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Investigation of domestic level EV chargers in the Distribution Network: An Assessment and mitigation solution

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Under the Supervision of

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Abstract

This research focuses on the electrification of the transport sector. Such electrification could potentially pose challenges to the distribution system operator (DSO) in terms of reliability, power quality and cost-effective implementation. This thesis contributes to both, an Electrical Vehicle (EV) load demand profiling and advanced use of reactive power compensation (D-STATCOM) to facilitate flexible and secure network operation. The main aim of this research is to investigate the planning and operation of low voltage distribution networks (LVDN) with increasing electrical vehicles (EVs) proliferation and the effects of higher demand charging systems. This work is based on two different independent strands of research.

Firstly, the thesis illustrates how the flexibility and composition of aggregated EVs demand can be obtained with very limited information available. Once the composition of demand is available, future energy scenarios are analysed in respect to the impact of higher EVs charging rates on single phase connections at LV distribution network level. A novel planning model based on energy scenario simulations suitable for the utilization of existing assets is developed. The proposed framework can provide probabilistic risk assessment of power quality (PQ) variations that may arise due to the proliferation of significant numbers of EVs chargers. Monte Carlo (MC) based simulation is applied in this regard. This probabilistic approach is used to estimate the likely impact of EVs chargers against the extreme-case scenarios.

Secondly, in relation to increased EVs penetration, dynamic reactive power reserve management through network voltage control is considered. In this regard, a generic distribution static synchronous compensator (D-STATCOM) model is adapted to achieve network voltage stability. The main emphasis is on a generic D-STATCOM modelling technique, where each individual EV charging is considered through a probability density function that is inclusive of dynamic D-STATCOM support. It demonstrates how optimal techniques can consider the demand flexibility at each bus to meet the requirement of network operator while maintaining the relevant steady state and/or dynamic performance indicators (voltage level) of the network. The results show that reactive power compensation through D-STATCOM, in the context of EVs integration, can provide continuous voltage support and thereby facilitate 90% penetration of network customers with EV connections at a normal EV charging rate (3.68 kW). The results are improved by using optimal power flow. The results suggest, if fast charging (up to 11 kW) is employed, up to 50% of network EV customers can be accommodated by utilising the optimal planning approach. During the case study, it is observed that the transformer loading is increased significantly in the presence of D-STATCOM. The transformer loading reaches approximately up to 300%, in one of the contingencies at 11 kW EV charging, so transformer upgrading is still required. Three-phase connected D-STATCOM is normally used by the DSO to control power quality issues in the network. Although, to maintain voltage level at each individual phase with three-phase connected device is not possible. So, single-phase connected D-STATCOM is used to control the voltage at each individual phase. Single-phase connected D-STATCOM is able maintain the voltage level at each individual phase at 1 p.u. This research will be of interest to the DSO, as it will provide an insight to the issues associated with higher penetration of EV chargers, present in the realization of a sustainable transport electrification agenda.

Declaration

I hereby certify that this thesis which I now submit for examination for the award of Doctor of Philosophy, is entirely my own work and has not been taken from the work of others, save and to the extent that such work has been cited and acknowledged within the text of my work.

This thesis was prepared according to the regulations for postgraduate study by research of the Technological University Dublin and has not been submitted in whole or in part for another award in any Institute.

The work reported in this thesis conforms to the principles and requirements of the Technological University Dublin's guidelines for ethics in research.

Technological University Dublin has permission to keep, lend or copy this thesis in whole or in part, on condition that any such use of the material of the thesis be duly acknowledged.

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In Dublin, Jan 4th 2022

Abbreviations List

APC	Active Power Control
ADMD	After Diversity Maximum Demand
BESS	Battery Energy Storage System
BEV	Battery Electric Vehicle
BSoC	Battery State of Charge
CAPEX	Capital Expenditure
CCDF	Complimentary Cumulative Distribution Function
CDF	Cumulative Distribution Function
DG	Distributed Generator
DPL	DIgSILENT Programming Language
DS	Distributed Storage
D-STATCOM	Distribution Static Synchronous Compensator
DSL	Dynamic Simulation Language
DSO	Distribution System Operator
DT	Distribution Transformer
EBs	Electrical Buses
EMTP	Electromagnetic Transient Program
EPRI	Electric Power Research Institute
EVs	Electrical Vehicles
FACTS	Flexible AC Transmission Systems
GHG	Greenhouse gas
ICE	Internal Combustion Engine
LCE	Low Carbon Economy
LCT	Low Carbon Technology
LVDN	Low Voltage Distribution Network
MC	Monte Carlo
Ofgem	Office of Gas and Electricity Markets
OLTC	On Load Tap Changer
PDF	Probability density function
PHEV	Plug-in Hybrid Electric Vehicle
PQ	Power Quality
PSO	Particle Swarm Optimization
RIIO	Revenue using Incentives to deliver Innovation and Outputs
RPC	Reactive Power Control
STATCOM	Static Synchronous Compensator
SVC	Static VAr compensator
TSO	Transmission System Operator
UK	United Kingdom
UPF	Unity Power Factor
US	United State
V2G	Vehicle to grid
VAT	Value Added Tax
XLPE	Cross-linked Polyethylene cable insulation
ZIP load model	Impedance, current and power based load model
Mathematical Abbreviations	
Σ	Summation

π_d	Probability of demand scenario
$P_{D_d}^{max}$ and $P_{D_d}^{min}$	Maximum/minimum power demand
π_s	Probability of scenarios
π_{ev}	Probability of EV load scenario
C1 and C2	Learning factor
D	Dimension
$gbest.$	Position of the best particle
$gbest_d$	Group best position w.r.t dimension
$pbest_{id}^t$	Best position of the i-th particle (personal best) in the space area in time
N	Penetration Level
$gbest_{id}^t$	Best position of the swarm in specific area in time
Ith	Particle
R_1^t and R_2^t	Random numbers
X	Particle position
x_{id}^t	Particle position of the i-th particle in d-th dimension
v_{id}^t	Particle velocity of the i-th particle in d-th dimension
V	velocity in a search area
w^t	Inertia of the particle.
w_{max} and w_{min}	maximum and minimum of inertia weight value

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Glossary of Terms

Central Generation	The large scale generation electricity facilities that can be transmitted through the end-user via transmission and distribution network.
Decentralized Generation	The generation of electricity closer to where it will be used by the customers. It can reduce transmission losses significantly.
Distribution Network	The electrical network involved in distribution of electricity to the end user ranging from 230V to 20 kV (AC supply).
Low Voltage	Voltage level between 50V (AC) and 1kV (AC)
Medium Voltage	In Ireland, the distribution network operates at 10kV and 20kV (AC)
Power Flow	The most commonly used tool to analyse the power system. It provides complete information about voltage angle and magnitude for each bus in the power system, for specified loading and generating conditions. Power flow studies are important for planning future expansion as well as in determine the best operation of the existing systems.
Deterministic load flow	The load flow calculation carried out at constant load and generation.

Probabilistic load flow	It is used to estimate the uncertainties associated with the renewable energy sources in the load flow calculation.
Apparent Power	Power consists of two components, active and reactive power. The total sum of active and reactive power is called as apparent power.
Prosumer	The customer that can generate and utilize the energy.
Voltage variation	It is an increase or decrease in voltage, due to variation in total load of the distribution system or a part of it.
Voltage unbalance	It is a condition where the root mean square (rms) value of the phase voltages or the phase angles between consecutive phases in a three-phase system are not equal.

1. Introduction

In decades to come, energy crisis is of a major concern. The environmental issues caused by the use of fossil fuels is raising the Earth surface temperature gradually. CO_2 emissions and global warming are primary issues humankind is facing. New policies and regulations are made to reduce the impact of these problems. Low carbon technologies can provide answers to these issues.

1.1 Chapter Outline

More than half of world's population lives in urban areas, occupying less than 3% of the Earth's ice-free land area. Cities are responsible for 71% to 76% of CO_2 emissions from global final energy use, much of it derived from fossil-fuel based electricity generation [1]. To transform into a sustainable low carbon economy (LCE), cities need to develop smart energy networks that can generate and deliver renewable electricity locally, in a predictable, consistent and optimised manner. Central to this transformation, is the linkage of primary energy resource understanding/modelling, with distributed generation (DG) and Electrical Vehicle (EV) optimisation in an urban context.

Recent trends suggests that, reduction of CO_2 emissions is one of the main challenges our society is facing [2]. Governments around the world are introducing targets to decrease CO_2 emissions. For instance, in 2030 the European Union (EU) has committed to have at least 27% of its energy demand met through renewable energy sources. To achieve the new targets, several international incentives have been set in place to facilitate the adoption of LCTs by the domestic customer [2]. For instance, taxi drivers can avail a grant of up to €7,000 towards the purchase of an EV in Ireland. The grant plays a fundamental role in developing public awareness of EVs and EV taxis provide a great opportunity for the public to experience an EV themselves [3]. Early-stage incentives are important if local citizens are to be mobilized. Grant programs requires ongoing monitoring and assessment, so the pitfalls in using them are avoided. Soft loans (low-interest rate loan) are necessary, for instance, the availability of soft loans (Kreditanstalt für Wiederaufbau (KfW)) in Germany are factors in promoting citizen investment [4]. Additional, non-recourse loans have been used effectively to address early-stage barriers of citizen investment in the UK and Ontario, Canada [4]. This introductory chapter discusses a human related CO_2 emission, what contribution domestic customer can make, and finally understand the impact of LCTs at a distribution level [2].

The aim of this chapter is to provide basic understanding of the research topic and how the subsequent chapters are organized in the formulation and work towards the realization of the challenges involved.

1.2 Background

It is becoming more and more evident that human behaviour is having an increasingly negative influence on the Earth's atmosphere. Excessive burning of fossil fuels, eradication of rainforests and increasing levels of agricultural activity have all led to a considerable increase in greenhouse gas emissions in the atmosphere. The effect of greenhouse gases rising steadily in the Earth's temperature is also known as global warming. According to climate change researchers, a global temperature rise of even 2°C could have a disastrous effect on the environment [5].

The world's urban population will double from 2010 (2.6 billion) to 2050 (5.2 billion) [6]. According to the revision of World Urbanization Prospects 2018 by the United Nation dataset, 55% of the world's population lives in urban areas, a proportion that is expected to increase to 68% by 2050 [6]. Projections show that the overall growth of the world's population could add another 2.7 billion people to urban areas by 2050. It further states that the future world's urban population are expected to be highly concentrated in just a few countries. Together, India, China and Nigeria will account for 35% of the projected growth of the world's urban population between 2018 and 2050. By 2050, it is projected that India will have added 416 million urban dwellers, China 255 million and Nigeria 189 million [6].

Increased energy demand, particularly for electrical energy, is inevitable. If a sustainable, LCE is to be achieved, cities need to develop smart energy networks that can both generate and deliver electricity in a predictable and consistent manner, and from renewable resources. Networks such as these require an understanding of the renewable energy source. DGs, by its nature, are intermittent. Hence, DG strategies require distributed storage (DS) options. These are not trivial matters.

The recent trends suggest, the second quarter of 2021 brought electricity consumption in Europe very close to pre-pandemic levels, however, power demand was still slightly below 2019 levels (-0.5%) [7][8]. Electricity is generated in centralized generation systems by large oil, gas, coal or nuclear power plants. Electricity generated through power plants passes through different stages of the network (transmission, medium voltage, low voltage distribution). These generators are connected to high voltage transmission network that feeds the power in one direction. Power is transmitted to the medium voltage network then down towards distribution network to the domestic customer. The end-user can be domestic, commercial and industrial customers, depending on the power requirement connected to the different stages.

1.3 The Irish Electricity System

In the late 1980s and early 1990s, most of the European energy markets were government-controlled monopolies with a full control and ownership over the complete value chain. Similar to other European countries, the energy sector in Ireland was disaggregated in 2000 as a result of EU directive 96/92/EC [9] and later on updated in EU directive of 2009/72/EC [10]. The directive comprises rules for the generation for domestic user to create competitive, secure and environmentally friendly market. This process introduced competition with respect to the electricity generation and retail, yet the transmission and distribution grid operation remained regulated monopolies due to the system's centralised nature. Hence, among the most important entities in the contemporary power system are the transmission system operator (TSO) and the distribution system operator (DSO) [11]. The electric industry in the Ireland comprises five functions Generation, Transmission, Distribution, Supply and Metering [12].

Large power plants generate bulk energy with the majority of it being currently produced in gas and coal fired stations (51% of net electricity supplied in the Ireland in 2020) [8]. There are interconnections in Northern Ireland and an East–West link with the transmission system in Britain via undersea cables.

1.3.1 Distribution Network

The distribution system is the electricity delivery network that connects the transmission system to domestic and individual customers. The transmission system terminates at substations where the voltage is stepped down to distribution level via transformers. Low voltage level is used in distribution system because the travel distance is comparatively much less than at the transmission level. Distribution voltages are classified as medium voltage (MV) and low voltage (LV), with MV usually referring to nominal voltages between 1 kV and 35 kV and LV being any voltage below 1 kV [13]. MV is used for delivery from the transmission system to step-down distribution transformers, while LV is employed between distribution transformers and customer connection points. LV is the voltage level that is utilised by most customers in their homes, businesses, etc. The voltage of LV systems is 230/400 V (line-ground/line-line) [13].

Distribution network have evolved in different forms around the world, with the two main design approaches being North American and European [14]. Both configurations are radial in nature although layouts and configurations are different. For example, in Europe, the MV distribution system connects to large distribution transformers which serve LV feeders that deliver power to hundreds, or sometimes thousands, of customers [14] while North American distribution system consists of the MV system connecting to a larger number of small distribution transformers, that connect directly to a few customers [14].

In a North American network, illustrated in Fig. 1.1, it is possible to connect EV charger up to 19.2 kW at MV level [15], however, in a European network illustrated in Fig. 1.2, (UK/Irish perspective) single phase EV chargers up to 7 kW are allowed to integrate at the domestic level [16]. According to the guidelines provided by the distribution network operator, EV chargers of 11 kW or above level requires three-phase EV connection [16].

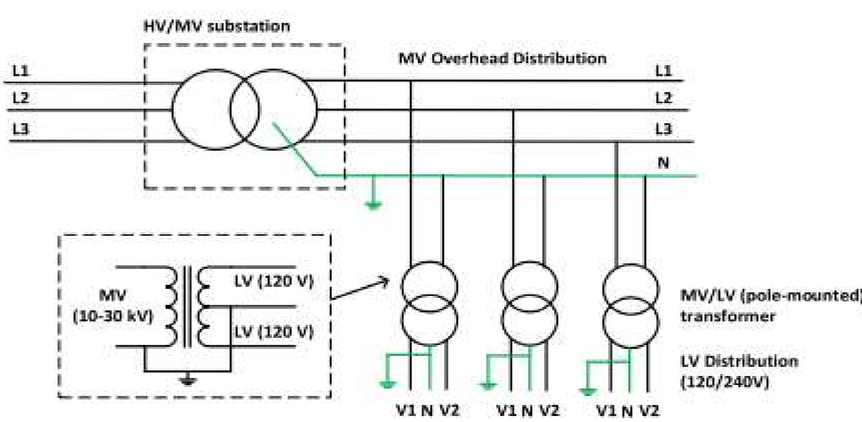

Fig. 1.1: The network configuration of North American distribution network [15]

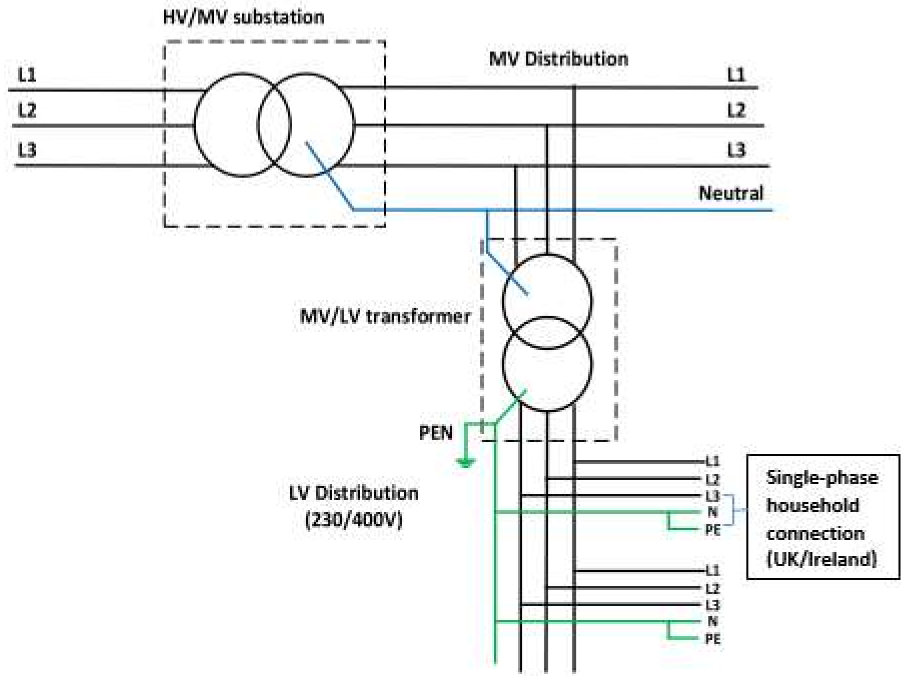

Fig. 1.2: The network configuration of European distribution network [15]

In the Irish context, the distribution system allows for the flow of electricity from the transmission system to 2.3 million customer premises in Ireland. It comprises networks operating at 110 kV in the Dublin area, and nationwide the networks operating at 38kV, 20kV and 10 kV and low voltage (LV). In Ireland, 30% of the population lives outside of cities, towns. The relatively scattered and widespread distribution of the rural population in Ireland is reflected in the extent and the characteristics of the distribution system. Ireland has four times the European average of length of network per capita. The ratio of overhead lines to underground cables is 6:1 [17]. As 150,000 km of overhead lines are exposed to weather and other events, there is a significant challenge in maintaining an adequate and reliable supply in rural areas.

1.4 The Scope of the Research

Catering for the uncertainties associated with EVs and residential loads, as well as their time-varying nature, is an important factor. It is important, to consider the time variant load model of EV and its impact on distribution network. In fact, having high resolution EV charging data is fundamental in understanding its relationship with residential loads. It can potentially impact the total load demand throughout the day as well as the power quality in LV distribution networks. The time-series representation allows the quantification of technical problems in the LV network.

Furthermore, there are several analyses available in relation to LCTs impacts on distribution networks. These analyses generally contain different methods such as, time-series, peak demand, balanced power flow, unbalance power flow, Monte Carlo analysis, deterministic scenarios, sequential charging etc. There are currently no analyses combining the following features: Monte Carlo analysis, time-series simulation, unbalanced power flow (four wire three-phase representation) and OPF on the realistic representation of distribution networks which is crucial in obtaining realistic findings that facilitate network operators to make appropriate decision.

The methodology for household demand decomposition, provides information about different load categories like resistive and inductive loads, but not of individual household appliances. Load appliances belonging to the same category have similar steady-state and dynamic voltage-dependent load characteristic [18][19]. This type of information is deemed acceptable for the DSO, as it classifies load flexibility into load categories with similar static and dynamic behaviour [18]. It aim is to establish the percentage of users that have to be monitored with high penetration level of flexible EV loads. EV loads are not managed through any type of sequentially charging, load curtailment or demand response techniques using smart meters. Information about the EV load charging and battery size information can be used for: i) estimation of the dynamic load response at specific time; ii) prediction of the load response based on future scenarios without having to perform field tests or measurements [20]. The aim is to monitor the time variant response of the network. For instance, large number of EVs connected simultaneously in the network can change the load demand requirement of the network which is considered for the network performance analysis. The network performance indicators like voltage level and Voltage Unbalance Factor (VUF) are used in this work to complement the distribution network response. The methodology for Optimal Power Flow (OPF) presented in the second part of the thesis can easily be replicated to other distribution network with inclusion of other network performance indicators like stability and losses. This thesis does not include economic analyses to incentivize or reduce cost. This thesis considers the recent incentives given to DSO, by UK/Irish government while participating in Delivering a Secure, Sustainable Electricity System (DS3) program.

1.5 Aim & Objectives

Most governments of the world are planning to reduce Green House Gas (GHG) emission. There are three main energy sectors that contributes GHG emissions namely, generation, agriculture and transport. EVs have less CO_2 emissions and electrification of transport sector is one way to reduce the GHG emission quickly and effectively. This work explores the potential of electrification of the transport sector and its impact on the distribution network. The main aim of this work is to analyses *the impact of higher penetration of EV chargers in the distribution network*. This thesis deals with the EV charger integration issues at the distribution level, particularly, the challenges and opportunities for the distribution system operator (DSO). The mitigating solution focuses on the methods and requirements for EV charging without any flexibility to assist the system operation and investigates the issues arising in practical/dynamic implementation. In this thesis, the studies are performed on an Irish residential low-voltage network. The primary research questions this work seeks to answer is: ***How can grid response associated with high capacity electric***

vehicle chargers be mitigated for secure system operation? The objectives of the research are given as follows:

- To identify the operational challenges that proliferation of EVs leads to the power system as well as the potential opportunities of EV charging through literature survey, distribution grid modelling, and simulation of various scenarios.
- The realistic modelling of LV distribution network, to analyse the impact of different EV charging levels scenarios.
- The creation of probabilistic load flow using Monte Carlo Simulation (MCS) approach to analyse the different EV charging level
- The creation of high-resolution profiles for loads and EVs to carry out time-series analysis.
- The development of a methodology, to reduce the impact of future EV charging and mitigating it through D-STATCOM.
- The identification of the main cause of technical problems in distribution network.
- The development and implementation of potential OPF solutions to increase EV penetration levels in distribution network.

1.6 Research Methodology

The research questions are based on future scenarios of EV charging, which requires new infrastructure as well as public interest in new technologies for EV charging. Currently, the proliferation of EVs are not significant in number and performing real experiments is not representative of future technology engagement ambitions. Instead, computer-based simulation scenarios are generated to explore the research questions. The research is thus based on future energy management scenarios relating to Ireland. However, the techniques used in this work can be applied to other parts of the world.

In the research questions considered here, there are many engineering and economic challenges that need to be addressed before the simulated scenarios can be implemented. For instance, the implementation of smart grid technology and suitable market tariff structures. These issues are not addressed in this work; rather, the focus is on evaluating the performance of network for managing variability in the charging of EVs.

The recent trend of increased dispersed load/generation in distribution networks will require new rules to maintain distribution network stability. New grid codes will evolve because of these new connections and their contribution/impact on the network. As illustrated in Fig. 1.3, the research has a broad scope that involves the synergetic consideration of wind/solar renewable energy in conjunction with storage options including the possibility for EVs to support the resource intermittency through controlled reactive power compensation.

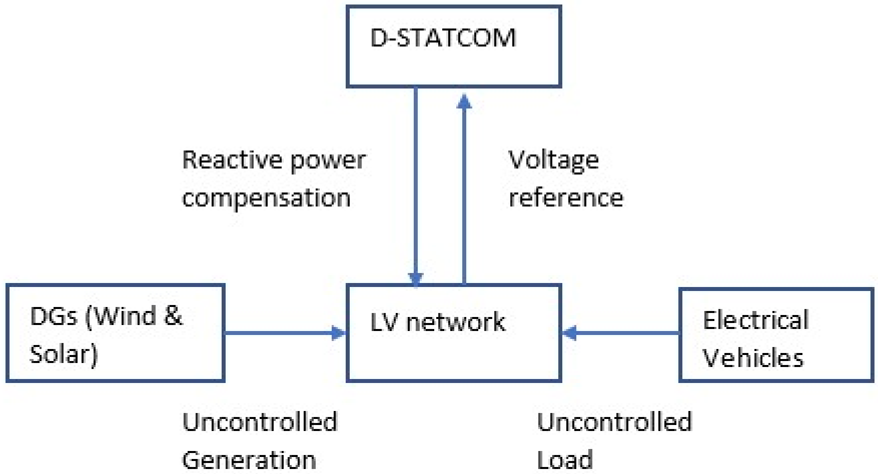

Fig. 1.3: Synergetic consideration of Wind/Solar Renewable Energy and Electrical Vehicle

The detailed methodology contains the assessment of impact of EV chargers and corresponding mitigating solutions on distribution network. This methodology can be summarized as follows:

- First part contains the detailed modelling of distribution network, then integration of EVs and household loads in the network. The Monte Carlo based approach is used for probabilistic impact assessment. It can facilitate the management of complex nature of EV charging in the EV load models. For each individual power flow calculation, locations and profiles of EV load are randomly allocated using appropriate distributions. The corresponding impact metrics are then quantified and stored for the simulation. The results provide key information about the performance of network at different EV charging scenarios. It provides an approach that will enable the network operators to determine the hosting capacity of the distribution network. This can be used by system operators as a preliminarily estimate method to assist the impacts of EV chargers on the distribution network.

- Second part allows the assessment of potential mitigation solution (i.e., D-STATCOM), making it possible to compare impacts and solutions under the different EV charging scenarios. It is important to highlight that, although the methodology is general enough, the results presented in this thesis are only related to the particular distribution network under analysis.

1.7 Thesis Structure

Chapter 2 outlines the general context of the research, the role of LCTs to reduce GHG emission and a summary of the technologies expected to play an important role in the transition away from fossil fuels. It presents the argument that increasing EV is an essential step towards reducing GHG emission, and hence it is important to address the technical challenges presented by these technologies.

Chapter 3 describes the network modelling, EV and household loads considered during the course of the research. The input data for Monte Carlo based probabilistic impact assessment approach is created. Later, the methodology of the Monte Carlo simulation used throughout the thesis. Finally, the simulation platform on which the Monte Carlo method is implemented is described. Results identifies several key metrics for evaluating the performance of any given energy scenario.

Chapter 4 provides an overview of a generalized D-STATCOM, dedicated to maintaining power quality throughout the network, at varying levels of EV charger. Dynamic STATCOM operation is investigated, within a realistic representation of the Irish network. Also, some evaluations on installing STATCOM inside the network, including 2 different levels of EV charger for worst-case scenarios with uncontrolled charging are considered.

Chapter 5 discusses the Particle Swarm Optimisation based load scheduling methodology which is developed to maintain the voltage stability of the distribution network.

This chapter extends the utilisation of D-STATCOM to obtain the voltage stability in the network.

1.8 Contribution

The main contributions of the research presented in this thesis are in the area of probabilistic demand profiling and its integration to optimal load flow. The research presented in this thesis makes the following original contributions:

- A review of Irish energy consumption, in the context of how transport can impact on energy policies for decarburization.
- This work combines the topology of the Irish distribution network and uses data to predict the influence of vehicle charging on the legacy grid.
- A critical overview of data analytic methods, including pioneering use/discussion on use of probabilistic data mining in power system studies and their possible applications in distribution system studies is provided followed by an illustrative methodology of probabilistic data mining application for distribution network asset management.
- A comprehensive overview of probabilistic requirements for present and future power network studies and network operation is given, with a special focus on the distribution network.
- The introduction of several future energy charging scenarios for electric vehicles, with an evaluation of their performance.
- A probabilistic based simulation framework for evaluating the relative effectiveness of high-power EV chargers in a real representation of distribution network is used.
- The proposed framework provides leverage to the DSO in predefining penetration levels of new EV charger installation with respect to existing assets.

- The identification of issues related to using high-power EV chargers, a potential solution (D-STATCOM) and its use.
- PSO based optimal power flow approach is used to improve voltage stability throughout the distribution network.

1.9 List of Publication

- Zaidi, A., Sunderland, K., Coppo, M., Conlon, M. & Turri, R. (2016).,"Reactive power control for smarter (urban) distribution network management with increasing integration of renewable prosumers" , UPEC16: 51st International Universities Power Engineering Conference, March 6-9 ,Dublin Institute of Technology (DIT), Ireland.
- A. H. Zaidi, K. Sunderland and M. Conlon, "The Potential for Power Quality Problem Mitigation Through STATCOM (BESS-STATCOM)", 2018 20th European Conference on Power Electronics and Applications (EPE'18 ECCE Europe), 2018, pp. P.1-P.9.
- Zaidi, A.H., Sunderland, K., Colon, M., "Role of reactive power (STATCOM) in the planning of distribution network with higher EV charging level", IET Generation, Transmission & Distribution Journal 2019, 13, (7), pp. 951–959
- Zaidi, A.,Sunderland, K. & Conlon, M. (2020), "An impact assessment of high-power EV charging proliferation of a Distribution Network", IET Generation, Transmission & Distribution Journal, 2020, Vol. 14 Iss. 24, pp. 5918-5926. DOI:doi: 10.1049/iet-gtd.2020.0673

2. Low Carbon Technologies

Climate change is the main global issue faced by humanity. Most of the countries are committed to reduce GHG emission in terms of national and international policy documents to limit global warming and GHG emissions. Globally, the main sources of GHG emissions are from electricity generation and transportation sectors. In 2010, the energy supply sector emissions amounted to 35% of global GHG emissions [21]. In 2015, the European Union (EU) agreed to adopt the Paris Agreement [21]. Every member state is required to address climatic change and its impacts through legally-binding nationally determined contributions (NDCs). NDCs requires adopting measures to limit global warming to well below 2°C. It further discusses the commitment from EU member states to reduce GHG emissions by at least 40% in 2030 compared to 1990 levels [22]. The reduction of GHG emission requires the deployment of LCTs in electricity generation, heating and transportation [23]. In the 2019 EU progress report, renewable energy accounted for 17% of the EU's total final energy consumption, and the aim is to reach at least 27% by 2030. Report further suggest EU is planning to ban diesel completely by 2050.

The Irish Government published the climate action and low-carbon development national policy position in April 2014, committing Ireland to an 80% aggregate reduction in Carbon Dioxide (CO_2) emissions in the energy sector on 1990 levels - from 38 million tonnes in 2017 to just over 6 million in 2050 [24]. The Government white paper on Ireland’s transition to a low carbon energy future 2015-2030 underlines the target to reduce CO_2 emissions from the energy sector by 2050 [25]. Furthermore, the targets are updated in 2020 [25]. Reducing GHG emissions from the energy system by 80-95% by 2050 will require the share of fossil fuels to be of the order of 19-30% of final energy demand [25]. It is worthwhile to mention that the demand of massive data centres in Dublin region has increased rapidly in 2021. EirGrid (TSO) said, it expects data centres to account for 15% of total energy demand by 2026 – up from less than 2% in 2015.

The Central Statistics Office (CSO) projections suggest the Ireland's population will grow from just over 4.98 million as of April 2021 - to 5.2 million in 2031 and 5.6 million by 2051 [26][27]. The elimination of GHGs cannot be achieved through energy efficiency and renewable energy sector alone. It requires a complete change in the way energy is consumed. Particularly, sectors that contribute more such as the transportation sector. The transportation sector is in a transition phase towards electrification but requires significant financial investment. The priority can be provided to the sector that can reduce the emissions meaningfully. It seeks to minimise the risk of stranded assets by looking at the probable shape of our low carbon energy system in 2050 using technologies that exist today and moving towards this in our plans with a "low regrets" series of options [24]. Transport and Electricity generation sectors, together account for just over 50 per cent of total GHG emissions in Ireland.

2.1 Introduction

Irish government published a plan for a long-term decarbonisation pathway for the Irish energy system leading to a reduction in GHG emissions by 80% - 95% on 1990 levels by 2050. The majority of GHG emissions in Ireland are from the agricultural sector (33%). The mitigation of emissions will be costly since no technology currently exists to address methane emissions from the agriculture sector. Methane (CH_4; with a greenhouse gas weightage) reached a preliminary record high value of 1869 parts per billion (ppb) in October 2018 [28].

Statistics show Ireland has the worst housing standards in Europe in terms of insulation, heating and energy efficiency. Poor insulation leads to increased use of heating or cold indoor temperatures that can potentially lead to health problems [29]. Although the government provide subsidies to retrofit older houses with better insulation, stricter regulations for new buildings are also being introduced. Ireland has a high rate of car ownership, 454 passenger cars out of 1000 habitants, due to inadequate public transport infrastructure [30].

