable location among them in accordance with the planned architecture. X. Huang et al. have proposed a model which utilizes Origin-Destination (O-D) lines to evaluate the travelled distance and uses a predetermined minimized state of charge (SOC) to simulate the location of EV charging. Hence the model implements the solution of WCS allocation. In a simulation, these positions were recorded to associate with a traffic node. Further, the Voronoi diagram has been used to divide the region into the service area, where the site of a WCS is the central location of each site. H. Zhang et al. presented a similar model in which EV arrival and parking generation rates were used to prepare the charging demand model [10]. Further, they also used O-D lines to predict the queuing model and EV charging demand to evaluate the charging station (CS) service time [11]. Furthermore, these studies follow a traditional mindset approach which is designed for vehicles at petrol refuelling stations with the charge when empty mentality. Since the WCSs will not be readily available as petrol refuelling stations, EV charging is much slower than refuelling a petrol or gas tank. Hence people will try to know in advance about the

WCS before they visit, with some additional amenities nearby. Thus, an advanced framework with suitable planning must be developed for WCS allocation. Conversely, the WCS sizing is also challenging; based on site and demand number of chargers needs to be determined. It could also need to know the charging rated power or power requirement per charger. Xie et al. emphasize the number of chargers as deciding factor for charging station capacity when DGs and battery energy storage system (BESSs) sizing that feeds the charger [12]. In [13], Simorgh et al. promotes that the powerline capacity from nearby substations can decide the size of CS, whereas in [14] author has assigned, based on the feeding area, the max power rating of CS. In [15], Erdine et al. have not considered the number of plugs needed and rated power of the charger but considered ESSs and DGs to design self-sustained off-grid CSs. In [9], X. Huang allows that the CS size depends on the demand without limiting the capacity of CS. The objective of allocation and sizing of WCS depends on the charging demands with minimized costs. The cost of WCS includes grid connection costs [12], grid upgrade, investment, losses, operation and maintenance costs [10], the penalty for unsupplied demand [11], land rented costs [13] as well as demand response costs [14]. As seen in [15], another objective of WCS allocation is to minimize the overall network energy losses.

In most of the literature, the unsupplied demand had been penalized, which is quite a strict constraint. However, the determination of optimal sizing and siting of RESs in the distribution network has also been explored in the cited papers, where many objectives have been considered. Such as, in [16], a probabilistic model has been proposed to determine the maximized multi-objective performance index for optimal allocation of solar DGs in distributed networks, i.e., including voltage-profile improvement indices and energy-losses reduction. A. A. Abdelsalam et al. have presented a similar approach to minimize harmonic distortions and annual energy losses [17]. A. S. A. Awad et al. have addressed DG siting to improve the reliability of DNs [18-19]. M. F Shabaan et al. have proposed a method to find the optimized siting of DER to increase the advantages of LDCs. These benefits contain a decrease in the cost of energy losses, deferral of upgrade investment and improvement in reliability. The framework developed is mainly for static conductive charging demand. However, the dynamic demands mainly depend on the willingness of EV users, which depends on the CS's waiting time and driving distance.

The above discussion shows insufficient information in the literature to accurately model the nature of WCSs and residential chargers. The use of outdated allocation ideas about the WCSs as petrol stations has been noted. Also, some impractical constraints have been applied by many authors to solve the charging allocation problem of CS; however, they have yet to present the allocation of WCS. In this paper, we have presented solutions to WCS deployment, including elastic charging demand. This paper could be the first to present the WCS network model on elastic demand. The two most significant features of WCS deployment have been discussed: WCS siting, sizing and WCS with DGs. The total profit to LDCs has been maximized with the best quality facility for EV users. The summary of the contribution of this paper is as follows.

The contributions of this paper are summarised as follows:

- A new scoring scheme that studies geographical characteristics has been developed to categorize the WCS locations built based on EV drivers' demand.
- Using recently available Electric Vehicle FCS data to prepare a probabilistic model such as probability distribution function (PDFs) based on residential EVs and WCS demand.
- The formulation of a random MINLP (Mixed Integer Non-Linear Program) based model to allocate and decide the size of the WCSs and photovoltaic-based DGs in DNs, the DN constraints, and profit maximization has been taken into account.

The remainder of this paper is organised into four sections. The problem description is outlined in Section II. Section III gives details of the methodology adopted, including the derived probabilistic models, optimization model, and calculation of attractiveness scores. A case is used to validate the performance of the developed planning methodology in Section IV. The conclusions are finally outlined in Section V.

2. Problem formulation for optimal allocation of Wireless Charging Stations

The basis of this paper is to encounter the rising demand for EVs and, more precisely, Wireless Charging Stations. Hence the installation of solar-based DGs on WCS can provide many advantages and benefits to the LDCs, such as

- Acceding distributed network upgrade, which is required given the increase in the demand for the system;
- Minimizing energy losses in the distributed networks by optimal siting of the wireless charging station and PV-based distributed generation units.
- Supplying the EVs and WCSs load along with the PV-based DG to reduce the carbon footprint.

To fulfil these goals, this paper focuses on the optimal placement and sizing of DG-enabled WCSs, which can reduce the total cost and upsurge the total revenue for the owners and investors. The total cost, i.e., operation and maintenance (O&M), operation costs for DG-based WCSs, and energy losses costs. Conversely, the total revenue suggests the sold electricity to electric vehicles through WCSs and sending the generated electricity from DGs to DN. Assuming stringent rules of DN upgrades [20], installing WCSs and DGs will be limited to the locations and sizes recommended by LDCs. Therefore, the presented model in this manuscript is beneficial for the utilities as a reference. Hence, utilities can recommend the investors for the optimized allocation and sizing of DG-based WCSs. Photovoltaic-based DGs have been used due to their dropping prices over the past few years, according to the annual reports released by the national renewable energy laboratory [21]. The user trends and collected data can explain the EV demand expected at the required DNs [22]. Based on this fact, the paper focuses on intracity wireless chargers, i.e., rural or urban.

3. Implementation methodology based on Electric Vehicle demand

The main objective of this research paper is to increase the profit obtained from both the WCS and the PV-based DGs. Hence the constraint applied contains LDCs constraints along with geographical constraints. The paper includes three stochastic elements:

power generation of solar panels, residential EV demand with generic load combined and the WCSs demand. The input to these elements is the probability distribution function (PDFs). Further, a scoring scheme has been allotted to the individual location of WCS. Moreover, the scoring schemes predict the demand of each location based on matrices discussed in sections 3.5. Since the result of that modelling is the optimized allocation and sizing of WCS with PV-based DGs, these results are precious recommendations for the related investors to maximize benefits to most stakeholders. The formulation of the Model is as follows.

