M.Tech. (Power Systems)

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EFFECTS OF ELECTRIC VEHICLE CHARGING ON POWER DISTRIBUTION SYSTEMS AND ITS MITIGATION STRATEGIES

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I, **Divyanshu Khandelwal**, Roll No. **2K21/PSY/01**, of M.Tech. Power Systems, hereby declare that the project Dissertation titled “**EFFECTS OF ELECTRIC VEHICLE CHARGING ON POWER DISTRIBUTION SYSTEMS AND ITS MITIGATION STRATEGIES**” which is submitted by me to the Department of Electrical Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

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CERTIFICATE

I hereby certify that the Project Dissertation titled "**EFFECTS OF ELECTRIC VEHICLE CHARGING ON POWER DISTRIBUTION SYSTEM AND ITS MITIGATION STRATEGIES**" which is submitted by **Divyanshu Khandelwal**, Roll No. **2K21/PSY/01**, Department of Electrical Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the student under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

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ABSTRACT

Continuously depleting fossil fuel reserves, rising fuel costs and the adverse impact of fossil fuel use on the environment have paved the way for the use of Electric Vehicles (EVs) as a popular mode of transportation. However, with increased EV penetration levels, the existing distribution network may suffer from distorted hourly demand profile, depleted bus voltages, increased unbalance, enhanced line losses and power quality issues. Moreover, the EV load in itself is random, unbalanced and dynamic in nature making it challenging to model accurately.

To prepare distribution networks for future situations where residential EV charging represents a significant portion of the total demand, two mitigation strategies are proposed to improve the network's performance: employment of EV charging policies and deployment of adequately-sized shunt capacitor banks in the network at suitable locations. The optimal sizes and the locations of the capacitor banks are obtained via Particle Swarm Optimization (PSO) algorithm.

Multiple case studies corresponding to different EV penetration levels are performed and the impact of the two mitigation strategies is analyzed on a practical 240-bus distribution system. In the Midwest U.S.A. The U.S. travel data extracted from the 2017 National Household Travel Survey (NHTS) corresponds to about 1800 EVs belonging to more than one thousand households. The results confirm the improvement in demand profile and the bus voltage profiles along-with reduction in system losses, thus validating the proposed mitigation strategies.

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LIST OF SYMBOLS

Symbol	**Meaning**
$\boldsymbol{\eta}$	PHEV Battery energy efficiency
$\boldsymbol{E_g}$	Amount of electrical energy required for PHEV battery charging
$\boldsymbol{T_{ch}}$	Charging time of a PHEV vehicle
C	Battery capacity
A	Factor representing the percentage of distance travelled by a PHEV in electric mode
3Ø-T	Three phase transformer
1Ø-T	Single phase transformer
1Ø-CT	Single phase central tapped transformer
$\boldsymbol{P_{Tloss}}$	Total active power loss
$\mathbf{Q_{CAP}}$	Total reactive power supplied by shunt capacitor banks

LIST OF ABBREVIATIONS

Abbreviation	Expansion
EV	Electric Vehicle
ICE	Internal Combustion Engine
NHTS	National Household Travel Survey
PHEV	Plug-in Hybrid Electric Vehicle
BEV	Battery Electric Vehicle
HEV	Hybrid Electric Vehicle
ACSR	Aluminium conductors steel reinforced
AER	All electric range
ECPM	Electrical energy consumption per mile
PNNL	Pacific Northwest National Laboratory
SOC	State of Charge
DG	Distributed Generator

CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

1.1 OVERVIEW

Petroleum-based fossil fuels, primarily petrol and diesel, have a near-monopoly as the source of energy for global transportation as their share is a humongous ninety percent. This factual detail can be observed the from the transportation energy resources data of 2017 in U.S.A. which lists 55% share of gasoline, 22% share of distillate (petroleum), 12% of jet fuel (petroleum), 5% of biofuel, 3% of natural gas, and 3% of the rest [1]. This in-turn makes the global transportation sector a major source of fossil fuel consumption that leads to a lot of emission of greenhouse gases. Also, the overwhelming and unmitigated use of fossil fuels for decades has been deteriorating the environment and consequently, catastrophic disasters like floods, tsunami and forest fires are destroying human settlements at a rapid pace. For rejuvenating the ecological balance, the consumption of fossil fuels must be minimised [2]. To accomplish such an ambitious task, urgency must be shown to overhaul the transportation sector by decreasing the carbon emissions and preserving the fossil-fuel reserves. Electric vehicles (EVs) have come up as a substitute to the internal combustion engine (ICE) vehicles [3]. However, with the increase in the level of EV penetration, the existing distribution network configuration will be affected adversely in terms of deterioration in demand profile, increased line losses, voltage dip, power quality and grid stability issues [4][5]. This degradation in the distribution systems can be mitigated using a couple of strategies that are listed below.

1. Adopting a suitable EV charging policy which essentially shifts the peak load in daily demand profile to off-peak hours so that the daily demand curve

doesn’t contain steep peaks and valleys, rather it evens out over the course of the day.

2. Another way to counter these adverse effects is to place adequately sized capacitor banks throughout the distribution grid so that the reactive power injection can raise the voltage profile of the system and reduce the system losses. Optimal sizing and placement of the capacitor bank(s) is achieved by utilizing particle swarm optimization (PSO) - a metaheuristic technique.

Both the above stated techniques are tested on a practical 240-Bus distribution utility located in the midwestern U.S. state of Iowa. The travel data of the vehicles is obtained from the U.S. National Household Travel Survey (NHTS) 2017 [6]. Three plausible future scenarios regarding EV penetration in the transportation sector are considered. In the first case, a conservative estimate for EV adoption is taken and it is assumed that each household has at least one EV. The second scenario considered is five years into the future where it is assumed that each household has at most two EVs. The third scenario considered is ten years into the future where it is assumed that each household has at most three EVs. To each of these scenarios, both of the above stated techniques to improve the network performance are applied and their respective results are compared.

1.2 PLUG-IN HYBRID ELECTRIC VEHICLES (PHEVs)

Currently, EV types are available in the market which broadly can be classified in the following three categories: Battery Electric Vehicles (BEVs), Hybrid Electric Vehicles (HEVs) and Plug-in Hybrid Electric Vehicles (PHEVs). They are briefly discussed in the Table 1.1. In this study, PHEVs are modelled as they appear to be the most convenient ones for households to use as they can be charged from the confinement of homes and people don’t have to run to their nearest gas station or petrol pump every time they need to charge or refuel their vehicles.

Table 1.1: Classification of EVs

BEV	HEV	PHEV
Battery is fully charged by electricity.	Battery can be charged by petrol engine and regenerative braking.	Battery can be charged by gasoline engine, power grid and regenerative braking.
Can be plugged into an external power grid for charging battery.	Cannot be charged by power grid.	Can be plugged into an external power grid for charging battery.

PHEVs consume substantial electric power which is being supplied by the distribution utility. For instance, the battery capacity of the Nissan Leaf is 30 kWh [7] which approximately equals 3 to 5 times the daily electricity demand of a household [8]. Hence, to investigate the impacts of PHEV charging on the power distribution systems, efficient and accurate representation of PHEV charging via mathematical modelling is imperative. PHEV charging can be classified into two scenarios – smart (coordinated) and non-smart (uncoordinated) charging. Smart charging is also termed as coordinated charging in which the cost of power and the time of PHEV charging is optimally determined employing an optimization algorithm. On the contrary, non-smart charging is known as uncoordinated charging in which the owners of PHEVs charge their vehicles straight after reaching home with a constant rate of power. Generally, uncoordinated charging is considered to have more adverse impact on the distribution network as compared to the coordinated charging scenario.

In this thesis, a study on the charging effects of about 1800 EVs belonging to more than one thousand U.S. residences is carried out on a 240-bus distribution network [9] in the U.S. Midwest. The dynamic nature of the demand due to the PHEV charging is taken into account by considering real EV travel profiles and demand data. The demand profile due to PHEV charging is constructed for residential customers on the basis of certain attributes like the vehicle type, vehicle ID, vehicle arrival time, house ID, person ID from a real transportation survey data – National Household Travel Survey (NHTS) 2017, carried out in the U.S. These demand profiles are then analyzed with respect to the base case demand profile of the 240-bus system [9]. Several case studies are performed in MATLAB to scrutinize the total demand and bus voltage profiles in the 240-bus U.S. distribution system, with and without PHEV charging. Subsequently, appropriate EV charging policies are adopted to reduce the distortion in the system demand profile and system losses due to EV charging. Finally, capacitors banks of suitable sizes are placed at appropriate buses in the 240-bus network to investigate the improvement in the network performance with EV charging.

1.3 LITERATURE REVIEW

Table 1.2: Summary of Literature relevant to this Thesis

Reference	Relevance	Test Cases	Contributions	Comments
[10]	Multi-day charging policy	A household during summer & winter	Policy shifts the peak EV charging load period	Policy proposed to maximize EV's battery capacity
[11]	Optimal capacitor placement in radial distribution systems	9 branch & 69 branch test systems	Peak power & energy loss decreased using capacitor banks in the system	Solved it as a master-slave problem
[12]	Optimal capacitor placement using heuristic techniques	9-bus test system, 69-bus test system, 135-bus test system	Solved via hybrid method with features of heuristic methods	Avoided sensitivity based selection of buses
[13]	Capacitor placement by simulated annealing	None	Determined location, size & control settings of capacitors	Objective function chosen to be cost
[14]	Capacitor placement by ant-colony search algorithm	3-feeder network, practical system from Taiwan power company	Considerable loss reduction achieved	Multi-objective function with cost and voltage constraints
[15]	Review of EV charging technologies	All charging standards	Conductive & wireless charging techniques	Review paper

[16]	Comprehensive review of charging levels, standards & challenges	All EV charging standards & levels	Impact analysis on distribution system & losses	Review paper
[17]	Optimizing system demand due to EV charging load	Entire UK's load profile is considered	Optimization to be implemented via incentive based demand response	Necessitates sensitivity analysis
[18]	Coordinated charging of many EVs	20kV feeder in Katerini, Greece	Increased peak demand in afternoon hours	Effective decentralized control
[19]	Impact of PHEVs on demand profile	NHTS 2001 data for 24-hour analysis	Range of EVs impacts load profile directly	Proposes a policy to shift EV load to off-peak hours
[20]	Impact of EVs on distribution network	Real residential & industrial distribution networks	Investment costs and system losses increase substantially	Losses increase up to 40% with significant EV load
[21]	Modelling of EV charging load	IEEE 69-bus test system	ZIP model more accurately models the EV loads	Constant power load model may mislead
[22]	Coordinated / smart charging of PHEVs	9-bus & 18-bus unbalanced system	Minimizing loss & load variance produce identical results	Objectives: loss, load factor &load variance
[23]	Financial impact of charging policies on grid	MV network in the Netherlands	Minimizing peak in network load leads to cost reduction	Charging level is considered 3kW
[24]	Impact of EV charging strategies	A Flemish residential grid	Voltage droop charging & peak shaving improve grid health	100% EV penetration considered
[25]	Capacitor placement, sizing using hybrid PSO	Unbalanced 13-bus distribution system	Objective formulated with Losses & capacitor cost	THD minimization also considered
[26]	Optimal EV charging with distribution network constraints	114 houses with 57 vehicles	Uncontrolled charging can only sustain 15% EV penetration	Load control enables to sustain high penetration levels

