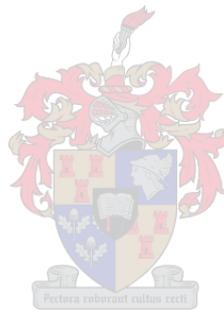


Impacts of Electric Vehicle Charging in South Africa and Photovoltaic Carports as a Mitigation Technique

by

Kevin Michael Buresh



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Supervisor: Prof M. J. Booysen
Department of Electrical and Electronic Engineering

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ABSTRACT

The rise of greenhouse gas emissions having detrimental impacts on the environment have raised concerns. Efforts to combat these emissions have been agreed upon by countries across the globe, including South Africa. Reducing emissions, such as carbon, is commonly proposed as moving from coal-based generation sources to renewable sources for electricity, along with shifting from internal combustion engine (ICE) vehicles to electric vehicles (EVs). EVs have gained popularity internationally and are becoming widely adopted as a greener alternative. Research has uncovered that this may not always be the case, provided the different electricity generation sources utilized. South Africa, having a coal-dependent grid, might not see a reduction of emissions with the adoption of EVs. Mass charging of EVs can also jeopardize grid stability by creating new peak demands, which could be detrimental for South Africa's currently fragile grid. Fortunately, through the use of renewable sources to offset electricity from the grid when charging EVs and implementing smart charging strategies, EVs could meet their acclaimed potential benefits.

A simulation model was developed to examine the effects of varying EV fleet sizes in South Africa, and the potential of mitigation strategies such as large employers providing solar photovoltaic (PV) carport charging stations and smart charging methods. A varying fleet size aids in investigating the impacts of EV charging from the perspective of a vehicle owner, a large employer and the national grid. The model incorporates a solar PV model with measured weather data, along with an EV model consisting of a mobility model and battery model. A smart charging method was developed to limit the number of vehicles charging simultaneously based on a maximum load peak demand. This demand-side management (DSM) strategy determines the charging urgency of EVs to formulate a prioritized charging schedule.

During this project, it was found that the current grid capacity would not be sufficient for more than four million EVs charging without any intervention. When supplementing charging with PV carports, the grid capacity could handle at least an additional 10% increase in fleet size. An employer providing PV carport charging would see an increase in revenue from electricity sales when customers only charge at work. A vehicle owner was found to have a cleaner carbon footprint travelling with a petrol ICE vehicle than an EV, except for scenarios where EVs utilize PV carports and would have the lowest operational costs when driving an EV that does not charge at home.

Supplementary PV energy does prove to be a useful mitigation strategy, but when EVs are allowed to charge freely at work, they do not take advantage of the full potential.

Employers, when coupling smart charging strategies with PV carports, gain further control of load demands, reductions in operational costs and grid energy consumption. An employer implementing charging imposed load limit restrictions, while still providing user comfort to vehicle owners, was seen to reduce the imposed peak demand by more than half and led to a doubling of the yearly revenue. Various levels of restrictions, when evaluated, were seen to have a significant impact on user comfort, with little impact on financial benefits. Overall, this project has demonstrated not only the need for EV charging mitigation strategies, but also the potential benefits of solar PV carports coupled with smart charging strategies.

UITTREKSEL

Die toename in kweekhuisgasvrystellings wat die omgewing nadelig beïnvloed is kommerwekkend. Lande regoor die wêreld, insluitend Suid-Afrika, het ooreengekom om pogings aan te wend om hierdie tipe vrystellings te bekamp. Die vermindering van koolstof gebaseerde uitlaatgasse word gewoonlik voorgestel as die verskuiwing van steenkoolgebaseerde bronne na hernubare hulpbronne vir elektrisiteitsopwekking, tesame met die verskuiwing van binnebrandenjins voertuie na elektriese voertuie. EV's het internasionaal gewild geword en word meestal aanskou as 'n "groener" alternatief. Navorsing het egter ontdek dat dit nie altyd die geval kan wees nie, as gevolg van die verskillende hulpbronne wat vir die opwekking van elektrisiteit gebruik word. Suid-Afrika, wat steenkool-afhanklike elektrisiteitsopwekking, sal moontlik nie 'n vermindering van die koolstof uitlatings met die aanvaarding van EV's ervaar nie. Die herlaai EV's op 'n groot skaal, kan ook die stabiliteit van die netwerk in gevaar stel deur nuwe piekvereistes te skep, wat skadelik kan wees vir Suid-Afrika se brose netwerk. Die goeie nuus is egter dat EV's hul gewilde potensiele voordeel kan bereik indien hernubare energie gebruik word om aanvullende elektrisiteit tot die elektrisiteitsnetwerk te voeg asook wanneer EV's deur middel van slim laai-strategieë gelaai word.

'n Simulasiemodel is ontwikkel om die gevolge van verskillende EV-vlootgroottes in Suid-Afrika te ondersoek. Die potensiaal van versagtingstrategieë, byvoorbeeld groot werkgewers wat sonkrag gebaseerde fotovoltaïese motoraflaaistaties en slim laai-metodes verskaf, is ook ondersoek. Deur verskillende vlootgroottes te ondersoek, help dit om die impak van EV-heffing te evalueer vanuit die perspektief van 'n voertuigeienaar, 'n groot werkgewer asook die nasionale netwerk. Die ontwikkelde model bevat 'n sonkrag-PV-model met versamelde weerdata, tesame met 'n EV-model bestaande uit 'n mobiliteitsmodel asook 'n batterymodel inkorporeer. 'n Slim-laaimetode is ontwikkel om die aantal voertuie wat gelyktydig laai te beperk, op grond van 'n maksimum aanvraag na laaikapasiteit. Hierdie bestuurstrategie vir die aanvraag na laaikapasiteit bepaal die dringendheid van laai-bestuurders om 'n vooropgestelde heffingskema te formuleer.

Tydens hierdie ondersoek is daar bevind dat die huidige netkapasiteit nie voldoende sou wees om vier miljoen EV's, wat sonder die hulp van enige addisionele herlaai instellings, kon ondersteun nie. Wanneer dié laai-zones met PV-motorafdakke aangevul word, kan die netkapasiteit 'n groter vlootgrootte van ten minste 10% hanteer. 'n Werkgewer wat PV-motorafdak herlaai fasiliteite verskaf, sal 'n toename in inkomste uit elektrisiteitsverkope sien as klante slegs by die werk laai. Daar is ook bevind dat 'n voertuigeienaar 'n

kleiner koolstofvoetspoor het vir die gebruik van 'n petrol-voertuig as die gebruik van 'n EV, behalwe in die geval waar motorvoertuie gebruik maak van PV-motorafdak herlaai fasiliteite.

Aanvullende PV-energie is wel 'n nuttige versagtingsstrategie vir die groot elektrisiteitsvoorsiening vraag wat EV's bied, maar as EV's toegelaat word om gratis vanaf die netwerk herlaai te word, benut hulle nie die volle potensiaal van die beskikbare PV-energie nie. Sodra werkgewers slim-laai strategieë met PV-motorafdak herlaaifasiliteite integreer, kry werkgewers verdere beheer oor vragvereistes, en verminder dit die bedryfskoste en die energieverbruik. Vanuit 'n navorsingsperspektief is dit duidelik dat werkgewers wat 'n heffing op beperkte vragbeperkings toepas, die opgelegde piekvraag met meer as die helfte verminder het en gelei het tot 'n verdubbeling van die jaarlikse inkomste, al het dit sekere vlakke van gebruikersgerief aan voertuigeienaars gebied. Daar was bevind dat verskillende vlakke van beperkings 'n beduidende impak op verbruikersgemak het, met relatiewe min impak op die finansiële voordele. In geheel, het hierdie projek nie net die noodsaaklikheid van 'n verbeterde EV-herlaai-strategie gedemonstreer nie, maar ook die potensiele voordele en belangrikheid van die integrasie van sonkrag-motorafdak herlaai fasiliteite tesame met slim laai-strategieë beklemtoon.

