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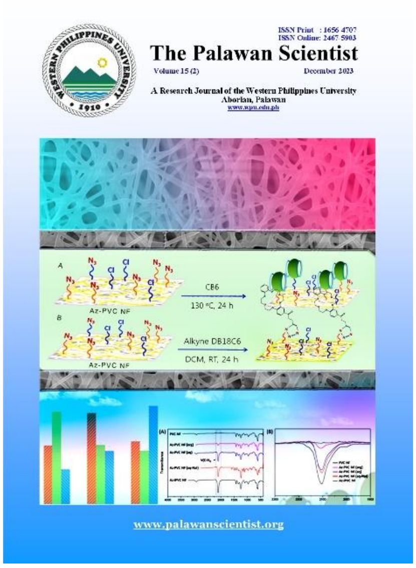

ISSN: 1656-4707
E-ISSN: 2467-5903
Homepage: www.palawanscientist.org

Comparative analysis of unidirectional and bidirectional electric vehicle charging stations (EVCS) optimal configuration in an IEEE 37-bus feeder system using Genetic Algorithm

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Received: 30 Apr. 2023 || Revised: 13 Oct. 2023 || Accepted: 27 Nov. 2023
https://doi.org/10.69721/TPS.J.2023.15.2.05

How to cite:
Balmeo Jr. AA, Aguirre Jr. RA, Castillo MDG, Maguindayao EJH and Manzano JPP. 2023. Comparative analysis of unidirectional and bidirectional electric vehicle charging stations (EVCS) optimal configuration in an IEEE 37-bus feeder system using Genetic Algorithm. The Palawan Scientist, 15(2): 41-54. https://doi.org/10.69721/TPS.J.2023.15.2.05

ABSTRACT

Various power system problems and challenges may arise in the future due to the large scale of deployment of electric vehicles (EVs). Hence, the proper placement of EV charging stations (EVCS) effectively mitigates the impact of high EV loads connected to the grid. The research intends to explore and analyze differences between the regulation effectiveness of unidirectional and bidirectional charging technologies by utilizing different comparison evaluation indices. Moreover, considering their penetration level, this study tackles the impact analysis of EV and EVCS integration through time. Specifically, this paper aims to identify the optimal EVCS sites in an IEEE 37-bus test feeder system to minimize power loss brought by EV integration. Through MATLAB R2022b simulation and OpenDSS power flow analysis, the EVCS are optimally located near the supply bus. The findings show a direct relationship between the EV penetration level and system power loss. Due to the EV technology growth, there is an observed voltage profile degradation of up to 1.7094 p.u. The paper also highlights that although EV bidirectional charging technology (BCT) might reduce the load on the grid in the next few years of low penetration compared to unidirectional charging technology (UCT), it will give no significant difference due to the rapid increase of load connected during its high EV penetration.

Keywords: electric vehicles, MATLAB, optimization, power loss reduction, voltage profile improvement

INTRODUCTION

Today's global challenges include reducing carbon footprints and mitigating energy risks. True enough, these will eventually become huge problems if not prevented. Thus, modernizing the transportation mode to electric vehicles (EV) is eyed to cut down the usage of internal combustion engines (ICEs)—the primary contributor to problems in energy security, air pollution, and global warming (Jacobson 2017). Sofana Reka et al. (2022) proved in their study that EVs have an enormous impact on the environmental aspects of ICEs, in particular with the emissions of CO_2 gas and maintenance costs. Meanwhile, EVs make a way towards sustainability by reducing greenhouse gas (GHG) emissions and fossil fuel consumption (Bayani et al. 2022).

However, other works disagree on the drive range aspect of EVs since they are unsuitable for long-distance travel and ownership cost is currently less cost-competitive (Sofana Reka et al. 2022; Bayani et al. 2022; Danielis et al. 2018). At present, three main charging methods have been conceptualized and developed: battery exchange, conductive charging, and wireless charging (Arif et al. 2021). EV users find the battery swap station (BSS) technique a convenient option since they will only pay a monthly rental fee for quick battery swapping for their convenience. However, this technique requires users to have high payments for the BSS owner to utilize high-end batteries with a long life span and can be recharged multiple times (Gschwendtner et al. 2021; Brenna et al. 2021). Meanwhile, the wireless power transfer (WPT) differs among the three, for it can recharge the battery conveniently and safely. Even so, due to the weak inductive power and a large amount of eddy current loss, it is not advisable in the long run (Sanguesa et al. 2021). The most widely accepted charging method is the conductive charging (CC), which has a high charging efficiency through direct connection. Moreover, a vehicle-to-grid (V2G) facility can be a way to incentivize compensation, lessen losses, and prevent power grid overload (Arif et al. 2021).

Aside from the charging methods, charging modes are continuously being improved to attain charging speeds comparable to gas refueling for ICEs. Currently and generally, there are three different EV charging levels, as defined by Narasipuram and Mopidevi (2021). In the level I charging, there is an AC to DC converter integrated inside the car and charges within the current range of 15–20 A at 120 V. Research found that the ratio of driving-mile distance per charging hour is 2:1. There have been many innovations over time. Level II charging station has charging characteristics of 80 A at 240 V, which can have a 9–52-mile travel distance after an hour of charging. Meanwhile, the level III charging provides DC power and is already attached to the station. It gives 300 A current flow at 480 V, which can have 170 miles of travel in just thirty minutes of charging. However, type III is only compatible with a few EV models, leaving the rest to choose between types I and II charging. For the purpose of this research, the paper utilizes the level II type of charging. The charging level of this type is the most preferable among all the abovementioned charging types since it enables sufficiently long-distance trips and charges an EV at a reasonable length of time (Lee et al. 2020).

