A Comprehensive Methodology for Impact Assessment Studies of Energy Storage Systems on Low Voltage Distribution Feeders

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Abstract

This research investigates the technical impacts of energy storage systems (ESSs) on low voltage (LV) residential feeders. A critical literature review on the existing impact assessment methodologies informs on the requirements of an efficient methodology that ensures the accurate and detailed assessment of feeder performance under ESS penetration. Based on the review’s findings, a comprehensive stochastic-probabilistic methodology is proposed that directly accounts for the unpredictability in customer behaviour and the subsequent impact on the diversity and variability in simulation inputs and outcomes of load flow analysis (something that most impact assessment methodologies do not adequately account for). The proposed methodology makes use of the Monte Carlo Simulation method as a stochastic simulator to simulate the uncertainty in the feeder placement of ESSs, and the Herman-Beta extended algorithm to solve the probabilistic load flow analysis. This proposed methodology can be used to assess the hosting capacity of radial LV distribution feeders to increasing penetrations of ESSs. The simulation results, from detailed and comprehensive input modelling, can provide helpful and more accurate and representative information to distribution network planners and policymakers, than simplified methodologies.

Opsomming

Hierdie navorsing ondersoek die tegniese gevolge van energieopbergings stelsels (EOS) op lae spanning (LS) residensiële toevoere. 'n Omvattende literatuuroorsig van bestaande impakbeoordelingsmetodologieë gee inligting oor die vereistes van 'n doeltreffende metodologie wat die akkurate en gedetailleerde assessering van die voerprestasie onder ESS-penetrasie verseker. Op grond van die oorsig bevindings, word 'n omvattende stogastiese-waarskynlikheids metodologie voorgestel wat die onvoorspelbaarheid van kliëntegedrag aanspreek en die impak op diversiteit en wisselvalligheid in simulasie-insette en simulasie-uitkomste van lasvloei-analise (iets wat die meeste impakassesseringsmetodologieë nie voldoende aanspreek nie). Die voorgestelde metodologie maak gebruik van die Monte Carlo Simulasie metode as ‘n stogastiese simulator om die onskerheid in toevoerplasing van die ESS te simuleer, en die Herman-Beta- uitgebreide algoritme om die waarskynlike lasvloei-analise op te los. Hierdie voorgestelde metologie kan gebruik word om die huisves kapasiteit van die radiale LV-verspreidingstoevoere te beoordeel met betrekking tot toenemende penetrasies van ESS's. Hierdie simulasie-resultate, van gedetailleerde en omvattende insetmodellering, kan nuttige, meer akkurate en verteenwoordigende inligting aan verspreidingsnetwerkbeplanners en beleidsmakers bied as vereenvoudigde metodologieë.

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List of Acronyms

AC	Alternating Current
BESS	Battery Energy Storage System
CDF	Cumulative Distribution Function
DC	Direct Current
DG	Distributed Generation
DLF	Deterministic Load Flow
EM	Electric Motorcycle
ES	Energy Storage
ESS	Energy Storage System
EV	Electric Vehicle
FMD	Feeder Maximum Demand
HEV	Hybrid Electric Vehicle
HB	Herman-Beta
HBE	Herman-Beta Extended
IMD	Interval of Maximum Demand
LF	Load Flow
LSM	Living Standard Measure
LV	Low Voltage
MC	Monte Carlo
MCS	Monte Carlo Simulation

PDF	Probability Density Function
PHEV	Plug-in Hybrid Electric Vehicle
PLF	Probabilistic Load Flow
PV	Photovoltaic
RQ	Research Question
SoC	State of Charge
TOU	Time of Use
UPS	Uninterruptible Power Supply

List of Symbols

σ	Standard deviation
μ	Mean
α	alpha (beta PDF shape parameter)
β	beta (beta PDF shape parameter)
C	circuit breaker value (beta PDF scaling parameter)

1 Introduction

This introduction chapter will provide background information to show the relevance of the research investigated. The specific thesis topic is motivated, and the hypothesis and research questions are presented. The chapter then gives an overview of the thesis structure to provide a map to guide the reading of the thesis.

1.1 Background and motivation

1.1.1 Principles of distribution network design

According to [1], there are three main criteria for an efficient power supply. The supply needs to be (i) compliant – supply power at a consistent and acceptable voltage level and frequency, (ii) adequate – reach all customer with enough capacity to meet their demand, (iii) reliable – able to meet the demand of customers at all times without interruption. Overall, the network design should be efficient and effective, designed to minimize losses and optimize network investments. To do this, appropriate distribution network design is key.

The objective of good distribution network design is to ensure that the three main criteria mentioned above are met. Knowledge of the expected loads, allowing capacity for load changes in a defined planning horizon, is important as this informs the process of component selection, sizing, and placement. Knowledge of the expected loads will ensure that the system can meet the demand requirements. Transformers are sized and selected so that the total power supplied does not result in prolonged periods of transformer overloading. Conductor cables are selected so that the total current flowing in any branch or section of the conductor cables does not exceed the current carrying capacity of the cable. The conductor cables are also selected so that the sum of the voltage drops to the most distant node does not violate the lower limit of the power quality standards regarding voltage level. The voltage-drop resulting in network losses are a function of the electrical properties of the conductor cables and the load current. Conductor and transformer loading are both directly proportional to the load current. From this, it is evident that knowledge of the expected loads is vital.

In the past, feeder designs assumed one-directional power flow and were based on deterministic methods that assume load homogeneity. The unpredictability and randomness in customer behaviour make deterministic load models inadequate. Detailed load research has demonstrated the extent of randomness in customer loads and has motivated the suitability of probabilistic methods over deterministic ones [2], [3]. In addition to this, the introduction of distributed generation (DG) and energy storage system (ESS) technologies such as hybrid photovoltaic (PV) systems, battery energy storage systems (BESSs), uninterruptable power supply (UPSs) systems, electric motorcycles (EMs) and electric vehicles (EVs) have become more common.

1.1.2 The penetration of new technologies and the need for appropriate planning tools

There has been a significant increase in the uptake of EVs especially over the last 10 years, with a 400% increase in EVs worldwide from 2015 to 2019 alone [4]. The increase in uptake is partly attributed to deliberate efforts by policymakers to promote EV adoption through rebates, tax breaks and incentives [5]. This resulted in the increase in EV sales and subsequently the number of EVs connecting to power systems. The world's total installed PV capacity increased by over 4 300 % in only 10 years from 9.2 GW in 2007 to 404.5 GW in 2017 [6]. Due to the misalignment in the peak demand hours and maximum PV output, the uptake of PV systems is often accompanied by BESSs [7]. This configuration is in many cases referred to as hybrid PV systems. This entire grouping (EVs, BESS, hybrid PV, UPS) will be referred to as ESSs from this point.

Traditional power systems were not designed to accommodate these newly introduced ESS technologies. As a result, variable load profiles and bidirectional power flow possible with these introduced ESS technologies have changed the net load profiles that traditional power systems were initially designed to handle. The introduction of these technologies has had a significant impact on the planning and operation of distribution networks. The introduction of ESS technologies as been associated with several technical issues including excessive voltage-drop, voltage unbalance, increase in network losses, thermal overloading, underfrequency and current harmonics [8]–[11]. The magnitude of the effect of ESS technologies is dependent on the penetration level of these technologies, which depends on the regulations regarding its uptake and conditions of operation (i.e. prohibiting charging or power export during certain periods). Therefore, impact assessment studies focussed on investigating the nature, scope, and severity of the technical impact of these technologies on distribution networks have become more important.

1.1.3 Limitations of modern planning tools and opportunities for research

Two load characteristics complicate the formulation and application of impact assessment studies: (1) the unpredictability and uncertainty in usage patterns, which affect the characterization of load profiles and load diversity within given intervals, and (2) unknown factors such as the placement of the ESS technologies, particularly the phase of connection. These issues are common to all ESS technologies but there are some differences. EV loads differ from other distributed ESS technologies in terms of the sources of unpredictability and uncertainty. For one, EV loads are significantly dependent on the individual customer's behaviour such as mobility, while PV exports are mostly influenced by common characteristics such as weather conditions. The EV owner's behaviour influences both the usage pattern and charging pattern of the EV. In addition to the behaviour of EV owners, another aspect of uncertainty unique to EV loads is the direction of power flow. EV batteries can act as a load (power import) or generator (power export), where the direction of power flow will determine the scope and magnitude of the technical issues experienced by the grid. ESSs in general have similar predicted growths, technical impacts and considerations that introduce uncertainty.

The most simplistic existing impact assessment methodologies tend to make use of simplified distribution feeder models, deterministic load models for the residential load and ESS load, worst-case scenario placement of ESSs and deterministic load flow analysis, as will be explored in greater detail in Chapter 2. Often in cases where probabilistic load models are used, placement will still be worst-case scenario based or too few placement scenarios are simulated to accurately account for the full scope of placement possibilities. Simplified feeder models do not allow the accurate representation of loading conditions on the feeder. Deterministic load models do not account for the diversity in both the residential customer loads and EV loads, due to the unpredictability of customer behaviour. And worst-case scenario placement strategies do not account for the randomness in location of ESSs due to the unpredictability regarding which customers will invest in the ESS under investigation.

1.2 Hypothesis and research questions

With customer behaviour being unpredictable, probabilistic customer load models are more suitable than the deterministic customer load models still widely used in impacts assessment studies [12]. Furthermore, the introduction of ESS technologies into LV networks has changed the net load profile expected at residential level. Traditional design and planning methodologies, which includes assumptions regarding load profiles and direction of load flow, are therefore less relevant now than in the past.

New planning tools for active distribution networks with ESS technologies need to accommodate various forms of uncertainty associated with the usage patterns and conditions of uptake such as the system capacity and location to node and phase.

The hypothesis of this research is phrased as follows:

A comprehensive impact assessment methodology for LV feeder performance under ESS penetration can be developed, which accounts for the load uncertainty resulting from unpredictable customer behaviour.

The following list of research questions are used to guide the research and answer the research hypothesis:

1. What are the technical impacts of ESSs (namely EMs, EVs and hybrid PV systems) on LV residential distribution feeders and to what extent are existing distribution network infrastructure technically impacted by increasing penetrations of these ESSs?

2. What are the state-of-the-art approaches for conducting impact assessment studies to determine the technical impacts and the estimation of a network's hosting capacity to EVs, and what are their limitations?

3. What are the characteristics of a comprehensive methodology for the impact assessment of EVs on LV distribution feeders?

4. Can a comprehensive impact assessment methodology that incorporates these identified characteristics be developed?

The answers to these research questions are reported in three conference papers, included as Appendix A [13], Appendix B [14] and Appendix C [15], one journal paper, included in Appendix D [16] and two content chapters (chapter 2 and 3).

1.3 Scope and limitations

This research is focussed on achieving detailed and accurate assessments of the impacts of ESSs on LV distribution feeders. Although studies investigating the impacts of EMs and hybrid PV systems are conducted, EVs are deemed a good proxy for ESSs in general as it represents all the aspects of ESSs (random uptake, ability to act as a load or generation, influenced by customer behaviour etc.). Therefore, a significant portion of the work conducted is based on EVs. However, the methodology developed and EV model proposed can be used for any ESS.

There are three types of EVs: hybrid EVs (HEVs), plug-in hybrid EVs (PHEVs) and battery EVs (BEVs). HEVs and PHEVs make use of both petrol and electricity, while BEVs are fully electric. This work makes reference to only BEVs and refers to these as EVs.

The research is further limited to LV residential feeders of radial configuration and 3-phase 4-wire topology.

1.4 Thesis structure

To answer the aforementioned research questions, a look at the network design and planning frameworks, a comprehensive review of impact assessment methodologies, investigation of the technical impacts of ESSs and extent of these impacts are necessary.

The research is approached as follows. This document consists of five chapters. Chapter 2 is a review of EV impact assessment methodologies proposed in literature, giving particular attention to the formulation of the load flow inputs, defining the scope of technical parameters assessed, method of load flow analysis and EV penetration scenarios. Chapter 3 describes the EV modelling and simulation approaches used in this research, allowing for accurate probabilistic modelling of the EV load, and ensuring extensive feeder analysis. Chapter 4 integrates the results of chapters 2 and 3 and consolidates the findings from papers [13]–[16] that have been written, to answer the research questions. Chapter 5 concludes the research. The papers written to support this thesis can be summarized as follows:

Appendix A [13]: *The Impact of Distributed Hybrid Photovoltaic Backup Systems on Shared Residential Feeders*

This paper explores the impacts of grid-interactive PV systems with self-consumption and uninterruptable power supply functionalities. The paper refers to these as “hybrid PV systems” simply meaning there is a battery as an additional component to the traditional PV system. The technical impacts of these hybrid PV systems, specifically looking at how the network is affected by grid charging of these systems and power injection into the grid, are described in this paper.

Appendix B [14]: *Probabilistic Impact Assessment of Residential Charging of Electric Motorcycles on LV Feeders*

This paper uses a stochastic-probabilistic approach to explore the impacts of the residential charging of EMs on LV distribution feeders. This paper is particularly relevant due to the expected increase in the number of EMs specifically in East Africa. Motorcycles, and soon EMs, are a popular mode of transport in these regions. EM loads and factors contributing the modelling of these loads are considered to be similar to those affecting EV loads.

Appendix C [15]: *Considerations for Impact Assessments of Electric Vehicles on South African Residential Networks*

This paper identifies considerations and inputs to guide impact assessment studies to determine the extent of the technical issues caused by EVs on LV residential feeders.

Appendix D [16]: *A Comprehensive Stochastic-Probabilistic Methodology for Assessing the Impact of Electric Vehicle Charging on Low Voltage Distribution Networks*

This paper proposes a comprehensive methodology, making use of a stochastic-probabilistic approach, for impact assessment studies investigating the effects of EV charging on LV distribution feeders. This paper documents a case study in which the methodology is demonstrated on a practical feeder in South Africa.

2 A Review of Impact Assessment Studies of Electric Vehicles on Low Voltage Residential Networks

EVs have gained interest over the past 10 years as the world becomes more environmentally conscious and resource sustainability becomes a priority. However, renewable and sustainable technologies do not come without challenges. The introduction of these technologies brought potential technical impacts to the environments into which they were incorporated. EVs have a significant impact on power systems due to the nature of the loads introduced by EVs. Because of this, many approaches to assessing and quantifying the impacts have been formulated.

This chapter reviews EV impact assessment methodologies reported in literature. The focus is on how the factors related to the diversity and uncertainty of load flow inputs, specifically the EV load and simulation characteristics attached to future EV penetration, are addressed. This is achieved by reviewing the technical impacts assessed and highlighting the inputs considered by the various assessment methodologies, and how these inputs are modelled during simulations. Informed by this, the chapter then discusses the advantages and limitations of the various methodologies.

Through this review, the required EV impact assessment methodology characteristics are identified, and the objectives defined to ensure that the simulation results accurately inform the decisions of planners and policymakers.

When assessing the impacts of ESS technologies, in this case EVs, it is one thing to know that EV charging will affect voltage level and another to know that this may result in severe voltage drops or strain on the physical infrastructure causing irreparable damage. Therefore, further than identifying the possible technical impacts on a network it is useful to conduct load flow analysis simulations to observe the extent of these technical issues. However, the usefulness of the results of such load flow analysis studies is dependent on the accuracy of the input models, the capability and suitability of the load flow method and the applicability of the technical parameters assessed in the output analysis. The relation between these components of a load flow analysis is shown in Figure 1 below.

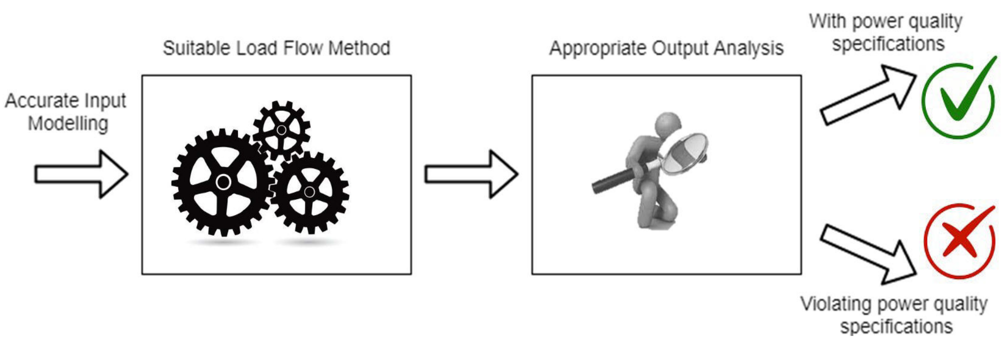


Figure 1: Impact Assessment Overview Illustration

This chapter will discuss the reviewed papers and their methodologies under the following headings: load flow inputs, scope of technical parameters assessed, methods for load flow analysis and simulation of EV penetration scenarios.

2.1 Load flow inputs

The following three load flow inputs have been identified and will be discussed in further detail below: network modelling, residential load modelling and EV load modelling.

2.1.1 Network modelling

The network model forms the skeleton for the assessment simulation. The residential customer load models and the EV load models are applied to the network model. Therefore before being able to assess the impacts of EVs, it is important to have accurate models for the distribution network [17]. The network model details several properties including the feeder topology, the transformer sizing and location, conductor lengths and electrical properties and customer location and phase distribution.

In most cases, distribution network operators (DNOs) or policymakers do not have accurate information regarding the customer phase distribution along an LV feeder. The impact on voltage-drop as a result of customer phase allocation has been previously studied and shown to be significant [18]. Though the study was based on systems without EVs, its results suggest that the detail of the network model used for simulation is likely to have a significant effect on the results of the EV impact assessment study. If the simulation network model is far from reality, the respective results will be misleading; leading to overly restrictive regulations that unnecessarily limits the uptake of EVs, or too relaxed regulations that result in frequent violations of statutory limits. Decisions made based on these simulation results may therefore not be the most suitable and could even be detrimental if careful consideration of the network model used is not taken.

There are several possibilities when modelling a network for an assessment simulation i.e. simplified or detailed models, real or test networks, models characterizing existing networks or those for new electrification projects etc. In general, most studies state the size of the transformer and the number of customers served. Details regarding the electrical properties of the conductors or customer distribution is seldomly given, if at all. Papadopoulos et al. [19] modelled a simplified network consisting of an ideal voltage source connected to two transformers and a substation with six outgoing feeders. Only one of the feeders was modelled in detail, with the single-phase loads distributed evenly across the three phases. The other five feeders were modelled as lumped loads having a single load representative of all the customers along that feeder branch. This does not allow for the assessment of the effects of voltage unbalance nor the effects of voltage-drop along these branched feeders. Simplified networks are not ideal as they do not allow for the full scope of technical impacts to be assessed [20], [21].

Since traditional power systems were designed and built before the introduction of technologies such as PV systems, BESSs and EVs, demonstrating the difference in accommodation of EVs in existing networks and new electrification projects improves the quality of planning decisions. Tie et al. [22] modelled both an existing (in the paper referred to as a mature network) and newly developed network. It should be noted that under passive conditions the feeder loading of the feeders in the mature network were on average 11.7 % higher than the feeder loading in the newly developed network. The results showed that the newly designed network could handle 10% more EVs than the mature network based on the voltage unbalance limit and as much as 50% more EVs in terms on the thermal loading limit of the conductor cables. Quirós-Tortós et al. modelled nine different LV residential networks in the UK [23]. These networks were found to be able to accommodate varying penetrations of EVs. That study demonstrated that the exact results from one network should not be blindly extrapolated to the next. However, trends and general conclusions may be applicable across multiple networks. Because of the difference in hosting capacity between long existing and newly developed networks as well as discrepancies between different networks in general, careful consideration for the network modelled should be taken, paying close attention to networks in areas that are likely to have an increase in EV uptake.

Some studies modelled test networks [9], [10], [18], [24], [25], however these synthetic or test networks are usually simplified and limited in their representation of practical feeder conditions. As a result, the use of such networks must be limited to the study of the nature of technical impacts and not the formulation of regulations or any other sensitive planning decisions. The importance of modelling a realistic network is acknowledged by several studies that modelled existing and detailed networks [20], [21], [26]–[30].

Overall, most networks experienced technical problems when dealing with increasing penetrations of EVs and therefore regulations are necessary. The bounds of these regulations are complicated by multiple factors whose correlation is extremely difficult to model and the large diversity of feeder conditions makes the application of assumptions inevitable. Also, unless a study is targeted at the detailed performance analysis of an individual feeder, the selection of representative feeders should ensure the results achieve global perspective of the technical impacts on most feeders and suitable limits of penetration. This review emphasizes the necessity of selecting an appropriate and detailed network model that is realistic and representative of conditions along a practical feeder (realistic customer distribution, transformer size, cable lengths and electrical properties). This is likely to yield realistic and practical results.

2.1.2 Residential load modelling

The residential load model forms the base that EV loads (and subsequently the effects of the EVs) will be superimposed onto. Therefore, the accurate modelling of the residential customer loads is important. Two main methods, namely deterministic and probabilistic, are used to model these loads. Several studies [24], [31]–[37] chose to model worst-case scenario, high consumption periods being winter weekday evenings, with [24], [33], [36] modelling both winter evening and summer noon peaks. Many studies [10], [34], [35], [38]–[40] modelled these loads deterministically, applying a single daily load profile to every customer along the simulated feeder. This method does not account for the diversity in the customer loads. The element of uncertainty and variability in customer behaviour is ignored. Such methods based on average and uniform demand, even with the application of empirical factors for diversity and unbalance, fail to account for the likelihood or risk of occurrence of the assumed input states. Depending on the relativity of the assumed input states to the distribution of the full range of possible states, the corresponding results may result in overly restrictive or relaxed EV uptake regulations, which impact the optimal use of resources and the reliability of networks, respectively.

In [41], Awadallah et al. ran multiple simulations, initially for two worst-case conditions being winter evening and summer noon peak hours. Then simulations for a typical spring day was conducted for three different time intervals corresponding to a minimum, medium and peak load consumption hour. Although multiple scenarios were conducted to assess various periods of interest, the customer diversity in each scenario was ignored as each customer was assigned the same constant load value. By simulating various time intervals, this model demonstrates the variability of the residential load with time. However, by assigning each customer the same constant load value this method fails to adequately model the customer load uncertainty and diversity within a specific time interval.

In both [23] and [37], Quirós-Tortós et al. made use of a tool that generates domestic load profiles based on various factors including the behaviour of British customers, the number of people at home, the type of day and the month. The tool generates a pool of 1000 load profiles and these profiles are assigned at random to customer nodes during the simulation. Unlike the aforementioned example, both of these methods acknowledge an important factor regarding customer behavioural uncertainty. Both methods attempt to model the residential loads incorporating the diversity within a specific time interval. In [7], 100 Monte Carlo (MC) simulations were conducted; however, the full spectrum of scenarios may not be tested with so few scenarios. In such a case it may be necessary to conduct considerably more (a few thousand) scenarios to get an accurate depiction of the possibilities. In [42], Flynn et el. used 15-minute time series load data for high, medium and low use customers, monitored for a year to generate probability density functions (PDFs) to describe the customers' load demand. This probabilistic characterization of the residential load is adequate, although it has been reported that 5-minute interval data is best for this application [43].

Traditional approaches based on deterministic load modelling in which the same single load profile or constant load value is assigned to all customers are not suitable under input uncertainty, and do not lead to realistic results. Methods based on iterative simulation of random scenarios have the potential to accurately model the input behaviour. However, a large number of scenarios, in the order of 10^4 are often required, which attracts high computational burden. Statistical characterization of load diversity using PDFs or cumulative density functions (CDFs) in each time interval in ways that allow analytic analysis supports high computational efficient tools. This review concludes that the approach to model the residential customer load should accurately and effectively address the diversity in customer loads and unpredictability in customer behaviour.

2.1.3 EV load modelling

EV load modelling (similar to residential load modelling) largely due to its dependence on unpredictable customer behaviour, has inherent variability. Subsequently, characteristics that affect the EV load model include variation with time and diversity within a specific time interval. Factors including charge rate and duration, EV location, time interval and coincidence of charging have all been reported to influence the impact that EV charging has on a network [44]–[47]. These have been incorporated and the following five factors that shape the EV load model have been identified and will be detailed below:

1. EV battery capacity,
2. Battery state of charge (SoC) when connecting to charge,
3. Mode of charging and therefore charging power rating,
4. Travel data informing home arrival and departure times,
5. Implementation of charge schemes or tariff incentives.

2.1.3.1 Battery capacity

The battery capacity will influence the duration of the EV load when charging. The battery capacity of the EVs modelled in the impact assessment simulations reviewed ranged from 10 kWh to 35 kWh. As far as specific EVs modelled, a few studies modelled the 24 kWh Nissan Leaf [22], [23], [38], [48], others modelled the 16 kWh Mitsubishi i-MiEV [18], [40], [48] and one study modelled the BMW i3 [39]. Many studies did not specify the specific EV modelled. Studies that based the battery capacity on a exact EV model, did so on the basis of high EV sales of that brand of EV in the country or city in question.

2.1.3.2 SoC

The SoC of the EV battery when connecting to charge will determine both the duration and size of the load. While the SoC affecting the duration of the load is intuitive, how the SoC affects the size of the load may not be. A battery SoC curve shows the relationship between the amount of power being drawn (size of load) vs battery SoC. Figure 2 below shows the SoC curve for the 22 kWh and 33 kWh Nissan Leaf. It is evident that the charge speed (load size) is almost constant for a considerable portion of the charging period.

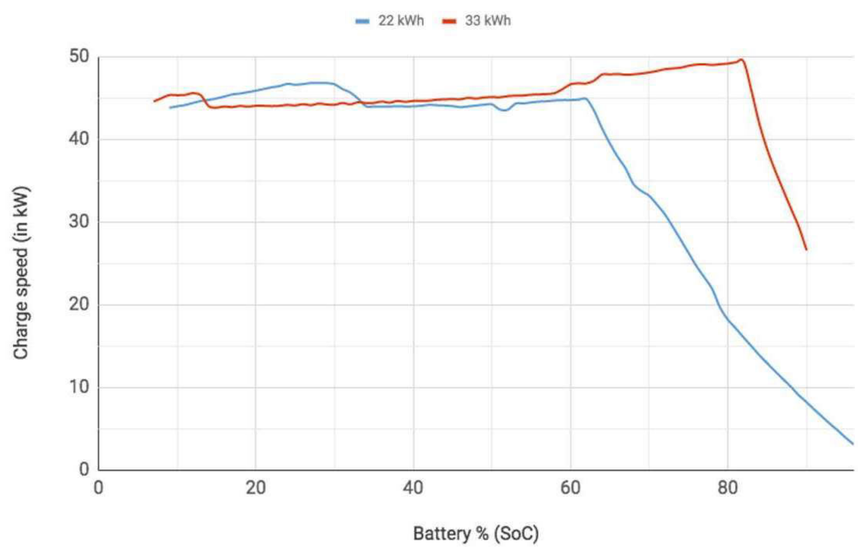


Figure 2: SoC Curve for 22 kWh and 33 kWh Nissan Leaf [62]

The SoC when connecting at home to charge is dependent on the usage pattern (including daily travel distance) of the EV and energy consumption rate as well as the use of a secondary charging facility. Extensive daily travel distances and high energy consumption rates will result in a lower SoC. However, the use of a secondary charging facility at work is likely to result in higher SoC percentages when arriving home and connecting to charge.

In [49], Kintner-Meyer et al., conducted one simulation in which charging was strictly done at home and another where charging was possible at home and work. When charging was possible at work, this introduced a morning peak in the charging profile, corresponding to ordinary work arrival times. This also resulted in a smaller evening charging peak compared to when charging was restricted to solely take place at home. Another study only modelled residential charging as majority of privately owned EVs are charged at home [50].

In [34], the initial SoC when connecting to charge was modelled as a Gaussian PDF with the mean SoC at 50%, while in [38] because of the lack of travel data available the SoC when connecting to charge was assumed to be completely flat. However, in [22] the battery longevity was taken into account and the SoC was controlled between 20 % and 80 %. Subsequently, the EV was modelled as a constant 3.3 kW load.

The incorporation of variability due to unpredictable customer behaviour is attempted by [23], [39], [42]. In [23], Quirós-Tortós et al. created 1000 EV profiles for initial and final SoC and in [42], Flynn et al. created a PDF for initial SoC based on one year's data collected in a trial. In [39] a Weibull distribution of travel data, along with an assumed energy consumption rate was used to determine the initial SoC.

Most studies assume that once an EV is connected to charge, the EV will only be disconnected once charging is complete. This is typical for overnight residential charging.

2.1.3.3 Type of charging

The type or charging (slow, quick, or fast/ rapid charging) that takes place affects the size and duration of the load and is determined by the voltage supply level and type of charger (power rating and connection type) used. Slow charging results in smaller loads for longer periods of time while rapid charging results in larger loads for shorter periods of time. The residential voltage supply level is dependent on the electricity supply standards adopted by the country. A summary of the residential voltage supply levels stipulated in [51] for Europe and North America is shown in Table 1.

Table 1: International EV Charging Standards in Europe and North America

Europe				
Charge Method	**Power [kW]**	**Maximum Current [A]**	**Connection**	**Location**
Normal (slow)	3.7	10-16	1-phase AC	Domestic
Medium (quick)	3.7-22	16-32	1- or 3-phase AC	Semi-public
High (fast)	>22	> 32	3- phase AC	Public
High	>22	> 3 225	DC	Public
North America				
Charge Method	**Maximum Power [kW]**	**Maximum Current [A]**	**Connection**	**Nominal AC Supply Voltage [V]**
Level 1	1.44	12	1-phase AC	120
Level 2	7.7	32	1- or 3-phase AC	240
Level 3	240	400	3-phase DC	208-600

Most ordinary residential sockets can accommodate slow charging in terms of European Standards or up until Level 2 charging in terms of North American Standards.

In [19], single- and three-phase residential quick (level 2) charging is modelled in addition to single-phase slow charging. The distribution of these various charging methods is made in favour of single phased slow charging. With 10 % of residents having single-phase quick charging facilities, 20 % having three-phase quick charging facilities and 70 % of residents making use of ordinary single-phase slow charging. Although it is possible to install fast charging stations at home, this is costly and most EV owners do no find this a necessity. Consequently majority of impact assessments solely model ordinary residential charging [23]–[25], [33], [37], [50], [52], [53].