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CONTENTS

Acknowledgements	i
Declaration	ii
Abstract	iii
Uittreksel	v
Publications	vii
List of Figures	x
List of Tables	xi
Nomenclature	xii
1. Introduction	1
1.1. Background	1
1.2. Problem statement and objectives	2
1.2.1. Problem statement	3
1.2.2. Proposed solution	3
1.2.3. Research objectives	3
1.3. Scope of work	4
1.4. Thesis structure	5
2. Literature study	6
2.1. Grid effect	6
2.2. Load shifting	8
2.3. Mobility models	9
2.4. Demand-side management	11
2.4.1. Centralized control	11
2.4.2. Decentralized control	12
2.4.3. Solving techniques	12
2.5. Chapter summary	14

3. Methodology	16
3.1. Perspectives and scenarios	16
3.1.1. Perspective 1: EV owner with one vehicle	17
3.1.2. Perspective 2: Large employer with 1000 EVs and 1000 carports	18
3.1.3. Perspective 3: The constrained coal-dependent grid with 1 million EVs and carports	21
3.2. Simulation setup	22
3.2.1. EV simulation	22
3.2.2. Solar PV simulation	27
3.3. Chapter summary	28
4. Results	29
4.1. Uncontrolled charging	29
4.1.1. Perspective 1: EV owner with one vehicle	29
4.1.2. Perspective 2: Large employer with 1000 EVs and 1000 carports	31
4.1.3. Perspective 3: The constrained coal-dependent grid with 1 million EVs and 1 million carports	33
4.1.4. Summary	35
4.2. Controlled smart charging	35
4.2.1. Incomplete trips	36
4.2.2. Large employer with 1000 EVs and 1000 carports	40
4.2.3. Summary	44
4.3. Chapter summary	45
5. Conclusion	46
5.1. Thesis summary	46
5.2. Suggestions for future work	48
Bibliography	50

LIST OF FIGURES

3.1.	Simulation system diagram	17
3.2.	A raw smart meter data set with outliers	19
3.3.	A raw smart meter data set after outliers have been removed	20
3.4.	A raw smart meter data set after its been cleaned	20
3.5.	Gaussian distribution of travel distance	24
3.6.	Gaussian distribution of work arrival times	24
3.7.	Gaussian distribution of work departure times	25
3.8.	Solar PV carport designs	27
4.1.	Vehicle owner perspective of a ICE and EV vehicle	30
4.2.	The employer’s perspective of uncontrolled charging for EVs	31
4.3.	The grid perspective of uncontrolled charging for EVs	34
4.4.	Failed trips due to insufficient charging	37
4.5.	Home charging of EVs to make a one-way trip	39
4.6.	Controlled and uncontrolled charging from the employer perspective	41
4.7.	Daily typical demand of controlled and uncontrolled charging of 1000 EVs	43

LIST OF TABLES

3.1. Parameters used in the simulation setup	23
4.1. Simulation results in yearly aggregates	33
4.2. Smart charging simulation results in yearly aggregates	40

NOMENCLATURE

Variables

T_h	Duration of time that an EV charges at the higher power level (P_h).
T_l	Duration of time that an EV charges at the lower power level (P_l).
T_p	Total time that an EV is parked.
P_h	High power charging level.
P_l	Low power charging level.
B_f	Battery capacity of an EV.
B_{SOC}	The SOC of an EV's battery.
R	Numerical representation of charge urgency relating to an EV.
T_{ECA}	Essential charge amount time of an EV to ensure it can complete its required journey.
P_{dr}	Constant indicating an EV requires charging with P_h .
T_r	Time remaining until an EV's departure.
E_{ECA}	Essential charge amount of an EV to complete its required journey.
E_{trips}	Energy required to complete a round trip for an EV.
E_{eff}	Efficiency of an EV.
D_t	Distance travelled for a single EV trip.
n_{trips}	Number of trips.

Acronyms and abbreviations

A	Ampere
AC	Alternating current
CO ₂	Carbon dioxide
DSM	Demand-side management
EV	Electric vehicle
g	Gram
GA	Genetic algorithm
ICE	Internal combustion engine
k	Kilo
L	Litre
LP	Linear programming
M	Mega
m	Meter
min	Minute
NP	Non-linear programming
PV	Photovoltaic
QP	Quadratic programming
RT	Real-time
RTS	Real-time scheduling
SOC	State-of-charge
TOU	Time-of-use
UK	United Kingdom
USD	United States dollar
V	Volt
VA	Volt-ampere
V2G	Vehicle-to-grid
W	Watt
Wh	Watt hour
W _{pk}	Watt peak
ZAR	South African Rand

CHAPTER 1

INTRODUCTION

1.1. Background

Over the past decade, policies have been put in place to address the concerns around rising greenhouse gases. These policies aim to guide the involved parties in reducing their emissions, including carbon emissions which account for two-thirds of the total greenhouse gas emissions. The Kyoto Protocol and the Paris agreement are just two examples of this on a global scale [1]. Through signing both of these agreements, South Africa agreed to take action in efforts to reduce their carbon emissions. South Africa, ranked the world's fourteenth largest CO₂ emitter in 2015, is hamstrung by its failing coal-dependent national electricity utility, which frequently applies rolling blackouts during peak times to prevent a national shutdown [2; 3; 4]. Coal accounts for more than 75% of the country's energy supply, with an annual CO₂ footprint of 512 billion kg [5; 6]. Added to this, the South African road transport sector is responsible for 43 billion kg of carbon emissions from combustion engines per year [7].

A move to electric vehicles (EVs) has been internationally advocated to reduce combustion emissions. The exact number of these vehicles imported into South Africa was not publicly available at the time of writing but it was estimated to be less than 1000 [8; 9; 10]. While the current penetration rate is low, it is just a matter of time before these vehicles appear in much greater numbers in South Africa. Knobloch et al. [11] when investigating emission reductions from use of EVs across 59 world regions, including South Africa, found that the full life-cycle emissions from average EVs could be higher than those of new efficient petrol vehicles. Therefore, even though EVs are generally seen as one way to reduce emissions; given the coal dependence of the national utility, Eskom, their widespread adoption could perversely increase emissions. Moreover, charging patterns could increase the likelihood of rolling blackouts during peak times [12]. The resultant strain on the power network from charging patterns can also be problematic during previously considered off-peak times, as a large group of vehicles charging at the same time has the potential to create new peak usage periods.

Fortunately, South Africa has high levels of insolation (a measure of solar energy at a particular place over a specified time). Most areas in South Africa average more than

2500 hours of sunshine per year and have average solar-radiation levels between 4.5 and 6.5 kWh/m₂ per day [13]. EVs, however, tend to be charged at home at night. Charging at these hours poses as a problem as it is a great opportunity missed. A possible way to prevent this loss is to incorporate battery storage into a photovoltaic (PV) system. Even with the falling prices of battery storage, it still drastically increases the overall cost of the system [14]. One way to make the best use of solar energy, without the need for expensive battery storage, is to charge vehicles during the day, using a solar PV carport at the workplace. In South Africa, with its limited public transport, approximately a third of South Africa's estimated 10 million households use a vehicle to drive to work each day, but the vehicle spends most of the day unused [15].

Considering that EVs will replace a large number of these vehicles in the future, it is paramount to plan for the energy that propels their usage. To do this requires taking into account their charging patterns that describe their charging needs, and the overall energy availability with the incorporation of renewable energy. A way to do this is through the use of demand-side management. Demand-side management (DSM) is a process that aims to influence consumers' electricity usage so that it better matches the electric utilities desired generation load curve [16]. Electric utilities aim to balance the load curve so that it's easier to monitor, control and utilizes generation sources efficiently. Techniques to achieve this include reducing peak demands by using direct control with peak shaving, creating a more uniform load by increasing low consumption periods with valley filling and shifting consumption during peak to off-peak periods with load shifting [16]. Balancing this generation supply and consumer demand is crucial to ensuring a stable power grid [17]. Utilities match the demand through different generation sources, some of which are expensive, inefficient and emit higher carbon emissions. As EVs have the potential to exacerbate previous peak demands or create new ones, incorporating DSM strategies is crucial. Implementing them with various charging techniques otherwise referred to as smart charging can reduce potential grid strain, maximize the use of renewable energy sources, and even use them as an energy source in a vehicle-to-grid configuration (V2G). Other beneficial impacts of DSM strategies also considered with EVs include frequency regulation and voltage imbalance, which can both negatively impact the grid stability if not corrected.

1.2. Problem statement and objectives

Based on the background and context of EVs discussed above, this section presents the problem statement identified for this study, a proposed solution and objectives formulated to reach the proposed solution.

1.2.1. Problem statement

Efforts to reduce emissions across the globe have led to the push for EVs. As they've become more popular and widely adopted overseas, it has raised questions of their actual impact. Dependent on the generation sources, findings on EVs' emissions are not always fewer than those compared to petrol vehicles. EVs are also known to consume large amounts of electricity and lead to significant peak demands, posing as a risk to the stability of the grid when charging simultaneously. South Africa, while currently sitting with a relatively small population of EVs, it is bound to grow much more. This growth, while initially expected to reduce South Africa's emissions, could perversely increase them given Eskom's heavy coal reliance. Incorporating these vehicles blindly onto the already severely constrained national grid could have detrimental effects on its stability. Fortunately South Africa has high levels of solar insolation, and vehicles driving to work spend most of the day unused. This creates an opportunity to utilize the available solar energy at places of work to charge EVs, placing less dependence on a fragile coal-driven grid to meet a future required load. Fortunately, vehicles parked at work provide an opportunity to implement local-based DSM smart charging strategies to alleviate problems from simultaneous charging.