3.1 Modelling of Electric Vehicle charging demand in Wireless Charging Stations

The recently made available data from the conductive charging project "The EV Project" has been used to build the wireless charging station load model [23]. The project data presents the stochastic demand for fast charging stations, which depend on the availability of the number of EVs participating in most of the charging events. Hence the same data has been used in the WCS allocation. The project data shows 100 DC fast charging stations with 71,803 charging events in 1 year (365 days). We have used the same data after manipulating it according to WCSs with a similar condition. The project data contains the daily charging power profile of all 100 under-study DC fast charging stations, including a daily aggregate demand of 196. Hence by distributing these aggregate daily powers into a number of EVs, we can find the daily power profile for each EV. The daily power profile of EV has been presented in Fig. 1. The figure shows the weekly and weekend profiles, where the peak demand has been noted afternoon and for weekdays around the evening from 6:00 to 8:00 PM, and weekends show a smoother curve peaking profile at 3:00 PM.

A histogram can be figured to present the data of entire year and probabilities of individual state for wireless charging, utilizing to find its the demand. Since a number of states may increase the computational complexity in the optimization model, only five states have been considered to present the diversity of the data. The different states with their probabilities have been shown in the Table 1 and the sates presents the peak demand percentage.

3.2 Combined modelling of residential Electric Vehicle and generic loads

Fig. 2 presents the summary of the important steps in the optimization as proposed methodology. The generic load demand has been assumed as IEEE RTS's (reliability test system) hourly load shape [23]. Further to reduce the complexity with not affecting accuracy the hourly load data has been clustered into 10 load states [24]. To account residential EV wireless charging demand the generic load model has been combined. Hence "The EV Project" data has been utilized, which contains the charging demand of private non-residential, Level 2 wireless charger in residential and public areas. "The EV Project" data has been combined with the generic demand profile assuming EVs penetration level of 25%. Further data has been normalised and filtered. The result of these operations is the development of another power profile at a certain pre-determined penetration level showing a realistic demand for EVs. Its ten states' probabilities have been calculated, and a combined load histogram is also obtained, as shown in Table 2.

3.3 Modelling of Photovoltaic-based Distributed Generations

Atwa et al. has presented the probabilistic model for PV-based DGs, where Weibull PDF has been used to present the solar radiation data. The continuous probability distribution function has been distributed into twelve states with their associated probabilities. Further, the generated power through PV-based DGS were calculated at each state of input solar radiation, hence the DGs output power probabilistic model has been created.

3.4 Optimal allocation and sizing of WCSs with photovoltaic-based DGs

In Section II, the objective of this manuscript has been clearly mentioned which is to maximize the investor's' profit, as well as increase benefits to the WCSs owners and PV-based DGs investors, and minimize the energy losses costs for LDCs. Thus, the objective function of proposed model has been expressed by Equation. 1.

$$Maximize\ OF_1 + OF_2 + OF_3 - OF_4 - OF_5 - OF_6 \tag{1}$$

Where OF_1 is the NPV (net present value) of the profit from the sold electricity to EVs at the WCS, OF_2 is the NPV of the profit from the generated electricity by PPV-based DGs sold to the grid, OF_3 denotes NPV of profit due to savings of WCSs and PV based DGs, OF_4 is the NPV of the total investment associated with the installation of PV based DGs WCS. OF_5 is the NPV of the cost of consumed energy by WCSs, and OF_6 presents the NPV of total cost wasted as energy losses in a distribution network. Further, Equation 1 can be expanded by the equations (Equation. 2 to Equation. 7) as follows.

$$OF_1 = \sum_{i \in \mathcal{B}_{WCS}} \sum_{h=1}^{N^{state}} H_{i,h} \times P(C_h) \times 8760 \times \rho_{EV} \times PA(int, n) \tag{2}$$

Equation 2 presents the total revenue of the WCS by selling the electricity to EV users annually, where $\mathcal{B}_{WCS}$ is the number of sets of buses to install WCSs, N^{states} is the denotes the generated states by convolutions of PDFs for all elements, i is the DN buses nodes index, h is system state index, $H_{i,h}$ power demand captured at WCS at bus i and state h, $P(C_h)$ is the combined state probability at state C_h. ρ_{EV} is the cost price of energy sold at WCS, and $PA($s the PVF of a yearly recurring disbursement, $PA(int, n)$ is the function of rate of interest and (n) number of years, which is shown as $\frac{(1+int)^n - 1}{int(1+int)^n}$.

$$OF_2 = \sum_{i \in \mathcal{B}_{DG}} \sum_{h=1}^{N^{state}} x_i \times SW_h \times P(C_h) \times 8760 \times \rho_{FIT} \times PA(int, n) \tag{3}$$

The Equation 3 presents the NPV of the NPV of the revenue earned from electricity sold from PV based DGs to grid. In Equation 3, $\mathcal{B}_{DC}$ installed PV based DGs candidate buses, x_i is a variable to control the quantity of DGs attached to bus, SW_h DGs generated output power at each state, and ρ_{FIT} is the is the FIT price paid based on generated electricity by solar PV based DGs.

$$OF_3 = \left[\sum_{i \in \mathcal{B}_{DG}} x_i \times Sal^{DG} + \sum_{i \in \mathcal{B}_{WCS}} z_i \times Sal^{Charger} \right] \times PF(int, n) \tag{4}$$

Equation 4 presents revenue due to savings from solar PV based WCS, where z_i is the decision variable to control the quantity of wireless chargers to be placed at each WCS, $Sal^{Charger}$ is the salvage rate of individual wireless charger, Sal^{DG} is the saving price of individual PV panel, and $PF(int,n)$ is the PVF of the future disbursement, expressed as function of time (year) of future disbursement, rate of interest (int), which can be evaluates as $\frac{1}{(1+int)^n}$.

$$OF_4 = \sum_{i\in\mathcal{B}_{DG}} x_i \times \left(C_{inv}^{DG} + C_{maint}^{DG} \times PA(int,n)\right) + \sum_{i\in\mathcal{B}_{WCS}} z_i \times \left(C_{inv}^{WCS} + C_{maint}^{WCS} \times PA(int,n)\right) \tag{5}$$

where C_{inv} and C_{maint} are the capital and annual O&M costs, respectively.

$$OF_5 = \sum_{i\in\mathcal{B}_{WCS}} \sum_{h=1}^{N^{states}} H_{i,h} \times P(C_h) \times 8760 \times \rho_{elec} \times PA(int,n) \tag{6}$$

$$OF_6 = \sum_{h=1}^{N^{states}} P_{loss,h} \times P(C_h) \times 8760 \times \rho_{elec} \times PA(int,n) \tag{7}$$

Where ρ_{elec} is the cost of electricity; and $P_{loss,h}$ represents the power losses in the distribution network at state h as given by

$$P_{loss,h} = 0.5 \times \sum_{i\in\mathcal{B}} \sum_{j\in\mathcal{B}} G_{ij} \times \left[V_{i,h}^2 + V_{j,h}^2 - 2 \times V_{i,h} \times V_{j,h} \times \cos\left(\delta_{i,h} - \delta_{j,h}\right)\right] \ \forall h \tag{8}$$

Where $V_{i,h}$ presents the magnitude of voltage and $\theta_{i,h}$ presents angle of bus i at the state h, $G_{i,j}$ is the conductance of line i,j and $B_{i,j}$ is the susceptance of line i,j.