Conversely, the switch to vehicle modernization through EVs also creates another issue requiring plenty of accessible EV charging stations (EVCS) to recharge their batteries, as ICE vehicles need gas stations for refueling purposes. Thus, EV owners expect to have available EVCS to charge their vehicles quickly and hassle-free, maximizing the growth of this particular technology. However, this innovation might challenge government policies on how to steer the market toward full electrification in transportation despite its growing disadvantages (Sofana Reka et al. 2022).

Even though it gives users convenience, large-scale EVCS deployment negatively impacts the power grid, such as transformer overloading and power quality degradation (Zhou et al. 2017). This impact is especially true given that the distribution systems are reaching their maximum capacities. This anticipated load growth, which is dynamic and highly intermittent, would be a challenging job for the electric power sector (Gupta et al. 2020). Implementing countermeasures, such as appropriate siting of EVCS and developing coordinated unidirectional and bidirectional charging types, plays a crucial role in effectively reducing the load impacts in the distribution network (Zheng et al. 2019).

Identifying suitable EVCS location in the distribution system is fundamental for maintaining the balance between load and generation, reducing power losses, and improving system stability (Rajendran and Kumar 2022). If not arranged properly, this will significantly affect the grid, including voltage fluctuations, flickering, sag, swell, imbalances, harmonics, and notches (Narasipuram and Mopidevi 2021). Researchers have been working on this issue, exploring the optimal location of the EVCS by delving into different perspectives and patterns necessary to real-life situations. Incorporating influencing parameters such as system buses and parking availability plays a significant role in solving the optimal EVCS problem (Zeb et al. 2020). Previous studies have analyzed different power systems such as in the work of Yenchachalit et al. (2018), which utilized the IEEE 30-bus test system to determine the trend in power loss with and without an EVCS installed. Moreover, Clairan et al. (2022), an actual distribution system in Quinto, Ecuador, to determine the effect of increasing electric taxi penetration; while Janamala (2022) investigated the optimal siting of EVCS considering EV load growth in IEEE 33-, 69-, and 85-bus systems.

Various emerging optimization methods are consistently used to compare power distribution and transmission system performances. For example, the hybrid technique consisting of moth-flame optimization (MFO) algorithm and particle swarm optimization (PSO) has been done in the paper of Shaikh et al. (2023) to examine the advantages of using different numbers of bundled conductors. On the other hand, the improved MFO has been applied to AC transmission line estimations considering different test case parameters (Shaikh et al. 2022). In calculating the transmission line parameters with load modeling uncertainty, Shaikh et al. (2021) used the whale optimization algorithm (WAO).

To determine the optimal EVCS location in the power network, a balanced mayfly algorithm was utilized to identify the best proposal for optimal allocation and sizing on a distribution system in India (Chen et al. 2021). Another literature used the Harris hawk optimization with differential evolution to solve the optimization problem in the EVCS allocation in a radial distribution network (Pal et al. 2021). The placement of EVCS in distribution systems, shunt capacitors, and distributed generators in the work of Gampa et al. (2020) used a grasshopper optimization algorithm to improve different electrical power system parameters. Lazari and Chassiakos (2023) used a genetic algorithm (GA) to minimize the overall cost of deploying the charging networks. Meanwhile, a modified GA in another study developed a mathematical program with equilibrium constraints (MPEC) in EVCS location and its discrete transport network designs (Qiao et al. 2023).

Determining possible locations not only by EVCS but also with distributed PV stations through GA was used based on chance-constrained programming (Zhang et al. 2021). Also, GA was utilized for efficient EVCS placements, taking Tunisia's urban area in North Africa as the research locale (Mehouachi et al. 2022). Nonetheless, the above-cited works of literature did not use any statistical test but instead focused on the objective function used in their respective research.

Most of these studies have only considered the unidirectional charging type, where EVs can only draw power from the grid. Bidirectional charging, as the improved type, which enables energy stored in EV batteries to discharge back to the grid, has received little attention. With the expectation that more EVs capable of bidirectional charging in the future, investigating its effect on the present distribution system is crucial in anticipating its benefits and adverse impacts (Isa et al. 2015).

Against this backdrop, this paper is primarily focused on the following aspects: (1) the investigation of the effects of new charging technologies on the power losses and voltage profiles with increasing penetration levels and its compatibility with the grid through EVCS modeling; (2) the optimal siting of EVCS to avoid negative impacts on the grid, particularly in the minimization of the additional system losses in the IEEE 37-bus test system; and (3) the comparison of the effectiveness of unidirectional and bidirectional charging types using four evaluation indices: voltage profile improvement index (VPII); real power loss reduction index (PLRI); reactive power loss reduction index (QLRI); and apparent power loss reduction index (SLRI). Cover cost-effectiveness in locating the EVCS in the test system is not covered in this paper.

The main contributions of this paper are as follows: (1) the increasing penetration levels will give theoretical trend for the simulation of EVCS optimal configuration between the two charging technologies to differentiate them in terms of power losses and total voltage deviation; (2) for the energy department of the country to pinpoint through genetic algorithm where in the bus system should the EVCS be located to obtain the minimized power losses in the grid; (3) for the policymakers to gain insight on the difference between the two charging technologies in terms of the charging behavior, and to decide on the EV charging policies that can help in grid load management.

The rest of the research paper is structured as follows: Section 2, the methods, explains the profile of the feeder, the selection method, EV specifications and modeling, the optimal model and algorithm implementation, the model construction, and indices for evaluation; Section 3, the results, includes reflecting the effect of the total integration of the new technology in increasing penetration levels, the EVCS optimal distribution configuration through genetic algorithm optimization, and charging technology comparison; and Section 4, the discussion, tackles the implications of the total integration of the advancing technology, the causes of the EVCS optimal arrangement, and the prospects, conclusions, and implications of charging implementation of unidirectional and bidirectional charging technologies.