2.1.3.4 Traffic data

Traffic data, along with the daily travel distance mentioned in the SoC section above, will inform likely home arrival times. This home arrival times could inform potential periods of interest during which mass simultaneous EV charging will be likely. Many studies assumed that if there are no restrictions regarding when charging may take place, most EV owners will connect their EVs to charge when arriving home from work, as is the case in [18], [38], [39], [48], [50], [53]. For the most part, this home arrival time is assumed to correspond to the evening peak consumption period.

In [33], for unrestricted charging, two common connection times were identified. The first when owners arrive home from work (coinciding with the evening demand peak) and the second at around 22:30, that is assumed to correspond to charging after the final trip of the day.

Both [23], [37] make use of historical data to create a pool of 1000 EV profiles, indicating connection time. In [42], a PDF of typical connection times based on data collected during an EV trial is used, while in [39], the connection time is modelled as a normal distribution function with a mean on 19:15 and standard deviation of 1.5 hours.

In [40], a curve of vehicle movement was obtained for Barcelona and shifted two hours earlier to be a better representation of Denmark. This mobility curve was used to indicate when vehicles were likely to be at home and available for charging.

The main purpose of traffic data informing home arrival times is to identify periods of interest. It has been widely concluded that without charge restrictions (charge schemes or tariff incentives), mass simultaneous charging is likely to coincide with the evening residential consumption peak.

2.1.3.5 Charge scheme and tariff incentive implementation

Charge schemes are mandatory. Charge schemes prohibit charging during specific periods or restrict charging to specific periods. Charge schemes can also be implemented to allow a certain group of customers to charge during specific time periods, giving all customers a designated charge period that will put the least amount of strain on the network.

Tariff incentives differ from charge schemes in the way that they can be seen as optional opposed to mandatory. Tariff incentives attempt to encourage a desired customer behaviour by making charging during certain periods more financially beneficial than during other periods. However, with tariff incentives it is possible to choose convenience over cost.

In [39], it is observed from the simulation results that a multi tariff system may result in the elimination of many violations to power quality standards, if EV owners make use of the favourable rates during specific time periods.

In [50], where charge schemes delayed charging until after the evening peak, it was found that nodal voltage deviations at locations furthest from the transformer were reduced compared to uncontrolled charging. This controlled charging was also found to reduce the coincidence of household peak demand and EV charging peak demand.

Charge scheme implementation is also found to reduce the need for investments for infrastructure modification [40], result in no increase in the peak load and decrease the maximum line loading [38].

With smart charging, which is different from charge schemes as it incorporates a control algorithm and monitoring system, a higher level of control is possible.

In [19], three levels of EV penetration (low, medium and high) was studied corresponding to 12.5 %, 33.3 % and 70.8 % respectively, with penetration being defined as a measure of households with EVs. The level of smart charging was also scaled from 0% (referred to as dumb charging where no form of control was allowed), 25 %, 50 % and 100 % (corresponding to all EV owners having smart charging abilities). It was found that in most cases, the wide application (100 %) of smart charging could decrease the number of alerts and violations of power quality standards to zero.

Overall, the implementation of charge schemes, tariff incentives or smart charging technology is concluded to decrease the extent of technical issues and power quality violations in a network. The widespread implementation of these strategies may in some cases alleviate all of the technical issues caused by EV charging and increase the hosting capacity of networks significantly.

To summarize, the uncertain variables that affect the EV load include the make and model of EV (informing battery capacity and energy consumption rate), owner behaviour (daily travel distance affecting SoC, charge patterns informing periods of interest, installation of fast charging facilities at residential level affecting charge rate) and the implementation of charge schemes and tariff incentives. All of these factors, with its effect of the load shown in Figure 3 below, bring diversity and uncertainty to the EV load. While some studies attempt to address these factors, most impact assessment studies fail to address them all. Some studies acknowledge the variability of the EV load with time but fail to address the diversity in the EV load for a specific time interval. This review concludes that motivated assumptions be made regarding certain factors of uncertainty, the diversity in the EV load be addressed and unpredictability in customer behaviour be incorporated in the EV load model.

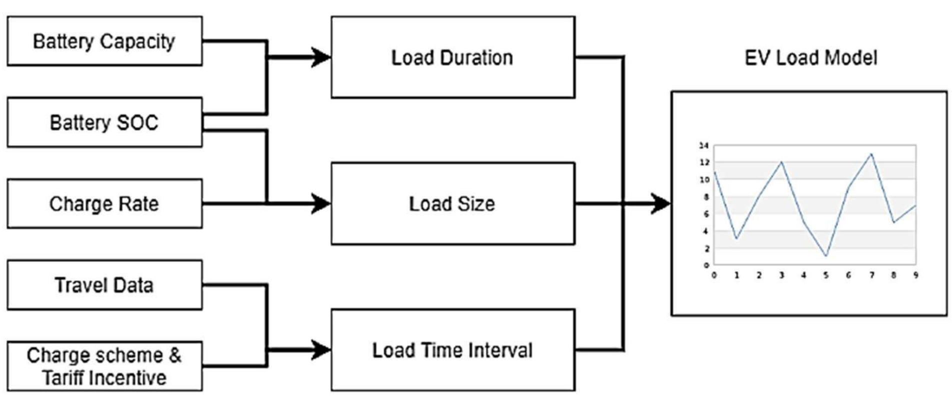


Figure 3: Factors that affect the EV Load Model

2.2 Scope of technical parameters assessed

The supply of electricity to customers is regulated through power quality standards to ensure the optimal performance of the network and connected equipment. An increase in EV penetration may have effects on the network, due to newly introduced loads and/or generations (when using the EV battery for energy arbitrage, self-consumption or UPS functionalities), that were not taken into account in the initial distribution network design. A range of technical issues is possible, and the extent of these issues depends on the penetration level of EVs and restrictions concerning operation.

The following parameters (voltage level, voltage unbalance and thermal loading of conductors and transformer) are usually used as indicators to assess the accommodation of the network to EVs. How each of these technical parameters are affected by EVs interacting with the grid is detailed below.

2.2.1 Voltage level

The additional load demand from the charging of EV batteries can cause large voltage-drops along a feeder. Although a voltage-drop along the feeder is normal and expected, due to the size of the additional loads, the voltage-drop could be excessive and cause the feeder voltage level to fall below the minimum voltage level prescribed by the power quality standards. Mass simultaneous charging of EV batteries has in many cases shown to cause severe voltage drops beyond the prescribed supply standards [10], [18], [19], [33], [34], [39], [40], especially if this mass charging coincides with peak demand loads. In most cases voltage-drop violations occurred at houses close to the end of the feeder (furthest from the transformer).

Similarly, when EV batteries are used as distributed generation (DG) and are allowed to export power into the network, feeder voltage may rise, which in excess may also be problematic. This export of power into the grid could cause the voltage level along the feeder to rise and exceed the maximum voltage level stipulated in the power quality standards. This is demonstrated in [33]. At 30% EV penetration (as a measure of houses with EV), when the EVs are in generation mode, the tap changer and the voltage level at all points along the feeder exceed their statutory limit.

Something to note is that although EV charging is likely to result in voltage drops along the feeder and EV discharging result in voltage rise, the effects of voltage unbalance should not be overlooked. Due to voltage unbalance, it is possible that EV charging may result in voltage rise and EV discharging in voltage drops.

2.2.2 Voltage unbalance

Electricity is generated, transmitted, and distributed as three-phase power. However, each household along an LV feeder is typically connected to only one of the three phases. If the three phases are not evenly loaded this could result in voltage unbalance. Power quality standards stipulate the percentage of voltage unbalance that is allowed. The utility cannot predict which customers will adopt EVs. This uncertainly implies that if charging of the EVs is done at home, the EV battery can be connected to an unknown node and phase in the network. This could result in the three phases being unequally loaded, causing voltage unbalance along the feeder. Voltage unbalance causes extra heating and results in increased losses [54].

In [19], for the deterministic analysis, Papadopoulos et al. ignored the effects of voltage unbalance by allocating the single-phase EV loads uniformly across the nodes and phases. Results from such simulations do not demonstrate the full scope of effects and extent of technical issues which may arise from the uneven distribution of EVs in a network. Other studies acknowledge the impacts of uneven loading of the three phases and the effect it may have on voltage unbalance. Ul-Haq et al. [10] analysed the effects of uneven phase loading using two placement scenarios. The first scenario distributed the EV loads across phase a, b and c in the ratio of 50%, 30% and 20% respectively. The second scenario distributed the EVs across the three phases in the ratio of 80%, 20% and 0% respectively. It was found that for the first scenario, the network could handle up to 50% EV penetration before exceeding a voltage unbalance limit of 2%. While scenario two only allowed a penetration of 25% before the voltage unbalance limit was breached. The uneven loading of the three phases is shown to have a significant effect on voltage unbalance and subsequently the hosting capacity of a network to EVs while adhering to power quality standards.

Although [42] assigned EVs randomly during the simulation process, the impact on voltage unbalance was not assessed. The study does however acknowledge the effect of voltage unbalance on voltage level and mentions the benefit of monitoring the phase allocation of EVs in future simulations in order to observe the full scope of technical impacts. More studies [18], [19], [22], [33], [34], [40] recognize the unpredictability of EV uptake (with regard to node and phase) and subsequently model the placement of EV randomly, allowing for uneven EV phase allocation.

2.2.3 Thermal loading of conductors and transformer

Transformers and conductors are sized and selected according to the expected loads. For design purposes, knowledge of the expected loads is required to accurately size these components. Traditional power systems that were designed and built before the broader based introduction of DG and ESSs, included additional capacity for traditional load growth, but it is not likely that this was in excess. Specifically, not to the extent of meeting the capacity demand requirements of these newer technologies. The demand during mass simultaneous charging of EVs, especially when coincident with ordinary pre-EV peak demand, is found to result in thermal overloading of both the transformers and conductors [18], [19], [22], [23], [40]. This leads to inefficient operation, loss of component life and increased network losses [22], [39]. This component overloading is addressed in [19], [35], [40], [50], by implementing charge schemes that coordinate EV charging from peak periods. These studies have found that this significantly decreases component loading.

2.3 Method for load flow analysis

There are two load flow analysis methods reported, deterministic and probabilistic. The load flow analysis method will be dependent on how the simulation inputs have been defined and therefore how these inputs will be handled during the simulation. Whether customers and EV loads are assigned single constant load values, whether different types of customer loads have been used or whether customer loads and EV loads are assigned as distributions. Whether EVs are characterized as constant power loads or whether EV loads made use of varying charging rates.

Deterministic load flow (DLF) methods applied in [25], [35], [36], [38], [41] are not able to explicitly simulate the effects of the load input uncertainty and variability and therefore this inherent uncertainty and variability is not factored in the results.

In [38], an average residential load was assigned to each customer for different EVs charging-load scenarios, in which a single iteration was run for each scenario. The scenarios are characterised by penetration percentages (5 %, 10 %, 20 % and 50 %), whether charging was regulated or unregulated and whether fast charging was prohibited or allowed forming a total of 12 scenarios.

In [36], simulations were conducted for both a summer and winter's day. The number of EV assigned to each customer was increased from one to seven and the charging rate increasing from 1 kW to 3.3 kW to 6 kW and finally 20 kW. This created two sets (summer and winter) of 28 scenarios each. Simply put, one scenario consisted of all customer being assigned the same residential load profile (either summer or winter), where each customer is assigned the same number of EVs (ranging from one to seven) at the same charging rate (1 kW, 3.3 kW, 6 kW or 20 kW). Running a single iteration of each scenario and changing the loads uniformly for all customers ignores the diversity in the residential load and EV load in the interval being analysed.

[41] implemented a process similar to [36], but instead of using four charging rates, only made use of two (3.3 kW and 6.6 kW), at three penetration percentages (33 %, 66 % and 100 %) at three time intervals (corresponding to the minimum, medium and maximum load hour). This produced a total of 18 scenarios.

Although [36], [38], [41] ran multiple scenarios, this is not close to the number of scenarios necessary to accurately model the full extent of variability in the load inputs.

Probabilistic load flow (PLF) methods are implemented by [19], [22]–[24], [34], [39], [40], [42]. To ease the computational burden some studies ran fewer iterations than what is usually deemed necessary to accurately model the input behaviour. Often this may come at the cost of not accurately representing the entire scope of possible scenarios and therefore the results might not depict the full extent of technical issues possible. [39] ran 200 MC based load flow analysis iterations per hour for each of the four penetration percentages (10%, 20%, 30% and 50%) analysed. Each MC iteration assigned a connection time from a normal PDF of plug-in trends and a charge duration based on a Weibull distribution of daily travel characteristics. [23], [40] used both a DLF and PLF analysis method where [23] conducted 100 MC simulations while [40] only conducted 50 load flows in the probabilistic section. In [23] the MC simulations handled the random allocation of residential and EV load profiles to each customer from a pool of 1000 profiles each, as well as the random placement of EVs.

[19], [22], [24], [34] acknowledged the need for significantly more iterations. Both [22], [24] ran 1000 iterations, while [34] set the simulation process to continue for 10 000 iterations or if the variation in the last 10 iterations was less than $1e^{-4}$. In [19] the MC method conducted power flows for 2 days until the terminating criteria was satisfied. This was when the standard error of each node's voltage magnitude for every time step that fell below 0.001%. When it comes to determining the appropriate number of iterations to run, a convergence or error margin can be used or a set number of iterations that has been tested to produce results that fall within a specified error margin can be used.

Studies that make use of PLF methods are particularly helpful to network planners and policy makes as the full and realistic extent of technical issues possible are addressed, especially studies that include some form of risk index in the interpretation of the simulation results [19], [22], [34], [42]. This informs the planner or policy maker of the risk involved when planning or allowing for a certain penetration of EVs in attempt to inform optimal network design strategies and EV uptake restrictions.

2.4 Simulation of EV penetration scenarios

The simulation of EV penetration scenarios can be separated into two sections (i) how penetration percentage is defined and (ii) the EV placement strategy adopted during the simulation process.

2.4.1 Definition and quantification of penetration percentage

There is not a standard way in which the measure of EV penetration should be defined. Some studies express the measure of penetration percentage as the number of EVs over the total vehicle fleet of the residential area analysed [23], [25], [53]. Other studies define penetration as the number of EVs over the total number of households considered in the assessment [10], [19], [22], [25], [33], [35], [37], [41]. These different definitions result in varying acceptable penetration percentages. Although neither definition is incorrect it is very important to clearly define the penetration percentage definition used and be careful when making direct comparisons from one impact assessment to another, especially when different definitions of penetration percentage have been used.

The penetration percentage definition found in an impact assessment of PV systems [43] was adapted in [15] to define the measure of penetration for EV impact assessment simulations. The adaption from equation 1 to equation 2 is found below.

$$\text{PV Penetration Percentage} = \frac{\text{Cumulative Power of PV Installed [kW]}}{\text{Feeder Maximum Demand [kW]}} \times 100\% \qquad (1)$$

$$\text{EV Penetration Percentage} = \frac{\text{Cumulative Power of EVs Loads [kW]}}{\text{Feeder Maximum Demand [kW]}} \times 100\% \qquad (2)$$

Both equations above define penetration percentage in relation to the feeder properties, specifically feeder maximum demand (FMD). This proposed definition allows the simulation results to be indicative of the maximum cumulative charging capacity that the network can handle as a percentage of the FMD. This definition can be manipulated based on the charging capacity of each EV and subsequently be used to calculate the corresponding number of EVs allocated. Using this definition ten EVs of 3 kW in network A may result in a penetration of 50%, while ten EVs of 3 kW in network B results in a penetration of 25%. The FMD of network A is 60 kW and the FMD of network B is 120 kW. Likewise, a penetration percentage of 20% in network A will be equivalent to four 3 kW EVs while 20% in network B will be equivalent to eight 3 kW EVs. Also, for network A if the penetration percentage that the network could handle was 50%, and if the EVs were modelled having a charging capacity of 6 kW opposed to 3 kW, this would result in an equivalent of 5 EVs opposed to ten. For both 3 kW and 6 kW the cumulative power is 30 kW. This definition defined above allows for simple conversion and easier comparison between network results.

2.4.2 Simulation of EV placement

EV placement strategies can be categorised into three approaches; (i) single, fixed scenario, pure deterministic placement, (ii) limited, manually selected worst-case scenario placement and finally (iii) stochastic placement.

[36] adopted a purely deterministic approach by allocating EVs uniformly across the network nodes, first allocating one EV to each customer, monitoring the network condition, then adding another EV to each customer then monitoring the network conditions and so forth.

The second approach makes use of multiple scenarios and places EVs at specified locations, determined by the planner, along the feeder that may be deemed to have the largest effect on the network [18], [25]. In [25] EVs were first placed at houses furthest from the substation bus, then at houses closest to the substation bus. This was done to assess the two polar cases. While this method of worst-case placement scenarios may be helpful in determining the extreme conditions along a feeder, given the most unfavourable placement regardless of how unlikely, this method may not mimic reality. Although this will give a good idea of the maximum effect of EVs and the results may lead to very conservative EV uptake policies, this may not be realistic. Similar to uniform pattern placement strategies, this worst-case placement scenarios do not account for the unpredictability in EV placement.

Finally, the stochastic approach accounts for the randomness in the placement of EVs, as the first and second approach may not result in realistic or probable placement. The random placement strategies are seen as more realistic, as it more often than worst-case scenario approaches, mimics actual EV uptake. This random placement strategy used in [22]–[24], [42], [52] recognizes and reflects the randomness and unpredictability in the placement of EVs along a feeder. Both [19], [48] conducted a deterministic and probabilistic analysis making use of different placement strategies for each analysis. In [19], for the deterministic section, EVs were allocated uniformly (approach (i)) among the network nodes while in [48] the deterministic analysis placed EVs at critical locations (approach (ii)). Both studies allocated EVs randomly for the probabilistic analysis section and acknowledge the importance thereof.

This review concludes that the stochastic placement approach is best as it caters for the uncertainties associated with the EV impacts, including the location (node and phase) of EVs, that the single scenario and worst-case placement approach fails to adequately address.

2.5 Chapter summary and conclusions

To conclude, this review identifies five key components necessary for a comprehensive analysis, and proposes the approach of these components as follows:

1. The network model needs to be detailed and realistic, and simulation conditions need to resemble the characteristics of a practical feeder.

2. The residential customer load and EV load models should account for the diversity in these loads, and the unpredictability of the customers' behaviour.

3. The method used to simulate the allocation of EVs should reflect the randomness in EV uptake and therefore the uncertainty in EV location (node and phase).

4. The load flow analysis method should explicitly account for the stochasticity and variability in both the residential customer and EV loads.

5. The technical parameters assessed to serve as an indicator of a networks hosting capacity to EV loads should ensure that the power quality standards and component loading limits are adhered to. The technical parameters identified are voltage level, voltage unbalance and transformer and conductor loading.

Figure 4 below visually illustrates components 1-4 from the list above and where each component fits within in the bigger simulation process. This forms the framework comprising the key components necessary for a comprehensive impact assessment study. In [16], this framework is expanded, and a methodology proposed for how each of these five components can be addressed and modelled when conducting an impact assessment simulation.

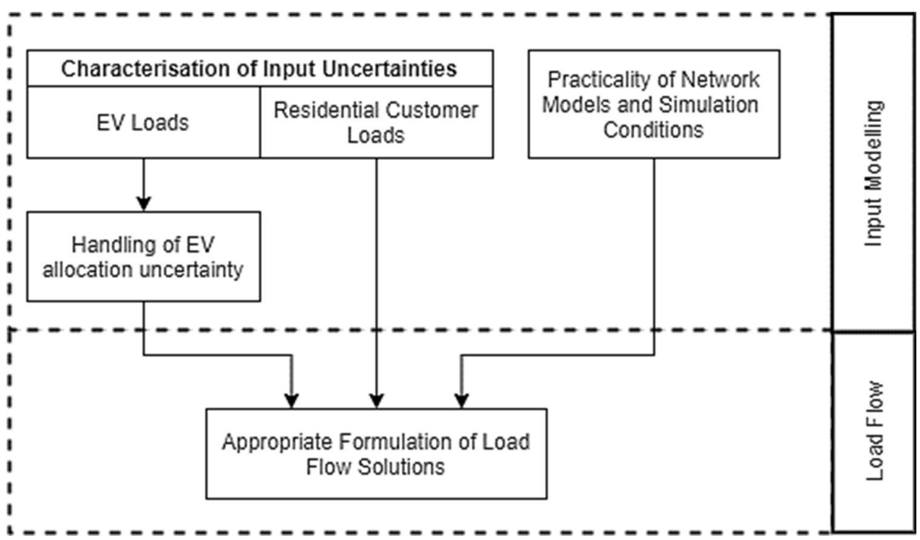


Figure 4: Components of a Comprehensive Impact Assessment Methodology

3 Probabilistic EV Modelling and Modified Use of the HBE-MCS Impact Assessment Tool

Chapter 2 informed the key components for a comprehensive impact assessment methodology. The key components identified include (i) detail network modelling, (ii) the use of residential customer and EV load models that account for the diversity in these loads and unpredictability of customer behaviour, (iii) the uncertainty in EV placement and (iv) a load flow method that explicitly account for uncertainty and variability in the load input models. This chapter describes the simulation methods used in this work, which is based on a combined stochastic-probabilistic approach called the Herman-Beta Extended-Monte Carlo Simulation (HBE-MCS) method, that has been used for impact assessments of PV systems. The chapter describes the preparation of the input models, definition of simulation conditions and modification of the HBE-MCS tool that was done in this research to make it suitable for EV applications.

3.1 Why the HBE-MCS tool?

The Herman-Beta (HB) transform was originally developed for PLF analysis to assess the impacts on voltage-drop of passive loads on radial LV feeders and ultimately the selection and sizing of conductors in feeder design [55]. The HB transform was adopted as the national standard for LV feeder design in South Africa [56]. In 2017, the transform was extended to allow for assessment of active LV feeders [32], and extended in 2019 to form the HBE transform [57], which removed restriction to LV feeders and added a variety of functionalities, making it widely applicable. The HBE transform is a single-pass analytical approach for PLF analysis. It calculates statistical bus voltages and branch currents, to assess the impacts on voltage level, thermal loading and voltage unbalance, on radial feeders at any voltage level. The HBE takes in beta-PDF inputs (of current, power or impedance) and produces beta PDF defined outputs [57], where these outputs can be interpreted using design risk margins. The modelling of the inputs (loads and generations) using beta PDFs allows for the representation of these loads and generations with the associated uncertainty. The HBE-MCS tool was used in both [32], [43] to assess the impacts of distributed energy resources (DERs), specifically PV systems, on LV feeders.

The following features of the HBE-MCS tool make it suitable for the intended application:

- The HBE-MCS tool is analytic and therefore supports the need for computational efficiency.
- The tool makes use of PDF based inputs accounting for the explicit modelling of input uncertainty. The use of the beta PDF specifically makes load modelling versatile.
- The MCS component allows for the extensive modelling and simulation of the unpredictability in EV placement.

- The HB transform is the standard for feeder design in South Africa and therefore its use in this application has the potential to advance design standards.
- The scope of technical parameters that can be monitored and the interpretation of these outputs to include design risk makes this tool particularly useful for comparison to power quality standards.

From this it is evident that the HBE-MCS tool meets all the requirements of a robust impact assessment tool set out in Chapter 2. The tool does however require some modifications to extend the application to EV penetration analysis.

3.2 Modifications to the HBE-MCS tool to include EVs

The following modifications are required to extend the application of the tool to EV penetration analysis:

- EV load modelling using the beta PDF
- Building the EV models into the HBE
- Modifying the conditions in the MC simulator

3.2.1 EV load modelling using the beta PDF

This section will explain the applicability of the beta PDF to model the EV load.

3.2.1.1 Why beta PDFs?

The beta distribution models probability, its domain is ordinarily bound between 0 and 1, and the distribution is defined by two shape parameters alpha and beta. The beta distribution is very flexible and by changing the values of the shape parameters alpha and beta, the distribution can be U-shaped, bell shaped, symmetrical, left and right skewed or even uniform. The versatility of the beta PDF to take on many shapes is shown in Figure 5.

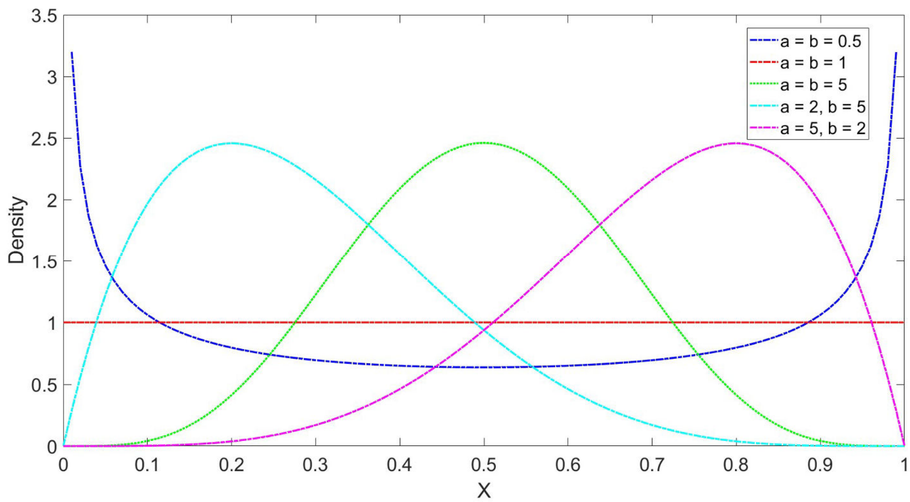


Figure 5: Versatility of Beta PDF Illustrated

The beta PDF can further be defined by a scaling factor C, that bounds the domain between 0 and C, where C can be representative of a maximum or full load condition. This is particularly useful as this matches the expectation of the loads and generations falling between zero and a maximum value (this maximum can be restricted to the customers' circuit breaker value for loads and the maximum inverter output capacity for ESSs).

The use of beta PDFs for PLF analysis is particularly convenient since the alpha and beta parameters are easily extracted from load data and captures all the statistical properties of the load such as mean, mode, skewness, moments and kurtosis [57].

One of the assumptions made is that the beta PDF is a suitable descriptor of residential customer loads at any specified interval. In South Africa, residential customers are clustered according to characteristics used to define Living Standard Measure (LSM) levels, that can inform expected loads. A load research study conducted in South Africa concluded that the loads of these customer groups during the interval of maximum demand (IMD) followed beta distributions [58]. Further work demonstrated the suitability of the beta PDF to model load measurements in extended periods beyond the IMD [59]. The question that remains is whether the beta PDF is a suitable descriptor for EV loads.

3.2.1.2 Beta PDF for EV load

As previously mentioned, the flexibility of the beta PDF allows for the modelling of various load shapes. The generic SoC curve of a lithium-ion EV battery (Figure 6 below), shows that for a majority of the charge period, the amount of power being drawn to charge an EV is almost constant. Let this constant value be called K.

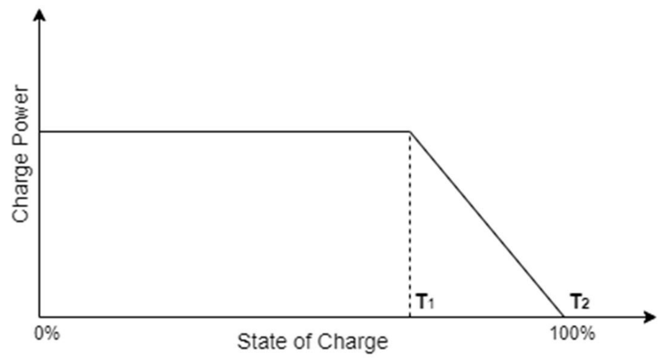


Figure 6: Generic SoC Curve for Lithium-ion EV Battery

This constant charge power being drawn is with the exception of the very beginning and final phases of charging. The very beginning portion of the SoC curve is not particularly important as it is not advised to allow the EV battery to deplete completely, to reduce battery degradation and prolong battery life. This means that if a random charge power was selected from this charge curve, the chances would be high that this charge power would be K, and less likely that it would relate to a charging power at the beginning or end of charge. It is possible to model this probability making use of a beta distribution. The assumptions and how the beta PDF shape parameters are extracted is explained in the following section.

3.2.1.3 Assumptions and procedures for extracting beta PDF parameters for EV load model

For the extraction of the beta PDF shape parameters alpha and beta, the following method is followed. The SoC curve is modelled as a piecewise linear function for values 0 to 100, representing completely flat to fully charged. It is assumed that the EV owners will not allow the batteries to drain completely to ensure longevity of the battery life, therefore the deviation of the power values at the beginning portion of the SoC curve will not be incorporated.

The piecewise linear function is constant from zero until a certain value, after which the curve can be described by a linear decreasing function. The value at which the SoC begins to decrease is between 65 % and 85 % SoC. For the purpose of demonstrating how the beta PDF parameters are extracted, let this value be 75 % and the constant charge value be 2.5 kW. Table 2 below shows this discretised SoC vs power values.

Table 2: Discretised SoC vs Power for EV SoC Curve

SoC [%]	0	1	2	3	…	75	76	77	…	99	100
Power [kW]	2,5	2,5	2,5	2,5	2,5	2,5	2,4	2,3	…	0,1	0

From this it is possible to calculate the mean (μ) and standard deviation (σ) for the data set. The mean and standard deviation values are then used to calculate the alpha and beta shape parameter values using equations 3 and 4 below.

$$\alpha = \left(\frac{1-\mu}{\sigma^2} - \frac{1}{\mu}\right)\mu^2 \qquad (3)$$

$$\beta = \alpha\left(\frac{1}{\mu} - 1\right) \qquad (4)$$

The value of the scaling factor C will be 2.5 kW in this case as the power value will not exceed this. For the data set above, the calculated shape parameters are as follows:

$\alpha = 0.4893$ and $\beta = 0.0699$.

The beta PDF is shown below in Figure 7.