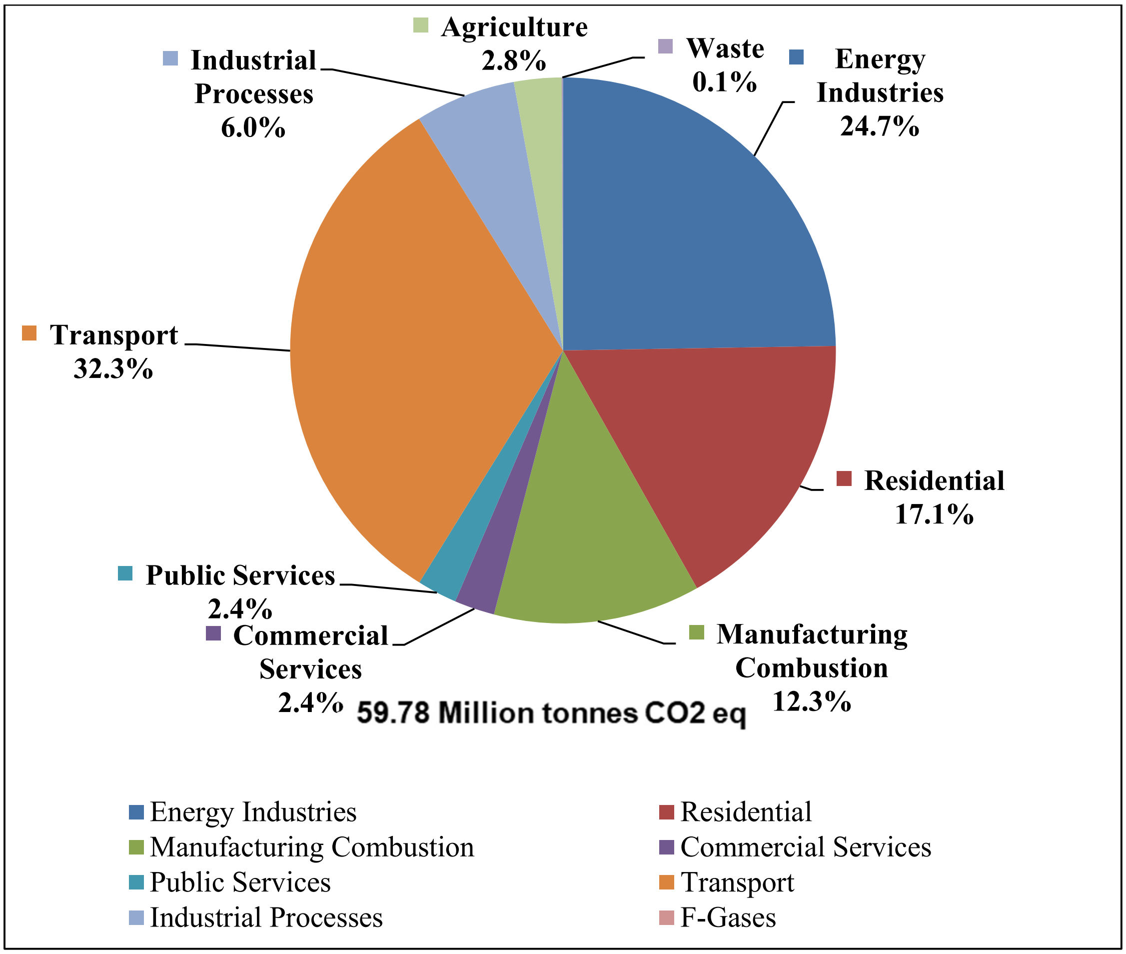

Fig. 2.1: Total greenhouse gas emissions in Ireland in 2019 [31]

As illustrated in Fig. 2.1, the present GHG is approximately 60 $MtCO_2eq$ each year. This needs to be reduced to just above 6 $MtCO_2eq$ per year. A total emission level of 6 Mt is around one-third of 2019 transport emissions as shown in Fig. 2.1 and Fig. 2.2. It shows that the extent of the task is huge; it cannot be reduced by only targeting one sector, and a long-term strategy is required to achieve the target in the time frame.

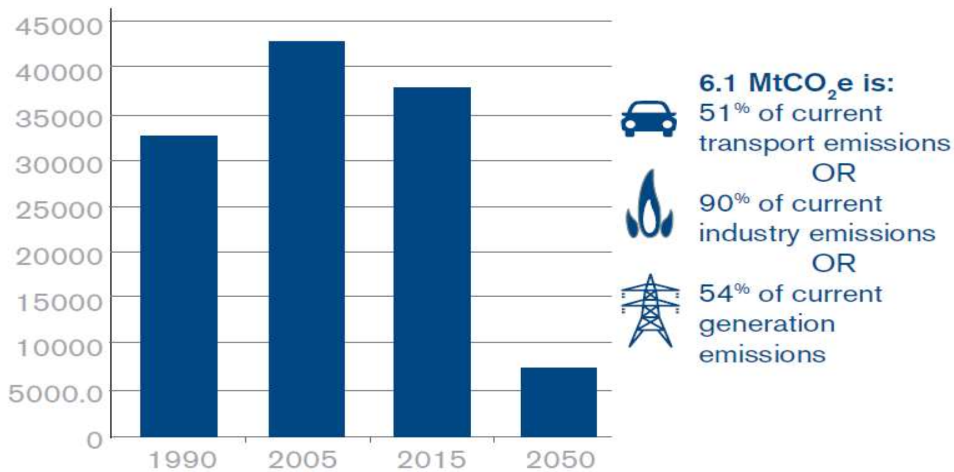

Fig. 2.2: Total energy sector emissions target in perspective (ktCO_2e) [24]

To reduce the GHG emissions, it is vital to first evaluate where the energy is used. Energy consumption in Ireland is illustrated in Fig. 2.3 based on data presented in SEAI 2019 Energy Balance [32]. The Energy consumption across three main categories are presented namely, Work, Transport and Home.

Transport is the largest of the three consumption sectors accounting for 40% of final energy consumption. A quarter of energy is consumed in the home, and the remainder is consumed in 'work' (a combination of industrial, commercial, public sector and agriculture). Only 20% of the total demand of these sectors are fulfilled through electricity. Fig. 2.3 also show that transport sector only utilizes 1% of electricity. The transport sector is one of the major contributors to the GHG emission. If Ireland must meet the energy policy requirement, electrification of the transport sector is necessary.

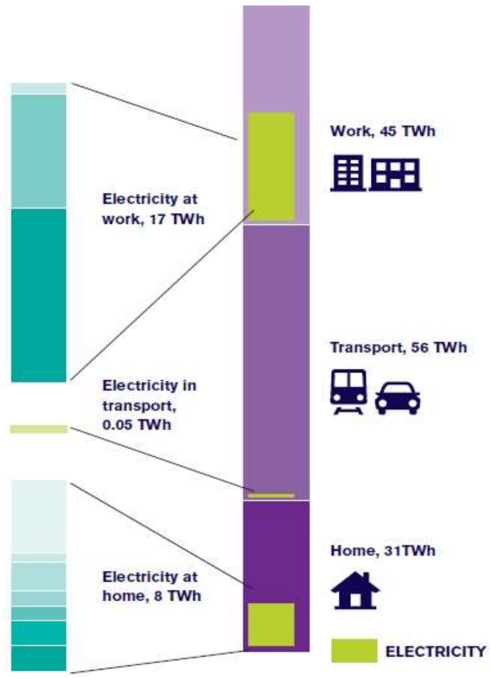

Fig. 2.3: Energy Consumption [24]

2.2 Overview

Over the last decade, cities are becoming engaged in strategic energy developments and availing of the opportunities therein to contribute towards achieving energy policy goals. Cities consume more than 70% of the world's energy requirements and produce more than 60% of the total GHG emissions [33]. If low carbon emissions are to be achieved, cities need to transform towards smarter infrastructures; networks that can generate and deliver electricity in a predictable manner from renewable energy sources.

The distribution system is transitioning towards a lower-carbon energy future. Ireland utilises 32% of its electricity needs from renewable sources in 2019 [34]. In 2021, the installed capacity of wind generation reached upto 4,489 MW on the all-island system [35]. ESB Network's initiative over recent years has resulted in more than 1,500 electric vehicle fast charging points being provided in public places. According to the Climate Action Plan 2018 report, it was suggested that to meet the emission level by 2030, the total number of

EVs required are 936,200, comprised of 840,000 passenger EVs, 95,000 electric vans and 1,200 electric buses [2]. The report further suggested that, to give people confidence to switch to EVs, over 90 high powered chargers have to be installed at key locations on the national road network with installation of 50 new fast chargers and replacement of over 250 standard chargers by 2025. A lot of this has been achieved by the end of 2020. Over the next five years, it is envisaged that the domestic and small business metering customers will be replaced by new smart meters which will allow electricity suppliers to apply time varying charges for electricity.

The adoption of LCTs at domestic level is increasing and is expected to rise furthermore in the coming years. These residential consumers are connected to low voltage (LV) distribution networks (230 V phase to neutral), and therefore the impacts of LCTs first appear on low voltage distribution network. The integration of a large amount of LCTs into the LV network can result in power quality issues such as voltage swell and sag, overloading of cables and/or transformers. Unfortunately, the extent of technical problems has not been researched deeply because DSO traditionally follow a *"fit and forget"* approach at distribution level [36]. In the past, this approach was sufficient because of the passive nature of the network (demand and diversity do not change drastically). However, the network is evolving into one with a pro-active nature [36]. Nonetheless, this historic framework is challenged by the adoption of LCTs. For example, EVs batteries are likely to encounter increased peak demand whilst the photovoltaic (PV) systems penetration could result in significant bi-directional power flows

2.3 Review of the Past Work in the Area

As previously mentioned, one of the requirements for successful integration of LCTs in the distribution network is to observe the power quality issues. Previous studies carried out in this field provided key information in this respect.

2.3.1 Proliferation of Photovoltaic Systems

This section summarises some of the studies undertaken in Photo Voltaic (PV) integration in distribution networks. At the residential level, penetration of distributed generation in LV networks is limited by the bottleneck presented by voltage variation and overloading of the network. The distribution system operator (DSO) provides guidelines and restrictions in terms of the percentage of penetration allowed for all technologies in the distribution network. In an Irish context, the DSO (ESB Ireland) allows limited penetration of the LCTs in distribution network.

In general terms, the studies are performed on Spatial (no-time-series simulation) and temporal (Time-series simulation) characteristics. The snapshot analyses on the adoption of PV in each house in the MV feeder under analysis is also used in [39]. It is noted in the literature [40], the hourly time step is utilised to estimate voltage profiles and voltage unbalance factor (VUF). In [41], the results suggest 15% of customers would have a voltage problem at 70% PV penetration, when considering 5 minutes time resolution and 4% when 60 minutes time resolution. It is sufficient to demonstrate that higher resolution dataset is required to understand the complete importance of power quality problems. Implementation of high-resolution data up to 5 minutes are utilized by other authors in LCT penetration in distribution network [41][42].

In [43][44], a Danish Network was analysed and the results suggests that the voltage magnitude is increased while uncontrollable DGs (PVs) are connected in the network. In [44], high penetrations of PV causes a voltage rise in the network resulting in voltage level breaches. In [45], a UK LV network was analysed with unbalanced load flow, having half of the total household with PV penetration. The voltage variation was observed up to 2V, and loading was unaffected. No considerable impacts were identified in this study. In [46], LV network was considered with varying PV penetration. A Static VAr Compensator (SVC) was proposed based on an economic study, to ensure voltage variations remain within limit. Based on the literature, the high penetration of DG (PV) in the LV network, cause significant voltage variation in the LV network. In [44], a Danish LV network is considered wherein, voltage variation occurred as a consequence of single phase connected PV and EV. It was observed that, on occasion, voltage breaches in excess of 1.10 p.u (upper limit of voltage tolerance for the DSO) occur. The author discusses the engagement of active and reactive control strategies to control the voltage variation. In [47], a Belgium LV network was considered and the voltage unbalance factor was observed to be increasing with PV penetration. To summarise, the authors highlighted the following possible impacts of PV in LV network: reverse power flow, voltage rise, voltage sag, voltage fluctuations, voltage imbalance, transformer loading and power losses increase.

2.3.2 Proliferation of Electric Vehicles

Maintaining the voltage level with increasing and unpredictable load will be a challenge for DSO in the future. Increasing environmental friendly policies, such as the incentives being offered by SEAI, where grants of up to €5,000 for a Battery Electric Vehicle (BEV) or a Plug-in Hybrid Electric Vehicle (PHEV) purchased and registered in Ireland [48] are being supported. EVs will account for 11.7% of light vehicle production by 2030 - up by 1.9% compared to 2019 or just 0.23% of new car sales in 2015 [25]. Indeed, the number of EVs are expected to increase in near future. With this in mind, coordination between network and load demand is essential, in order to sustain power quality (PQ) standards currently being assured by ESB Networks (Irish DSO) in the context of power flow management.

Electric transportation, including Electric Buses (EBs) and Electric Vehicles (EVs) is one of the important measures for greenhouse gas reduction. According to the 'Zero Emission Urban Bus System Project' statistical data, collected from 19 public transport operators, covering 25 European cities, was published in Electrical Bus (e-bus) strategy for 2020 [49]. More than 2,500 electric buses operate in the cities, representing 6% of their total fleet of 40,000. However, the potential for electrical transport to reduce greenhouse gas emissions depends on the nature of electricity generation, used to charge transport batteries. Although, integration of EBs in the distribution network is likely to be increased in the near future, however, for the sake of simplicity, only EVs are considered in this work. Energy demand is increasing, particularly in urban areas. So along with the potential for the mass penetration of new technologies such as electric transportation and micro-generation, the power quality associated with distribution networks is likely to be affected. Promoting EV use in urban environments has practical implications around electric grid capacity for mass EV charging, as the increased capacity required by a mass uptake of EV will require significant infrastructure investment to upgrade the existing grid supply. In this work, electrical transportation only considers electrical vehicles in the distribution network.

Most of the EVs will be charged at home and as a result, will put stress on distribution networks. Hence, most of the studies referred in this thesis analyses the impact of single-phase EV connections (i.e., slow charging and fast charging) on distribution networks. EVs can be divided into two main categories.

- Battery Electrical Vehicles (BEV) which only uses battery as a source of energy.

- Plugin Hybrid Electrical Vehicles (PHEV) which derives power from a combination of battery and Internal Combustion Engine (ICE).

Travelling requirements of passenger cars are considered to design more realistic EV battery load profiles. In general, slow charging (3kW) can take approximately eight hours to fully replenish an EV battery from empty. Fast charging (7-22kW) will take around three to four hours to fully replenish an EV battery from zero charge [50].

The normal battery size is 20 kWh but recent advancement in EV battery size suggest 52 kWh batteries are available in the market [51]. Electrical Bus battery size goes up to 200 kWh [49]. It is practically possible to convert PHEV to BEV completely. If BSoC is approximately 0%, it is not practically possible for frequent EV users to connect 40 kWh battery for 10-12 hours with 3.68 kW single-phase charger [52]. So, an alternative faster rate of charging is required at the domestic level. Fast rate of charging and their impact on distribution network is discussed later in Section 2.6.

In the last two decades, a significant amount of research has been carried out to analyse the impact of EVs on power systems [53]–[56]. The power quality issues are taken into account in [57]–[60]. The studies can mainly be divided into two categories: Controlled and Uncontrolled Charging. In [53], controlled and uncontrolled charging are considered. Although one-hour resolution data is analyzed, the study is limited to power flow analysis. In [54], an optimal dynamic charging method is proposed observing power grid thermal ratings and voltage quality. In [57], the feeder daily load models, electric vehicle start charging time, and battery state of charge are considered in the analysis. Distribution operation security risk information, such as over-current and under-voltage, is obtained from three-phase distribution load flow studies. Stochastic parameters are obtained from Roulette wheel selection [57]. The Roulette wheel selection concept and Monte Carlo simulations are used to take various uncertainties into account based on driving pattern and battery state of charge. The capability of providing security risk information by the deterministic and stochastic analytical approaches is compared and impacts due to a controlled and uncontrolled charging are analysed. In [58], the probabilistic harmonic simulation method to study the power-quality impact of electric vehicles is considered. The proposed method takes into account the random operating characteristics of the vehicles, such as random charging time, charging duration, and vehicle locations. The Monte Carlo simulation method has been employed to identify EV's impact at both fundamental and harmonic frequencies. The results suggested the EV chargers have negligible harmonic impact on power systems. It is therefore necessary that the need for essential reinforcements to the network and substations would be analysed prior to the large-scale EV penetration. In [60], Voltage deviations in terms of under/over voltage and voltage imbalance are probabilistically analysed using Monte Carlo simulation. Moreover, distribution transformers overload and unbalance are assessed for different EVs. In an Irish context, the Richardson method [61], studies uncontrolled charging and centralised controlled charging. In particular, uncontrolled charging was analysed in [62] by the same author. The network under analysis was a representative LV feeder with 134 customers, and the time step considered for the simulations was 15 minutes. Only a 15% penetration level was possible with uncontrolled charging. In contrast, the maximum penetration level studied (50%) was possible with the controlled charging approach.

2.3.3 Potential Solution

Another prospective solution is on-load tap changer (OLTC), although, in Irish/UK distribution networks, OLTC's are not commonly used. OLTC are able to mitigate only the voltage problem. So, any prevalent voltage unbalance factors, exacerbated by single-phase distributed load/generation connections, remains an issue. In [63], decoupled OLTC control was proposed to increase the hosting capacity of PV from 20%-70%. The results were promising but voltage unbalance factor (VUF) remained between 2-3.5%, which is relatively a high value. (VUF needs to be less than 2% for 95% of the time). OLTC control is not able to reduce the voltage unbalance factor, which is ultimately a pre-requisite in increasing Low carbon technologies (solar, wind and EV) penetration/ hosting capacity in the distribution network. OLTC control are slow response device.

Another prospective solution is PV inverter dispatch of reactive power. In [64], reactive power support is proposed based on inverter ratings. Although only limited reactive power support is possible due to the power rating of the inverter, additional power losses and importantly due to limited reactive power support, there is a small effect on voltage profile. In [65], a hybrid voltage scheme based on real and reactive power management embedded with centralized OLTC is discussed. The results are quite promising but the effects of reactive power are limited and not all distribution level transformers are equipped with OLTC functionalities. OLTCs have, in some instances, failed to correctly regulate voltage as a consequence of the line-drop compensation used, which assumes no reverse power flow [66]. Finally, the slow response time of OLTCs is considered a significant drawback by some authors.

Previous studies have dealt, to an extent, with the influence of low carbon technologies on voltage stability in the distribution network. Authors in [67] considered preventive voltage control (PVC) to improve short-term voltage stability. In this study, load was modelled as static and dynamic, and the author does not use demand side management for curtailment of voltage level. D-STATCOM was used, which is an effective but expensive dynamic var compensator in distribution networks, which was installed at the starting busbar and three different reactive power capacities were used, namely, 80 MVAr, 100 MVAr and 120 MVAr. D-STATCOM with 100 MVAr power rating, was used to control the voltage level. The study fell short of finding the optimal location of D-STATCOM in the network at different loading margins. Similarly, [68] examined how demand side management (DSM) can affect the estimated voltage stability margin by considering different load models. Authors used a multi-objective optimisation. The objective function included: generation scheduling, voltage stability margin and load margin. The only shortfall of the study was that it required a communication protocol between customer and distribution system operator to implement practically. The other notable study [69], voltage stability index was used to find the optimal location and bat algorithm is used to find the optimal size of a D-STATCOM. Bat algorithm is a metaheuristic algorithm for global optimization. The objective function included: power loss minimization, cost, voltage drop, voltage stability margin, network loss. The method discussed is applied to a 33-bus radial distribution system and the results are compared with other heuristic methods. The proposed approach is tested with different loading conditions of the network including peak load. The response of the D-STATCOM is tested on light, medium and peak loads. A single and multiple D-STATCOMs are considered. The result indicates that the power rating of D-STATCOM is the optimal solution in terms of different loading conditions [69]. The results provide indication that the reactive power rating requirement of distribution network is less than 1.1 MVAr. The shortfalls are the demand-side flexibility was assumed, but not clearly evaluated. The criteria for shifting different load types were not defined. In [70] a detailed literature review about the FACT devices that are utilised in distribution networks is presented. The paper uses Genetic Algorithms (GAs) for integration of various types of Distributed Generation (DGs), involving Static Synchronous Compensator (STATCOM) and PHEVs with different static load models (DSLMs). A STATCOM is utilised to maintain the power factor in the network. The power rating of the STATCOM required to maintain the power factor is not discussed. The physical testing of the D-STATCOM is presented in [71]. A 500 kVAr D-STATCOM is installed in an industrial environment with significant abrupt loads changes causing voltage deviations. The D-STATCOM simulation have verified through laboratory tests - based at distribution level, voltage level upto 400V and frequency level of 50 Hz [72]. In [66] D-STATCOM voltage control structure is proposed and an impedance estimation algorithm is proposed to tune the controller gains in order to achieve the desired voltage level. The voltage unbalance factor is not considered in the analysis. From a UK/Irish perspective, the experimental validation of dynamic response of D-STATCOM to maintain the voltage level are discussed in [66][72]. The model was tested in the University of Nottingham. The paper establishes that D-STATCOM can maintain voltage level in the network and can be installed in the existing network configuration.

2.3.4 Load Modelling Approaches

In the absence of real measurements, probabilistic approaches are taken to model demand composition. In [73] Markov chain based Monte Carlo approach was used in to derive individual residential load profiles. The authors use the concept of polynomial/ZIP load, it is commonly use to illustrate the temporal variations in load profiles. The 10,000 different customer loads are aggregated based on ZIP load model equations. The accuracy of the approach, however, was not compared with the actual measurements. In [74], the electric vehicle impact assessment trial currently being undertaken in Dublin, Ireland. The trial involves investigated electric vehicles were driven and charged by typical residential electricity customers. The data recorded during the trial details the charging patterns of the vehicles. The EV trial data are presented in [62] are tested against actual measurement, the data is presented in probabilistic distribution function of the daily energy requirements of the EVs recorded. Each EV had a battery capacity of 20 kWh. The most common daily EV energy requirement was between 8 kWh and 9 kWh, approximately half of the rated battery capacity of the EVs [62]. The probabilistic distribution function presented in [62] are used in the thesis. The EV load profile are further discussed in Section 3.2.3

In [68], the ZIP load model is considered to define controlled and uncontrolled load margin. (*Z* is for impedance, *I* is for current and *P* is for power). Load at each individual network bus is represented using a realistic composite load model comprising controllable and uncontrollable loads. The demand side load management is proposed based on optimal power flow calculation to ensure that the voltage stability throughout the network.

2.3.5 Different Approaches to Estimate Technical Issues

The integration of LCT can cause significant stress on the network, it can lead to power quality issues. In a broader term, the researchers analysis of these issues is based on two approaches: Probabilistic and Deterministic approaches.

In [15], the hosting capacity of existing assets is defined based on the penetration level of EVs, however, the work does not consider the voltage unbalance factor. Based on the analysis and results presented in this work, the author asserts that voltage level and VUF are the primary concern. In [6], the grid voltages are analysed according to the probabilistic and deterministic limits of the EN50160 standard, for a 100% EV penetration rate. A scenario-based modelling approach is considered. The voltage unbalance factor is calculated and presented. However, the result doesn’t replicate the probabilistic facilitation of hosting capacity. In the deterministic approach, it is not possible to appreciate how many customers are going to be affected by different EV penetration level.

In [75], the steady-state time-variant proliferation of EVs are considered in the analysis, to estimate the critical number of EVs that can be integrated in a distribution line. The hosting capacity of an existing asset is not defined based on the penetration level of EV.

All the studies [15], [57], [75]–[77] consider probabilistic and deterministic approaches to provide planning models of the distribution network. In this chapter, the author proposes an approach using predefined penetration levels for EV chargers and how much EV charging can impact the existing assets. The hosting capacity of existing assets based on the percentage of customers can be affected.

In the past, researchers also utilized a combination of deterministic and probabilistic approaches to appreciate the technical issues that arise from the low carbon technologies integration in distribution network [15][78][79]. The summary of modelling approaches used to estimate the technical issue is presented in Table 2.1. There are two common approaches adopted by different researchers. However, there is general trend in researcher's approaches. Most of the researchers are using deterministic approaches with the random selection of input data profiles [76][80]. A probabilistic approach is used with estimation techniques like Monte Carlo Simulation, Point Estimation Method [15][42], [81], [82]. All the researchers used these techniques to estimate the performance of the distribution network.

Table 2.1: Summaries of uncertainty modelling applications

Applications	Deterministic approach	Probabilistic approach
Voltage drop	[15], [76], [78], [79], [83]	[15][43], [61], [77]–[79], [82], [84], [85]
Voltage Unbalance Factor	[76]	[82], [86], [87]
Optimal time of charging	[15]	[61][15]
Hosting capacity	[15], [79]	[79], [84], [88]
Cost estimation	[83]	[77] [46]

Based on the literature review, PLF analysis can be divided into three main categories: Monte Carlo simulation (MCS) based method [89], analytical methods [90][91] and estimation/approximation methods [92]. Monte Carlo simulation (MCS) is widely used for planning purposes. It does not involve any sort of approximation during solving of power flow problem. MCS method based on the repetitive iteration of the random input variable until it converges. The simulation computation time and storage are the main pitfall of this method.

The probabilistic load flow technique can give relatively accurate results. On the other hand, a potential disadvantage of the method is that the result is meaningless if the probability distribution of the input values and the range of mathematical modelling are not accurate. Monte Carlo simulations can become very time-consuming. The time to compute the outcome of a scenario will increase as the complexity of the used model increases. Besides, it may take a large number of scenarios to keep the uncertainty of the final results within acceptable levels [93]. To reduce the number of scenarios per simulation it is possible to use so-called variance reduction techniques [93].

2.4 Electrification of the Transport Sector

The transport sector electrification is essential for meeting the European Union goals of decarbonisation and energy security, as it accounts for 25% of all CO_2 emissions in Europe [94]. As shown in Fig. 2.2, all sectors need to contribute to the low-carbon transition in order to meet the target. In an Irish prospective CO_2 emissions from transport could be reduced to more than 60% below 1990 levels by 2050 [95]. Due to a lack of maturity of energy storage technologies, as well as lack of infrastructure investment, electrification in the transport sector is unlikely to achieve significant reductions prior to 2030. Currently, in Ireland, results suggest only 2.6% of transport sector able to transform on electricity [8]. Although, the government plans for 90% of transport sector to utilize electricity with current rate of progress it is highly unlikely to be achieved.

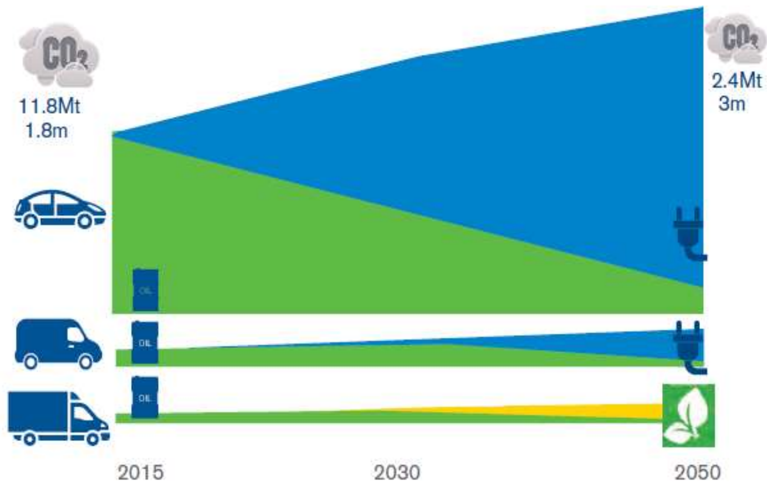

Fig. 2.4: Electrification of Transport sector roadmap [24]

To achieve 80% energy emission reductions the following actions across the transport sector are required:

- The transport sector sees a transition to a passenger vehicle fleet that is ***90%*** electric vehicles in 2050.
- The share of oil, the most carbon intensive fuel, in the country's energy mix must be drastically cut by 2050, falling from around 55% today to 5% by 2050.
- Electrification will have to be at the heart of the transformation in the road vehicle sectors.
- Deployment of new technologies such as electric vehicles will need to accelerate in the coming decade if there is to be any chance of meeting targets.

2.5 Electric Vehicle Battery

Currently, electric vehicles have not met mainstream acceptance because of high costs, limited house charging points and long "refuelling" periods and limited travelling distance, and concerns about electricity infrastructure requirements. This section explores the current state of EV technology, trends, and concerns.

EVs are the clean form of transportation, Tailpipe emissions from EVs are zero but the emission does occur elsewhere, as a result of proliferation of EV, including electrical generation used for charging of EVs. When LCTs are used for electric generation and utilized in EV charging, reductions of 60% are expected.

The main drawback of EVs are associated with charge storage and capacity of the battery. For instance, the purchase cost, long charging periods, and limited distance range. The energy storage of EVs falls into four main categories; batteries, ultra-capacitors, hydrogen fuel cells, and hybrid systems [96]. The transportation sector mainly uses batteries as a storage technology. Batteries, primarily lithium-ion based, are the dominant form of storage device, while hydrogen fuel cells are not yet commercially competitive. Recent advancement in battery technology in terms of small size and higher charge storage capacity have occurred but then still suffer degradation through repeated charging and discharging cycles and have limited power handling ability. Ultra-capacitor technology offers low degradation with repeated charge and discharge cycles, but have a very low energy storage capacity [96].

2.6 Charging Consideration

The best EV charging method still remains an open question. Different charging approaches are based on tariff variation, the degree of convenience, charging times, driving range, and infrastructure requirements. The different EV charging levels are discussed below.

2.6.1 Domestic Charging

Most of the time, EVs may be charged at a household LV network level, with a 3.68 kW connection being feasible for Irish houses, or 2.3 kW requires no modification to existing wiring, Some houses may only be able to accept the 7.2kW charger, provided that not all households charge vehicles at the same time [48]. It is expected that 85% of all charging requirements can be met during overnight hours at homes [96], while the other 15% of charging will occur sporadically throughout the day [96]. The average distance passenger cars travel in Dublin is 15 km/day [97] and such distances require 34.5 minutes or 2070 seconds to charge on daily basis at 3.68 kWh/single phase charger in Table 2.2. Domestic charging can impact existing electricity peak demand, putting more stress on distribution infrastructure. While domestic charging is convenient for most vehicle travel, it is not well suited to longer trips away from home.

The standard charging profiles considered are presented in Table 2.2. The first column presents the distance that an EV car can travel (in kilometers) before it requires recharging. The second column presents the power consumption of battery during travelling. The third, fourth, fifth and sixth columns indicate the time duration required to charge the EV battery completely with different types of chargers. The amount of charging energy required by the vehicle to travel the desired distance is presented therein. If one assumes that a car travels 10 km, it will therefore, require 1.4 kWh of energy and '*3 phase 230V-16A'* charger can provide it in 8 minutes. EV capability to provide initial state of charge (SOC), active power support is based on time duration that the car is connected to the network. A 'Single phase 230V-10A' charger can charge (in respect to this 10 km) in 37 minutes. It can be noted from Table *2.2*, the time required to charge a 42 kWh battery, with single-phase charger is 11 hours and 30 minutes. It suggest that overnight charging is adequate.

Table 2.2: Charging specification of EV [98]

Distance Travelled (km)	Charging Energy (kWh)	230V/10A 2.3kW (hr:min)	230V/16A 3.68kW (hr:min)	3x230V/16 A 11kW (hr:min)	ChaDeMO DC 50 kW (hr:min)
10	1.4	00:37	00:23	00:08	00:02
20	2.8	01:14	00:46	00:15	00:03
50	7.1	03:04	01:55	00:38	00:06
100	14.1	06:08	03:50	01:17	00:12
150	21.2	09:12	05:45	01:55	00:18
200	28.2	12:17	07:40	02:34	00:24
250	35.3	15:21	09:35	03:12	00:30
300	42.4	18:25	11:30	03:50	00:35

2.6.2 Public Charging

Public charging stations utilise high power connections to minimise the time spent charging an EV, 7 kW is most common rating in business applications [96]. It can charge the battery in 10-12 hours, enable a journey up to 300-400km [96]. The nature of fast charging stations will require high power on-demand—likely during daytime hours—leaving little opportunity to control charging rates. However, since the majority of vehicles don't travel long distances on any given day, the demand for fast charging is not likely to be significant if other, charging methods are available.

2.6.3 EVs Technologies Provision to Distribution System Operator

The creation of a realistic model of the distribution network is necessary to get the full understanding of the proliferation of EVs. DSO generally do not produce/replicate these models, mainly due to the passive nature of LV network. Recent advancement in technologies suggests a paradigm shift from passive to the pro-active distribution network. In the past, the DSO follows the fit-to-forget approach in Ireland. But will not be sufficient with high level of prosumers being introduced in the distribution network. The information available at distribution level is mostly very limited and is typically produced for asset management proposes.

Challenges:

- Most of the EVs are connected to the distribution network. It will require significant investment into upgrading distribution capacity and grid strengthening and planning to install additional EV charging stations.
- Grid strengthening will need to be carefully planned in order to avoid overloading of the grid (transformers and cables). Urban and rural areas planning needs to be examined based on future EV intake. Comprehensive planning is required in order to avoid asset and investment mismanagement.
- Transformer loading monitoring is considered essential for future energy scenarios.

2.6.4 Technical Definition & Standards

In this European context, low voltage distribution network refers to an electrical system with a nominal voltage of 230 V between each phase and the neutral. It is also important to highlight the fact that the LV distribution networks investigated in this work, besides being radial and having a 230 V nominal voltage.

The several supply voltage standards are documented in EN50160. It contains detailed descriptions about voltage parameters of electrical energy in public distribution systems. The most important are [99]:

Supply voltage – the rms value of the voltage at a given moment at the point of common coupling, measured over a given time interval.

Nominal voltage of the system (Un) – the voltage by which a system is designated or identified and to which certain operating characteristics are referred. Declared supply voltage (U_c) – is normally the nominal voltage U_n of the system. If, by agreement between the supplier and the user, a voltage different from the nominal voltage is applied to the terminal, then this voltage is the declared supply voltage U_c.

Voltage variation – is an increase or decrease of voltage, due to variation of the total load of the distribution system or a part of it.

Voltage unbalance – is a condition where the *rms* value of the phase voltages or the phase angles between consecutive phases in a three-phase system are not equal.