METHODS

Institute of Electrical and Electronics Engineers (IEEE) 37-bus Test Feeder Profile and Optimal Location Selection

This research considered the medium voltage IEEE 37-bus test system. It has highly unbalanced load characteristics, differentiating it from other feeder systems. Shown in Figure 1 is the single-line diagram of the renumbered IEEE 37-bus feeder system adopted from the work of Miras et al. (2019).

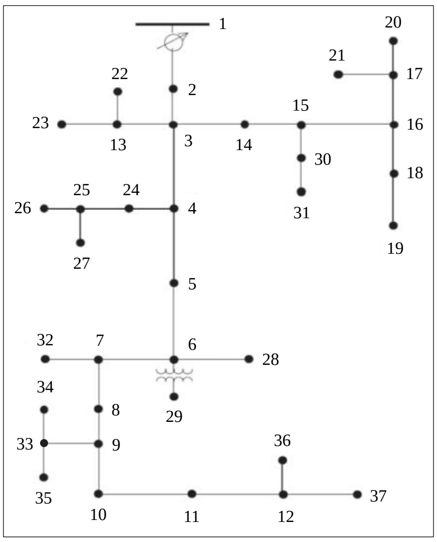


Figure 1. Single line diagram of the renumbered Institute of Electrical and Electronics Engineers (IEEE) 37-bus test system (Miras et al. 2019).

Different approaches can be used to select the optimal locations in a test bus system. In studying bus feeders, the researchers can include a constraint in geographical location employing divisions into different clusters or zones. Considering the whole network is the best option for this paper to achieve the optimal EVCS configuration. Thus, it will exclude the geographical location aspect as a constraint. Moreover, this assessment focuses on taking the feeder as a pure distribution system, minimizing power loss and improving voltage profiles.

Electric Vehicles (EV) Specifications and Modeling

Electric vehicles (EV) charging and discharging rates. The charging and discharging rates, integral to this study, were adopted from Khan et al. (2021) and are expressed in Equations 1 and 3. These mathematical models can be further elaborated expressed as Equations 2 and 4 to determine both the charging and discharging rates and the state-of-charge (SOC) trend per 15-minute interval, respectively.

$$P_{charging}(t) = [V_i(t) - 1] * Chr_{rate} \tag{1}$$

$$SOC_{new} = SOC_{old} + \frac{[V_i(t)-1]*Chr_{rate}}{(TEV)(B_{cap})} * \Delta t \tag{2}$$

$$P_{discharging}(t) = [1 - V_i(t)] * \ Dischr_{rate} \tag{3}$$

$$SOC_{new} = SOC_{old} - \frac{[1-V_i(t)]*Dischr_{rate}}{(TEV)(B_{cap})} * \Delta t \tag{4}$$

where:

$P_{charging}$	is the charging wattage (kW)
$P_{discharging}$	is the discharging wattage (kW)
V_i	is the specific voltage at bus i (kV)
Chr_{rate}	is the charging rate (A)
$Dischr_{rate}$	is the discharging rate (A)
B_{cap}	is the EV battery capacity (kWh)
SOC_{new}	is the updated state-of-charge
SOC_{old}	is the previous state-of-charge
Δt	is the change in time (hr)
TEV	is the total number of EVs
$E_{useable}$	is the useable battery capacity (kWh)
$\Delta SOC_{charging}$	is the SOC difference for charging
$\Delta SOC_{disharging}$	is the SOC difference for discharging

State-of-charge (SOC) based EV charging and discharging load modeling. The equation used to identify SOC-based coordinated instantaneous charging and discharging powers, which was lifted from Akil et al. (2022), is employed in this study. This relationship was formulated from the real-time charging profiles of EVs, as shown in Equation 5.

As per the piecewise model dictates, SOC-based instantaneous charging and discharging power reach their maximum when SOC is less than 73%. When SOC is at least 73% but less than 93%, there is a gradual decline in the maximum charging and discharging power. Finally, once SOC reaches 93% and above, the power remains constant.

$$P_i^n(SOC) = \begin{cases} P_i^c = P_{max} & if\ SOC < 73\% \\ P_i^c = P_{max} \cdot 3.17 \cdot -\ln(SOC) & if\ 73\% \leq SOC < 93\% \\ P_i^c = 0 & if\ SOC \geq 93\% \end{cases} \tag{5}$$

where:

P_i^n *(SOC)*	is the SOC-based instantaneous charging/discharging power (kW)
P_i^c	is the maximum instantaneous charging/discharging power (kW)
P_{max}	is the maximum charging power (kW)
SOC	is the state of charge

Electric vehicle (EV) load growth and penetration model. The penetration level is used in power engineering to anticipate the future possible impacts and real-case scenarios for power distribution networks. For instance, the Grid Integration Tech Team (GITT) and the Integrated Systems Analysis Tech Team (ISATT) of the United States have developed a real-life diagram that proposes low, medium, and high penetration scenarios from 2010 to 2050 (GITT and ISATT 2019) as shown in Figure 2.

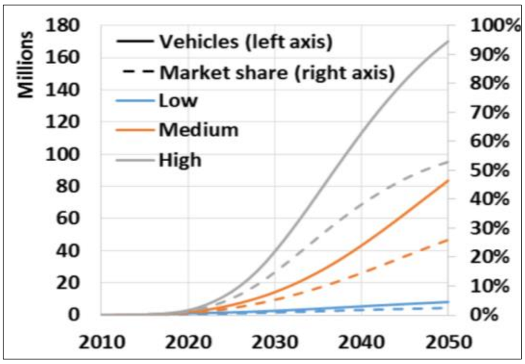


Figure 2. Electric vehicles market penetration scenarios (GITT and ISATT 2019).

In examining the differences in the optimal placement between two possible types of EVCS installations, the unidirectional charging and bidirectional charging stations serve as the two main test cases in this study. These are examined through subtest cases according to EV penetration forecast and its corresponding optimal sites: 23% in 2030, 62% in 2040, and 94% in 2050 (GITT and ISATT 2019). The three subtest cases have corresponding optimal site parameters of 11, 30, and 25, respectively (Zambrano-Perilla 2016). The base, observed in 2015, serves as a reference point when no EV penetration rate recorded (GITT and ISATT 2019).