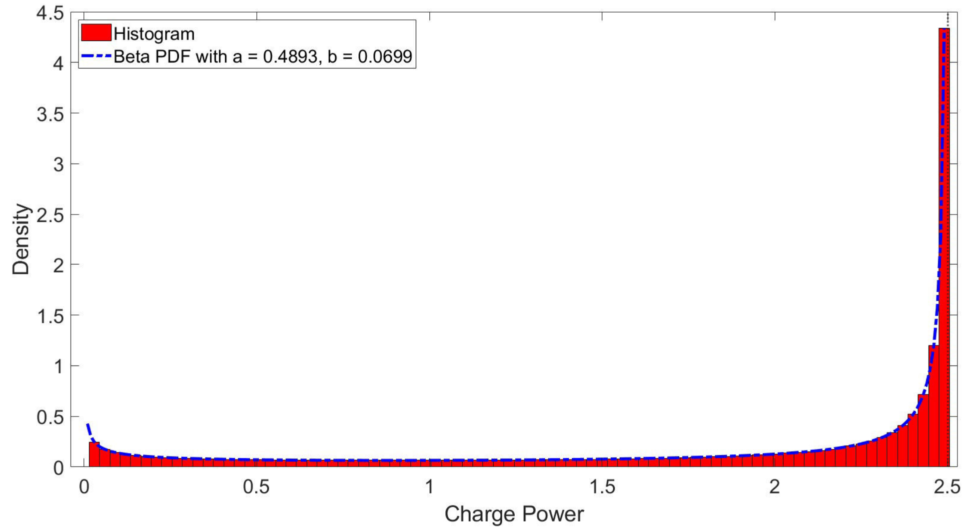


Figure 7: Beta PDF for EV Load

The shape parameters would not be the same for all time intervals, as the discretised SoC versus power curve should reflect the likelihood that the EVs have been charging for a few hours already (and many vehicles may be closer to the end section of the charge curve) or whether most EV owners have just connected their EVs to charge. This would be informed by the daily travel distance and the home arrival time in relation to the time of connection and time period under analysis.

3.2.2 Building the EV models into the HBE

As already stated, the HBE-MCS tool has been used to assess the impacts of PV systems on LV feeders. This was achieved by modelling the PV as negative loads and separating the residential customer loads and the PV loads by implementing sub-nodes. These nodes were separated by an insignificant distance (e.g. 0.01 m) that allowed algebraic integrity and the principle of superposition to be easily applied [32]. Each household was now represented by two nodes, illustrated in Figure 8.

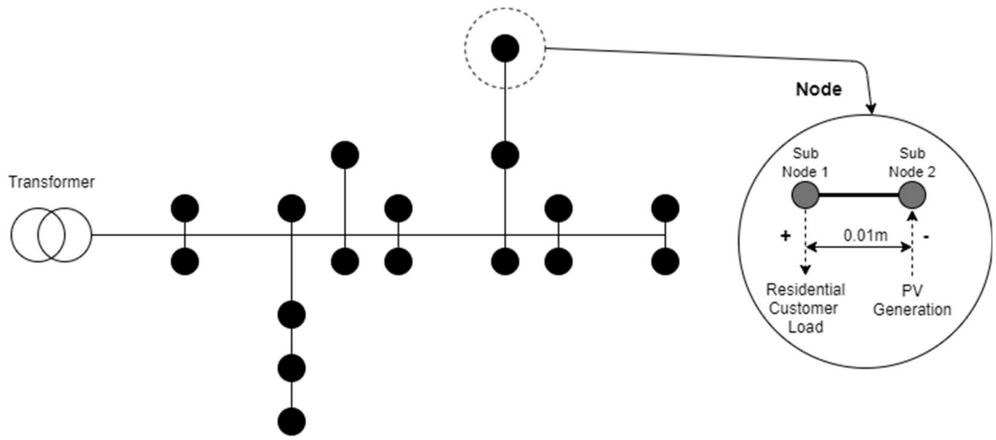


Figure 8: Household Node Separation Illustration

The first sub-node received the beta PDF representing the positive residential customer load. If the household was assigned a PV system, the second sub-node is assigned a beta PDF model for the generation (negative load) of the PV system. In [43] it was concluded that this approach was not limited to PV systems but that different types of loads could be modelled using this approach.

In [15] the application of this approach is extended to EVs where the PV loads are replaced by EV loads. As with the PV loads, the EV loads are separated from the residential loads because not only can an EV battery act as both a load and generator, but the beta distribution representing the EV load model has different shaping parameters and a different scaling factor to the residential customer load distribution. The reason for this algebraic separation is because beta PDFs with different shape parameters cannot be readily summed. This extended approach is also applied to EMs in [14] and again to EVs in [16].

3.2.3 Modifying the conditions in the MCS simulation

In addition to the EV load modelling being probabilistic, a stochastic placement strategy provides means to the simulation of a representative distribution of EVs across the network. The MCS method has been used in EV impact assessment studies for the purpose of random EV placement [23], [34], [37]. This random placement of single phased EV loads explicitly accounts for unbalanced allocation of EVs and therefore unbalanced phase loading across the three phases in a distribution network. This allows for a detailed analysis of the conditions of voltage unbalance and its impacts on other technical variables such as voltage level and conductor loading.

When used for PV systems, the HBE-MCS tool makes use of the MCS method as a stochastic simulator to mimic random PV allocation (location and capacity). Where a PV unit, of a given capacity (e.g. 2 kW), is randomly assigned one unit at a time. The maximum number of units that may be assigned to any household is specified upfront. If a specific household is selected at random after it has already been assigned a PV unit, but the household has not reached the maximum number of units specified, the household is assigned an additional unit. This allows the tool to assign PV systems of varying capacities.

This approach needed some adjustment for the EV application. Since it is not possible to own half an EV, the EV “unit” assigned should resemble one full EV load. And similarly to the maximum number of PV units that may be assigned to a household, the maximum number of EVs that may be assigned to any customer should be specified upfront.

At each penetration percentage, a number of MCS placements that balances simulation accuracy and computational speed is conducted. When this HBE-MCS tool was used in [60], 1000 MCS placement scenarios were found to be sufficient. The results at each penetration percentage will represent 1000 of the worst cases along the feeder of each technical parameter monitored (i.e. maximum and minimum voltage, maximum voltage unbalance, and maximum transformer and conductor loading).

The level of risk incorporated indicates the likelihood that the technical parameter assessed will violate the stipulated power quality standards. According to the South African quality of supply standards stipulated in [56], the electricity supply should comply with the standards and therefore fall within the specifications 95% of the time. Because the HBE transform is probabilistic, a risk factor (e.g. 5%) can be incorporated in the PLF analysis. However, since the output of a defined number of MCS runs (e.g. 1000) gives information about the distribution of the most extreme technical parameter values at each penetration percentage, it is possible to incorporate an additional factor of risk. This second factor of risk can be incorporated in the analysis of the stochastic results. In this case, when the making use of the combined risk factors, 2.5 % can be applied in the PLF analysis and 2.5 % in the secondary process of interpretation, resulting in an overall risk factor of 5%, or inversely a confidence of 95% in the results. This overall combined risk is therefore compliant with the power quality standards. However, the level of risk incorporated in the simulation and results interpretation is influenced by how accurately the loads have been modelled and the application of the results [61]. If there is uncertainty with the load model adopted, a larger level of risk should be incorporated in the analysis of the results.

3.3 Simulation procedure

After the modelling of both the residential customer load and EV load using beta PDFs, the incorporation of the EV loads into the HBE using the node separation approach, and the modification of the conditions of the MCS placement simulator, the HBE-MCS tool is now suitable for EV penetration applications.

The simulation process is explained in the following five steps, fully described in [14].

1. Determine the FMD by loading the residential customer load subnodes and linearly incrementing the load until the first occurrence of either a voltage or conductor loading violation.

2. Reset the load to the original residential customer loads and add ESSs (hybrid PV systems, EMs or EVs) randomly using the MCS method guided by the penetration level under analysis and the limits per household.

3. Perform the HBE and record the worst-condition of each technical variable (maximum voltage, minimum voltage, maximum voltage unbalance, maximum conductor loading, and maximum transformer loading) based on a desired level of risk.

4. Repeat processes 2 and 3 for a defined number of scenarios selected (e.g. 1000) to balance simulation accuracy with computational speed.

5. Increment the penetration level and repeat processes 2 to 4 until every node reaches the maximum specified ESS limit per household.

The program flow into which these five steps are incorporated is presented in Figure 9 below.

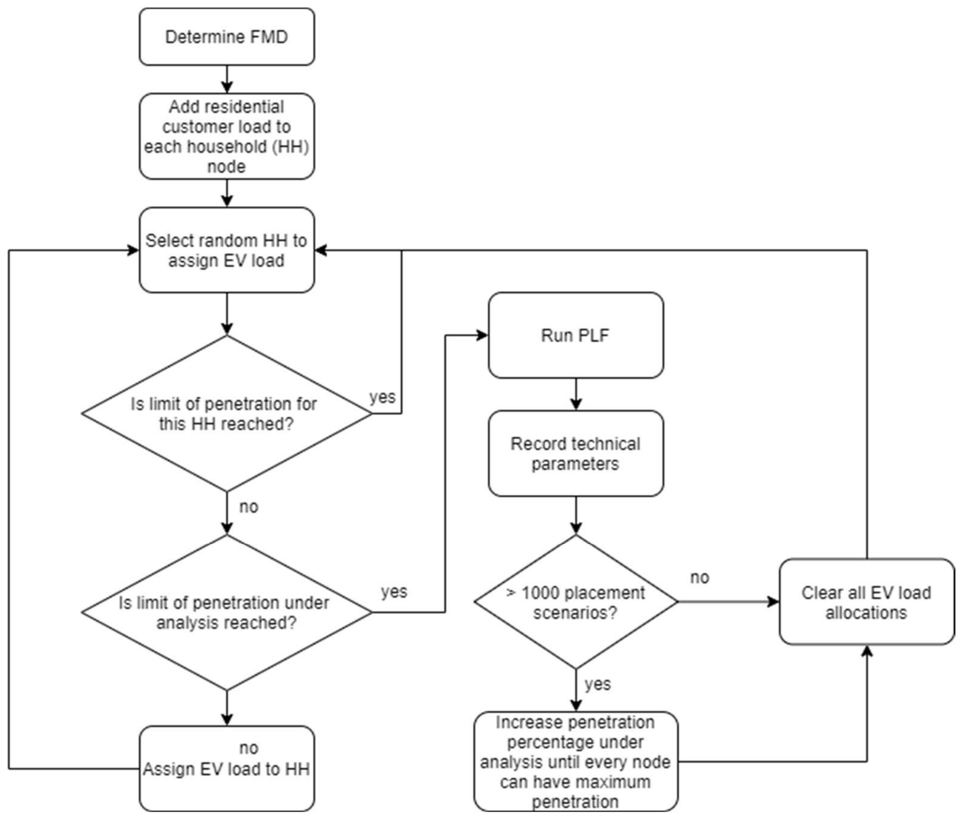
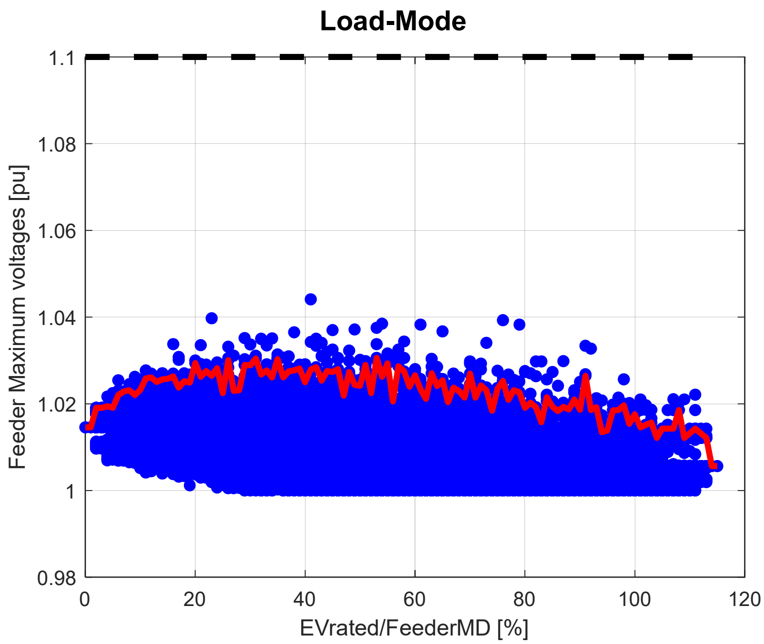


Figure 9: Overall Program Flow for MCS-HBE Tool

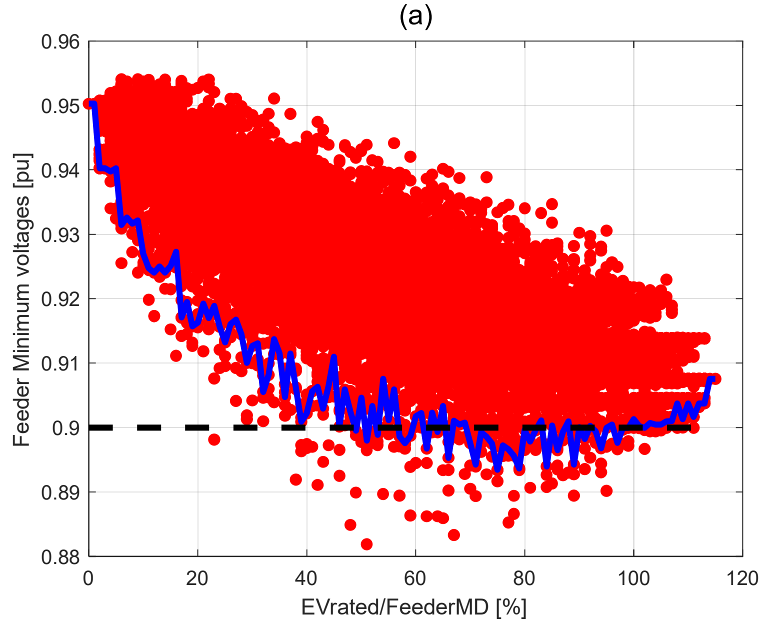
3.4 Verification of Modified HBE_MCS Tool

The modified HBE-MCS tool is verified by simulating two sets of simulations. The first set of simulations shows how the tool is able to simulate load-mode (battery charging) and generation-mode (battery discharging). In the first scenario the EV is simulated in load-mode. The beta PDF representative of the EV load will be a negative load, indicating load-mode. In the second scenario the EV is simulated in generation-mode and the EV load will be positive, injecting power into the network.

The maximum voltage level and minimum voltage level for both modes are monitored. This is shown in Figure 10 and Figure 11 below.



(a)



(b)

Figure 10: Simulation Results for Modified HBE-MCS Tool in Load-Mode

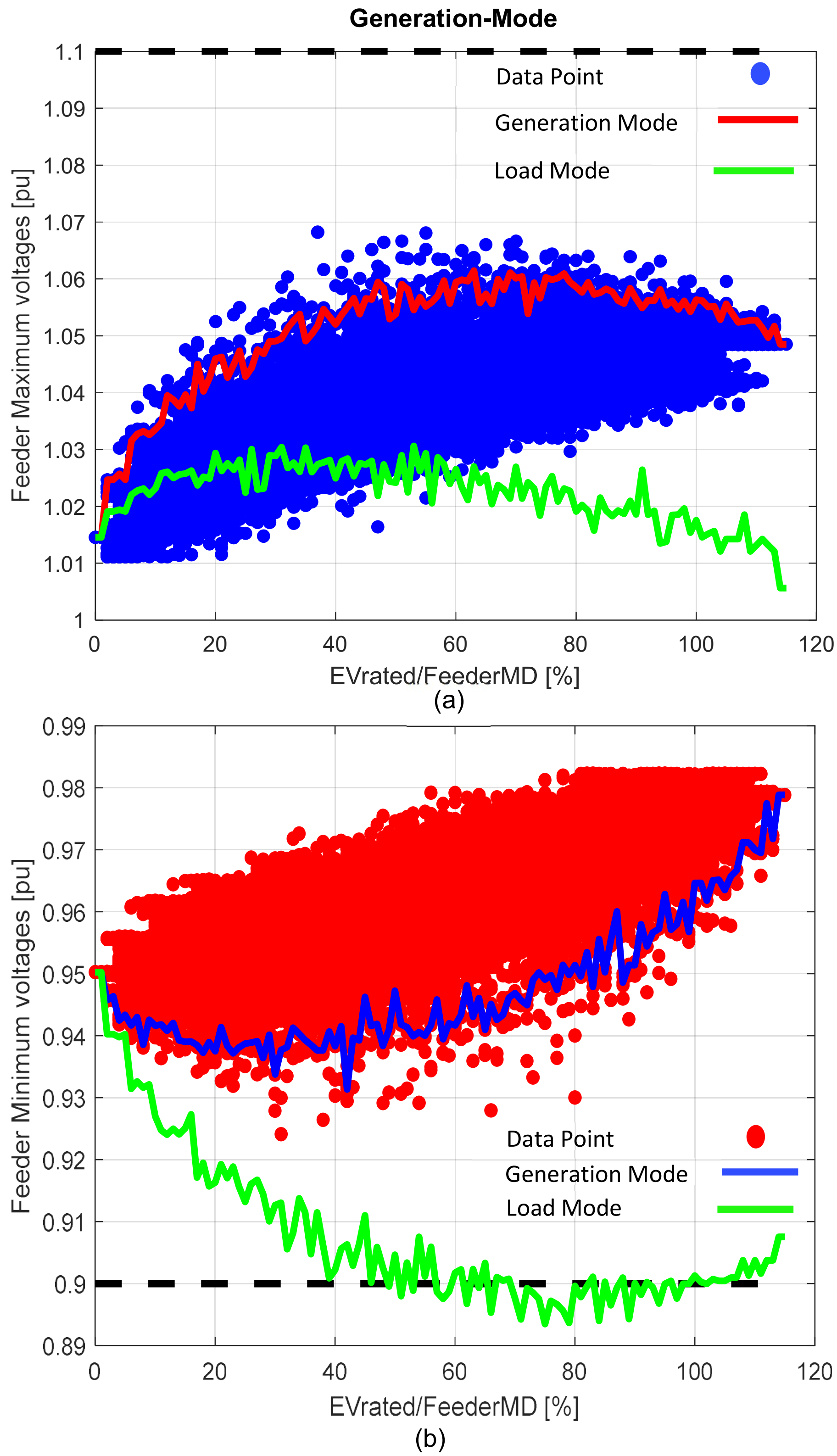


Figure 11: Simulation Results for Modified HBE-MCS Tool in Generation-Mode

The red trendline in the feeder maximum voltage curves (top curve) and blue trendline in the feeder minimum voltage curves (bottom curve) indicate the 95 % confidence interval referred to in section 3.2.3. For the red trendline, 95 % of the data points observed falls below this line. Inversely, for the blue trendline, 95 % of the data points lie above this line. These trendlines simply aid in assessing the results while incorporating a 5 % level of risk.

The green trendlines in Figure 11 represent the 95 % trendline from load-mode that has been superimposed onto the generation-mode curves for easy comparison. In generation-mode the extent of voltage rise is higher than when the EV is placed in load-mode. This is illustrated by comparing the green trendline in (a) of Figure 11 to the red trendline. In load-mode it is evident that the extent of voltage drop is considerably higher than when the EV is simulated in generation-mode. This is illustrated by comparing the green trendline in (b) of Figure 11 to the blue trendline. This decrease in voltage rise and increase in voltage drop is to be expected as charging results in voltage drop and discharging in voltage rise. The extent of voltage rise in load-mode and voltage drop in generation-mode is attributed to the effect that voltage unbalance has on voltage level.

For the second set of simulations the EVs will be simulated in load-mode only, while the shape parameters for the beta PDF representing the EV load will be changed (Scenario 1: $\alpha = 2$, $\beta = 5$; Scenario 2: $\alpha = 5$, $\beta = 2$).

Once again, the minimum voltage level and maximum voltage level for both scenarios are monitored. The results are shown in Figure 12 and Figure 13.

In scenario 1 the shape parameter alpha is smaller than beta. As a result, the beta PDF is skewed to the right. In scenario 2 the shape parameter alpha is larger than beta. As a result, the beta PDF is skewed to the left. Because both scenarios are making use of the same scaling factor, the mean of the load is smaller in scenario 1 than in scenario 2. The green trendlines seen in Figure 13 represent the 95 % confidence interval from scenario 1 superimposed onto the curves of scenario 2. When comparing the green trendline in (b) of Figure 13 to the blue trendline, the results from scenario 1 show a smaller voltage drop than in scenario 2. This confirms that the mean of the load in scenario 1 is in fact smaller than the mean of the load in scenario 2. As with the previous set of simulations, the increase in voltage level from scenario 1 to scenario 2 can be attributed to the amplification in the effects of voltage unbalance due to the larger load.

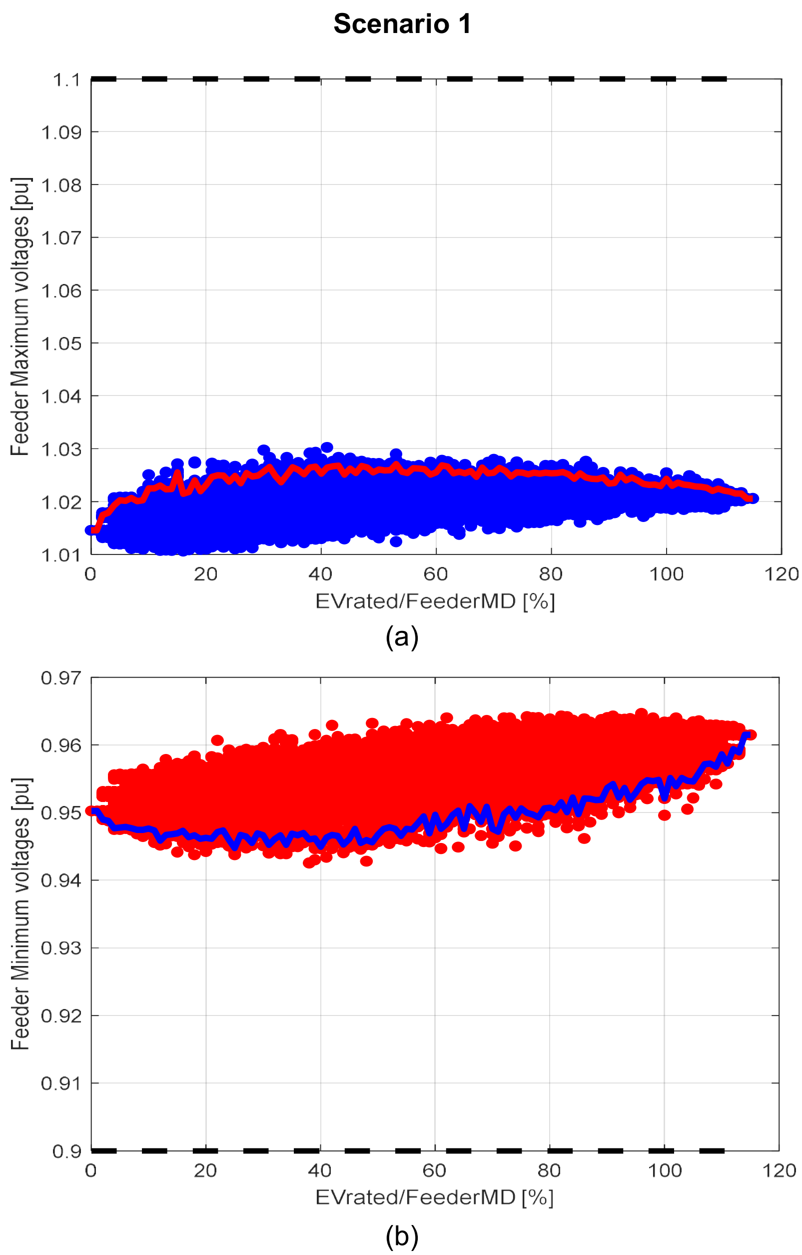
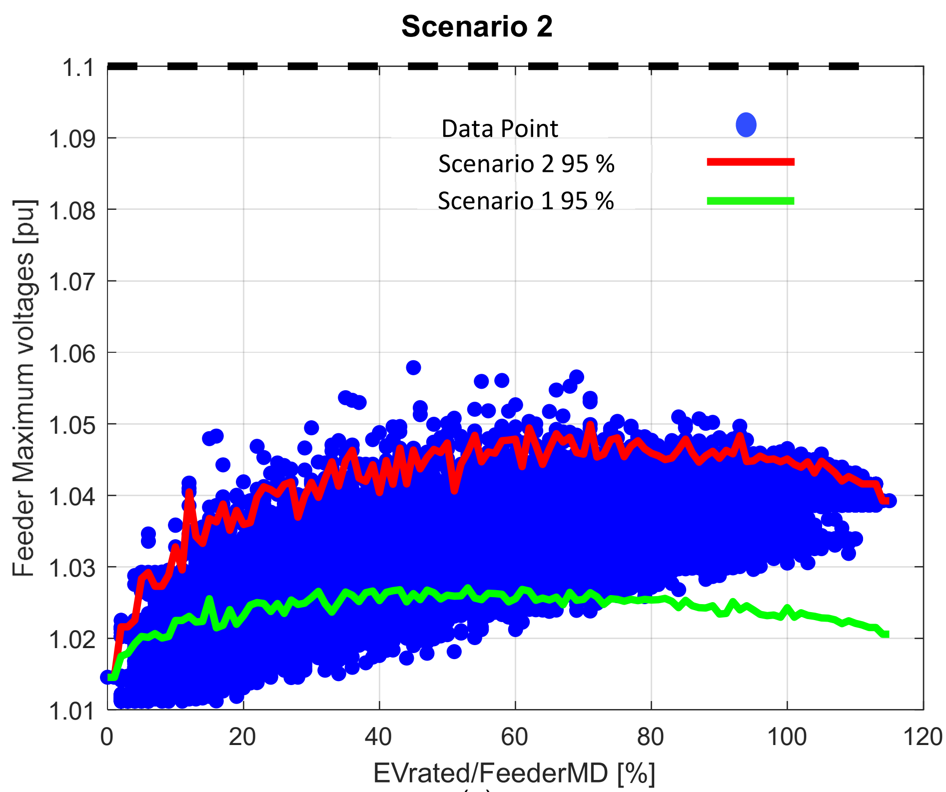
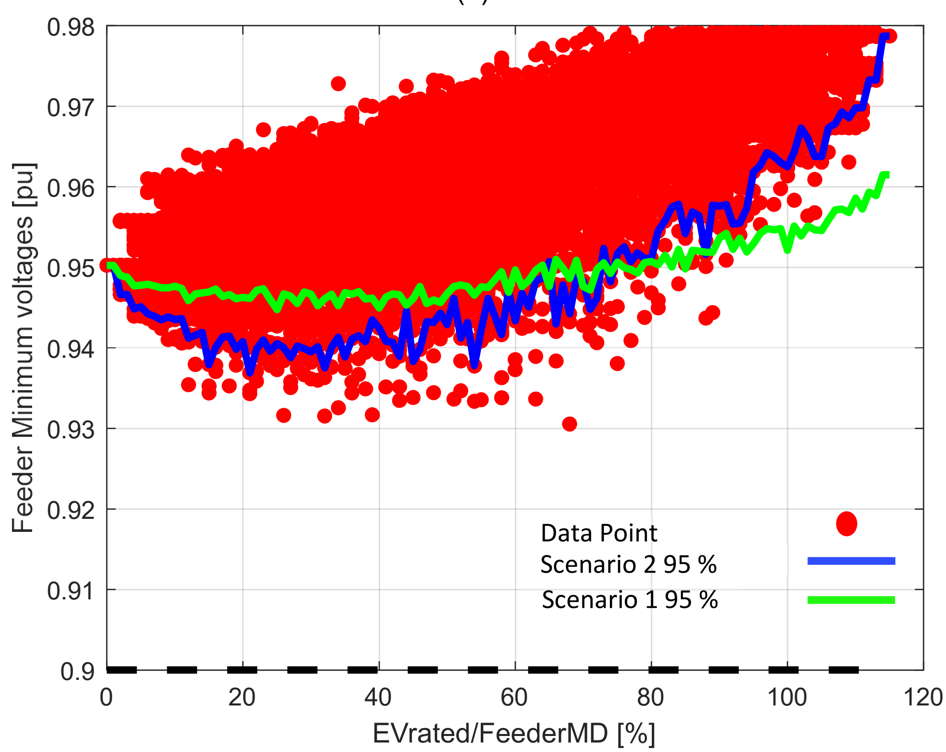


Figure 12: Results of HBE-MCS Tool Verification - Scenario 1



(a)



(b)

Figure 13: Results of HBE-MCS Tool Verification - Scenario 2

These straightforward simulations verify that the HBE-MCS tool has been successfully modified.

3.5 Chapter conclusion

This chapter motivates the selection of the HBE-MCS tool based on the tool's computational efficiency, the explicit modelling of input uncertainty, the ability to model the unpredictable placement of EVs and the scope of technical parameters that can be monitored.

The tool is adapted to model the EV load using the beta PDF and include the EV model in the HBE while the conditions in the MC simulator is modified for EV allocation. The simulation procedure, for the modified HBE-MCS tool, detailed and verified in this chapter, is used for the EV studies in [15] and [16] and an EM study in [14].

4 Results Informing the Thesis Research Questions

In this chapter the primary results, conclusions and contributions of the research will be discussed, consolidated and used to answer the four research questions. The four research questions that this thesis aims to answer are all directed towards proving the hypothesis. Furthermore, the research questions are directed towards developing a robust and comprehensive methodology to be used for ESS impacts assessments, that can be used to help planners and policy makers make informed decisions regarding components selection, infrastructure upgrade recommendations and uptake regulations around ESSs.

4.1 Results relating to research question 1

Research Question: What are the technical impacts of ESSs (namely EMs, EVs and hybrid PV systems) on LV residential distribution feeders and to what extent are existing distribution network infrastructure technically impacted by increasing penetrations of these ESSs?

In order to develop a comprehensive impact assessment methodology, it is necessary to determine the technical impacts of ESSs, review the proposed methodologies reported in literature and identify the characteristics necessary for a comprehensive methodology.

To answer research question 1, the technical impacts of ESSs on LV residential distribution feeders is investigated, and to what extent these existing networks are affected by increasing penetration levels of these ESSs is determined.

The research assessing the impacts of ESSs (hybrid PV systems, EVs and EMs) identify voltage level, voltage unbalance and component loading (of the transformer and conductor cables) as the primary technical impacts of ESSs on distribution networks [13]–[15]. Voltage unbalance is found to be affected by the unbalanced location of these ESSs on the network due to the unpredictability regarding which customers will adopt these technologies. Feeder voltage level rise or drop is primarily affected by whether the ESS is charging (consuming power) or discharging (exporting power). Additionally, the effect of voltage unbalance on feeder voltage level is also acknowledged. Components loading is found to be largely influenced by mass simultaneous charging or discharging of these ESSs.