The EN 50160 indicates the nominal voltage (U_n) in the distribution network is 230 V (between phases and neutral) under normal operating conditions, including situations arising from faults or voltages interruptions [99][84].

- During each period of one week 95% of the 10 minutes mean rms values of the supply voltage shall be within range Un ±10%
- All 10-minutes rms values of the supply voltage shall be within the range of U_n +10%/-15%.
- In cases of electricity supplies in networks not interconnected with transmission systems or for special remote network users, voltage variations should not exceed +10%/-15% of U_n.

Voltage magnitude and voltage unbalance are the concerns associated with power quality in LV feeders with EVs. The unbalanced adoption of EV load (allocated to each individual phases) can lead to increased levels of voltage unbalance in LV feeders. Level of voltage unbalance is dependent on the location, size of the battery and impedance of the feeder.

Supply voltage unbalance is another issue that is restricted by standards [84]. For example,

- Under normal operating conditions, during each period of one week, 95% of the 10 min mean rms values of the negative phase sequence component of the supply voltage should be within the range 0% to 2% of the positive phase sequence component [99].

2.7 Summary

This chapter has provided motivation for a case study involving the high-power EV chargers deployment in Ireland, including an overview of the characteristics of the major technologies likely to be involved in a future energy scenario. The following chapter discusses research related to the widespread deployment of EVs chargers and technical standards, and establishes the course of research to be discussed in the remainder of this thesis.

This chapter provided an overview of the typical EV chargers used in power system studies, mainly focusing on distribution network. Different types of EV chargers and their rate of charging are discussed in detail. One of the most important tasks when dealing with the ever-growing very high rating EV chargers in power utilities is to determine the key level that can integrated at the distribution level. In UK/Ireland, each household is facilitated with a 63A protective device. The analysis demonstrated that it is not feasible to consider more than 11 kW EV charger at distribution level. An overview and critical appraisal of different analysis methods, including load modelling, for application in distribution system studies are discussed in this chapter.

3. Probabilistic Impact Assessment

There is no doubt, that Electric Vehicles (EVs) and renewable electricity generation technologies are expected to play a critical role in reducing GHG emissions and fossil fuels dependence. The widespread proliferation of these technologies will challenge the traditional operation of electricity networks. Renewable generation can introduce uncertainty in electricity generation and EV charging can cause overloading of electrical transmission and distribution infrastructure.

Managing variable load in electricity system is not a new challenge, however, a high proportion of renewable generation and a large number of synchronised high-power loads (e.g. EVs) are difficult to manage [96]. Alternative approaches, such as battery energy storage [100], reactive power support are therefore of increasing interest.

Although trends suggest that 85% of EVs will be charged during night, customer behaviours are changing, for instance, during the COVID-19 pandemic, even small businesses and companies are allowing their employees to work from home. According to statistical data, 15% of total workforce employees, work remotely. In 2025, it is predicted to go up to 42% [101]. It is important to consider trends and customer behaviours in the proposed approach and in this regard, probabilistic approaches can facilitate more accurate estimations.

Majority of researchers estimate the performance of distribution networks in terms of power quality variations such as voltage drop, voltage unbalance, cable loading etc. as previously mentioned in Section 2.3.5. Limited studies have been carried out to quantify the performance of networks in terms of extreme conditions. In terms of research gap/ contribution, the author combines the ***realistic topology of the Irish distribution network*** (Section 3.2.1) and use Monte Carlo Simulation (MCS) to predict the influence of EV charging and power quality variations on the legacy grid. This method aims to assist the DSO in the assessment of different EV chargers' impact on the network. Different voltage metrics are studied, allowing a better understanding of the different EV chargers and their effects on the network. This work can further facilitate novel approaches for DSO to implement an energy transitive framework featuring the presence of utility owned EVs; as a novel planning model based on programming, which is suitable to properly utilise their existing (and future) assets.

Power flow studies are used to investigate the power system in terms of voltage magnitude and angle at busbars. Power flow studies were solely deterministic in nature. Although power flow provides useful information about load and generation, time-varying (dynamic) uncertainties are not considered. Uncertainties associated with EVs load cannot be addressed through power flow analysis [83]. So as a result, the power flow analysis cannot influence the decision making of distribution systems operators (DSO). Probabilistic aspects of these uncertainties can provide a better understanding of the input load/generation variation. These uncertainties can be represented through probability analysis using Monte Carlo Simulation (MCS) technique as the benchmark. The Monte Carlo Simulation technique is quite accurate but presents a high computational burden. The probabilistic aspect of load/generation embedded in the power flow studies is known as 'Probabilistic load flow (PLF)'.

To quantify the uncertainties associated with EVs, a Monte Carlo based Probabilistic impact assessment methodology is adopted. To answer the uncertainties of EVs in terms of size, location, and capacity, 100 simulation/iteration are implemented from 0% to 100% penetration level. The justification of 100 iterations is based on the results presented in [85]. Within the proposed Monte Carlo based approach, different simulation numbers (i.e., 25, 50, 75, 100, 400, 600, and 1000) were analysed with the error deviation reducing from 0.01 (100 simulation) [85]. The analysis is divided into two strands namely, Balanced and Unbalanced Network configuration. Future energy scenarios are created and discussed in detail with respect to different types of EV chargers. Firstly, balanced network configuration results are presented and thereafter, results for an unbalanced network configuration. In the unbalanced network, 30% of EV penetration is possible without any PQ breach.

3.1 Analysis (Extent of Voltage problem)

Deterministic (only one case) or snapshot (minimum demand and maximum generation or vice versa) approaches can be misleading as a means to model the realistic nature of power quality issues and, furthermore, such considerations lack the probabilistic aspects associated with the proliferation of Low Carbon Technologies. Deterministic load flow (DLF) can used for an adequate starting point. It is challenging to predict customer behaviour accurately especially in the case of EVs and, hence, the probabilistic approach is required to quantify the impact of EV proliferation. However, there are different probabilistic approaches (e.g., the Monte Carlo method) proposed in the literature to assess the impact of EVs in LV feeders. It can be noted in the literature, some authors utilize US-style distribution network configuration which is different from European style network configuration [39][79].

The probability density function implemented in this work in terms of size, location and charging of the EV batteries via Monte Carlo Simulations is described in Fig. 3.6. Three penetration levels are selected like 30%/ 60%/ 100%. (3 penetration levels in total as shown in Fig. 3.1) in the *Balanced Network configuration*. Five minutes time-series profiles and three-phase four-wire distribution networks are adopted. The following steps are repeated for 100 simulations steps for the selected MCS iteration.

- The same profile per consumer as illustrated in Fig. 3.5. EVs are randomly allocated to households in the network.

- Once the household load and EV load profiles are assigned to each individual household in the network, load flow is executed using DIgSILENT power factory.
- The initial load flow calculated results provide reference value for Monte Carlo simulation. MCS subroutine is developed using DIgSILENT, DPL (DIgSILENT Programming Language) as shown in Fig. 3.1.

The simplified programming approach is presented in Fig. 3.1. The programming approach is sub-divided into three parts: the different penetration level, the Monte-Carlo simulation and then the calculation of voltage level throughout the network. Firstly, the penetration level is selected (for example 30% EV penetration level) and 100 different MCS are considered as EV charging scenarios. Then voltage levels are obtained throughout the network. Same process is repeated for 60% and 100% penetration level.

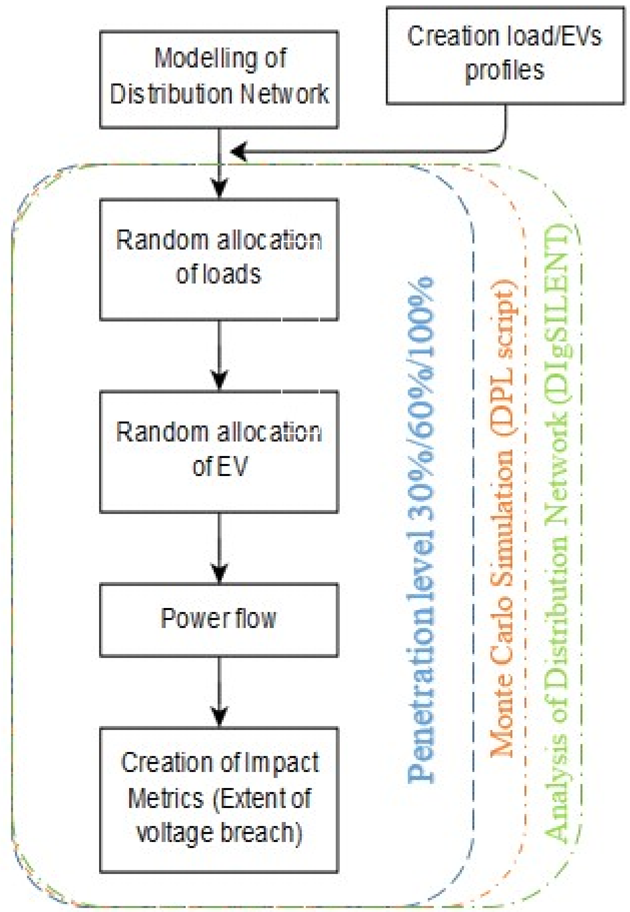

Fig. 3.1: Representation of probabilistic impact assessment approach

3.1.1 Methodology

Probabilistic Impact Assessment methodology considers Monte Carlo analysis, in balanced and unbalanced configurations to calculate power flows in the distribution network. The approach for a single step, given a particular EV penetration level, are summarised in Fig. 3.2.

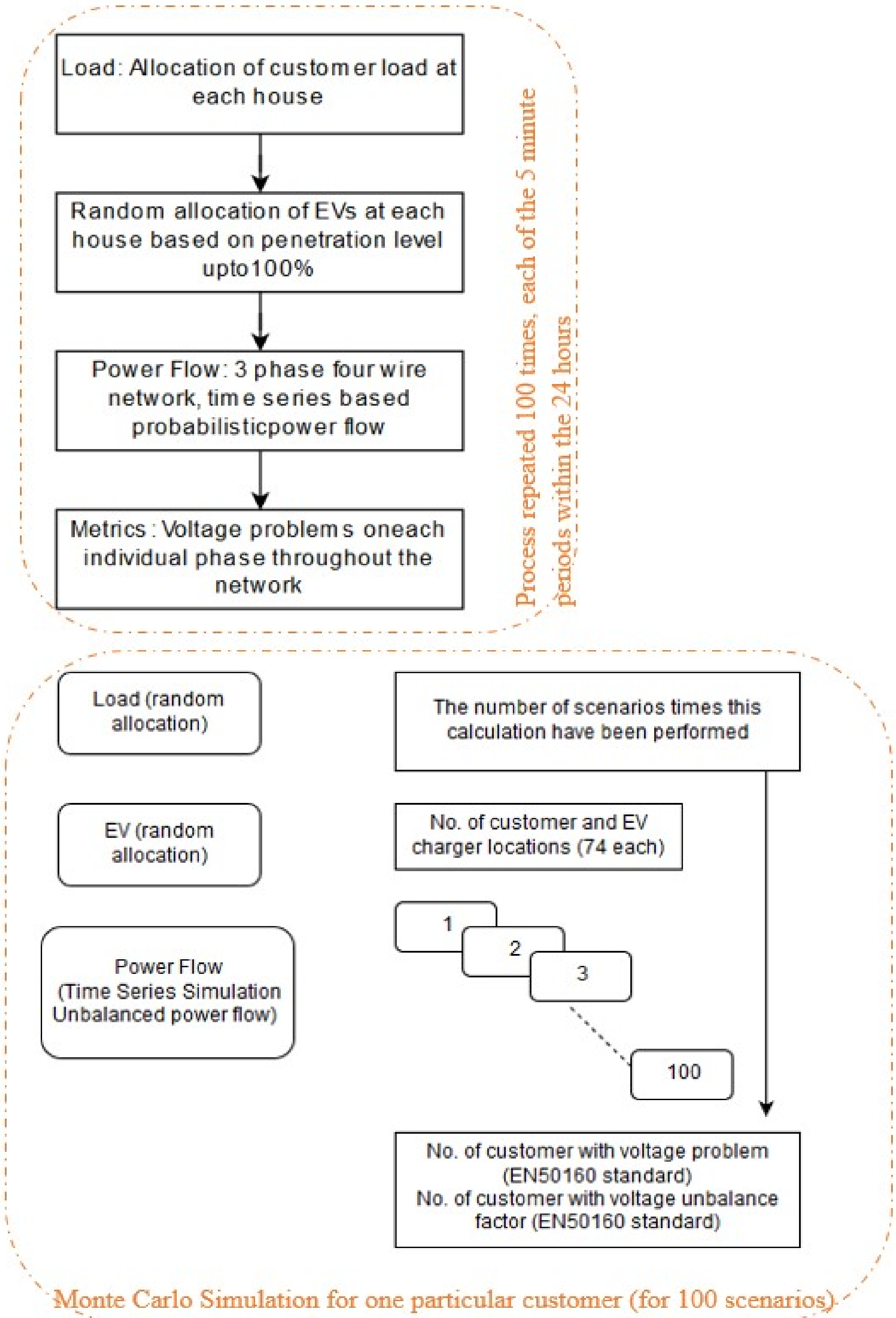

Fig. 3.2: Monte Carlo Simulation (Probabilistic Impact Assessment) methodology for EVs in distribution network

The random allocation of EV load profile throughout the day is illustrated in Fig. 3.2. There are 100 different datasets available for EV profiles. Out of these 100 EV random profiles, 74 EV profiles are randomly selected. One pool of dataset contains 288 inputs readings, representing the load demand of EV after every 5 minutes, throughout the day. The same profile per consumer for household load (time-series daily profile with 288 periods, i.e., 5 minutes resolution). Different types of EV chargers are considered (3.68 kW, 7 kW and 11 kW), while maximum possible penetration level (up to 100%) is considered for each case study. A 100% EV proliferation means the maximum penetration possible is one EV per household. Once the household load and EV load profiles are assigned to each individual household in the network, power flow is calculated using DIgSILENT power factory software. After (100 different) consideration of all random scenarios, power flow calculation is obtained in terms of a voltage metric. In simple words, voltage metrics replicate voltage on each individual phase at different pillars of the network. Voltage metrics contain voltage magnitude of individual phase connected to the three-phase pillar. For example, if analysis suggests 30% EV proliferation is possible without any voltage level and voltage unbalance breach at Pillar J, 30% EV proliferation is possible across the network without voltage standards violation (on the basis that Pillar J represents the furthest location on the network, and this would be the location experiencing the worst voltage drop as a consequence of the EVs). The analysis is designed to simulate a realistic consideration of household load in conjunction with one EV charger (maximum charge being one EV in a day). The EV datasets are designed based on EV demand, derived from probabilistic distribution [62]. The accuracy of MCS are highly dependent on the quality of input data. For instance, if average EV profiles are considered or lumped EV loads are considered as inputs for one of the EV datasets then the accuracy of the output result will be compromised. In short, every assumption in the input pool of dataset and network configuration parameters can undermine the credibility of the result. To generate credible input data, the statistical analysis presented in Richardson work [62] and one year field trial of EVs in Dublin, Ireland, are used to create the 100 random EV pools of profiles for a day. For brevity, only EV dataset generation and utilization in MCS is explained in this section.

It is noted that 20 kWh battery size is considered in Richardson work [62] and, keeping in mind the recent advancement in battery size, 40 kWh battery size is utilized in this work. The probability density function of EV battery initial state of charge (SOC), which represents a linear interpolation of a 20 kWh battery assignment profile (up to 40 kWh) as a rough estimate of the market available capacity.

The MC simulations are used randomly to assign the charging pattern of the EV over a 24-hour period. Once the pattern is selected then BSOC is selected. For each instance, after every 5 minutes, BSOC is monitored and updated. It is assumed, once the battery is connected to the network, it will remain connected until it is fully charged. Random selection of EV charging pattern implies uncontrolled charging pattern is utilised. For the simulations considered, all residential households are randomly assigned an EV charging profile with different BSOC. The breakdown of EV allocation is based on a probabilistic distribution as well as the energy requirement of the EVs in each individual phase; as presented in Table 1.

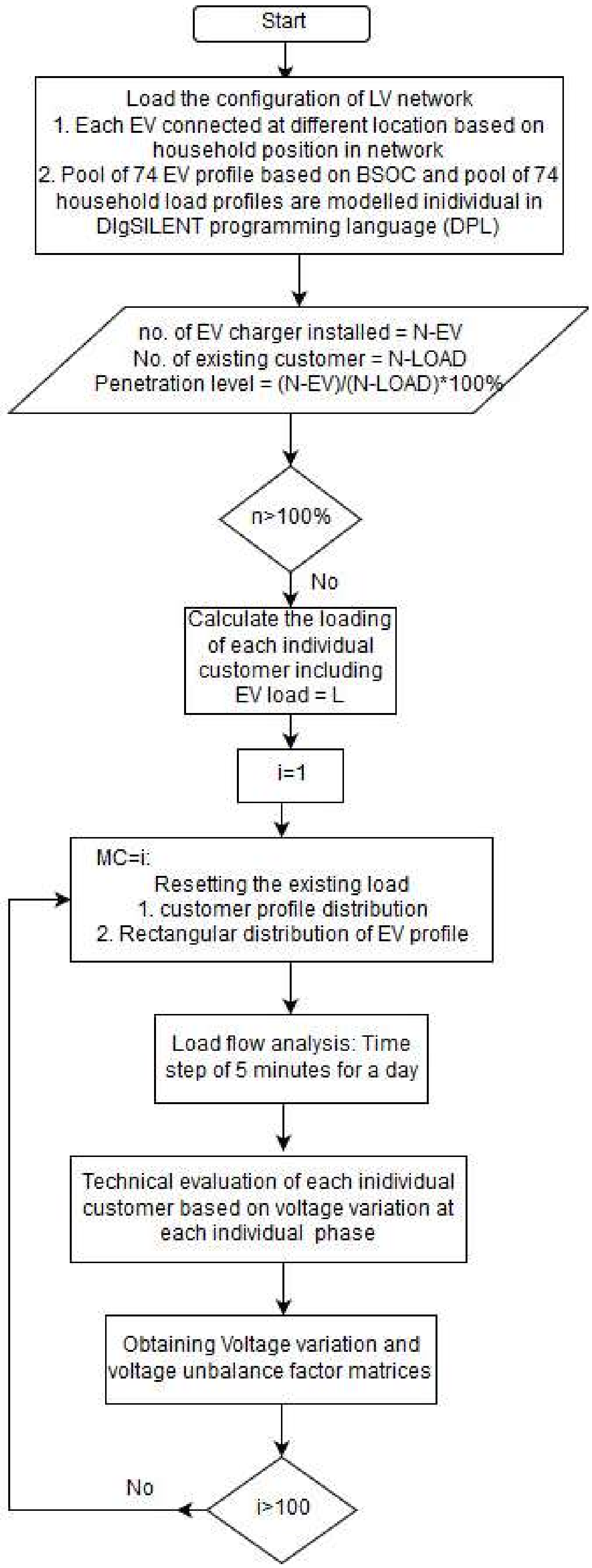

Fig. 3.3: Monte-Carlo simulation to obtain voltage variation and unbalance metrics

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The steps over each MCS iteration, given a particular EV charging level and consumer load, are summarised in the flowchart presented in Fig. 3.3. The associated steps are repeated for each of the 100 simulations; for each case study of the EV charger namely 3.68kW, 7 kW and 11 kW respectively. Each iteration generates random input variables cognisant of the maximum import capacity (MIC) for each network connection.

For each successive iteration, the load profiles (customer load and EV profile) are reset to include a new specific MCS profile. Load flow analysis is performed for a time step of 5 minutes over a day (24 hours). A technical evaluation is performed for each individual customer based on voltage variation. Voltage variation and voltage unbalance factor matrices are obtained. The penetration level of EV load (maximum penetration allowable being 100%) is calculated for the network based on line/phase voltage and transformer loading for each MCS iteration. MCS iterations and EV/customer loading are bound by the pre-defined limits as defined by the DSO code (EN5160). The maximum number of iterations is limited to 100.

3.2 Input Data

3.2.1 Network Modelling

The network model is implemented in the DIgSILENT power factory platform. There are 74 customers, connected from a 10/0.4 kV transformer in a radial network topology. In this regard the LV distribution network considered in [40], as provided in Fig. 3.4 below, is employed. The network consists of nine (three-phase) pillars, namely, Pillar B-J, through which customers are connected. These pillars subsequently facilitate a radial connection to the substation transformer (Fig. 3.4). Pillar B is nearest to the transformer and Pillar J is the furthest away from the transformer. The pillars accommodate single-phase consumer connections (domestic installations), each with the distinct Earthing provision (TN-C-S).

Service cabling, from pillars to consumers is 25/16mm^2 concentric neutral [40]. The cabling from the substation transformer to the first pillar (and each pillar thereafter) is either 185/70mm^2 crosslinked polyethylene (XLPE) or 70mm^2 paper-insulated (NAKBA) [40]. Fig. 3.4 illustrates the network structure from the transformer down to the consumer in context with the pillar/consumer Earthing provision. The Earth electrode impedances are modelled as 5Ω resistances at customer's connections and 1Ω resistances at the pillars. In the analysis presented, and for brevity, there is a focus on the start of the network (Pillar B), the middle (Pillar E) and the end (Pillar J) to describe the potential issues/concerns. Furthermore, only the important specification of network is presented in this section. Full technical details and modelling approach are discussed in [40].

In Ireland, consistent with EN50438, microgeneration is defined as generation units that can produce 25A at 230 V or 16A at 400 V, as for the guidelines published by ESB Networks (Irish DSO) [40]. It is worth mentioning, 11kW (single-phase) connected EV load is in excess of guidelines published by ESB. Under current regulations, 20% EV load penetration is allowed with charging rate of 3.68 kW.

As defined in the EN50160 standard [99], the voltage at every bus of the medium and low voltage network should be within ±10% of its nominal value, with ±6% being employed by the network designers. The detail model of distribution network implementation on DIgSILENT power factory is also included in Appendix 7

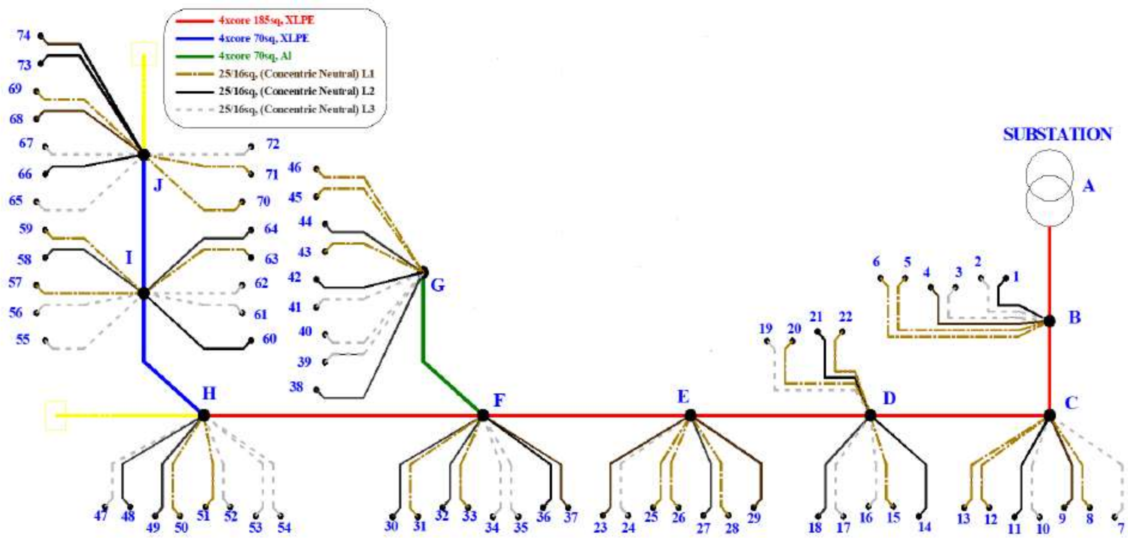


Fig. 3.4: Section of Irish distribution network [40]

3.2.2 Load Profiles

In order to analyse the impact of EV on the distribution network, the identification of demand profiles (e.g., residential customers) is important. The household load demand profile is obtained from the DSO. The household load is represented by an average after diversity maximum demand (ADMD) value of 0.49 kW per customer; based on an annual consumption of electricity of 4300 kWh in Ireland [102]. For that reason, the Irish residential demand profile has been used [103] as shown in Fig. 3.5. The data is available in the hourly format, however, the time scale is further reduced to 5 minute scale timeframe (for simulations, to replicate 1 hour, 12 readings are taken for same value). Fig. 3.5 illustrate the maximum load profile with and without 100% penetration of EV load. The maximum load without EVs is 80 kW at 22:00 hrs. The maximum peak load value with EV is 150 kW at 24:00 hrs. The EV load presented in the Fig. 3.5, is representative of EV charging load distribution over a day (5minutes x 288 = 24 hours). It is the representation of uncontrolled

EV charging load, in a deterministic manner. The random charging selection pattern adapted during the calculation of load flow suggests the creation of new peak value.

The battery state of charge is monitored every 5 minutes. If the battery is completely recharged, it will be disconnected from the network. The maximum energy taken by the EV battery is 3.68 kW in 5 minutes, with a 3.68 kW charger. The same approach is adopted for 7 kW and 11 kW charger load. For example, 7 kW and 11 kW charger can take up to 7 kW and 11 kW in 5 minutes respectively. For brevity, only the 3.68 kW EV charger, for the impact of load profile, is explained in detail and presented in Fig. 3.5. It is worth mentioning here, for a UK perspective, demand profile can be created through the freely available tool developed by CREST (Centre for Renewable Energy Systems Technology) at Loughborough University [104]. This tool can generate a single-phase load profile based on a number of residents and in that regard, is utilized to generate household profile.

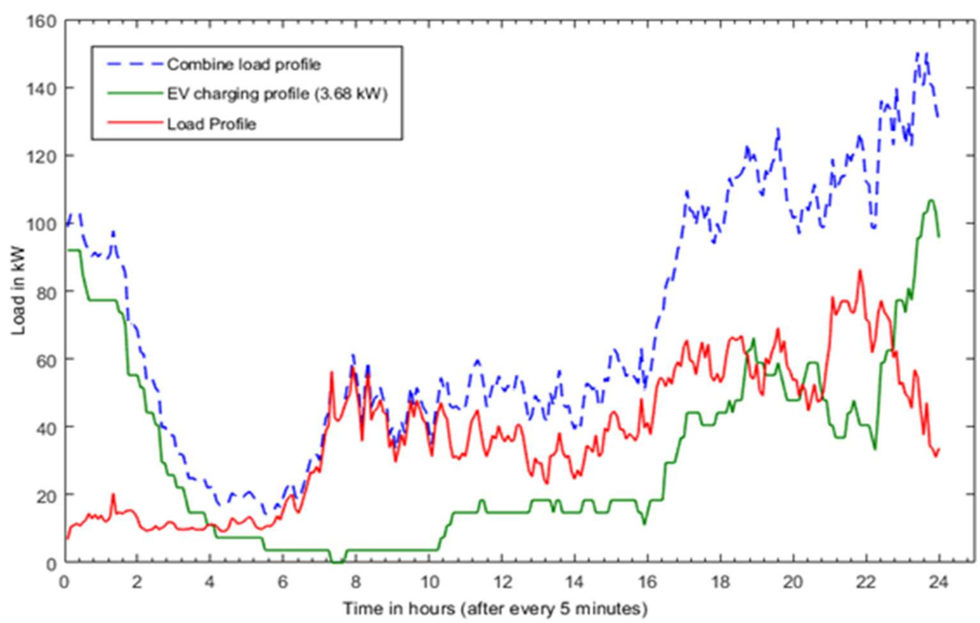


Fig. 3.5: Maximum recorded EV load and load demand profile

3.2.3 Electrical Vehicle Profiles

It is impossible to get the realistic EV load profile without the consideration of uncertainties associated with it. EVs are most likely to get charged in different patterns. The main factor is battery state of charge (BSOC), battery size and charger rating. These characteristics determine how long the battery needs to be connected to the energy source (the LV feeder).

In this work, the statistical analysis presented in Richardson work [74], corresponding to a recent one year field trial of EVs in Dublin, Ireland, is used to create the profiles. A probability density function (PDF) is applied to the network such that a mean BSOC of 10.75 kWh and standard deviation of 6 kWh are selected for initialization [61]. It is important to note that while 100% penetration of EVs on a distribution network is considered, to examine the worst future energy scenarios in order to completely capture the impact of charging (extreme condition). The approach to define the probability of EVs, battery state of charge and implementing it to initialization of EVs are taken from Richardson method [61].

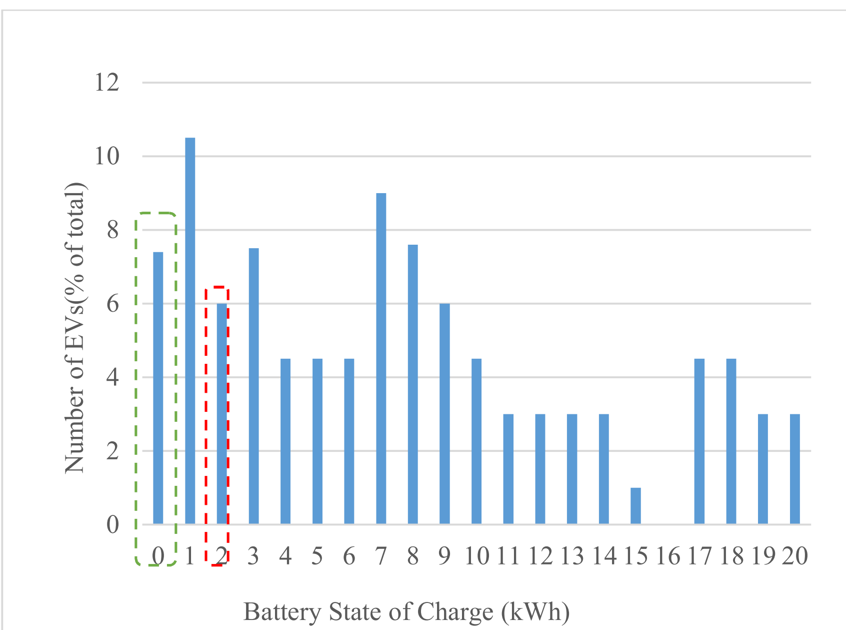


Fig. 3.6: Distribution of the initial BSOC for each EV [74]

In Fig. 3.6, the initial BSOC of 74 EVs out of 100 EVs are connected randomly across the distribution network. As illustrated in Fig. 3.6, three of the EVs have 20 kWh of initial BSOC (20 kWh battery). For example, if seven EVs have 0 kWh of initial BSOC, as highlighted in the dotted green line in Fig. 3.6 (20 kWh battery and 20 kWh of energy is required from 3.68 kW charger), five hours is required for charging as shown in Table 2.2 [105]. It is noted that a 20 kWh battery size is considered in Richardson work [62].

For probabilistic load flow, the following procedure is used to implement the input EV profile. By using the battery characteristics (20 kWh), the probability distribution of connection times and the probability of energy requirements, a pool of 100 slow charging residential EV profiles has been created, implementing the following procedure:

- Battery initial state of charge is defined based on Fig. 3.6, to represent 100 EV initial BSOC.
- The amount of energy required by the car is randomly selected by following the probability distribution presented in Fig. 3.6. For instance, 6 EVs have 2 kWh of initial BSOC as highlighted in red dotted lines in Fig. 3.6, these 6 EVs required 18 kWh/EV to replenish completely. Fig. 3.6 illustrate total of 100 EVs initial BSOC, to get the 100 EV profile, each EV charging profile is considered once in the simulation.
- Once, 100 randomly EV charging profile is generated then random selection of 74 EV profile out of 100 EV profile is done.
- Each EV profile replicates 5 minute resolution time scale, equalling 288 readings throughout a day.
- For every 5 minute resolution input reading, 100 different combinations are considered through Monte Carlo Simulations.

- In the simulations and to make the EV charging more realistic, once EV is connected, it will remain connected until it is fully charged.
- The charging time is therefore, the connection time and the total charging period.

3.3 Result

3.3.1 Extent of Voltage problem (Balanced Network configuration)

Given the statistical nature of the analysis from the Monte Carlo simulations, the result needs to be presented in a probabilistic way. The impact of the EV load on maximum voltages of each pillar is presented in Fig. 3.7. Each box plot represents the voltage drop caused by the EVs (considering 100 simulations) up to 100% EV penetration level. It is crucial to analyse the voltage drop impact according to the standard of EN 50160 and employ a timely approach for different penetration levels in order to be more realistic. 100 simulations from 0% to 100% EV penetration level are carried out in order of 30%, 60% and 100% respectively. The results are presented in Fig. 3.7. The result suggests that the 30% EV penetration can be sustained by the network without any need for modification. If the hosting capacity reached up to 60%, 55% of the customers will face a low-level voltage problem. If the EV penetration level goes up to 100%, the number of affected customer group goes up to 66%.