1.2.2. Proposed solution

This project addresses the problem statement above with aims to examine the impact that EVs will have in South Africa. It will begin by conducting a thorough literature study, outlining how EVs can be modelled, common impacts of their charging and mitigation strategies attempted. The second task will be developing a model capable of simulating EV fleets applicable for various perspectives. Thirdly, the EV model needs to be easily incorporated with a solar PV model to determine any benefits from the designed PV carports. Fourthly, the EV model will be redesigned to be capable of finding the maximum EV fleet size for a given grid capacity. Finally, a smart charging algorithm that makes use of DSM to compare to uncontrolled charging needs to be created.

1.2.3. Research objectives

The following research objects were formulated to assist in addressing the problem statement, as they help break up the proposed solution into smaller tasks:

Research objective 1:

A thorough literature study needs to be conducted in order to identify how common EV models are implemented, the possible impacts of EV charging and the methods researchers have attempted to mitigate them.

Research objective 2:

To be capable of investigating different fleet perspectives, develop an EV simulator that can model an EV fleet of a chosen size over a requested period. It should incorporate realistic mobility behaviour and battery characteristics. The simulation should output relevant information on a combination of carbon emissions, energy usage, the peak load demand and financial costs/revenue from charging of the fleet.

Research objective 3:

Use a trusted solar PV model to design and model a PV carport system. Incorporate this with the EV model to assess any potential benefits to EVs.

Research objective 4:

Adapt the original simulator to be able to determine the maximum fleet size that the grid can support using a given grid capacity and historical grid data.

Research objective 5:

Develop a smart charging algorithm that utilizes a DSM strategy to determine the potential mitigation effects of controlled charging strategies compared to uncontrolled charging strategies.

1.3. Scope of work

There exists a large number of things to explore and techniques to implement when it comes to EVs. Due to the nature and length of this project, the number of items investigated needed to be limited. This project investigates the impact of uncontrolled and controlled charging strategies for EVs in South Africa. It focuses on the impacts of electricity usage in charging, proposing mitigation strategies. The electricity usage impacts entail the carbon emissions, overall energy consumption, load demand and financial costs/revenue. These impacts are measured relative to the baseline of the previous or estimated usage. We, therefore, do not explore techniques aimed at changing their previous energy consumption such as peak shaving, valley filling or V2G technology. Also, frequency and voltage regulation are not explored. As this project focuses on the impacts of charging electricity usage, our carbon footprint analysis looks at the CO₂ emissions associated with the operation of these vehicles, not the entire life cycle of each vehicle. Given the abundance of sunshine in this country, the main strategy is to make use of solar PV carports at work, followed by scheduled smart charging. Carports pose as a viable option as most cars are parked at work during the week, presenting an unutilized opportunity. As

the focus is on workplace interventions, our EV mobility model only incorporates weekday trips that represent travelling between work and a residence.

1.4. Thesis structure

Chapter 2 outlines the relevant literature aiding the techniques used to approach the problem statement. It includes investigations on EV impacts on the grid, the potential of solar PV and load shifting to reduce these impacts, various mobility modelling methods used and their influence, the main types of DSM to mitigate charging effects and the relevant solving techniques employed.

Chapter 3 defines the two experiments proposed and describes the design of the simulator. It includes parameters and design choices that build on gaps found in the literature study. First, the different charging strategies or scenarios along with the three evaluation perspectives considered with their corresponding metrics are described. Continuing on, the simulation setup consisting of an EV and solar PV model is explained. The charging strategies are explained in detail in the EV model section. These include the uncontrolled and controlled smart charging strategy.

Chapter 4 presents the results obtained from performing both experiments. Firstly, it starts by comparing uncontrolled charging strategies with a petrol vehicle from the three evaluation perspectives in separate sections, namely the owner, an employer and the grid. Following this, the results from the second experiment comparing uncontrolled to controlled smart charging are discussed. It is split into two separate sections, incomplete trips and the employer perspective. Incomplete trips cover the resultant user satisfaction of controlled smart charging, whereas the employer perspective evaluates two main charging strategies with the same metrics explored for the first experiment.

Chapter 5 concludes the project by evaluating the four research objectives described in the problem statement. Additionally, recommendations for future work regarding advanced DSM strategies and extended EV analysis are proposed.

CHAPTER 2

LITERATURE STUDY

Given the growing prominence of electric vehicles, researchers have begun to ask questions about their use and impact. They have investigated such areas as battery technologies, charging strategies, and impact on supply networks and generation utilities. Recent research shows concern regarding this impact, estimating that it has the potential to be significant with a substantial EV population. Many studies develop charging strategies to try and alleviate this impact with demand-side management. In efforts to better predict these impacts and mitigation techniques, researchers have investigated different methods to accurately simulate driving and charging behaviour. Our study builds on four specific areas of this EV research: the effect on the grid of increasing EV penetration; load-shifting applied to EV charging; the mobility and usage models used in EV studies; and demand-side management strategies aimed at reducing the impact of EV charging.

2.1. Grid effect

In a study of the impact of EVs and different charging strategies on the grid in China, Li et al. assessed the aggregated load and the economic and environmental impacts [18]. Their goal was to provide a clear understanding of how these impacts can be influenced by the charging strategy. This understanding is presented to aid conversations surrounding policies concerning EV charging, assisting in utilizing the full potential of EVs. They compared two forms of uncontrolled charging with two centralized control charging strategies. The uncontrolled charging strategies differ by one only charging vehicles at home, whereas the other charges them whenever they are parked. Both centralized control strategies charge vehicles when optimal to do so. In one centralized control strategy, they considered EVs not only as a load but also as a grid-stabilizing energy source in a vehicle-to-grid (V2G) configuration. In their model, they base travel behaviour on data collected from a travel survey done in the Netherlands. They use this data with a kernel density estimate approach to formulating a probability density function that describes the availability of EVs. This availability is combined with their power system model that uses a unit commitment approach. It looks at the generation units on an hourly basis, aiming to minimize the total generation cost. The study took 2030 as the baseline year, which determined the number of

vehicles considered, the available infrastructure, and the expected generation capacity from either renewable or non-renewable sources. Estimating the generation changes required to meet the demand, they found a 3 to 4% increase in coal consumption would be needed, and concluded that even that small increase could put grid stability at risk. However, the stability would depend on the charging strategy used. Controlled charging strategies, such as those proposed in V2G strategies, could help prevent additional peak loads and reduce the risk. However, because the quality of China's coal varies, in some regions these strategies would produce higher CO₂ emissions than traditional internal combustion engine vehicles.

In New Zealand, Monigatti et al. ran a simulation similar to that used by Li et al., but incorporating wind generation as the energy source and looking particularly at how V2G strategies could help to increase New Zealand's use of wind generation [19]. Monigatti et al. also makes use of a travel survey to base travel behaviour on, theirs being from New Zealand. They model travel usage by randomly sampling the survey results, including travel times and distances in the form of cumulative and other distributions. Their work largely differs by simulating individual vehicles, along with utilizing recorded wind speed and grid load data. They simulate the charging and discharging of these EVs, taking into account the state of the grid. The state of the grid is considered by looking at the load data and the wind generation data, which is simulated using wind speed data. Using EVs to balance the required generation and the load, they found that peak generation requirements could be substantially decreased by using a million EVs in V2G operations.

Qian et al. devised a method to model the load from EVs charging in a distribution network [20]. They aimed to provide a quantitative approach for determining the expected impact from charging, to assist in better equipping utility companies with information on preparing for these impacts. Their model of EVs uses a numerical statistical approach, making use of distributions and probability density functions, to estimate when vehicles will be charging and travelling. They define the charging of vehicles as a function based on the UK electricity tariff structure and vehicle usage. The vehicle usage, consisting of travel distance and typical travel times between a place of residence and work, was gathered from respectively a national survey and fact sheet provided by the UK department of transport. To test this method, they simulated a typical distribution system in the UK and examined the loads, split between residential, industrial and commercial areas. They considered domestic charging, public charging and smart charging. The smart charging scenario optimized the number of vehicles charging at a given time to reduce costs and prevent new peak loads. This was designed as a future scenario and assumed a wide incorporation of communication and metered charging technologies. While this is a simpler way to reduce the grid impact than the controlled charging discussed by Li et al., it would be hard to implement in a developing country like South Africa that is already financially constrained and struggling to keep up with technological advances. Qian et al.'s study found that a

10% penetration of EVs would increase the daily peak demand by 17.9% for uncontrolled domestic charging. This scenario was found to have the highest peak demands, while their smart charging proved to be the most beneficial. However, they found that while smart charging can prevent an increase in legacy peaks, it can cause new peak loads from chargers starting simultaneously.