Operational constraints are found to cause varying degrees of impacts on the network, where constraints refer to whether grid charging and export of power into the network are allowed or not. Systems in which grid charging and power export are prohibited are generally assumed to have a smaller effect on the network than systems that are allowed to grid charge and export power into the grid. Table 3 summarizes the technical impacts of ESSs (hybrid PV systems) based on the operational constraint applied [13].

Table 3: ESS Operational Constraints vs Technical Impact

Operational Constraint	**Voltage Conditions**		**Component Thermal Limits**
	Level	**Unbalance**	
Grid charging	Mass simultaneous charging will increase the magnitude of load currents, therefore significant voltage drops.	Charging of single-phase systems results in unequal phase load currents which leads to voltage unbalance.	High and continuous load current from simultaneous charging can cause thermal overloading of components.
Power export	High enough power export levels can cause reverse power flow and therefore voltage increase.	Unbalanced power export will cause phase unbalance.	High enough reverse power flow current can cause thermal overloading of components.

Based on these constraints, four scenarios in which the constraints regarding grid charging and power export are toggled, are identified. These scenarios are displayed in Figure 14 below.

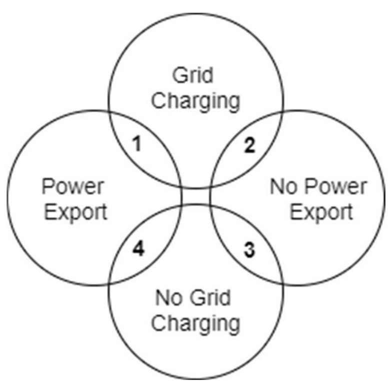


Figure 14: ESS Operational Scenarios [13]

With ESSs, self-consumption of stored energy is possible. In fact, in South Africa most utilities encourage self-consumption, and although power export is not prohibited, it is discouraged through tariff instrumentation. Also, although self-consumption of generated or stored power is encouraged, its effects should not be overlooked. Self-consumption leads to load reduction. Load reduction (specifically to the point of load elimination) seems to have significant effects on voltage unbalance, especially for customers with large loads. The effects on voltage unbalance is significant enough to cause violations to the power quality standards. From the simulations conducted in [13], it is concluded that distribution networks are designed to accommodate specified load capacities, without a large allowance of load changes with time.

For the simulations conducted in the three studies mentioned [13]–[15], the technical parameter (voltage level, voltage unbalance, transformer loading and conductor loading) first violated is deemed the limiting factor for ESS uptake. For the simulation conducted for hybrid PV systems, the technical issue that limited uptake was voltage unbalance. No violations were recorded for any of the other technical parameters monitored. For the assessment of EMs, the loading of the conductor cables and transformer were the factors limiting uptake closely followed by voltage unbalance.

Up until this point, the technical impacts of ESSs on LV residential distribution feeders and how these technical impacts are affected by grid charging and discharging (power export) have been identified.

4.2 Results relating to research question 2

Research Question: What are the state-of-the-art approaches for conducting impact assessment studies to determine the technical impacts and the estimation of a network's hosting capacity to EVs, and what are their limitations?

The literature review in *Chapter 2* addresses research question 2 by analysing the current state-of-the-art methodologies proposed for EV impact assessment studies. The review reveals the shortcomings of existing approaches that account for some of the factors but fail to address the full scope of factors that introduce variability and uncertainty to the load modelling and simulation approach.

The literature review is approached by analysing impact assessment methodologies addressing four major areas:

1. How the load flow inputs are modelled,
2. the technical parameters assessed,
3. the method of load flow analysis,
4. and finally, the simulation of EV penetration scenarios.

The first load flow input explored is the network model. The importance of accurate, detailed and realistic network modelling is identified and acknowledged in a literature review reported in [14]. One of the characteristics of the network model is the customer distribution. In both [13], [14] the importance of customer distribution is highlighted. In both studies, three different customer distributions shown in Table 4 below were tested.

Table 4: Customer Phase Distribution Illustration

	Balanced			Cyclic			Cosine		
Phase → **Node ↓**	**A**	**B**	**C**	**A**	**B**	**C**	**A**	**B**	**C**
1	1	1	1	2	1	0	3	0	0
2	1	1	1	0	2	1	0	3	0
3	1	1	1	1	0	2	0	0	3
4	1	1	1	0	2	1	0	3	0
5	1	1	1	2	1	0	3	0	0
…	…	…	…	…	…	…	…	…	…

The table shows the number of customers connected to each phase at each node along the feeder for the three distributions tested. The results of the simulations conducted revealed that even under passive conditions (no ESS) the customer distribution plays a significant role in voltage unbalance, enough to cause the network to fail to comply with power quality standards.

The second load flow input identified is the residential load model. The review found that deterministic modelling of residential loads is not suitable and does not lead to realistic results. Some studies acknowledged this and attempted to model the changes in residential load with time but failed to accurately model the diversity in the residential load within a specific time period. The statistical characterization of the residential load in each time interval allows analytic analysis and supports high computational efficient tools.

Both the literature review in chapter 2 and [15] identified factors that influence and bring diversity to the EV load model. These factors are indicated below:

1. The EV battery capacity,
2. the battery SoC when connecting to charge,
3. the mode of charging and therefore charging power rating,
4. travel data informing home arrival and departure times,
5. and the implementation of charge schemes or tariff incentives.

The second part of the literature review explored the technical parameters assessed during impact assessment simulations. The technical parameters assessed in the impact assessment studies reviewed correspond to the technical impacts of ESSs identified when answering research question 1.

The method used to conduct the load flow analysis is influenced by how the inputs have been defined and the ESS penetration scenarios simulated. The review of ESS penetration scenarios was split into (i) how the measure of penetration of ESSs was defined and (ii) the placement strategy used to assign ESSs during the simulation process. The review mentions the need for a load flow analysis method that directly accounts for the variability in the input load models and a placement strategy for the allocation of EVs that resembles the randomness and unpredictability in EV location (node and phase). Many studies were either found to ignore this diversity in the loads and uncertainty in EV placement by conducting a DLF analysis with worst-case scenario placement. Or attempted PLF analysis but did not conduct enough simulations or placement scenarios to model the full scope of possibilities.

4.3 Results relating to research question 3

Research Question: What are the characteristics of a comprehensive methodology for the impact assessment of EVs on LV distribution feeders?

After highlighting the inadequacies of the existing approaches, the literature review outlines the key components for a robust and comprehensive EV (ESS) impact assessment study, listed below.

1. The network model and simulation conditions need to be detailed and realistic and resemble the characteristics of a practical feeder.
2. The residential customer load and EV load models should account for the diversity in these loads, and the unpredictability of the customers' behaviour.
3. The method used to simulate the allocation of EVs should reflect the randomness in EV uptake and therefore the uncertainty in EV location (node and phase).
4. The load flow analysis method should explicitly account for the stochasticity and variability in both the customer and EV loads.
5. The technical parameters assessed to serve as an indicator of a networks hosting capacity to EV loads should ensure that the power quality standards and equipment limits are adhered to. The technical parameters identified are voltage level, voltage unbalance and transformer and conductor loading.

These requirements listed above and the factors that bring diversity to the EV load model informed the required modifications, listed below, to be made to the existing HBE-MCS tool that had been developed and tested in PV penetration applications [32].

The modifications to extend the application of the HBE-MCS tool to EV penetration analysis are as follows:

1. Definition of the Measure of ESS Penetration.
2. Preparation of beta PDF models of EV loads.
3. Building the EV models into the HBE.
4. Modifying the conditions in the MC simulator.

In Chapter 2 and [15], various definitions for penetration percentage are discussed. It is concluded that (i) the varying definitions of penetration caused a wide range of acceptable hosting capacities making it difficult to compare results between two assessments using different definitions and (ii) because of this, these definitions may not be of direct use to the planner during distribution network design or to the DNO when defining standards or regulations. Therefore, a definition of penetration level as a measure of the capacity (in kW or kVA) of installed ESSs in relation to the technical characteristics of the network, such as the peak demand or FMD, could be deemed more useful. In [15] the definition of penetration percentage, as explained in *Chapter 2*, was adapted and first used. In addition, the other three modifications to the HBE-MCS tool detailed in *Chapter 3* were completed, and the HBE-MCS tool was first used for EV penetration applications in [15].

4.4 Results relating to research question 4

Research Question: Can a comprehensive impact assessment methodology that incorporates these identified characteristics be developed?

Informed by the key components identified in research question 3, [16] proposes and demonstrates a comprehensive methodology to assess the impact of EV charging on LV residential feeders.

The study proposes the probabilistic modelling of the residential customer and EV load making use of beta PDFs, accounting for the unpredictability in customer behaviour and subsequently the diversity in these loads. The study also proposes using the MCS method as a stochastic simulator to mimic the random placement of EVs throughout the network due to the uncertainty in EV location. The HBE algorithm is proposed to solve the PLF analysis. The technical parameters recorded will be analysed and interpreted accounting for a specified level of risk. Where this level of risk is informed by the accuracy of the input modelling and the intended application of the results. This proposed methodology is demonstrated through a case study applied to a practical LV residential feeder located in South Africa.

The network model simulated for the case study is detailed and is that of a real residential area in the Western Cape, South Africa. For the residential load model, the period of interest identified from travel data, average commuting times and electricity consumption data is 7 pm. This corresponds with the likely resident home arrival times, therefore anticipated period of mass simultaneous charging, as well as the residential electricity consumption peak period for a winter weekday. The period of interest selected for a simulation may vary depending on the season, type of day and even the purpose of the study. For the case study, the period of interest selected was based on the period of maximum impact. The data used for the residential load modelling was data recorded for a year from 42 different residential consumers. The diversity in the residential load can be seen in Figure 15 in the beta PDF representing the residential load at 7 pm.

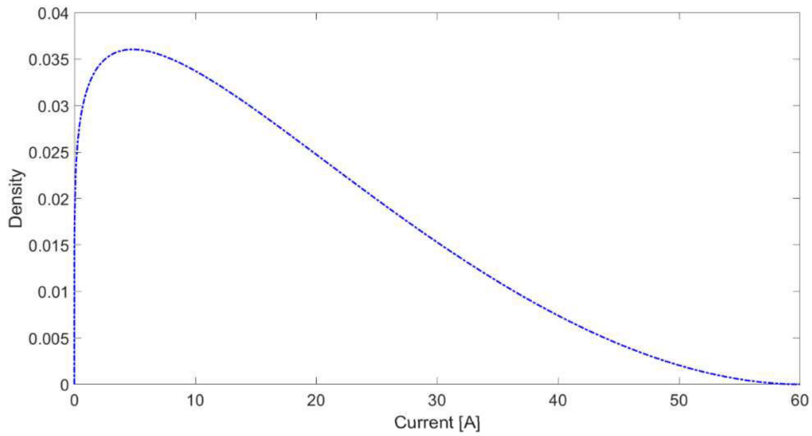


Figure 15: Case Study Beta PDF for Residential Load at 7 PM

The EV modelled for the simulation is the 33 kWh BMW i3, as this is the most common EV in South Africa. Although the BMW i3 is modelled for the case study simulation, it is possible to model any EV model and feed this into the HBE-MCS tool. The diversity in the EV load, although not a lot, is also simulated by modelling the EV load using a beta PDF. The EV load is modelled to have an average power rating of 2.76 kW (230 V, 12 A).

EVs are randomly assigned to households along the feeder using the MCS method, with the maximum penetration limit of one EV per household. The maximum penetration limit is a variable that is specified upfront when initializing the HBE-MCS tool for the given simulation.

The results revealed that the factor limiting the uptake of EVs in the network simulated is the conductor cable loading, while the least pressing factors area the maximum voltage and voltage unbalance. The results in Figure 16 are illustrated including a 5 % level of risk . It should be noted that the hosting capacity of 63 % (as a measure of the FMD) corresponds to all (100 %) of the households in the simulated network having one EV.

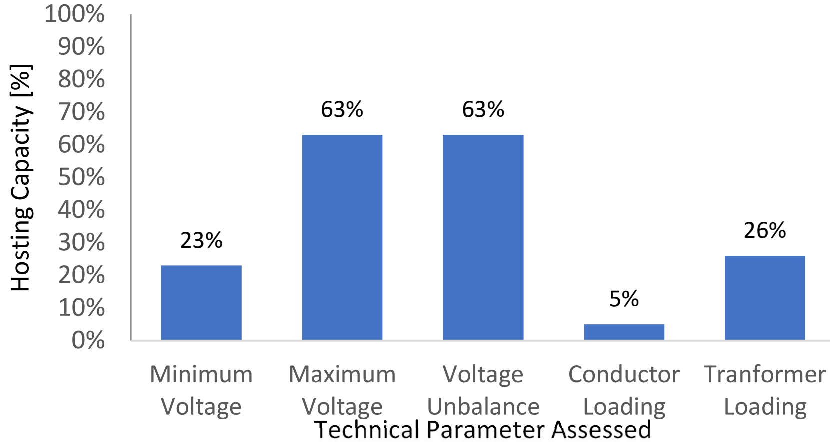


Figure 16: Technical Parameter vs Hosting Capacity

The case study reiterates that when mass simultaneous EV charging is coincident with the residential consumption peak, the network is placed under severe strain and the hosting capacity of the network is lowest. In this case study, a simulation in which EV charging is conducted during off-peak hours revealed considerably higher hosting capacities. For the network simulated, this period was found to be between midnight and 6 am. The hosting capacity during this period is shown in Figure 17.

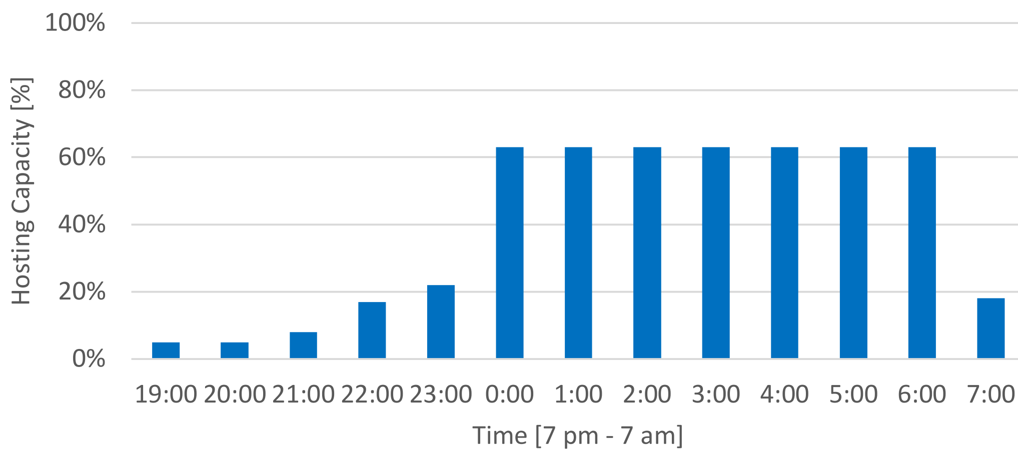


Figure 17: Hosting Capacity Vs Time

Furthermore, during this period between midnight and 6 am, three different EV charge rates were simulated. The first charge rate (2.76 kW) corresponds to AC charging at the South African residential voltage supply level (230 V), using the standard EV charger for the BMW i3. Under these condition every household in the network simulated was able to charge its EV with no violations to any of the technical parameters monitored when compared to the power quality standards, When this charge rate was increased to 3.45 kW and then 4.6 kW, the hosting capacity decreased. At 3.45 kW only 55 % and at 4.6 kW only 44 % of households could charge its EV before violating the power quality standards. This reveals that charge scheme implementation can aid in EV accommodation.

If uptake policies and regulations are informed and put in place based on the results of studies conducted during periods of maximum impact, the regulations might be overly restrictive and unnecessarily curb the uptake of EVs. The case study demonstrates the usefulness of the proposed methodology in informing policymakers and network planners who through using the methodology are able to conduct detailed simulations for different time periods. In doing so this revealed that when charging is restricted to certain hours, during which the network can accommodate these EV loads, the hosting capacity of the network is significantly increased.

5 Conclusions

To conclude, a concise summary of the answers to the research questions will be presented, and the research hypothesis validated. This chapter ends by summarizing the research contributions and providing recommendations for further work.

5.1 Summary and conclusion of findings

The research hypothesis guiding this research states:

A comprehensive impact assessment methodology for LV feeder performance under ESS penetration can be developed, which accounts for the load uncertainty resulting from unpredictable customer behaviour.

This section concisely answers the research questions defined in Chapter 1.

Research Question 1: What are the technical impacts of ESSs (namely EMs, EVs and hybrid PV systems) on LV residential distribution feeders and to what extent are existing distribution network infrastructure technically impacted by increasing penetrations of these ESSs?

The technical impacts of ESSs are explored in [13]–[15]. The identified technical impacts on LV distribution feeders are (i) increase in voltage-drop (primarily due to ESS charging), (ii) increase in voltage rise (primarily due to ESS power export), (iii) increase in voltage unbalance (due to random, single phased placement of these ESS loads), (iv) increase in conductor and transformer loading (due to the load current increasing during ESS charging). The technical impacts, such as voltage-drop, voltage-rise and component loading, are exacerbated when the penetration of ESSs connected to the network is increased, while voltage unbalance actually decreases with an increase in EV penetration (given that customer phase distribution is not severely unbalanced).

The placement of ESSs is found to have a significant impact on the severity of the technical impacts experienced. Placement of ESSs systems at locations of highest impact (such as the furthest end of the feeder) or severely unbalanced phase placement of ESSs is found to cause violations to the power quality standards at low penetration percentages.

It is also found that feeders that have a significant phase unbalance in the customer distribution or higher transformer loadings prior to ESS penetration, tend to have lower hosting capacities as these issues are amplified with increasing penetrations of ESSs. Because of the sensitivity of the simulation results to factors like initial component loading and customer distribution, generalizations regarding hosting capacities cannot be blindly extrapolated across feeders.

Detailed studies, as conducted in [13]–[16], provide realistic feeder conditions and prevent over-restrictive or lenient restrictions as a result of the hosting capacities found.

Research Question 2: What are the state-of-the-art approaches for conducting impact assessment studies to determine the technical impacts and the estimation of a network's hosting capacity to EVs, and what are their limitations?

The state-of-the-art approaches for impact assessment studies are reviewed in Chapter 2. Many studies make use of deterministic modelling approaches, using fixed or specified locations for EV placement and fixed (averaged) residential customer load and EV load capacities. Although these models are simple and the computational burden low, this comes at the cost of the location scenarios not being representative of reality, the effects of random placement affecting voltage unbalance being ignored and the effects of averaged capacities overlooking the residential customer load and EV load diversity.

Some studies do make use of probabilistic load modelling approaches but, in order to reduce the computational cost, either make use of deterministic EV placement strategies or do not compute enough stochastic placement scenarios. This does not allow the full scope of possible scenarios to be tested and the full extent of technical issues to be determined.

The review concludes that these approaches either fail to adequately address or fail to address all of the factors that introduce uncertainty and diversity to the impact assessment simulation inputs, method and load flow analysis.

Research Question 3: What are the characteristics of a comprehensive methodology for the impact assessment of EVs on LV distribution feeders?

The review in Chapter 2 identified and summarized the characteristics of a comprehensive impact assessment methodology into the following five components:

1. The network model and simulation conditions need to be detailed and realistic and resemble the characteristics of a practical feeder. This will yield accurate and representative results.

2. The residential customer load and EV load models should account for the diversity in these loads, and the unpredictability of the customers' behaviour.

3. The method used to simulate the allocation of EVs should adequately capture the randomness in EV uptake and therefore the uncertainty in EV location (node and phase).

4. The load flow analysis method should explicitly account for the uncertainty and variability in both the customer and EV loads.

5. The technical parameters assessed to serve as an indicator of a network's performance and hosting capacity to EV loads should ensure that the power quality standards and equipment limits are adhered to, including the provision for risk margins. The technical parameters identified are voltage level, voltage unbalance and transformer and conductor loading.

Research Question 4: Can a comprehensive impact assessment methodology that incorporates these identified characteristics be developed?

The components identified in answering research question 3, especially those identified to influence the EV load model, were used to inform the necessary modifications to the HBE-MCS tool, detailed in Chapter 3.

The HBE-MCS tool combines PLF analysis (using the HBE transform) and stochastic placement at every penetration level (using the MCS method). This tool balances computational efficiency and result accuracy. The modifications made to the HBE-MCS tool makes it feasible for analysis of any ESS (hybrid PV systems, EMs, EVs, BESS etc). The features of the tool include probabilistic input modelling of the residential customer load and ESS load, random placement of ESSs, PLF analysis directly accounting for input modelling variability, a measure of ESS penetration more useful to network planners than most widely used definitions and analysis of simulation outputs incorporating risk.

The accurate and probabilistic residential load and EV load modelling, in addition to the other components identified are combined and a robust and comprehensive methodology for EV impact assessment studies is proposed in [16]. This proposed methodology is demonstrated in a case study.

The hypothesis is confirmed as the proposed methodology meets the requirements of adequately accounting for the full scope of factors that introduce uncertainty and diversity to both the residential load and ESS load. The methodology addresses all the criteria identified for a comprehensive methodology for ESS impact assessments on LV distribution feeders. However, a limitation of the proposed methodology is that it is currently only applicable to radial feeders.

5.2 Summary of contributions and future work

This work has proposed a comprehensive methodology for assessing the technical impact of ESS technologies on radial LV feeders. The proposed methodology can be used to determine the hosting capacity of a particular network to various ESS technologies such as hybrid PVs, EVs, EMs, and BESSs. Although the results will reveal the hosting capacity of the network simulated, multiple simulations on various networks under different conditions can allow for broader conclusions to be drawn. This proposed methodology can be used in further studies to inform EV uptake policies under various operation restrictions (including charge scheme implementation), to identify possible future network upgrades and reinforcements, and to aid network planners in component selection and sizing.

The summary of contributions is as follows:

- The acknowledgement that even under conditions in which power export is prohibited and self-consumption is encouraged, which is often the case as this is generally deemed less intrusive, ESSs penetration can still cause power quality violations.

- A detailed review of existing methodologies and scope of the critical considerations for a comprehensive assessment of feeder performance under various scenarios of ESS penetration.

- The description of data requirements and the derivation of EV statistical models for probabilistic analysis of feeder performance.

- A comprehensive stochastic-probabilistic methodology with capabilities of uncertainty propagation, simulation of unknown future scenarios of ESS penetration, and demonstration of an extensive range of feeder performance interpretable using design risk factors.

This work is particularly important for network planners, DNO and policymakers in understanding the extent of technical issues associated with ESS penetration and equipping them with the necessary information for setting design standards, component selection, infrastructure upgrade recommendations and the formulation of relevant penetration and ESS uptake regulations.

It is accepted that transformers can operate beyond rated conditions for brief periods. From the results of simulations conducted throughout this research it is concluded that because of this tolerance for brief overloading, networks are designed will little headroom, particularly during periods of peak demand. This problem of component overloading is augmented, and time periods of such overloading extended, by mass simultaneous charging of ESSs especially when coincident with this demand peak. Future work focussing on the correlation between component headroom available under passive conditions during demand peak and the hosting capacity of a network could provide valuable insight, in conjunction with the proposed methodology, to inform network planning and ESS uptake policy implementation.

Further studies could include detailed load modelling making use of extensive mobility data as well as the analysis of BESSs based on load measurements of power imports and exports from already installed systems. Further work could also include expanding the feeder topology that the methodology may be applied to. The HBE-MCS tool could further be expanded to include multiple ESS load nodes per household and simulations with multiple ESSs applied could be conducted. For the case study simulation in [16] each household was assigned a maximum penetration of one EV and only single-phased charging was considered. Simulations in which three-phase charging is simulated and compared to single-phased charging or simulations in which the maximum penetration of ESS allowed per household is increased, could also be conducted.

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Appendix A Conference Paper - Hybrid PV System [13]

C.K. Rhoda, M.J. Chihota and B. Bekker, “The Impact of Distributed Hybrid Photovoltaic Backup Systems on Shared Residential Feeders”, 6th Southern African Solar Energy Conference, Eastern London, South Africa, November 2019, 8 pages

THE IMPACT OF DISTRIBUTED HYBRID PHOTOVOLTAIC BACKUP SYSTEMS ON SHARED RESIDENTIAL FEEDERS

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Abstract

Battery energy storage systems will increasingly be connected to shared low voltage (LV) feeders, as the uptake of electric vehicles (EVs), hybrid photovoltaic (PV) backup systems (i.e. grid-interactive PV systems with self-consumption and uninterruptable power supply functionalities) and other behind-the-meter storage technologies rises. While there are many benefits from the increase in these technologies they may also pose several issues.

This paper discusses the potential impacts of hybrid PV system installations on LV networks in various scenarios of net load capacity (the offset between generation and consumption), grid access regulations and the customer's battery-use behaviour. Using one of the scenarios, the paper demonstrates the potential impacts of increased hybrid PV system penetration on voltage levels, phase unbalance and thermal loading of the feeder, referenced against the relevant quality of supply standards. A stochastic-probabilistic approach is used to conduct the simulations; the Monte Carlo Simulation method is used to simulate the stochastic nature of the unknown hybrid PV system placement while the extended Herman Beta transform accounts for the uncertainty and variability in both the PV generation and loads. The results show that hybrid PV systems can cause the violation of voltage unbalance limits even if injection into the grid is not allowed. Further simulations demonstrate that the distribution of customers along the feeder affects the extent of the unbalance and thus the permissible penetration.

Keywords: hybrid PV systems; stochastic PV distribution, probabilistic load flow; LV network hosting capacity, PV grid impacts.

1. Introduction

The placement, size and usage patterns of battery energy storage systems (BESS) on shared LV feeders are not centrally planned, but rather decided by the end customer, informed by technology pricing and electricity pricing signals, amongst other factors. This is similar to the roll-out of embedded generation (EG) on shared feeders.

The technical impacts of the random and subsequently difficult-to-predict roll-out of BESSs will also be similar to that of EG: the introduction of current flows for which the LV feeder was not designed, impacting feeder voltage profiles, thermal loading and phase unbalance. Regulations like NRS097-2-3 [1] provide some guidelines on managing the impact of the roll-out of EGs but does not include BESS yet.

Currently in South Africa, the BESS with the highest uptake is likely to be hybrid PV backup systems, primarily due to frequent load shedding, favourable return on investment of PV and self-consumption requirements. This paper focuses on the impacts of these hybrid systems on shared LV feeders, further limited to residential applications to allow for a sufficient depth of analysis.

The primary objective of this paper is to gain a better understanding of the effects on voltage level, thermal loading and phase unbalance as the number of hybrid PV backup systems connected to a shared residential feeder increases. The research applies a stochastic-probabilistic methodology initially developed by Gaunt et al. [2] and recently extended for enhanced accuracy and further applications [3]. This methodology is explained and was used successfully in [4] for LV feeders with PV EGs without storage and with feedback limits of 50% of the customer's rated circuit breaker. In this paper, it is used to map the impacts of hybrid PV systems at different penetration levels, for a large number of placement scenarios that are randomly generated.

The difference with BESSs compared to EGs is however that many variations of charge-discharge schemes exist, defined by customer behaviour, pricing signals, regulations to name a few, compared to EGs based mainly on solar irradiation. The value of this work will be in understanding how these different charge-discharge schemes correlate to the technical impacts as a function of uptake.

The next section discusses the potential technical impacts of BESSs on the LV grid. It also illustrates how various system configuration constraints affect these technical impacts. Section 3 explains various power generating energy system configurations and how they affect the grid. In section 4, six hybrid PV system scenarios are explained, one of which is simulated to study the technical impacts of self-consumption hybrid PV systems without grid export. The simulation process and load flow analysis method are also described in section 4. This is followed by a discussion of the results and finally, conclusions are drawn and recommendations for possible further studies made.

2. Grid impacts

There are several impacts that increasing penetrations of hybrid PV systems will have on an LV feeder. In this paper, the various hybrid PV system configuration scenarios will be analysed based on the following technical impacts: feeder voltage level, phase unbalance and thermal loading. These technical impacts are defined below, followed by explanations on how different system scenarios contribute to these technical issues.

2.1 Feeder Voltage

The feeder voltage level can be affected mainly by two factors namely the amount of current being drawn along a feeder (the load current) and phase unbalance.

2.1.1 Load

Quality of supply (QoS) standards define margins in which certain parameters, like feeder voltage level, need to operate within. For South Africa, the voltage received on a residential LV distribution network level is 230 V within a 10% tolerance band [5].

The flow of current from the distribution transformer to connected customers (electric load points) results in voltage drop due to the impedance characteristic of the distribution cables. The larger the load current the larger the voltage drop. Accordingly, a large enough voltage drop could cause the voltage level received by the consumer to fall below the limit stipulated in the QoS standards.

The inverse is also true. EGs can also independently affect the feeder voltage level if injection of power into the grid is allowed. If a resident is allowed to inject stored battery power or excess power generated from a PV system into the grid, this could cause a voltage rise that could violate the QoS standards if the feeder voltage becomes too high. When injection is not allowed, the reduction in the net load is anticipated to limit voltage drop. However, where this occurs unequally between the phases, voltage rise due to unbalance may also result. This is discussed in detail in the subsequent section.

2.1.2 Unbalance

Electricity is generated and transported in three phases and each household along an LV feeder is typically connected to only one of the three phases. If the three phases are not evenly loaded this could result in voltage unbalance. QoS standards stipulate that the voltage unbalance allowed is up to 2% [5]. This voltage unbalance, although possibly small, can in three-phase motors result in large negative-sequence currents which causes poor efficiency, excess heat generation causing increasing operating temperature affecting equipment lifespan and even permanent damage or failure [6], [7].

Apart from possible damage to equipment, voltage unbalance affects the voltage level of the feeder itself. If one phase is more heavily loaded than the other two, because the phase voltages are dependent on each other, this will affect the voltage level of the other two phases. However, the variation may not be significant enough to violate the QoS standards.

A cause for these unbalanced residential loads is the stochastic uptake of EG, PV and hybrid PV systems as well as BESS. However, this is something the utility has limited control over. Standards that regulate this uptake may however aid in reducing the impact on load and phase unbalances.