Genetic Algorithm Implementation

Genetic algorithm (GA) is an iterative method inspired by the Darwinian theory of the survival of the fittest (Kathoch et al. 2021). It is a common optimization method used in investigating the behavior of the power system. It starts with the random generation of *n* chromosomes in a population. After the initialization, the fitness function is computed for each chromosome in the population, followed by ranking for the whole generation. Next, offspring are produced by selecting parents from the existing population using the single-point crossover. The resulting offspring will undergo mutation to produce new offspring. This cycle continues until the desired number of generations is achieved (Liu 2013).

Using MATLAB R2022b, the implementation of the GA in the study involving EVCS integration to the distribution network is shown in Figure 3. Various penetration levels at different periods were introduced, with 100 population and 100 generations as GA parameters. Single-point crossover and a 0.05 mutation rate were utilized to optimize the location of EVCS.

The integration of EVs and EVCS into the distribution network results in an increase in average real and reactive power losses (Khalkali et al. 2015). The parameters were analyzed using OpenDSS as a power flow tool.

In the first subcase, UCT considers only the charging process, while the second subcase, BCT, considers both charging and discharging setup. Moreover, half of the BCT participated in two-way charging, and the other half only utilized one-way charging (Mehrabi et al. 2020). Simulation time varies based on the number of EVCS to be located and the consideration of charging/discharging setups. Overall, more than a day of simulation runtime was spent for six subcases. The simulations were conducted on a computer with an i5-8500 CPU Processor @ 3.00 GHz, 8.00 GB installed RAM and a 64-bit operating system.

Objective Function

This paper primarily focused on the grid performance with the integration of EVCS into the network, in particular, to minimize the additional losses in the distribution network with the increase in EV penetration. Mathematically, the objective function is expressed in Equation 6:

$$F = \min \sum (S_{loss,EVCS} - S_{loss,base}) \quad (6)$$

where:

F	is the minimum additional losses (kVA)
$S_{loss,\,EVCS}$	is the total system apparent losses with EV integration (kVA)
$S_{loss,\,base}$	is the total system apparent losses without EV integration (kVA)

For the different cases, the voltage profile, system losses, and optimal sites were compared before and after the addition of EVCS. Moreover, the VPII, PLRI, QLRI, and SLRI were utilized to differentiate unidirectional and bidirectional charging.

Constraints

Maximum EVCS of each bus. It is highly recommended to have at least one charging station at each optimally selected bus to ensure the proper operation of the power distribution network. In this