In a Belgian study, Leemput et al. evaluated the impact of vehicle charging strategies on the power profile, voltage magnitude and voltage imbalance of a residential grid [21]. Their focus on the residential grid is from the likelihood that EV charging will coincide with residential peak power consumption, as vehicles are likely to be plugged in after arriving home. The two strategies they investigated were uncoordinated charging and “peak shaving”, both with and without voltage droop. Their uncoordinated strategy makes use of a 3.3 kW charger, whereas the peak shaving technique charges vehicles at a power determined by the duration parked and their battery percentage. When either of these strategies includes voltage droop behaviour, the charging power can be adapted to balance the distribution voltage magnitude if it deviates from its regulated range. They simulated a residential grid of 39 households, each with an EV, using Flemish electricity usage profiles for these households, with the addition of some residential photovoltaic energy generation. The mobility behaviour of each EV is modelled with a tool developed by Van Roy et al. [22]. It makes use of data from a Flemish transportation survey to generate vehicle behaviour. While the charging model also allowed vehicles to be charged at a workplace, that energy usage was not included, since the workplace was not within the residential grid. They found that the simulated grid failed to comply with European voltage standards when uncoordinated charging strategies were used. This was resolved when peak shaving techniques were applied.

2.2. Load shifting

Load shifting, a common theme in EV research, is a logical way to reduce the impact on the grid by reducing usage at a given time and avoiding new peaks. In a study in the Netherlands using solar photovoltaic generation, Chandra Mouli et al. examined the ability to charge vehicles at work [23]. They attempted to maximize the solar energy usage through different charging profiles, which were chosen to align with an average photovoltaic generation profile. This shifting of EV charging loads to around midday was coupled with dynamic charging, i.e. using variable rather than fixed charging power, to better fit the photovoltaic curve. They compare those charging profiles to others that were generated using two different types of fixed power chargers. One only being capable of operating at a single power level while the second is capable of charging at two different power levels. All of the profiles were generated for a single vehicle and make use of a simplistic mobility behaviour model. This model consists of assuming that the EV will park at work from

8:30 am to 5:30 pm, that it travels 50 km/day and that it needs to be charged 10 kWh/day. The capacity of local battery storage was also assessed to minimize grid dependence. The proposed system examined only a single vehicle and a single charger. They also propose a possible method to handle charging three vehicles with this system. This method prioritizes each vehicle in terms of how long they are parked and the amount of energy required. This promising research is limited by the small sample and the simplistic mobility model.

In a study of the potential to shift EV charging loads, Babrowski et al. evaluated six European vehicle mobility studies through generating charging load curves for the corresponding countries [24]. This allowed them to analyze how charging may differ between European countries, and they found no major differences between the charging curves. These load curves were generated by simulating the energy required for EVs to complete the trips found in the mobility studies. Vehicles were allowed to charge at work and at home for these load curves. After evaluating the national differences, they then used mobility data from the German study to give examples of potential load shifting benefits by decreasing the variability of the increased demand response and maximizing the use of photovoltaic energy generation.

2.3. Mobility models

A vehicle's mobility model is used to describe its usage patterns, such as the distance travelled and the time of traveling. To model EV performance accurately requires accurate models of their mobility and the resulting electrical energy impact. This is especially true for the charging requirements. Quiros-Tortos et al. proposed a method to produce realistic EV profiles consisting of mobility and charging parameters [25]. They warned that travel surveys can produce unrealistic demand profiles, as such surveys require assumptions to be made or use historic vehicle charging data that are often drawn from small unrepresentative datasets. This can further result in under- or over-estimations of charging impacts. Their model used probability density functions based on Gaussian mixture models to represent EV mobility characteristics. They created these Gaussian mixture models by combining multiple Gaussian distributions with weighted averages. This allowed them to determine hourly probabilities for each characteristic that can be sampled to generate these charging profiles. They did this to determine how many EVs charge on a given day, the number of times each vehicle charges, when each charging event begins along with the battery percentage before and after these events. Their method is a more statistical-based approach than the more common method of simulating a group of EVs travelling and their required charging as a result. They evaluated their model against measured EV charging data. Comparing their model to other models based on surveys and trials, they found that the profiles it generated were not only realistic but described EV mobility more accurately.

A noteworthy study by Kara et al. estimated the potential benefits of smart charging for vehicles at non-residential locations [26]. They aimed to improve on identifying these potential benefits for various stakeholders with a method that makes fewer EV assumptions. This was done through the use of a large EV dataset, preventing the need to make assumptions on characteristics such as travel behaviour including time and distance. This large dataset comes from a group of more than 2000 non-residential vehicle charging stations in Northern California. It is used to apply and assess the author's smart charging strategy. The strategy was to shift the charging period to make use of cheaper charging rates. The ability to shift the load was bounded within the period during which the vehicle was parked. These parking periods are formulated using the power measurements from the observed charging event found in the dataset. Each event contains these measurements recorded in 15-minute intervals. The potential benefits they investigated were limited to the economics associated with two types of stakeholder: the owner of a charging service provider and the operator of the grid distribution system. In South Africa the stakeholders are grouped differently. The state utility Eskom serves as the generator, and in some situations as the distributor and retailer. Municipalities often serve as a distributor and retailer.

To estimate the demand impact of EVs at a regional level in the US, Harris and Webber developed a model based on national travel survey data and using Monte Carlo methods [27]. They examine this demand as a result of uncontrolled charging, as they believe that data enabling controlled charging may not be readily available to utility providers. The demand impact is estimated with charging load profiles. Before the national travel survey data is used, it is first filtered. They filter it to remove unsuitable vehicles and weekend data. A vehicle considered to be unsuitable for their pool of EVs was defined as one that travels more than 200 miles (322 km) in a day. Each vehicle's trip data is then evaluated with the probability that charging will occur to generate a vehicle demand profile. This probability corresponds to the time of trip completion and is from a piece-wise uniform distribution function. In the generation of these profiles, a charging power of 5.5 kW is used. These profiles are then used in Monte Carlo simulations to create a more suitable charging impact estimate. The Monte Carlo simulations are performed by randomly sampling the pool of vehicle charging profiles until there is a group of these profiles that meet a required size. They record the sum of these profiles in this group and repeat this process until it has run a set number of iterations. In their simulations, this process is done for 500 iterations. They validated their model by comparing its charging behaviour to a small set of actual EV data. They investigated how unscheduled or uncontrolled charging could affect different regional peak demands. However, they considered only one charging scenario and did not consider any interventions to reduce the impact of the charging.

2.4. Demand-side management

In efforts to reduce the impacts of EVs and to better ease their integration, demand-side management (DSM) is a common approach found in recent literature. DSM makes use of smart grid infrastructure to better match energy production to energy consumption [28], often through load scheduling. In the context of EVs, load scheduling refers to charging being controlled, otherwise known as smart charging. Some of the previously discussed techniques implement smart charging, such as load shifting or V2G technology. There is a vital need for controlled charging strategies when considering the future high EV penetration rates, as uncontrolled charging will place stress on existing power systems [18; 26; 29; 30; 31]. Smart charging provides a method to manage the energy supply and demand, incorporate more renewable energy and possibly postponing any required grid expansion [19; 32; 33; 34; 35].

Smart charging strategies manage the charging state of EVs in either a centralized or decentralized method [36]. These two methods differ from one another by whom the authority to control the charging state belongs. Centralized control involves an entity known as an aggregator managing the charging of each vehicle in that area. Decentralized control gives each EV the authority to manage its charging. These approaches to controlling loads are implemented throughout research to achieve various goals, such as: reducing CO₂ emissions, frequency regulation, minimize energy generation costs or power losses, reducing peak usage, etc. [35]. Depending on the goal and the desired accuracy, simple or complex techniques can be employed. These techniques range from simple rescheduling or delayed charging to numerous forms of optimization of different mathematical models [34].

2.4.1. Centralized control

In the centralized control method, the aggregator will formulate a charging schedule that results in the desired demand profile. The aggregator is responsible for creating and managing this schedule so that it meets a specified goal [36]. The schedule is made based on the state of the grid and each vehicle's information such as the desired level of charge, maximum charging power, time of departure and time of arrival. This data is either collected or estimated with historical data daily, providing the aggregator with a forecast of the required power. Aggregators will send a request for the availability of this power to grid operators (in the case that they are separate entities). Upon approval, they can proceed in purchasing this power in the day-ahead market [35; 36]. The vehicles' state and the grid state is monitored in real-time, ensuring that the resultant load profile matches the estimate as close as possible and meets the specified goal. We previously discussed examples of this method implemented in the work of Li et al. [18], Babrowski et al. [24] and Kara et al. [26]'s with their efforts to minimize generation costs, charging costs by

optimizing load shifting, and the costs for various stakeholders by maximizing cheaper electricity rates for charging respectively.