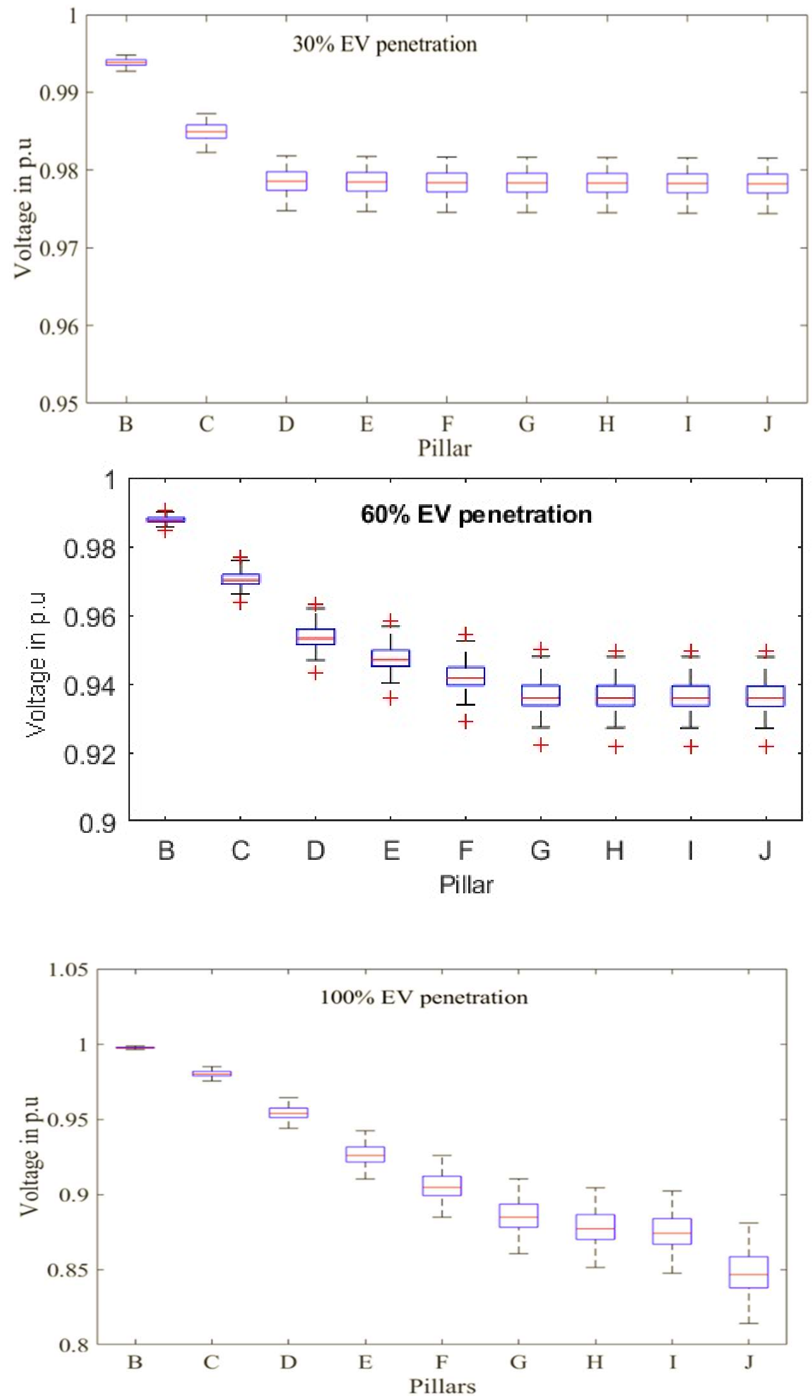


Fig. 3.7: Probability of Voltage drop range at each Pillar with 30%, 60% and 100% EV penetration based on MCS (Balanced Network)

3.4 Probabilistic Nature of Result (Unbalanced Network Configuration)

Given the statistical nature of the analysis from the Monte Carlo simulations, the result also needs to be presented in a probabilistic way. In particular, the probability associated with the occurrence of technical issues such as voltage drop at each phase and VUF. They can be used to determine whether a certain EV penetration level is acceptable for the DSO. In other words, by quantifying this probability, the DSO might conclude that it is feasible to accept penetration levels that represent a low probability of technical issues (line voltage drop and VUF) instead of opting for significant reinforcements or looking into other solutions. The probability of occurrence associated with the voltage drop and VUF is presented for a particular feeder. Cumulative distribution functions are subsequently considered to determine the probability of encountering certain problems in a particular portion of the feeder (position: start, middle or at the end of the network portion under consideration). Thus, a DSO can establish the extent of a potential power quality problems based on the corresponding percentage of EVs that are integrated across the feeder.

3.4.1 Cumulative Distribution Functions

Cumulative distribution functions (CDF) can be extracted for each EV charging level (namely 3.68 kW, 7kW and 11kW); one for each metric (voltage drop and VUF). For voltage metrics, ‘x’, represents the voltage in per unit and the corresponding CDF or F(x) allows a quantification of the voltage magnitude probability. In total, there are 9 CDFs for each case study (such as 3.68 kW). These CDFs enable the probability of the voltage drop at a specific location for each case study to be understood. For example, in Fig. 3.8, the probability of a voltage drop being of magnitude less than 0.95 p.u in the network with 100% EV penetration, is 0.05 (approximately). Further, if a voltage breach occurs for the worst condition (100%

penetration), it will impact 5% of the customers. Then for all the others potential penetration considerations (60% or 80%) can be accommodated by the network without voltage breach.

3.5 Energy Scenarios

Consideration of the different future energy scenarios will facilitate a comparison of the results obtained from the probabilistic study in further assessing the impact metrics due to increased proliferation of EV. For the metrics, three worst-case scenarios can be considered. Case Study 1 considers a 3.68 kW charger, i.e., 100% penetration level of EVs. In Case Study 2, a 7 kW charger is considered. Finally, in Case Study 3, an 11 kW charger is considered.

3.5.1 Case Study 1: 3.68 kW charger, 100% penetration level

For the Case Study 1, all the 74 customers have EV chargers installed in their premises, one EV charger can consume up to 3.68 kW at any instant. The rate of battery charging depends on the EV charger rating rather than battery size; battery sizes can only influence the charging time of the battery. Different numbers of EV are considered during the MCS with maximum and minimum EV load peaks being considered over the 24-hour analysis (5 minutes) periods.

For simulation, the standard voltage is set 1.05 per unit. For instance, in Fig. 3.8, the Pillar E, Phase B, the probability of 1 per unit voltage is 0.7 approximately. Furthermore, the Pillar J, Phase B of 1 per unit is 0.5.

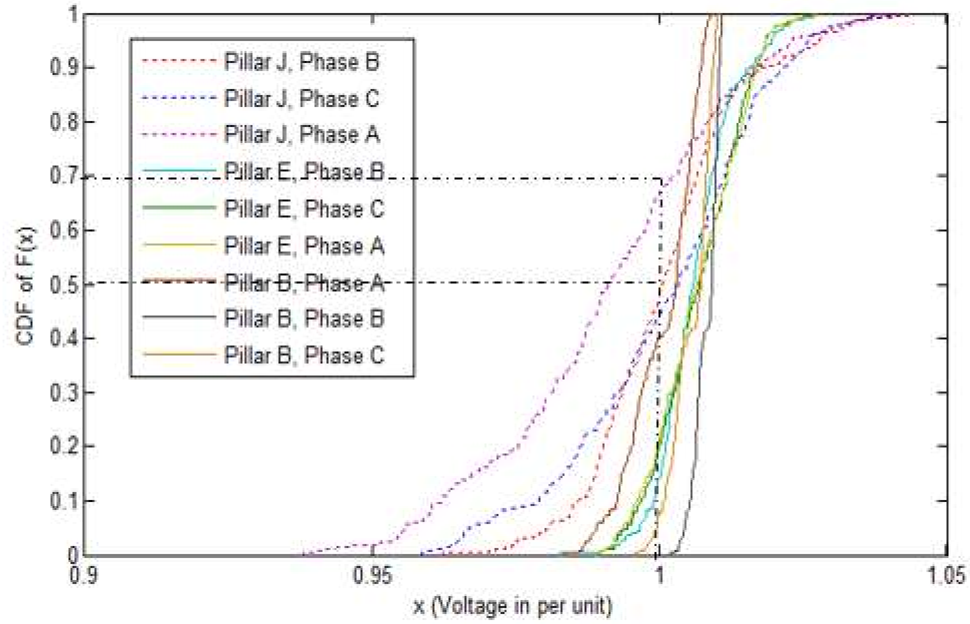


Fig. 3.8: Each individual phase voltage change throughout the network

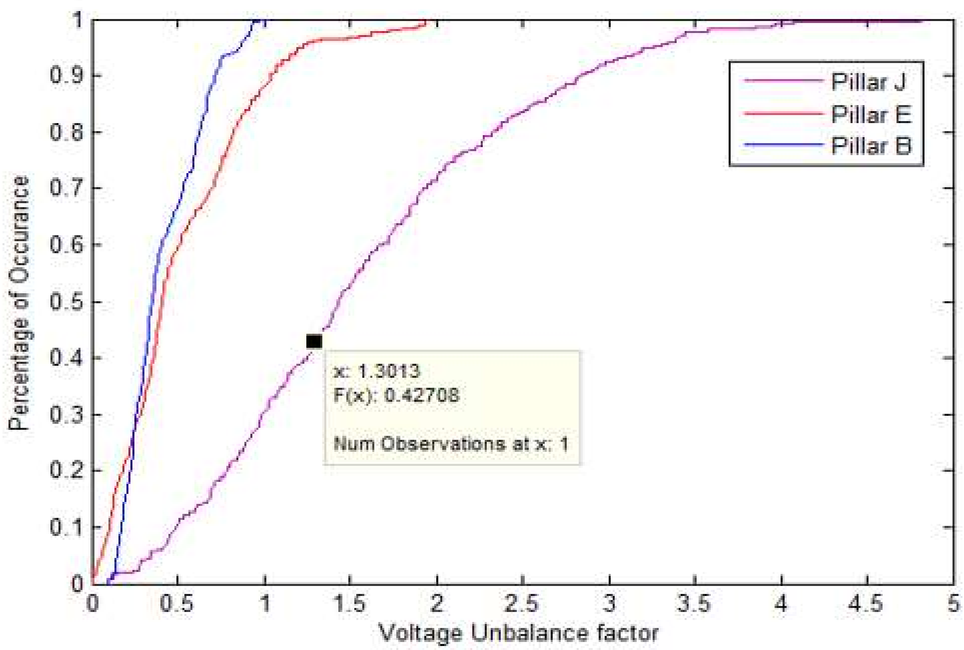


Fig. 3.9: Percentage of voltage unbalance factor

The voltage unbalance profile over the benchmark for the test distribution network on different pillars at 3.68 kW EV charging scenario is illustrated in Fig. 3.9. It is evident that the VUF value is increased meaningfully at Pillar J, as the probability of the VUF exceeding **1.3%** is 0.4. This result suggests that, if 100% of the EVs are connected and charging, there is a probability that 40% or less household customers will have no power quality issue in terms of VUF. In term of a DSO perspective, it may accommodate only 40% EV penetration, to facilitate an acceptable VUF. Based on this result, the DSO can decide what level of VUF can be allowed to be tolerant in the network. For example, in a planning context, the DSO may set VUF maximum limit up to 0.5%, then 10% proliferation is permitted

3.5.2 Case Study 2: 7 kW charger, 100% penetration level

EVs are connected to the network as single-phase load, but as such, they can impact voltage level on all (three) phases with the voltage unbalance factor also being affected. In Fig. 3.11, which illustrates the impact of 7 kW chargers, voltage breaches are Pillar J, Phase B and Phase C are considered. The probability of under-voltages lower than 0.95 per unit is 0.2 (approximately). In Fig. 3.11, the probability of VUF exceeding **1.3%** is 0.27 at Pillar J respectively.

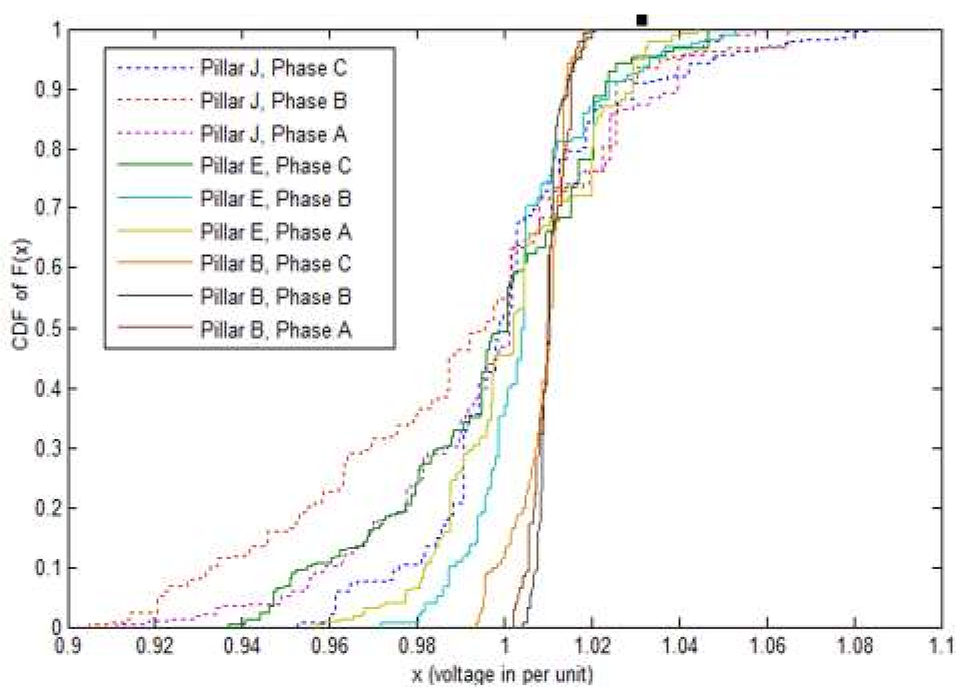


Fig. 3.10: CDF of network indices for under voltage metrics

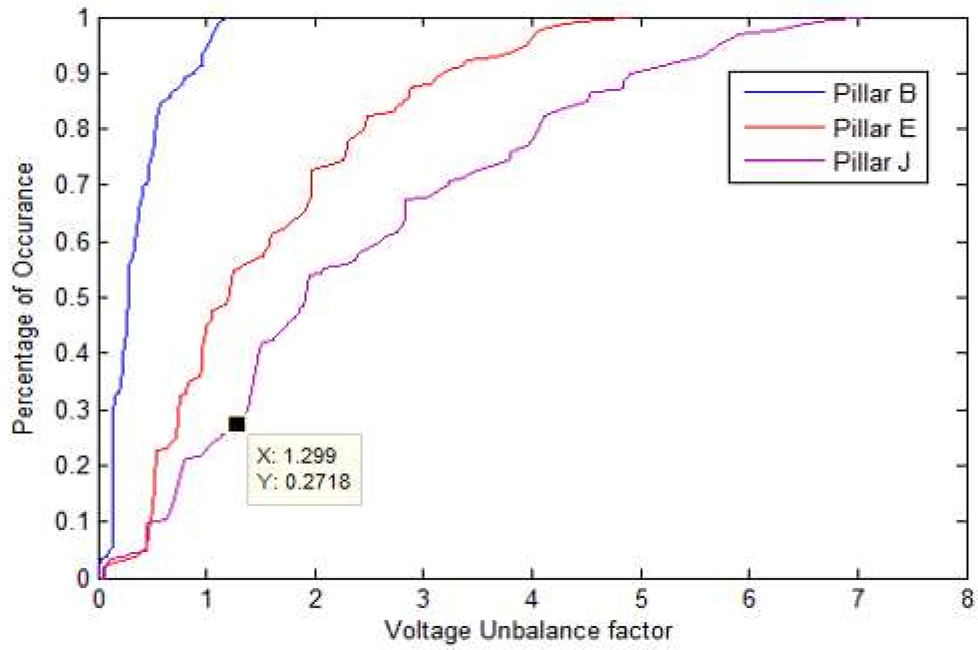


Fig. 3.11: Percentage of voltage unbalance factor

3.5.3 Case Study 3: 11 kW charger, 100% penetration level

Fig. 3.12, illustrates the voltage metrics of different pillars for 11 kW EV charging scenarios. The probability of an under-voltage below 0.95 p.u at Pillar J is 0.3. The manifestation of voltage breaches is evident at Pillar J and the probability of VUF breach at Pillar J is 0.3. 30% or less customers are affected by under voltage problem. Based on this result DSO can decide if they are going to allow 11 kW charger at single-phase and at what level of VUF is tolerant with respect of EV penetration. It is important to mention here, 11 kW charger is not allowed to be installed in domestic premises by DSO (ESB Ireland).

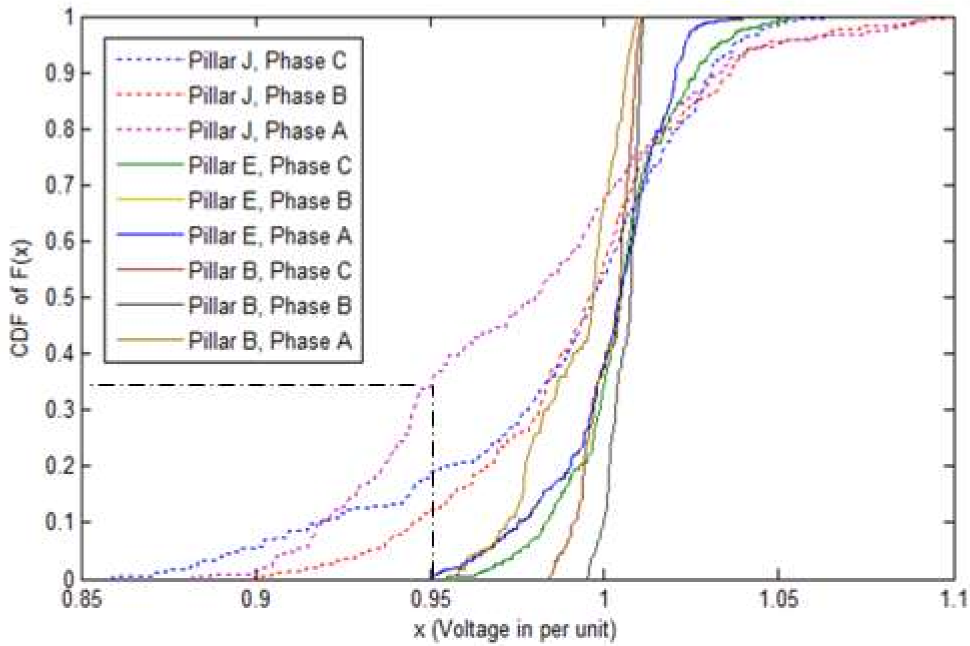


Fig. 3.12: CDF of system indices for under voltage metrics

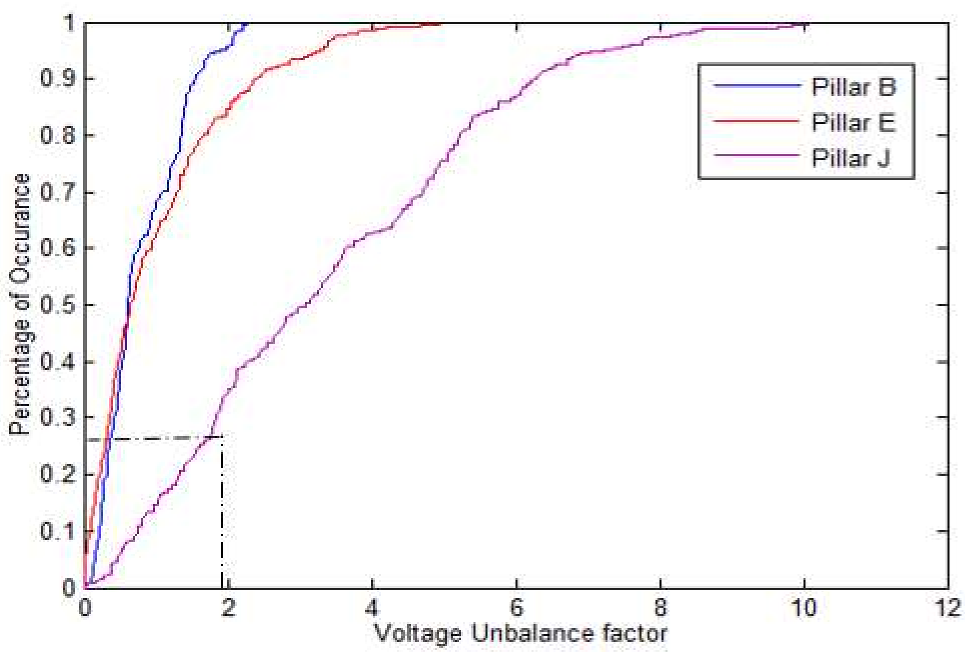


Fig. 3.13: Percentage of voltage unbalance factor

3.5.4 Complementary Cumulative Distribution Functions (CCDF) analysis

For each case study, the voltage unbalance is computed and quantified against the standard of 2% for 95% of the defined time period [106]. To quantify the percentage of occurrence of VUF that exceed the threshold value is generated. The graphical plot of percentage of customer effect versus percentage of voltage unbalance factor is shown in Fig. 3.14, as a CCDF. The corresponding CDF enables measurement of the probability of under-voltage occurrences at the site for each case study. Again, from Fig. 3.11 and Fig. 3.13, the case studies, namely VUF of 7 kW and 11 kW chargers show that there is a probability of occurrence of VUF breaches by a certain meaningful percentage of the customers. The meaningful percentage of customers affected by the different types of chargers namely 7 kW and 11 kW chargers are explained in Fig. 3.14 where the percentage of customers violations represented by the random variable *xs* and *F(xs)* represents the complementary CDF (CCDF) evaluated at *xs* in six scenarios, namely Pillar B at 7 kW and 11 kW charger, Pillar E at 7 kW and 11 kW charger and Pillar J at 7 kW and 11 kW charger. The CCDF allows representing how frequent a random variable exceeds a particular limit. For instance, Fig. 3.14, in consideration of an 11 kW charger and specifically Pillar J, the probability of ~80% of customers violating VUF limit 2% in the case of 100% penetration level. For the 7 kW charger case, a probability of ~60% of customers violates the VUF limit. Again, the probability of maximum percentage, i.e., 100%.

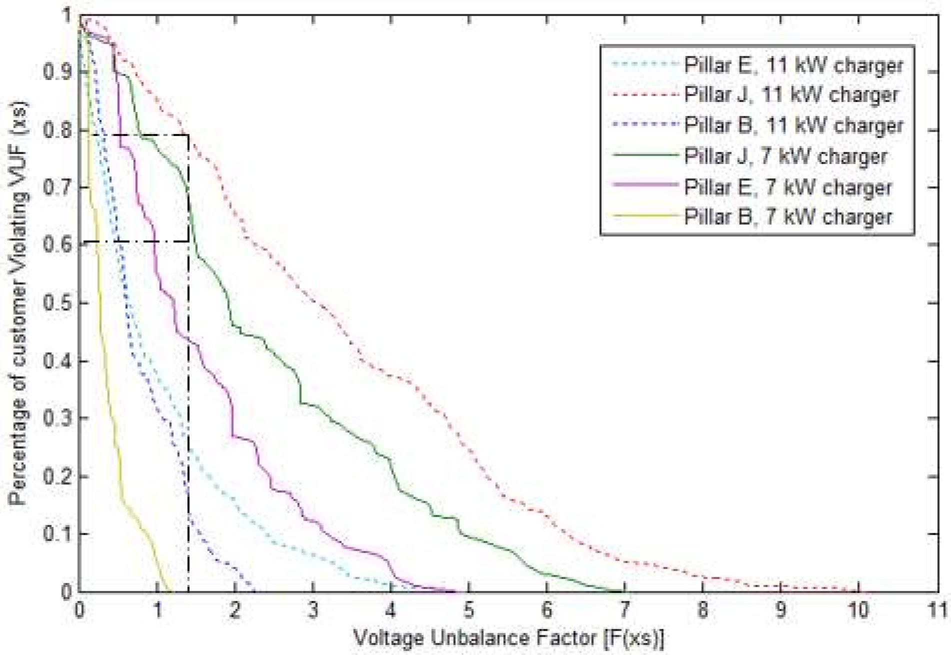


Fig. 3.14: CCDF of % customer violating Voltage Unbalance factor

3.6 Summary

From the *Unbalance Network configuration* results, power quality issues in terms of under voltage and voltage unbalance factor shows a likely impact that will persist as the EV charger level increases. In this work, EV proliferation (up to 100%) is considered in a Low Voltage Distribution Network (LVDN) with respect to different charger levels. This study proposes the consideration of a means to measure the likely impacts of increased EV integration under spatial and temporal behaviour. A Monte Carlo Solution is chosen as a tool for considering the probabilistic aspect associated with EVs. The existing assets of the distribution network (DN) are analysed to define the maximum stress it can sustain in terms of EV penetration. Based on the results, the DN can face power quality issues in terms of line voltage drop and voltage unbalance factors, in term of increased EV facilitations. In the DSO perspective, EVs customers are only allowed to charge with a 3.68 kW charger in domestic premises. The analysis suggests 40% of EV proliferation in the network does not cause any technical issue, with respect to the EN50160 standard. It is important to quantify the technical issues in the network before proposing any solution. This network can sustain 40% of EV penetration without any network modification or utilization of the mitigating device. The proliferation of EVs and higher rate of EV charger are inevitable; the DSO must act proactively to define the limit of the network. The author suggests, based on the analysis, if the proliferation of EV goes up to 100%, then network modification or mitigating solutions (i.e., custom devices) might be required.

From the preliminary analysis, based on the *balance network configuration*, 70% EV penetration can cause a voltage unbalance breach. The voltage level breaches are monitored throughout the study.

The keys points of this chapter are

- This study suggests the balanced network configuration and the EV load considered as a lump load can provide misleading results.
- From the unbalanced network configuration, the case study with a 3.68 kW charger, the **40% EV** penetration is possible based on the probabilistic result in term of voltage at each phase and voltage unbalance factor, with a 95% of confidence level.
- Based on MC analysis should EV proliferation go up to 100% (one EV per house), then network modification or mitigating solutions (i.e. custom devices) are required to maintain PQ throughout the network.
- If a mitigation solution is required, in term of storage device or reactive power support, the power rating of such a mitigation device is critical. The power rating is directly proportional to the cost. In this chapter, probabilistic EV and household load is used for the analysis, for more realistic representation of EV load, dynamic modelling is required. The power rating of mitigating devices can be more accurately predicted through dynamic modelling. In the next chapter, a dynamic EV model and mitigation device (D-STATCOM) are presented.

4. Potential Solution to Mitigate Impacts of EV's chargers

The previous chapter outlined the different types of EV chargers and battery size, and the energy consumption impacts on the network, and established the need for simulation tools to assist with the exploration of future worst-case transportation scenarios.

This chapter begins by establishing the requirements for the mitigation device and follows with a modelling approach. Subsequent sections describe the EV load models, data formulation, and the implementation details of the software.

To establish the requirements of the simulation, the primary research questions are revisited.

- What are the potential energy demands of EV chargers like 3.68 kW to 11 kW?
- What are the technical issues that arise from potential future energy charging scenarios of EV?
- What is the potential solution to overcome worst-case charging scenarios, and how successfully can their adoption support the expansion of EVs?

The best EV charging method is an open-ended question, dependent on many factors. Therefore, the different charging levels scenarios (up to 11 kW) are considered, keeping in mind charging times, driving range, and infrastructure requirements.

Answering these questions requires dynamic simulation software. Firstly, the modelling of a dynamic EV load, cognizant of the EV charger rating, needs to be considered, including data related to household load and EV battery size. The simulation must use these inputs and produce an output in a form that is useful for further analysis; for example, the instantaneous energy balance through a mitigating device, including the EV fleet, over the entire simulation period. The details of inputs, outputs, and models used in the simulation are described in Sections 4.3.

This chapter is dedicated to the distribution system planning framework, and in particular, the formulation and methods focusing on the uncoordinated flexible EV load and the network for planning purposes. The focus is the enhancement of the hosting capacity of EVs on distribution networks while maintaining power quality (especially voltage magnitude and voltage unbalance), which is ultimately a pre-requisite for increasing prosumer engagement. Several EV charging scenarios, in the context of UK/Irish distribution networks with increased penetration of EV prosumers with sustainable charging time is considered.

In Europe, distribution networks are designed based on a 'fit-to-forget' approach [107] without considering uncertainties in a deterministic way. For instance, for extreme load scenarios for small time durations, voltage collapse can occur as highlighted in the previous chapter. Voltage collapse cannot be tolerated in the network. Some sort of centralized, fast responding and controlling device is consequentially required to mitigate power quality issues associated with EV proliferation. Custom devices like SVC and D-STATCOM are such fast responding devices. The response of D-STATCOM devices is faster than capacitor banks. Placing FACTS devices is an effective way for utilities to manage the loading margin and voltage profile of the system [87].

Voltage problems can be solved by reinforcing the distribution network, although upgrading existing network infrastructure requires a significant amount of investment.

4.1 Potential Solutions

This section features some of the passive solutions that come under the 'fit and forget' approach and they have the capacity of solving the voltage stability issues.

4.1.1 Feeder reinforcement

The network reinforcement is the most common approach used by DSOs to update the network. Transformers and cables are replaced with a new one having sufficient capacity to maintain power quality without violating thermal ratings. This approach is based on the assumption that demand diversity does not change significantly. It is worth mentioning here that this approach worked well in the traditional network. The primary drawback of this method is capital infrastructure expansion e.g. extension of street work and electrical supply disruption [77].

4.1.2 Three-phase connection of EVs

From a UK/Irish perspective, the domestic household is connected to the single-phase network and to change the demography of distribution network from single-phase to three-phase requires significant investment in terms of network modelling and infrastructure. The typical underground network in urban areas would require a lot of excavation work if modifications were to be considered along with new cables and equipment cost. It is important to keep in mind, the cost perspective with respect to the benefit achieved.

In short, the traditional approaches are not able to compensate for the modern requirement of load management.

4.2 FACTS (Custom Device consideration)

The failure of OLTCs to regulate the voltage level and accommodate reverse power flow, and the slow response time of OLTCs is considered a significant drawback [66]. This has led to the consideration of Flexible AC Transmission System (FACTS) technologies at distribution level. In the last decade, as discussed in Section 2.3.3, considerable research has been ongoing, based on the simulation and experimental implementation of FACTS devices like Static VAr Compensator (SVC) and D-STATCOM on the distribution system. The most notable work in terms of D-STATCOM implementation and validation at distribution level is presented in [66] which presents the results in terms of how much D-STATCOM capacity is able to maintain the voltage level. The SVCs are FACTS devices consisting of inductors, capacitors and both controlled using power electronic switches, usually thyristors, and are an example of a device which controls reactive power flow to indirectly regulate voltage. The authors concluded that the SVC gave superior voltage control and a faster response when compared to the OLTC [108].

Flexible Alternating current transmission system devices can be shunt, series or a combination of both. Shunt devices are commonly used for reactive power or harmonic current sources [109]. They are used for instantaneous voltage regulation, power factor correction and reactive power control. Shunt devices inject current into the system that is quadrature in phase compared to the line voltage, and this device only supplies or consumes reactive power. Among the shunt controller types are static VAr compensators and static synchronous compensator (STATCOM). As shown in Fig. 4.1, STATCOM can operate bi-directionally namely: i) the STATCOM generates reactive power, if $Vg < Vstatcom$ and ii) STATCOM absorbs reactive power when $Vg > Vstatcom$.

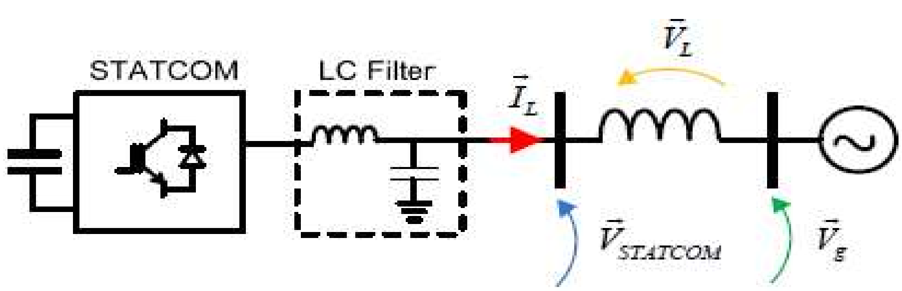


Fig. 4.1: Schematic diagram of STATCOM

It is a shunt device that can generate a controllable reactive power through a power electronic converter. Essentially, it is a Voltage Source Converter (VSC) connected to the network by an inductive filter (LC Filter) as shown in Fig. 4.1. Injected reactive current is controlled by means of a Pulse Width Modulation (PWM) technique, where the carrier frequency is much higher than the power (network) frequency. In comparison to SVC, STATCOMs use reduced size passive components and possess higher dynamics. STATCOM operating in distribution networks is often called as D-STATCOM and they can be equipped with energy storage. These devices can exchange active power with the grid, which facilitates an extended compensation capability for the system.

The performance of FACTS devices depends upon the controlling technique and placement in the network. Lahaçani et al. presented a model STATCOM power flow using the Newton-Raphson method [110]. Placement and sizing of STATCOM are not considered in that study, due to the relative expense of the device and the relative planning concerns. Roy et al. [111], considered the controlling of parameters and sizing of STATCOM but balanced three-phase modelling (DG and load) was prioritised, whereas, in reality (and particularly in the Irish context), loads are mostly connected through single-phase supplies as are micro-generation capacities. D-STATCOM used to reduce total harmonic distortion (THD) and load balancing [112][113], to stabilize the voltage.