[27]	Capacitor placement & sizing	6 & 18 bus IEEE distorted network	Yearly benefits of up to $ 45,000	Genetic Algorithm employed
[28]	Capacitor placement & sizing	10, 15, 34, 69 & 85 bus distribution systems	Loss reduction in the range (10 – 48) %	PSO algorithm employed
[29]	Mitigating Impacts of EVs in grid	UK based system with peak load of 4.37 MVA	Suggests DG allocation in presence of high EV penetration	Rural case study was done
[30]	Modeling the daily distance of EVs	830 days, 4409 trips in Michigan	Modelling reproduces real world data	This allows PHEV control design
[31]	Modelling demand of PHEVs	UC Davis PH&EV centre data	Simulates demand of EVs from arrival time & charging pattern	Charging station, not domestic demand
[32]	Charging strategy for PHEVs	16 kWh battery with range of 64 km	Determines optimum start charging time for PHEVs	Strategy developed using game theory
[33]	Commercial building microgrids containing EVs	Peak load of 500 kW for building with 60 EVs	Feasible EV charging model & algorithm for real-time EV demand	EV charging rate depends on SOC & PV output in real-time
[34]	Modelling of power demand due to EVs	Scenario with 1 million EVs in the Netherlands	EV charging load is random due to random driving patterns	Modelling done using Copula function
[35]	Integration of PHEVs into a distribution residential grid	IEEE 34-node feeder with NHTS 2009 data	Optimally allocates V2G capacity for peak load shaving	2-layered evolved PSO technique is used
[36]	Load management to coordinate EVs in a smart grid	449 node smart grid distribution system	Time divided into priority charging time zones	Real time smart load management control
[37]	Impact of V2G on distribution systems	None	Significant investment needed	Review paper
[38]	Simulating impacts of EV charging on distribution systems	IEEE 13-bus & TPC 25-bus distribution systems	System losses increase as EV penetration increases	Average & peak load scenarios considered

[39]	Impact of residential PHEV charging on grid	IEEE 34-node test feeder downscaled to 230V	Coordinated charging minimizes power losses in the grid	Charging coordination achieved by dynamic programming
[40]	Particle Swarm Optimization (PSO)	None	Optimizing non-linear functions	Simulation of behaviour observed in nature
[41]	Placement & sizing of capacitor banks	34-bus radial distribution network	Buses identified by loss sensitivity index	By whale optimization algorithm (WHO)
[42]	Capacitor placement in radial distribution systems	IEEE 10-bus radial distribution system	Results in power factor improvement at the buses	ETAP tool is used & cost is taken as the objective function
[43]	Capacitor placement by differential evolution	IEEE 69-bus system	1400 kVAr placed in the system results in $8000 savings	Reactive power by capacitors reduces losses
[44]	Capacitor placement from the point of view of utilities	5-feeders substation of north-eastern PEA region in Thailand	4.5 MVAr compensation results in 6% loss reduction of the demand	Fixed capacitors of 300 kVAr each are placed
[45]	Capacitor placement using improved PSO algorithm	34-bus distribution network	Improved PSO performs marginally better than the conventional one	Objective function- losses & cost of capacitors
[46]	Power flow for radial distribution systems	IEEE 4, IEEE 34 node test feeders	Backward / Forward sweep method	Load flow by considering unbalanced lines
[47]	Modified backward/ forward sweep method	45, 90, 135, 180, 270 node feeders	BIBC and BCBV matrices to solve radial & weakly meshed load flow problems	Faster backward forward sweep convergence
[48]	Impact of EV fast charging stations on grid	IEEE 33 bus test system	Ideal bus selection for placing station is necessary	Strategy for placing station is proposed
[49]	Load increase due to household EV charging	IEEE 34 node test feeder	PHEV model, quantifying EV charging load for diff. scenarios	Impact on load analyzed, voltage neglected

[50]	EV charging at diff. loading conditions	IEEE 34 node test feeder	Quantification of load increment due to diff. no. of EVs	Impact on load analyzed, voltage neglected
[51]	EV charging at off-home location using Fuzzy logic	Shopping centre load at weekdays & weekends	Deciding which level of charging to use (level 1/2)	Considers a solitary charging location
[52]	Modelling load demand due to EV charging	38-bus distribution system	Smart domestic charging	Used diff. tariff rates at diff. times of the day
[53]	Modelling load due to multiple PHEVs	Modified IEEE 30-bus system	Behaviour of multiple PHEVs	Residential & EV station charging
[54]	Smart PHEV charging strategy with max. RE	Modified IEEE 33-bus system	Voltage profile of the system was plotted	Integrating RE with micro-grids

Some major takeaways from the above tabulated literature review are:

- The studies tabulated above comprise of places like U.S.A, U.K., Belgium, Netherlands, Thailand, Greece and Taiwan. This forms a strong base for this thesis as it incorporates all these different proposed techniques used in different parts of the world.

- In almost all the above listed papers, various different EV penetration levels were considered keeping in mind future developments.

- While implementing charging policies, the central theme of all the studies were to propose guidelines by which peak demand can be reduced and can be shifted to off-peak hours.

- While opting for placement of shunt capacitor banks in the radial distribution network, the method by which ideal buses were identified was by the loss sensitivity indices of the buses in the system.

CHAPTER 2

POWER FLOW IN DISTRIBUTION SYSTEMS

2.1 NATURE OF DISTRIBUTION SYSTEMS

Distribution systems are inherently different from the transmission networks due to various factors like system topologies, i.e., distribution systems are radial in nature and in some cases, weakly meshed if required. Three-phase transmission systems are always operating in balanced condition (or very close to balance), whereas due to the intermittent and highly unpredictable nature of power demand, distribution systems seldom operate under a three-phase balance. Also, the ACSR conductors and cables used in distribution systems have a high R/X ratio while those employed under transmission networks have a high X/R ratio.

Due to these stark differences, the load flow analysis in distribution systems can’t be done using the same methods which are employed to determine the power flow in transmission systems like Newton-Raphson or Gauss Siedel as these are ill-conditioned for distribution systems [46]. Hence, power flow in distribution systems is calculated via other approaches. In this study, the widely popular backward forward sweep method is employed for load flow. It is discussed in the following section.

2.2 BACKWARD FORWARD SWEEP METHOD

The backward forward sweep method is derived from the Kirchhoff's current and voltage theorems. Using these basic circuit theorems and an initial value of the voltage magnitude and angle, an iterative process to solve the power flow may be developed. The development of the method used in this study involves the following steps:

2.2.1 Nodal Current Calculations

This is merely an initialization step. In this, the initial values of the load currents are determined as:

$$\begin{bmatrix} I_i^a \\ I_i^b \\ I_i^c \end{bmatrix}_k = \begin{bmatrix} (S_i^a/V_i^a)^* \\ (S_i^b/V_i^b)^* \\ (S_i^c/V_i^c)^* \end{bmatrix}_{k-1} \tag{2.1}$$

where, I_i^a, I_i^b, I_i^c are the current injections for the three phases at the i^{th} node; S_i^a, S_i^b, S_i^c are the scheduled power injections for the three phases at the i^{th} node and V_i^a, V_i^b, V_i^c are the three phase voltages at the i^{th} node [46].

2.2.2 Backward Sweep

The backward sweep process involves calculating the nodal currents beginning from the last/ending node and moving toward the reference node. During this process, the voltage values at the nodes are held constant. Once the initial load current values have been calculated by equation (2.1), the next step is to evaluate the branch currents as:

$$J_{i-1,i}^k = I_i^k + \sum J_{i,i+1}^k \tag{2.2}$$

where, $J_{i-1,i}^k$ is the vector representing the three-phase currents of the branch connecting the i^{th} node to its upstream node (i-1), I_i^k is the vector representing the load currents at the ith node and $\sum J_{i,i+1}^{k}$ represents the sum of currents of all the branches emanating from the ith node. ‘k’ denotes the iteration count [46].

2.2.3 Forward Sweep

The forward sweep is equivalent to a voltage update step. As the reference node voltage is known, therefore voltages of the successive nodes are calculated up until the last/ending node by making use of the branch current values calculated in the previous step. During the forward sweep process, the branch current values are held constant. The node voltage values are determined as:

$$V_i^k = V_{i-1}^k - J_{i-1}^k . Z_{i-1,i}^k \tag{2.3}$$

where, V_i^k is the vector representing the three-phase voltages of ith node at kth iteration, V_{i-1}^k represents the voltage values of the immediate upstream node, J_{i-1}^k denotes the vector representing the currents of the branch connecting the ith node to its immediate upstream neighbour (i-1) and $Z_{i-1,i}^k$ denotes the impedance matrix of the branch connecting node ‘i’ to node ‘i-1’ [46].

2.2.4 Convergence Criteria

The above three equations are iteratively solved until a convergence criterion is reached. In this study, the following criteria has been followed:

$$max. (V^{k-1} - V^k) < 10^{-6} \tag{2.4}$$

i.e., the algorithm stops when the maximum difference in node voltage values among all the involved nodes between any two successive iterations is less than 10^{-6}.

This basic load-flow technique is central to all the studies conducted as a part of this thesis.

2.3 240-BUS DISTRIBUTION TEST SYSTEM

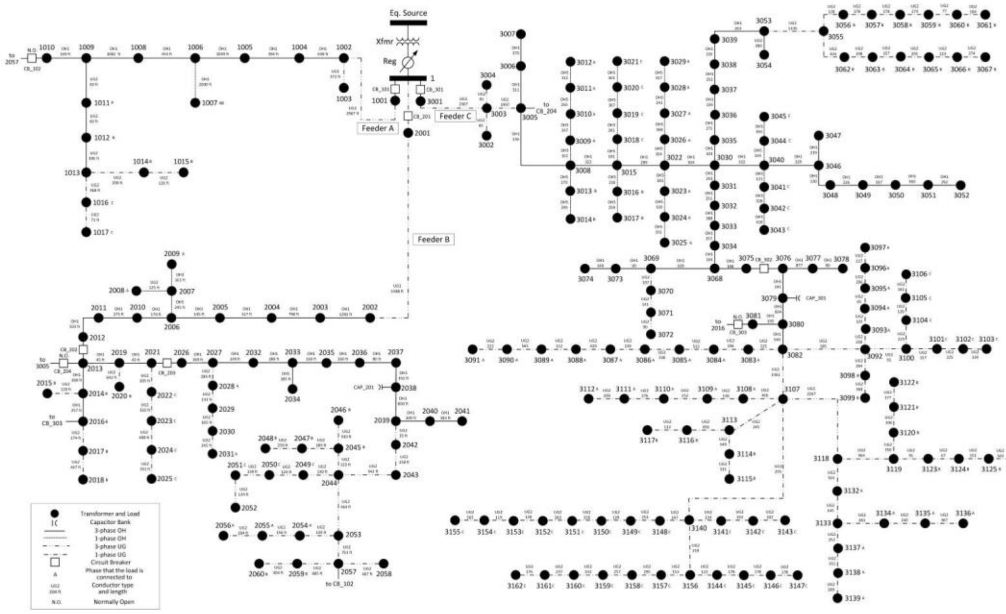

Figure 2.1: 240-Bus Distribution Test System

A 240-Bus Distribution Test System located in the Midwest USA is used in this study.. It is a real distribution network located in the midwestern U.S. state of Iowa and belongs to a municipal utility. It consists of three feeders emanating from a common node. It is a system with smart meters installed at all the customer locations. Hence, with the placement of smart meters, it is possible to fetch hourly data regarding the real and reactive power flow in the system. The distribution network consists of 240 primary network buses connected with one another via 23 miles of primary feeder conductor constituted by five different varieties of overhead conductors and three different types of underground cables. The domestic charging effects of about 1800 PHEVs pertaining to more than one thousand U.S. households are considered. The customers (households) are connected to the primary network buses of the 240-bus distribution network via secondary distribution transformers. The distribution network data is taken from [9].

In modelling the 240-Bus distribution test system for this study, the following salient points have been incorporated:

- The phase admittance matrices for all the branch connections were neglected while formulating the distribution system model as their elements are very small as compared to the elements in phase impedance matrices and hence their impact is negligible.

- The mutual coupling between the phases has been considered while modelling the distribution system and while applying the forward backward algorithm.

- The power flow has been performed in per unit system.

- The two 50 kVAr shunt capacitor banks placed inherently in the system have been distributed equally among the three phases.

- Tap changers have not been employed while modelling the system.

- MATLAB version 2022a has been employed to model the distribution system and for subsequent analysis in this study.

CHAPTER 3

CHARGING MODEL OF A PHEV

3.1 CALCULATING THE EV CHARGING DEMAND

The new genesis of vehicle includes PHEVs having the ability to charge either from an electrical plug outlet or via on-board electricity generation. These vehicles can drive entirely in electric mode at maximum power but for a limited range. PHEV charging affects the distribution grid since it results in the consumption of a large amount of electric power which in-turn leads to undesirable peaks and distortions in the network demand profile, increased system losses and deterioration in the bus voltage profile. This chapter discusses the parameters used in the charging model of a typical PHEV that are described below.