2.2 Thermal Limits

The thermal limits referred to here are in relation to the current carrying cables and the transformer windings. As previously mentioned in Section 2.1.1, the cables can be modelled having an impedance comprising of a resistance and inductance, this being a physical property of the cable. If a current passes through the cable, the cable will heat up due to this resistance. A large enough current will cause the cable to heat up significantly. This can not only cause fires and irreparable damage but will also decrease the efficiency of the cables and windings. Larger loads than accommodated in the network design could cause the thermal limits of the cables to be exceeded. Knowledge of the expected loads is therefore imperative when doing distribution network design to ensure that these cables and transformers are chosen

Condition	Voltage Conditions		Thermal Limits
	Level	Unbalance	
Grid charging	Mass simultaneous charging will increase the magnitude of load currents, therefore significant voltage drops.	Charging of single-phase systems results in unequal phase load currents which leads to voltage unbalance.	High/continuous load current from simultaneous charging can cause thermal overloading.
Injection	High enough injection levels can cause reverse power flow and therefore voltage increase.	Unbalanced injection will cause phase unbalance.	High enough reverse power flow current can cause thermal overloading.

Table 1: Grid charging and injection effects on technical grid impacts

appropriately and will be able to handle the expected currents. Table 1 summarises the effects of grid charging and injection on the technical impacts discussed in this section.

3. Power generating energy system configuration scenarios

Different system configurations or the same system under different constraints will have varying impacts on the network. PV systems and BESS that are not allowed to inject excess generated power into the grid might have a smaller impact on the network compared to PV systems in which injection into the grid is allowed. Similarly, PV systems that have batteries to store excess power generated for self-consumption at a later stage will affect the network differently to PV systems with batteries that can inject into the grid during peak tariff periods. Whether injection into the grid is allowed and whether charging of batteries take place via excess PV power generated versus grid power will play a role in the penetration percentage a network can accommodate while meeting QoS standards.

When conducting distribution network design, specifically referring to LV feeders in this case, knowledge of the expected loads is important. After Diversity Maximum Demand (ADMD) is used and based on the type and number of customers connected to the feeder, the network is designed accordingly. However, the ADMD assumptions without modification become invalid as soon as EG and batteries are introduced; as the capacity and characteristics of the loads change significantly. For instance, with grid charging of batteries, the loads will be more continuous opposed to traditional loads like geysers, ovens and refrigerators controlled by thermostats causing varying loads due to the on-off switching.

Table 2 illustrates the potential technical impacts of various PV and battery system configurations with injection of power into the grid prohibited and allowed. Although the extent to which the technical impact is affected is not noted, this could be determined through simulations.

The very first row shows a system than consists of only PV with no battery for storage and regulated such that no excess generated power may be injected into the grid. This scenario, when applied to single phase systems, may significantly affect phase unbalance as some customer loads are reduced while others completely offset by the PV generated power causing them to appear off-grid. This may cause uneven loading of the three phases, resulting in voltage unbalance. This scenario will not have an impact on thermal loading as the load current will decrease and no reverse power flow is allowed due to the injection restriction.

Scenario	Technical Grid Impacts		
	Voltage Conditions		Thermal Limits
	Level	Unbalance	
PV only (no export)		✓	
PV only (export allowed)	✓	✓	✓
Battery only (grid charging, no export)	✓	✓	✓
Battery only (grid charging, export allowed)	✓	✓	✓

Table 2: Effects of scenarios on technical grid impacts

The batteries mentioned in the table above could refer to batteries of EV's. When no export is allowed, the battery is only charged with the grid power and injection into the grid is not allowed. In the scenario in which injection is allowed, this may be during periods in which the vehicle is not being used. Reverse power flow is possible and feeder voltage increase is likely.

Without explaining each scenario as extensively as the first, it is evident that the diverse states of configuration will lead to different constraints on the network indicating the complexity of planning as a result of new technologies. References to papers investigating the technical impacts associated with the other scenarios of Tables 2 include [8], [9], [10], [11].

4. Simulation Process

The following section will introduce six operating scenarios specific to hybrid PV systems. The scenario most relevant to typical South African shared LV feeders will then be simulated to demonstrate how the stochastic-probabilistic load flow method can be used to study the impacts of hybrid-PV systems on LV feeders.

4.1. Background

4.1.1 Possible Scenarios

Systems consisting of a PV and wind combination or PV and other forms of EGs are often also referred to as hybrid PV systems [12], [13], [14]. However, in this paper, the term "hybrid PV" refers to PV systems with an additional component being a battery. This allows for charging of the battery when the PV generation is higher than the load and self-consumption of battery power at a later stage when the PV generation might be low or unavailable. This could be particularly beneficial during load shedding periods or even for energy arbitrage.

When simulating the impact of hybrid PV systems, a range of scenarios are possible. Four scenarios are visually represented in figure 1 in which the restriction on grid charging of the batteries and injection of battery or generated power is toggled.

For the scenarios in which grid charging is allowed, time of use (ToU) tariffs may introduce an additional two scenarios; with ToU and without ToU tariffs. Grid charging without ToU tariffs would be purely for UPS functionalities when load shedding events take place, while ToU tariffs makes energy arbitrage a possibility.

4.1.2 Load Flow Analysis Methods

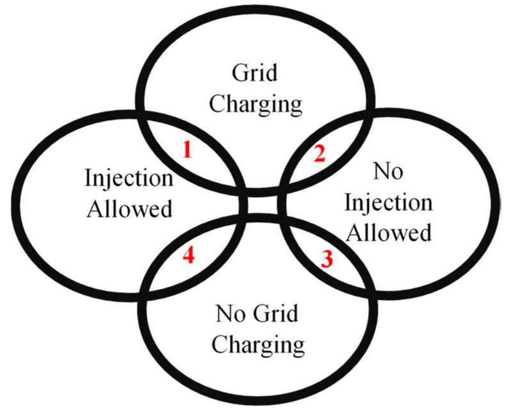

Fig. 1. Scenarios for Hybrid-PV System Operation Restrictions

Placement and Capacity of Connected Systems:

Because the uptake of power generating energy systems (in this case hybrid PV systems) is dependent on factors like the interest of the resident and pricing of the technology, the uptake subsequently lies outside the control of the utility. This means that it is very difficult for the utility to predict the capacity and location of these installations making network planning with PV uptake a challenge.

To simulate the randomness in capacity and location of the hybrid PV system installations in the load flow analysis, a stochastic approach can be taken to account for the unknown placement of hybrid PV system installations along a feeder. The Monte-Carlo Simulation (MCS) is one such method. Gaunt et al. [4] applied the MCS approach for random capacity and placement allocation of PV in a study to determine the hosting capacity to only PV (no battery) on an LV network. Several other authors [15], [16], [17] and [18] identified the need to use this approach to account for the stochastic placement of loads (EVs) during impact assessments on LV feeders. Valsera-Naranjo et al [19], used both a deterministic and probabilistic approach to account for the placement of EVs in an impact assessment to determine the effects of EV on a network. It was noted that although a deterministic method accounted for various worst-case scenarios; the stochastic method was deemed more appropriate as it is more consistent with the nature of EV uptake.

Solving the Load Flow:

When it comes to the load flow calculation, once again either a deterministic or probabilistic approach can be taken. Deterministic load flow analysis uses fixed, predetermined values for the loads and generations. Using this method, a single scenario in a spectrum of thousands of possible operating scenarios is analysed. This approach does not however take into account the likelihood of such scenarios. Without the knowledge of the full spectrum of feeder performance, a planner cannot tell the risk associated with a particular design, which, may impact network performance and total investment.

On the other hand, probabilistic load flow (PLF) methods take the uncertain and varying characteristics of both the loads and generators into account. Extreme cases can still be analysed but the likelihood of such cases is known. The result is that the planner has full awareness of the operating states of the network, which enables informed decisions.

Several PLF approaches of different speed, complexity, and accuracy exist. The MCS, when used with adequate samples, is regarded the most accurate. However, it is very slow due to the iterative approach. With the requirement of an MCS to solve the random allocation problem, speed is a critical characteristic in the selection of the PLF approach. The Herman-Beta Extended (HBE) is a single-pass statistical method used for PLF analysis [20]. When the HBE is compared to the MCS, the computational speed of the HBE is significantly faster without loss of accuracy [21], [22]. Accordingly, the HBE is appropriate for use in the combined stochastic-probabilistic approach and is used in the simulations in this paper.

4.2. Conditions and Assumptions of Simulated Scenario

Now that different placement and capacity methods, load flow solving methods and potential technical grid impacts have been discussed, in addition to six system operation scenarios, one of these scenarios will be simulated.

Scenario 3 in figure 1, in which grid charging and injection is prohibited is simulated. This scenario is chosen specifically because it is practically relevant currently in South Africa. Most utilities encourage self-consumption of generated power and although injection is not prohibited, it is discouraged through tariff instrumentation. For instance, in Cape Town, the current electricity rate for a home user is 201.78 c/kWh (incl. VAT), while residential small scale embedded generation (SSEG) can inject into the grid at 84.95 c/kWh [23]. This may be seen as a way in which the City of Cape Town encourages users to self-consume and deter injection into the grid. A question which arises is that should the customers comply with the suggested regulations (by fully self-consuming without export), what is the associated technical performance of the network? To study this, Scenario 3 from figure 1 will be simulated. The following baseline conditions and assumptions are applied:

- To increase the service life of the battery, the battery will never be discharged past a certain point. Therefore, only a certain maximum percentage referred to as depth-of-discharge (DoD) will be used.
- A portion of the battery capacity will always be assigned for UPS functionality in the case of load shedding.
- The battery can be used for self-consumption up until a minimum point equal to the percentage retained for protection plus that retained for load shedding.
- When the PV generation is less than the load, the battery will be used to match the load. If the battery has reached the minimum point, grid power will be used to match the load.
- When the PV generation is more than the load, the battery is charged.
- Injection into the grid is not allowed.
- If the battery is full, excess PV generation will be curtailed.
- The battery will never be charged with grid power.

With the conditions and assumptions clear, the load flow analysis method used will be explained below.

This paper makes use of a simulation approach combining the MCS method and the HBE. The MCS deals with the random placement of hybrid PV systems along the feeder while the HBE is used for the probabilistic load flow analysis.

When using the HBE, the loads and PV models are characterised as Beta probability density functions (PDFs) of currents. The simulation was conducted for a very extreme case period of the day in which PV production would be high while consumption is low. In South Africa, this usually occurs around midday during summer. Only the effects on the grid during that interval were simulated. The charging of the battery with excess PV power for later use does not have affect the grid in the worst-case interval. The battery is assumed to be at its minimum due to consumption the previous evening, so the load was not supplemented with the battery when PV generation was less that the load.

4.2.1 Description of Test System

A simple, three-phase four-wire, 11-bus, radial feeder supplied by a 11/0.4 kV transformer is used. Each bus (apart from the source bus) supplies three residential customers and is separated from the subsequent bus by a 45-metre conductor branch.

4.2.2 Input modelling: Load and PV

For the selected simulation scenario, to simulate the condition of no injection into the grid, the net load conditions at each node must be zero or bigger. This presents a huge computational challenge: since the loads and PV are characterised by different statistical models, they are treated separately in the HBE; PV nodes are separated from load nodes by a dummy, 'negligible voltage-drop', branch. This means it is difficult to control the net load capacity without reformulating the algorithm, which is beyond the scope of this work. However, two approaches, based on the modification of inputs, are possible.

The one involves redefining the load model to include the effects of PV generation. This would result in net load probabilistic models for various levels of PV generation. With net load models and no allocation to PV nodes, the HBE can be used to simulate the stochastic reduction of the load as a result of PV generation. However, the definition of probabilistic models for the net load has not been done and thus requires separate attention.

Another approach, which is relatively easier has two components; the allocation of PV installations matching the load capacity, and the modification of the statistical parameters of the input beta PDFs to ensure the stochastic sum of the two does not result in significant negative currents. This can be achieved by reducing the variance of the load while maintaining its after-diversity-maximum-demand (ADMD) and modelling the PV generation under optimal conditions in which the output from each customer is mostly high.

The reduction in variance is achieved by setting the alpha and beta parameters for the loads and PV models very high, resulting in high-pitched, tall distributions. This ensures that in majority of the scenarios PV generation would either be less than or equal the load. In cases where this is not so, the negative currents are negligible as a result of the reduced variance. It should be noted that by reducing the stochasticity of the loads and PV, the hosting capacity determined by the simulation will be affected. As shown in [4], when the loads are modelled with little variance, the impacts of PV installations were reduced by almost 100% compared with the result achieved using a full stochastic load. The reduced penetration observed with the full stochastic load is due to increased diversity in the load which in turn increases unbalance. Therefore, the results shown in the following section may in actual fact be conservative.

4.2.3 Simulation Investigations

The technical impacts of hybrid PV system without grid injection were simulated using two investigations with a total of five case studies. The first investigation looks at the influence of load magnitude on the technical impacts of hybrid-PV systems. The customer distribution was balanced having one customer connected to each phase at each node along the feeder. PV installations were assigned at random in 1 kW increments. This implies that for a house with a 4 kW load to be completely offset by PV generation and appear off-grid, that specific house needed to be chosen four times at random. Two test cases are conducted; Case 1 loads have a 2 kW afternoon customer load while in Case 2 higher customer loads of 4 kW are used. The 4 kW loads are those of customers that most likely have air-conditioners installed and pool pumps that may be running during the

Simulation	Customer Load [kW]	Maximum PV Load [kW]	Penetration percentage at which violations occur		
			Unbalance	Minimum Voltage Level	Transformer Maximum Loading
1	2	2	No violation	No violation	No violation
2	4	4	20 %	No violation	No violation

Table 3: Simulation results for 2 kW and 4 kW customers with balanced distribution

Case	Customer Distribution	Penetration at which violations occur		
		Unbalance	Voltage-drop	Transformer Loading
1	Balanced (1-1-1)	20 %	No violation	No violation
2	Cosine (3-0-0)	16 %	No violation	No violation
3	Cyclic (2-1-0)	15 %	No violation	No violation

Table 4: Simulation results for 4 kW customers with different distributions

summer midday period. In each case, the maximum PV capacity is matched to the load.

The second investigation focusses on the impact of different customer distributions on the gravity of technical issues. Three case studies are used; Customers were assigned in both a cosine (3-0-0) and cyclic (2-1-0) pattern and compared to that of a balanced (1-1-1) distribution.

5. Results

The results from the first investigation are shown in Table 3. The penetration percentages at which violations to voltage unbalance, minimum feeder voltage and transformer maximum loading are shown.

Because injection of excess power generated into the grid is not permitted, violations to the upper limit of the feeder voltage are not expected and only the lower limit (minimum) feeder voltage level is shown.

Customers consuming 2 kW during the midday summer period did not appear to have any violations even when all customers were assigned the maximum PV load. However, when the noon load was increased in Case 2, the voltage unbalance limit was exceeded at 20 % penetration. The results demonstrate that for a class of customers with high noon demand, the impacts of unbalance are likely to be significant.

Table 4 shows the results from the second investigation on the impacts of customer allocation. The results show that when the customer distribution is balanced, violation of unbalance occurs at a higher penetration percentage than both the cyclic and cosine configuration. On further analysis, looking at unbalance at passive conditions (with no DG), the cyclic customer allocation had the highest unbalance while the cosine configuration was not much lower and the balance configuration nearly no unbalance. It can be deduced that the initial unbalance on a feeder, usually as a result of customer distribution along a feeder, will constrain the uptake of non-injecting PV systems as unbalance is easily aggravated beyond the permissible limits.

The results also illustrate that when injection into the grid is prohibited, the effects on unbalance are a lot more significant than the effects on feeder voltage level and thermal loading. In fact, as PV penetration increases (without export), thermal loading decreases as the customer consumes less and less from the grid. While the maximum recorded voltages on the feeder may in some cases increase due to the effect of unbalance, the magnitude of voltage rise is very small (less than 2% in the simulated case). Accordingly, violations of thermal loading and voltage level are much more unlikely compared to voltage unbalance violations.

From the results it is evident that the basis for the encouragement of self-consumption and deterrence of injection based on the premise that this will not have an effect on the grid, is flawed. Distribution networks are designed to accommodate a specified load capacity, with little allowance of load changes with time. Self-consumption, which leads to load reduction and ultimately causing customers to appear off grid, appears to have significant effects on unbalance.

6. Conclusions

This paper discussed three technical impacts that power generating energy systems have on the grid namely: voltage unbalance, voltage level and thermal loading. Then the power generation energy systems and the effects that increasing penetrations of these systems have on the three technical impacts were discussed.

The paper has identified four major operation configurations which are crucial when considering hybrid PV systems and their effects. These can be expanded to six if ToU tariffs are introduced to regulate grid charging and injection. The discussion also covers the simulation requirements for these applications. The work shows the complexity associated with the design of future networks, even the assessment of the adequacy of existing networks to host the new technology.

To demonstrate the potential impacts of hybrid PV systems, and the manner in which the simulations can be conducted, one of the many possible scenarios was simulated. The scenario involves cases in which grid charging and injection into the grid is not allowed. Simulation results demonstrated that the penetration of hybrid PV systems for self-consumption is likely to cause significant issues of voltage unbalance. Severity studies show the severity of the unbalance is higher on feeders with high demand in summer noon, due to air conditioners and pool pumps for instance, and feeders with high unbalance under passive conditions.

It is worthwhile noting that the simplified inputs models used in this paper were only sufficient to demonstrate the potential technical impacts of hybrid PV systems for one operating scenario. The accurate statistical modelling and probabilistic simulation of the full scope of technical parameters and operation scenarios, including the randomness of parameters such as the system location, PV and storage capacity, and operation mode, remains a research gap that encourages future work.

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Appendix B Conference Paper – Electric Motorcycles [14]

C.K. Rhoda, M.J. Chihota and B. Bekker, "Probabilistic Impact Assessment of Residential Charging of Electric Motorcycles on LV Feeders", 6th IEEE International Energy Conference, Gammarth, Tunisia, September 2020, 6 pages

Considerations for Impact Assessments of Electric Vehicles on South African Residential Networks

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***Abstract*— There has been a rapid increase in the uptake of electric vehicles (EVs) worldwide. However, this uptake of EVs is accompanied by network planning and operational challenges on power systems, particularly low voltage (LV) networks. This paper aims to identify considerations and inputs to guide impact assessment studies to determine the extent of the technical issues caused by EVs on LV residential networks. The importance of selecting an appropriate network model is discussed and the significance of the customer distribution, in the network selected, is demonstrated in a straightforward simulation. The paper then discusses how customer loads can be modelled, as well as factors to consider when modelling the EV load, including the impacts of charge schemes and time-of-use tariffs. This is followed by a simulation demonstrating how the various inputs and considerations discussed are taken into account. Within the simulation the Monte Carlo Simulation method is used to randomly allocate EVs along a residential feeder, while the extended Herman Beta algorithm is used to account for the stochasticity of the customer load during the power flow analysis. The results of the simulation can be used to inform penetration limits for EV charging along the specific feeder simulated. However, further studies conducting such impact assessments on different networks can be used to inform general limits stipulated in network standards and uptake policies regarding the penetration of EV in residential networks.**

Keywords- electric vehicles, residential networks, impact assessment, South Africa.

I. INTRODUCTION

Energy storage system (ESS) refer to any system that can store energy and therefore when connected to the grid can act as a load when charging or as distributed generation (DG) when discharging (supplying power to the grid). Photovoltaic (PV) systems that have batteries for uninterruptible power supply functionalities or even the battery of an electric vehicle (EV) can both be categorized as ESSs. The impact of PV systems has been widely investigated and thoroughly documented. This paper aims to guide impact assessment studies of ESSs on residential feeders, specifically looking at EVs, providing insight into the modelling of inputs and simulation considerations.

The worldwide uptake of EVs can be attributed to a combination of aspects including financial and environmental factors as well as the introduction of policies and incentives. This substantial increase in EV uptake introduces various challenges to the power grid. The charging of EVs on the network, particularly at home, changes the load profiles used for network planning and increases the residential load demand. Depending on the penetration, the changes affect the performance of the grid as it was not designed to accommodate such loads. The effects of ESSs (especially EVs) on the load profiles, used for network design, maintenance and operation, is an area that could use further research.

I. TECHNICAL IMPACTS OF ES SYSTEMS ON DISTRIBUTION NETWORKS

The supply of electricity to customers is regulated through quality of supply (QoS) standards to ensure the optimal performance of the network and connected equipment. An increase in ESS penetration may have effects on the network, due to unforeseen loads and generations, that were not taken into account in the initial distribution network design. A range of technical issues reported in [1]–[6] is possible, however, effects on voltage level, thermal limits of the cables and transformer windings and voltage unbalance have been identified as most critical, and will be discussed in further detail in this section.

A. Voltage-drop and voltage-rise

The additional load demand from the charging of ESS batteries can cause significant voltage-drops along a feeder. A voltage drop along the feeder is normal and expected. However, due to the size of these additional loads, if the resulting voltage drop is large enough, the feeder voltage level may fall below the minimum voltage level prescribed by the supply standards. Mass simultaneous charging of EV batteries have shown to decrease voltage levels below the prescribed supply standards [6], especially if this mass charging coincides with peak demand loads.

When the batteries of ESSs act as DG and are allowed to inject power into the network, the opposite may become an issue. Injection of power into the grid could cause the voltage level along the feeder to rise and exceed the maximum voltage level stipulated in the QoS standards.

It should also be noted that although ESS battery charging is likely to result in voltage drops and injection result in voltage rises, due to voltage unbalance, charging can also result in voltage rises and injection in voltage drops.

B. Thermal Loading

It is possible that the large currents being drawn during ESS battery charging may cause the transformer to be overloaded and the thermal limits of the conductor cables to be exceeded. This is shown in the case study conducted on a residential LV feeder in a suburban area in Dublin, Ireland [1]. The case study was conducted when the coincidence in the peak customer demand and mass simultaneous EV charging is the highest. The loading of the transformer reaches 100% at a penetration percentage of only 25%, where penetration percentage is defined as the ratio of households with EVs over the total number of households.

C. Unbalance

Electricity is generated and transported in three phases and each household along an LV feeder is typically connected to only one of the three phases. If the three phases are not evenly loaded this could result in voltage unbalance. QoS standards stipulate that at a residential level in South Africa the voltage unbalance should not exceed 3% [7]. The utility cannot predict which customers will install ESSs, which creates uncertainty. If charging of the ESS is done at home, the battery can be connected to an unknown node and phase on the network. This could result in the three phases being unequally loaded, causing voltage unbalance along the feeder.

From these technical issues explained, it is clear that the uptake of ESSs may, depending on the penetration, impact the performance of the grid. However, to investigate the extent of these technical issues at various penetration levels, detailed impact studies are required.

II. IMPACT ASSESSMENT INPUTS AND CONSIDERATIONS

A. Network Model

In this paper "network model" refers to an amalgamation of properties. These include the feeder configuration (radial, parallel, ring or meshed), the customer distribution along the feeder and conductor cables properties (length and impedance). The significance of the customer distribution is illustrated in the example below. The simulation is run under passive conditions.

Consider the feeder shown in Fig. 3. Initially the customers are uniformly distributed, meaning the same number of customers are connected to each phase at each node along the feeder. The customer loads are all the equal, for this example 4 kW loads were used.

The voltage unbalance under these conditions is insignificant, 1.135 x 10^{-14} %. Now consider the exact same feeder, but instead of the customers being uniformly distributed along the feeder, the customers are distributed in a cosine (3-0-0) and cyclic (2-1-0) pattern across the three phases. The voltage unbalance for the cosine and cyclic

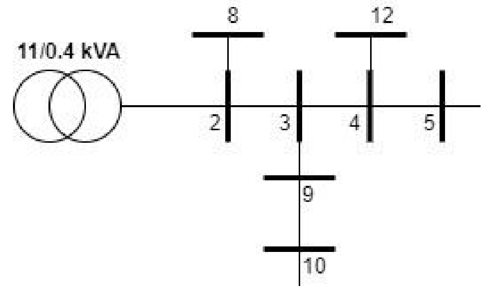

Figure 1: Simulation 1 Sample Network

customer distribution is 3.806 % and 1.101 % respectively.

From this it is evident that the customer distribution plays a significant role in the simulation results, especially unbalance even under passive conditions. If the network is not modelled correctly, it may be difficult to determine whether the effects on the network simulated are as a result of the ESS or the inaccurate modelling of the network itself.

In most cases the distribution network operator does not have the information regarding the customer phase distribution along an LV feeder. The planner's assumptions regarding this will have a significant effect on the results of the simulated impact assessment study.

Decisions made based on these results may therefore not be the most suitable and could even be detrimental. Careful consideration with regard to customer distribution must be taken because as illustrated by this example, QoS standards can be violated even under passive conditions.

Although trends may be common across more than one network, specific penetration percentages at which violations of QoS standards occur cannot blindly be extrapolated across different networks. Careful consideration of the network model chosen must be taken.

B. Modelling of the Customer Load

In South Africa, consumers have been grouped into 10 Living Standards Measure (LSM) levels [8]. Consumers are grouped according to their standard of living, looking 29 aspects including the ownership of commodities such as motor vehicles and large appliances [8], [9].

When doing distribution network design, knowledge of the expected loads is important to ensure that the network infrastructure can handle these loads. Residential areas are classified according to these LSM levels to give the network designer insight into the expected loads.

The load that the network "sees" is dependent on the amount of current a customer is drawing at a specific point in time. Even though the customers are grouped according to these LSM levels and their ADMD may be the same, the load coincidence for these group customers need to be taken into account as all the customers in the group do not necessarily hit their peak demand at the same time [10].

It is possible to model the customer loads deterministically, giving one specific and predefined value for all the customer loads. However, it is important to keep in mind that customer behaviour is unpredictable. Modelling the customer loads probabilistically may be more appropriate, accounting for the uncertainty of the customer behaviour and therefore the variable and stochastic nature of the customer loads. It is possible to model the load probabilistically using a common representative model and still keep the load diversity of the grouped customers.

C. Modelling of the ESS as a Load

When the battery of the ESS is connected and is discharging the battery will be seen as DG and can be modelled accordingly. When the battery is charging, the battery acts as an additional load to the ordinary household consumption load.

Three factors will affect the instantaneous current drawn namely, the battery capacity, state of charge (SOC) and charging method. These characteristics determine the magnitude and duration of the load and are explained below.

1) Battery Capacity

The battery capacity will affect the duration of the load in the case of charging the battery, or generation in the case of discharging. The operating temperature and depth of discharge (DoD) of a battery largely affects the operating lifespan of the battery [11]. To increase the service life of a battery, the battery should not be discharged past a certain point referred to as the DoD.

2) SOC

The SOC of a battery when connecting to the grid will also affect the duration of the load or generation seen by the network. The SOC is dependent on the usage pattern on the battery. In the case of an EV battery, the SOC when arriving home is a stochastic variable as it is directly related to the customer mobility, the distance travelled since the previous charge and whether the customer makes use of a secondary charging facility. If the customer is able to charge their EV at work or elsewhere, the SOC of the EV battery when arriving home will differ from a customer who charges at home exclusively. The SOC will determine the amount of current drawn and the duration of charge till the battery is full or the duration of discharge till the DoD has been reached. Accurately estimating the SOC is important as it informs the user of the remaining useful energy and also avoids discharging past the minimum point.

One method to determine the SOC is to make use of traffic flow studies to determine the average distances travelled to and from work and relating this to the battery capacity. These can also be used to anticipate home arrival times and subsequent likely times that EV charging/discharging may start.

3) Charge Method

Looking at literature to determine a power rating that can be used to model an EV battery during charging might prove difficult as this is dependent on multiple factors. The international standards and categorization of EV charging in Europe and North America is shown in the table 1[12].

Most EV charging takes place at home [13], [14]. South African households receive 230 V from an ordinary wall socket, with a wall socket circuit breaker value of 15/20 A and a main circuit breaker value of 60 A [15], [16]. This allows for a 3.45/4.6 kW supply from a wall socket, and 13.8 kW if a designated outlet is installed allowing 60 A. Residential charging in South Africa would fall under level 2 (AC) charging according to North American standards and normal to medium charging according to European standard.

The diversified daily travel distances as well as the time and duration of charge affects the SOC. Where the SOC affects the load current. Therefore, the load current is also a diversified variable, brining variability to the EV load.

4) Charge Schemes and Tariff Incentives

The implementation of charge schemes, or tine-of-use (TOU) tariff incentives largely affects the charging or discharging behaviour of energy storage users. Charge schemes can be seen as regulatory, where charging and discharging of ESS batteries is restricted to certain periods and this restriction is controlled by the distribution system operator (DSO). While time-based tariff incentives act as guidelines, encouraging residents to charge and discharge during certain periods. These incentives are optional while charged schemes are mandatory. The user can choose to ignore these incentives and pay the higher rate for the freedom of being able to charge and discharge when they please.

When no tariff incentive or charge scheme exists to restrict or encourage charging during a specific period, residents will charge whenever it is most convenient. Once again taking the example of EV owners, to ensure that their EV will be fully charged by morning or whenever they may need it, they are likely to charge their EVs when arriving home from work [17].

TABLE I. INTERNATIONAL EV CHARGING STANDARDS IN EUROPE AND NORTH AMERICA

Europe				North America			
Charge Method	**Power [kW]**	**Maximum Current [A]**	**Connection**	**Charge Method**	**Nominal AC Supply Voltage [V]**	**Maximum Power [kW]**	**Maximum Current [A]**
Normal	3.7	10-16	1-phase AC	**Level 1 (AC)**	120	1.44	12
Medium	3.7-22	16-32	1- or 3-phase AC	**Level 2 (AC)**	240	7.7	32
High	>22	> 32	3- phase AC	**Level 3 (DC)**	208-600	240	400
High	>22	> 3 225	DC				

It may be found that when the DSO has full control over when charging and discharging takes the penetration percentage of ESSs that a network can handle before violating QoS standards may be higher than when no charge scheme or tariff incentive is implemented.

Norway is undeniably the leading country in terms of EV adoption, when looking at EV as a percentage of total vehicle sales [18]. As far as sales numbers go, China is in the lead followed by the United States, then Norway [19]. One thing that all of these countries have in common is the implementation of charge schemes, off-peak, TOU tariffs and rebates [20], [21], [22].

Currently, South Africa has no charge scheme or widely implemented TOU tariff incentive scheme. Looking at countries with a much higher EV penetration percentages, the introduction of such schemes may be necessary and something South Africa may need to consider soon.

5) ESS Location

Customer distribution is not known upfront when doing distribution network design. The uptake and therefore placement of ESSs is not known either. The uptake of ESSs is decided upon by the end customer and is dependent on interest and finances related to the technology and electricity prices, amongst other things.