The following constraints are subjected to Objective Function (OF) as,

3.4.1 *Power Flow*: The constraints at each bus as active and reactive power balance in the distributed network can be give as:

$$PG_{i,h} - SD_h \times P_i^{Peak} + SW_h \times x_i - y_i \times H_{i,h} = \sum_{j\in\mathcal{B}} V_{i,h} \times V_{j,h} \times \left[G_{i,j} cos\left(\theta_{i,h} - \theta_{j,h}\right) + B_{ij} \sin\left(\theta_{i,h} - \theta_{j,h}\right)\right] \quad \forall i,h \tag{9}$$

$$QG_{i,h} - SD_h \times Q_i^{Peak} = \sum_{j\in\mathcal{B}} V_{i,h} \times V_{j,h} \times V_{j,h} \times \left[G_{ij} \sin\left(\theta_{i,h} - \theta_{j,h}\right) - B_{ij} \cos\left(\theta_{i,h} - \theta_{j,h}\right)\right] \ \forall i\ ,h \tag{10}$$

where $\mathcal{B}$ is the nodes (set of all DN buses), index of DN buses is assumed as j, $QG_{i,h}$ and $PG_{i,h}$ are the reactive and active power supplied by the nearby substations. SD_h is the normalized load combining EV demand and generic load, Q_i^{Peak} and P_i^{Peak} is the rated reactive and active power of the total load at the bus i, and y_i is the binary variable which means one if WCS is not placed at bus otherwise it is zero.

3.4.2 *Network security:* Equation 11 to Equation 12 presents the network security constraints which consists of line thermal limit and limit of voltage magnitude.

$$0.95 \le V_{i,h} \le 1.05 \qquad \forall\, i, h \tag{11}$$

$$0 \le I_{ij,h} \le I_{ij}^{max} \qquad \forall\, i, j, h \tag{12}$$

3.4.3 *Substation power:* the from Equation 13 to Equation 17 presents the substation power constraints in which reactive and active powers with voltage magnitude and angles have been given as follows;

$$PG_{1,h} \le PG_1^{max} \quad \forall\, h \tag{13}$$

$$PG_{i,h} = 0 \quad \forall\, i \ne 1, h \tag{14}$$

$$QG_{1,h} \le QG_1^{max} \quad \forall\, h \tag{15}$$

$$QG_{i,h} \quad \forall\, i \ne 1, h \tag{16}$$

$$V_{1,h} = 1.025 \;\; \& \;\; \delta_{1,h} = 0.0 \quad \forall\, h \tag{17}$$

3.4.4 *Distributed Generation:* The DG constraints are shown from Equation 18 to Equation 19 which restricts the installation of PV based distributed generation at individual buses, and the overall DN which follows Atwa *et al.* [24], Where P_{DG}^{rated} is the rated power of DG; $P_{bus,DG}^{max}$ maximum power at one bus by all connected DGs, $k1$ the ratio of the peak load of the distributed network. DGs capacity factor can be evaluated by dividing the average weighted power of the DG to its rated power. and is denoted as CF.

$$x_i \times P_{DG}^{rated} \le P_{bus,DG}^{max} \quad \forall\, i \in \mathcal{B}_{DG} \tag{18}$$

$$\sum_{i \in \mathcal{B}_{DG}} CF \times x_i \times P_{DG}^{rated} \le k1 \times \sum_{i \in \mathcal{B}} P_i^{Peak} \tag{19}$$

3.4.5 *Wireless Charging Station:* The following constraints of WCS have been applied and shown from the Equation 20 to Equation 21, which limits the number of wireless chargers to be installed on each location hence the overall DN, where rated power of wireless charger is $P_{Charger}^{rated}$, rated maximum power of all the wireless chargers connected at one bus, and the fraction of peak load of DN is $k2$.

$$z_i \times P_{charger}^{rated} \le P_{bus,WCS}^{max} \quad \forall\, i \in \mathcal{B}_{WCS} \tag{20}$$

$$\sum_{i \in \mathcal{B}_{WCS}} z_i \times P_{charger}^{rated} \le k2 \times \sum_{i \in \mathcal{B}} P_i^{Peak} \tag{21}$$

Further, to minimize the extra investment in reinforcement of grid and support the high demand from WCS, the utility may limit the maximum number of WCSs in a specific area, such as in Equation 22, hence this constraint is very important for the investors and to confirm the saturation of WCS in the market. Based on market size and region, the parameter used is shown in Equation 22.

$$\sum_{i \in \mathcal{B}_{WCS}} y_i \leq k3 \tag{22}$$

In Equation 23 the constraint confirms that WCS can accommodate a charger in a bus, the notation M can be used as

$$M \times y_i \geq z_i \quad \forall i \in \mathcal{B}_{WCS} \tag{23}$$

In Equation 24 the WCS's peak demand can be calculated using (n^{EV}) the number of EVs in that region, (υ^{EV}) is the percentage of those EVs that use WCS, $P_i^{Peak,WCS}$ is the peak-per-EV power demand and WCS. Furthermore, the lowest value of the demand of that station and capacity of that station are the constraint of captured power demand of a WCS $H_{i,h}$. The captured demand can be calculated in Equation 25 and Equation 26 respectively.

$$P_i^{Peak,WCS} = n^{EV} \times \upsilon^{EV} \times P_i^{Peak,EV} \quad \forall\, i \;\in\; \mathcal{B}_{WCS} \tag{24}$$

$$H_{i,h} \leq z_i \times P_{charger}^{rated} \qquad \forall\, i \;\in\; \mathcal{B}_{WCS}, h \tag{25}$$

$$H_{i,h} \leq P_i^{Peak,WCS} \times SS_h \; \times a_i \quad \forall\, i \;\in\; \mathcal{B}_{WCS}, h \tag{26}$$

where h is the attractiveness matrix appointed t individual candidate bus, SS_h is the normalized load of a WCS. These can be explained the subsection 3.5.