3.1.1 PHEV Battery Capacity

PHEVs are defined by their respective All-Electric Range (AER), which is the distance covered by a PHEV with a completely charged battery. So, for example, PHEV30 indicates that the PHEV can travel 30 miles in the electric mode with a fully charged battery. Table 3.1 describes the battery capacity and the electrical energy consumption per mile (ECPM) for PHEV33 of different types according to the study done by the Pacific Northwest National Laboratory (PNNL) [55]. This calculation can be extended further for PHEV40 as shown in the same table. Therefore, the conception of the usable battery capacity (C) of a PHEV is as follows:

$$C = AER \text{ x } ECPM \tag{3.1}$$

Table 3.1: PHEV33, PHEV40 Battery Capacities & ECPM for different vehicle types

Vehicle Type	**ECPM (kWh/mile)**	**PHEV33 Battery Capacity (kWh)**	**PHEV40 Battery Capacity (kWh)**
1. Compact Sedan	0.26	8.6	10.4
2. Mid-size Sedan	0.30	9.9	12.0
3. Mid-size SUV	0.38	12.5	15.2
4. Full-size SUV	0.46	15.2	18.4

3.1.2 State of Charge (SOC)

The SOC of a PHEV battery is the amount of energy stored in that battery. In the case studies conducted here, the SOC is regarded as the residual energy in the PHEV battery at the time it reaches home. The formula for the SOC of a PHEV can be written as:

$$SOC = \left(1 - \frac{\alpha * \mathrm{d}}{AER}\right) \; 100 \qquad (3.2)$$

where ‘α’ represents percentage of distance covered by the PHEV in electric mode, ‘d’ is the total distance covered and their product, ‘α*d’ is the distance covered by the PHEV in electric mode. In this thesis, the values of α and AER are considered respectively as 0.6 and 40. It is worth noting that (3.2) is applicable only when the product ‘α*d’ is less than AER or else SOC will be considered zero or negligible.

3.1.3 Energy required for battery charging

For charging the battery, the energy required by a PHEV mainly depends upon battery capacity and the SOC of the battery. Therefore, the electrical energy ‘E_g’ needed by a PHEV for charging its battery can be written as a function of the battery capacity ‘C’ and ‘SOC’ as:

$$E_g = \left(\frac{1 - \frac{\mathrm{SOC}}{100}}{\eta}\right) \; C \qquad (3.3)$$

where η is the battery efficiency. In other studies, η is considered as 90% [56] and 88% [57]. Here, the efficiency is considered to be 90% i.e., η = 0.9.

3.1.4 Charging Time (T_{ch})

The time required for PHEV charging depends on parameters like its SOC, AER, C and the charging standard followed. Hence, the charging time needed by a PHEV (T_{ch}) is determined by 'E_g' and the charging level (ch level) as:

$$T_{ch} = \left(\frac{E_g}{ch\ level}\right) \tag{3.4}$$

With the help of equations (3.1) - (3.4), a charging model of PHEVs is developed and is subsequently used for further analysis in this thesis.

3.2 FILTERING NHTS 2017 DATA

In this thesis, NHTS 2017 data is used for depicting the travelling characteristics of vehicles. NHTS publishes an encyclopaedic travel pattern data in the U.S [6]. From this database, ten attributes for each vehicle are used namely: HOUSEID, TDAYDATE, TRAVDAY, PERSONID, VEHID, VEHTYPE, ENDTIME, TDTRPNUM, HHVEHCNT and BESTMILE. This data exhibits the trip characteristics and the sample size is more than 1 million trips. The last column 'BESTMILE' is the best approximation of the annual distance travelled by the vehicle. It is divided by 365 to get the value of daily mileage of the vehicle. Table 3.2 represents some of the extracted data.

Table 3.2: Filtered NHTS 2017 Data

HOUSEID	TDAY DATE	TRAV DAY	PERSO NID	VEH ID	VEH TYPE	END TIME	TDTRP NUM	HHVE HCNT	BEST MILE
30000007	201608	2	3	1	1	900	1	5	14611.92
30000008	201608	5	1	4	4	2340	2	4	9192.44
30000012	201607	5	1	2	3	605	1	2	4002.55
30000019	201605	5	1	1	1	1515	1	2	7027.68
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.

3.2.1 Charging Standard followed in the study

EVs can be charged through various facilities like charging stations at public places, wall outlet connection at home, battery swapping stations and fast DC charging stations. Consequently, there are various charging standards (both AC and DC) for EVs [57] [58]. SAEJ1772 and Type 1 IEC62196 couplers are used extensively in Japan and the US for public and residential charging via AC while Type-2 IEC62196 is employed in the European market. With reference to voltage levels, in USA, 120V for level-1 and 240 V for level-2 charging is used whereas other countries use a single phase 230 V and three phase 400 V supply connection for AC charging. In this thesis, residential charging is considered. Since in the U.S. 120V AC is available at the single-phase charging outlets at homes, therefore, level-1 SAEJ1772 charging standard is employed in this study.

Table 3.3: AC Charging Standards for EVs

SAEJ1772	SAEJ1772	SAEJ1772	IEC62196	IEC62196	IEC62196
Level 1	**Level 2**	**Level 3**	**Level 1**	**Level 2**	**Level 3**
Single Phase	Single Phase	Three Phase	Single Phase	Single/Three Phase	Three Phase
120 V 12 A 1.44 kW	(208-240) V 32 A (6.66-7.68) kW	(208-600) V 400 A >7.68 kW	16 A (4-7.5) kW	32 A (8-15) kW	250 A (60-120) kW

There are a total of 1079 customers in the network [9] and each one of them is represented as a single-phase 120V supply receiving household. The distribution network consists of 139 single phase load buses and customers allocated to them belong to the phase (either A, B or C) of that particular bus. There are 55 three phase load buses and customers allocated to them are distributed equally among the three phases to minimize the phase unbalancing. Also, all the customers are equipped with smart meters which provide hourly energy consumption in kWh. The above data is not available in the standard IEEE distribution systems and therefore, this 240-Bus distribution system was preferred over them. It is assumed in this thesis that all customers charge their EVs from a single-phase 120V plug outlet in their homes following the last trips of their EVs. This necessitates the adoption of single phase, 120 V AC, 12 A, 1.44 kW outlet as the charging standard. This makes the study more practical and realistic. For acquiring the daily load curve, the smart meter data of the customers of the 240-bus distribution test system is collected. With this, a 24-hour demand curve is plotted which is considered as the base case for this study and relative to this, all the further observations are made that suggest an improvement in the distribution system profile and performance.

3.3 EV CHARGING LOADS AT HOMES

The following figures show the EV charging pattern of a few selected houses in the network with 1EV, 2EVs and 3EVs being charged.

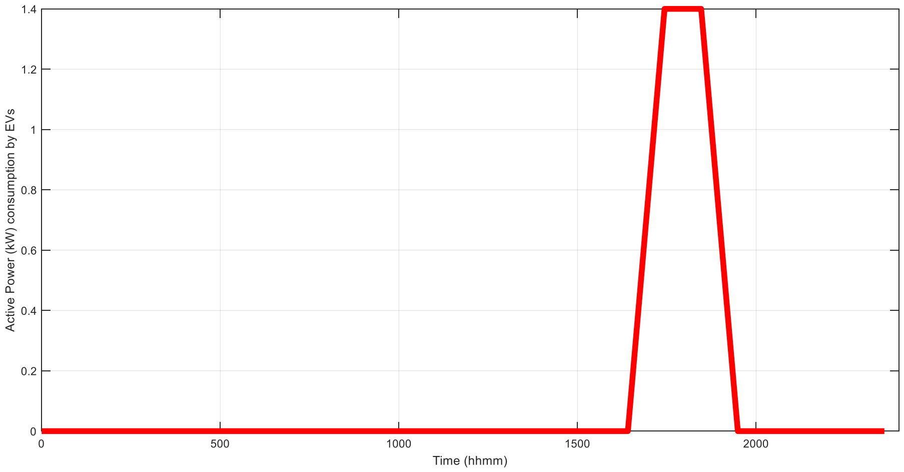

Figure 3.1: EV charging pattern for House ID 30000019

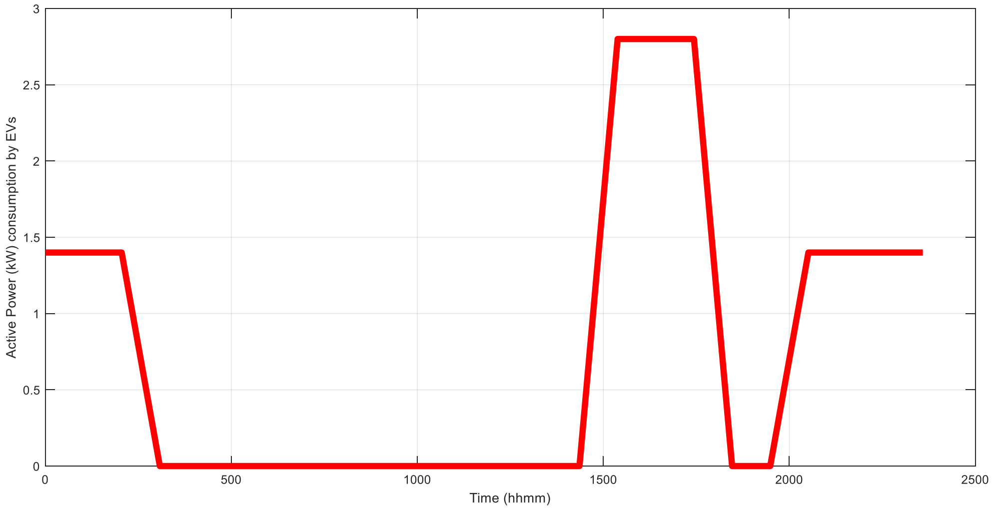

Figure 3.2: EV charging pattern for House ID 30000007

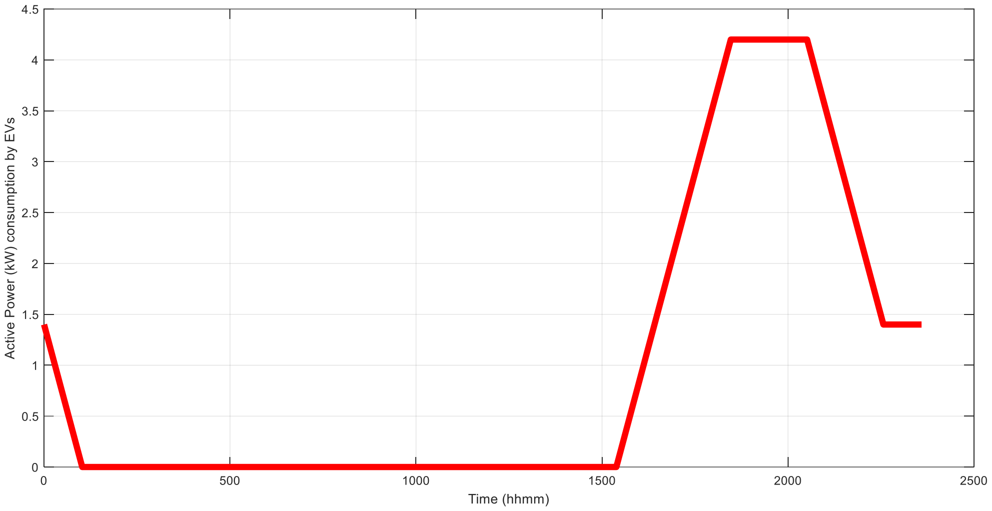

Figure 3.3: EV charging pattern for House ID 30001998

Whenever a single PHEV from a house is being charged, the active power consumption is 1.44 kW pertaining to the SAEJ1772, Level1 charging standard. When two PHEVs are simultaneously being charged, the active power demanded at that instant doubles and reaches 2.88 kW as is evident from Fig. 3.2 and similarly if three PHEVs require simultaneous charging, the active power demanded by them shoots up to 4.32 kW as is the case in Fig. 3.3.

CHAPTER 4

EFFECT OF EV CHARGING ON DISTRIBUTION NETWORK PERFORMANCE

4.1 NATURE OF PHEV CHARGING LOAD

PHEVs predominantly consume active power to charge their batteries, i.e., they act almost as unity power factor load. Hence, when EVs become the norm in the near future, their charging is going to massively burden the system with increased active power demand. As would be evident in the upcoming case studies, the active power demand in the system would increase by as much as twice the original value at peak hours due to the PHEV charging loads.