In Fig. 4.2, the connection of D-STATCOM to the distribution network is presented. It is shunt connected to the network. It is connected to the Pillar J in the distribution network. It is equivalent to a capacitor or reactor connected in parallel to the pillar, or a reactive current source or voltage source connected in parallel to the pillar, injecting or absorbing to meet the network requirements of voltage regulation.

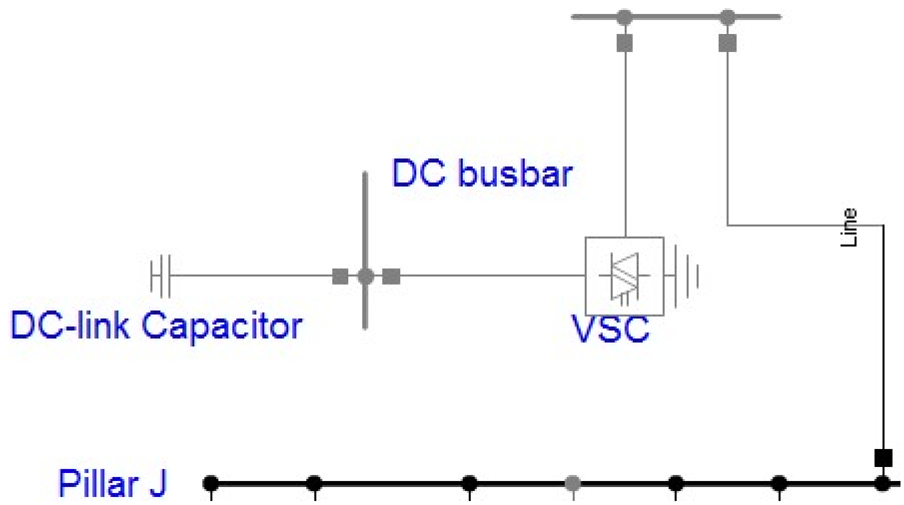


Fig. 4.2: Schematic representation of D-STATCOM

It is a voltage source converter device, in which the voltage source is generated through the DC-link capacitor. The active power compensation can be added if suitable energy storage device is embedded across DC-link capacitor. EV technologies could potentially provide additional active power support, although the management of the EV power flows and avoidance of incurred losses would be a preclusive issue.

Cascade controllers are commonly used to control the voltage source controller (*VSC*). The controller loops are applied to constantly monitor the status of the system. Based on the status of the system, the controller decides to initiate the D-STATCOM or not. In this case, the reactive power compensation is through a DC-link capacitor. Two controller loops: an outer controller and inner controller, as shown in Fig. 4.3, are employed in this regard. The voltage controller is implemented as an outer loop, which tracks the reference load terminal voltage to realize the voltage drop mitigation. The outer controller consists of two proportional-integral (*PI*) controllers which facilitate control through direct-quadrature (*dq*) transformation where the three AC quantities are transformed into two DC quantities. These controllers are primarily employed to eliminate error *PI cont P* as shown in Fig. 4.3, the outer controller box, uses active current control and the *PI cont Q* is employed to facilitate reactive current controlling. They generate signals of *d* and *q* currents for the inner controller. The inner controller also known as current-control loop has two inputs, (*d* component and *q* component of current). The main function is to regulate the ac side voltage of VSC by using pulse width modulation (PWM). This controller compares measured and reference voltage at the AC side and sends an error signal to the *PI cont Q* controller and is responsible for the AC voltage control. The error signal is processed by *PI cont Q* controller, and their corresponding outputs are augmented with the decoupled feed forward signals (reactive current reference (*vq*)). The associated *PI cont Q* controller subsequently generates a reactive current reference (*vq*) and on that basis, the D-STATCOM absorbs or injects reactive power in the network. The PI controller parameters are tuned by the systematic trail-and-hit method to achieve the desired step response, settling time and overshoot less than 10% [114].

The controller compares the measured and reference DC-link voltages and sends an error signal to the *PI cont P* and therefore active current reference '*vd*'.

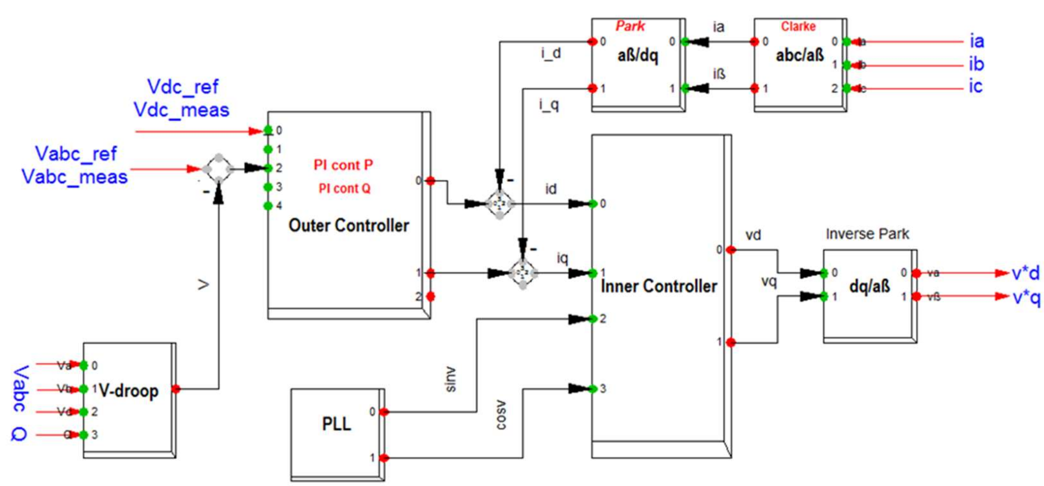


Fig. 4.3: Basic controller of D-STATCOM

Clarke transformation is used to transform time domain signals (voltage, current) from three-phase coordinates into a stationary two-phase reference frame (αβ frame) [115]. The Park transformation converts the stationary αβ frame into a rotating a *dq* frame. A Phase

Locked Loop (PLL) is used to compare the actual voltage with the reference voltage, for synchronizing purposes.

The inner loop contains current controllers. One controller '*PI cont P*' is for *id*, the other one '*PI cont Q*' is for *iq* [115]. Using PLL, the d-component of current becomes an active current component (d-current) and the q-component becomes reactive current component (q-current) [116]. The actual current *id* is compared and a difference signal is sent from the PI controller to the built-in current controllers. The output of the PI controller is the reference voltage signal (*Vq*).

4.3 D-STATCOM

The rapid proliferation of EV in the network forces utility companies (DSO) to operate their systems much closer to the limits of instability. One of the primary issues that may relate with such a stressed system is voltage instability or voltage collapse resulting in increased occurrences of the blackout, which have been reported globally. The main reason for voltage instability is reactive power imbalance in the network. To recover the system from voltage collapse under stressed condition, D-STATCOM controllers can be placed at appropriate locations to provide reactive power support [117].

D-STATCOM have the advantage that they can inject almost sinusoidal three phase balanced current, D-STATCOM also can inject unbalanced and harmonic distortion current to eliminate harmonic distortion. D-STATCOM are used to reduce total harmonics distortion and power quality maintenance [118]. D-STATCOMs are characterised as reactive output power (capacitive or inductive) only compensators. In this regard the compensator uses reactive power to control the voltage at given terminals, to maintain desired power flow under possible disturbances. The control requirement of the compensator depends on power flow variation and associated requirements to stabilize power system reactions to network contingencies and dynamic disturbances. The basic compensation needs to fulfil one of two main categories: direct voltage support (to maintain voltage in case of disturbance) and transient and dynamic-stability improvements (to increase the stability margin). The D-STATCOM in this regard, is essentially designed as a static generator to facilitate direct voltage support [118]. The D-STATCOM model is designed as a current source to produce reactive power. The concept of reactive power generation is similar to synchronous generation, where reactive power output is changed by excitation control. The equivalent circuit model is taken from reference [119]. The control signals are identified as *id_ref* (d axis reference current in pu) and *'iq_ref'* (q axis reference current in pu). Fig. 4.4 illustrate the design concept of D-STATCOM is explained below [119] based on power flow relationship.

$$i_1 = \left(id_{ref}.cosu - iq_{ref}.sinu\right) + j\left(id_{ref}.sinu + iq_{ref}.cosu\right) \tag{4.1}$$

$$cosu = u_r/u \quad , \quad sinu = u_i/u$$

where $u_1 = (u.\ (cosu+jsinu) = ur + j.ui)$ is the complex voltage at the controlled bus, i_1 is the complex current that D-STATCOM injects/absorbs into/from the network, u_r is the real component of bus voltage, u_i is the imaginary component of bus voltage, i_r is the real component of current and i_i is the imaginary part of current.

u = positive sequence voltage in p.u

i_1 = current in p.u.

$$i_1 = (id\_ref.\tfrac{u_r}{u} - iq\_ref.\tfrac{u_i}{u}) + j(id\_ref.\tfrac{u_i}{u} + iq\_ref.\tfrac{u_r}{u}) \tag{4.2}$$

The static generator is controlled in current oriented coordinates (*dq* rotating reference frame), whereas the control inputs to the static generator are in stationary reference frames. Based on the D-STATCOM bus connection, it is possible to calculate the apparent power.

$$S = U.I^* = (u_r + j.u_i).(i_r - j.i_i) = P + jQ \quad (4.3)$$

$$P = u_r.i_r + u_i.i_i \quad (4.4)$$

As the active power flow from D-STATCOM is zero, P=0, so equation (3) becomes

$$Q = u_i.i_r - u_r.i_i \quad (4.5)$$

$$i_i = -\frac{u_r.i_r}{u} \quad (4.6)$$

If D-STATCOM injects controllable reactive current into the system, the current magnitude can be represented as shunt reactive current source ($i_{SH} = i_1$). The reactive power exchange of the D-STATCOM with the AC system is controlled by regulating the output voltage amplitude of the voltage source converter (VSC)

$$i_{SH}^2 = i_r^2 + i_i^2 = i_r^2 + \left(-\frac{u_r.i_r}{u}\right)^2 \quad (4.7)$$

$$i_{SH} = \frac{u.i_r}{u_i} \quad (4.8)$$

Now, i_r and i_i can be determined with respect to i_{SH}, from this result, it is possible to relate the static generator to the D-STATCOM controller. It shows a direct relationship between quadrature current (*id_ref*, *iq_ref*) with respect to D-STATCOM current.

$$iq\_ref = -i_{SH} \quad (4.9)$$

$$id\_ref = 0 \quad (4.10)$$

The reactive shunt currents that can be injected by the D-STATCOM are based on voltage droop characteristics (Vdroop as shown in the red box provided in Fig. 4.4). The slope of the droop characteristics determines the voltage regulation requirement of the system. A droop controller requires a reactive power reference value from the network. The reactive power input value is taken from '*Q*' block and sent to the controller '*qac*' reactive power signal directly into the droop controller block. D-STATCOM can be operated over a complete range even at very low change voltage level in the system (typically 0.2 pu). Thus, the D-STATCOM can maintain the AC system voltage and reactive power generation independently to support voltage under abrupt system disturbances which are outside the operating range of the compensator.

4.3.1 Dynamic Modelling of D-STATCOM

D-STATCOM as a dynamic model is based on Milano method [120]. For brevity, only equations used are presented in equations (4.11)-(4.16). A detailed and simplified modelling of D-STATCOM is comprehensively discussed in [120]. The detailed model of D-STATCOM mainly consists of three parts: the DC network, the voltage source converter, and the associated controllers.

In the controller, the reference voltage is measured on each individual phase, then converted to three-phase voltage. The individual phase voltage measurement provides leverage to tackle extreme loading conditions on individual phase. For instance, if all the EVs are simultaneously charging, the customer household load increases drastically for short duration or single line ground (SLG) fault occurs, then the D-STATCOM needs to effectively provide voltage compensation during these events. In other words, the D-STATCOM provides reactive power compensation based on each individual phase voltage.

4.3.2 DC network

The DC side consists of a RC network connected in parallel to the DC node as shown in Fig.4.4. i_{dc} and v_c are DC capacitor current and voltage respectively. R is the resistance and C is the capacitor, v_{dc} is the DC terminal voltage [120].

The differential equations are:

$$\dot{v_c} = \frac{-(i_{dc}+v_c)/R}{C} \tag{4.11}$$

$$0 = v_c - v_{dc} \tag{4.12}$$

4.3.3 VSC model

Due to the fast response of the power electronic switches and of the capacitor, in most transient stability applications, the VSC can be modelled considering only the power balance and simplified control equations. The simplified control equations do not explicitly include the firing angle and the modulating amplitude but only consider input and output variables [120]. Hence, to regulate the active and reactive powers on the ac side, the control differential equations can be written as:

$$\dot{p_{ac}} = \frac{(P_{ref} - p_{ac})}{T_p} \tag{4.13}$$

$$\dot{q_{ac}} = \frac{(q_{ref} - q_{ac})}{T_q} \tag{4.14}$$

Pac and *qac* are active and reactive power. *Pref* and *qref* is the reference active and reactive power. *Tp* and *Tq* is the time constant of active and reactive power measurements.

4.3.4 Controller

In order to keep the consistency and better understanding of D-STATCOM frame in Fig. 4.4, controller equations are presented in '*s*' domain. The dynamic control equation of dc and ac voltages are,

$$id\_ref = \left(V_{dc}\left(\frac{1}{1+sT_{fdc}}\right) - V_{dc_{-ref}}\right)\left(\frac{k_{dc}+1}{sT_{dc}}\right) \tag{4.15}$$

$$iq_{-ref} = \left(V_{ac}\left(\frac{1}{1+sT_{fac}}\right) - V_{ac_{ref}} - iq_{-ref}\left(\frac{k_{droop}}{1+sT}\right)\right)\left(\frac{k_{ac}+1}{sT_{ac}}\right) \tag{4.16}$$

Tfdc & *Tfac* are low pass filter time constant. *Kdroop* is the gain of the voltage control loop, *T* is time constant of voltage control loop. *Kac & Kdc* are the constants of ac and dc measurement and *Tac & Tdc* are time constant of ac & dc measurement. The differential equation can be obtained by converting equations 15 and 16 from frequency domain to time domain using Laplace transformation. The control scheme utilised in this regard should be able to maintain constant voltage magnitude when dynamic load and generation are connected to the network and particularly in the context of abrupt system disturbances on a three-phase unbalanced network. The proposed controlling scheme with two different functionalities are highlighted in the blue dashed areas in Fig. 4.4.

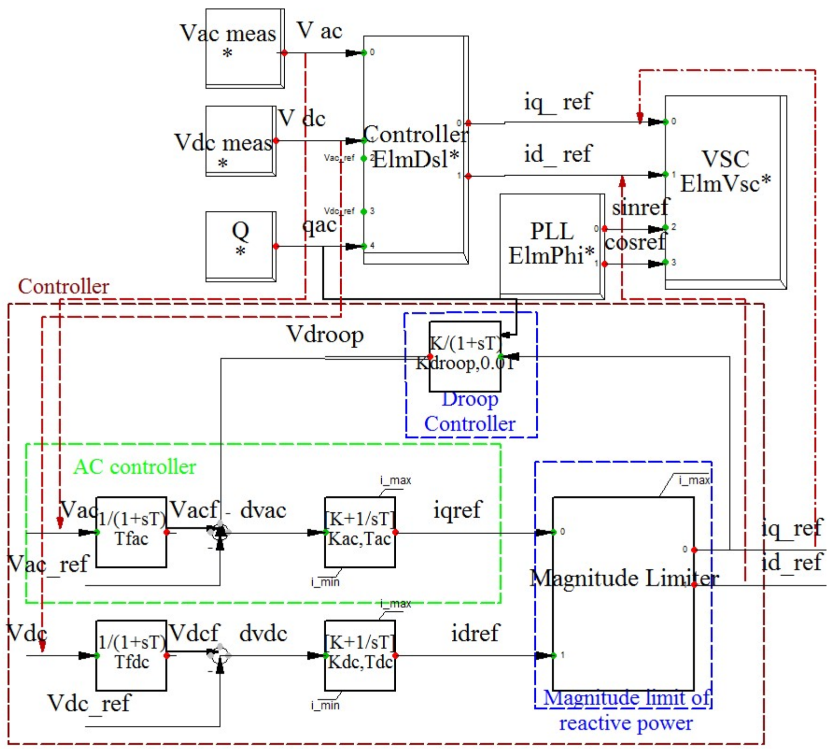


Fig. 4.4: Implemented frame of D-STATCOM

In the D-STATCOM controller, '*Vacmeas*' facilitates measurement of the three phase voltage as dynamic voltage reference at the desired location. The '*Vacf*' block takes the reference voltage, '*Vacmeas*', input and matches it with '*Vac_ref*'. If '*Vac'* is less then reference voltage stipulated by the *Tfac* block then '*dvac'* signal sends a positive value to '*iqref*' signal. If the control 'i*qref' signal* is positive, it is subsequently forwarded to '*mag Limiter*', where it is compared with the limit set in the controller according to the D-STATCOM capacity. If the signal is within the upper and lower limit, the reactive power is injected/absorbed corresponding to that value. The final '*iq_ref*' signal is forwarded to the Voltage source converter (VSC) as shown in Fig. 4.4. The '*iq_ref*' signal feedback it of value '*Vdroop*' through the droop controller, and it compares '*Vac'* and '*Vac_ref'* signal again until '*dvac*' signal become zero. If '*Vac*' signal and '*vac_ref'* signal match each other, the '*iq_ref'* signal will not send signal to compensate.

The Phase-Lock-Loop (PLL block) is used to generate an output signal that relates the phase of the control variable with respect to the input reference signal. The PLL utilises a controlled oscillator that synchronizes the control variable to the reference network signal. Essentially, the *PLL* provides a reference for the voltage angle that the D-STATCOM employs to relate voltage and current while calculating the active and reactive powers.

In general, the terminal voltage is varied through an appropriate reactive power correction, facilitated by the '*iq_ref*' signal (as derived from the '*Vacmeas*' input value). The varied terminal voltage is essentially compared to a fixed reference '*Vac_ref*', which through the PI controller and phase matching (through the *PLL*) obtains the desired effective reference signal '*iq_ref'*

4.3.5 EV load modelling granularity based on Battery size

In this section, recent advancement in the EV battery capacity available in the market are considered up to 40 kWh. The standard charging profile considered for simulation and analysis is discussed previously in Section 2.6.1. The same table is used to extrapolate the battery charging time for 20 and 40 kWh as shown in Table 3 and Table 4.

EVs like Renault ZOE ZE 40 has a 400 km range, through a 41 kWh Battery [51]. It is not efficient to charge EVs from the scratch for 13 hours for a frequent car user. From the DSO perspective, to facilitate the EV customer either the capacity of single-phase charger needs to be increased or all household customers need to use a three phase connection. For 11 kW (three-phase charger) 3 hours and 20 minutes would be required to recharge (from a completely discharged state). The recent trend of small battery size with high power rating will prompt the Irish DSO to look for different solutions in the range of 7-11kW (single phase) in the context of a manageable household load inclusive of charging. In this chapter, all EV batteries are modelled with a capacity of 20 kWh for 3.68 kW charging and 40 kWh for 11 kW charging. For the sake of simplicity, two scenarios are considered. EV batteries are modelled as constant power loads with unity power factor.

4.3.6 Dynamic Modelling of EV load

To demonstrate the benefits of the implemented technique, two specific types of chargers and battery sizes are selected. Based on Fig. 3.6, a probability density distribution of EV battery state of charge varies from 0 to 20 kWh. Out of 74 EVs (if each household has an EV), 3 EVs are fully charged, and remaining (90%) of EVs state of charge remains in the range of 0%-90%. The remaining 67 EVs are randomly distributed on different phases on the network. It is noted that 20kWh and 40 kWh battery sizes are considered for 3.68 kW and 11 kW charging respectively, keeping in mind the recent advancement in battery size. It is noted in Table 3, Phase B, 26 EVs are connected but only required 32.67 kWh of energy to fully replenish the battery. 24 EVs are connected to Phase A and require 145 kWh of energy. On average, each EV on Phase A requires 6.04 kWh and 90 minutes of 3.68 kW charging. The rationale for the simulation time is based on an uncontrolled charging duration. In uncontrolled charging, all EVs are connected simultaneously, although charging time varies based on individual SOC. In this particular scenario, all EV charging time varies from 37 minutes to 90 minutes. For the simulations considered, all residential households are randomly assigned an EV. The distribution of the initial battery state of charge (BSOC) for each EV is shown in Fig. 3.6. The breakdown of EV allocation is based on probabilistic distribution as well as the energy requirement of the EVs of each individual phase. In an Irish context, real-time charging data is difficult to obtain. Based on previous research, a probability density function (PDF) is applied with a mean of 10.75 kWh and a standard deviation of 6 kWh for initialization of

BSOC [61]. For the 3.68 kW charger, the battery size of 20 kWh is selected. While 40 kWh battery is charged through 11 kW charge. While 100% penetration of EVs on a distribution network may not be experienced in reality, it is likely appropriate to examine the worst case scenarios in order to fully capture the benefits of controlling strategy based on uncontrolled charging. The approach to define the probability of EVs, battery state of charge (BSOC) and implementing initialization of EVs as shown in Fig 3.6, Table 4.1 and Table 4.2 are taken from Richardson method [61].

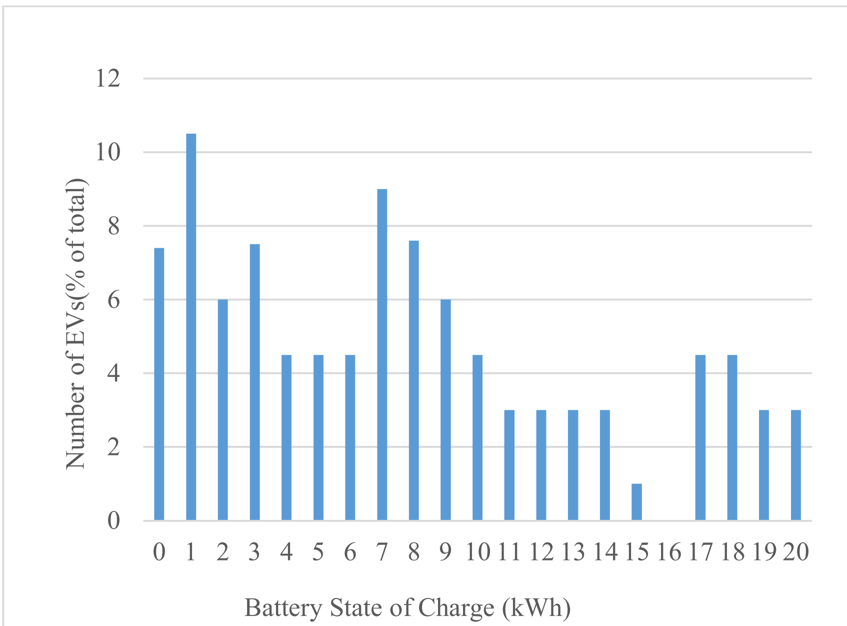


Fig. 4.5: Distribution of the initial BSOC for each EV [74]

Table 4.1: Initial of EV (20 kWh battery)

	Number of EVs	Combined Battery Capacity (kWh)	Combined Initial BSOC (kWh)	Total Energy Required (kWh)
Phase a	24	480	335	145
Phase b	26	520	487.33	32.67
Phase c	24	480	380	100
Total	74	1480	647	277.67

Table 4.2: Initial of EV (40 kWh battery)

	Number of EVs	Combined Battery Capacity (kWh)	Combined Initial BSOC (kWh)	Total Energy Required (kWh)
Phase a	24	960	670	290
Phase b	26	1040	974.66	65.34
Phase c	24	960	760	200
Total	74	2960	2404.66	555.34

In Fig. 3.6, the initial BSOC of 74 EVs, connected randomly in the distribution network is considered. As illustrated in Fig. 3.6, 3 EVs have 20 kWh of initial BSOC with each battery having a size of 20 kWh. So if these 3 EVs are connected to the network, the net energy requirement of these EVs are zero. For example, 7 EVs have 0 kWh of initial BSOC, with a battery size of 20 kWh, 20 kWh of energy is required from a 3.68 kW charger over a period of 5 hours. To simplify this complexity of each EV BSOC, EV batteries are randomly placed on the distribution network. Then for each phase, the number of EVs connected, total battery capacity, total BSOC and energy required is calculated. It is noted, each phase will have a different number of EVs connected and different energy requirements. For instance, Phase C, in Table 3, requires 100 kWh for 24 EVs. On average it requires 4.16 kWh and according to Table 2.2, they require approximately 60 minutes of charging with 3.68 kW to top up the battery completely. For an individual car with a battery size of 40 kWh and an EV battery SOC of 60% (24 kWh), 16 kWh is required. A 11 kW charger can provide 16 kWh of energy in approximately 87.3 minutes. Similarly, if battery size is 20 kWh and the EV battery is 60% (12 kWh) charged, for the remaining 40% (8kWh), will require approximately 2 hours to charge, according to Table 2.2. Once the battery on the particular phase is fully replenished it will be automatically disconnected from the network. Each EV load is programmed in DIgSILENT, Dynamic simulation language (DSL) environment in such a way that once BSOC is 100 % it will automatically get disconnected from the network.

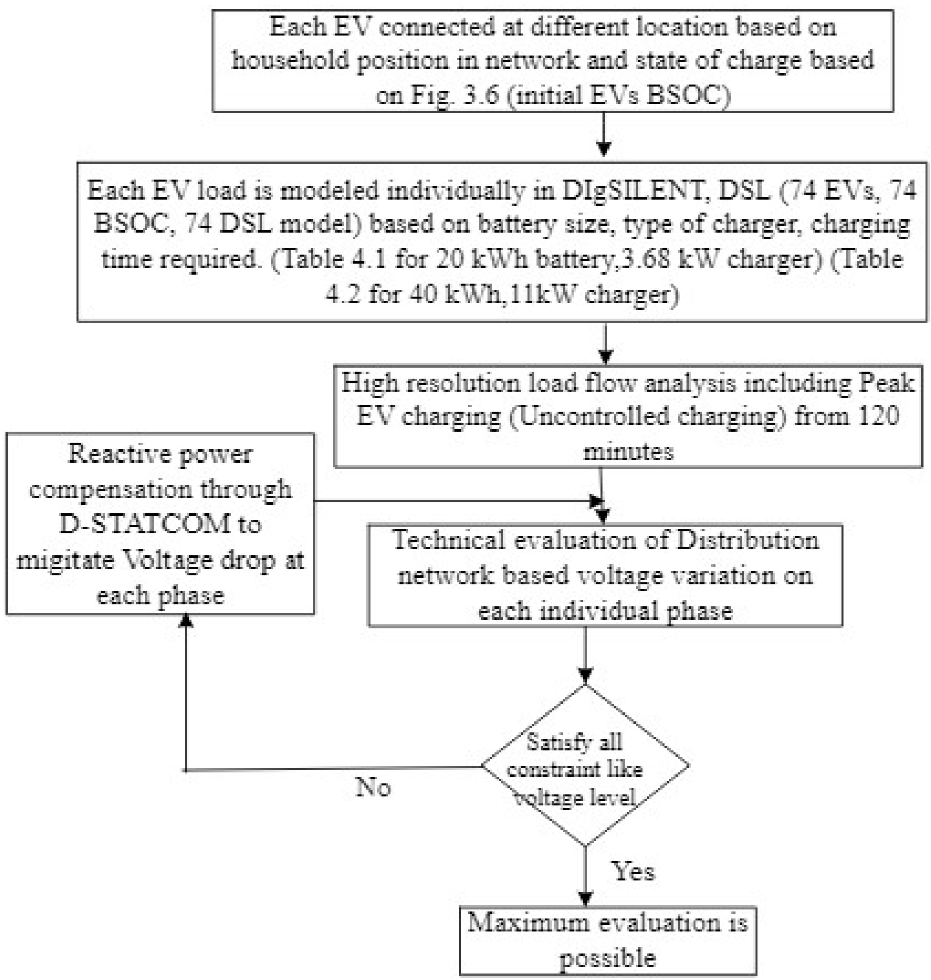


Fig. 4.6: Technical evaluation model of EV demand

4.4 Results

4.4.1 Voltage Profile with 3.68 kW charger

EV charging load is simulated in a test LV network with 74 houses. It is supplied with single phase 230V (line to ground voltage) via a distribution transformer with power rating of 0.4 MVA. In the test system, the distribution system's model is implemented in DIgSILENT power factory. The purpose in this regard is to get better appreciation of voltage unbalance or voltage profile and associated breaches.

Results are presented such that the voltage profile response throughout the network is prioritised while EV charging is taking place. In this regard, the voltage of each individual phase at Pillar B, Pillar E and Pillar J (respectively representing the start, middle and end of the network) are presented from 00:00-02:00 time duration. Voltage profile behaviour for 2 hours are calculated but EV charging time duration is contributing meaningfully for 100 minutes (00:00-01:40)

It is evident that a voltage drop below 0.95 p.u (without D-STATCOM intervention) can occur at Pillar J. The grid is unable to maintain the voltage profile while abrupt EV load is connected on each individual phase. The voltage drop on Pillar J, as presented in Fig. 4.7, clearly presents the limitation of the grid to overcome abrupt changes in load. D-STATCOM is, however, able to compensate but support is provided in this regard to nearby pillars rather than those further away. All households have EV charging connection available. All households have EVs but based on PDF, 3 EVs are already fully charged. In the simulations, all EV loads connect simultaneously to consider the maximum impact of EV battery charging load on the network. The relative positioning of these EVs are considered based on household load connected in distribution network.