3.5 Novel scoring scheme

Each candidate locations of WCS have been assigned with a scoring scheme, to evaluate the attention of those location by the EV drivers. Further, three scores can contribute to the overall score of each individual sites. Firstly, range extension, which is rationale of constructing WCS. Which means that the long distance travelled EVs may rely on WCSs to recharge their batteries in the mid of there journey, generally these types of drivers may use highways. The EV drivers may exit the highways and navigate to the nearest WCS.

As shown in the Equation 27, the score 1 evaluates the WCS candidates sites attractiveness based on the range between the all-individual sites within 1 km radius and commuter road exits.

$$S1_i = \sum\nolimits_{\forall c} \left(1 - D_{i,c}^{commute}\right) \quad \forall\, i \;\in\; \mathcal{B}_{WCS} \tag{27}$$

where $D_{i,c}^{commute}$ is a matrix signifying the distance between a candidate location i and a major road exit c in the 1 km radius.

In Equation 28 the score 2 enumerates the correlation between high-tech companies and WCSs. In [25] the understanding with high-companies is the one of the factors of correlation for the highly utilized WCSs. The EV drivers of working industries may use the WCS before, during and after the daily work routine, then the WCS can be easily and publicly accessible to other EV drivers. All those advanced firms around 0.3 km radius of candidate location can be assumed as point of interest.

$$S2_i = \sum\nolimits_{\forall t} \left(1 - D_{i,t}^{tech}\right) \quad \forall\, i \;\in\; \mathcal{B}_{WCS} \tag{28}$$

where $D_{i,t}^{tech}$ is a matrix signifying the distance between the a candidate location and advanced firms located around a radius of 0.3 km. In Equation 29 score 3 specifies the traffic flow near a WCS candidate location. A grater score can be given to a candidate location with higher foot-traffic due to high probability of stopping of EV driver to top-up nearest candidate location of WCS. In Equation 29, all the roads within 0.5 km radius (Euclidean) have been included.

$$S3_i = \frac{\sum_{n=1}^{G} T_{i,n}^{near}}{G} \quad \forall\, i \,\in\, \mathcal{B}_{WCS} \tag{29}$$

where $T_{i,n}^{near}$ is a matrix which signify the daily traffic flow count near a candidate location i in a traffic node within a range of 0.5 km. The overall approximation of traffic flow in that area can be obtained by obtained averaging the traffic flow in those nodes. The AADT has been used to present the traffic flow.

All those three scores discussed above are having the value between 0 and 1. For a candidate bus i the overall attractiveness score (a_i) can be found by normalizing and averaging which shown in Equation 30. The attractiveness of EV driver proportionally depends on the attractiveness score (a_i) for a candidate location. Hence the overall addition of attractiveness score for all the WCS candidate location resulted to 1.

$$a_i = \frac{1}{3}\left[\frac{S1_i}{\sum_{\forall i \in \mathcal{B}_{WCS}} S1_i} + \frac{S2_i}{\sum_{\forall i \in \mathcal{B}_{WCS}} S2_i} + \frac{S3_i}{\sum_{\forall i \in \mathcal{B}_{WCS}} S3_i}\right] \qquad \forall \;\; i \in \mathcal{B}_{WCS} \tag{30}$$

4. Performance Evaluation

4.1 System under study

Considering DN, the geographical considerations related to traffic system and the amenities near WCS locations as well as the constraints needs to be considered to develop a genuine model to find optimal allocation and sizing of WCSs. Western part of Delhi, India has been selected as a case study since there is no any WCS or consider virtually zero WCS, further the sales of EVs in Delhi increasing day by day [26]. Furthermore, due to capital region of India, a series of information can easily be available about the region to develop a research model and can be tested and applied in future. A 41-bus distributed network has been assumed to be overlaid in the region under consideration in Delhi, as shown in Fig. 3. The load in these regions followed by the generic model of standard IEEE-RTS model [23]. Further, the demand of residential EV wireless chargers and generic load model has been combined which is explained in the subsection 3.2. The used parameters are presented in Appendix A.

4.2 Calculating the attractiveness scores

Wireless Charging Stations should be allocated near the most easily accessible region [25]. Those locations should have open air parking lots, community colleges, plazas, shopping malls etc. It also important to consider the WCS location connectivity to DN bus based on its serving area. In Fig. 4, a star marked location is shown within 1 km, regarding score 1, which presents a point of concern for one of the candidate sites. In Fig. 4, a blue dotted line shows the shortest path between the candidate location and highway exits and the distance has been calculated using Google Map. Score 1 assigned to a candidate bus is high if the highway exits are closer to the candidate locations. In the same way, based on the number of high-tech companies within the radius of 0.3 km, the score 2 has been given to each candidate bus. To consider the high-tech company’s employees, who are to be considered as precious users of wireless charging, a smaller distance range has been assigned. More the number of high-tech companies with nearby distances to the candidate bus, the higher would be the score 2. ADTC data has been used to find the Score 3 for western Delhi. By considering the single location of WCS, all the other ADTC data within the range of 0.5 km has been plotted on the map. A smaller distance of 0.5 km has been considered here since this distance is very convenient and traverse to charge if they need to top-up their EV. Fig. 5 shows a 0.5 km area with ADTC points which is denoted by yellow color and surrounded by 0.5 km radius black circle. Then the points within this area have been averaged and evaluated.

In conclusion, the total attractiveness score for each candidate location has been calculated by averaging all the three scores. At 0.15 points, the two of those highest scores are tied. Table 3 shows the WCS scores at the candidate location in Delhi west. According to the Table 3, Bus 22 shows steady values in all three scores, whereas Bus 23 show smaller score 1 however higher values in score 2 and score 3. Further, Bus 26 shows smallest values in score 1 and score 2, but higher in score 3, since more traffic near bus 26. Hence from above analysis it can be concluded that the candidate location where there is high traffic, near to highway exits and also near to high-tech companies will receive high scores, which is similar to the recommendation in [25].