When doing an impact assessment and deciding upon placement strategies for a simulation, one can either choose to take the randomness of ESS placement into account or do scenario-based placement cases.

ESS placement can have a significant impact on voltage unbalance. If the placement of ESSs causes one phase to be more heavily loaded than the other, this could result in the feeder's unbalance percentage violating the QoS standards. Careful consideration needs to be given to the placement strategy used, keeping the purpose of the impact assessment in mind, to yield useful, realistic and accurate results.

D. Definition of the Measure of ESS Penetration

The definition of "penetration percentage" differs widely across literature as is no clear-cut way in which penetration percentage must be defined.

In [3], [5], and [4] the penetration level is defined as the percentage of houses that have EVs over the total number of houses along the feeder. [23] defines penetration level as a the number of EVs as a percentage of the total light vehicle fleet while [24] and [25] define penetration level as a the number of EVs as a percentage of the total vehicle fleet in that specific area.

The definition of penetration can cause a wide variation of acceptable capacity. If two assessment are run on the same network each with a different definition of penetration percentage, the results may show that the networks can handle different penetration levels. Therefore, these definitions may not be of direct use to the planner during distribution network design or the to the DSO when defining standards or regulations.

It may be more useful to define penetration level as a measure of the capacity (in kW or kVA) of installed ESSs in relation to the technical characteristics of the network, such as the peak demand or feeder maximum demand. It may then be possible to compare results from one simulation to results of another.

III. SIMULATION DESCRIPTION AND RESULTS

The ideal simulation would take all of the previously mentioned inputs and considerations into account. Customer load models taking the variability in customer behaviour into account, EV load models incorporating traffic flow studies to determine SOC and home arrival times, chargers used for EV charging assigned to customers based on data showing the distribution of chargers used by EV owners. This would require the necessary load models and data in order to model the inputs accordingly. Although possible, it may be difficult if all the data is not readily available. However, making simplifications and assumptions in a simulation can still render accurate results. Such a simulation was run to illustrate the effect of EVs on a residential LV feeder under the assumptions, simplifications and conditions stated below.

A. Description of Simulation Inputs and Assumptions

1) Network Model

A time series analysis would be ideal and provide useful information regarding SOC, especially because of the time dependence of this variable. Whether the EV battery was charged earlier, will determine the capacity the battery has available to discharge later. However, this simulation aims to give a snapshot of the effect of EV charging at what could be considered to be a worst-case scenario time period explained in the EV modelling section below.

The network model chosen is a three-phase four-wire, 11-bus, radial feeder supplied by a 11/0.4 kVA transformer. All of the conductors are modelled with the same electrical properties having a resistance of 0.186 Ω/km and an X/R ratio of 0.451. The feeder is based on a real-life feeder model, so the customer distribution is realistic and does not follow a generic balanced, cyclic or cosine pattern.

2) Customer Load Model

The residents in this area are classified as an LSM 10 group. The customer load is taken for a winter weekday at 18:00, corresponding to the evening peak consumption period in the specific residential area. The load is modelled probabilistically as current, using a beta PDF with the following shape parameter values: alpha = 1.418 and beta = 4.145, a scaling factor C = 80 A and an ADMD of 4.689 kVA.

3) Charge Scheme, Tariff Incentives and EV Load Model

As there are no charge schemes currently realized in South Africa and ToU tariffs not widely implemented, no tariff incentive or charging scheme is incorporated in the simulation. The implementation of charge schemes in the simulation is possible. This is done by only allowing a percentage of EVs allocated to be connected to the grid to charge (act as loads during the power flow analysis) during a certain period. However, for the purpose of this simulation, this was omitted, and no charge scheme was in effect.

Only a single moment in time was simulated, corresponding to what could be considered a worst-case time instance, in which the evening peak of the ordinary customer load coincides with mass simultaneous charging of EVs. Because no charge scheme or tariff incentive is put into effect, all EVs allocated are assumed to be connected to the grid and charging is assumed to start upon arrival home from work. Only EV charging is simulated (no discharging), and the EV is modelled as a load.

Due to the lack of daily travel distance data to determine SOC, a simplification regarding the EV load is made. All EVs allocated are modelled as 3.45 kW loads, calculated from 230 V (residential supply level in South Africa) and 15 A. (wall socket circuit breaker value). To do this, the EV node is given a beta PDF with high alpha and beta values to represent the EV model almost deterministically having a value of 3.45 kW. (alpha = beta = 255.5, C = 30). These shape parameters are chosen because the co-incidence of all the EV users connecting to charge at the exact same time may not be probable. With the shape parameters selected, although little, there is still some variance in the EV load.

4) Load Flow Tool

In [26], the HB transform is modified from modelling loads to also modelling DG. Modifications to the use of the algorithm was done, explained below and simulated, as the HBE does not accommodate EVs.

Each household was simulated having two nodes. To do this, an additional node was modelled an insignificantly short distance from the household node. The second node is where the EV load model was placed. The EV load then acts as an additional load to the ordinary customer load mentioned above. The reason for the separation of nodes is because not only can an EV act as a load or generation, the beta distribution of the EV load model has different shaping parameters (alpha and beta) and a different scaling factor to that of the ordinary customer load.

The EV penetration is defined as a percentage of the maximum feeder demand. The EV penetration percentage is calculated as the follows:

$$\frac{\text{Total Capacity of EV Chargers}}{\textit{Feeder Maximum Demand } [kW]} \times 100\% \qquad (1)$$

The MCS method is used to assign EVs to a random node and phase along the feeder for 1000 placement scenarios for each EV penetration percentage, with a maximum of one EV per household. The extended Herman-beta algorithm is used to solve the power flow analysis. In this simulation the minimum and maximum voltages observed along the feeder for each of the 1000 placement scenarios per EV penetration percentage are recorded.

B. Results

The initial increase of maximum feeder voltage, shown in Fig. 4, can be attributed to the effect that unbalance may have on the voltage level and it is safe to assume that the effects of unbalance are mitigated after this. Thereafter the maximum voltage level decreases. It is evident that violations to the upper limit of the voltage level is highly unlikely and no violations occurred in the simulation.

Fig. 5 shows that violations to the lower limit of the voltage level start to occur at a penetration percentage of approximately 156%, this is excluding outliers found already at 125%. The results can however also be interpreted to include risk. Allowing a 2.5% chance of the voltage level being violated, the feeder can handle a penetration percentage of approximately 192%.

IV. Conclusion

This paper begins by explaining how voltage rise and drop, thermal loading and unbalance are affected by the introduction of ESSs on LV networks.

The importance of customer distribution is highlighted in the network modelling section and demonstrated with a simple simulation in which a balanced (1-1-1), cosine (3-0-0) and cyclic (2-1-0) customer distributions are tested under

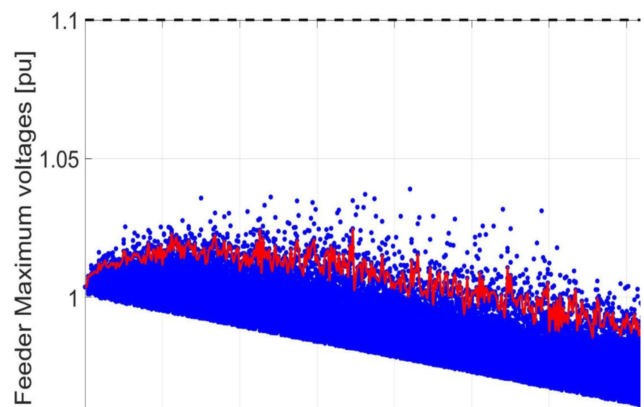

Figure 4: Feeder Maximum Voltage vs Penetration Percentage

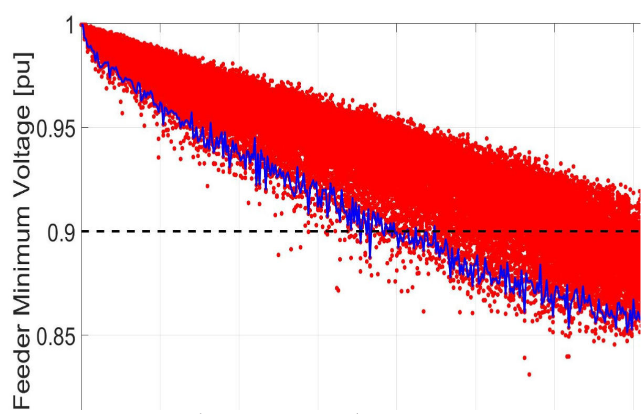

Figure 5: Feeder Minimum Voltage vs Penetration Percentage

passive conditions. The results show that even under passive conditions the cosine and cyclic distribution results in voltage unbalance that fail to comply with QoS standards.

A simulation demonstrating how the inputs and considerations detailed in the paper is conducted. For this simulation the use of the HBE is modified to accommodate EVs. The show that for the feeder modelled, violations to the lower limit of the voltage level began at approximately 156% while no violations to the upper limit of voltage occurred.

Due to lack of data available, the simulation made assumptions and simplifications. However, in future studies the inputs to the simulation including the implementation of charge schemes or tariff incentives and a more probabilistic model of the EV load can be done, making use of traffic flow studies. This will improve the accuracy of the results and help inform regulations that may need to be out in place regarding the uptake of EVs and EV charging.

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Appendix C Conference Paper – Electric Vehicles [15]

C.K. Rhoda, M.J. Chihota and B. Bekker, “Considerations for Impact Assessments of Electric Vehicles on South African Residential Networks”

Intended for Submission to the 29th Southern African Universities Power Engineering Conference

Probabilistic Impact Assessment of Residential Charging of Electric Motorcycles on LV Feeders

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***Abstract*—Motorcycles form a popular mode of transport in East African countries, and policies in countries like Rwanda are encouraging a transition to electric motorcycles (EMs). This paper aims to identify the impacts of EM charging on a low voltage residential distribution network in future high uptake scenarios. A stochastic-probabilistic analysis is conducted on a residential network, looking at the effect of EM charging on voltage level, voltage unbalance as well as cable and transformer loading. The Monte Carlo Simulation method is used to account for the randomness in the placement of EMs along the network while the extended Herman Beta transform is used to account for the variability in the residential consumer loads. This paper found transformer overloading to be the limiting factor with regard to EM uptake for the sample network modelled. A sensitivity analysis then highlighted the effects that the feeder properties, transformer size as well as EM and residential load model had on the simulation outcome. The sensitivity analysis found the results most sensitive to the residential load modelling as this affected the transformer loading prior to any EM charging.**

Keywords*— *Rwanda, electric motorcycles, impact assessment, residential charging, stochastic-probabilistic analysis

I. INTRODUCTION

With a global transition towards a cleaner and greener environment many countries have set national targets with regard to electric vehicles (EVs), with the implementation of EV policies worldwide [1] and campaigns such as EV30@30 launched by the Eighth Clean Energy Ministerial in 2017 [2]. As the world moves towards electric mobility, it is anticipated that the movement from carbon-based fuel motorcycles towards electric motorcycles (EMs) will follow suite. There are millions of motorcycles in East Africa, with between 20 000 and 30 000 in Kigali, Rwanda [3]–[5]. This makes countries like Rwanda a good basis for information to use in case studies regarding the impacts of EMs.

Ampersand, an EM company, with a mission to “build affordable electric vehicles and charging systems for the three million motorcycle taxi drivers in East Africa, starting with Rwanda.” plans to extend to Uganda and Kenya in the near future [6], [7]. In May 2019, Ampersand launched their pilot programme with 20 EMs to test its battery swap out system [8]. The system makes use of three battery swap out stations where users exchange their fully or partially depleted battery for a full one and only pay for the battery capacity consumed [4], [8]. In August 2019, Paul Kagame, president of Rwanda, announced the movement of the entire country towards EMs stating “We will find a way to replace the ones (motorcycles) you have now” and implored current motorcycle operators to help with the “phase-out process” [3], [4]. Since then, the waiting list of users for the Ampersand EM grew from 1 300 to 7 000 [7]. Ampersand is planning to build 500 more EMs in 2020, however the government wants them to build 5 000 more [7], [9].

Following this, Safi Motors - a local EM company in Rwanda - launched in late October 2019 [10]. Safi Ltd does not make use of a battery swap out system, and were the first company to install EM charging stations in Rwanda [11]. To reduce the downtime due to charging and to accommodate different financial positions, charging works similarly to filling up with fuel, where one can charge depending on how much time or money one has available [10]. The first phase of the launch introduced 60 EMs and three charging stations located next to fuel stations, allowing a total of six EMs to charge at a given moment [12].

A variety of impact assessment studies have been done focusing on the impacts that EV charging and discharging has on the grid [13]–[16]. A study has also been done looking at the economic and environmental effects of each section of the EM life cycle, from manufacture, operation, to end of life [17]. However, the technical impacts of EMs on the distribution network have not been explored. This is likely due to the fact that EM loads may be considered smaller than EV loads and the possible negative effects deemed insignificant. With little research done to assess the technical impacts of EMs, it may not be sufficient to simply assume that the effects of EM charging are negligible. This paper explores whether, with high uptakes of EMs, the effects of these loads may be significant when superimposed onto residential consumption loads, especially during periods of mass simultaneous charging.

The aim of the paper is to investigate the technical impacts of EM charging on LV residential feeders. The paper proposes a stochastic-probabilistic approach that is implemented to address the diversity in customer loads and EM loads, and the uncertainty in EM allocation. The approach makes it possible to analyse an extensive set of EM penetration scenarios: varied scenarios of EM location and size, and varied penetration limits per household. The performance of the studied networks, and the respective hosting capacity are determined based on the conditions of four technical variables: voltage-deviation, unbalance, thermal loading of conductors, and transformer loading.

The next section describes the simulation methodology while the case study simulation inputs, considerations, method and parameters of interest are discussed in section III. The simulation results are reviewed in section IV. This is followed by a sensitivity analysis of the simulation inputs in section V. The paper then concludes.

II. Simulation Methodology

A stochastic-probabilistic approach, as explained in [18] lists considerations for the inputs required to conduct impact assessments of dispersed energy storage systems (ESS) - in this case EMs - on distribution networks. The following considerations for the inputs and simulation method were noted:

- the uncertainty and variability in the residential and ESS loads need to be accounted for.
- informed, accurate and appropriate modelling of the network, residential load and dispersed ESS load model applied.
- the uncertainty in the size and randomness in location of the dispersed ESSs needs to be addressed.
- an appropriate penetration percentage definition should be used.

The stochastic-probabilistic approach consists of two components, which are now discussed in detail.

A. Simulation of EM placement

A stochastic approach accounts for randomness. In the case of dispersed ESSs, the unknown and random location of these devices along a feeder is due to the unpredictability of which residents will adopt ESSs. Instead of assigning ESSs to residents in a specific pattern or even a worst-case scenario method, an approach that aptly mimicked the randomness of ESS uptake is used.

At a selected penetration rate, the corresponding number of EMs is allocated randomly to phase and node using a Monte-Carlo simulation (MCS). This is done repeatedly, with replacement, and within the permissible uptake limit per household set in the simulation, until all EMs are allocated. The MCS random selection is based on a uniform distribution, resembling equal EM uptake potential between customers. In this paper, 1,000 MCS scenarios of EM allocation are performed at each penetration level. For each scenario, the corresponding feeder performance is determined using the Herman-Beta extended (HBE) probabilistic transform.

B. Calculation of the load flow using the HBE

This paper proposes using a probabilistic load flow (PLF) approach above a deterministic one. A deterministic approach cannot explicitly represent the variability in the loads and generation and therefore input uncertainty is not factored in the results [19]–[21]. The HBE transform is an analytical PLF approach that allows the loads and generation to be modelled using beta probability density functions (PDFs) to account for the associated uncertainty [22]. The HBE method is built on the current prescribed method for the design of LV feeders in South Africa [23]. Using this approach, feeder performance in terms of voltage-deviation, unbalance, and thermal loading can be easily assessed factoring in design risk.

This stochastic-probabilistic analysis approach was therefore deemed more appropriate as both the variability and uncertainty in loads, and the randomness in the location of EM loads are addressed. A schematic of the overall simulation program flow is shown in Fig. 1.

A more detailed look at the inputs, considerations, method and parameters of interest is found the following section.

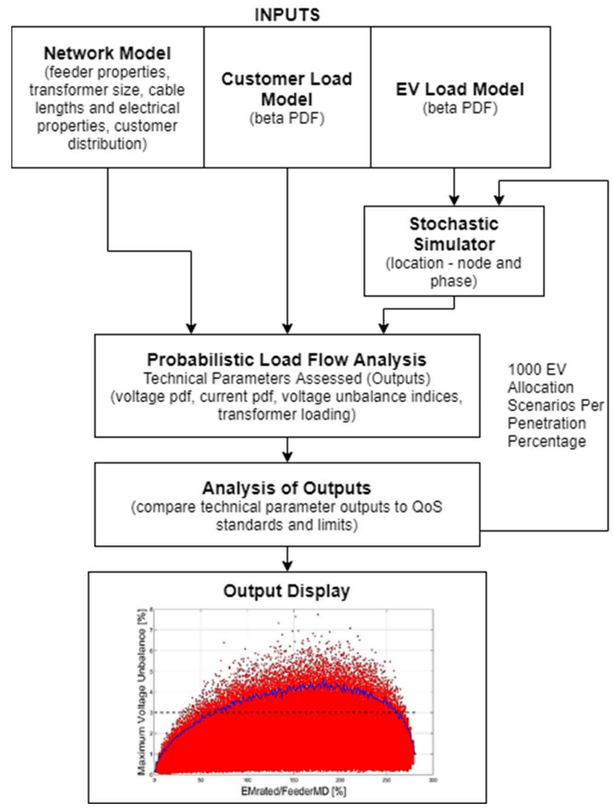

Figure 1: Overall Simulation Program Flow

III. Case Study

The MCS-HBE approach is now used to investigate the impacts of addition loads due to EM charging on residential feeders. The simulation is focussed on quantifying the impacts and the maximum capacity of EMs that can be hosted on existing feeders. Therefore, the interval of interest is one in which the feeders are most loaded leaving little headroom for additional loads. The coincidence of EM charging with high feeder load is anticipated to be the determining factor to the hosting capacity (HC) of a feeder. For LV feeders, the peak load is usually experienced during winter evenings where there is a high coincidence of heating elements. For this reason, the influence of distributed generation on HC is not included. The characteristics of the conducted simulations are described below.

A. Simulation Inputs

1) Network Model

The initial business model of companies like Ampersand and Safi Motors appears to be based on battery exchange schemes and/or central charging stations. As countries like Rwanda progresses towards a fully electric motorcycle sector the assumption is made that the primary EM charging method will move towards charging at a residential level, as seen in the EV sector [24], [25].

Although the need and relevance of such studies is motivated by countries like Rwanda, a more generalised case study in which a practical LV residential topology typically used in low-income, medium density urban areas in South Africa is modelled in the simulation. A single branch three-phase four-wire, 10 node network, 30 m apart with a 150 kVA

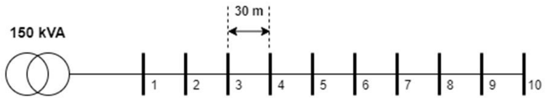

Figure 2: Simulation Network Model

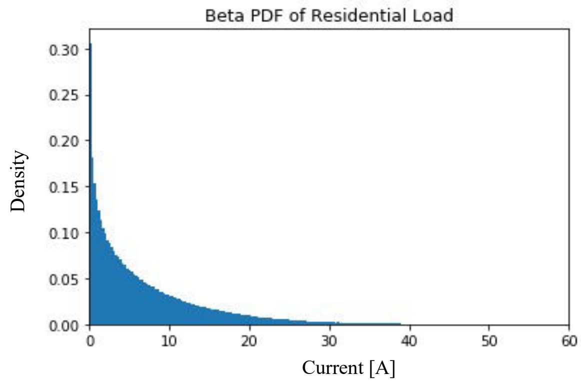

Figure 3: Beta PDF - Residential Load Model

transformer supplying 50 customers was modelled and is shown in Fig. 2 above. The conductor lines were modelled as having the following electrical properties; a resistance value of 0.282 Ω/km and an X/R ratio of 0.3034.

2) Residential Load Model

For the case study, the impacts of EM charging on South African networks are tested. In South Africa domestic consumers are groups according to their living standards. This allows for customers in a specific area to be grouped according to an expected residential load. The residential load modelled was that of a class 4 (township area) consumer [26]. For the simulation, the load was modelled probabilistically using a beta PDF shown in Fig. 3. The load parameters used relates to a recently electrified area (electrified for about 7 years) having an after diversity maximum demand (ADMD) of 1.56 kVA and shape parameters alpha = 0.692, beta = 5.437 and a scaling factor C = 60 amps. This load model is based on 5-minute readings of load currents during the interval of maximum demand, on a winter, week-day evening.

3) Electric Motorcycle Model

The following assumptions and simplifications were made regarding the exact EM charging and battery specifications. The Super SOCO TC-Max was chosen as representative of the EM to be modelled for this simulation [27]–[29] since its non-electric motorcycle equivalent is a typical 125 cc motorcycle similar to the ones in widespread use in Rwanda [29]. The driving range is about 97 km and charge rate 3.5 kW, fully charging in 4.5 hours [28], [29]. The EM load was modelled as a current using a beta PDF, with a residential voltage level of 230 V [30] resulting in a current of 15.22 A. The alpha and beta parameters affect the shape and skewness of the beta PDF. For the simulation, the alpha and beta values were set equal and high to model the load symmetrically about a specific value (3.5 kW) and with little diversity.

B. Simulation Considerations

1) Placement Strategy

With a fully electric motorcycle sector it is assumed that this could become the primary mode of transport in densely populated areas and is likely that each household will at least own one EM.

The placement of EMs in the residential network chosen for the simulation was allocated at random, with a maximum of two EMs per household.

2) Penetration Percentage Definition

The penetration percentage definition used in this paper is based on a measure of the loadability of the feeder, which is dictated by its electrical characteristics and configuration. The maximum load the feeder can handle without violating quality of supply limits, termed the feeder maximum demand (FMD), is used as an indicator of the feeder's loadability.

Expressed in mathematical form, the electric motorcycle penetration percentage (EM PP) definition is as follows:

$$EM\ PP = \frac{Cumalative\ Power\ of\ EMs\ Allocated\ [kW]}{Feeder\ Maximum\ Demand\ [kW]} \times 100\% \qquad (1)$$

C. Parameters of Interest

1) Voltage level

In South Africa the Nersa 048 standards state that the residential supply voltage level should be 230 V ± 10% [31]. It is anticipated that mass simultaneous charging of EMs will cause the voltage along a residential feeder to drop as seen with EVs in [13], [32]. The lower limit of the supply standard is therefore a parameter of interest. The upper limit of the voltage level may also be of interest due to the effect that unbalance may have on the voltage level as shown in [18].

2) Voltage Unbalance

Voltage unbalance, due to the random single-phase placements and therefore possible unbalance of loads across the three phases, is expected. According to the South African supply standards, voltage unbalance should not exceed 3% [31].

The following equation based on the quantile values was implemented to calculate the voltage unbalance:

$$UB = \frac{Max.Deviation\ of\ Pha\quad Voltages\ from\ Average}{Average\ Voltage} \times 100\% \qquad (2)$$

3) Cable and Transformer loading

It is not likely that these newly introduced loads from EM charging was a consideration during the initial low voltage distribution network planning. It is hypothesized that existing loads augmented with mass simultaneous charging of EMs would overload the transformer. The maximum cable and transformer loading were therefore parameters of interest that were recorded during the simulation.

D. Simulation Method

The simulation procedure can be broken down into the following five steps.

I. Determine the FMD by loading winter loads and linearly incrementing the load until the first occurrence of QoS violation.

II. Reset the load to winter loads, and add EMs randomly using the MCS guided by the penetration level under analysis and the limits per household.

III. Perform the HBE and record the worst-condition of each technical variable based on 2.5% risk.

IV. Repeat II and III for 1,000 scenarios

V. Increment the penetration level and repeat processes II-IV until every node has maximum penetration.

IV. RESULTS

For each penetration percentage, 1 000 different placement scenarios were analysed and the minimum voltage, maximum unbalance, maximum transformer loading and maximum conductor current along the feeder for each scenario was recorded. The simulation was run until an EM penetration percentage of about 281% was reached. This penetration percentage related to each household along the feeder having the maximum (in this simulation it was restricted to two) number of EMs assigned to it.

Fig. 4 shows the minimum feeder voltage. The blue line indicates a risk margin included in the representation of the results. At each penetration percentage there is a 95% chance that the minimum voltage along the feeder will lie above the blue line. Therefore, when including risk in the interpretation of the results and allowing a 5% chance of violating the lower limit of the supply voltage level, the feeder can handle a penetration percentage of 111%.

Violations to the lower limit of the voltage quality of supply standards start at about 56% if no risk factor is allowed for. There were no violations to the upper limit of the voltage level and the graph is not shown.

In Fig. 5 initial violations to the allowable voltage unbalance percentage is recorded at penetration percentages as low as 31%. When taking risk into account, the feeder could handle penetration percentages up to 66%. The bell shape indicates how unbalance initially increases as random unbalanced allocation occurs. The unbalance eventually decreases as the number of EMs assigned increases, reducing the level of diversity in EM loads between customers. At the extreme end of the penetration range, every customer has the same number of EMs hence the initial conditions of unbalance (without EMs) are retained.

When looking at Fig. 6 the transformer is overloaded at about 26%. Fig. 7 shows that the cables exceed its maximum current carrying capacity at 24% without risk and 31% with a 5% risk of exceeding the current carrying capacity. The 5% risk is comprised of a 2.5% that is incorporated in the PLF analysis mentioned in the Simulation Method section and an additional 2.5% in the analysis of the stochastic results.

The results show that the feeder is thermally constrained and the limiting factor for the penetration of EMs that this feeder can handle is the cable loading followed by the transformer loading.

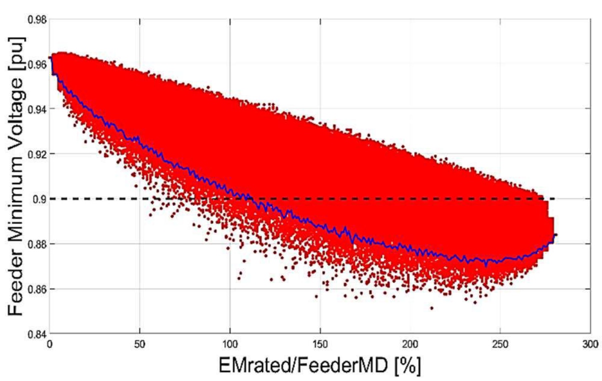

Figure 4: Lowest voltages along feeder with increasing penetration of EMs

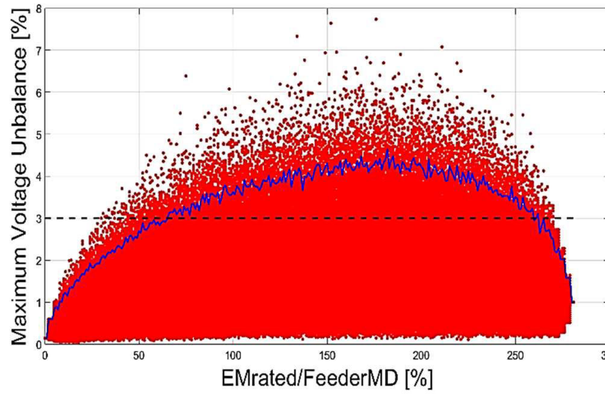

Figure 5: Highest voltage unbalance along feeder with increasing penetration of EMs

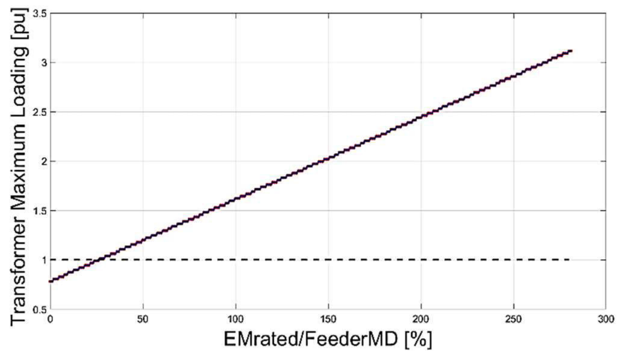

Figure 6: Highest transformer loading along feeder with increasing penetration of EMs

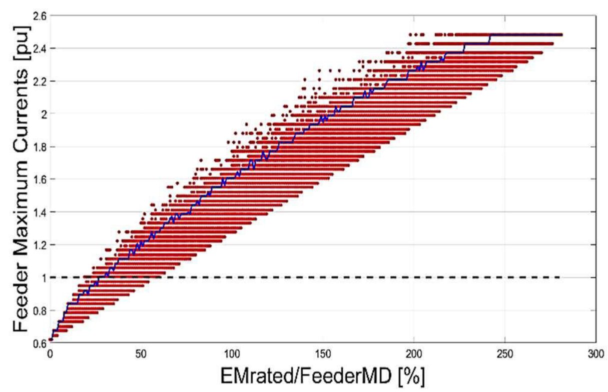

Figure 7: Highest conductor currents along feeder with increasing penetration of EMs

V. SENSITIVITY ANALYSIS

In reality many variations of networks - in which residents may be closer together or further apart, load models differ, and transformers may be more or less loaded - exist. Because of many assumptions regarding the simulation inputs a sensitivity analysis becomes useful when interpreting the results.

The following section will have a look at the sensitivity of the results to the following four variables; feeder properties, transformer size, EM load size and lastly the residential load model used. These were the simulation inputs that did not have data readily available and assumptions needed to be made.

A. Feeder Properties

Feeder properties refer to several characteristics including the network topology, distances between customer nodes and cable properties. For this analysis, the effect of the distance between the customer nodes was tested. For the base case-study the customer nodes were 30 m apart and violations occurred as shown in the first (grey) row of Table 1. The distance between the customer nodes was then adjusted to 45 m. The results are shown in the second row of the table.

When the distance between the nodes was increased, the factor limiting the uptake of EMs changed from transformer loading to voltage unbalance. Although when including risk, the limiting factor was still the transformer loading and the allowable penetration percentage did not decrease, the effect of the feeder property tested was significant. This is highlighted by the fact that when the distance between nodes increased from 30 m to 45 m, the percentage at which the minimum voltage level is violated drops from 111% to 34% and the percentage at which voltage unbalance exceeds the allowed value drops from 66% to 28%.