2.4.2. Decentralized control

The decentralized control method gives each vehicle autonomy over its charging while still meeting set goals. If the goal is for vehicles to charge at the lowest cost, this is possible through a price based incentive strategy [35]. In the simplest form, it works with an aggregator providing each vehicle with a pricing scheme of charging throughout the day, with higher rates for peak usage hours to deter charging during these periods [36]. A more competitive pricing scheme can be generated by an aggregator using estimated or received charging demand profiles. Many extend this by iteratively communicating between a vehicle and the aggregator. Updating the vehicle's optimal schedule with a new pricing scheme and vice versa, allowing both the aggregator and the user to reach an optimized solution [35]. These communication signals are performed dynamically in real-time. In Qian et al.'s work, their smart charging strategy aims to minimize the charging cost by charging over cheaper periods in the applicable tariff structure [20]. This structure is unaffected by the number of vehicles charging. Leemput et al. utilized decentralized control with voltage droop behaviour and their peak shaving technique applied independently for each vehicle which is discussed in more detail above [21]. Monigatti et al. used the decentralized control method when looking to increase wind energy utilization and better match the generation to the load [19]. They did this by communicating with vehicles the state of the grid which they aimed to optimize.

2.4.3. Solving techniques

Researchers have implemented many techniques and algorithms to solve the potential problems with integrating EVs into the grid [34]. Depending on the difficulty and number of goals related to solving the problem, it may be doable with a simple technique or require complex modelling methods. Regardless of the complexity, it will often include constraints that need to be adhered to, such as a maximum peak load or charging power allowed. Techniques implemented range from simple charge scheduling to more mathematical methods capable of providing optimized solutions. A few of the commonly used mathematical methods include heuristic and meta-heuristic approaches, linear programming and non-linear programming [34; 36].

A simple charge schedule can reduce grid impact by utilizing the parked time to provide flexibility to EV charging. Vandael et al. developed two scheduling methods to ensure the resultant load from a fleet of charging vehicles does not exceed a specified threshold [37]. The first schedule is a reactive response. At each instance, the strategy will charge as many vehicles as possible without exceeding the threshold. Once the threshold is met, the

remaining vehicles will only charge when there is available capacity. The second method is a proactive response, calculating the expected capacity beforehand and spreading out charging out throughout the day, providing a lower peak usage. This study found that the reactive response results in shorter charge times but is prone to higher peaks. A proactive response is more favourable to balancing loads evenly throughout the day.

Heuristics approaches make use of simple modelling to find a solution to a problem. Generally, this involves describing a problem in terms of an objective function with constraints defining what is realistic or required. The objective function is what describes the goal and needs to be minimized or maximized. In Kang et al., the authors try to minimize the load variance from a day-ahead estimate to improve on the previous valley filling techniques [38]. They do this by making use of the earliest deadline first prioritizing scheduling policy to formulate a real-time scheduling (RTS) techniques. Throughout the simulation, the algorithm dynamically ranks each vehicle charger according to its charging urgency. Results showed that the RTS provided higher user satisfaction than traditional valley filling techniques when simulating a fleet of 100 EVs.

For complex problems that are not able to be modelled with basic heuristics can be attempted with meta-heuristics techniques. A popular meta-heuristic method is the genetic algorithm (GA). Alonso et al. developed a strategy that uses the GA to optimize smart charging coordination [33]. This coordination is not a simple problem as they apply it a low voltage residential environment, considering thermal line limits, voltage limits and transformer loading. The developed method results in benefits to the load profile with flattened curves, valleys filled, and reduced stress on transformer equipment.

Similar to a heuristic approach, linear programming (LP) involves simple modelling with a function and some constraints. As the name suggests, the function describing the problem and its constraints must be linear. In a study focused on smart charging EVs with photovoltaic power and V2G technology, van der Kam and van Sark compares uncontrolled charging to smart charging where vehicles are either managed with a real-time technique or an optimized LP technique [39]. Two real-time techniques are implemented, with one incorporating V2G technology. The LP technique also incorporates V2G technology. Their goal is to maximize the amount of PV power consumed. They found that the RT technique can consume 13% more PV power than uncontrolled charging and has a lower peak demand. Their proposed LP technique performs the best with consuming 25% more PV power than the RT technique, along with the RT peak demand being twice that of LP.

Non-linear programming (NP) models, similar to linear programming ones, include an objective function and some corresponding constraints. NP differs by the presence of a non-linear term present in the constraints or the objective function. Quadratic programming (QP) is a higher-order NP technique, often used for their ability to formulate a wider range of objective functions [40]. Mets et al. investigates how various smart charging techniques fair with reducing the peak load and demand variability from EVs [41]. They compare

a QP and a market based coordination technique to the baseline case of uncontrolled charging. In the QP approach, vehicle information including mobility and battery details are available beforehand, allowing the charging schedule to be optimized ahead of time. The market based coordination technique operates with a decentralized control approach. Vehicle information is only made known on arrival, requiring dynamic scheduling to take place. They found that in the worst case scenario, an uncontrolled charging strategy could lead to a peak demand load doubling in a distribution grid. In evaluating a residential area of 64 households, they determined that the QP technique was able to yield better results in the reduction of peak demand and variability of demand. They conclude that the results of the QP represent a benchmark, as actual measurements will differ from predictions.

2.5. Chapter summary

The studies reviewed above, with the numerous models proposed, all discuss issues of carbon emissions, energy usage, load demand and cost. These issues are considered from one, or at most two, of three possible perspectives: residential, commercial or energy supplier. However, none of the studies discusses all of those issues, or considers all three perspectives. Further, none of them take into account a range of EV penetration, from small to medium, and large. This reveals a gap in the literature: at the time of writing no study had yet assessed the overall impact of EVs charging on all parties involved.

To mitigate these issues, the majority of the studies reviewed propose strategies in the form of demand-side management. Their strategies either fall under a central entity (aggregator) managing vehicle charging or persuading vehicles to charge at specific moments, these methods are referred to as centralized and decentralized control respectively. These are implemented to reach a specified goal such as reduce carbon emissions by incorporating more renewable energy, reduce the peak demand imposed by charging, maximizing the use of cheaper energy resources to minimize power generation costs, grid voltage regulation, etc. The complexity of meeting these objectives varies depending on if one looks at them from a residential, regional or distribution level. Finding an optimal solution or one acceptable is possible with various techniques. The technique chosen is largely dependent on the number of objectives and factors considered, along with how the problem is described. For instance, linear programming can only be for characteristics or objectives described linearly, whereas non-linear programming can model higher-order polynomial functions. However, higher-order functions can be time-intensive or difficult to model. Heuristic and meta-heuristic approaches become useful for this reason, as they are often easier to model and less time-consuming. A downside to these two approaches is that they cannot always guarantee the most optimal solution, but can often provide something close to it.

Considerable research has been done on using solar energy to supplement vehicle charging [21; 24; 39; 42] and some researchers have proposed using PV-equipped carports for this purpose [23; 43; 44; 45]. However, such studies generally involve a scenario of a developed country with limited solar energy insolation. The scenario of a developing country with a financially constrained grid and abundant solar energy has not yet been considered.

CHAPTER 3

METHODOLOGY

The fundamental problem with charging an electric vehicle (EV) from a privately owned solar energy charger is that the vehicle owner will usually be obliged to charge it at night and therefore have to use another energy source or install battery storage to use the solar charger. Individual solar installations are bound to be more costly per kW_{pk} than a large solar farm. A solution is for large employers or car park owner (hence referred to as employer for simplicity) to sell electric vehicle owners solar energy at the workplace. Any shortfalls could be made up from the grid at a lower rate, as large employers typically buy cheaper electricity at bulk prices. A further advantage is that employers could use the surplus solar energy to offset their own demands.

This chapter discusses the details and design of the experiments conducted in this project. The first experiment investigates uncontrolled charging, whereas the second compares uncontrolled charging to controlled smart charging. This chapter covers three evaluation perspectives and scenarios, evaluated against petrol-fuelled vehicles for the first experiment, the relevant perspective and charging scenarios for the second, and the simulation models: the vehicle mobility model, the vehicle's battery model, and the solar photovoltaic (PV) generation model. The simulation setup, including the historic energy data, is depicted in Figure 3.1. The metrics used to assess the results in the charging scenarios are also discussed in this chapter.