The dramatic rise in the active power demand of the system would most certainly lead to voltage drops across the distribution system. To ensure that the network handles the change in dynamics of the system effectively and doesn’t lose synchronism, it would have to be compensated adequately such that the voltage throughout the system remains within the stability bounds. It is quite obvious that the PHEV charging load won’t stay the same for the course of an entire day. During the office hours i.e., roughly between 08:00 and 16:00, since most people and therefore, most EVs aren’t at home, the total demand of the network is expected to be near the base case demand while the peak in the network load demand is expected to hit between 16:00 and 22:00 hours, as customers arrive home and plug in their EVs for charging.

4.2 CASE STUDIES AND RESULTS

All the test cases performed in this study are done for a typical summer weekday in the month of April and consequently, the load demand depicted caters to the load in the locality for a typical summer weekday. Fig 4.1 represents the active power demand in the system over the course of an entire summer weekday under the subsequently mentioned scenarios:

1. Base Load Case. It is the load demand before the introduction of PHEVs.
2. Each household in the network has one PHEV.
3. Each household in the network has at the most two PHEVs (5 years from now).
4. Each household in the network has at the most three PHEVs (10 years from now).

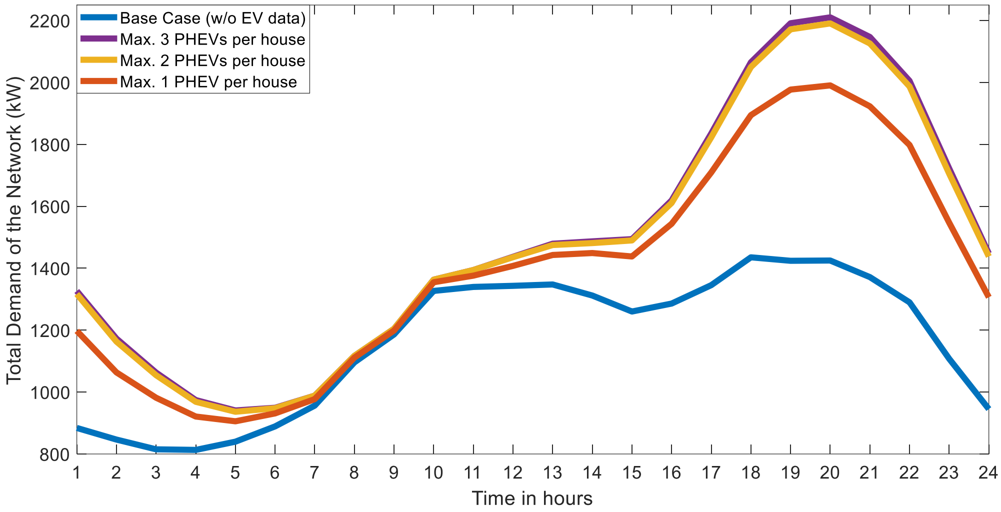

Figure 4.1: Demand Profile for 240-Bus Distribution System under various scenarios

Some interesting observations can be made by looking at the above figure. The base case load peaks around 1400 kW. But as soon as the PHEV charging load comes into picture, the demand rapidly shoots up and reaches over 2200 kW, which corresponds to a massive increase in the load of over 50%. Such a large increment is bound to perturb the normal grid operation and hence, mitigation strategies to raise the voltage profile are pertinent in ensuring smooth functioning of the distribution system. Unfortunately for the grid, such a large increase in the load is accompanied by a proportionally large increase in the ohmic losses in the network as well. Without the PHEV charging load, the system losses amounted to only 31.06 kW. However, with the introduction of PHEVs, the losses steeply rise up to 56.61 kW for the case with max. 1 PHEV per house, 66.05 kW for the case with max. 2 PHEVs per house and 67.22 kW for the case with max. 3 PHEVs per house.

Table 4.1: Maximum load demand and ohmic losses in different test cases

Test Case	**Max. Load Demand (kW)**	**% Increase in Demand**	**Ohmic Losses (kW)**	**% Increase in Losses**
Base case (w/o PHEV Load)	1435	-	31.06	-
Max. 1PHEV per house	1990	38.67%	56.61	82.26%
Max. 2PHEVs per house	2190	52.61%	66.05	112.65%
Max. 3PHEVs per house	2210	54%	67.22	116.42%

As is evident from Table 4.1, with the introduction of the PHEVs and the trend of household charging, the maximum demand in the system may rise by as much as 54% while the losses in the system may exhibit a tremendous increase of 116%. Such a transition could have disastrous consequences for the grid and its stable functioning if suitable measures to accommodate these changes aren’t carried out.

CHAPTER 5

EV CHARGING POLICIES

5.1 THE NEED FOR CHARGING POLICIES

As observed from the previous section, the introduction of PHEVs and their charging loads to the grid are going to substantially raise the peak hour load demand. To mitigate the consequence of EV charging on the demand profile of the distribution network and bus voltages across the network nodes, it is better to invoke a coordinated charging technique rather than to have no such policy at all. The employment of a ‘smart charging policy’ has the potential to flatten the daily load profile as it essentially shifts some of the loads from peak hours to off-peak hours. It in-turn may lead to an improvement in the bus voltage profiles throughout the network and hence, would lead to fewer losses. The case studies conducted in this particular section would ultimately reveal how beneficial such policies turn out to be for both the customers and the power distribution utility.

5.2 PROPOSED CHARGING POLICIES

Most of the charging policies in the literature are only time dependent as their sole motive is to fill the valleys in the daily load profile from the peaks and hence, they either subsidise charging during off-peak hours and/or penalise consumers by charging more for electricity during peak hours..

However, in this study to involve consumers in drafting the charging policies, the proposition is done based on both time and the PHEV battery SOC. Such robust policies could turn out to be mutually beneficial to both the consumers and the power distribution company. The following three alternatives are proposed for adoption as the EV charging policy. It is also envisaged that only one out of the following alternatives may be implemented:

1. Charging Policy 1: As per this policy, vehicles having SOC greater than 50% and reaching home for charging between 16:00 hours to 05:00 hours (following day) will be permitted to charge their vehicles only after 05:00 hours.

2. Charging Policy 2: As per this policy, vehicles having SOC greater than 60% and reaching home for charging between 16:00 hours to 05:00 hours (following day) will be permitted to charge their vehicles only after 05:00 hours.

3. Charging Policy 3: As per this policy, vehicles having SOC greater than 70% and reaching home for charging between 16:00 hours to 05:00 hours (following day) will be permitted to charge their vehicles only after 05:00 hours.

It is envisaged that depending on the needs of the users and the utility, the policy which gives the best results may be suggested for adoption.

5.3 PHEV DEMAND CALCULATION METHODOLOGY

To calculate the PHEV charging demand of the vehicles, the methodology mentioned below is adopted:

1. Every household from the NHTS 2017 data is equivalent to a single-phase customer. The number of customers are allotted to the buses according to the customer data [9].

2. The charging demand of the customers is calculated according to the number of PHEVs, PHEV type (e.g., SUV, sedan, etc.) and its travelled distance using the equations (3.1) – (3.3) and the customer data.

3. The allocation of number of customers to an individual phase is done with the help of the customer data. At all the three-phase buses in the network, customers are distributed evenly across the three phases to minimize the phase unbalancing.

4. Finally, the demand due to PHEV charging load of each phase is calculated by adding up the demands of all the customers belonging to that phase. This activity is performed for all the buses in the distribution network.

In this way, all the 1079 customers are distributed across the 240-bus distribution network and the charging demand of each of the 1781 PHEVs is calculated. It is also worth noting that SAEJ1772 (Level 1) charging standard is employed in the household/residential charging that we are concerned with in this study. As discussed earlier, this standard corresponds to 120V AC, 12A and hence, a 1.4 kW charging outlet which is available in every household from which the PHEVs are meant to be charged.

Table 5.1: Customer Data [9]

Bus Number	**Transformer Type**	**Voltage (V)**	**Connection & Load Model**	**Number of customers**
1003	3Ø-T	208	wye-PQ	4
1004	3Ø-T	208	wye-PQ	2
1005	3Ø-T	208	wye-PQ	2
1006	1Ø-T	208	delta-PQ	2
1007	1Ø-T	208	delta-PQ	2
1008	3Ø-T	208	wye-PQ	3
1009	3Ø-T	208	wye-PQ	2
1010	3Ø-T	208	wye-PQ	4
1011	1Ø-CT	120	wye-PQ	13
1012	1Ø-CT	120	wye-PQ	7
1013	3Ø-T	208	wye-PQ	3
.	.	.	.	.
.	.	.	.	.

3031	3Ø-T	208	wye-PQ	8
3032	3Ø-T	208	wye-PQ	9
3033	3Ø-T	208	wye-PQ	7
3034	3Ø-T	208	wye-PQ	9
.	.	.	.	.
3147	1Ø-CT	120	wye-PQ	17
3148	1Ø-CT	120	wye-PQ	8
.	.	.	.	.
.	.	.	.	.
3160	1Ø-CT	120	wye-PQ	4
3161	1Ø-CT	120	wye-PQ	5
3162	1Ø-CT	120	wye-PQ	3

5.4 CASE STUDIES AND RESULTS

Various case studies are carried out in the 240-bus network. At first, the base case power-flow (without PHEV loads) is carried out. Subsequently, the power-flow with PHEV charging load but without any EV charging policy is carried out. Finally, the power-flow with PHEV charging load and with EV charging policies is carried out.

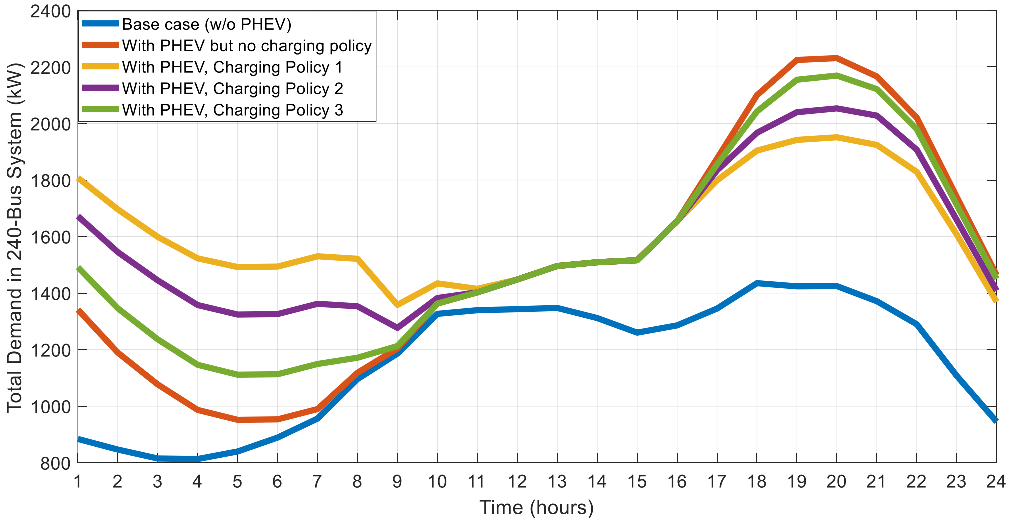

Figure 5.1: 24-hour Demand Profile for the system under different scenarios

The system demand starts increasing significantly after 15:00 hours (3PM) as the domestic customers start plugging in their EVs after arriving home. Therefore, in order to counter this peak charging demand, three practical PHEV charging policies, are considered, only one of which is to be adopted. The policies restrict the charging of a no. of vehicles between the duration when the load on the grid is maximum (i.e., between 4PM and 5AM the following day) based on the SOC of the PHEV battery. The three different EV charging policies are detailed in Section 5.2 earlier. Fig. 1 shows the 24-hour system demand profile for these five cases: (i) base case (without any EV charging load) (ii) with PHEV charging load but without any policy (iii) with PHEV charging load and with EV charging policy 1 implemented (iv) with PHEV charging load and with EV charging policy 2 implemented and (v) with PHEV charging load and with EV charging policy 3 implemented. From Fig. 5.1, it can be observed that with different charging policies, the total network demand with PHEV charging load is substantially flattened. The effect on the system losses and the bus voltage profiles are discussed later.