4.3 Results of the planning framework

The allocation problem of wireless charging stations (WCSs) in conjunction with distributed generators (DGs) is a challenging mixed-integer nonlinear programming (MINLP) task that is computationally demanding using deterministic methods. To address this, a Genetic Algorithm (GA) is employed to evaluate the results, as GAs have proven to be effective in solving complex optimization problems such as distributed network planning with distributed generation. In terms of execution time and solution error, the GA outperforms certain meta-heuristic techniques, demonstrating superior performance. The developed model is implemented in MATLAB, utilizing the Genetic Algorithm (GA) toolbox. Appendix B provides details on the code parameters, including 11 locations with a total of 33 chargers and four PV-based DGs distributed across three sites. The attractiveness score and the relationship between locations and WCS sizing are considered, where a higher score corresponds to a greater number of chargers. Thus, prior to WCS sizing, the expected demand and attractiveness score for each candidate location are recorded. The solution and decision for PV-based DGs obtained by the model adopt a distributed strategy, ensuring support for different areas and reducing power losses. Fig. 6 illustrates the total costs and revenue evaluated over the planning horizon. The expected revenue from WCSs, facilitated by DGs, is significant, with a revenue-to-cost ratio of 1.8 for WCSs and 3.3 for PV-based DGs. Over the 20-year planning period, the net profit exceeds $30 million, considering the cost and total revenue. Incorporating PV-based DGs effectively minimizes energy losses, as evidenced by the comparatively low cost of energy loss of $1,212,600. In contrast, without PV-based DGs but with the same WCS loads, the total cost of energy losses amounts to $2,976,900, highlighting the substantial improvement achieved by installing PV-based DGs. Furthermore, WCS loads without PV-based DGs lead to an average overload of 1080 kW on the distributed network, equivalent to 189216 MWh over the planning horizon, with a peak overload of 1980 kW. By avoiding the need for DN capacity expansion and incorporating four PV-based DGs, the importance of DGs in siting and sizing WCSs is confirmed.

Tables 4 and 5 present the outcomes of the siting and sizing decisions for solar photovoltaic (PV) based distributed generators (DGs) and wireless charging stations (WCSs) respectively. The results indicate that in three specific locations, four solar PV based DGs are deployed, while in eleven locations, a total of 33 wireless chargers are installed. The relationship between the sizing and siting decisions for WCSs and their corresponding attractiveness scores is observed, where a higher score corresponds to the installation of a greater number of chargers. This comparison clearly demonstrates that the attractiveness score and projected demand at each location are taken into account during the evaluation of WCSs.

Regarding the decisions concerning solar-based DGs, the solutions generated by the developed model exhibit a distributed strategy, effectively supporting the load across different areas while minimizing power losses. This strategy aims to optimize the performance of the DGs by strategically locating them in various regions, resulting in an improved load balancing and a reduction in energy wastage.

Investment comparison between the WCSs and PV based DGs shows a significant difference based on the costs such as $699,798 for WCSs and $5,200,000 for PV based DGs. As shown in Fig. 7 which presents a cost breakdown, a significant difference has been analysed between the cash flow requirement for PV based DGs and WCS. Since the majority of the investment have been done in the beginning of PV based DGs installation, however the annual O&M costs of WCSs are relatively higher. If we compare O&M costs and investment cost of WCS, it has been observed that the former is three-fold as former, confirming the high cost of maintenance which has been already expected from WCS for overall lifespan of its services.

Several additional case studies were conducted to supplement the primary analysis, focusing on the profits and energy losses of WCSs. Cases explored scenarios without DGs and WCSs, optimal DG deployment, exclusive WCS integration, and a combined approach mirroring the main case with doubled EVs. Results in Table 6 highlight the profound impact of DGs on energy loss reduction. Case 4 demonstrates model scalability, indicating increased WCS demand or chargers per WCS with doubling EVs. The study showcases a 75% rise in fast chargers with a 100% EV increase, revealing the model's efficiency in optimizing charger numbers relative to WCS demand [27].

5. Conclusion

In this proposed planning framework that challenges the conventional approach of treating WCSs as petrol stations. Instead, we introduce new probability density functions (PDFs) that accurately capture the stochastic characteristics of residential electric vehicle (EV) and WCS loads, leveraging recently available EV charging data. To address the needs of investors, we formulate a stochastic mixed-integer nonlinear programming (MINLP) model focused on profit maximization. This model assists in determining optimal locations and sizes for WCSs and photovoltaic-based distributed generators (DGs). Additionally, we develop a novel scoring scheme that incorporates practical geographical factors to rank WCS candidate locations. By integrating this scoring scheme into our planning framework, we achieve revenue maximization for potential investors. To evaluate the effectiveness of our approach, we conduct a case study in the Delhi, India area, overlaying its geographical map onto a typical distribution network (DN). The results demonstrate the efficacy of our planning framework in strategically siting and sizing WCSs and photovoltaic-based DGs, while simultaneously maximizing profit, minimizing energy losses, and deferring the need for DN upgrades.

6. Appendices

Appendix A

The parameters used in the model are as follows. The number of years for the planning horizon is 20; the cost of electricity incurred by the electric utility, including transmission, distribution, and regulatory charges is 0.14 \$/kWh [28], represented by ρ_{elec}; the price of electricity sold to EVs at an FCS is 0.30 \$/kwh [29], represented by ρ_{EV}; the feed-in-tarriff rates paid by the government for power sold to the electric grid is 0.12 \$/kWh [30], represented by ρ_{FIT} ; the investment cost of a single solar-installation rated at 1.1MW is 1,300,000 [31], represented by C_{inv}^{DG} ; the annual O&M cost of a wind turbine is \$30,000, represented by C_{maint}^{DG} ; the investment cost of a single wireless charger rated at 11.5kW is \$21,206 [2], represented by C_{inv}^{WCS} ; the annual O&M cost of a fast charger is \$3,800, represented by C_{maint}^{WCS} .

Appendix B

The maximum number of generations is 400, Stall generation number is 80, crossover function 0.8, migration fraction is 0.2, population size 200, the elite count is ½ of the population, A random number is taken as mutation function from standard deviation of one and Gaussian Distribution with a mean of zero for the first generation and then a linearly decreasing standard deviation every generation till the final generation that will have a standard deviation of zero.

7. References

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Captions

Figure Captions:

Figure 1 The proposed daily power profile of FCSs

Figure 2 Flowchart of the proposed methodology

Figure 3 Delhi west with distribution network overlaid

Figure 4 Presentation of the distance between the highway exit and wireless charging station

Figure 5 Detailed traffic data presented on Google Map.