3.1. Perspectives and scenarios

The first experiment explores the concept of workplace charging for privately-owned electric vehicles with three charging scenarios; (i) charging solely at home from the electricity grid, (ii) charging solely at work from grid-augmented PV carports, and (iii) a combination of these two, charging EVs at home and at work. A fourth scenario (iv) is, of course, to consider the situation of no EVs, with all personal transport utilizing internal-combustion vehicles. These four scenarios have been examined from three perspectives; (1) that of the owner of the vehicle, (2) the perspective of the employer (assumed to be a large-scale employer), and (3) the perspective of the grid. The study focuses on the situation in South Africa, and we evaluate each perspective using vehicle fleet sizes of one, 1000 and 1 million

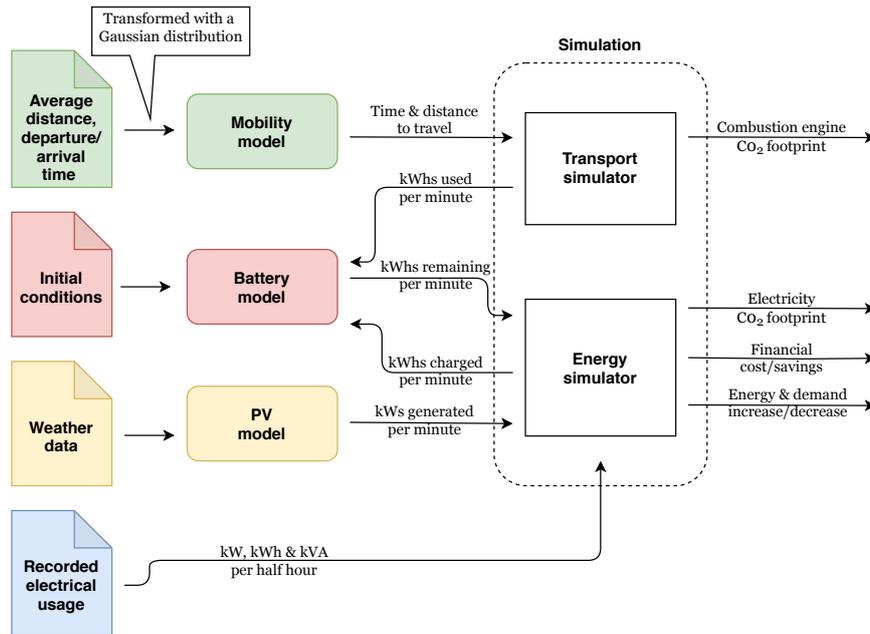


Figure 3.1: Simulation system diagram

EVs respectively. The second experiment builds on from the first, exploring how workplace charging at work can be improved. Investigating this compares work-only uncontrolled charging with our controlled smart charging strategy. It is applied with four levels of peak demand limits (kW/EV); (i) 0.5, (ii) 0.65, (iii) 0.8 and (iv) 0.95. These four levels are chosen to limit the number of EVs charging at one time and reduce monthly peak demands. They are explored from the employer perspective as described for the first experiment. For each perspective we evaluate a combination of the following metrics: energy usage (and resultant CO₂ emissions), monthly peak demand, financial costs, and monthly PV carport energy. In addition to these metrics, we also consider two types of incomplete trips in the second experiment, which indicate when there is insufficient charging of an EV. In the calculation of financial costs, we use the local municipal electricity tariffs [46] and the local regulated petrol prices [47], both for the year 2019. We use South Africa's electricity carbon rates for the CO₂ calculations, as shown in Table 3.1.

3.1.1. Perspective 1: EV owner with one vehicle

Our owner has one vehicle, which is either a petrol vehicle or an electric vehicle. This owner cares most about their personal expense and carbon footprint. Our metrics for this perspective are therefore the cost of either refuelling the petrol vehicle or charging the EV, and the resultant CO₂ emissions. We calculate the refuelling cost of a petrol vehicle using the distance travelled at an average fuel usage of 6.3L/100km and the prevailing petrol price [48].

It is the norm in developing countries to bill domestic electricity usage using a municipal meter that measures only aggregate energy used [49]. To penalize heavy users and help poor

users, the monthly billing uses an incline block tariff rather than the time-of-use typically used in developed countries. With this tariff structure the per-kWh rates¹ increase with the total monthly usage, with the final tier activating when the monthly usage surpasses 600 kWh. A study by Goliger and Cassim [50] demonstrated that South African households in the upper Living Standards Measure groups use more than 600 kWh each month, even without the additional load of an EV. In a developing country these households are likely to be the ones who will own EVs [51]. We therefore use only the highest rate of the incline block tariff to calculate the costs of charging an EV at home.

When charging at work, for our study, the EV owner pays the employer a fixed rate of 1.5 ZAR/kWh (0.094 USD/kWh). We chose this rate as being between the rate at which the grid supplier sells electricity and the rate at which it buys back electricity, benefiting both the employer and the employee.

We calculate the carbon emissions from charging at home from the grid using the total energy used and South Africa's average carbon intensity of electricity. Work charging causes emissions at the same rate; however, the energy considered is only what the EV absorbs from the grid. This means that losses in the inverting system incurred while charging at work do not contribute to the emissions in this perspective, and any solar energy used reduces them. To calculate the carbon emissions for a petrol vehicle, we use the amount of petrol used and the concomitant petrol CO₂ rate [52].

3.1.2. Perspective 2: Large employer with 1000 EVs and 1000 carports

The large employer (we have used the example of Stellenbosch University) cares most about its finances and its carbon footprint. The monthly electricity bill is determined mainly by the energy usage (kWh), the monthly peak demand (kVA), and the time-of-use (TOU) for each tariff period (kWh). Since the employer is defined as large, its usage has a consequential impact on the fragile grid. For the employer's perspective, we therefore consider the financial costs entailed, the carbon emissions, the energy usage and the monthly peak power demand for both experiments. The second experiment also looks at the energy output from the PV carports, along with taking into account failed trips and one-way trips. We evaluate these types of incomplete trips with the following metrics: the probability of an incomplete trip occurring, the daily number of EVs experiencing an incomplete trip and the amount of kWh associated to the trip. One-way trips also consider the carbon footprint corresponding to EVs charging at home.

Historic smart metered energy data from Stellenbosch University was overlaid with the simulated load from the 1000 EVs and the generation from the 1000 carports. The historic

¹Tariff Rates: <https://www.stellenbosch.gov.za/documents/finance/rates-and-tariffs/8176-tariff-book-2019-2020-1/>

data include the apparent power, power factor and real power in 30-minute intervals. This data was received initially grouped in individual smarter meter data sets. These data sets were first cleaned and then combined before being used with the simulated load. For the purpose of this project, data cleaning entailed removing major outliers and filling in any missing data entries. The reason for this is that using this data in its raw format can cause errors. One being unexpected results due to large, unrealistic outliers being present in some but not all the data sets. An example of these outliers is shown in Figure 3.2, with the apparent power reaching values in the magnitude of 20 million kVA. These major outliers when present in the data sets, are identified by the apparent power exceeding a set threshold. This threshold was chosen as 5000 kVA, which was based on being marginally larger than the values in the data set with the highest electricity consumption. Upon being identified, these entries were replaced with a corresponding mean value for that period. These mean values were calculated monthly for each data set, and provide averages for each field grouped in half hour increments. Replacing these type of outliers provides a clearer image of the data, and is shown in the example in Figure 3.3. The other likely problem when working with this raw data is missing entries, possibly leading to compiler failures. This can happen when attempting to combine the raw data, or when overlaying EV data on top of it. We addressed this by filling in any empty fields with the mean values described above. The data at this stage is cleaned sufficiently and can be seen in Figure 3.4.

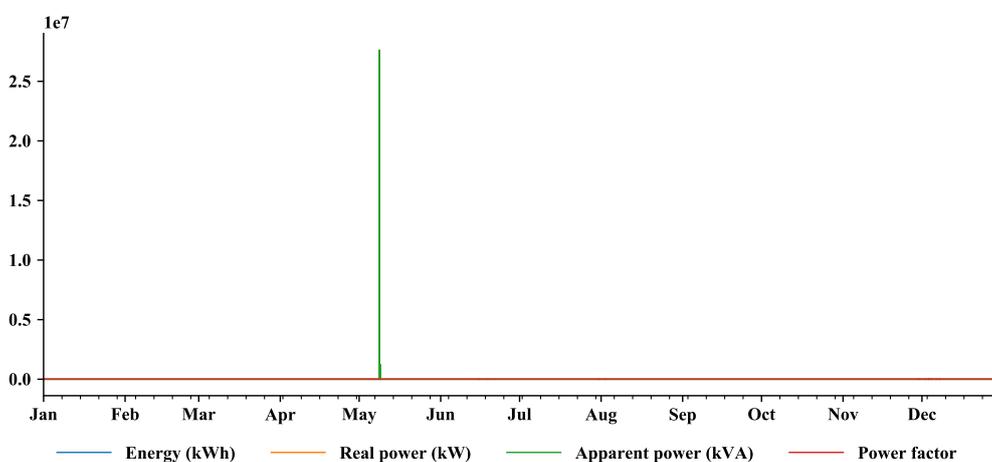


Figure 3.2: An illustration of a raw individual smart meter data set that still contains outliers.

The setup cost of the PV system and charging infrastructure are compared with the electricity bills and the income from selling electricity to charge employees' EVs. The cost of this system is calculated using a typical value of 14 ZAR/ W_{pk} (0.88 USD/ W_{pk}). We use an infrastructure cost of 15,008 ZAR (\$938) for each charger [53].