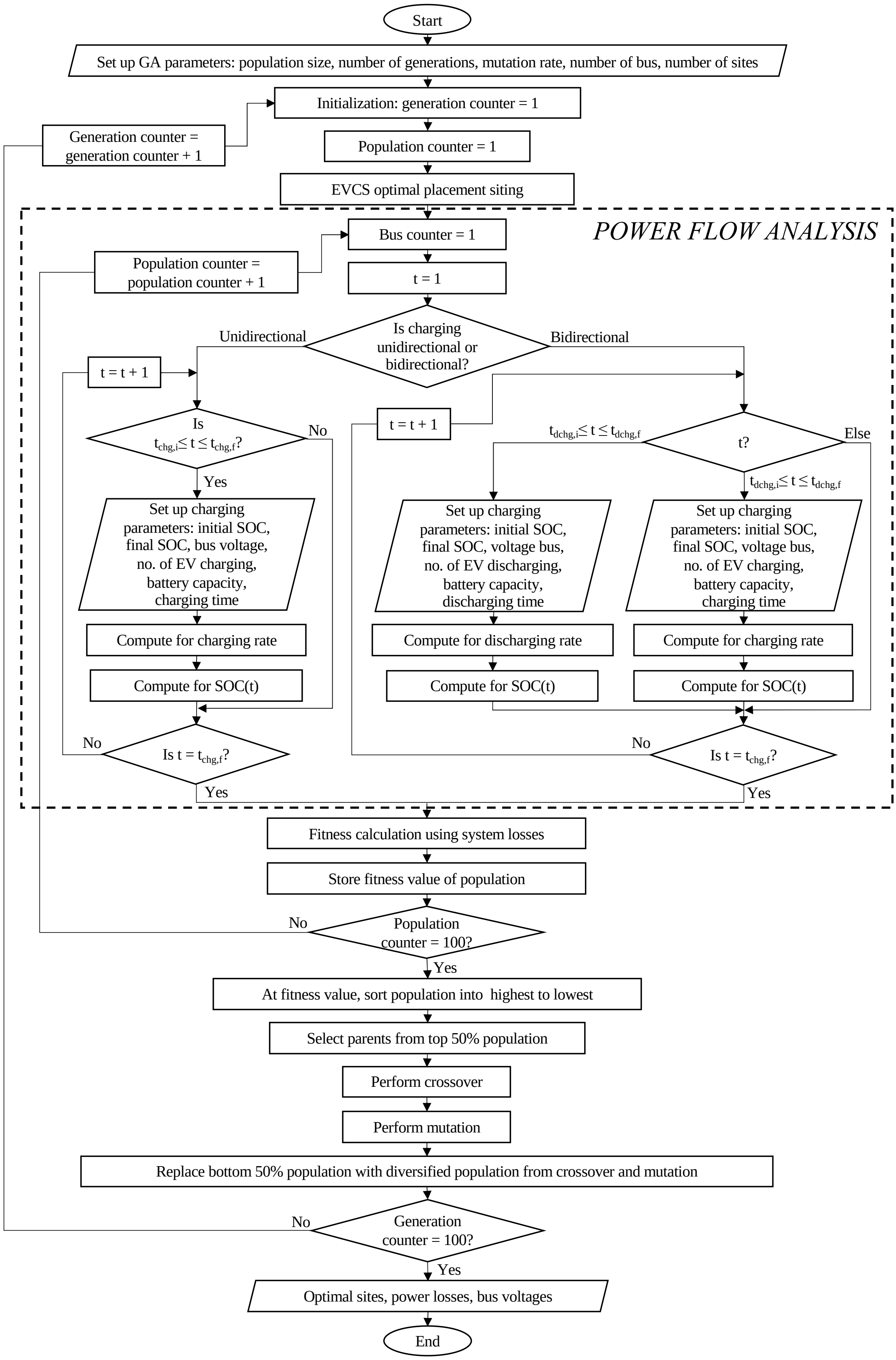


Figure 3. The process of integrating electric vehicle charging station (EVCS) unidirectional and bidirectional charging technologies into the distribution network.

scenario, the algorithm will accommodate a possible transportation route area without sacrificing the objective function (Fredriksson et al. 2019). However, for the purpose of this paper, particular buses suitable for station placements were limited to one to ensure that the EVCS infrastructure planning does not negatively affect the power grid.

Maximum capacity of EVCS. Each charging station within the specific area has limited charging ports. This limitation is attrivuted either to the connection's point inaability to serve a large load or lack of budget. According to US DOE EERE (2023), the public EVCS at the Sacramento Parking Garage, located at #939, 10th Street, Sacramento, California, has a total electric vehicle supply equipment of 27 charging ports by which the same number of EVs can charge at the same time. Taking a real-life scenario, the assumed maximum charging capacity of a standard charging station is 27 EVs. However, due to the vast penetration of EVs in the last subcase, 50 charging ports per EVCS was assumed instead, which were used as the capacity in other studies (Kunj and Pal 2020). Equation 7 shows the allowable number of charging ports in each EVCS located at bus *i*:

$$CS(i) \leq CS_{max};\ \sum_{i=1}^{N_{CS}} = N_{ch,max} \tag{7}$$

where:

$CS\ (i)$ is the charging station capacity at bus i
CS_{max} is the maximum charging station capacity
N_{CS} is the number of charging ports
$N_{ch,\,max}$ is the maximum number of charging ports

Permissible state of charging and discharging. EV usage, mainly when it is to be charged, depends on the owner's decision. This study used the SOC range of 10% to 90% for charging, which is typical for an EV battery (Khalkali et al. 2015). Meanwhile, a range of 20% to 80% is used for discharging purposes due to the anticipation that EV owners will aim to maximize the sale of unused EV battery charge during peak electricity prices (Su et al. 2019). Thus, the limitation of the charging or discharging process as expressed in Equation 8 should be:

$$\begin{cases} SOC_n \leq SOC_{n,min}\ ; for\ charging\ only \\ SOC_{n,min} \leq SOC_n \leq SOC_{n,max};\ for\ charging/discharging \\ SOC_n \geq SOC_{n,max}; for\ discharging\ only \end{cases} \tag{8}$$

where:

SOC_n	is the chosen state-of-charge (%)
$SOC_{n,\,max}$	is the maximum state-of-charge (%)
$SOC_{n,\,min}$	is the minimum state-of-charge (%)

Bus voltage tolerance. Bus voltage can vary provided that it does not exceed the range of allowable voltage values and does not have an adverse effect on the distribution network operation. To maintain the voltage range, it must be restricted between 0.9 and 1.1 per unit, as shown in Equation 9:

$$0.9\ p.u. \leq V_i \leq 1.1\ p.u. \tag{9}$$

where:

V_i	is the voltage at bus i (p.u.)

Evaluation Indices

Voltage profile improvement index (VPII). One of the significant parameters that must be observed in the distribution network is its voltage deviation. The indicator assesses the nodal voltages concerning reference nodes and must be within acceptable limits. In evaluating the given cases, the voltage profile and system losses of different penetration scenarios were compared to the base case. Then, the optimal sites were compared after adding EVCS for charging and charging-discharging scenarios. The mathematical equations are shown in Equations 10 to 11:

$$TVD_x = \frac{1}{n}\sum_{i=1}^{n}(V_i - V_{ref}^i) \tag{10}$$

$$VPII = \frac{TVD_A + TVD_B + TVD_C}{3} \tag{11}$$

where:

TVD_x	is the total voltage deviation of the system per unit at phase x
V_i	is the bus voltage at the bus i per unit
V^i_{ref}	is the reference bus voltage
n	is the total number of buses
$VPII$	is the voltage profile improvement index

System power loss reduction indices. The system losses and their respective reduction indices were used to compare the two charging technologies and their corresponding optimal sites. The mathematical equations of the indices are given in Equations 12 to 14:

$$PLRI = \frac{P_{withUCT} - P_{withBCT}}{P_{with\ UCT}} x\ 100 \tag{12}$$

where:

$PLRI$	is the real power loss reduction index due to EV integration (%)
$P_{withUCT}$	is the real power losses with EVCS UCT (kW)
$P_{withBCT}$	is the real power losses with EVCS BCT (kW)

The second evaluation indicator in Equation 12 assesses whether the EVCS charging technology enhances or minimizes power losses. In particular, it also indicates the loss reduction trend due to the bidirectional participation of the EVCS in the grid relative to the unidirectional charging process.

$$QLRI = \frac{Q_{withUCT} - Q_{withBCT}}{Q_{withUCT}} x\ 100 \tag{13}$$

where:

$QLRI$	is the reactive power loss reduction index due to EV integration (%)
$Q_{withUCT}$	is the reactive power losses with EVCS UCT (kVAR)
$Q_{withBCT}$	is the reactive power losses with EVCS BCT (kVAR)

One of the indicators of a stable grid is when the reactive power losses do not exceed a threshold value (Chen et al. 2021). The QLRI in Equation 13 aims to determine if reactive power loss is within the definite threshold value to maintain the power grid stability. Thus, the QLRI has been included in the study.