Table 5.2: Comparison of Charging Policies

Test Case	**Max. Load Demand (kW)**	**Min. Load Demand (kW)**	**Demand Regulation** $\frac{Max-Min}{Max}*$ **100%**	**Max. Loss (kW) at any hour**	**Total Loss (kW) (24 hours)**
No Charging Policy	2231	951	57.37 %	79.38	863
Charging Policy 1	1951	1358	30.39 %	59.04	936
Charging Policy 2	2053	1277	37.79 %	65.87	906
Charging Policy 3	2169	1111	48.77 %	74.68	877

Let’s look at the improvements in the grid quantitatively now. The demand profile over the course of 24 hours is most levelled in case Charging Policy 1. The following figures depict the voltage profile improvement throughout the network with the adoption of these charging policies.

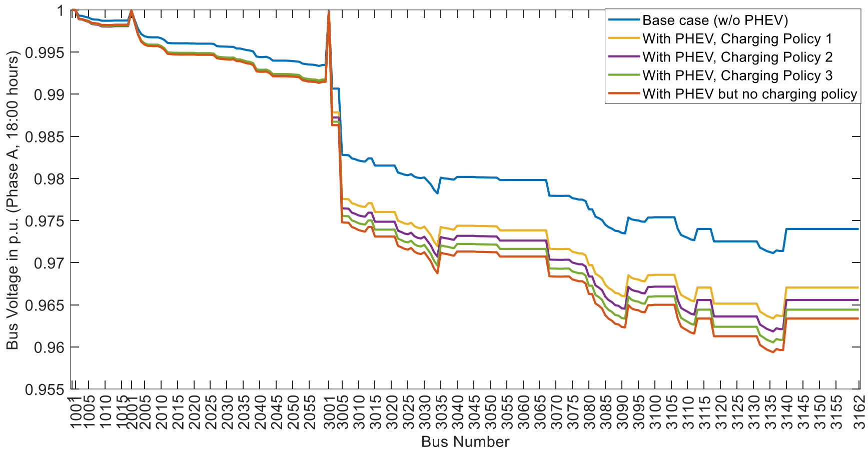

Figure 5.2: Bus Voltage for 240-Bus Distribution System for Phase-A at 18:00 hours under different scenarios

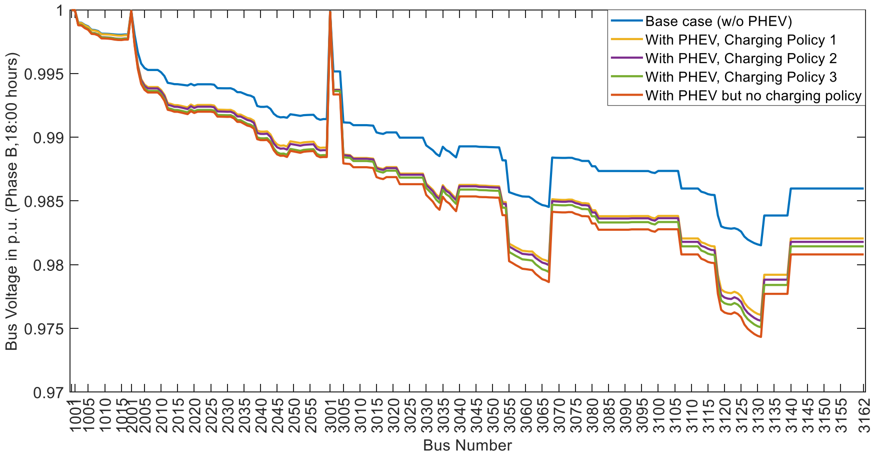

Figure 5.3: Bus Voltage for 240-Bus Distribution System for Phase-B at 18:00 hours under different scenarios

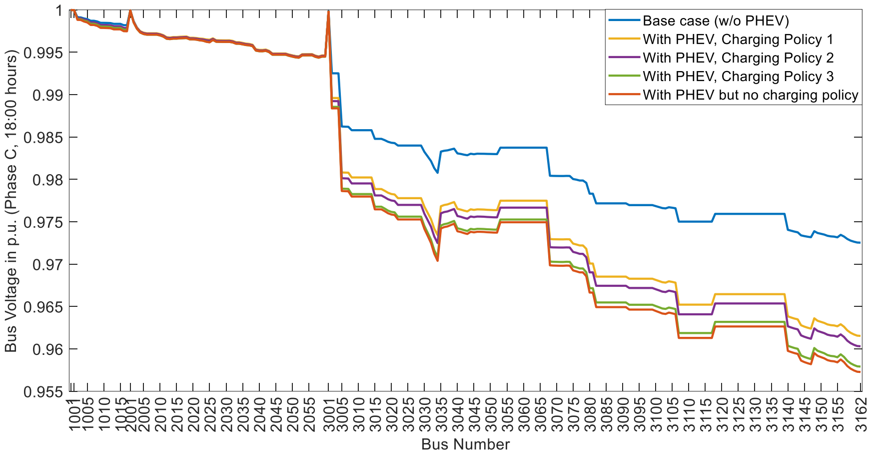

Figure 5.4: Bus Voltage for 240-Bus Distribution System for Phase-C at 18:00 hours under different scenarios

Figs. 5.2-5.4 depict the profile for bus voltages of the distribution system without and with PHEV charging at 18:00 hours for the three phases A, B and C respectively. From the above plots, it is visible that the bus voltage profiles after considering PHEV charging have deteriorated as compared to the base case (without any PHEV charging load). With the adoption of charging policies, improvement in the bus voltage profile is observed throughout the network. The system losses for the base case (without PHEV loads) and with PHEV (without any charging policy) amount to 31.06 kW and 70.02 kW, respectively. But with the introduction of charging policies, the losses reduce to 56.71 kW with Charging Policy 1, 60.92 kW with Charging Policy 2 and 66.42 kW with Charging Policy 3. The peak loss reduction with the advent of policies is 19 % (Policy 1), 13 % (Policy 2) and 5.14 % (Policy 3).

For showing the impact on individual bus profiles over the course of an entire day, buses that have the most customers connected to them are chosen because they would have the maximum no. of charging PHEVs. Consequently, with the help of the customer data, the single phase bus 3147 which has 17 connected customers and the three phase bus 3034 which has 9 connected customers are targeted for further investigations.

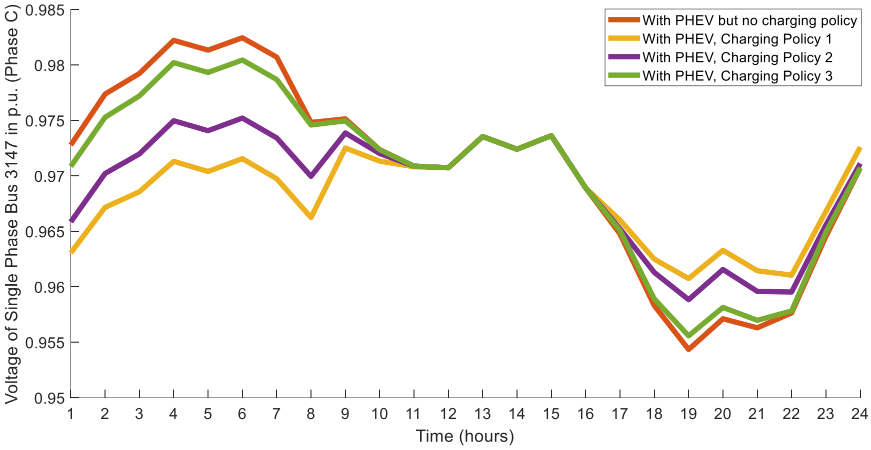

Figure 5.5: 24-hour Voltage profile for Single Phase Bus 3147 without and with PHEV Charging Policies

Fig. 5.5 shows how the voltage varies throughout the day at the single phase bus 3147 that has 17 customers connected to it. During the peak hours, i.e., the interval between 16:00 hours and 22:00 hours, the charging policies help in raising the voltage levels by shifting the excessive PHEV charging load to off-peak hours, thereby levelling the voltage profile. Similar patterns of voltage profiles are expected at all the single-phase buses.

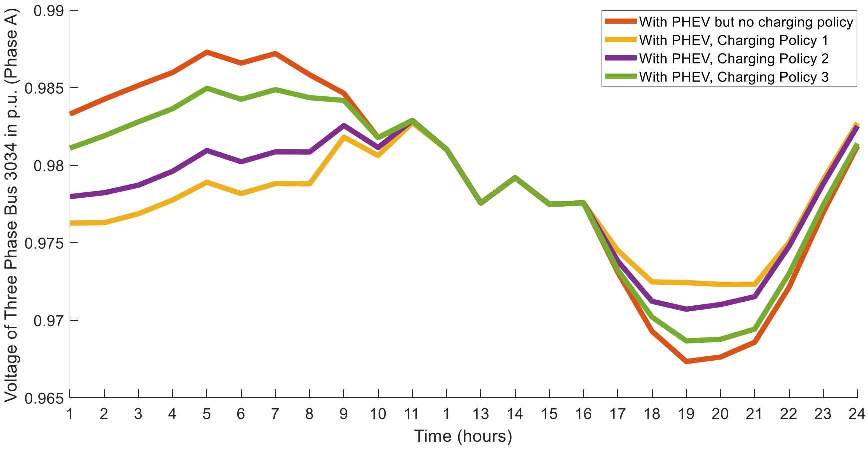

Figure 5.6: 24-hour Voltage profile for Three Phase Bus 3034 (Phase-A) without and with PHEV Charging Policies

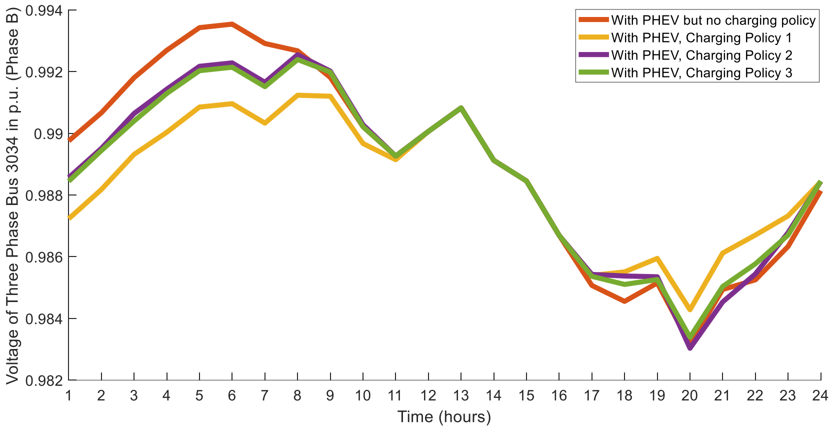

Figure 5.7: 24-hour Voltage profile for Three Phase Bus 3034 (Phase-B) without and with PHEV Charging Policies

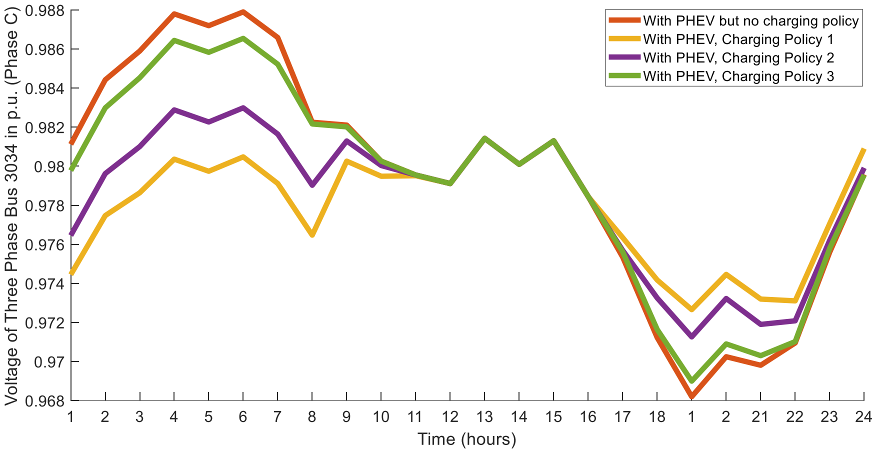

Figure 5.8: 24-hour Voltage profile for Three Phase Bus 3034 (Phase-C) without and with PHEV Charging Policies

Figs. 5.6-5.8 show the voltage variation at all the three phases of the three phase bus 3034 which has 9 different households connected to it (three customers each in phase A, B and C). The voltage patterns obtained here are similar to those obtained at the single phase bus. It is again observed that the charging policies lower the peaks and raise the valleys and hence, successfully flatten the individual bus voltage profiles in the distribution network.