To reduce the impact on costs and also assist the grid, in our simulation EV chargers are disabled during the peak TOU hours of 6 am to 9 am in winter, which is from June to

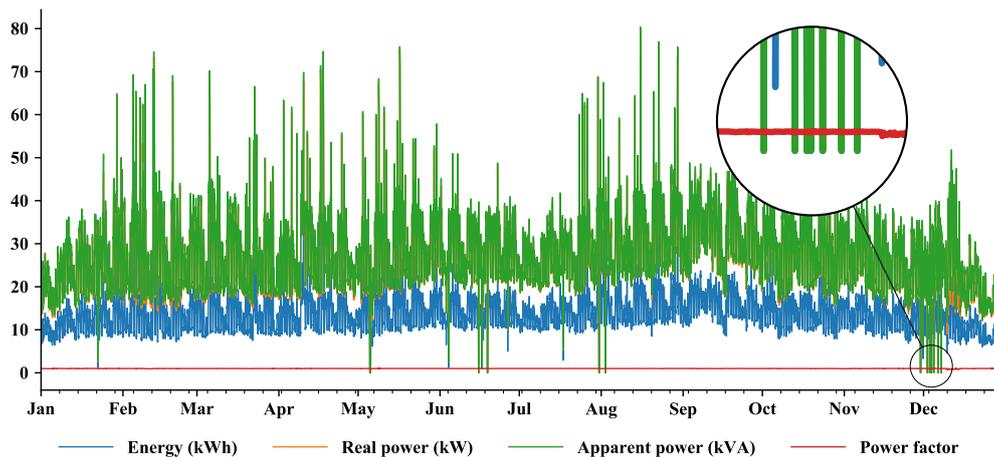


Figure 3.3: A representation of an individual smart meter data set after its unrealistic outliers have been removed.

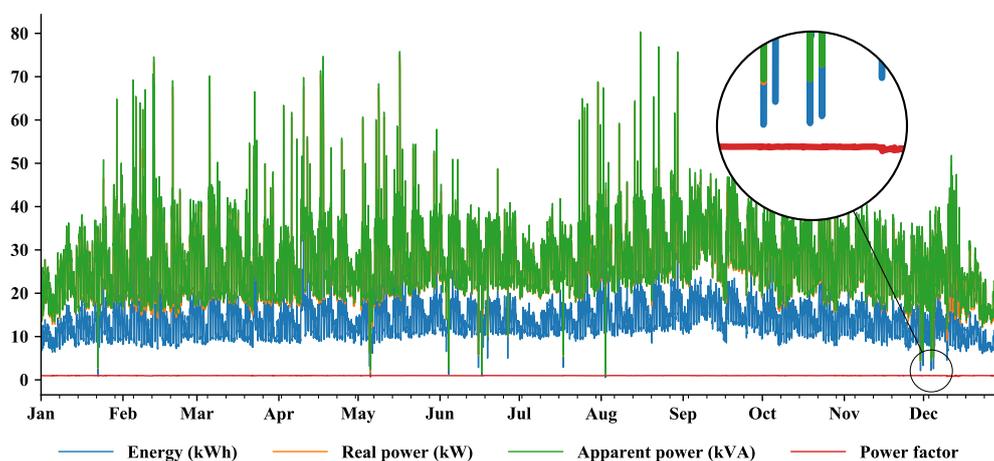


Figure 3.4: A depiction of an individual smart meter data set after its unrealistic outliers have been removed and empty entries are filled.

August in South Africa. This schedule also ensures that the EVs' charge cycle overlaps better with strong sunlight, as Stellenbosch during winter receives daylight from around 7:30am to 5:30pm.

The employer's carbon emissions are calculated according to the net energy used when compared to the status quo base case in the absence of EVs. We therefore consider the impact on the grid of the additional burden of charging EVs compensated by the supplementary generation of the PV carports.

We investigate failed and one-way trips for the second experiment. This is not a metric for the first experiment, since it doesn't make use of the controlled smart charging strategy which causes these incomplete trips. Both of these metrics are used to evaluate the effectiveness of the charging algorithm with the various limits imposed. We define a failed trip as an EV being unable to complete its trip back home due to insufficient

charge, whereas a one-way trip is when an EV cannot complete a round trip and requires home charging to have sufficient charge to travel back to work. If a failed trip occurs, we assume that the EV will be towed back to the employee's residence, where charging of the battery is resumed until it's charge allows the employee to travel back to work the following day. Similarly, we assume that if an employee is not able to complete a round trip, they will only charge their EV enough to make the trip back to work. We evaluate the likelihood of an incomplete trip occurring as the normalized daily probability for a single EV. We calculate this by comparing the total number of incomplete trips recorded for a fleet, to the maximum amount that can occur, which is normalized by dividing it with the fleet size. The daily number of EVs with incomplete trips, the associated kWhs, and their averages and percentages don't take into account days that only have complete trips.

3.1.3. Perspective 3: The constrained coal-dependent grid with 1 million EVs and carports

South Africa's state owned utility, Eskom, is at the focal point of our grid perspective. Eskom cares most about its energy usage (i.e. the need for electricity generation), the resultant emissions for legislative purposes, and the peak demand.

To assess the impact on the grid, we overlaid historic data from the Eskom generation plants with the simulated impact of EV charging for the 1 million vehicles and PV generation for the 1 million carports.

In the base case, only petrol vehicles are used, which is the effective status quo. For scenarios involving work charging of EVs, reduction of grid energy from PV systems is also taken into account. For the grid's perspective, we simulate a range of EVs on top of the historic data, to determine how many EVs are required to exceed Eskom's installed grid capacity. Achieving this is done by simulating each scenario with a fleet size ranging from 1 million to 8 million EVs in ten thousand increments. We do this by redesigning the original simulation so that it can simulate multiple fleets without supervision. The new simulation runs each iteration and stores them in separate columns inside a comma-separated values (CSV) file, as the amount of data generated is too large to store each iteration in memory. The data is broken up further by dividing it into smaller pieces by running the simulation in monthly intervals for a year, storing each month in a separate CSV file. Following this, each monthly CSV file is loaded into memory and processed. Processing this data entails comparing each entry to the installed capacity to determine if and where it surpasses the capacity.

3.2. Simulation setup

South African conditions were used to generate the EV mobility and charging data, and estimate solar energy potential data from solar PV carports. Figure 3.1 shows that the EV's mobility model travel distance affects the state-of-charge (SOC) of the EV's battery model, while the battery model records the total energy used when charging. The PV model's energy potential output reduces this total energy used, based on the charging strategy used. Chargers will make use of any available solar energy supplied by the carports before using energy from the grid. The charging strategies are investigated using the solar and EV data. The EV data also provide a way to compare EVs and petrol vehicles. The data are generated over a year with per-minute resolution.

The code used in generating the EV and PV data can be found at: <https://github.com/bureshkevin/EV-charging-in-SA>.

3.2.1. EV simulation

The EV simulation creates output data for an EV fleet of a specified size. The model steps are daily increments, discharging and charging each EV that is active. When EVs are set to be inactive, it results in no SOC changes. In our first experiment, EVs are set to be inactive during weekends and the Christmas holidays (December 20th - January 5th). During the South African school holidays (June 17th - July 8th) half of the EVs in a fleet are set to be inactive. These conditions are based on the first experiment's focus on workplace charging, and account for the reduction in vehicles traveling to work during the holidays. For the second experiment, EVs are only set to be inactive over weekends. This change allows one to compare months with ease, without having to take into account holidays, while still providing the option for them to be applied later by omitting those days.

When EVs are actively in use, discharging occurs for trips made between home and the workplace, resulting in two discharge periods a day per EV. Recharging takes place at home, at work, or at both, depending on the scenario. In the second experiment, EVs only charge at home when they cannot complete their trip back to work, and only charging until the point where the trip will be successful. Charging at home is done using a common fixed-power AC charger operating at 3.68 kW, while charging at work uses a proposed variable-power single-phase AC charger. The operating levels for the chargers are listed in Table 3.1. The charging process is assumed to be 85% efficient, which is typical for these levels of AC charging [54].

Two aspects of the EV are modelled: the battery and its mobility. The battery model is based on a second-generation Nissan Leaf, and contains the following important parameters:

Table 3.1: Parameters used in the simulation setup

Parameters	Value	Units	Source
Battery model			
Battery capacity	40	kW h	[55]
Travel range	240	km	[55]
Energy consumption, E_{cons}	16.6	kWh/100 km	[55]
Low charging power, P_l	3.68	kW	
High charging power, P_h	6.67	kW	
Mobility model - Gaussian			
Work arrival time			
Mean, μ	0	min	
Standard deviation, σ	7.5	min	
Work departure time			
Mean, μ	0	min	
Standard deviation, σ	7.5	min	
Distance			
Mean, μ	30	km	
Standard deviation, σ	10	km	
Carbon emissions			
Carbon intensity of electricity	954	kg CO ₂ /MWh	[56]
Carbon intensity of petrol	2.3	kg CO ₂ /L	[52]
PV modules			
Maximum power	330	W _{pk}	[57]
Max voltage	37.2	V	[57]
Max current	8.88	A	[57]
Open circuit voltage	45.6	V	[57]
Short circuit current	9.54	A	[57]
Tilt angle	15	°	
Azimuth	0	°	
Inverter			
Maximum usable DC power	4200	W	[58]
Maximum AC output power	4000	W	[58]
CEC efficiency	97	%	[58]

capacity, SOC, range, energy consumption and charging power levels. These parameters are specified in Table 3.1.