Shown in Equation 14 is the SLRI, which is one of the important parameters to assess whether the distribution network has improved. When it goes beyond the threshold value, the distribution network is unstable.

$$SLRI = \frac{S_{withUCT} - S_{withBCT}}{S_{withUCT}} x\ 100 \tag{14}$$

where:

$SLRI$	is the apparent power loss reduction index due to EV integration (%)
$S_{withUCT}$	is the apparent power losses with EVCS UCT (kVA)
$S_{withBCT}$	is the apparent power losses with EVCS BCT (kVA)

RESULTS

Total Integration of EVs and EVCS Considering Increasing Penetration Levels

The graph in Figure 4 illustrates the power losses at each penetration stage for their respective technologies. The anticipated apparent power loss of EV integration in the year 2050 is extremely high at 465.2930 kVA for both charging technologies, as its penetration level is expected to reach 94%. Meanwhile, the year 2040 in the graph has a relatively lower penetration than the year 2050 at 62%, which gives apparent power losses of 364.5683 kVA for both unidirectional and bidirectional modes. In the year 2030 EV integration, forecasted losses are at 96.3131 kVA for unidirectional charging and 92.0304 kVA for bidirectional charging, given a 23% penetration rate. All these values are relatively higher than the base power loss of 82.5268 kVA in the year 2015 when there was no EV integration.

In Figures 5 and 6, the plots of UCT and BCT per-unit bus voltage for phase A of the system depict a gradual decrease in bus voltages with increasing EV penetration levels, regardless of the charging technology. On the other hand, in terms of VPII, as shown in Table 1, there is an increase in the indices concerning the considered years. Moreover, in the years 2040 and 2050, similar results were observed for both unidirectional and bidirectional charging. Meanwhile, the UCT in the year 2030 has a higher VPII than the BCT.

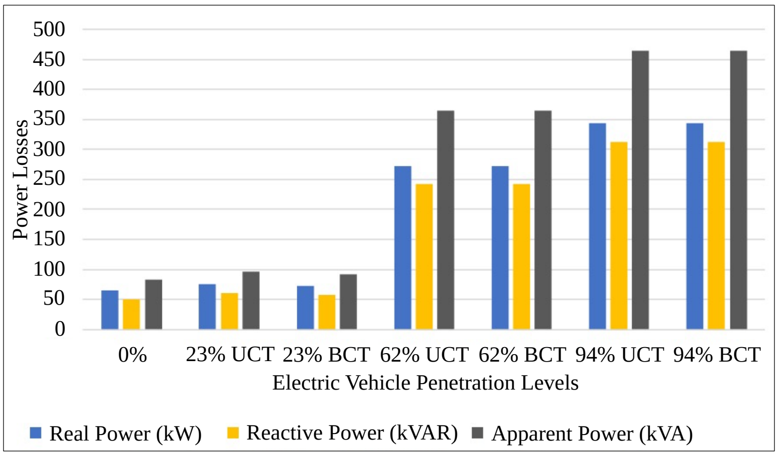


Figure 4. The graph of power losses vs. EV penetration levels. UCT- unidirectional charging technology; BCT- bidirectional charging technology.

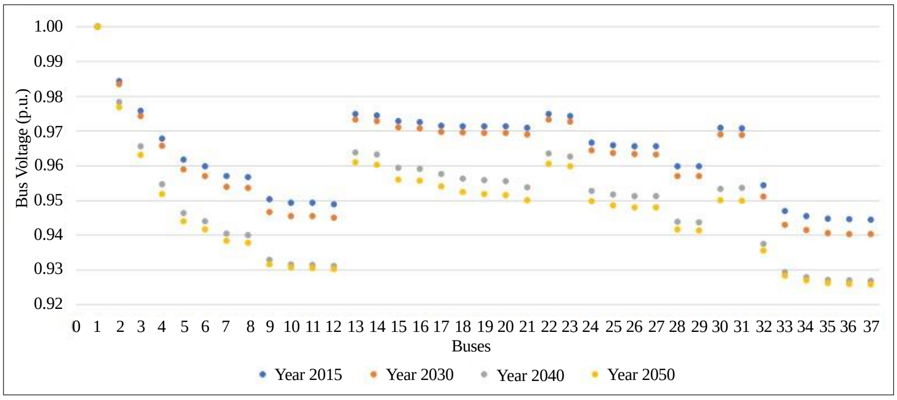


Figure 5. The per-unit bus voltage profile in different test case scenarios in unidirectional charging technology setup for phase A.

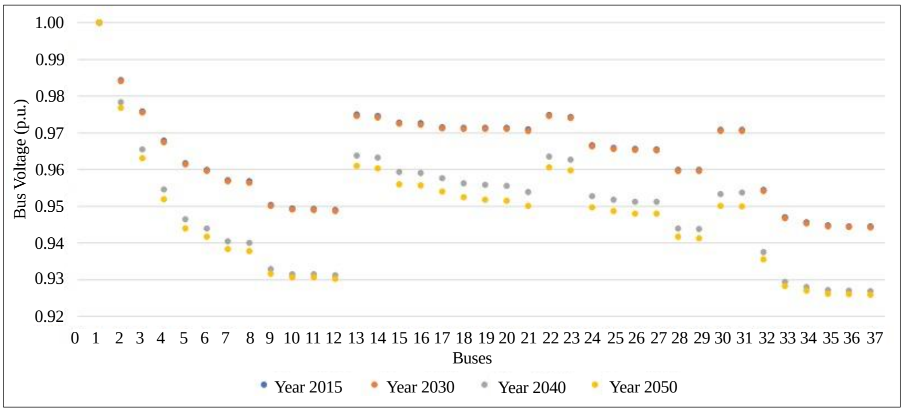


Figure 6. The per-unit bus voltage profile in different test case scenarios in bidirectional charging technology setup for phase A.