Figure 6 Revenue VS cost between wireless charging station and PV based DGs

Figure 7 Breakdown investment for WCSs and photovoltaic-based DGs

Table Caption:

Table 1 Probabilistic Load Model for Wireless Charging Stations

Table 2 Probability Load for Generic and Residential EV Demand

Table 3 WCS attractive score for candidate locations

Table 4 Decisions of siting and sizing of Solar PV based DGs

Table 5 Decisions of siting and sizing of Solar PV based DGs

Table 6 Detailed results of different Cases

Figures

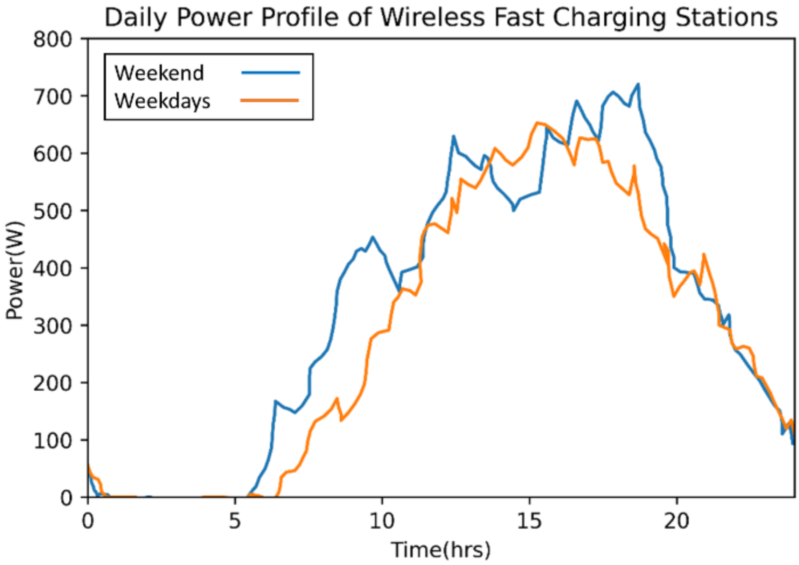


Figure 1 The proposed daily power profile of FCSs

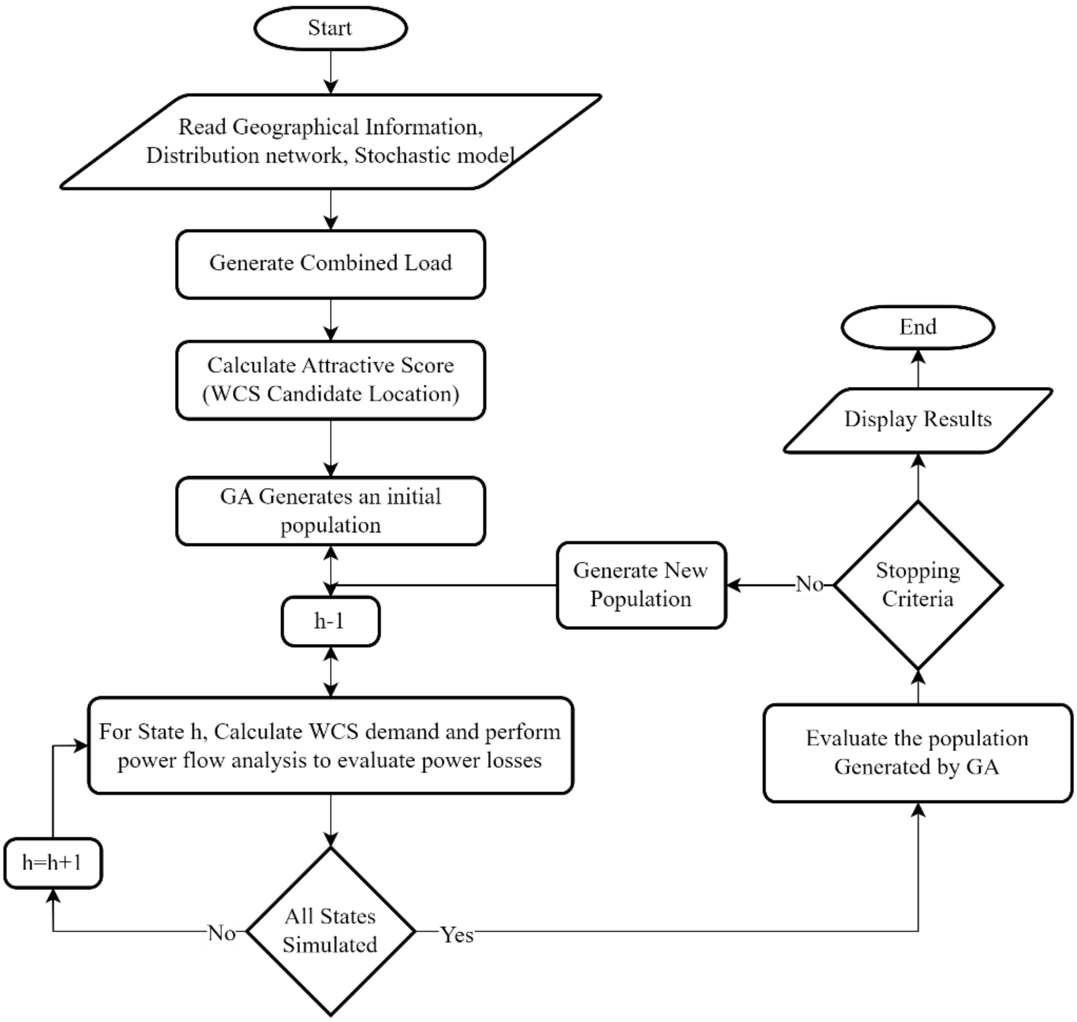


Figure 2 Flowchart of the proposed methodology.