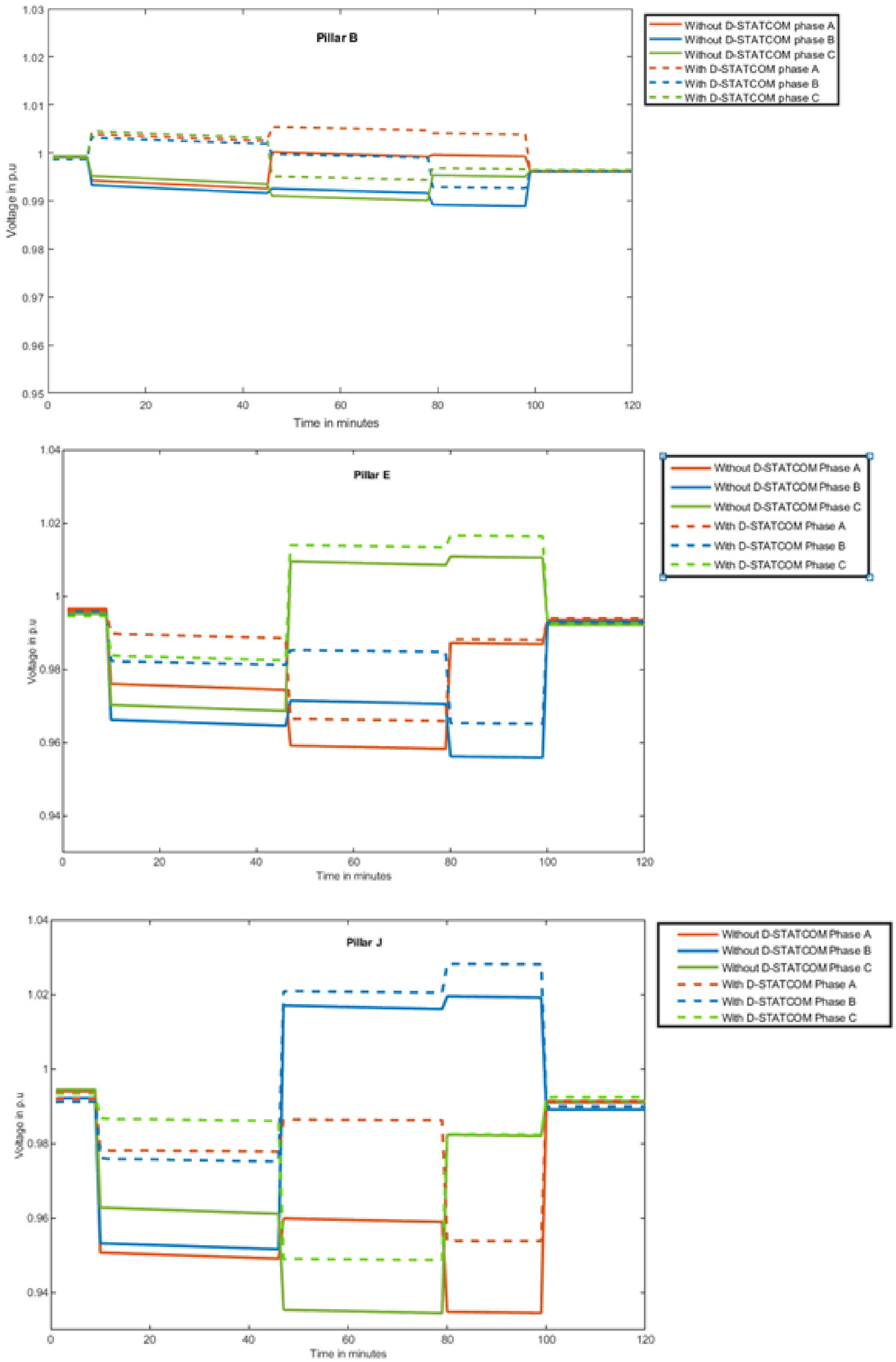


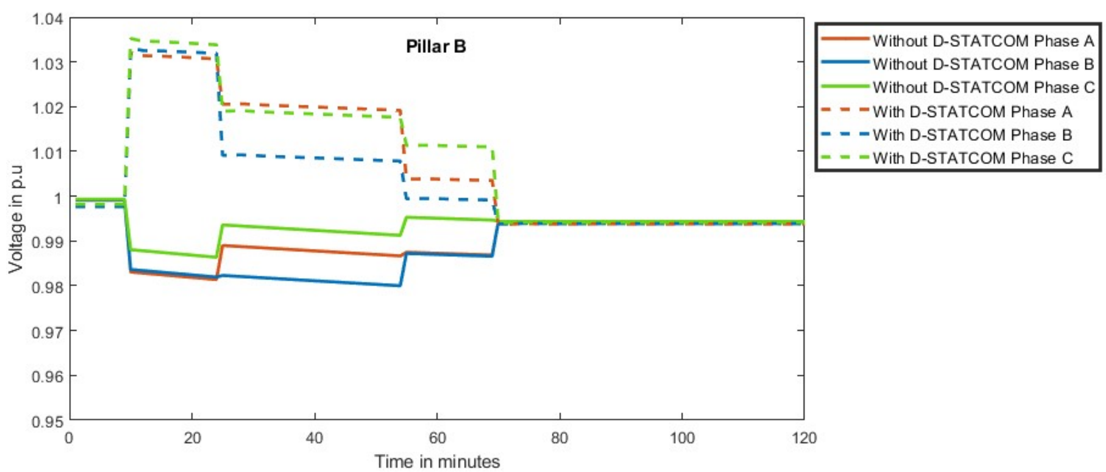
Fig. 4.7: Network voltage with and without D-STATCOM at Pillar B, Pillar E and Pillar J with 3.68 kW charging

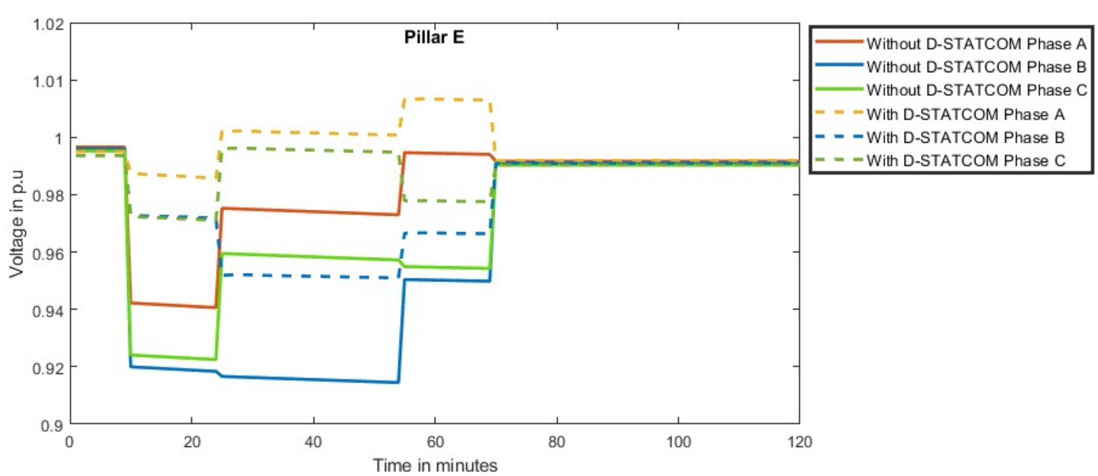
The controlling technique utilizes reactive power only to support voltage drop. Pillar B is located next to the transformer and as a consequence, displays less sensitivity to additional EV load as it is located at the network connection. Pillar J, is located at the end of the network. If the D-STATCOM is placed at pillar J, the impact of D-STATCOM on voltage profile of individual phase is maximised at Pillar J but Pillar B is less sensitive to it because it is furthest away from the D-STATCOM. It is placed at pillar J as the maximum voltage drop is expected at the end of the (radial) network. In Fig. 4.7, the voltage profile of individual phases with respect to battery size and charger, over a 2 hour analysis duration is presented. If the SOC is randomised, there will be sufficient time (within a two hour frame of reference) to charge all EV batteries completely. When all EVs have connected simultaneously the voltage drop in all individual phases which can be seen in Fig. 4.7. D-STATCOM can maintain the voltage level across all phases within limits, with a slight overvoltage on Phase B at Pillar J instead of reducing it. It injects reactive power in the network because Phase A and Phase C are overloaded and face an under-voltage condition at the same instant. It can provide reactive power support to all the phase simultaneously if required (individual phase support is not possible)

4.4.2 Voltage Profile with 11 kW charger

In this scenario, 90% EV penetration means 67 residential households have EVs connected. The specific worst-case scenario considered in this research is with respect to EV charging in order to highlight the advantages of D-STATCOM. The 11 kW charger is connected to the individual phase of each household. It is unable to maintain the voltage range between 0.95-1.05 pu, on Phase A at Pillar J. The breaches are presented in Fig. 4.8. In fact the voltage breach between 00:00 am and 01:00 am is out of the range or power capacity of the D-STATCOM. It injects 0.4 MVAr into the network at the same instant as shown in Fig. 4.12 but voltage at Phase A is only able to recover from 0.87 p.u to 0.93 p.u.

The results suggest that EV penetration closest to the upstream MV grid, in the context of an exemplar urban distribution network, will have less impact on voltage profile than EVs connected to the far end of the radial network. The voltage profile across the network will vary according to location and rating of EVs. EVs are connected to the network as single-phase load, but as such, they can impact voltage level on all (three) phases with the voltage unbalance factor also being affected. Under the conditions considered (April, 2018) in terms of the consumer demand, voltage breaches were not observed until the high penetration of EV connected simultaneously in the network. D-STATCOM however, is able to reduce voltage drop effectively and as such also serves to reduce voltage fluctuations in the network.





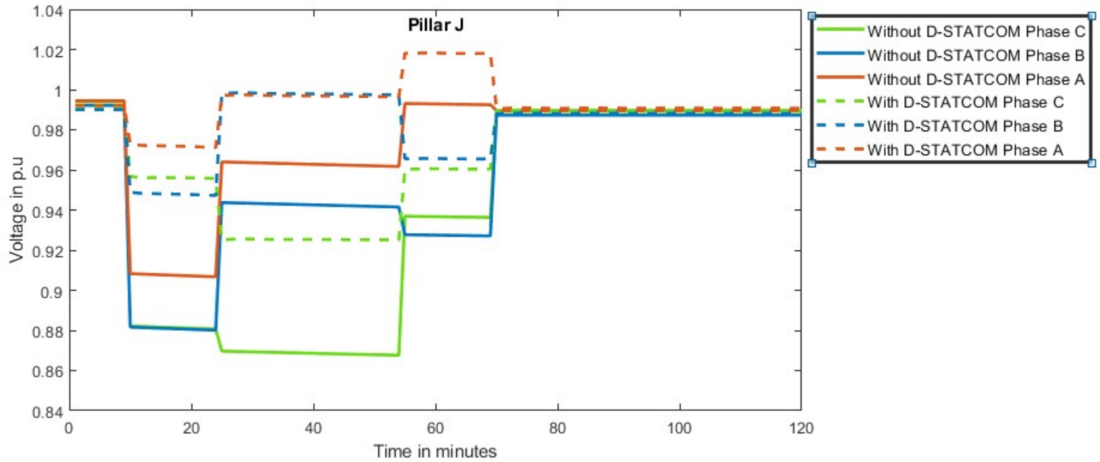


Fig. 4.8: Network voltage with and without D-STATCOM at Pillar B, Pillar E and Pillar J with 11 kW charging

4.4.3 Voltage Unbalance Factor

Single phase penetration of EV can cause voltage unbalance in low voltage network and this is another aspect to be investigated. For Distribution System Operators (DSO), maintaining power quality is a big concern in the context of increasing EV connections. From a voltage profile perspective, voltage drop and voltage unbalance can cause damage to electrical equipment and likely issues are encountered by DSOs in consideration of increased DG capacity [121]. This is particularly the case with voltage unbalance caused by increased single-phase connected EVs. The voltage unbalance factor (VUF) [86] is defined by the IEEE [122] as,

$$VUF\% = \left| \frac{V_-}{V_+} \right| * 100 \tag{4.17}$$

where V_- is negative sequence component and V_+ is positive sequence component of the voltage. According to the IEEE standard [123], voltage imbalance must be limited to 2% in low voltage and medium voltage networks. Voltage imbalance greater than 2% should be reduced through rebalancing of single-phase loads. EV connections in LV networks could result in the possibility that one phase might have more load connections relative to the other two in the network. Such a scenario could result in a lack of compliance with standard limits.

Fig. 4.9 illustrates the voltage unbalance profile over the benchmark of 2 hours for the test distribution network on different pillars at 3.68 kW EV charging scenarios. The D-STATCOM can reduce the VUF as the EV loads are the main cause of abrupt changes in VUF. It is evident that the VUF value is reduced meaningfully during the EVs charging period. The EVs are placed randomly, so one phase has more EVs connected than the other two phases, based on Table 2 and Table 3. The D-STATCOM has to provide reactive power to reduce VUF. In short, it has the ability to reduce VUF while EVs are connected to the network.

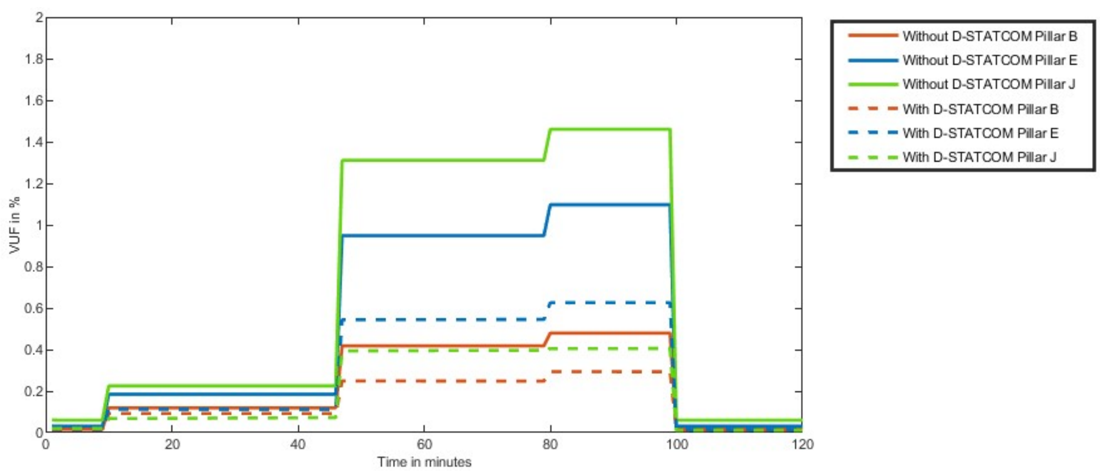


Fig. 4.9: Voltage Unbalance Factor (VUF) at Pillar B, Pillar E and Pillar J with 3.68 kW charging

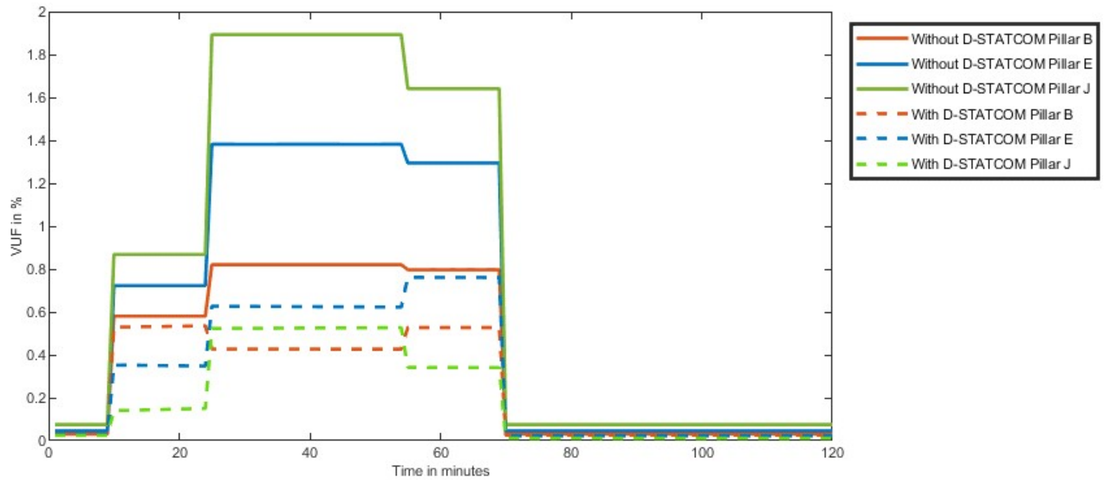


Fig. 4.10: Voltage Unbalance Factor (VUF) at Pillar B, Pillar E and Pillar J with 11 kW charging

Fig. 4.10 illustrates the voltage unbalance profile over the benchmark of 2 hours for the test distribution network on different pillars at 11 kW EV charging scenarios. The VUF breaches the limit of 1.3% at 3.68 kW and 11 kW charging in the network, but the 1.7% VUF realized with 11 kW charging would require significant intervention. With D-STTCOM intervention, VUF is reduced on all individual phases quiet significantly upto 0.7. The D-STATCOM has the ability to reduce VUF in all conditions.

4.4.4 Transformer Loading

The thermal loading of the transformer is presented in Fig. 4.11. Prior to the connection of EVs, the majority of loading measurements are found to lie in between 10% to 15% at normal household load. In case of 3.68 kW charger, the transformer loading remains between 45-60%, which is within the range of transformer rating. The utilization of 11 kW single phase chargers increases the loading drastically from 11% to 183% due to high penetration of EV load at 11 kW charging (as shown in Fig. 4.11). When D-STATCOM injects reactive power into the distribution network, transformer loading further increases up to 300%, to balance active and reactive power requirement of the network. Overloading can cause permanent damage to the transformer and the transformer capacity in this context would need to be increased in this network. The transformer loading can be reduced if fewer EVs are connected to the network. Instead of 100%, 30% EV penetration is considered so that with the D-STATCOM, loading is approximately 52%. In this network, with current power rating of transformer (0.4 MVA), 20% to 30% of EV penetration with 11 kW chargers can be sustained. Overloading of network cables and the associated transformer need to be considered while installing compensation devices in distribution network.

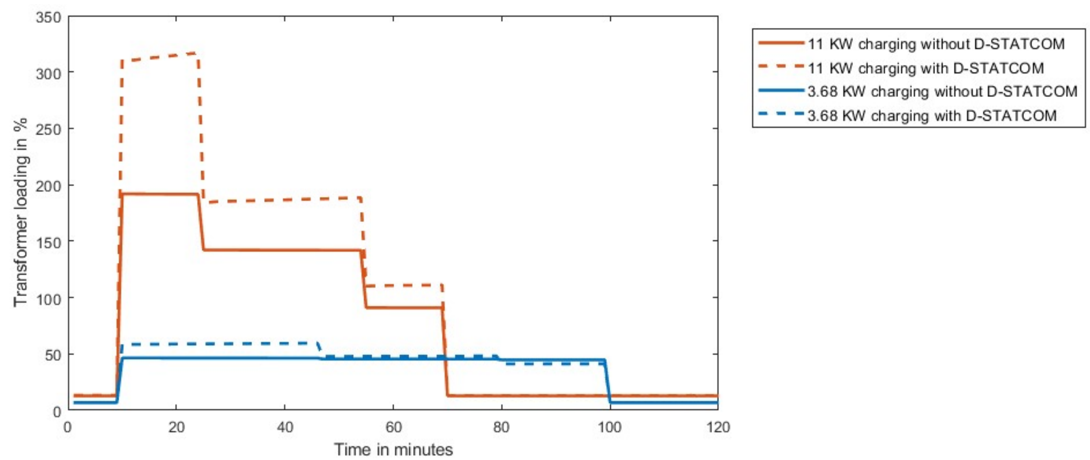


Fig. 4.11: Transformer loading with 3.68 kW and 11 kW chargers, with and without D-STATCOM on complete network

4.4.5 Reactive power compensation through D-STATCOM

A D-STATCOM is connected to Pillar J and the reactive power injected by the D-STATCOM during 3.68 kW and 11 kW charging with 90% EV penetration scenarios are shown in Fig. 4.12.D-STATCOM injects a maximum 0.4 MVAr while 90% EV penetration is available at 11 kW charging. The sizing of a D-STATCOM is dependent on the required MVAr to support the network. It is clear from the analysis that the D-STATCOM can maintain voltage level at each phase and achieve reducing VUF. In this particular network, 90% EV penetration can be overcome through 0.4 MVAr rated reactive power compensation device. However, the transformer needs to be upgraded to higher power rating from 0.4 MVA to 1.2 MVA.

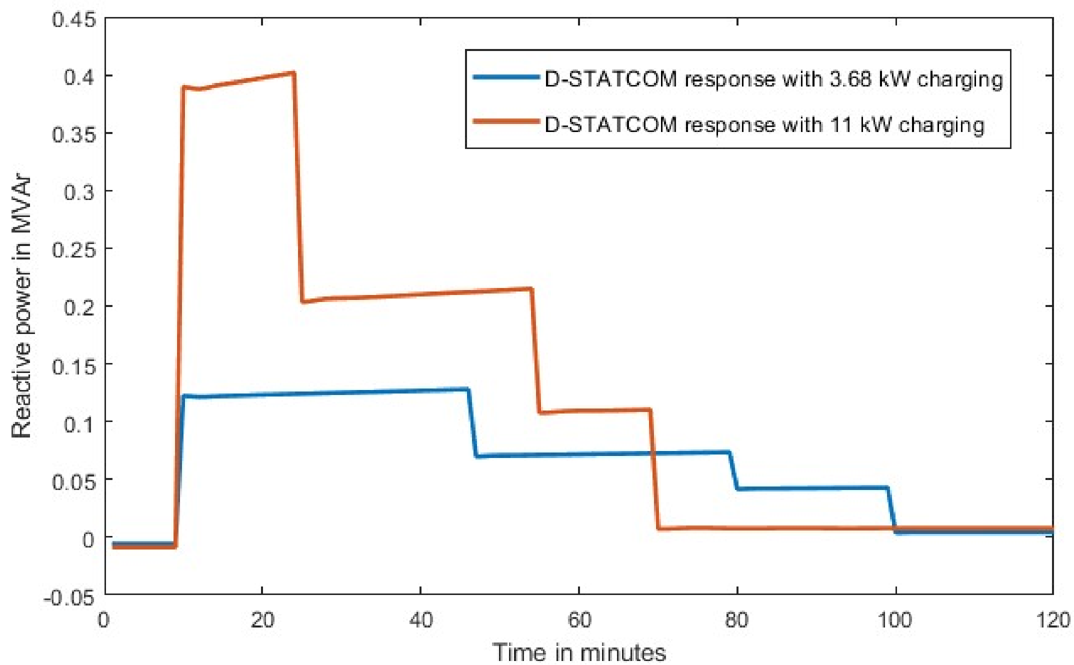


Fig. 4.12: Reactive power injected by D-STATCOM at Pillar J with 3.68 kW and 11 kW chargers

4.5 Economic Justification

Currently, D-STATCOM technology is in the research and development phase (testing phase). In this work, D-STATCOM is tested based on paradigm shift of policy planning between TSO and DSO. If DSO has to implement the technology throughout the LV network, the cost of D-STATCOM could reduce substantially. In the UK, there is a policy shift in that Ofgem (Office of Gas and Electricity Markets) are introducing a network regulation model based on RIIO (Revenue using Incentives to deliver Innovation and Outputs) [124]. The current electricity distribution price control RIIO-1 will end in 2023. The next phase RIIO-2 will establish more onerous and stringent conditions on network companies to deliver innovation, reliability and investment at the least cost to consumers. It is noted that incentives are given to companies which can integrate more EVs in the network or increase prosumer engagement [125]. Therefore, the revenue of the company is increased substantially based on penetration levels of EVs. In an Irish policy context, the TSO (EirGrid) and DSO (ESB network) are working together to make the network more secure and sustainable under the Delivering a Secure, Sustainable Electricity System (DS3) initiative [126]. The main objective therein is to maintain voltage levels throughout the transmission and distribution network. In this regard, the main emphasis is how to increase low carbon technologies penetration in distribution system. The Irish Government is willing to accept the financial impact in this regard in order to prompt green technologies in a sustainable manner.

4.6 Summary

The focus in this chapter was to establish the extent that a D-STATCOM can offer as a viable means to alleviate voltage concerns across a distribution network with a significant number of EV connections. Other mitigation solutions, such as OLTC transformers, network reinforcement, capacitor banks and PV inverter control are well established as a viable means of voltage support [127]. Indeed, these approaches for voltage violation mitigation can be cost effective, but in the context of an increasingly stochastic and variable PQ environment (exacerbated by the inclusion of EV), alternative solutions are needed. This chapter, therefore investigated if a solution originally devised for transmission networks can also be a solution for distribution networks. From a UK/Irish perspective, a comprehensive economic analysis, based on mitigating solutions such as OLTC, network reinforcement in the context of three-phase EV connections is available in [77]. The report suggests that OLTC transformers can accommodate 100% of EV in the network at normal/slow charging rates, but the upgrade cost of the transformer is £60,000 [77], which is a quite expensive option. The authors considered economic analysis for each LCT technology (PV, EV, CHP) at different penetration levels. One of the outcomes of that research was that for UK/Irish DSOs, to sustain 90% of EV penetration, a D-STATCOM facilitating 0.4 MVAr reactive power is required. The authors identified in their report that the cost associated would be the same for an inverter with similar capacity to D-STATCOM [128] and a similarly rated capacitor bank with a suggested installation cost of $4000 (approximately £3200) [128]. It is to be noted that in the context of inverter or capacitor bank options, the installation and maintenance cost is not included in the cost estimations. The authors concede that D-STATCOM may not be the most cost-effective solution, but as a leverage opportunity for enhanced controllability and response time, it could be an optimal approach in a P/Q environment characterised by increasing EV installations.

5. Multiple Objective optimal planning of distribution network

The work presented herein can evolve in a few directions. Whereas work is required in the context of cost estimation and justification in a technical prospective. A bigger more imminent challenge is the optimal placement of D-STATCOM so that the probabilistic impact assessment for a variety of load conditions (including some extreme conditions), in the presence of D-STATCOM are appreciated more comprehensively. In the context of an economic justification, D-STATCOM technology is relatively new. It should be stated that this thesis is not focused on the selection of the most favourable cost-effective solution. The primary focus of the research is reducing voltage variation throughout the network.

This chapter focuses on demonstrating the concept of advance network management by monitoring the chosen network performance indicator (voltage level and VUF), before and after demand side load variations (loading margin) over a period of time. The voltage level is one of the prime network performance indicators as it is related to the load variations in the distribution network. If the network is operating at the highly loaded condition (near to maximum capacity), even a small load change can significantly impact the voltage level. For instance, if high power rating EV chargers are placed at residential loads, then the load margin will change significantly, since the charger could require double the current as compared with domestic load at a particular instant of time [68]. It may cause additional stress to the network, which will be transferred to the transmission level and cause a major blackout. Hence, voltage level monitoring throughout the network is considered as the prime network performance indicator. The requirements of the appropriate network performance indication such as voltage level and VUF are already discussed in Section 2.6.4.

The EV charging profiles are stochastic in nature, which makes it difficult to predict accurately. This will change load demand in different portions of the network. Moreover, it can impact the demand composition (static and dynamic) of load at each individual network busbar [129]. The repeated change in load demand can cause network disturbance and impact the overall voltage level creating power flow calculations [130]. Studies in [131][132] use sequential EV charging to reduce the voltage drop throughout the network. However, sequential charging requires a mode of communication between customer and the network operator which is the biggest challenge to implement a smart charging related solution. It requires an extra layer on top of existing infrastructure for software communication that determines how much energy is available at what moment and decides where it should go. In reality, most of the distribution network does not (currently) have this facility available.

On the demand side there are a lot of loads such as household devices and unexpected demand for charging. On the supply side there is fluctuation in availability of renewable energy. In addition to these, there are various variables that influence the energy network and make it difficult for such a smart charging system to plan the energy supply and allocation. In contrast, D-STATCOM is a fast responding voltage mitigating devices. It can maintain voltage throughout the system.

5.1 Contribution

This chapter introduces a methodology for advanced management of a distribution network to support transmission system operation. From a TSO's perspective, the distribution network management is the responsibility of DSOs. It needs to provide the energy management services at distribution level like load shedding and operating contingency reserves at fast response (seconds to few minutes). The aim of this chapter is to improve system performance by flattening the voltage level throughout the network. This work does not consider a sequential timing approach to flatten the loading curve by shifting or controlling loads from peak to off-peak time periods. Sequential timing approaches are used for load levelling of the network daily load curve, to maintain the target load scheduling (for instance, reducing the peak load of the system). The approach can be effective but a communication protocol (like smart meter technology) requirement, to coordinate between customers and network operators, is not currently available.

The program is built on the methodology developed in Chapter 3, which facilitates the increased demand consumption of EV chargers using probability density function. The methodology derived has an improved accuracy of loading margin, as required by the end-user. This improvement in estimation of load demand is used in this chapter to allow: i) more accurate modelling of EV loading demand at individual busbar. ii) Better planning by taking into account the probabilistic EV demand and aggregated demand of household load. This flexible demand composition information can be used to calculate/estimate network performance indicators (like voltage level) affected by the changes in power flows coming from the different load composition of each busbar. Through clear appreciation of EV demand, the key novelties in this chapter include:

1. Considering different demand loads (load mix) at network buses ensure minimal disturbance in the network using Particle Swarm Optimization (PSO) based Optimal Power Flow (OPF).

Furthermore, the majority of researchers in this space are motivated by economic benefits in maximising the use of renewables generations [46], and particle swarm optimization (PSO) was used as an optimal technique to solve economic dispatch [133] and OPF including voltage stability indicators [68]. As it is already established in the literature, PSO has higher computational speed over genetic algorithms [134], which is another heuristic optimisation method used in similar problems [135]. This work introduces for the first time (as its third distinct novelty) the application of the D-STATCOM in network performance as a constraint in planning of distribution network. The proposed methodology is illustrated through a case study analysis using a 74 bus (Irish) test network.

Previous chapters have discussed the complexities involved in the integration of EV chargers. Chapter 3 establishes the extent of the technical issues in the network and the implications for customers as they would be affected by increased EV proliferation. Related issues concerning EV load profile and household customers are also explained in Chapter 3. More importantly, in Chapter 4, a D-STATCOM is utilised to overcome the technical issues associated with voltage quality. Moreover in chapter 4 in the analysis Section 4.5, the results suggest that to accommodate 11 kW EV chargers for 100% EV penetration, reactive power support is required to maintain voltage levels within standard. It has been demonstrated that the D-STATCOM can accommodate the technical issues quite effectively,

This chapter illustrates the concept of optimal power flow in a distribution network. The methodology builds on the concept of probabilistic integration of EV charging profile, as discussed in Section 3.2.3. The decomposition load demand model is used to accurately place the EV load at each busbar of the network. It will help to obtain the network performance indicators such as active and reactive power and voltage level at each individual busbar. The optimisation algorithm can be useful for DSO, as a decision-making tool as part of network planning and observation. DSO can select (one or more) network performance indicators within predefined limits. This method can be applied to different network topology or even at transmission level.

The proposed method considers the stochastic nature of EV loads. In addition, it provides an optimal size of D-STATCOM enabled with Q-V (Var-Volts) functionalities. However, in the context of an optimisation starting point, an estimation technique is utilized. It can provide an indication of where the optimal solution can be achieved. In other words, the portion of the network likely suitable for D-STATCOM placement. The estimation technique utilised is based on an inspection of where a D-STATCOM position might operate satisfactory and refers to inspecting the network configuration and quickly making an assumption about the placement of the D-STATCOM without calculations. Such a technique is used as an initial starting point, from which an optimal position, through the optimization technique, can be ascertained.

5.2 PSO based Methodology

The DSO is mandated to maintain the network performance through the network. The high penetration levels of EV charger load with instant power demand greatly influences power flow in the distribution network. If the influence of EV chargers are not tackled at a distribution level, they have the potential to influence the transmission network as well. The network performance indicators are frequency, voltage levels, line flows, network losses, etc. These indicators can be affected by high penetration level of EV. The voltage level is more likely to be impacted by the large-scale demand side load changes (for example, frequency is more critical in transmission network than in distribution network).

This section only discusses a general overview of the methodology used to solve the problem. In this work, network planning and scheduling is designed, with two objectives, namely: voltage stability throughout the network and reactive power requirement to stabilize the voltage level throughout the network. It can be met by the following steps: 1) ensuring the distribution network load follows the pre-defined load profile, considering load changes 2) preservation of demand composition in terms of EV load and domestic load; 3) preservation/ improvement of the voltage level and VUF throughout the network.

The first objective is to calculate the power flow with participation of flexible load distributed throughout the network. The method needs to take different busbars with different flexible loading conditions, and so the load shift at any busbar, at any time step without any restrictions. The output of each time step is forwarded to the optimization technique. The second objective is to maintain the voltage level, after any action or unexpected load behaviour, such as in the case of load change. The output of this optimisation step therefore informs the distribution network operator what portion of a particular amount of reactive power is required to rectify the disturbance. Finally, the EV loading (of each time step) is sequentially checked relative to the previous time-step. When the network loading corresponds to a maximum V-Q curve value, the network is at the verge of collapse. In this condition, D-STATCOM will have to be disconnected, as it is considered critical and corrective actions are required. Otherwise, in normal conditions, D-STATCOM will operate. The maximum reactive power required to maintain the voltage level is an unfeasible working condition.

Fig. 5.1 represents the approach to analyse the problem in the power system analysis. In Fig. 5.1, the distribution network contains 74 household customers including EV connection available in all the houses. The infrastructure of the distribution network is explained in Chapter 3 (Section 3.2.1). The distribution network has nine busbars/pillars (three-phase connection points at which single-phase supply is facilitated to end (domestic) consumers, namely Pillar A to Pillar J.

After each simulation, the voltage level is calculated and forwarded to the optimization process to obtain the optimal solution. The optimal solution needs to have the voltage level remain between 0.95 per unit (which is standard operation lower limit) and 1.05 per unit. If the voltage level breaches this limit, then reactive power support is available through the D-STATCOM to maintain a voltage level in between 0.95 to 1.05 per unit. The optimization algorithm decides, to increase or decrease the reactive power and find out the best position to install the D-STATCOM. The minimum reactive power required to satisfy voltage level across all the pillars throughout the network is the best position to install D-STATCOM. If, the voltage level reaches more than 1.05 per unit, then the D-STATCOM reactive power supply is reduced until the voltage level is under the pre-defined limit. If the voltage level falls to less than 0.95 per unit, the D-STATCOM will start providing reactive power support, in steps of 0.1 MVAr. The controller is used to provide balance between the optimization technique and D-STATCOM power exchange. For instance, in case of short circuit or extreme load condition, if the voltage breach cannot be mitigated through the power rating of the D-STATCOM, then the controller does not allow the D-STATCOM to provide support. It is used to formulate the input data and decide if the D-STATCOM can mitigate the voltage stability issue throughout the network. If the voltage level is maintained throughout the network, then D-STATCOM reactive power support is stored along with the position in the network that facilitated the optimal voltage support at variable loading conditions. For example, the voltage drop can be mitigated through the placement of D-STACOM at pillar C or Pillar D, but then the controller selects the D-STATCOM position based on the power rating. If Pillar C requires 0.4 MVAr reactive power to maintain the voltage level and Pillar D required 0.3 MVAr reactive power support to mitigate the voltage issue throughout the network, then controller will select the 0.3 MVAr value with the optimal location as Pillar D. The controller is used to select the best option available from a range of solutions. This process of reactive power (Q) exchange between distribution network and D-STATCOM will continue until the voltage level (V) stabilises throughout the network. The correction of the voltage level (V) in the network (i.e., calculated throughout the power flow analysis) is obtained by optimising Q-V values using Particle Swarm Optimization (PSO).