Table 1. The voltage profile improvement index (VPII) between undirectional charging technology (UCT) and bidirectional charging technology (BCT) for different penetration levels.

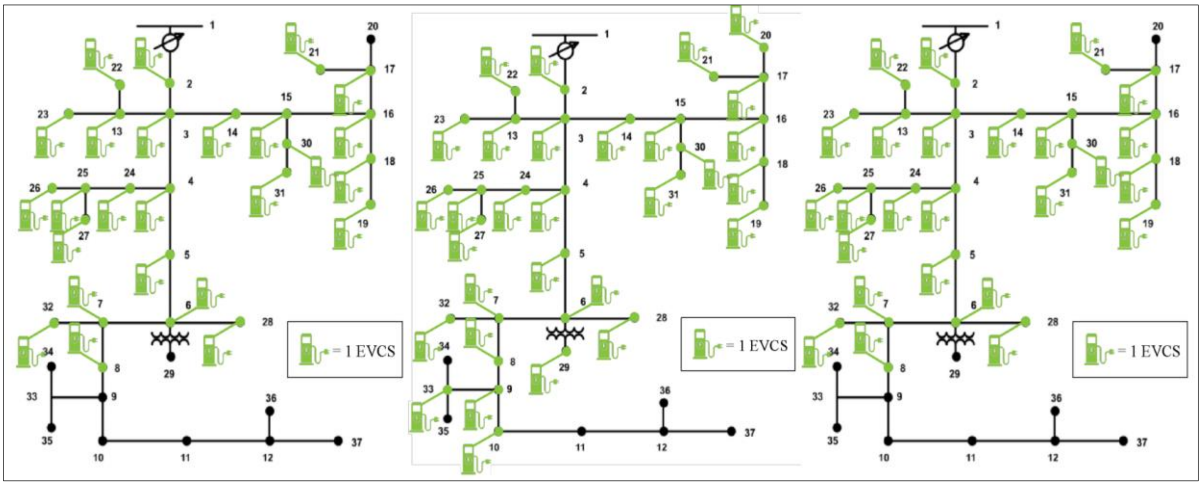
Year	Subcase (penetration level)	VPII (p.u.)	
		UCT	BCT
2015	0%	1.1139	
2030	23%	1.2020	1.1249
2040	62%	1.6260	1.6259
2050	94%	1.7094	1.7094

Electric Vehicle Charging Station (EVCS) Optimal siting

Optimal placement assesses the possible site combinations to attain the objective function. To facilitate a comparison of optimal locations for each subcase based on the penetration level, Table 2 presents a summary of the optimization results. The same buses were identified in the subcases of both power charging technology for every penetration level. Lastly, Figure 7 illustrates that the resulting optimal sites are concentrated in specific locations.

Table 2. Optimal electric vehicle charging station sites at different penetration levels.

Main Cases	Subcase (penetration level)	Year	Optimal Sites
Unidirectional	23%	2030	2, 3, 4, 5, 13, 14, 15, 22, 23, 30
Bidirectional			2, 3, 4, 5, 13, 14, 15, 22, 23, 30
Unidirectional	62%	2040	2, 3, 4, 5, 6, 7, 8, 9, 10, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33
Bidirectional			2, 3, 4, 5, 6, 7, 8, 9, 10, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33
Unidirectional	94%	2050	2, 3, 4, 5, 6, 7, 8, 13, 14, 15, 16, 17, 18, 19, 21, 22, 23, 24, 25, 26, 27, 28, 30, 31, 32
Bidirectional			2, 3, 4, 5, 6, 7, 8, 13, 14, 15, 16, 17, 18, 19, 21, 22, 23, 24, 25, 26, 27, 28, 30, 31, 32



(a) **(b)** **(c)**

Figure 7. The electric vehicle charging stations (EVCS) installation at (a) 23%, (b) 62%, and (c) 94% EV penetration rates.

Comparison of Index Values Between Charging Technologies

The VPII of all buses connected to phase A in the test system was calculated with the year 2015 as the reference. Figure 8 reveals that there is almost no difference in VPII for the bidirectional case of the year 2030 compared to the base case. On the other hand, a slight distortion is apparent in the graph of unidirectional charging.

Using the results of unidirectional charging as reference values for the bidirectional case, system power losses were analyzed to compare the characteristics of the charging technologies. Table 3 shows that only the year 2030 has non-zero index values.

Table 3. Real, reactive, and apparent power loss reduction indices. PLRI - real power loss reduction index; QLRI- reactive power loss reduction index; SLRI-apparent power loss reduction index.

Subcase (penetration level)	Year	Evaluation Indicators of Comparison		
		PLRI	QLRI	SLRI
23%	2030	4.142878856	4.916659909	4.44664329
62%	2040	0	0	0
94%	2050	0	0	0

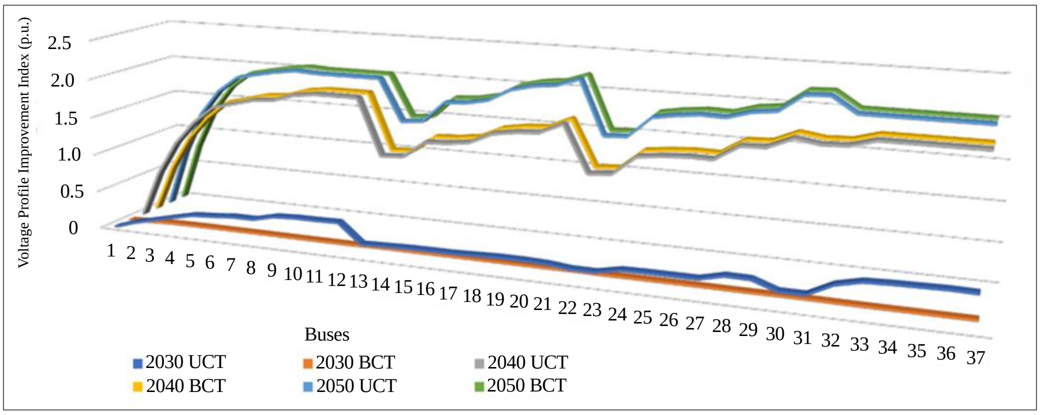


Figure 8. Phase A voltage profile improvement index (VPII) of the entire network. UCT- undirectional charging technology; BCT- bidirectional charging technology