5.5 REMARKS REGARDING THE CHARGING POLICIES

From the results obtained above, it can be inferred that each of the EV charging policies has its own advantages and disadvantages that are summarized below.

- Charging Policy 1 results in the lowest maximum network demand and the lowest demand regulation in the system, but its range anxiety is the highest as customers with PHEVs whose SOC is slightly above 50% have to wait until 5AM the following day to charge their vehicles and they might not get sufficient time to adequately charge their respective vehicles before leaving.

- Charging policy 3 caters more toward customers' comfort as its SOC threshold for charging is set to 70% resulting in minimum range anxiety. However, the system losses are much more increased than with Charging Policy 1.

- Charging policy 2 offers a compromise between Charging policies 1 and 3 and incorporates the qualities of the former two policies by providing a moderate SOC threshold and not letting the demand profile distort heavily.

It is shown that all the three proposed charging policies help in improving the performance of the 240-bus distribution system. Any of these policies may be employed in a distribution network to handle the PHEV charging loads.

CHAPTER 6

PLACEMENT OF SHUNT CAPACITORS TO IMPROVE NETWORK PERFORMANCE

6.1 NEED FOR CAPACITOR PLACEMENT

From the previous chapter, it can be inferred that though the EV charging policies help in improving the distribution system performance, the gains acquired through them are marginal and even after the policy deployment, the system performance is degraded as compared to the base case. If further enhancement is desired in the system performance, it could be accomplished by placing adequately sized capacitor banks at various buses in the distribution grid so as to minimise the voltage dip due to excess PHEV charging load. This technique is sure to boost the voltage levels throughout the network. The primary objective remains to reduce peak power losses and in-turn, minimize the cost, along with minimizing phase unbalance.

6.2 OVERVIEW OF THE CHAPTER

The final chapter is this study deals with sizing and placing shunt capacitor banks in the distribution grid to improve the system performance with PHEV charging load. To accomplish such a complicated task, many factors have been taken into consideration like the extent of EV penetration (no. of EVs allocated to individual households), active power loss in the system, cost of acquiring capacitor banks, their life expectancy, minimizing the voltage deviation in the distribution network, selecting the buses best suited for the deployment capacitor banks and a heuristic algorithm which takes in all the above mentioned factors into consideration and gives the optimal result. The heuristic algorithm used in the study is the widely popular Particle Swarm Optimization (PSO) technique [40].

Firstly, the voltage profile of the distribution system without the EV charging load is determined at 18:00 hours by employing backward forward sweep load flow method. Secondly, the EV charging demand is incorporated for three different scenarios, one where only one EV is allowed per household, another where a maximum of two EVs are allocated to each household and finally the last one where a maximum of three EVs are allocated to each household. The voltage profile for each of these cases is determined. As the introduction of EV charging loads in the network deteriorates its voltage profile thereby impairing the system stability, it is advisable to take counter measures like using capacitor banks to enhance and raise the voltage profile of the system. Lastly, the objective function is formulated and then case studies are carried out with the placed capacitor banks in the network.

6.3 EV PENETRATION LEVELS CONSIDERED IN THE STUDY

In the coming years, the EVs would continue to gain more acceptance among the general public as they become affordable and their charging poses no longer to be an inconvenience and becomes a normal part of our daily routines just like the charging of other electronic gadgets. The following three practical test cases representing three different EV penetration levels are considered in the study:

1. Each household is assumed to have one EV.
2. Each household is allocated at the most two EVs. This situation is estimated to occur five years from now.
3. Each household is allotted at the most three EVs. This situation is estimated to occur ten years from now.

To each of these three test cases, the placement of capacitor banks is done by selecting the adequate buses via their Loss Sensitivity Factor coefficients and their sizing is done by using the PSO algorithm.

6.4 PARTICLE SWARM OPTIMIZATION (PSO)

6.4.1 Introduction

The PSO algorithm is a heuristic technique developed by Kennedy and Eberhart to solve non-linear problems [40]. It takes inspiration from natural phenomena that is the swarming process (e.g., fish schooling and bird flocking) and simulates the swarming behaviour with a few lines of code. It explores the sample space by adjusting the trajectories of moving particles in a multi-dimensional space and within a few iterations, it converges to a solution called as the “quasi-optimal solution” which is very close to the global optimum value of the problem function. The only minor issue with the PSO and other such heuristic techniques is that they are incapable of reproducing the same result.

6.4.2 Methodology

The PSO algorithm performs searches using a predefined population of particles that correspond to the no. of individuals in a flock of birds. Each particle with its unique position represents a candidate solution to the function, which in our case is the capacitor sizing problem. In this technique, the particles of the swarm migrate to their new positions by moving around a multi-dimensional search space until a relatively unchanged position has been encountered or the no. of iterations have been exceeded.

6.4.3 Fundamental Elements of PSO

i. **Swarm**: A disorganized population of moving particles that tend to cluster together as a group while each particle seems to be moving in a random direction.

ii. **Population**: It is a set of ‘n’ number of particles at a time t that can be visualized as $\{X_1(t), X_2(t), X_3(t),\ldots.., X_n(t)\}$.

iii. **Particle X(t)**: It is a k-dimensional vector which represents the candidate solution. For an ith particle at a time t, it is characterized as $X_i(t) = \{X_{i,1}(t), X_{i,2}(t), X_{i,3}(t),\ldots.., X_{i,k}(t)\}$.

iv. **Particle Velocity**: Velocity with which the particles in the swarm are moving. It is represented by a k-dimensional vector as $V_i(t) = \{v_{i,1}(t), v_{i,2}(t), v_{i,3}(t),\ldots.., v_{i,k}(t)\}$.

v. **Inertia Weight w(t)**: This is a control parameter used to control the impact of the previous velocity on the current particle velocity.

vi. **Particle Best (Pbest)**: It is akin to an autobiographical memory. While moving through the search space, a particle compares its fitness value at its present location to its best fitness value attained in any of the previous iterations. The best position thus arrived is referred to as the particle best. This is determined for each particle in the swarm and updated at the end of every iteration.

vii. **Global Best (Gbest)**: As the name suggests, it refers to the best position attained among all the individual particle best thus far. It is also updated in every iteration.

viii. **Velocity Upgradation**: Using the values of Pbest and Gbest, the ith particle velocity corresponding to the kth dimension is updated in each iteration as per the following equation:

$$V[i][j] = K \ast (w \ast v[i][j] + c1 \ast rand1 \ast (PbestX[i][j] - X[i][j]) + c2 \ast rand2 \ast GbestX[j] - X[i][j])). \qquad (6.1)$$

where, K is the constriction factor, c1 and c2 are the weight factors, w is the inertia weight parameter and rand1, rand2 are random numbers between 0 and 1.

6.4.4 Algorithm for Capacitor sizing and placement using PSO

The algorithm for capacitor sizing and placement is realized with the following steps in this study:

1. Run the load flow with PHEV charging data and determine the active power loss. This would be treated as the base case before PSO algorithm gets applied.

2. Select the optimal buses for the placement of capacitors using the Loss Sensitivity Factor coefficients.

3. Run the PSO algorithm while feeding it the necessary objective function and other important parameters like the upper and lower bounds for the search space, no. of locations where the capacitors need to be placed, no. of particles in the swarm and the maximum iteration count.

4. After the PSO terminates, run the base case power flow by adding to it the results obtained via PSO algorithm and compare the original results with those obtained after placing the capacitor banks.

6.5 LOSS SENSITIVITY FACTOR

In the case of capacitor placement, the loss sensitivity factor coefficients help in determining the desirable buses for placing them. It is calculated as:

$$\frac{\partial P_{Tloss}}{\partial Q_{eff}} = \frac{2 * Q_{eff}[q] * R[k]}{(V[q])^2} \tag{6.2}$$

where, $Q_{eff}[q]$ is the total effective reactive power supplied beyond the node ‘q’ and R[k] is the resistance of the k^{th} line. The loss sensitivity factor is calculated at all the candidate nodes in the system and the values are then arranged in descending order. This orders the elements and governs the sequence in which the buses are considered for capacitor bank allocation. Also, at these buses, the normalized voltage magnitudes are calculated as:

$$Norm[i] = \frac{\mathrm{V[i]}}{0.97} \tag{6.3}$$

The buses whose Norm[i] is more than 1.01 are not considered for capacitor placement as already their voltage is sufficiently high and after placing the capacitor bank, over-voltages may arise in the system. The rest of the buses that fulfil the above criteria are stored in descending order of their loss sensitivity factor values and are considered for capacitor placement in that sequence.

6.6 OBJECTIVE FUNCTION FORMULATION

Two types of objective functions are formulated in the study: a single objective function which only minimises the system losses, and in-turn the cost, and a multi-objective function which apart from considering the losses (cost), also factors in the voltage deviation in the network.

6.6.1 Single-Objective Function

The single objective function for capacitor sizing and placement is formulated as:

$$C_{SO,cap} = (K_p * P_{Tloss}) + (K_1 * Q_{cap})/Life_{exp} \tag{6.4}$$

where, P_{Tloss} is the total active power loss in the system in kW, and K_p is the cost of annual power lost and it is determined to be 1576.80 \$/kW [59]. Q_{cap} is the total kVAr rating of the capacitor banks placed in the system, $Life_{exp}$ is their life expectancy and is considered to be 20 years for this study and K_1 is the cost kVAr supplied by the capacitor banks and its value is taken as 5 \$/kVAr [60].

6.6.2 Multi-Objective Function

While formulating the multi-objective function, the new parameter that is considered is the voltage deviation and is described as:

$$VD = \sum_{k=1}^{n} (|V_k| - V_{rated})^2 \ (p.u.) \tag{6.5}$$

where, n refers to the total number of nodes in the system, which in our case study equals 240. $|V_k|$ refers to the voltage magnitude at the kth bus in the network and V_{rated} corresponds to the rated bus voltage.

Therefore, the multi-objective function for capacitor sizing and placement is given as:

$$C_{MO,cap} = \left(w_1 * C_{SO,cap}\right) + (w_2 * VD) \tag{6.6}$$

where, w_1 and w_2 are the weights associated with the single-objective loss or cost function and the voltage deviation respectively and their values are considered as 0.5 each in this study.

6.7 CASE STUDIES AND RESULTS

A maximum of four Capacitor Banks is to be placed in each phase in the network. The demand curves corresponding to all the different cases have already been plotted in Fig. 4.1. The subsequent sub-sections will have the results of capacitor sizing and placement via PSO for different test cases.