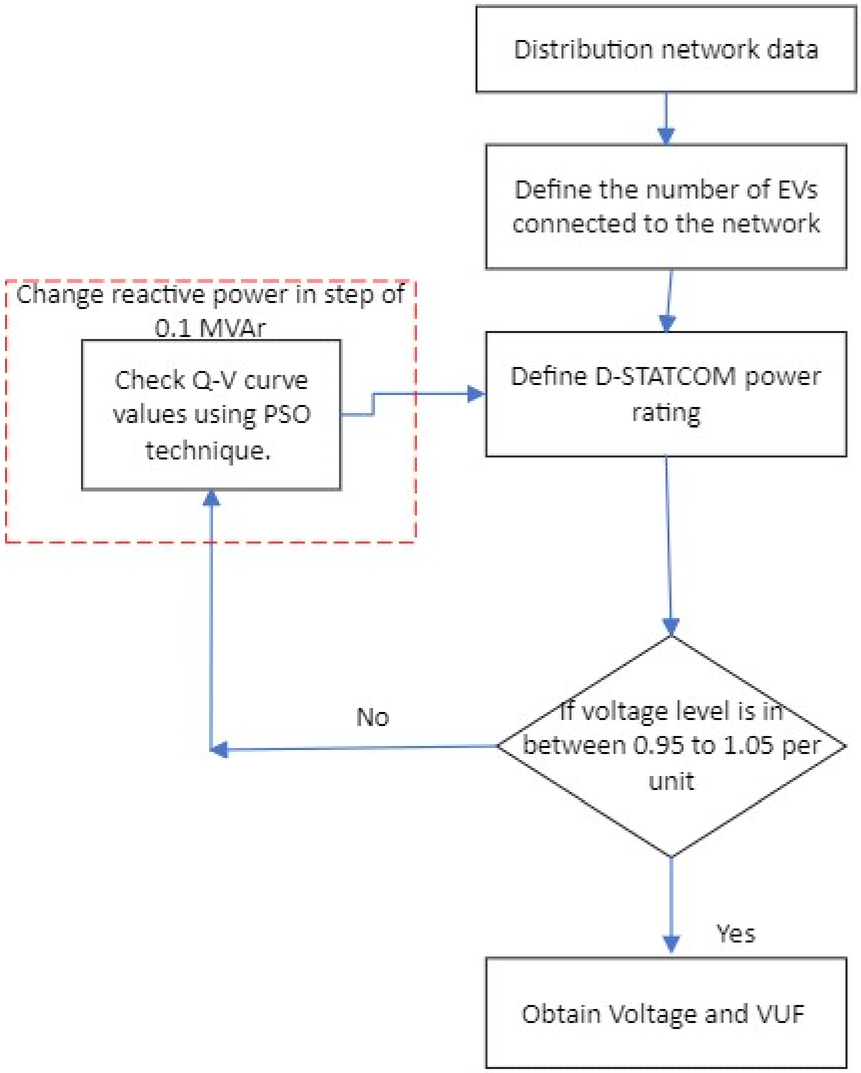


Fig. 5.1: Basic Methodology

5.3 Optimal Power Flow (OPF)

The first task is to apply the power flow (PF) with participation of flexible load buses (pillars) acting as distributed EV charger load. The algorithm considers different buses having different controllability. Load shift at any bus at any time step is limited by the available predicted EV charger load profile as discussed in Section 3.2.3. The output of power flow is processed through the optimisation algorithm. The optimization technique helps the operator to define limit of flexible load that can be placed on the busbar. The optimal technique helps to find the best possible Q-V operating point to maintain the voltage level throughout the network. Once, the power flow starts to acquire Q-V results for the optimal technique, then the power flow is known as *optimal power flow* (OPF). The output of this optimisation step informs the operator how much of the reactive power is required at each load bus and when to ensure the voltage stability in the network.

5.3.1 Objective function

The main objective of the optimal problem is to maintain the voltage level throughout the network. The secondary objective is to minimize the voltage unbalance factor throughout the network. Optimal placement of D-STATCOM will make sure the voltage level remains within the limit. Any voltage limit violation can reduce the efficiency and reduction of the electrical equipment life. The objective function of voltage taken from [136] is given by Eq. 5.1

$$Vmin \leq V \leq Vmax \quad (5.1)$$

where V_{min} and V_{max} are the the maximum and minimum values of the voltage levels respectively.

Constraints:

In the steady state power flow calculation model, the pillar accommodating the D-STATCOM connection can add reactive power in a controllable manner. The D-STATCOM is therefore modelled as an ideal controllable reactive power source that can inject or absorb reactive power with the following constraints.

$$Qstatcom_{min} \leq Qstatcom \leq Qstatcom_{max} \tag{5.2}$$

where $Qstatcom_{min}$ and $Qstatcom_{max}$ are the the maximum and minimum values of the STATCOM volt ampere reactive (VAr) capacity, respectively.

5.4 Analysis

The proposed method is divided into four different stages. A flow diagram of the proposed method is shown in Fig. 5.2. It provides a step-by-step, detailed description of how to obtain the optimal solution for the D-STATCOM placement in achieving the objectives of voltage profile optimsation. Although, an example of Irish distribution network, is presented in section 3.2.1, some salient features are also presented here, to explain the proposed method more clearly.

The network model is implemented in the DIgSILENT power factory platform as previously discussed in Section 3.2.1. There are 74 customers, connected from a 10/0.4 kV transformer in a radial network topology. In this regard the LV distribution network considered in [40], as provided in Section 3.2.1, is employed. The network consists of nine (three-phase) pillars, namely, Pillars A-J, through which single-phase domestic customers are connected. These pillars subsequently facilitate a radial connection to the substation transformer. Pillar B is nearest to the transformer and Pillar J is the furthest from the transformer.

5.4.1 Stage I: Network Structure and Configuration

The first step is to implement the distribution network. There are 74 household customers with each household having one EV charger up to 11 kW rating. The household and EV load profiles are defined using a probability distribution function (PDF), as already explained in Section 3.2.2 and Section 3.2.3. The maximum EV penetration is 100% meaning all 74 household have one EV each. Each household is connected via single phase connection to the distribution network. The EV and household load demand are modelled in such a manner, that each household and EV are included as a separate load profile. Once all the input parameters are defined the system configuration is completed.

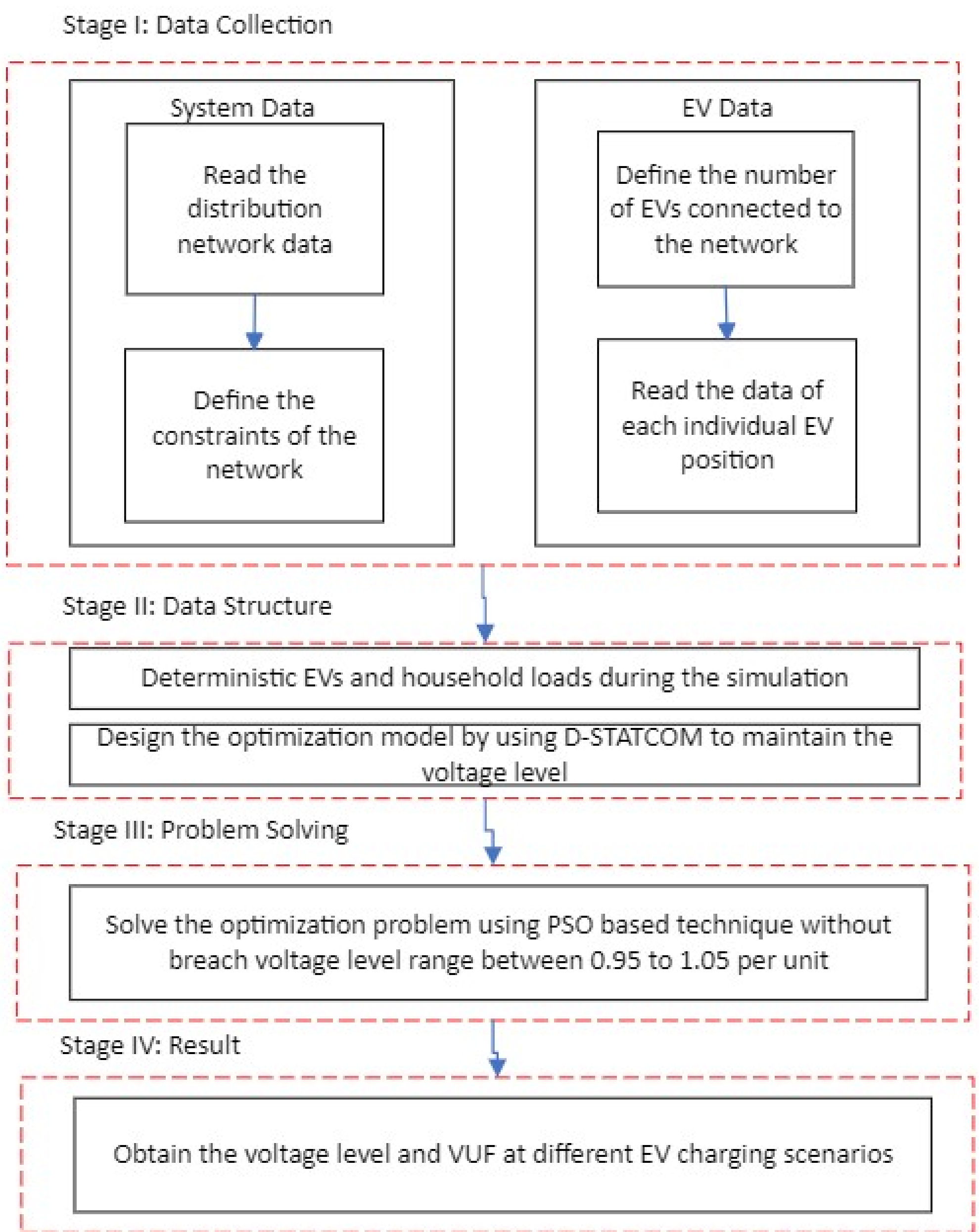


Fig. 5.2: Proposed Optimization

5.4.2 Stage II: Data Structure and Processing

One hundred different EV charging scenarios are defined. The voltage matrices are obtained at nine different pillars, namely Pillar B-Pillar J. If the voltage level throughout the network, remains within the range at 100 different scenarios then size and location of D-STATCOM is optimal.

In this work, the scenario-based method is proposed. Monte Carlo (MC) simulation is based on the principle of repetitive iteration. The problem is simplified, by using scenario-based approach instead of MC simulation. The probabilistic approach will be able to provide the range of reactive power required to maintain the voltage level stability. The scenario-based analysis is able to provide the exact value of the reactive power requirement. The reactive power required to compensate the event can be obtained through the proposed method. If the lower power rating device can maintain the voltage level, then there is no need install the oversized device at the start of the network.

In the preliminary analysis, uncertainties in load demand are defined using normal or Gaussian PDF. It is assumed that the mean and standard deviation are known. A probability density function (PDF) with a mean 'μ' of 5.12 kWh and standard deviation 'σ' of 0.2 kWh is applied, a brief explanation is available in [74]. The probability of *d-th* load scenario is represented by π_d (probability of demand scenario *d*) and calculated by Eq. 5.5.s $P_{D_d}^{max}$ and $P_{D_d}^{min}$(maximum/minimum power demand) are the boundaries *d-th* interval.

$$\pi_d = \int_{P_{D_d}^{min}}^{P_{D_d}^{max}} \frac{1}{\sqrt{2\pi\sigma^2}} \; exp^{\left[-\frac{\left(P_{D} - \mu_d\right)2}{2\sigma^2}\right]} \, dP_D \tag{5.3}$$

Fig. 5.3 illustrate the approach to interpolate the probabilistic chart into tabular form. The household loads are divided into five sub-categories namely, d1, d2, d3, d4 and d5 based on probabilistic quantification as shown in Fig. 5.3. Similarly, by using the battery size (20 kWh), the probability distribution of connection times and the probability of energy requirements of 20 different EV battery charging states (1-20 kWh) are considered. For instance, as illustrated in Fig. 5.3, the probability of a EV battery having 1 kWh state of charging is 0.11 and in the tabular form it is represented with ev2 in column 'π_{ev}'. The probability of the EV battery having 5 kWh state of charging is 0.05, it is represented with ev6. For a 20 kWh battery size, 20 different residential EV scenarios 'π_{ev}' have been created.

- EV charging scenarios are based on Fig. 5.3, to represent 20 EV BSoC in a probabilistic manner.
- Load charging scenarios are based on Fig. 5.3, to represent 5 different household load scenarios 'π_d' in a probabilistic manner.
- The probability of each demand scenarios for EV and household load demands are calculated individually and then merged using Eq. 5.6, to get 100 different probabilistic scenarios 'π_s' as illustrated in Fig. 5.3.

$$\pi_s = \pi_{ev} * \pi_d \tag{5.4}$$

Load Scenarios	
	πd
d1	0.68
d2	0.06
d3	0.06
d4	0.1
d5	0.1

EV scenarios	
	πev
ev1	0.07
ev2	0.11
ev3	0.06
ev4	0.07
ev5	0.05
ev6	0.05
ev7	0.05
ev8	0.09
ev9	0.07
ev10	0.06
ev11	0.05
ev12	0.03
ev13	0.03
ev14	0.03
ev15	0.03
ev16	0.01
ev17	0
ev18	0.05
ev19	0.05
ev20	0.03

Scenario number	
	πs
s1	0.0476
s2	0.0748
s3	0.0408
s4	0.0476
s5	0.034
s6	0.034
s7	0.034
s8	0.0612
s9	0.0476
s10	0.0408
s11	0.034
s12	0.0204
s13	0.0204
s14	0.0204
s15	0.0204
s16	0.0068
s17	0
s18	0.034
s19	0.034
s20	0.0204
s21	0.0042
s22	0.0066
s23	0.0036
-	
-	
-	
s100	

Fig. 5.3: Illustration of scenario generation procedures

5.4.3 Stage III: Particle Swarm Optimization (PSO)

PSO belongs to the group of heuristic optimisation methods along with genetic algorithms and evolutionary algorithms [137][138][139]. Some researchers have focused on optimal power flow, with respect to voltage stability index [18], other researchers [140][141] consider the optimal position of FACT devices using different optimization techniques like PSO, ANN and analytical methods. These methods start from a random choice in the search space and based on the evaluation of the objective function at every iteration, gradually move from the position of the result towards the optimal solution. PSO optimization techniques are selected here for optimal power flow calculation because it is commonly used to obtain optimal power flow calculations by the researchers [134][18][140].

The PSO algorithm consists of three steps: Generating positions and velocities of the particles, velocity update and position update. Velocity is the mechanism used to move the position of a particles to search for optimal solution. In other words, PSO, as an optimization tool, provides a swarm-based search procedure in which particles change their positions with time [136]. In a PSO system, particles are allowed to move in a search area. During the search, each particle adjusts its position according to its own experience and the experience of neighbouring particles, making use of the best position encountered by itself and its neighbours. When improved positions are discovered these will then come to guide the movements of the swarm. The process is repeated and by doing so it is anticipated, but not guaranteed, that a satisfactory solution will eventually be discovered.

The initial positions and velocities are allocated randomly, from the search space, and the velocities are updated in the following iteration based on the values of the fitness function of the particles within a swarm. The velocity update (v_i) in Eq. 5.8 uses information about the particle with the best global value in the current swarm (the so called local best – $Pbest$i), and the best position of any particle over time (the so called global best solution – $Gbest$i). Finally, the particle position is updated based on the velocity update. The position of the i-th component of the particle vector X(Xi+1) is updated based on the previous time step t.

Following are the conventional terminology of the variables in PSO: Let x and v denote a particle coordinate (position) and its corresponding moving around (velocity) in a search area, respectively. Therefore, the i^{th} particle is represented as [140],

$$x_i = [x_{i1}, x_{i2}, x_{i3}, \ldots\ldots, x_{iD}] \tag{5.5}$$

$$v_i = [v_{i1}, v_{i2}, v_{i3}, \ldots\ldots, v_{iD}] \tag{5.6}$$

The particle can move in D-dimension is based in the search area. The best previous position of the i^{th} particle is recorded and represented as *pbest* [140].

$$pbest_i = [pbest_{i1}, pbest_{i2}, pbest_{i3}, \ldots\ldots, pbest_{iD}] \quad (5.7)$$

$$gbest_i = [gbest_{i1}, gbest_{i2}, gbest_{i3}, \ldots\ldots, gbest_{iD}] \quad (5.8)$$

The position of the best particle among all the particles in the group (swarm) is represented by the *gbest*. In a particular dimension *d* there is a group best position which is $gbest_d$.

The modified velocity and position of each particle can be calculated by using the following scheme [140].

$$v_{id}^{t+1} = \left[w^t v_{id}^t + c1R_1^t\left(pbest_{id}^t - x_{id}^t\right) + c2R_2^t(gbest_{id}^t - x_{id}^t)\right] \quad (5.9)$$

$$w = w_{max} - \left(\frac{w_{max} - w_{min}}{iter_{max}}\right) * iter \quad (5.10)$$

where c_1 and c_2 are acceleration constants, defining the linear attraction towards the direction of the particle. Coefficient c_1 and c_2 define attraction towards the local best (found by the given particle at any iteration) and global best solution (found by any particle at any iteration), respectively [142]. The first coefficient should not be too large or too small, to prevent slow or premature convergence, respectively [135].

5.4.4 D-STATCOM based on PSO algorithm

PSO algorithm is used to calculate the reactive power requirement of D-STATCOM every time the EV load demand changes. 100% EV penetration is considered to ensure that the system is able to withstand increases in demand or disturbances without endangering network voltage stability. The PSO algorithm is used to check the Eq. 5.1 subject to Eq. 5.2, where Q_{min} is the reactive power required prior to the EV penetration, and Q_{max} is the reactive power required after rescheduling of EV loads on each busbar. The PSO algorithm is implemented in DIgSILENT Programming Language (DPL), with the swarm size (number of particles) set to 100 [68]. The default values for acceleration constants of $0.1 \leq c1 \leq 1.1$, and $c2 = 1.5$ are used [18][68][135]. The swarm size and acceleration constants values selection and justification are discussed in detail in [135]. Similar values are selected to solve optimal power flow problem using the PSO algorithm [18]. PSO algorithm converged to a fixed value after 9 iterations on an average, hence this number was chosen as the maximum number of iterations in order to reduce the computational time [68]. The working of the convergence process in PSO is illustrated in Fig. 5.4. The simulations are run simultaneously in each iteration and the objective function value is recorded. Once, the value satisfies all the constraints, the best recorded objective function value is selected as the optimal solution. It takes 15 minutes for overall algorithm to run (for 74 bus network, along with 74 different EV load profiles). For the first iteration, once the objective function value reaches in the range, the number of iterations required to stabilise the value is calculated. For instance, 9 iterations are required to complete first simulation and the 9 iterations are fixed, to calculate the complete planning horizon (i.e., 100 time steps). There is certainly a scope to increase time step sensitivity in the planning horizon, but to reduce the computation burden, it is limited to 100.

For t=1, the stopping criterion of the iterative process is determined by either the maximum number of iterations (9 in this case) being reached, or when the constraint of voltage level reaches a limit value equal to 0.95 or 1.05 per unit throughout the network. Then, for T= t+1, the same procedure is repeated until it reaches maximum time step (i.e., 100). Therefore, the aim of the optimisation process is not necessarily to maximise the EV penetration (load margin), but to keep voltage level within limits.

The detailed illustration of the methodology is presented in Fig. 5.4. It clarifies the steps to integrate the PSO within the power flow analysis to obtain optimal power flow (OPF). OPF can integrate the combined load models and optimisation can be solved together with power flow in DIgSILENT power factory environment. To avoid the practical complexity/limitations of the software in use, two-layer solution is proposed as illustrated in Fig. 5.4. Namely, Layer I is for solving optimal power flow and Layer II is where optimization of objective function is incorporated. Layer I is implemented in DigSILENT PowerFactory which executes power flow analysis and the Particle Swarm Optimisation algorithm in Layer II is implemented using DigSILENT Programming Language (DPL). The demand profile of EV charging with 100 different scenarios as illustrated in Chapter 3, utilizing the probabilistic density function is used. For instance, 74 load buses have 74 different EV charging profile, each profile have 100 different readings. The maximum time step of 100 is reached. In the next step, Q-V curve simulations are run DIgSILENT Power Factory, using the distribution network configuration and each composite EV load model. In Level II, as shown in Fig. 5.4, if the voltage level breach occurred than PSO algorithm is applied, starting with initialisation of N = 100 particles in the swarm [68]. Each particle is a vector containing relevant demand values of EV loads (represented as L1, L2 in Fig. 5.4) at all the load buses in the network (74 of them), assigned randomly by the algorithm, respecting the load flexibility limits at each load bus. The objective function of the PSO algorithm is calculated based on the outputs of the Q-V simulations performed in DIgSILENT Power Factory for every particle in the swarm. The iterative process updates the swarm using Eq. 5.4 and until the stopping criterion is met. Finally, based on the new optimal values of $Q_{statcom}$ and voltage level is obtained. In the next time step, T= t + 1, EV load values are updated (upcoming time steps following the resulting EV load change in the current time step).

In previous work, [18][68] authors are using different softwares like Matpower/DIgSILENT Power Factory for power flow calculation and import results in MATLAB for PSO algorithm implementation. In [18], PSO algorithm is used to find optimal voltage stability index while considering different load margins. In [140], PSO algorithm is implemented used to find the optimal location and size of BESS-STATCOM. The PSO algorithm and implemented equations are quite similar to [18][140] but reactive power required to maintain the voltage level is not considered in previous studies. The implementation of PSO algorithm on DPL required network configuration simulations data from DIgSILENT Power Factory.

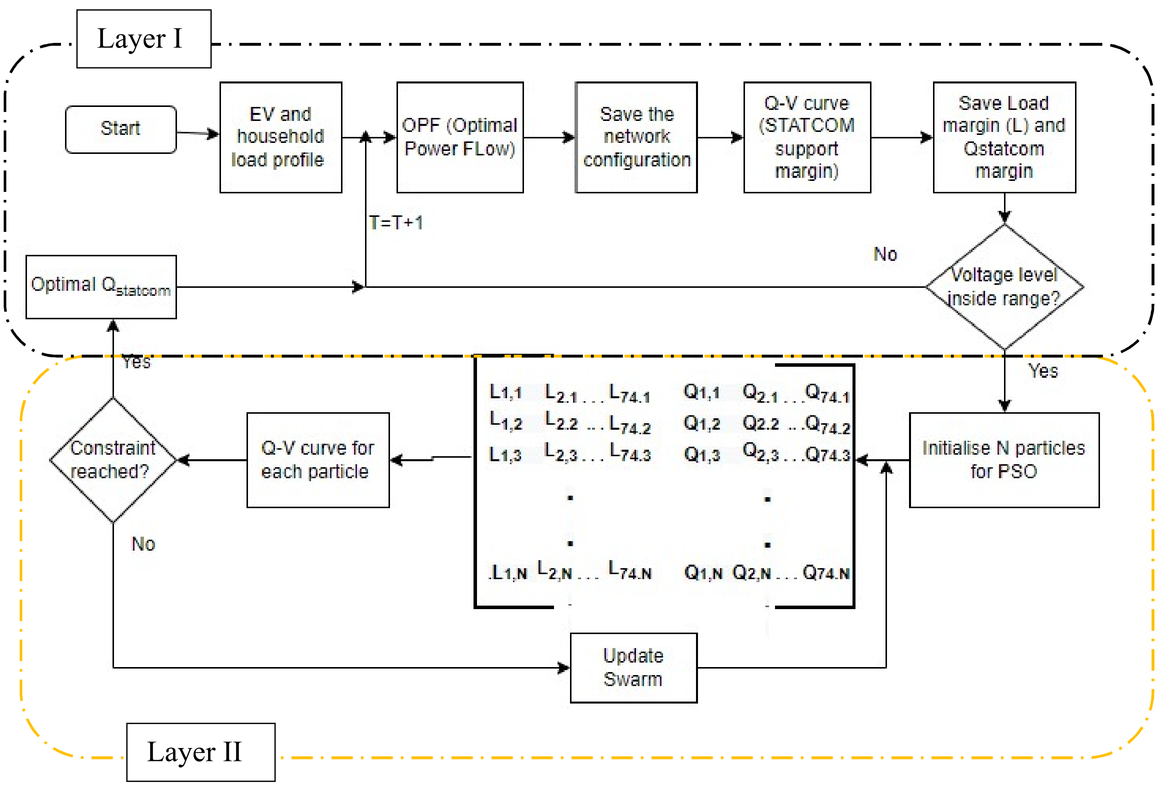


Fig. 5.4: Flowchart of Methodology with detailed integration of PSO [140]

The first two optimisation steps (OPF and V-Q curve simulations) are run in DIgSILENT Power Factory, while the PSO algorithm is run in DIgSILENT programming language. It represents a distribution network with 11 kW EV charging scenario.

1. Self-reliant, relying on reactive power support by D-STATCOM, and adjusting its voltage level based on uncontrollable flexible EV loading.

The objective function of the reactive power only formally participates (no. of total busbars in the network), as the output of each OPF calculation is fixed. It serves only to target EV flexible loading, it should be adjusted in each iteration. The constraint control/minimise the flow of reactive power (either positive or negative) based on the voltage level throughout the network. All the load busbars (74 of them) are considered to be uncontrollable flexible loads, however each load bus has different load composition throughout the 100 different iterations. The assigned daily domestic household load curves and demand composition are generated using the CREST load model, as detailed in section 3.2.2. The EV profile are generated using PDF as discuss in Section 3.2.3. As the typical consumption of residential EV ranges between 3.68 kW to 11 kW, it is adopted, for simplicity reasons, that each EV connected to the load bus in DIgSILENT Power Factory has the load of 11 kW. Higher granularity than this one was deemed unnecessary.

The proposed methodology is demonstrated on a distribution network. The effectiveness of D-STATCOM is evaluated with voltage level management throughout the network, the closer this ratio is between 0.95 to 1.05, the more successful reactive power support is. In addition, the D-STATCOM location were observed before and after each loading iteration, to evaluate the extent to which D-STATCOM contributes can reduce voltage variations. Finally, the case study illustrates how different the outcome is when the load is modelled as constant power, and constraints such as load margin are considered.

5.5 Results

The input data are probabilistic in nature, in particular, the probability associated with the occurrence of technical issues such as voltage drop and VUF at the pillars (as three phase sources) and the results needs to be presented in probabilistic manner. Fig. 5.5 summarises the voltage levels at different section of the network, including the most successfully flattened voltage level curve. The nature of the results is such that they can be used to determine whether a certain EV penetration level, is within acceptable limits for the DSO. In other words, by quantifying this probability, the DSO can conclude that it is feasible to accept penetration levels that represent a low probability of technical issues (line voltage drop and VUF). The probability of occurrence associated with the voltage drop and VUF are presented for a particular network scenario and then, cumulative distribution functions are considered to determine the probability of encountering certain problems in a particular portion of the network (position: start, middle or at the end of the network portion under consideration).

Cumulative distribution functions (CDF) can be extracted for EV charging level (namely 11kW); one for each metric (voltage drop and VUF). In the context of voltage metrics, 'x', represents the voltage in per unit and the corresponding CDF or F(x) allows a quantification of the voltage magnitude probability. In total, there are three different positions namely Pillar A, E and J in the network. These CDFs enable the probability of the voltage drop at the specific location for each case study to be understood.

5.5.1 Case Study: 11 kW charger

For the case study, all the 74 customers have EV chargers installed in their premises, one EV charger can consume up to 11 kW at a given instant. The penetration level is 100% meaning that each household has at a maximum, one EV charging slot. The rate of battery charging depends on the rating of the EV charger rather than battery capacity. Battery capacities are influential primarily during the battery-charging period. Different penetration levels of EVs are considered during the scenarios where generation with maximum and minimum EV load peaks is being considered. For simulation, the nominal voltage is set at 1.05 per unit (p.u.). The under-voltage limit is set at 0.95 p.u. in all simulations.

The effectiveness of the proposed approach is based on the functionality of the D-STATCOM. The PSO based OPF technique can be used for accommodating high power rating EV chargers with respect to voltage level control. To reveal the effectiveness of the suggested approach, it is compared with the approach without any OPF functionalities. The results shown in Fig. 5.5 provide comparison of voltage level using two approaches: 1) Approach I: Before OPF (without considering OPF-PSO based D-STATCOM placement) and 2) Approach II: After OPF (considering the OPF-PSO based D-STATCOM placement). It is clear from the results presented in Fig. 5.5, the voltage level limit is breached in Approach I, while voltage level remains within the limits in Approach II. The results have shown that voltage constraints imposed by reactive power (D-STATCOM), are able to preserve the voltage level within the limit. i.e., 0.95 pu to 1.05 pu. This improvement implies consideration of D-STATCOM that can guarantee an optimal accommodation of EV chargers penetration with respect to voltage level.

Finally, Fig. 5.5 illustrates the resulting voltage level curve at different locations in the network, showing more successful curve flattening before and after the OPF. Fig. 5.5 also shows, without OPF 20% of customers in the network will have under voltage problem. After OPF, 0% of customers have under voltage problem.

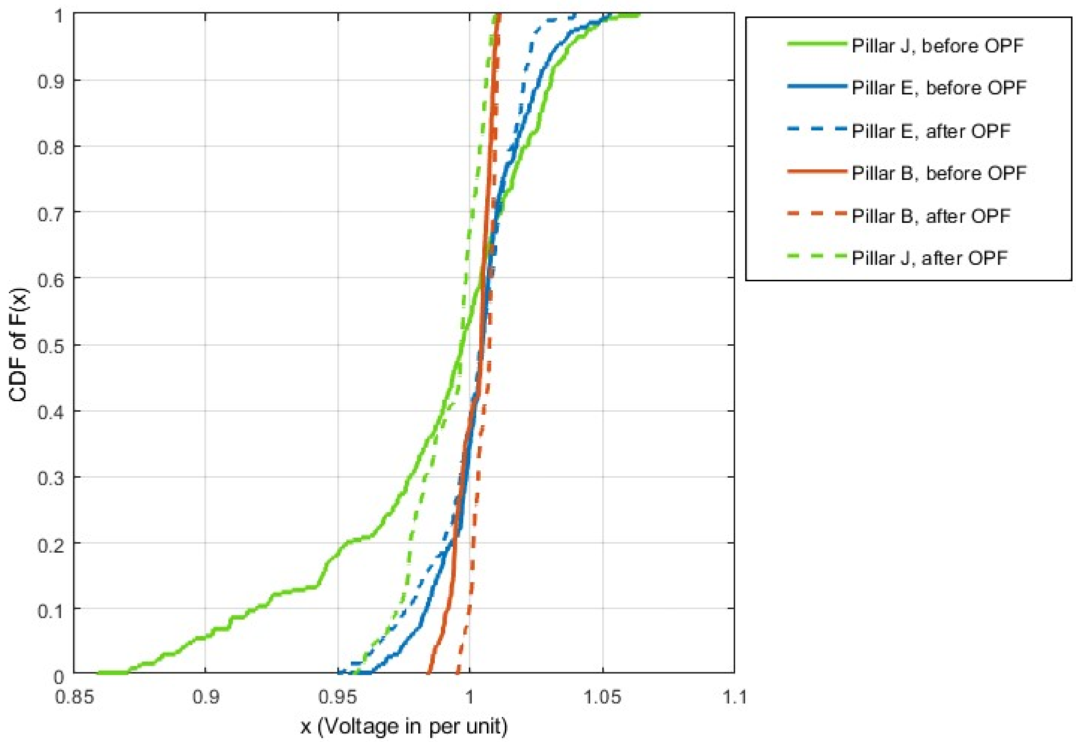


Fig. 5.5: CDF of system indices for under-voltage metrics before and after OPF

In Fig. 5.6, the voltage unbalance profile of the benchmark test distribution network on different pillars for a 11 kW EV charging scenario is illustrated. It is evident that the VUF value is significant at Pillar J, as the probability of the VUF exceeding 2% is 0.3 (without OPF). This result suggests that if the network has 100% EV connections (one per 74 customers), the probability of no households having a VUF power quality issue is 0.3 (without OPF). After OPF based analysis, the probability of no households having a VUF power quality issue is 0.5. In terms of a DSO perspective, this implies that network can accommodate only 50% arbitrary EV penetration across the network using D-STATCOM at optimal location, to facilitate an acceptable VUF. Based on this result, in terms of VUF, the network can tolerate 50% instead of 30% EV penetration.

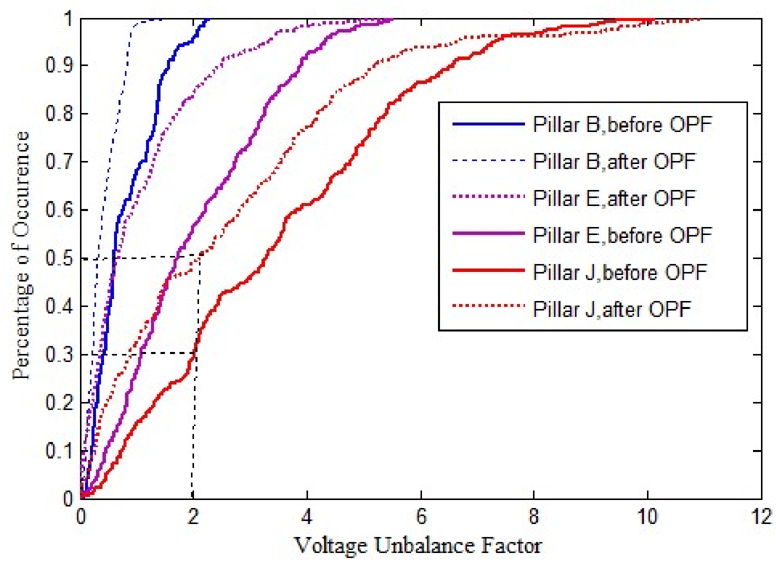


Fig. 5.6: Percentage of Voltage Unbalance Factor (VUF) at Pillar B, Pillar E and Pillar J before and after OPF

5.6 Discussion

This chapter presented a comprehensive methodology for optimal planning of distribution network loads in support of distribution network operation. The main objective is to use OPF for voltage profile shaping, as a balancing service to be offered to maintaining the one or more network performance indicators (voltage drop and VUF). The influence of 11 kW EV chargers load, demand flexibility (including different no. of customers to participate in the OPF) was considered. PSO–based reactive power scheduling is used to meet the 11 kW EV charging demand, maintaining the voltage level in the network

Unlike previous work, the proposed approach provides extended distribution planning options as it optimizes the interfacing D-STATCOM functionalities. This improvement implies that considering the smart functionalities can ensure an optimal accommodation of the high EV charger penetration with respect to voltage level. The PSO technique helps to find the optimal solution. Based on the calculated results, the effectiveness of the proposed optimal approach is demonstrated with and without OPF. This is the one of the contributions of this thesis.