DISCUSSION

Total Integration of EVs and EVCS Considering Increasing Penetration Levels

As observed in the graph presented in Figure 4, there exists a direct relationship between the penetration of EVs and the apparent power loss. Higher integration of EVs results in a higher apparent power loss, regardless of the charging technology employed in the system. The anticipated transition from ICE vehicles to EVs is expected to contribute to higher apparent losses in the power grid. Variations in the penetration level have caused changes in the power loss, the number of optimal sites, and the capacity of the EVCS. It can be concluded that there is a significant increase in real, reactive, and apparent power losses. Thus, the higher anticipation of EV loads due to the increasing penetration level through time is expected to be caused by the advancements in the transportation sector. Without proper intervention, additional EV loads could alter the normal grid operations.

On the other hand, the varying penetration levels in this study assessed the impacts of the EV integration. The dramatic increase in penetration rate has a negative effect on the voltage profile of the power grid. As the injected EV load increases, the bus voltages deviate from the ideal value. With the expected technological advancement in EVs, there is an anticipated voltage profile deterioration by as much as 1.7094 p.u. Based on the trend analysis of Table 1 values, the voltage profile is deteriorating in the subsequent years.

Electric Vehicle Charging Station (EVCS) optimal siting

Overall, there is a commonality among the respective penetration levels where the resulting optimal sites in the test system cluster in the nodes near the supply bus. Indeed, these results are consistent with recent works. One of these studies has presented that connecting an EVCS at any bus in the distribution network increases the active power loss due to the resistance of the branches from the slack bus to the considered node (Bilal et al. 2021). Thus, to reduce the resulting power loss, the EVCS should be located closer to the upstream network near the supply (Hadian et al. 2020).

The observation shows similar results when the number of optimal sites increases in the distribution network. Another factor contributing to this trend is the bidirectional participation of EV owners. According to Mehrabi et al. (2020), the willingness of the drivers to participate in the bidirectional charging is 50%. This means the ratio of charging and discharging in the bidirectional technology is 2:1, indicating that for every two charging vehicles, only one can discharge. With this, the research suggests that all EVs still need to be charged before this half undergoes discharging energy into the power system. Hence, UCT and BCT had the same optimal sites since they usually acted as a load.

Comparison of Index Values Between Charging Technologies

After identifying the optimal sites where minimum power losses are observed, there is a noticeable difference between the two power charging directions. During the years with low penetration, there is less power loss in UCT than in BCT. However, during higher EV penetration beyond the year 2040, the distribution network experiences more apparent power losses, considering that BCT has become the norm in society. Correspondingly, power losses increase as the EV penetration rate increases from the base case year 2015 when there is no EV integration.

The BCT in the year 2030 exhibits a more improved power loss relative to the UCT of the same year since it deviates mainly from the base case. On the other hand, the EV load integrated into the system contributes to the fluctuations in the UCT in 2030, as observed in Figure 8. Meanwhile, power losses in both charging technologies are the same for the years 2040 and 2050, where EV penetration is higher than in the former cases. The discharging scenario in BCT positively affects the distribution network by providing additional power to the system. Nevertheless, due to the high EV loads, both the UCT and BCT negatively affect the grid, which resulted in high VPII values.

Table 3 presents the system loss indices for the BCT subcases relative to their corresponding UCT counterparts. For 2030, the power loss index values of 4.14%, 4.92%, and 4.45% are determined for PLRI, QLRI, and SLRI, respectively. Since there is a positive value in PLRI at 4.14%, there is a minimization and loss reduction trend this year brought by utilizing BCT over the UCT case. Moreover, the 4.92% QLRI implies a more stable power grid from BCT application in the said year. Lastly, the 4.45% SLRI shows an overall improvement in the system due to the reduction in apparent power losses from using bidirectional charging.

Meanwhile, the three evaluation indices have zero values at higher penetration rates of 62% and 94%. These results signify that the system losses from using BCT and UCT are the same, and there is no advantage in using the former over the latter.

The results suggest that bidirectional charging can provide opportunities to improve the distribution system if more EV owners utilize it. A 50% EV bidirectional participation is insufficient to make the distribution system better since the result shows no difference compared to unidirectional charging at high EV penetration. Hence, further studies can examine the possibility of incentivizing participation in bidirectional charging through tariffs and tax credits. The distribution system operator can do proper grid interventions, such as replacing the lines with lower resistance and utilizing power loss compensator equipment in anticipation of higher EV loads in the future. Moreover, another path of future research on differentiating the two charging technologies is studying the cost-effectiveness, battery efficiency and deterioration, and grid communication, particularly with traffic demand management of the mixed flow of two charging technologies.

FUNDING

The authors declare that this research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

ETHICAL CONSIDERATIONS

This study is guided by ethical and legal principles, responsibly ensuring that this is free of research misconduct and presents the results accurately. Moreover, the authors of the references were duly acknowledged and cited with proper citations.

DECLARATION OF COMPETING INTEREST

The authors declare that there are no competing interests among any authors.

ACKNOWLEDGMENTS

The authors acknowledge the support of the University of the Philippines Los Baños and the valuable comments of the external reviewers who evaluated this paper.

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