B. EM Load Model

The EMs were initially modelled as 3.5 kW loads when charging. To account for the uncertainty in the EM load model, the network was also tested with EMs modelled as both 2.1 kW and 4 kW loads, and the results compared to that of the initial (grey row in the table) 3.5 kW loads. Table 2 shows that when the EM load size is reduced to 2.1 kW, when including risk there are no violations to the minimum voltage level or voltage unbalance even when each customer is assigned the maximum number of EMs allowed in the simulation. It is also noticed that when the load size is increased, the penetration percentage at which violations occur decreases.

TABLE 1. HC SENSITIVITY TO FEEDER PROPERTIES

d (m)	**Hosting Capacity based on Technical Variable**							
	Voltage		***Unbalance***		***Trfmr Loading***		***Conductor Loading***	
	Excl. risk	*5% risk*	*Excl. risk*	*5% risk*	*Excl. risk*	*5% risk*	*Excl. risk*	*5% risk*
30	56	111	56	66	56	26	56	31
45	20	34	20	28	20	26	20	31

TABLE 2. HC SENSITIVITY TO EM LOAD MODEL

EM Load [kW]	**Hosting Capacity based on Technical Variable**						
	Voltage		***Unbalance***		***Trfmr Loading***	***Conductor Loading***	
	Excl. risk	*5% risk*	*Excl. risk*	*5% risk*		*Excl. risk*	*5% risk*
2.1	116	none	62	none	26	27	33
3.5	56	111	31	66	26	24	31
4	55	99	28	60	26	23	28

TABLE 3. HC SENSITIVITY TO RESIDENTIAL LOAD MODEL

Load Class	**Hosting Capacity based on Technical Variable**						
	Voltage		***Unbalance***		***Trfrmr Loading***	***Conductor Loading***	
	Excl. risk	*5% risk*	*Excl. risk*	*5% risk*		*Excl. risk*	*5% risk*
4	56	111	31	66	26	24	31
3	116	160	48	72	67	49	57

C. Transformer Size

The transformer used for the initial simulation was sized to operate at around 80% of its peak capacity under passive conditions (no dispersed ESS). As shown in the results section, this transformer became overloaded at an EM penetration percentage of 26%. If the transformer was sized to operate at 90% of its peak capacity under passive conditions, it would become overloaded at an EM penetration percentage of 11%. Increasing the size of the transformer would be effective at alleviating the transformer overloading problem. However, before significantly increasing the transformer size it is advised to look at the next most pressing issue limiting uptake so that the transformer is not unnecessarily oversized.

D. Load Model

The residential load model needs to be characterized by the consumer class behaviour. When the load used for the simulation was changed from class 4 (township area) to class 3 (informal settlement), the residential load beta PDF was given the following parameters: alpha = 0.248, beta = 1.008 and scaling factor C = 20. The ADMD of the load was then 0.91 kVA. Table 3 shows the results, the grey row showing the results of the initial simulation and the white row the results of the adjusted load. With the adjusted load model, the penetration percentage at which violations to minimum voltage, unbalance and cable loading occurred all increased.

When interpreting the results including risk the minimum voltage level drops below the allowed value at 160% while the voltage unbalance exceeds the supply standards at a penetration percentage of 72%. The cables become overloaded at a penetration percentage of about 57% and the transformer around 67%. With this smaller residential load, the cable overloading became the factor limiting the uptake of EMs.

VI. CONCLUSIONS

It is evident that even with the assumptions and simplifications made in the case study due to a lack of available information, EM charging will affect low voltage distribution networks especially if the uptake of EMs is significant and charging takes place at a residential level.

The simulation shows that the primary factor limiting the uptake of EMs is the transformer loading. A solution to this may be to increase the transformer size, while a second and cheaper way may be to control or disincentivize the charging of EMs during the peak demand period.

The voltage drop along the feeder length caused by mass simultaneous charging appears to be the least problematic issue. Violations occur at relatively high penetration percentages without allowing risk and over 100% when allowing a 5% risk margin and chance of violating the limit.

The simulation highlights some risks that policy makers and network planners need to at least be aware of, especially when embracing technology before its effect on the network is fully understood.

The sensitivity analysis calls attention to the importance of accurately modelling the simulation inputs as the effect of these inputs significantly affects the simulation results. Because these results inform policy makers and network planners, it is suggested that further research – ideally with more accurate data, network and load models if available - be done to see the full extent of the issues shown in this sample network simulation.

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Appendix D Journal Paper – Proposed Methodology [16]

C.K. Rhoda, M.J. Chihota and B. Bekker, "A Comprehensive Stochastic-Probabilistic Methodology for Assessing the Impact of Electric Vehicle Charging on Low Voltage Distribution Networks"

A Comprehensive Stochastic-Probabilistic Methodology for Assessing the Impact of Electric Vehicle Charging on Low Voltage Distribution Networks

Courtney K. Rhoda, Munyaradzi J. Chihota, Bernard Bekker

Abstract The transport sector is following the global movement towards a cleaner and more sustainable environment. This is evident in the rapidly increasing number of electric vehicles (EVs) around the world. This substantial increase in EV uptake introduces various technical challenges to the power network. To ensure that power quality standards are adhered to, and to inform network planners and policymakers, the extent and associated risk of these challenges need to be determined. This is achieved by conducting impact assessment studies on distribution networks. However, many existing methodologies for conducting such impact assessment studies fail to model the inherent uncertainty and variability in several critical assessment inputs. This paper proposes a comprehensive methodology, making use of a stochastic-probabilistic approach, for impact assessment studies investigating the effects of EV charging on low voltage residential distribution networks. The methodology makes use of the Monte Carlo method to account for the randomness in the EV placement, while using beta probability density functions to account for the uncertainty and variability in both the residential customer and EV load models. The extended Herman-Beta algorithm is used to solve the probabilistic load flow analysis. A case study is documented in which the methodology is demonstrated on a practical feeder located in South Africa. The case study finds that the primary factor limiting the uptake of EVs, especially during the evening residential consumption peak, is the conductor cable loading, and that the period during which the hosting capacity is the highest falls between midnight and 6 am – highlighting the potential value of implementing charge schemes in increasing the hosting capacity of the network. Although more studies are required before generalised conclusions can be made regarding the technical impacts of EVs on LV distribution networks, the methodology proposed in this paper offers a comprehensive framework within which to conduct detailed integration studies, ultimately providing valuable information to policy makers and distribution network planners.

***Index Terms*— distribution network, electric vehicles, impact assessment, stochastic-probabilistic**

I. Introduction

A. Context

AS the world becomes more environmentally conscious, actions to combat climate change and increase sustainability have been deliberate. In December of 2015, the Paris Agreement was adopted by more than 195 nations and marks a conscious effort to fight global climate change [1]. Governments have implemented many policies, incentives, rebates, and mandates to ensure the transport sector plays its part in this change. For instance, by 2040 China's target is to completely terminate the production of internal combustion engine vehicles. Norway and South Korea aim to place a ban on the sale of petrol and diesel vehicles by 2025, while France and the UK aim to do so by 2040 [2]. Germany, India, Israel, Japan and the Netherlands intend to cease internal combustion engine vehicles sales by 2030 and ensure all vehicles on their roads are at least partly electric by 2050 [2].

In 2019, the top five countries in terms of electric vehicle (EV) uptake were China, Norway, Netherlands, Sweden and the USA [3]. Research also indicates that currently most EVs, owned by private individuals, are charged at home [4]–[8]. However, in high density countries like China, where space is limited, a dedicated parking spot where residential EV charging can take place is a luxury that a substantial portion of the country does not have [5], [9]. Here the government promotes the development of public charging networks to ensure the efficient coverage of charging stations thereby encourage EV uptake [9].

Countries with high EV penetrations are starting to experience technical challenges due to the charging of EVs, especially in residential, low voltage (LV) networks. Sweden's EV sales, for example, has increased substantially due to the increase in government grants, causing the electricity demand in cities like Stockholm to grow and exceed the local grid capacity in some areas [4], [6]. High EV uptake has been reported to be associated with a range of technical challenges, such as voltage level and voltage unbalance [10]–[17], an increase in network losses [10], [12], [16], [18], [19], and frequent transformer and cable current overloading and associated overheating [10]–[12], [15], [16], [18], [19].

Impact assessment studies to determine the likelihood and severity of these problems are of critical importance to distribution network planners and energy regulators. These studies can be used for short-term planning and operational purposes considering the current penetration of EVs, or for future planning based on forecasted scenarios. The studies for example inform EV uptake policies and regulations, decisions on the necessity for network upgrades and reinforcement to accommodate desired EV penetration levels, and mitigation techniques such as smart charging.

The formulation of impact assessment studies is complicated by a combination of uncertainties affecting the modelling of inputs and the simulation of feeder performance: customer loads are influenced by stochastic factors, EV loads are influenced by variable customer behaviours primarily mobility, and conditions of EV placement in future uptake scenarios are unknown. These complexities have stimulated a lot of research on the formulation of suitable solutions.

B. Review of existing EV impact assessment methodologies

Several methodologies for simulating the impacts of EVs charging on residential LV feeders have been proposed [10]- [22]. The methodologies differ in several aspects linked to uncertainty characterization: modelling of the input uncertainty (loads and EV loads), propagation of the uncertainty using an appropriate probabilistic load flow (PLF) approach, the simulation of unknown EV placement details, and the interpretation of the uncertain outputs.

Most methodologies do not adequately represent the uncertainty in the load flow inputs [10], [16], [18]–[20]. In most cases, deterministic modelling – based on a single load profile applied to each household in the network – is applied without explicit characterisation of load diversity [16], [19]. Several studies have identified the limitation in deterministic models and have attempted a broader characterisation of load diversity. In a study conducted on nine different residential networks in the UK, the diversity in the residential consumer load is addressed by means of a Monte-Carlo simulation (MCS) method using a pool of 1000 load profiles generated using the CREST tool [11]. Using this tool, appropriate feeder-specific profiles can be generated considering a series of factors including the characterization of consumer electrical behaviour and segmentation, such as the type of day and the month. This data-based approach allows for detailed load modelling. However, the approach has two limitations. Firstly, the MCS approach for load flow analysis attracts huge computational burden, often leading to a compromise on the number of samples applied, which affects accuracy. Secondly, the load modelling approach could not be extended to EV loads, which are characterised deterministically as fixed loads. Similarly, in [15], extensive modelling using probability density functions (PDFs) is applied to characterize the diversity of grouped customer loads but without addressing the diversity in the EV loads. The authors in [12] attempted to model the uncertainty in the EV load by generating 24 different EV profiles based on diversified customer behavioural factors such as start charging times (or home arrival time) and battery state of charge (SOC) at arrival. However, the residential customer load model is based on a single profile without diversification.

The approach to input modelling is usually linked to the load flow approach applied. In cases where deterministic models are used, deterministic load flow (DLF) techniques are applied to solving the load flow [16], [19]. Similarly, approaches with statistical input models, whether MCS-sampled or PDF-characterized inputs, would be linked to probabilistic load flow (PLF) approaches [11], [12]. DLF methods, although widely applied and with correction factors that can be adjusted in an attempt to account for the diversity and stochasticity of the input variables, are not able to fully simulate the effects of the inherent load input uncertainties the way PLF methods do.

In addition to input modelling and load flow computation, the simulation of unknown EV uptake conditions is another critical aspect of impact assessment methodologies. Here three approaches are possible: deterministic or fixed placement [19], worst-case scenarios [20], and stochastic simulation [12]. Fixed placement, which usually involves uniform loading of EVs to each customer, is not consistent with the expectation of gradual adoption and is based on a single scenario whose likelihood of occurrence cannot be clearly determined. Worst-case approaches based on a few extreme scenarios do not lead to optimal decisions as they do not adequately reflect the range of feeder performance. For instance, in [20], the effect of uneven distribution of EVs assigned per phase is simulated using only two scenarios whose conditions are based on arbitrarily selected phase allocation proportions: a moderate unbalance scenario involving a (50:30:20) % proportion and an extreme unbalance scenario with (80:20:0) % proportion to phases a, b and c respectively. Although the uneven distribution of EVs across the phases is addressed, with only two scenarios, the broader scope of possibilities is not, nor the likelihood of the two scenarios simulated. The limitations in worst-case simulation led to proposals on the use of stochastic approaches that allow the simulation of larger number of scenarios [12], [14], [21], [22].

Most papers acknowledge the effect of EVs on voltage level, voltage unbalance and component loading of the conductor cables and the transformer [11]–[14], [20]. However, studies that make use of uniform EV placement across the three phases [19] or worst-case scenario placement strategies [20], fail to account for the effect that unpredictable EV placement has on voltage unbalance.

The detailed review points to the significance of the following key characteristics of a comprehensive analysis of feeder performance under EV penetration:

1. The residential customer load and EV load models should account for the diversity in these loads, and the unpredictability of the customers' behaviour.
2. The method used to simulate the allocation of EVs should reflect the randomness in EV uptake and therefore the uncertainty in EV location (node and phase).
3. The load flow analysis method should accurately and efficiently propagate the input uncertainty to the outputs.
4. The scope of technical parameters assessed should include all sensitive variables linked to power quality standards and equipment loading limits.

A comprehensive methodology should fulfil all the listed characteristics (1) – (4).

C. Contribution and organisation of this paper

Informed by the key characteristics of a comprehensive EV impact assessment study explored above, this paper formulates and demonstrates a comprehensive methodology to assess the impact of EV charging on LV residential networks. The methodology makes use of a stochastic-probabilistic approach to cater for the uncertainty associated with customer loads and EV placement, covers the key technical parameters for thermal loading and power quality assessment, and ensures computational efficiency by employing an analytical PLF method.

In addition to demonstrating the proposed methodology, a charge scheme intervention and various EV charge rates are tested to demonstrate the possibility of hosting capacity enhancement.

The remainder of the paper is organised as follows: firstly, the description of the proposed methodology is detailed in Section II. Then, in Section III the methodology is demonstrated through a case study involving a practical LV residential feeder located in South Africa. Section IV discusses the case study simulation results and the applicability of the proposed methodology. The paper finally concludes and gives recommendations for further work.

II. Proposed EV Impact Assessment Methodology

The proposed methodology consists of three key assessment inputs (network model, residential customer load model – defined as excluding any EV loads - and EV load model) and accounts for three key assessment considerations (simulation of unknown placement, definition and quantification of EV penetration, and charge scheme or tariff incentive implementation). This methodology uses four technical parameters (voltage level, voltage unbalance, transformer loading and cable loading) as indicators to assess the hosting capacity of the distribution network to EVs. All of these components will be discussed in more detail below.

A. Assessment Inputs

1) Network Model

In this paper 'network model' refers to an amalgamation of properties. These include the feeder type (radial, parallel, ring or meshed), the customer location and phase distribution along the feeder, transformer size and properties of the conductor cables such as length and impedance.

In the case of assessing the hosting capacity of an existing network, the proposed method is to make use of a detailed and real network model or models that closely reflect conditions on practical feeders. This would ensure realistic network properties such as customer location and phase distribution, transformer size as well as conductor cable lengths and impedances, which are expected to influence the hosting capacity significantly.

2) Residential Load Model

When conducting distribution network design for new networks, knowledge of the expected residential customer loads is important to ensure that the network infrastructure can handle these loads. When conducting EV impact assessments on existing networks to inform planners and policymakers, insight into the existing residential loads is valuable as the additional EV loads will be superimposed onto these loads.

The load that the network "sees" is dependent on the customer load at a specific point in time. Even though the customers in a specific residential area may have similar overall consumption totals, the load coincidence for these customers need to be taken into account as all the customers do not necessarily hit their peak demand at the same time [23].

It is possible to model the customer load deterministically, giving one specific and predefined value for all the customer loads, but it is important to keep in mind that customer behaviour is unpredictable. Modelling the customer load probabilistically may be more appropriate, as such models account for the stochasticity and variability inherent in such loads. It is possible to model the load probabilistically using a common representative model, while still keeping the load diversity of the grouped customers.

Numerous approaches to probabilistic load modelling are reported in literature. The use of standard PDFs is one of such approaches. Load modelling using the beta PDF has been shown to be convenient for efficient analytical solutions of the PLF [24]. Moreover, the beta PDF is versatile; it can model a wide range of distribution shapes using only three parameters. Two shape parameters, α and β, control the shape of the distribution, and a third parameter allows for scalability. Based on this motivation, the EV loads (described in the following subsection) and residential customer loads are modelled using beta PDFs in the proposed methodology.

3) *EV Load Model*

The modelling of the EV load is dependent on several factors including the EV battery capacity, method of charging, EV connection time and location, the SOC of the EV battery when connecting to charge or discharge and the availability of a secondary place to charge [10], [25]. An additional factor to consider is the implementation of a charge scheme or tariff incentive, as this will influence the EV load model simulated.

The battery capacity, method of charging and SOC of the battery when connecting at home to charge or discharge will determine both the size and duration of the EV load. The SOC of the EV battery when connecting to charge is dependent on the usage pattern of the EV, energy consumption rate and whether the owner makes use of a secondary charging facility. The EV connection time and location will inform time periods of interest and sections in the network of maximum effect, respectively. The unpredictability of EV uptake and therefore the unknown location (node and phase) of EV loads is discussed in more detail in the Assessment Consideration: Simulation of Unknown EV Placement section.

The battery of an EV can charge, and therefore act as a load, or discharge and act as distributed generation (DG) along the feeder. The EV load model will be superimposed onto the residential load model, which means that in the case of EV charging, the size of the net load will increase, while in the case of discharging the net load will decrease up to the point where reverse power flow might occur. Information regarding whether EVs will only charge, will both charge and discharge, and whether restrictions apply to reverse power flow at the utility point of connection will influence whether a “time instant” or time series analysis is deemed appropriate. In the case where only the effects of either EV charging or discharging are considered, the analysis of a single time instant representing the period of maximum impact on the network is typically sufficient.

According to British, German and French standards, electricity to LV consumers is supplied predominantly as single phase, at 230 V [26], while according to American standards electricity is supplied as 2-phase at 120/240 V [26]. The residential charge voltage level is therefore dependent on the standards adopted by the country in question. As previously mentioned, most privately owned EV charging takes place at home [4]–[8]. It is therefore proposed that the charging curve for residential level EV charging, depending on the country’s standards, be modelled. It should however be noted that the charge curve modelled should be adapted to represent the likelihood that customers make use of their ordinary household wall sockets to charge their EVs and customers who have fast charging units installed at home.

The SOC of the EV battery is dependent on the availability of a secondary charging point, energy consumption rate of the EV and the daily travel distance. When looking at the generic charging profile of a lithium-ion EV battery shown in Figure 1 below [27], the amount of power being drawn during charging is almost constant for a substantial period of charging. To ensure longevity of the battery life, it is not advised to let the battery discharge below around 15-20 % SOC [28], [29] . After about 65-85 % SOC (T1 in Figure 1), the power being drawn decreases, until the battery is fully charged (T2).

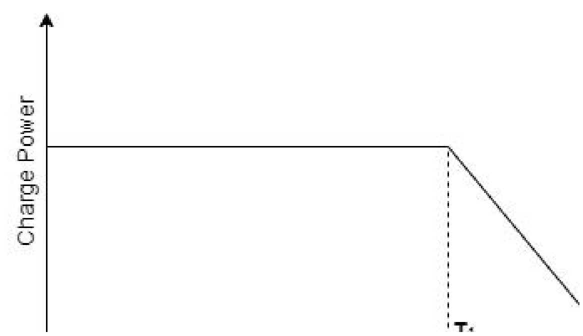

Figure 1: Generic SOC Curve for Lithium-ion EV Battery

To account for variability the proposed methodology suggests modelling the EV load probabilistically. Once again, due to the versatility of the beta PDF explained in the Residential Load Model subsection above, the beta PDF can be used to model the SOC curve (charge power and corresponding likelihood) above.

Restricting uptake of EVs as a result of static penetration limits under worst-case scenario conditions is called into question when the network can accommodate these EVs during less constrained periods. The modelling of charge schemes and tariff incentives should therefore also be considered as part of a comprehensive methodology.

a) *Charge Scheme and Tariff Incentive Modelling*

Although charge schemes and tariff incentives are identified as assessment considerations, it is discussed under the EV load modelling section as it relates to the EV profile. To reiterate, the EV load model will be superimposed onto the residential load model. The net effect of this superposition is what the network will “see” as a single load coming from a household along the feeder. The period of maximum grid impact would typically be when mass simultaneous EV charging coincides with the evening peak in the residential load. When the EV is charging, this net load will be higher than that of the ordinary household load. A way to reduce the coincidence of the residential peak demand and EV charging would be to introduce a charge scheme or flexible time of use (ToU) tariff.

Charge schemes are restrictions that prohibit charging of EVs during certain periods (usually peak consumption periods) and allow charging during other (usually off-peak) periods. Tariff incentives aim to achieve the same, but through financially incentivising charge behaviour.

The implementation of charge schemes and tariff incentives could increase the "hosting capacity" of the network as shown in [5], [11], [12], [34] . In an attempt to accommodate as many EVs as possible, impact assessment studies could assist policymakers in optimizing charge schemes to ensure a higher "hosting capacity" while adhering to power quality standards and maintaining the integrity of the network infrastructure.

Depending on the purpose of the impact assessment study, it is necessary to consider whether a charge scheme or tariff incentive should be implemented or not. It may even be beneficial to run more than one simulation scenario. In one scenario no charge scheme or tariff incentive might be implemented, so that the baseline effect of EV charging can be observed. Further scenarios can then investigate the impact of charge schemes or tariff incentives on EV charging and its effects on the network.

B. Assessment Considerations

1) Simulation of Unknown EV Placement

A stochastic placement strategy is proposed. Such a strategy is proposed and is deemed more suitable and realistic than worst-case placement strategies as it accounts for the unknown location (node and phase) of EVs. One such stochastic simulation method is the Monte Carlo (MC) method. The MC method is a well-known and widely used algorithm that uses repeated random sampling of probability distributions to model risk or uncertainty in a variable. It is proposed that the MC method be used to account for the uncertainty in EV location (node and phase). The MC method will be used to first select a random household (node) along the feeder then select a random phase (phase a, b or c) and assign the EV loads in this manner during the simulation.

2) EV Penetration Percentage Definition

There is not a strict or specific definition for penetration percentage as far as impact assessments are concerned. However, when it comes to EV impact assessments there have been have a variety of penetration percentage definitions introduced. One definition defines the penetration percentage of EVs as the number of EVs over the total number of vehicles considered for the impact assessment [22], [35]. Another defines the penetration of EVs as the number of EVs over the total number of households or customers considered for the study [12], [14], [18]. Identical technical problems in the network might be found at very different penetration levels, based on which penetration percentage definition is used, producing a wide range of what is deemed "acceptable" penetration percentages. Therefore, without the same measure of penetration percentage used, direct comparison of assessment results may not be possible and these definitions are subsequently not of direct use to the distribution network planner or the to the DSO when defining standards or regulations.

This proposed definition, used in [36], as a measure of the capacity (in kW or kVA) of installed EVs in relation to the technical characteristics of the network, such as the peak demand or feeder maximum demand (FMD), could be deemed more useful. This measure of penetration is defined in Equation 1 below.

$$EV\ Penetration\ Percentage = \frac{Cumalative\ Power\ of\ EVs\ Assigned\ [kW]}{Feeder\ Maximum\ Demand\ [kW]} \times 100\% \tag{1}$$

C. Technical Parameters Assessed

In the review of EV impact assessments, it was found that the purpose of the study is important as this influences the technical impacts that are monitored during the assessment simulation. For the purpose of informing policy implementation where the aim is to understand to what extent the existing network can accommodate the charging of EVs, it is proposed that the following four technical parameters be monitored; voltage level, voltage unbalance and transformer loading and conductor cable loading. The maximum and minimum voltage value throughout the feeder will be monitored to ensure that the voltage level remains within the bounds of the power quality standards. Voltage unbalance will be calculated using the Equation 2 below and once again be compared to the power quality standards.

$$UB\ \% = \frac{Max.Deviation\ of\ Phase\ Voltages\ from\ Average}{Average\ Voltage} \times 100\% \tag{2}$$

Finally, the total current in each branch of the feeder can be calculated and compared to the rated current carrying capacity of the conductors and rated transformer output to assess whether these components are being overloaded.

D. Simulation Method

1) Probabilistic Load Flow

The proposed methodology makes use of the HBE-MCS tool used is [36]. The residential customer and EV loads are modelled using beta PDFs. The HBE-MCS tool takes in beta PDF inputs and produces beta PDF defined outputs. Each household node is split into two sub-nodes that are placed an insignificantly short distance apart. The first sub-node receives a beta PDF representative of the residential customer load. If the household is selected to have an EV, the second sub-node receives a beta PDF representative of the EV load.

For each PLF assessment, the maximum and minimum voltage, maximum voltage unbalance and maximum transformer and conductor loading on the feeder are recorded and displayed.

2) Overall Program Flow

The overall program flow can be split into the following five steps.

1. The FMD is determined by loading the first sub-node of each household (residential customer load node) and linearly incrementing the load until the first occurrence of either a voltage or conductor loading violation.
2. Reset the first sub-nodes of each household to the original residential customer loads. Randomly add EV loads to the second sub-node of households using the MCS method guided by the penetration level under analysis and the limits per household.
3. Perform the HBE and record the worst-condition of each technical variable (maximum voltage, minimum voltage, maximum voltage unbalance, maximum conductor loading, and maximum transformer loading) based on a desired level of risk.
4. Repeat processes 2 and 3 for a defined number of scenarios selected (e.g. 1000) to balance simulation accuracy with computational speed.
5. Increment the penetration level and repeat processes 2 to 4 until every node reaches the maximum specified EV limit per household.

Figure 2 shows a schematic of the overall simulation program flow.

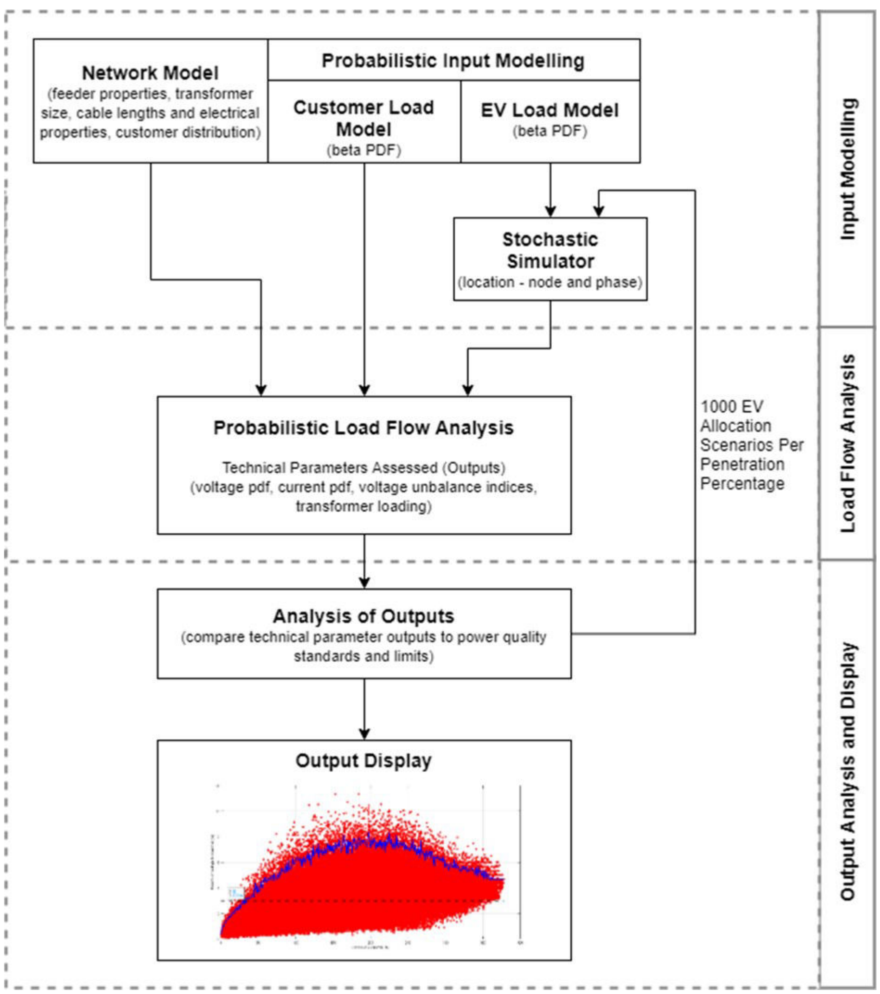

Figure 2: Simulation Program Flow Diagram

III. CASE STUDY

The availability of detailed distribution network and residential load data plays a significant role in the reliability of the impact assessment results. Because of access to such information, the case study will focus on South Africa. In the global picture regarding EV uptake, South Africa has room for improvement with approximately only 1 119 EVs on South African roads [37]–[39]. South Africa does not manufacture any EVs locally, and the steep import tax has been said to be a major contributing factor to the slow EV uptake [37], [38], [40]. South Africa has about 214 public chargers, located at malls, airports and along major highways [38]–[40]. Because public charges are not abundantly available, an EV owner in South Africa may need to rely on residential charging as the primary charging place. South Africa is a signatory to the Paris Agreement adopted in 2015, in which the goal for 2030 is for 20 % of all road vehicles to be EVs and 35 % of all new vehicle sales to be EVs by 2035 [37], [40]. Given the current EV statistics in the country, this is a seemingly optimistic goal. However, if South Africa wishes to increase the EV uptake significantly over the next few years, the country needs to be prepared. As seen in many countries with ambitious EV uptake goals, they ran into trouble due to unexpected issues with the distribution network not being able to accommodate the new loads introduced by the EVs. Therefore, before policies are implemented and incentives are put in place in South Africa, EV impact assessment studies aimed at getting a better understanding of the potential technical impacts and severity thereof could prove helpful.

The simulation inputs and considerations used in the case study simulation is described below.

A. Simulation Inputs

1) Network Model

South African residential areas are grouped according to 10 Living Standards Measure (LSM) classes based on 29 different factors including the ownership of a motor vehicle and certain large appliances [41], [42]. LV residential distribution networks are designed accordingly, to accommodate the loads expected from the type of customers residing in these different areas. The LSM classes that are most likely to adopt EVs are LSM classes 9 and 10. The residential network chosen for the simulation is that of an LSM class 10 area in Western Cape, South Africa. The network modelled is a three-phase four-wire, 11-node radial feeder with a 225 kVA transformer serving 53 customers.