6.7.1 Max. 1 PHEV per Household

Table 6.1: Single-Objective PSO Capacitor Placement (1 PHEV)

Bus Number - Phase	**Cap Size (kVAr)**
3132 - 1	21.651
3077 - 1	44.1292
3136 - 1	7.4155
3138 - 1	2.4621
3127 - 2	4.8825
3131 - 2	2.159
3126 - 2	24.3905
3129 - 2	1.2672
3160 - 3	18.2095
3152 - 3	14.7638
3151 - 3	8.0035
3037 - 3	38.4119
Total Q_{CAP}	**187.7457 kVAr**
Power Loss	**55.2632 kW**

Table 6.2: Multi-Objective PSO Capacitor Placement (1 PHEV)

Bus Number - Phase	**Cap Size (kVAr)**
3132 - 1	13.7172
3077 - 1	44.5048
3136 - 1	8.7357
3138 - 1	8.772
3127 - 2	3.8963
3131 - 2	0.8322
3126 - 2	25.3829
3129 - 2	2.559
3160 - 3	17.761
3152 - 3	5.6113
3151 - 3	17.7686
3037 - 3	38.2013
Total Q_{CAP}	**187.7422 kVAr**
Power Loss	**55.2628 kW**

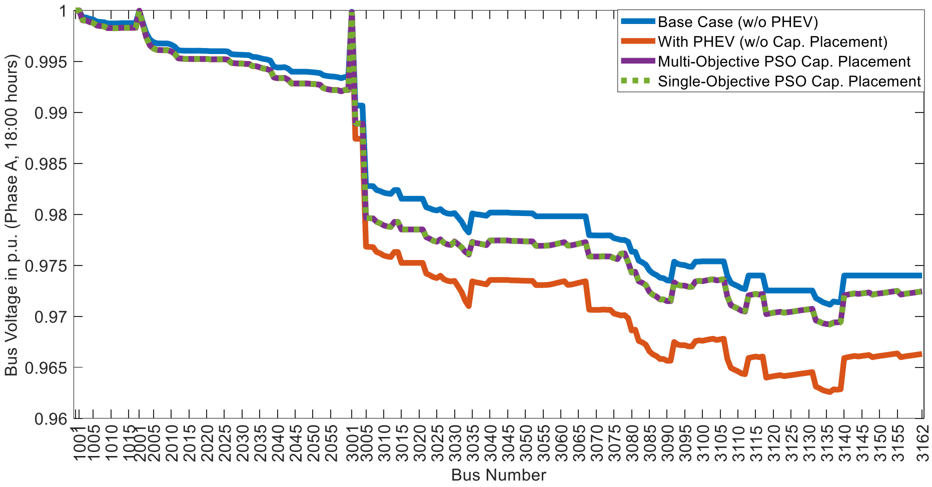

Figure 6.1: Bus Voltage Profile for Phase-A at 18:00 hours

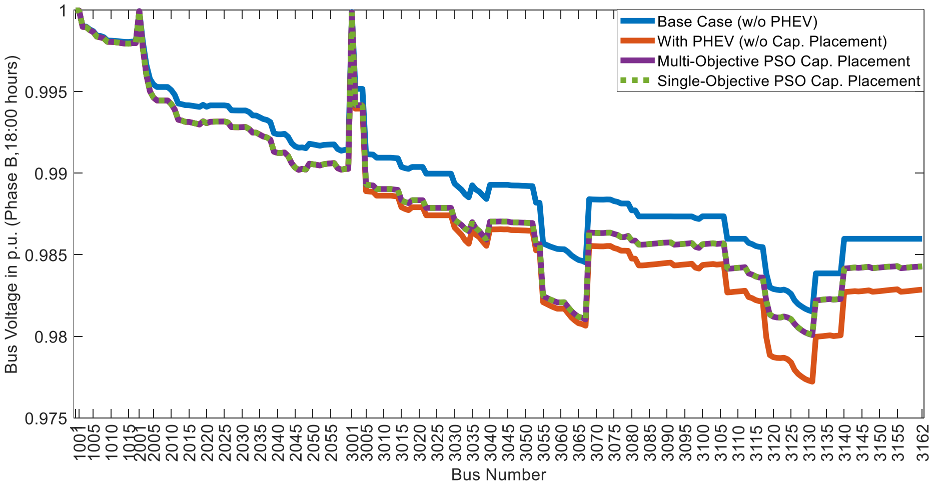

Figure 6.2: Bus Voltage Profile for Phase-B at 18:00 hours

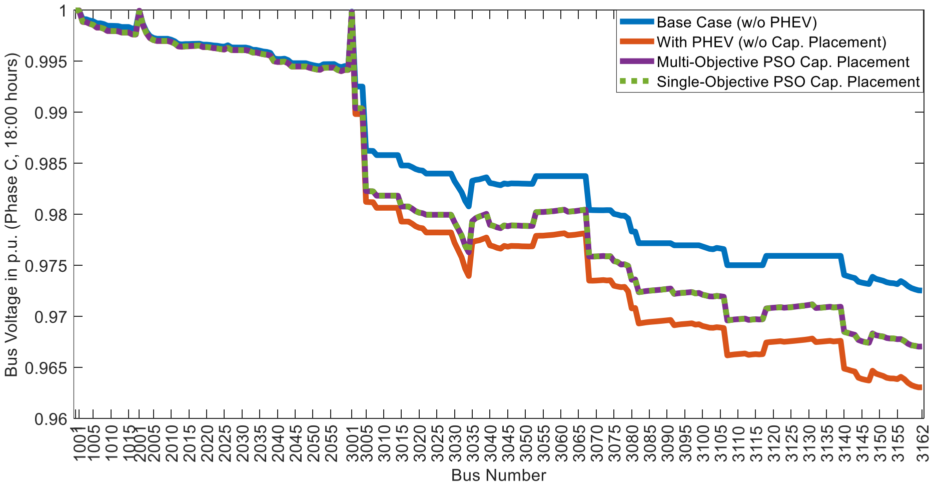

Figure 6.3: Bus Voltage Profile for Phase-C at 18:00 hours

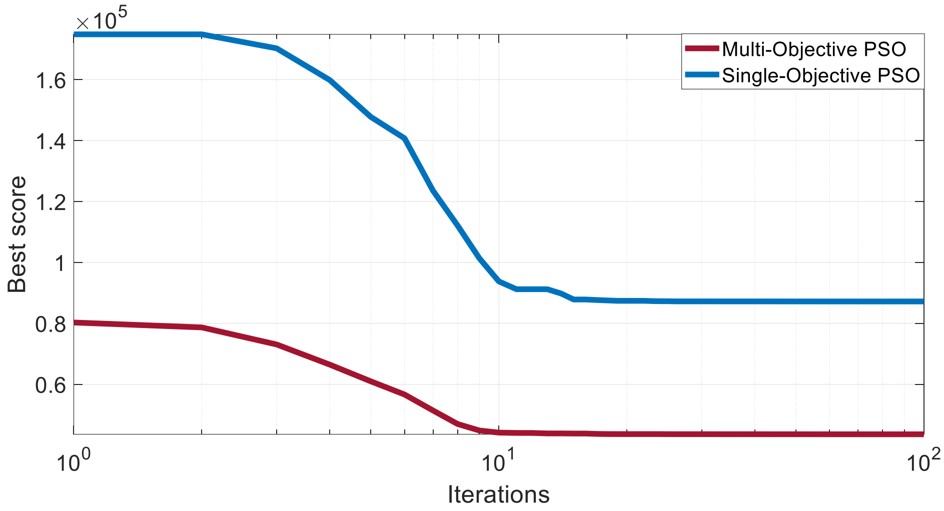

Figure 6.4: Convergence curves for capacitor placement (Max. 1 PHEV per house)

6.7.2 Max. 2 PHEVs per Household

Table 6.3: Single-Objective PSO Capacitor Placement (2 PHEVs)

Bus Number - Phase	Cap Size (kVAr)
3132 - 1	21.6549
3077 - 1	44.7881
3136 - 1	5.1431
3138 - 1	5.6755
3127 - 2	0.9403
3131 - 2	4.2274
3126 - 2	23.7393
3129 - 2	3.5606
3160 - 3	15.7718
3152 - 3	17.9411
3151 - 3	30.3112
3037 - 3	19.0033
Total Q_{CAP}	**192.7566 kVAr**
Power Loss	**64.5939 kW**

Table 6.4: Multi-Objective PSO Capacitor Placement (2 PHEVs)

Bus Number - Phase	**Cap Size (kVAr)**
3132 - 1	17.6093
3077 - 1	45.5172
3136 - 1	9.4685
3138 - 1	4.6176
3127 - 2	1.1648
3131 - 2	0.2931
3126 - 2	27.8568
3129 - 2	3.7906
3160 - 3	17.88
3152 - 3	18.2404
3151 - 3	29.6565
3037 - 3	17.4505
Total Q_{CAP}	**193.5453 kVAr**
Power Loss	**64.5939 kW**

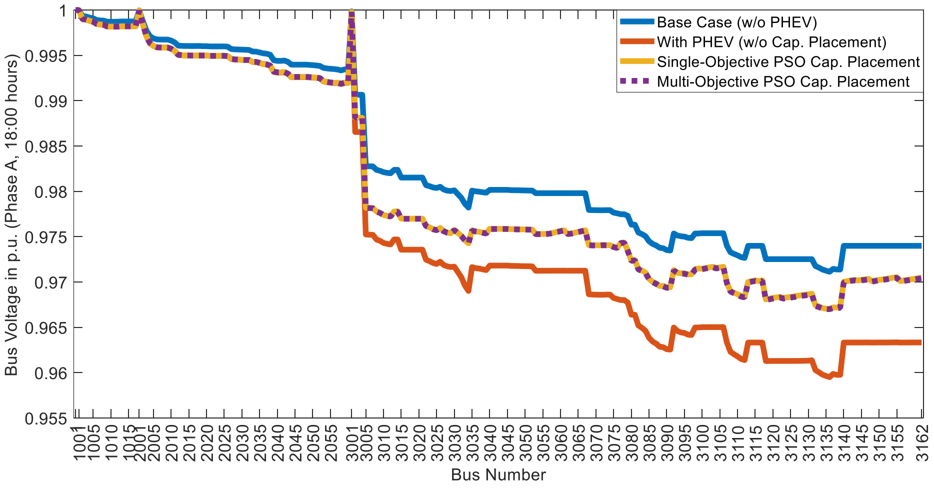

Figure 6.5: Bus Voltage Profile for Phase-A at 18:00 hours

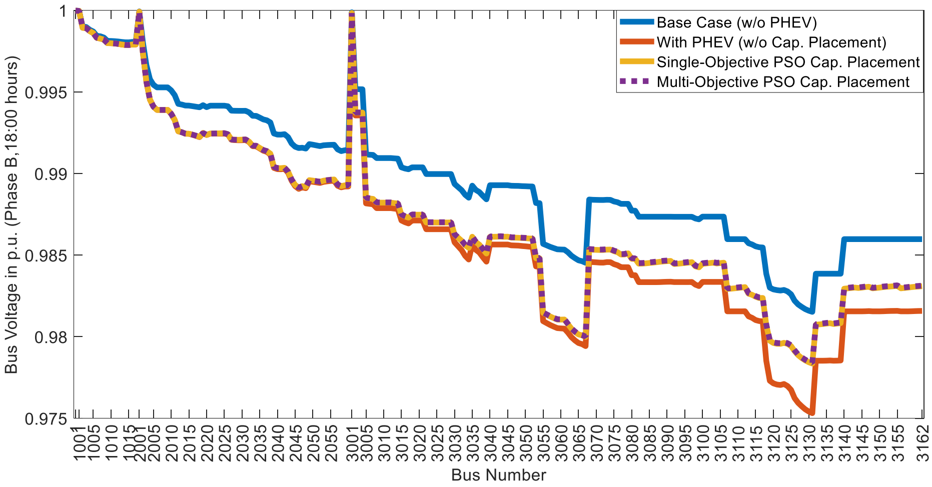

Figure 6.6: Bus Voltage Profile for Phase-B at 18:00 hours

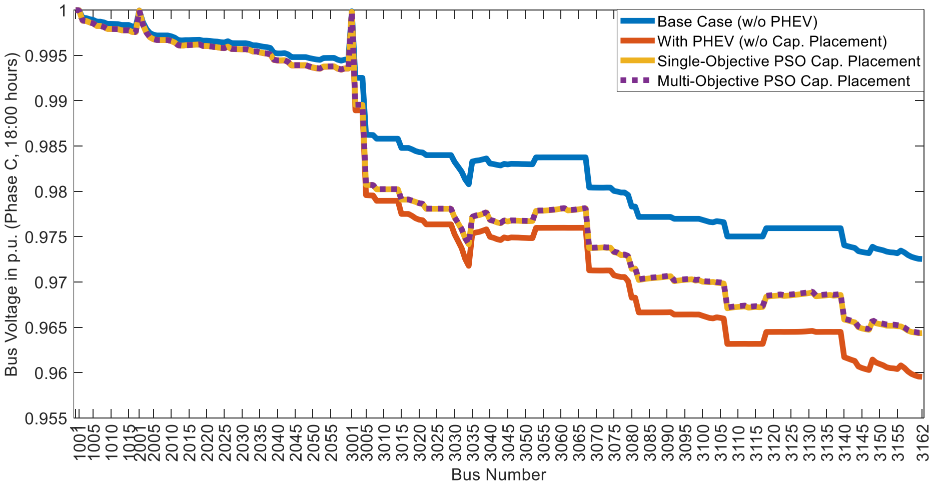

Figure 6.7: Bus Voltage Profile for Phase-C at 18:00 hours

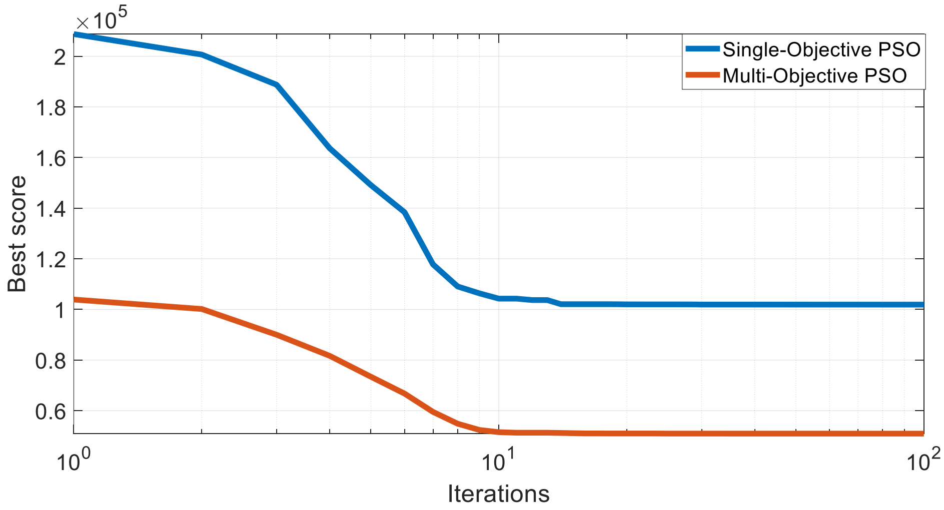

Figure 6.8: Convergence curves for capacitor placement (Max. 2 PHEVs per house)