6. Conclusion

6.1 General Overview

Electrification of the transportation system has the potential to reduce GHG emission substantially. From an Irish perspective, the DSO only permits 20% penetration of EVs in the distribution network [143][144]. This accommodation is unlikely to substantially reduce the amount of GHG emissions. The investment required to upgrade the existing distribution network to accommodate 20% EV penetration is 350 million euro [144]. It is also unlikely that without incentive, the DSO will take measures to enhance the penetration level. The DSO has the responsibility to maintain power quality throughout the distribution network. To convince the DSO, concrete research based on real-time monitoring of the network and system response to uncertainties is essential. The main theme of this work is to convince the DSO through different proliferation level of EVs and extent that the current distribution network infrastructure can accommodate EVs without power quality violations.

In other words, can EVs with higher battery capacities, higher rates of charging prevail in current distribution network standards? It is noted that, higher rates of charging can introduce power quality problems. In this regard, the work presented prioritises cities and focuses on two themes: firstly, the amount of energy consumed by the EV battery on daily basis. Based on an accurate EV battery consumption model, a representative and appropriate stochastic power flow algorithm is required to investigate impacts on distribution network in terms of power quality. Secondly, dynamic modelling of a mitigating solution through D-STATCOM is considered, to quantify the voltage mitigation limit of the implemented device. Finally, the optimal solution for distribution network planning is implemented.

Previously, researchers also considered the stochastic nature of LCTs and loads [85]. The power quality issues were comprehensively discussed. Previously, researchers also considered the mitigation solution in terms of upgrading OLTCs (on-load tap chargers) transformer, loop connection of distribution feeders and feeder reinforcement. There is an absence of detailed analysis of mitigating solutions based on the time-variant stochastic nature of EVs, the work in this thesis has focused on this gap. The main contribution of this work is the probabilistic impact assessment to examine the power quality issues arising from EV penetration and potential optimal solutions required to minimise those impacts on distribution networks. This methodology can be applied to any type of feeder, based on location and stochastic nature of EVs in distribution network, based on Monte Carlo Simulation.

The distribution network consists of the three-phase four-wire structure of LV networks, and therefore, their inherent imbalance features. Different EV penetration scenarios are created, ranging from 0 to 100% in steps of 30%, 60% and 100%, which were investigated in a balanced configuration. For the unbalanced network configuration ranging up to 100% were investigated. Finally, to quantify these impacts, performance metrics related to voltage at each phase were computed for each of the 100 simulations executed per penetration level.

6.2 Research Findings: Specific Outcomes

As highlighted in the literature considered in this report, it is noted that the emphasis remains on the high resolution input data, probabilistic load flow analysis and the potential solution in terms of D-STATCOM. A major concern in relation to EV penetration in distribution networks is voltage magnitude control. This work describes the mechanism of the voltage support and the possible mitigation solutions through reactive power compensation.

In this report, D-STATCOM is employed in a distribution network to support EV penetration. In this regard, testing is done against the worst possible loading scenarios in terms of how voltage magnitude might be affected. With 90% EV penetration, the results show that voltage level compensation of each phase in an unbalanced network is achievable. The voltage limit (0.95-1.05 p.u) is defined in EN 50438 standard [145] and IEEE standard [146] and this tolerance is not breached while D-STATCOM is connected to the pillar J. The voltage magnitude regulation limit can be maintained more precisely up to 1 p.u if higher power rating D-STATCOM is selected. In practical environments, D-STATCOM with the capacity range of 350kVAr for 480V grid AC connection is identified [147].

The work summarises the voltage drop mitigation methods developed using D-STATCOM against the effects of EV penetration. The concept implemented is to employ the D-STATCOM reactive power compensation, in conjunction with a DC-link capacitor bank. This control methodology can effectively control the voltage on each phase of three phase unbalanced distribution network. The aim of this work, therefore, is to model the controllability of the LV distribution networks, in the context of voltage profile management, by using a D-STATCOM. EV integration scenarios are considered in this regard. This analysis facilitates a prediction concerning an enhanced potential for EV in respect to deferring the potential impacts such as reactive power compensation could have on the distribution network.

It is worth mentioning that it is not uncommon to see that overvoltage in a 3-phase LV system only occurs at single phase, instead in all the phases, due to significant amount of single-phase unbalance caused in the assignment of the household and Electrical vehicle load. In that case, the control should be designed not only considering a balanced situation and simply reacting upon an average voltage of the 3 phases but rebalance the three phases to accommodate more EVs in the system.

It has been observed that D-STATCOM can provide peak power leveraging and reactive power support to enhance the operational efficiency. Correlation between the D-STATCOM and the EVs penetration has been extensively investigated in this work.

The feasibility level of penetration for electric vehicles embedded with the V2G (Vehicle-to-grid) functionalities is one of the challenges which undermines the EVs adoption in the energy market. For an effective implementation, the efficiency of EV battery technologies remains a concern under frequent charging and discharging cycles. The negative effects of the EV technologies like the V2G concept can reduce the battery lifetime significantly due to frequent charging and discharging cycles. Research have shown some promising results for lithium ion battery (time decay) but still charging efficiency need to improve.

6.3 Probabilistic load flow

Chapter 4, outlines modelling and a step-by-step procedure to implement the proposed methodology for an electrical model of a real LV network and high resolution profiles for loads and EVs. From these processes, step-by-step processes are the following:

- The creation of a methodology to translate EVs time-variant data into DIgSILENT programming language (DPL) models of LV distribution feeders.
- The successful development of DIgSILENT based modelling of 74 customers connected to the distribution network.
- The creation of residential-scale profile pools of EVs, each with 288 realistic five minutes resolution profiles.

6.3.1 Methodology and its Application

The probabilistic impact assessment methodology is applied on one portion of a 74-household network with EVs and the following observations are noted during analysis

- The assumption of balanced distribution network and consideration of one hour resolution data underestimate the real nature of EV's impact on the distribution network. Hourly data does not capture the full picture, for instance, if battery required small amount of charge to replenish completely, it cannot be replicated in hourly data. EV batteries that require more than one hour to charge completely only will be captured in the hourly data.
- The probabilistic nature of the approach allows DSO-TSO to determine the occurrence of problems according to the penetration level.
- From a UK/Irish perspective, distribution level transformers are usually not equipped with OLTC functionalities. So, it is highly unlikely, in the current infrastructure of distribution network to integrate more than 30% of EVs, with higher rate of charging up to 11 kW.

6.4 Mitigation Solution (D-STATCOM)

In this work, the potential solutions to increase the adoption of EVs were implemented and analysis in terms of capacity is required, including location and percentage of EVs that can be connected to the network. Although, the comprehensive study on the placement of custom devices like D-STATCOM and SVC were previously available in the literature review [87], the capacity/ sizing of a custom device was still unanswered. The optimal sizing according of the distribution network is investigated in this work that can be implemented on any distribution network. The optimal sizing capacity of the network may change, based on the size of distribution network. This work is limited to testing/modelling of custom devices (D-STATCOM) with the uncertainties associated with EVs. D-STATCOM is tested for normal and fast charging EVs chargers. Although, the result shows that the D-STATCOM is able to mitigate the fast charging up to 11 kW charger, a bottleneck is present in terms of transformer loading capacity. The main findings are:

- The normal EV charging rate up to 3.68 kW charger is highly unlikely to cause the problem in the implemented testbed of distribution network. (It is worth mentioning here, travelling patterns of EVs may vary from country to country. The probability density function implemented is based on Dublin, Ireland travelling data. It is likely, the average distance in Australia or America may not be similar to the average distance covered by passenger car in Ireland or UK.)
- The fast charging up to 11 kW, can cause a voltage breach but can be overcome by using D-STATCOM. Up to 90% penetration of EV, with 11 kW charger is possible if a suitable amount of reactive power support using D-STATCOM is available. In the testbed, the transformer rating is limiting the EV penetration with 11 kW charger up to 30%, but it is possible to have higher rating transformer at a different feeder. It is possible to have up to 90% EV penetration at other feeders.
- The dynamic nature of VUF is another aspect analysed. VUF change abruptly (VUF increases to 1.7%, which is relatively quiet high) when any uncertainties is integrated/ connected to the network. D-STATCOM can reduce VUF quiet effectively in the network.
- The analysis of the potential solution (D-STATCOM) shows that it can increase the adaptation of EVs not only from a technical point of view, but a brief economic justification is provided. The results highlight the higher EV charging rate penetration levels under investigation and therefore should be incorporated in the portfolio of potential ‘smart’ mitigation solutions by DSO-TSO.

6.5 Further work

Some of the research problems identified during this research could not be addressed and presented in this thesis, mainly due to the limited time. These research areas, detailed below, will be considered in future work.

6.5.1 Investigation of Other LCTs

The proposed methodology can be applied to other LCTs (e.g., fuel cells, PV, battery storage, etc.) to understand their impacts in LV distribution networks. For instance, the utilisation of home PV can be investigated, particularly their voltage and congestion effects in suburban and rural LV feeders. The other form of transport electrification like electrical buses can also be explored to assess their potential benefits. The Probabilistic Impact Assessment methodology is also suitable to study the impacts of adopting battery storage in LV distribution networks.

6.5.2 Improvements to the Probabilistic Impact Assessment Methodology

The analysis of a larger LV network or the analysis of a different LV network is required to test the probabilistic impact assessment methodology. Moreover, the results could also be improved if better relationships were found from the analysis, for instance by analysing more than one technical parameter at a time. It can also be used to analyse other LCTs, the penetration level of LV network can sustain.

With respect to the solutions explored, LCT penetration levels in LV networks can be increased by combining different alternatives. For instance, the OLTC can be connected with the loop connection of LV feeders. Probabilistic Impact Assessment methodology can be able to find out the potential benefits.

6.5.3 The use of smart meter data

Apart from the analysis of benefits for distribution network operators coming from smart meter data, further research should investigate other possible applications of smart meter data mining, especially when combined with other types of data, such as, sociodemographic data, transport patterns, etc. Similarly, smart metering of EV charging can be used to foresee possible traffic congestion problems. The possible ideal location to install the commercial EV charging points can be considered. In addition, there is still need for improved understanding of end-user's behaviour and daily load profiling. For example, monitoring the social media trends can give idea of changing customer behaviour and preferences. The trends circulation on social media can give an insight into changes in customer preferences with respect to EV charger installation, EV batteries etc., which can be valuable for understanding the changes in daily load profiles recorded by smart meter.

6.5.4 Optimal planning approach

Multi-period optimisation should be investigated instead of optimisation presented in this thesis, as it allows for optimal scheduling of EV charging demand considering both previous and future time steps of the planning time horizon. The proposed multi-objective approach should be further extended and validated on a different and larger distribution network. This would enable a more realistic use of optimal planning in system operation. Considering that the computational complexity of the task would rapidly increase with more network buses and more parameters and performance indicators to consider, other dedicated and potentially more efficient optimisation approaches for load scheduling should be investigated.

7. References

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8. Appendices

8.1 Modelling of Distribution Network in DigSILENT power factory

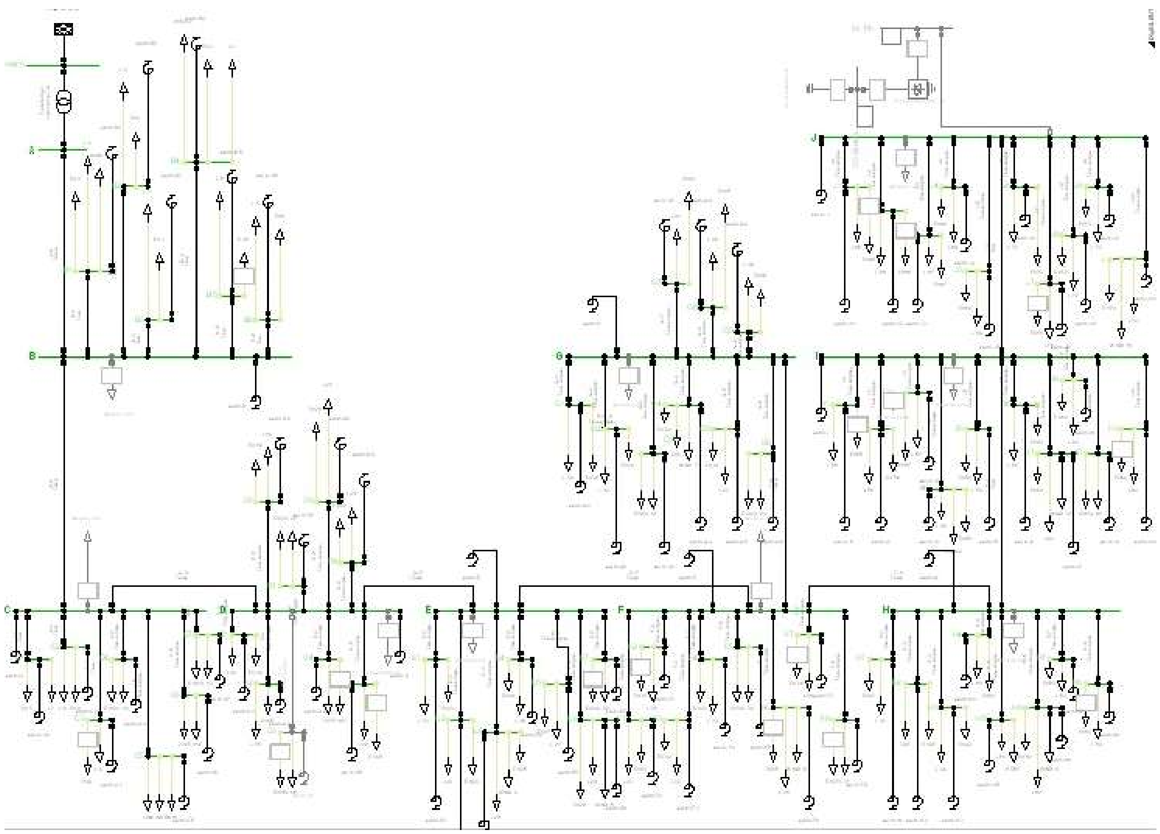

Fig. 8.1: Representation of Irish Distribution Network modelling in DIgSILENT power factory

Distribution Transformer

Voltage level: 10/0.4 kV

Power rating: 400 kVA

5% impedance

X/R Ratio of 15

Customers are supplied evenly along the LV feeders.

Cable

1.5km of 185mm^2 PICAS Cable (0.164+j0.08)Ω/km

1.5km of 95mm^2 PICAS Cable (0.32+j0.087)Ω/km

400V Detailed Feeder

Each feeder facilitates 74 customers

150m of185mm^2 PICAS Cable (0.164+j0.074)Ω/km for the phase conductors

150m of 95mm^2 PICAS Cable (0.32+j0.075)Ω/km

74 customers distributed evenly along each of the 300m feeder lines

Consumer connection

Feeder Cable to consumer is via 30m of 35mm2 (0.851+j0.090)Ω/km

The customer load/EV connection is developed from two perspectives

Static load/EV connection based on specific load and capacity ratings (as defined in each charging scenario)

ADMD of 1.28kVA, unity pf

Minimum Demand of 0.16kVA, unity pf

11 kW, rating (generic) of EV charger

8.2 Voltage Sags (Predictable Extreme Conditions)

For instance, if there is an instant when EVs are charging as usual, but there is a higher-than-normal electricity demand (for instance, a public holiday), the distribution network could become overloaded and fail. Other examples include lightning and switching surges, causing stress to the steady-state voltage in the network. In network planning, it is important to define the possible extreme conditions and estimate the distribution network response during these conditions. Such predictable extreme conditions are introduced in the network with 11 kW EV chargers if all 74 EVs are connected simultaneously.

Another example of an extreme event could be a single line to ground (SLG) fault during the peak EV charging time. A short-circuit study of a SLG fault at Pillar E for Phase A is considered to establish the ramifications. In this regard, a fault time duration (less than 1 min), location (Pillar E) and fault clearance are considered. A SLG fault study was performed in DIgSILENT Power Factory, utilizing the dynamic simulation language (DSL) toolbox. As shown in Fig. 8.2, highlighted in the red box, the SLG fault event caused the voltage on Phase A to drop to 0.84 per unit at Pillar J with the 11 kW charger. At pillar E, the voltage drop was 0.88 per unit approximately. Fig. 8.2 illustrates the short circuit event occurring at Pillar E (middle of the network) and the maximum deep voltage sag is at Pillar J (end of the network). It is apparent that the voltage level remains within limits at Pillar B during a short circuit event. The shallow voltage sag is observed near the transformer (Dy configuration). Under such abnormal events (extreme conditions), large reactive power flows are required to facilitate voltage recovery post-fault. High reactive flow, can generate high inrush currents from the fault which can damage electrical equipment [42]. During the simulation, it was observed that the fault impedance (distance from the transformer to fault location) has a significant role in limiting voltage sag depth. If fault impedance of the network is high, voltage sag magnitude remains high (shallow sag is observed). Short-circuit fault analysis is out of the scope of this work.

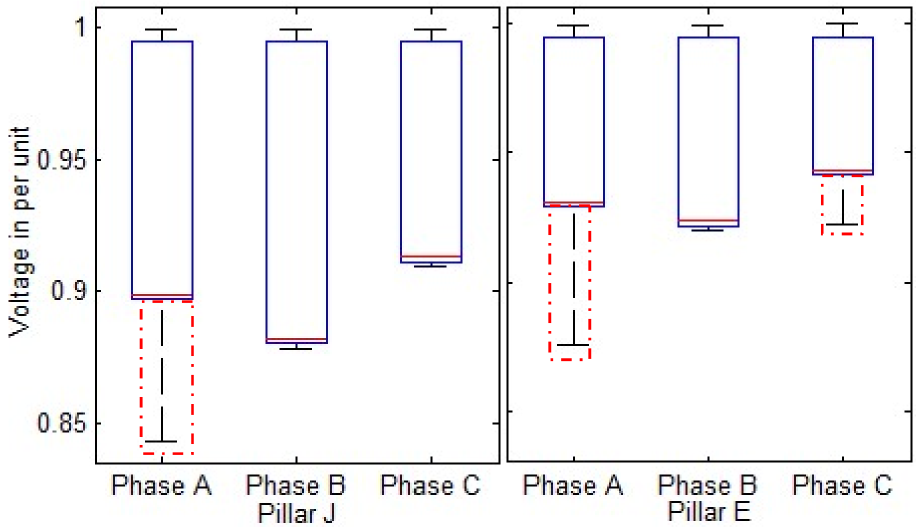

Fig. 8.2: Probability of Voltage drop at each Phase, on Pillars during SLG fault along with 11 kW charger

8.3 Transformer Loading

In the network under analysis, the power rating of transformer is 0.4 MVA. The thermal loading of the transformer is monitored under different charging level namely, 3.68 kW, 7 kW and 11 kW charger, at 100% EV penetration level. The thermal loading of the transformer is presented in Fig. 8.3. In the case of 3.68 kW charger, the transformer loading remains between 5-25% approximately. In the 11 kW single-phase charger scenario, the loading goes up to 48% approximately (as shown in Fig. 8.3). In this network, transformer loading result remains below 50%. Transformer loading results are calculated but not analysed probabilistically because in this feeder, there are no customers effected by the loading problem.

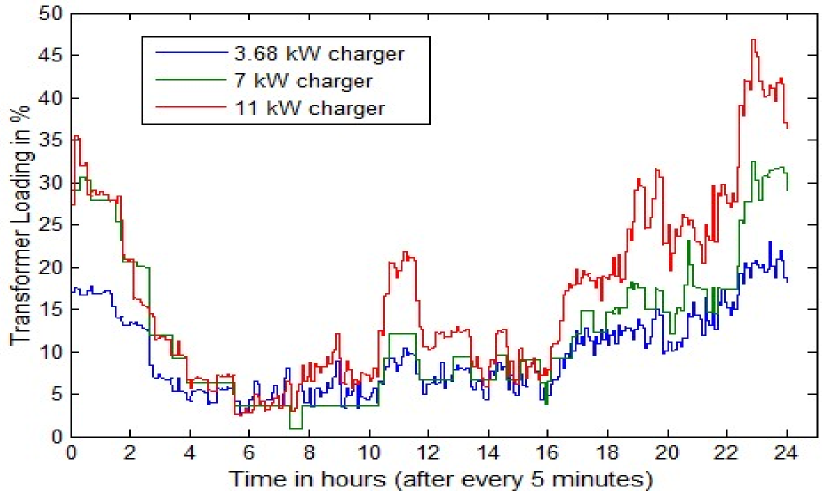

Fig. 8.3: Transformer loading at 3.68 kW, 7 kW and 11 kW chargers, with 100% EV penetration on complete network

8.4 Single-phase D-STATCOM

The challenge is to implement the D-STATCOM model in distribution network. The literature prioritises STATCOM modelling for transmission network. Indeed, one of the justifications for investigating STATCOM application to Distribution Network is the lack of literature and the confidence that with increased embedded generation and EV connections there is likely a role for what STATCOM can facilitate Transmission Networks.

The configuration and modelling equations can only facilitate the three-phase D-STATCOM connection. To replicate it for distribution network and for single phase connected D-STATCOM device is one of the challenges. The D-STATCOM model consists of two main parts namely, DC link capacitor and voltage source converter (VSC). The main function is to regulate the ac side voltage of VSC by using pulse width modulation (PWM). If single-phase D-STATCOM is to be modelled, the extensive changes are required like the PWM modulation needs to replaced with no modulation required. The alternative is to remove the VSC and use static generator with reactive power control only but that will compromise the accuracy and reliability of the results. Afterall, VSC dynamic control is one of the main part of STATCOM modelling. This analysis is not possible with the DIgSILENT software available. Therefore the problem was tackled using the general model available in DIgSILENT and by consulting the technical knowledge base forum concerning single phase connected D-STATCOM. The single-phase D-STATCOM is design based on static generator with only reactive power control. The compromise is that the single-phase D-STATCOM does not replicate the pulse modulation and DC link source. However, it is the view of the candidate that placing three different D-STATCOM to maintain the voltage level and VUF is not a feasible solution.

D-STATCOM modelling is discussed in detail in Section 4.3. Previously, one D-STATCOM was connected with three-phase to neutral at Pillar J in the network and was not able to control the voltage level at each individual phase. Hence, three different D-STATCOM based on per phase to neutral connection are installed. The representation of per phase D-STATCOM connections are presented in Fig. 8.4.

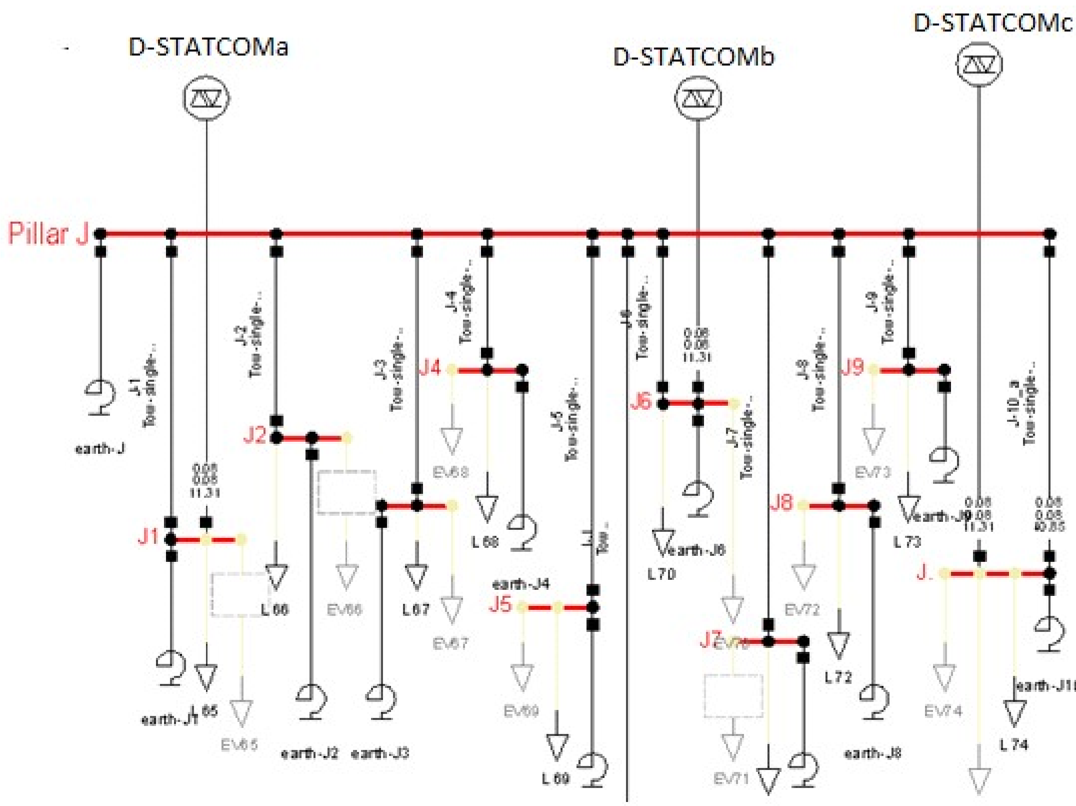

Fig. 8.4: Representation of Single phase D-STATCOM connection at Pillar J

8.4.1 Voltage Profile with 3.68 kW charger

EV charging load is simulated in a test LV network with 74 houses. It is supplied with single phase 230V via a distribution transformer with power rating of 0.4 MVA. In the test system, the distribution system's model is implemented in DIgSILENT power factory. The purpose in this regard is to get better appreciation of voltage unbalance or voltage profile and associated breaches.

Results are presented such that the voltage profile response throughout the network is prioritised while EV charging is taking place. In this regard, the voltage of each individual phase at Pillar B, Pillar E and Pillar J (respectively representing the start, middle and end of the network) are presented from 00:00-02:00 time duration.

It is evident that a voltage drop below 0.94 p.u (without D-STATCOM intervention) can occur at Pillar J. The grid is unable to maintain the voltage profile while abrupt EV load is connected on each individual phase. The voltage drop on Pillar J, as presented in Fig. 8.5, clearly presents the limitation of the grid to overcome abrupt changes in load. Single phase D-STATCOM is, however, able to compensate voltage regulations throughout the network. It can maintain the voltage level approximately at 1 p.u during the EV charging time duration.

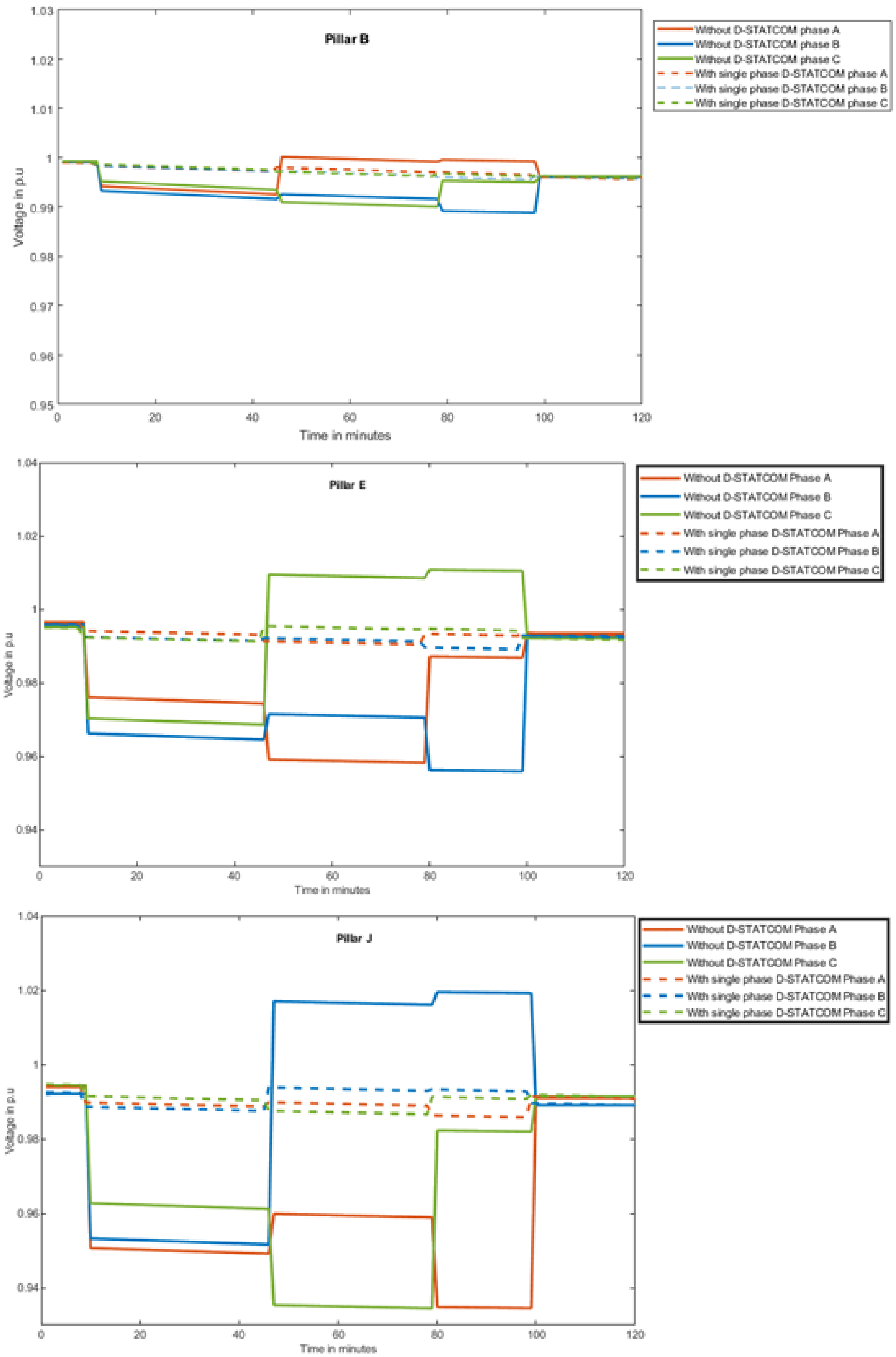

Fig. 8.5: Network Voltage with and without single phase D-STATCOM at pillar B, Pillar E and Pillar J at 3.68 kW charging

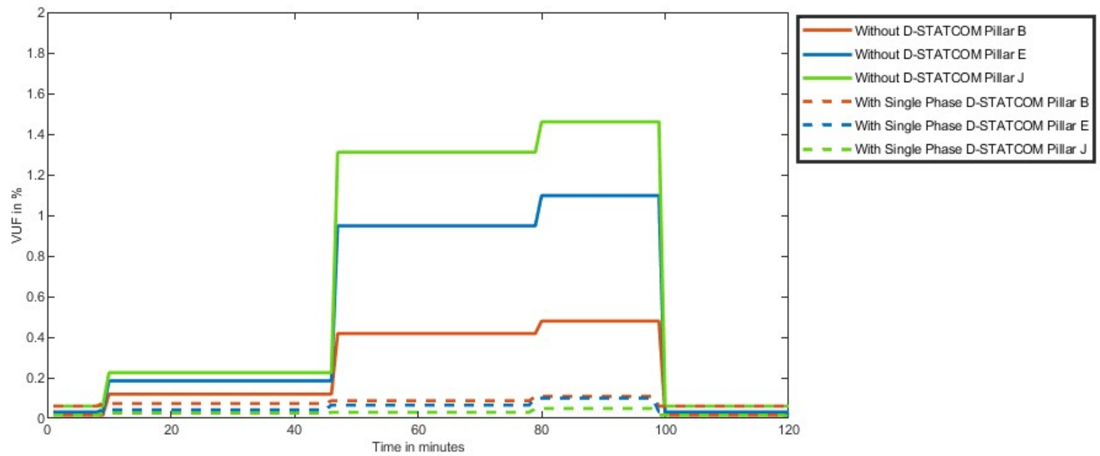

Fig. 8.6: Voltage Unbalance Factor (VUF) with and without single phase D-STATCOM at Pillar B, Pillar E and Pillar J at 3.68 kW charging

Fig. 8.6 illustrates the voltage unbalance profile over the benchmark of 120 minutes for the test distribution network on different pillars at 3.68 kW EV charging scenarios. The VUF reaches 1.5%. With single phase D-STATCOM intervention, VUF is reduced on all individual phases quiet significantly upto 0.1. It has the ability to reduce VUF in all conditions.

The performance of single phase connected D-STATCOM is monitored on the network. The measurement of its effectiveness on time variant EV charging and its impact on the distribution network. The key points are:

- Single-phase connected D-STATCOM is able to maintain the voltage level at 1 p.u.
- Single phase connected can be able to reduce the voltage unbalance more effectively than the three-phase connected D-STATCOM.
- With single phase D-STATCOM intervention, VUF is reduced on all individual phases quiet significantly from 1.5% to 0.1%.

Single-phase D-STATCOM can provide better leverage and voltage unbalance control than three-phase connected D-STATCOM.