2) Residential Load Model

As mentioned in the previous section, the residential area modelled for the simulation is one having residents that fall under an LSM class 10. To account for the worst-case scenario, the simulation is conducted under residential load conditions corresponding to the maximum demand interval. In South Africa this is usually a winter weekday evening during which the use of heating appliances is high and coincides with the evening consumption peak.

A study done on the traffic flow on roads in South Africa stated that the peak traffic period is between 4 pm and 6 pm [43]. A different study on the cost of daily commuting in South African cities concluded that people in the higher labour income quintile (LSM class 9 and 10 and most likely owners of EVs) have an average commuting duration of between 48-50 minutes [44]. This places the likely home arrival time between 5 pm and 7 pm. Data collected from monitoring the electricity consumption of 42 LSM 10 customers for a year was used to generate a daily load profile showing the mean and standard deviation of LSM 10 customers for a winter weekday. The likely home arrival period corresponds to the period of significant rise in electricity consumption with the peak at around 7 pm. Using the mean and standard deviation values for the peak time period (7 pm) identified in Figure 3, the alpha and beta parameters for the beta PDF modelling the residential load is calculated.

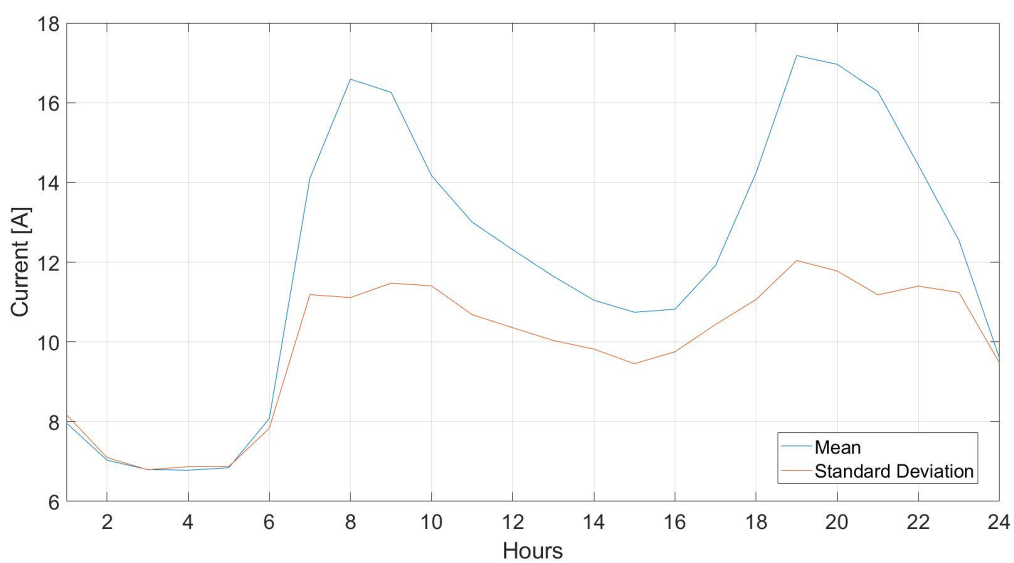

Figure 3: Winter Weekday Load Profile

The residential load model, shown in Figure 4 below, used in the simulation is defined by a beta PDF with the following parameter values: alpha = 1.167, beta = 2.908, shape parameter C = 60 and an after diversity maximum demand (ADMD) of 3.952 kVA. The beta PDF is representative of a winter weekday evening at 7 pm.

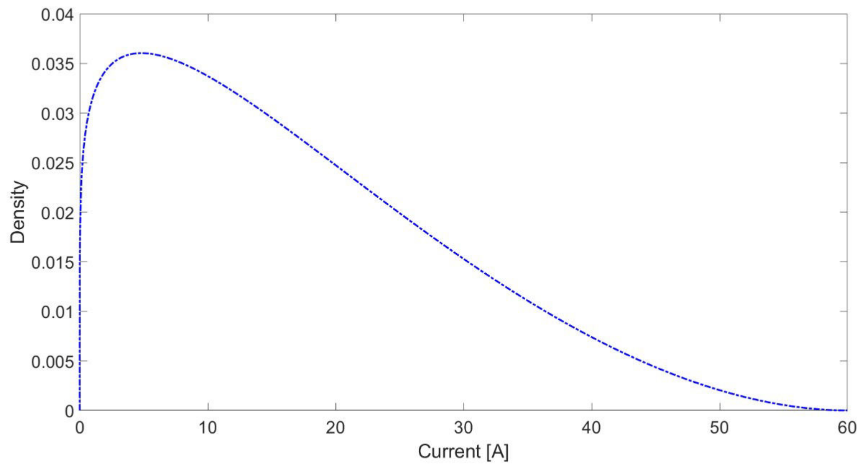

Figure 4: Beta PDF for Residential Load at 7 PM

3) EV Load Model

There are currently three models of battery electric vehicles in South Africa namely the Nissan Leaf, BMW i3 and Jaguar i-Pace [37]–[39]. Although the Nissan Leaf has been present in South Africa the longest - introduced in 2013 - since its launch in 2015 the BMW i3 quickly surpassed the Nissan Leaf in sales. The BMW i3 currently dominates the EV sector in South Africa, accounting for more than 70 % of EVs [39]. Characteristics of the BMW i3 is modelled in the simulation.

a) EV Specifications

The battery capacity of the BMW i3 is 33 kWh [45]. Looking at the charge curve of the BMW i3, it is confirmed that for majority of the charging period, the power being drawn during charging is almost constant [46]. At home charging of the BMW i3 takes less than 9.7 hours to reach 80 % of the maximum capacity [45], when using an ordinary residential wall socket in South Africa, where the supply voltage is 230 V [47].

b) Charge Scheme/Tariff Incentive

For the case study simulation, while no tariff incentives are implemented, two scenarios are simulated.

- Scenario 1: No charge scheme (EVs can charge at any time, including during residential consumption peak)
- Scenario 2: All EV charging restricted to start after midnight until 6 am (charge scheme 1)

c) Final EV Load Model

As with the residential load model, the EV load model is defined using a beta PDF, shown in Figure 5. The alpha and beta values were chosen to model the EV load with little variability. This is done to mimic the almost constant power being drawn for majority of the charge period. The constant power value modelled (2.76 kW, 230 V, 12 A) is based on AC charging with a standard BWW i3 charging cable from a household socket [45].

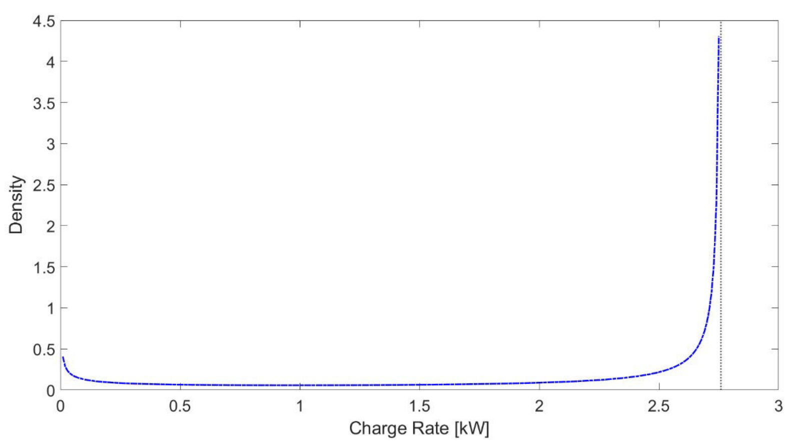

Figure 5: Beta PDF for EV Load

B. Simulation Considerations

The MCS method is used to account for this random placement of EVs along the feeder. For the simulation, the household limit is set to one EV. This means that each household may be assigned a maximum of one EV. The case study simulation makes use of the EV penetration percentage definition previously defined in section 2 under Assessment Considerations. This definition may be of more use to the network planner than the average person. Therefore, the results make use of a second measure of penetration. This definition defines the measure of penetration based on the number of households, along the simulated feeder, that has EVs.

C. Limits to Technical Parameters

The following technical parameters will be monitored to determine the successful accommodation of the network to EV charging; voltage level, voltage unbalance, transformer loading and cable loading. The maximum hosting capacity of the network to EV charging is reached when the limits of any one of these technical parameters are exceeded.

In South Africa, the NRS048 power quality standards state that at a residential level, the supply voltage level should be 230 V ± 10 % [47]. The voltage level should therefore lie between 207 V and 253 V. This standard also states that the maximum voltage unbalance allowed is 3 % [47] and that the electricity supply should comply with these standards 90 % of the time. This allows a 10 % risk of the standards being violated. The risk applied to the results and the interpretation thereof of discussed in more detail in the following section.

The transformer and cables are sized to operate under certain rated conditions. Operating beyond the bounds of these rated conditions, for prolonged periods of time, not only decreases efficiency but can cause permanent damage. As a result, the limits for the thermal loading of conductors and transformers are set to 100 % or 1 pu.

IV. Simulation Results

The scatterplots that follow represent the technical performance of the simulated feeder corresponding to the 1000 MCS placement scenarios and PLF assessments conducted at each penetration level. The penetration level ranges from zero (passive conditions without EVs) to a maximum, where each customer has the maximum number of EVs. These results are compared to the power quality standards. The scatter plot shows the statistical distribution of values for the 1000 placement simulations and can therefore be analysed incorporating risk. The PLF outputs are at 2.5 % risk, while the blue trendline is generated by considering a further 2.5 % risk in the MCS allocation of EV represented by the variation of outputs in the y-direction. The results are therefore displayed with a 5 % level of risk, or inversely 95 % confidence. The red dots in the plots represent the results for each of the 1000 placement scenarios per penetration percentage, while the blue trendline indicates the risk interval. The results will be discussed based on the trendline incorporating risk.

The measure of penetration is defined as a percentage of the FMD. At 63 % penetration each household is assigned the maximum number of EVs (in this case one EV). Hence, the simulation results stop at 63 %.

A. Scenario 1 Results

From Figure 6, the feeder minimum voltage of 0.9 pu is violated at a penetration percentage of 23 %. Figure 7 and Figure 8 shows that there are no violations to the maximum voltage of 1.1 pu and the maximum voltage unbalance allowed of 3 %, when interpreting the results to include risk. Figure 9 and Figure 10 show that conductor cable overloading and transformer overloading occur at penetration percentages of 5% and 26% respectively.

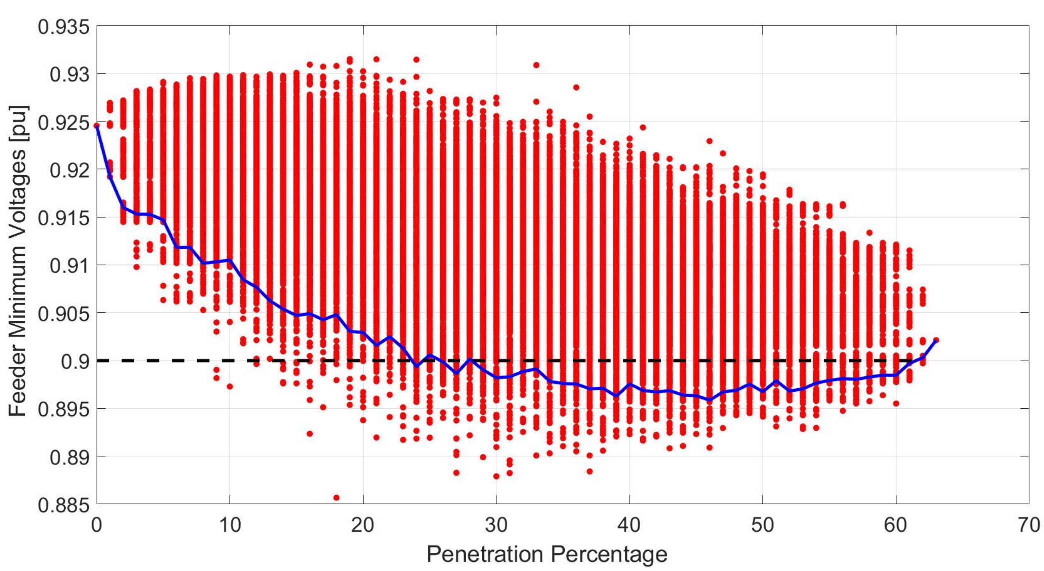

Figure 6: Feeder Minimum Voltage

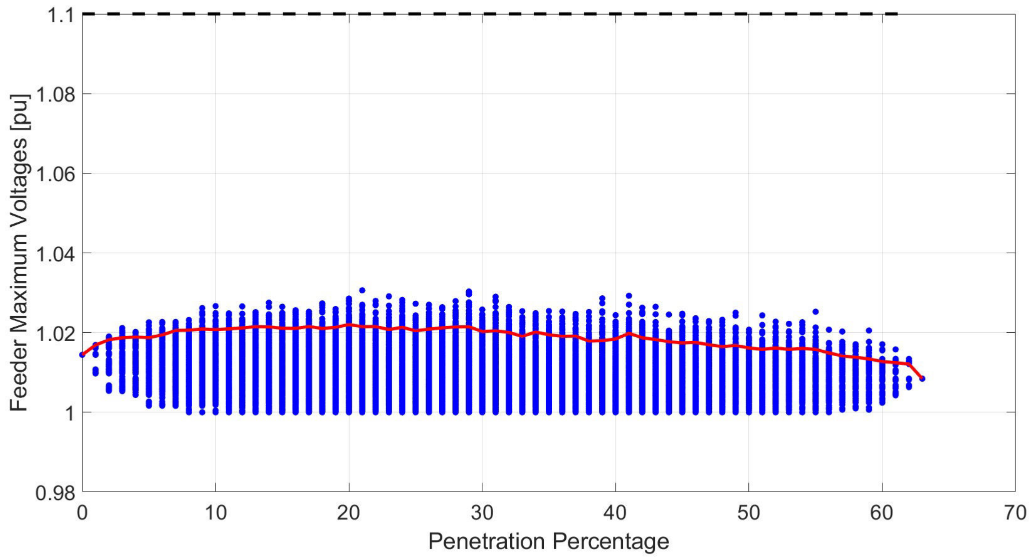

Figure 7: Feeder Maximum Voltage

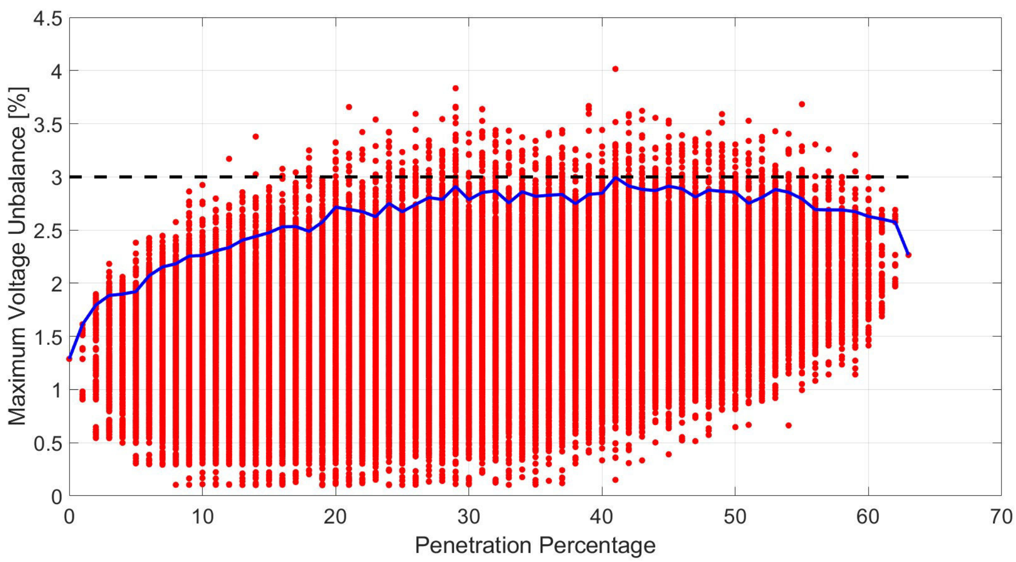

Figure 8: Maximum Voltage Unbalance

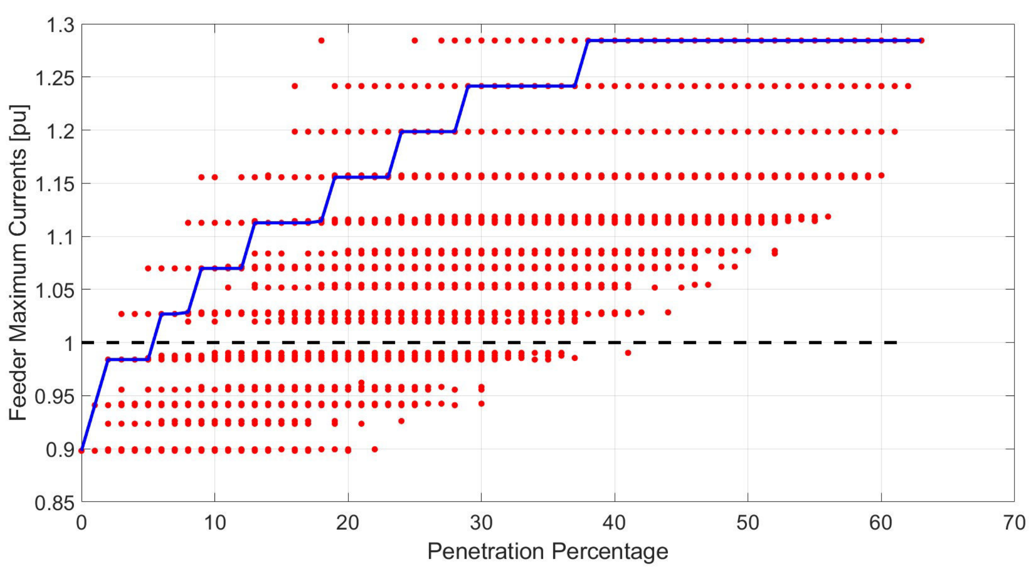

Figure 9: Conductor Cable Loading

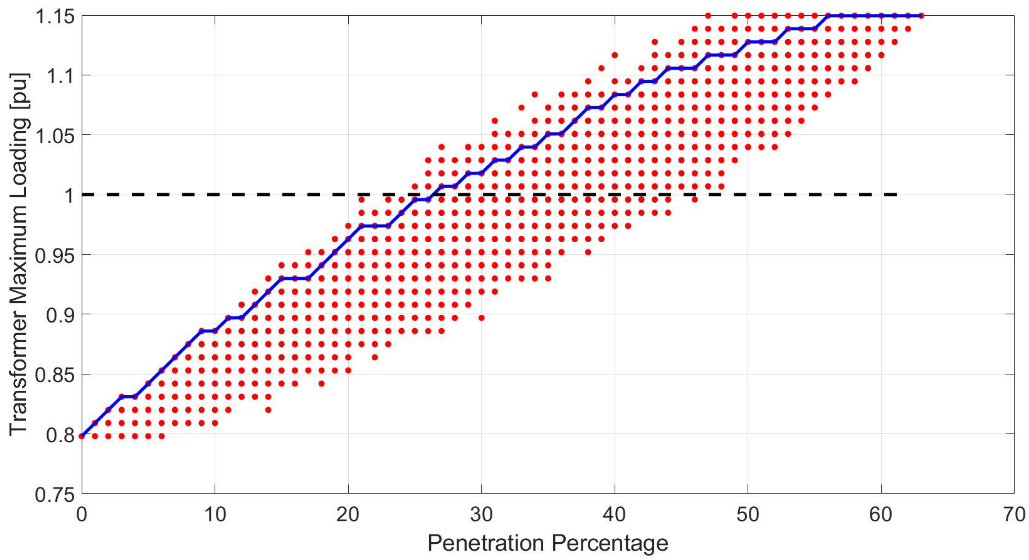

Figure 10: Transformer Loading

Although EV charging is likely to result in voltage drop, Fig. 6 shows scenarios (red dots) in which the minimum voltage level observed actually rises. This is attributed to the effects of voltage unbalance on voltage level. It should also be noted that under passive conditions, the feeder loading is unbalanced. Random single phased assignment of EV loads cause the voltage unbalance along the feeder to increase. As seen in Fig. 8, as more and more EVs are randomly assigned to household along the feeder the unbalance of the loads across the three phases is reduced and the voltage unbalance actually decreases.

The results are summarised in the bar graph in Figure 11 below. The blue bar (left bar) shows the penetration percentage as a measure of the FMD while the orange bar (right bar) the penetration percentage as a measure of the number of households that have been assigned an EV.

The technical impact that results in the lowest hosting capacity is deemed the limiting factor for uptake. In this case, the factor limiting uptake is the conductor cable loading, resulting in a hosting capacity of 5 % penetration (as a measure of FMD). This can also be expressed as 7.55 % of households in the simulated network having an EV.

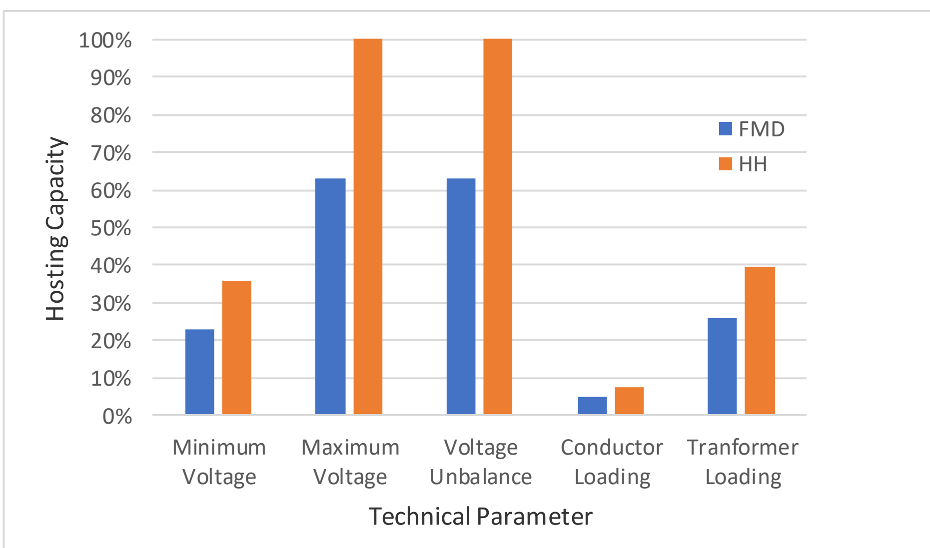

Figure 11: Hosting Capacity vs Technical Impact at 7 PM

B. Scenario 2 Results

Figure 12 shows the hosting capacity as a function of time, from 7 pm till 7 am. From the figure it is evident that the simulated network's hosting capacity is the highest between midnight and 6 am. The electricity consumption rises again at 7 am as residents wake up and start their day, shower, make breakfast etc.

For the period between midnight and 6 am, all of the households in the simulated network can charge their EV with no violations to any of the power quality standards. This is at a charging rate of 2.76 kW.

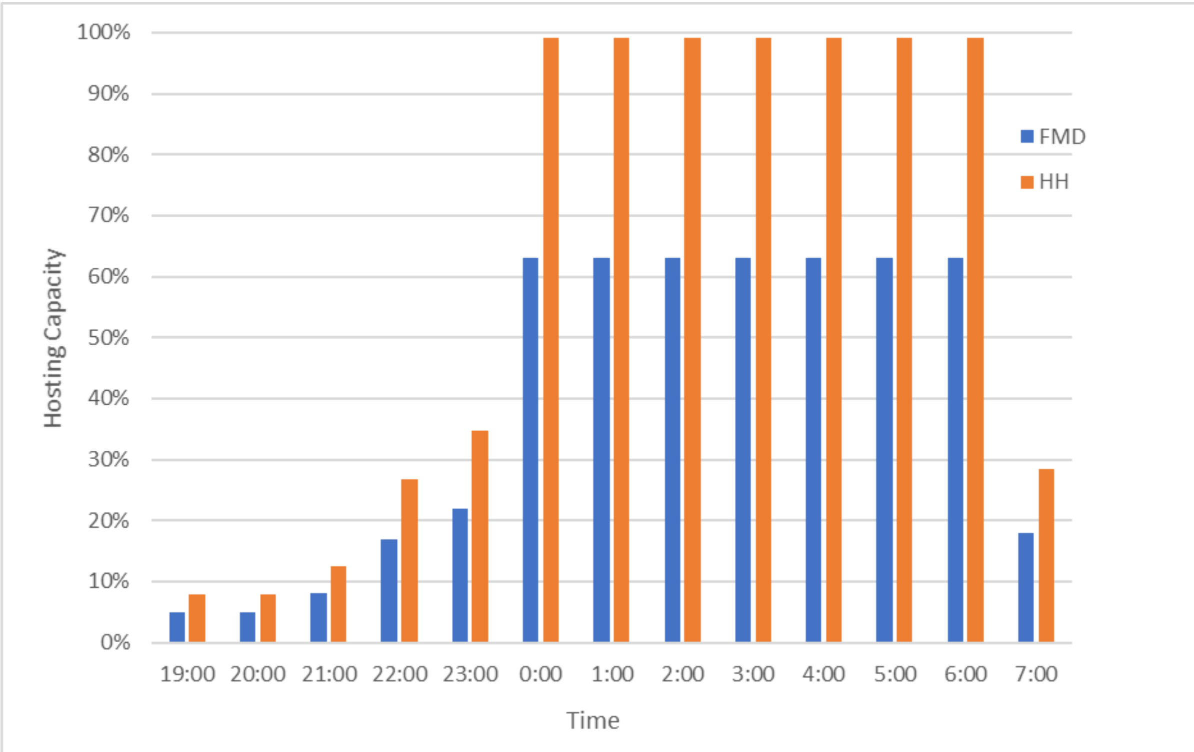

Figure 12: Hosting Capacity from 7 PM till 7 AM

As previously mentioned, the BMW i3 requires 9.7 hours to achieve 80 % SOC. This 6-hour period may therefore not be sufficient. If the charge rate is increased from 2.76 kW to 3.45 kW and further to 4.6 kW, Figure 13 below shows how the hosting capacity during this period is affected.

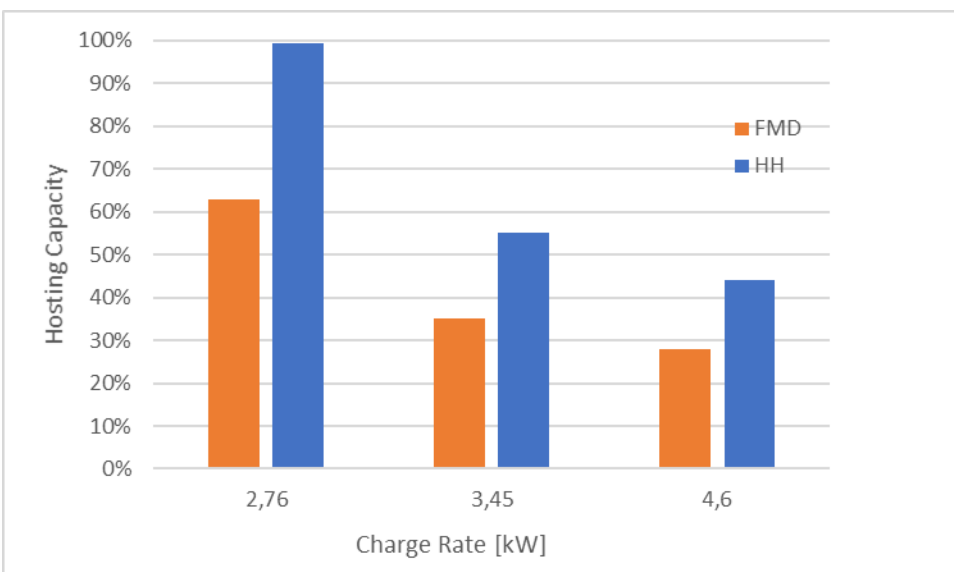

Figure 13: Hosting Capacity vs Charge Rate

When the charge rate is increased to 3.45 kW, the hosting capacity decreases and only 55 % of households may charge their EVs before violating power quality standards. When the charge rate is increased again, to 4.6 kW, the hosting capacity is decreased even further resulting in 44 % of households charging their EVs before violations occur.

C. Result Summary

It is evident that the hosting capacity of EV charging is the lowest during the residential peak consumption period. During this period, for the network simulated, the conductor cable loading is the factor limiting EV uptake. A time-series simulation indicates that the highest hosting capacity is possible between midnight and 6 am. Different charge rates are simulated during this period. When charging at 2.76 kW, all households in the simulated network charge without power quality violations. While at 4.6 kW, less than 50 % of the households may charge their EVs before violations to the power quality standards start to occur.

V. Conclusion

This paper proposed a comprehensive impact assessment methodology with the following characteristics: (1) the aspects of stochasticity and variability in the residential loads and EV loads are addressed, (2) the network model simulated is detailed and represents practical feeder conditions, (3) the placement strategy used to assign the EVs during the simulation accounts for the unpredictability in location (node and phase) of EVs, and (4) the load flow method directly accounts for the stochasticity and variability in the simulation inputs modelled.

This proposed methodology was demonstrated in a case study on a practical feeder in South Africa. The case study first simulated unconstrained charging of EVs which occurred coincident with the residential consumption peak, analysing a single time instant. This resulted in significant feeder voltage-drops and overloading of both the transformer and the conductor cables. The technical parameter that limited the uptake of EVs for the simulated network first was found to be the conductor cable loading.

A second simulation was then conducted investigating a full time series as opposed to a single time stamp and the period during which the hosting capacity is the highest was identified. This was between midnight and 6 am. During this period three different charger ratings were tested (2.76 kW, 3.45 kW and 4.6 kW). At 2.76 kW, all of the households could charge their EVs with no violations to any of the technical parameters monitored. As the charge rate was increased (to 3.45 kW and then 4.6 kW), the percentage of households that were able to charge their EVs decreased to 55% and 44 % respectively. It can be concluded that charge scheme implementation considering both charging period and charger power rating can aid in EV accommodation.

The case study demonstrated how the proposed methodology can be used. The results obtained from the simulations conducted on a single network do not allow for general conclusions to be made regarding hosting capacities of networks but are applicable to the network model simulated. Further studies, exploring the sensitivity of the technical impacts to various input parameters and conditions, are however needed before generalised conclusions can be made. The methodology proposed here does however offer a comprehensive framework within which future studies may be conducted, ultimately informing policy makers and distribution network planners regarding the required EV uptake regulations, new network component sizing and the need for future upgrades to existing networks.

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