6.7.3 Max. 3 PHEVs per Household

Table 6.5: Single-Objective PSO Capacitor Placement (3 PHEVs)

Bus Number - Phase	Cap Size (kVAr)
3132 - 1	23.797
3077 - 1	46.5531
3136 - 1	5.5035
3138 - 1	2.9655
3127 - 2	2.2151
3131 - 2	2.2983
3126 - 2	21.8119
3129 - 2	5.8742
3160 - 3	17.0986
3152 - 3	23.4083
3151 - 3	29.0852
3037 - 3	14.944
Total Q_{CAP}	**195.5548 kVAr**
Power Loss	**65.7464 kW**

Table 6.6: Multi-Objective PSO Capacitor Placement (3 PHEVs)

Bus Number - Phase	Cap Size (kVAr)
3132 - 1	21.6706
3077 - 1	44.4489
3136 - 1	7.51
3138 - 1	3.1283
3127 - 2	0.6157
3131 - 2	3.6242
3126 - 2	26.5993
3129 - 2	2.3696
3160 - 3	15.4171
3152 - 3	24.5041
3151 - 3	27.866
3037 - 3	16.1333
Total Q_{CAP}	**193.8871 kVAr**
Power Loss	**65.7463 kW**

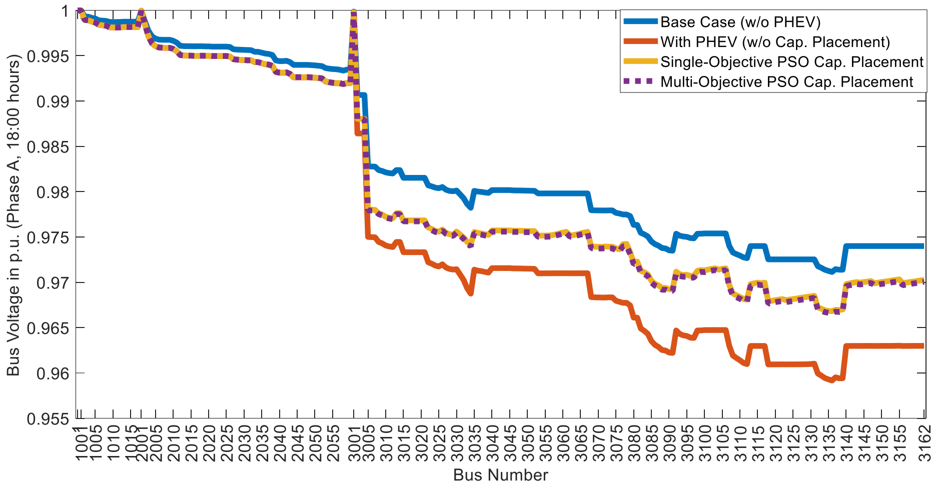

Figure 6.9: Bus Voltage Profile for Phase-A at 18:00 hours

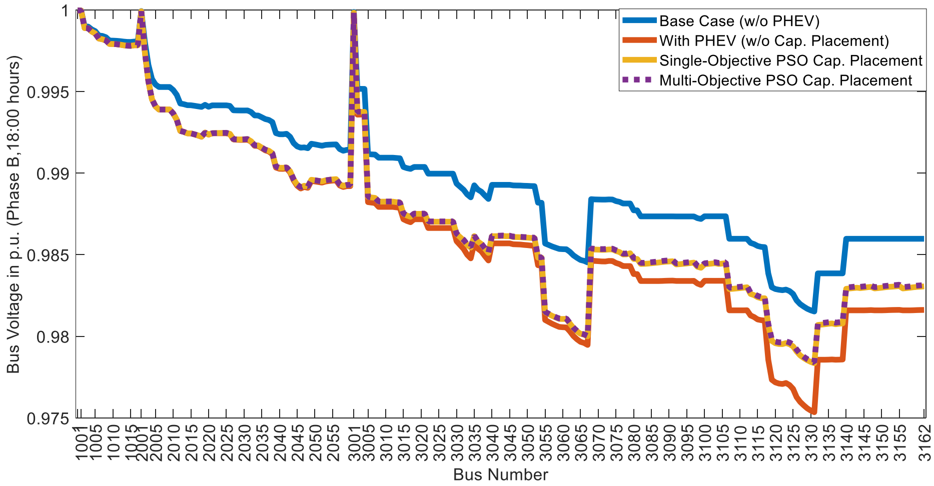

Figure 6.10: Bus Voltage Profile for Phase-B at 18:00 hours

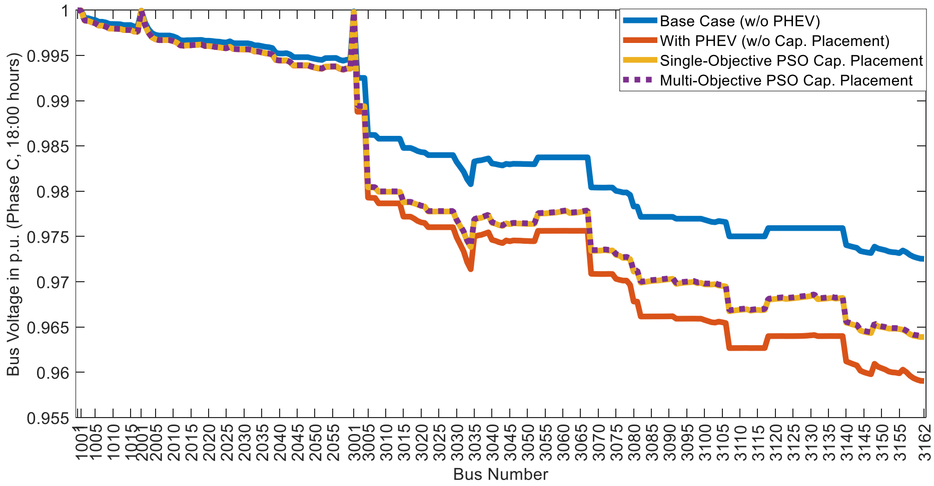

Figure 6.11: Bus Voltage Profile for Phase-C at 18:00 hours

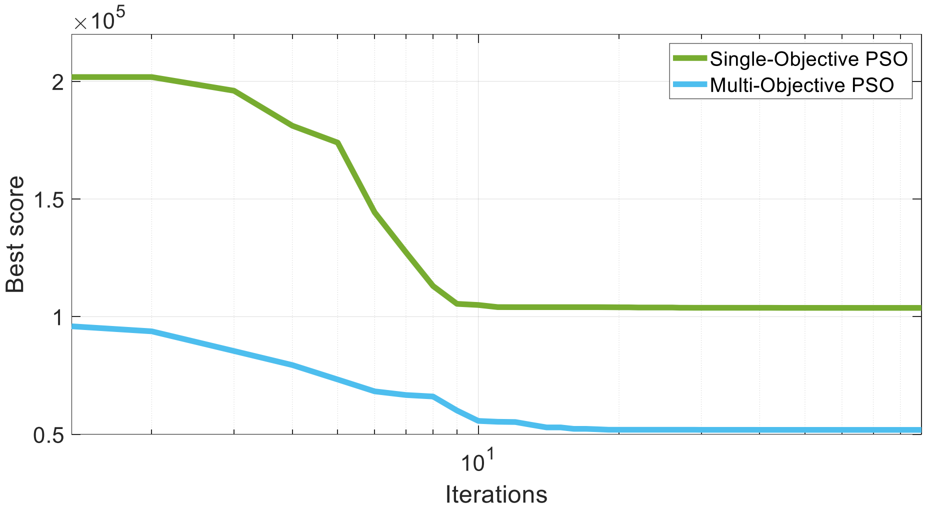

Figure 6.12: Convergence curves for capacitor placement (Max. 3 PHEVs per house)

6.8 REMARKS REGARDING CAPACITOR PLACEMENT

- The single-objective and multi-objective PSO algorithms for capacitor placement arrive at similar results in all the above three cases.
- The improvement in voltage profile is more enhanced as compared to the cases where PHEV charging policies were deployed.
- As the EV charging load keeps on increasing, it results in a less amplified voltage profile and as a consequence, the power losses also soar.
- The reduction in power losses in the system from the uncompensated case is marginal when capacitor banks are deployed at the candidate buses.
- There is a considerable increase in load and in-turn a significantly degraded voltage profile without any compensation is obtained as the EV threshold in households is raised from 1 to 2.
- However, in the latter two scenarios where no. of EVs is restricted to 2 and 3 per household respectively, the load demand and the voltage profile graphs of these two cases almost entirely concur with each other.

- Final Cost in Table 6.7 represents the optimal value of single-objective fitness function while the initial cost corresponds to the annual cost due to losses in the network without shunt capacitor banks.
- Multi-objective PSO algorithm converges slightly faster than single-objective PSO algorithm.
- This is an effective and inexpensive way to improve the performance of the distribution network.

Table 6.7: Summary of capacitor placement test cases (single-objective)

Test Case	**Loss w/o Cap. (kW)**	**Initial Cost ($)**	**Loss after Cap. (kW)**	**Final Cost ($)**	**Annual Savings ($)**
1PHEV	56.6108	89,264	55.2632	87,185	2,079
2PHEVs	66.0587	104,161	64.5939	101,899	2,262
3PHEVs	67.2224	105,996	65.7464	103,717	2,279

CONCLUSIONS

- The effect of about 1800 PHEVs pertaining to more than a thousand U.S. households is considered in the 240-bus radial distribution network located in mid-western U.S.A. The PHEV charging load is modelled as a function of time considering level-1 residential charging as per SAEJ1772 standard.

- With the introduction of EV charging demand in the distribution network, the network faces several challenges to meet the increased active power requirement. This causes distortion in the daily load profile, introduces dip in bus voltages and leads to increased losses. To counter this, two mitigation strategies are proposed.

- In the first strategy, three PHEV charging policies are proposed in this thesis. These policies are SOC based and they restrict PHEV charging to the time of the day when the base load is not too high.

- The second strategy involves placing appropriately sized shunt capacitor banks at pre-determined locations.

- Both the mitigation strategies, i.e., the proposed charging policies and shunt capacitor bank sizing and placement, prove effective in raising the voltage profile of the system, reducing the peak maximum demand by shifting some of the EV charging demand from peak load hours to off-peak hours and lowering the system losses.

- Multiple case studies carried out in MATLAB demonstrate that with the adoption of EV charging policies and capacitor placement, the distribution network performance drastically improves.

SCOPE FOR FURTHER WORK

- Along with capacitors placement, adequately sized Distributed Generators (DGs) can be placed at appropriate system buses. If renewable sources like Solar or wind are exploited as DG resources, then the carbon emissions also decrease.

- More efficient metaheuristic techniques than PSO can be used for the analysis.

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