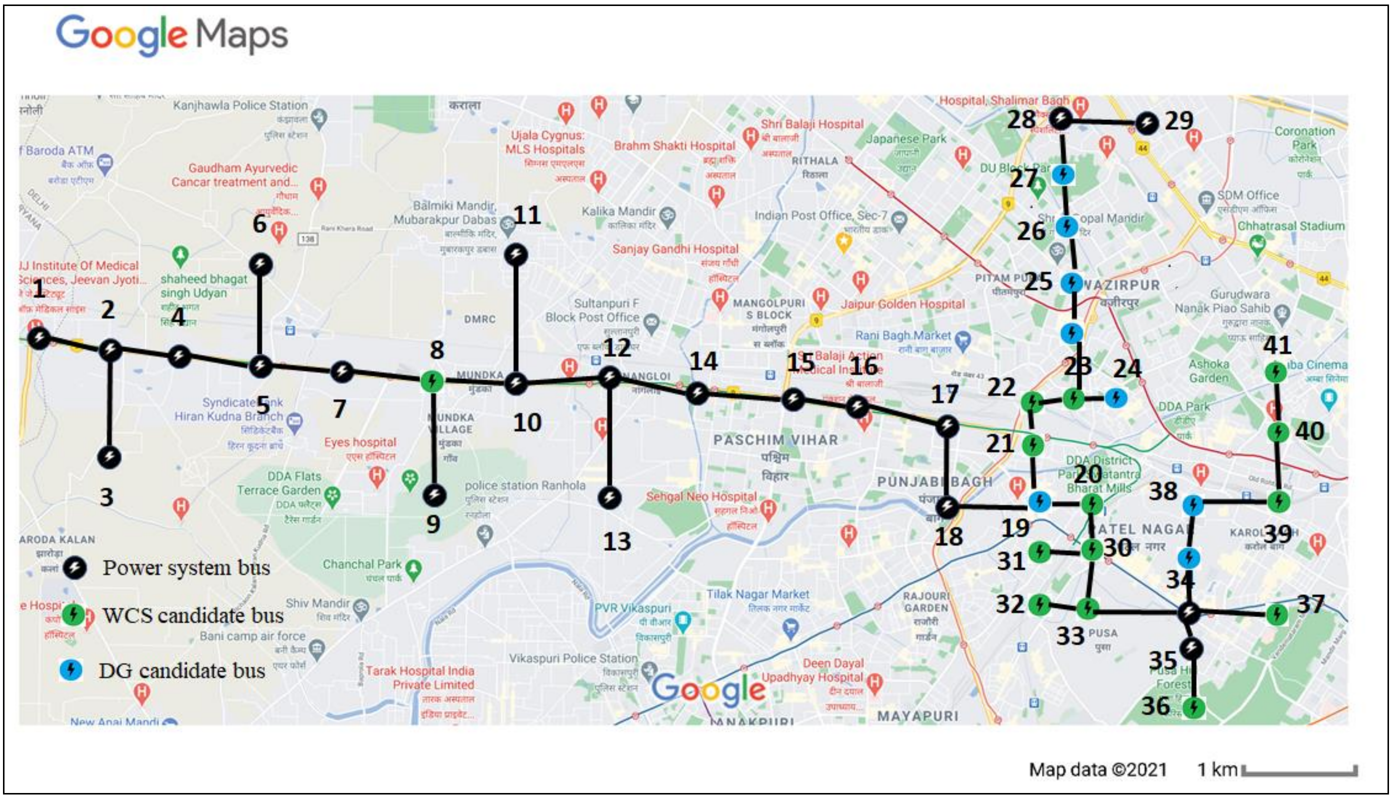


Figure 5 Delhi west with distribution network overlaid

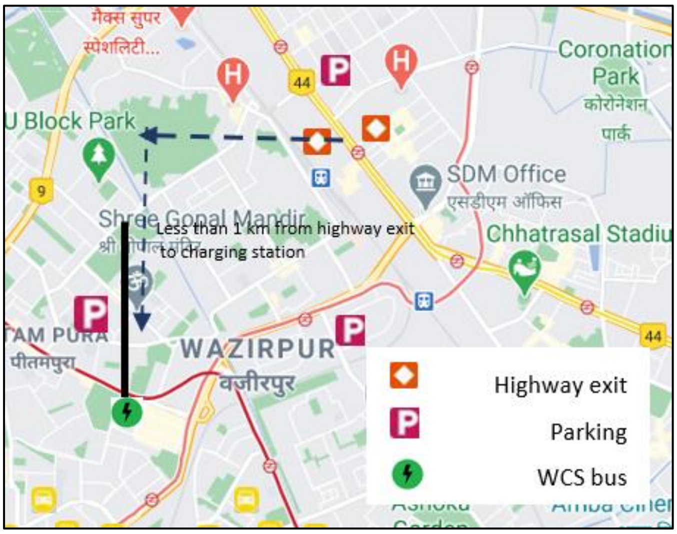
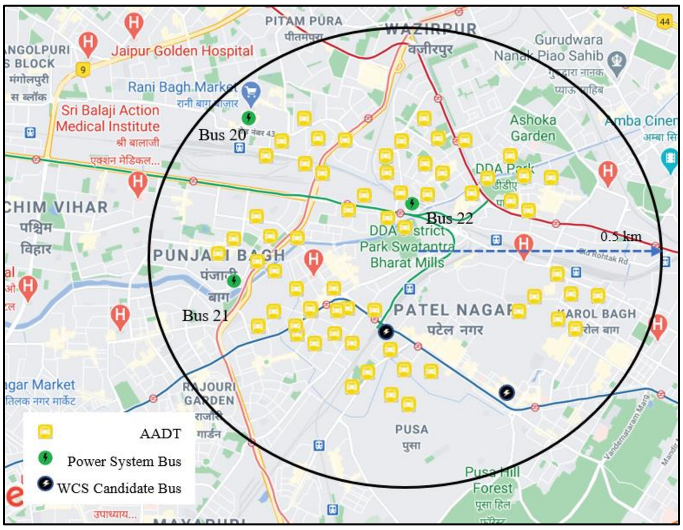


Figure 3 Presentation of the distance between the highway exit and wireless charging station



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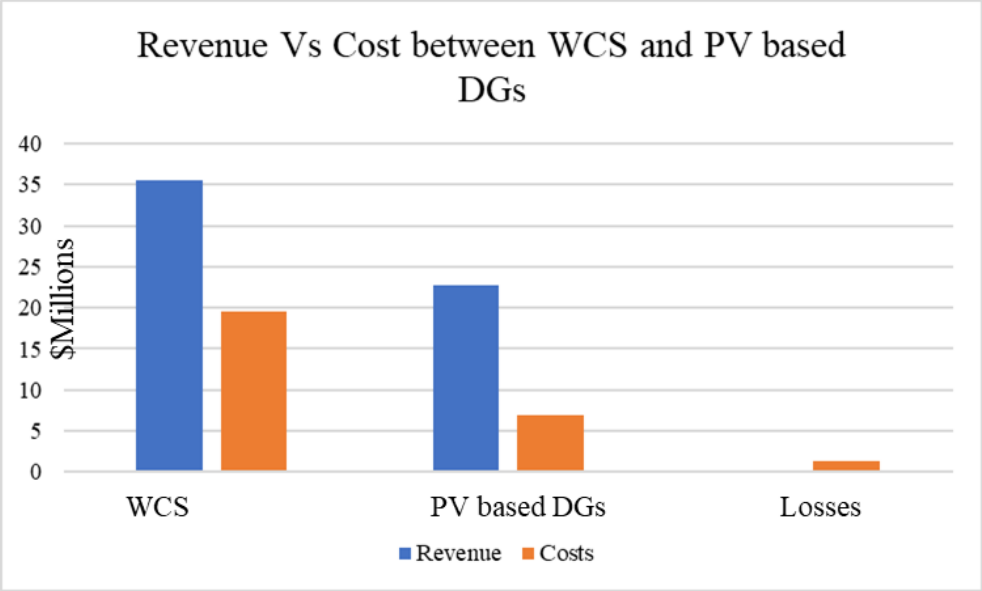

Figure 6 Revenue VS cost between wireless charging station and PV based DGs

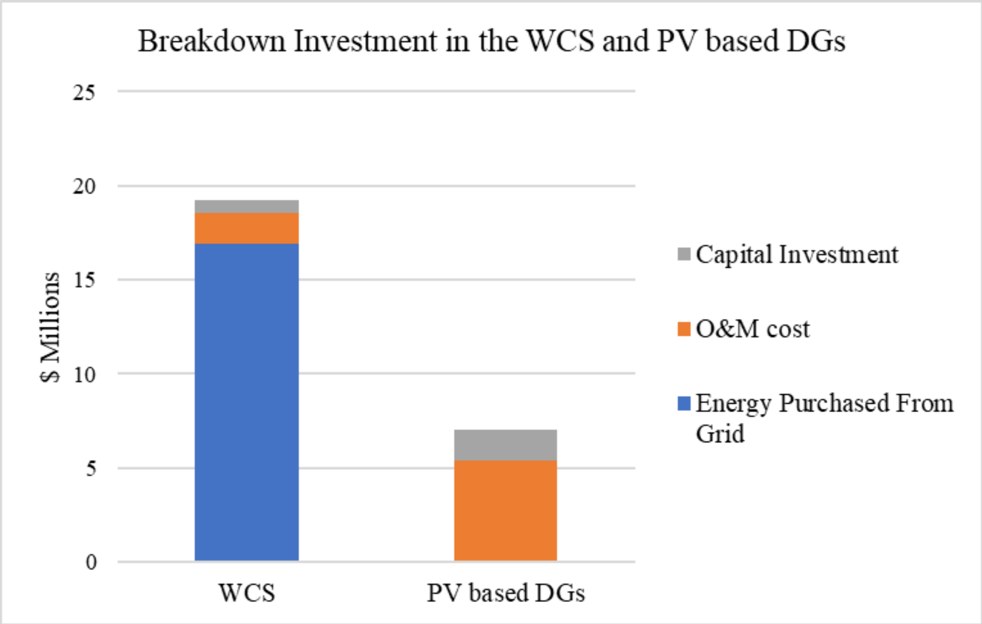

Figure 7 Breakdown investment for WCSs and photovoltaic-based DGs

Tables:

Table 1 Probabilistic Load Model for Wireless Charging Stations

No.	% of peak load	Probability of each state
1	0	0.1875
2	10	0.1354
3	State 30	0.125
4	57.40	0.2396
5	87.40	0.3125

Table 2 Probability Load for Generic and Residential EV Demand

State no.	% of peak load	Probability of each state
1	0.444	0.018
2	0.503	0.071
3	0.561	0.128
4	0.62	0.184
5	0.678	0.207
6	0.737	0.174
7	0.795	0.122
8	0.854	0.067
9	0.912	0.027
10	0.971	0.003

Table 3 WCS attractive score for candidate locations

Bus No	Score 1 (Highways)	Score 2 (High-Tech Companies)	Score 3 (Traffic)	Overall Attractive Score
36	0.29	0	21408	0.044
31	0.7	0	17669	0.049
30	2.32	0	8200	0.078
27	0.27	0.92	14886	0.070
26	0.13	0	15082	0.029
25	0.1		**16300**	0.030
24	0	0.74	17179	0.059
23	0.35	2.57	21214	0.150
22	1.69	1.78	18229	0.150
21	2.27	0.73	19300	0.125
20	1.67	1.41	13329	0.125
7	2.23	0	16625	0.090
	12.02	**8.15**	**199421**	**1.00**

Table 4 Decisions of siting and sizing of Solar PV based DGs

Bus Number	Number of Solar PV based DGs
39	2
32	1
19	1

Table 5 Decisions of siting and sizing of Solar PV based DGs

Bus Number	Number of Wireless Charger	Bus Number	Number of Wireless Charger
36	2	**24**	2
31	0	**23**	5
30	2	**22**	5
27	3	**21**	4
26	2	**20**	4
25	1	**7**	3

Table 6 Detailed results of different Cases.

Case	**Main Case**	**1**	**2**	**3**	**4**
WCS maintenance cost ($ thousand)	1704	0	0	1704	2995
WCS Investment Cost ($ thousand)	700	0	0	700	1230
WCS revenue ($ thousand)	35400	0	0	35400	65261
WCS energy cost ($ thousand)	16992	0	0	16992	31325
Number of Wireless Charger	33	0	0	33	58
No. of EVs	16499	0	0	16499	32998
Cost of Energy Losses ($ thousand)	1213	1253	881	1783	1611
WCS Net Profit ($ thousand)	16004	0	0	16004	29711

Authors Biography

Aqueel Ahmad:

Dr. Aqueel Ahmad, Research Associate at Center of Advanced Research in Electrified Transportation, AMU, is an eminent figure in the Electric Vehicle (EV) domain. He dedicated three years to pioneering Wireless Charging advancements under the DST IMPRINT project. In 2019, he earned a Ph.D. in Electrical Engineering from AMU. Dr. Ahmad's expertise spans intricate wireless charging design, Pantograph charging, and dynamic EV scenarios. Overseeing EV bus charging innovations, he leads in DC-DC Converters, Wireless and Pantograph Charging for Electric Buses. Notably, he orchestrated a solar-based wireless charging station and established an advanced Hardware in the Loop (HIL) Research Lab. His remarkable achievements reflect expertise in renewable energy, research development, and EV innovation.

Om Kumar:

Om Kumar is Head of Advanced Engineering and EV Aggregate at Switch Mobility. A Product Management Leader with an illustrious career defined by his mastery in Transmission and Driveline technology and Electric Vehicle (EV) innovation. For over two decades, he has been a catalyst for engineering excellence, propelling global success through adept product planning, development, and management in Auto, Agri and Off-highway Industry. His expertise spans strategic planning, technical consulting, leadership, and the design of critical driveline components for ICE and EVs. Specializing in Battery Electric Vehicles, his comprehensive knowledge extends to EV products, market dynamics, and technology trends. With 16+ years in People Management, he honed skills in building and leading efficient teams, aligning engineering strategies with business goals.