The mobility model is derived from a recent survey of the distance Stellenbosch University staff travel to campus. This model consists of a departure and arrival time, the distance covered and the time it takes to complete the trip. Each vehicle's travel distance is randomly sampled from a Gaussian distribution of the survey responses. They are initialized once at the beginning of testing each perspective to ensure consistency when comparing scenarios. This distribution consisting of 5000 samples, is portrayed in Figure 3.5. An average work day of eight hours, from 8 am to 4 pm, serves as a basis for the departure and arrival time means. Each trip's departure and arrival time are randomly sampled from a Gaussian distribution around the mean arrival and departure times. This sampling, unlike the travel distance, is done in daily steps. Both of these distributions are shown with histogram plots provided in Figure 3.6 and Figure 3.7 respectively. The travel time is calculated from the travel distance and an average speed of 60 km/h.

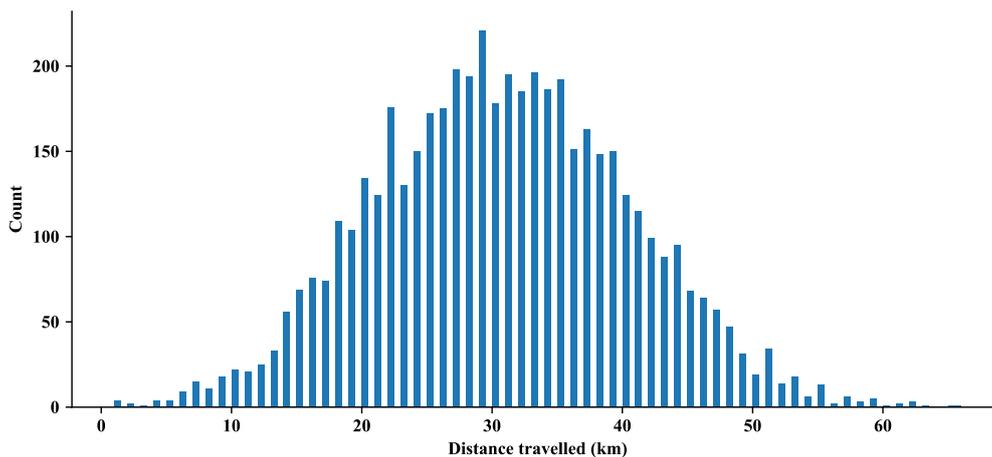


Figure 3.5: Histogram of the travel distance distribution for the mobility model

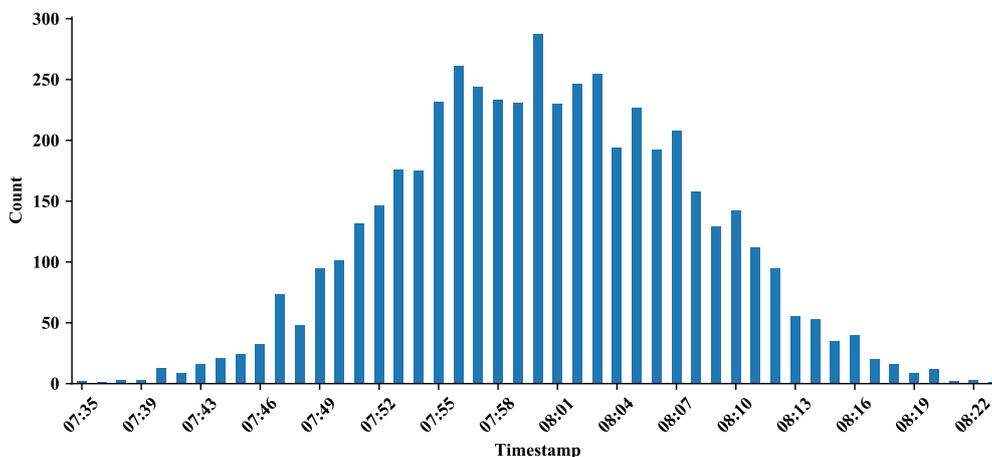


Figure 3.6: Histogram of the work arrival distribution for the mobility model

The battery discharge depends on the distance travelled, while the charge depends on the time until travel and the battery's SOC.

Our proposed work-place variable power charger is designed to operate in two different configurations, namely uncontrolled work charging and controlled smart charging. These configurations aim to achieve different goals which we base on the two experiments explored by this project. The first experiment utilizes uncontrolled work charging, in which the consumers are catered to with their EVs always departing with a full charge. The second uses controlled smart charging, which ensures that a set peak demand limit is never exceeded while maximizing the charging of EVs.

Uncontrolled work charging

This configuration of the work-place variable power charger is geared towards the consumer and can come at a cost to the employer. Mainly, a service provider or employer may see large peak demands ensuing a higher electric bill or placing strain on a network. In this

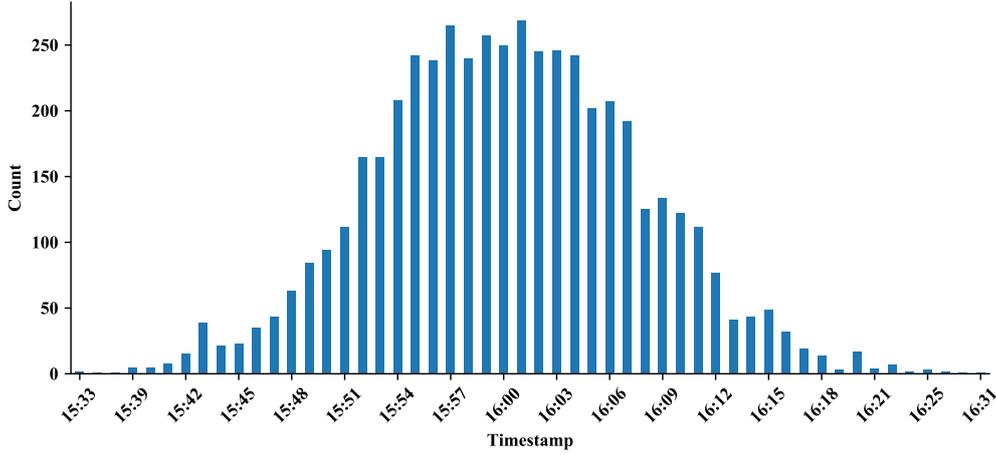


Figure 3.7: Histogram of the work departure distribution for the mobility model

configuration, the charger adapts its power delivery according to the EV battery's SOC and the amount of time remaining in the employer's car park. The combination of these two provides a measure of charge urgency. If an EV's SOC is below 30% and it cannot fully charge at work from the lower power level, the charger will operate at a higher power level for as long as necessary before reducing the power to ensure a charged vehicle is able to leave the car park for its journey home. The length of time an EV will charge at the respective power levels is calculated by

$$T_h = ((B_f - B_{\text{SOC}}) - P_l \times T_p) / (P_h - P_l) \quad (3.1)$$

$$T_l = T_p - T_h \quad (3.2)$$

where B_f is the full capacity of the battery, B_{SOC} is the current SOC, P_h is the high power charging level, P_l is the low power charging level, T_p is the duration that an EV is parked, T_h is the duration charging at P_h , and T_l is the duration charging at P_l .

Controlled smart charging

The controlled smart charging configuration is ideal for an employer, although it can have a negative impact on consumers wanting to charge their EVs at work. It can prevent their EVs from charging fully or even sufficiently for the upcoming trips if there is insufficient charging availability. This availability is dependent on the level of restriction imposed by the employer and other various factors, such as the monthly solar insolation or the number of EVs charging. This charger configuration operates on a priority system, charging EVs based on their urgency. EVs being charged, and their level of charging depends on their priority and the amount of available energy. Initially, all chargers are set to charge at the lower power level.

The system governing the network of EV chargers first determines the amount of available energy by summing the PV energy produced by the carports with the demand limit. We describe this limit in kilowatts per vehicle for simple scalability, however, its operation is implemented across the entire fleet. EVs with batteries that are not full and are still in the car park will transmit requests to charge. These requests are evaluated in terms of their urgency, which is weighted against the other EVs requesting to charge. The urgency of each of these requests is determined by a cost function, making use of the time until departure and the time required to charge the essential amount, as shown in

$$R = T_{ECA} - T_r + P_{dr} \quad (3.3)$$

where R represents a numerical value for the urgency, T_{ECA} represents the essential charge amount time, T_r represents the remaining time that an EV is parked, and P_{dr} represents the indication of a EV requiring charging with the higher power level. An EV requires the higher charging level when the essential charge amount time is larger than the remaining parked time. The essential charge amount time is the required charging duration to ensure that an EV's SOC is enough to make a round trip, where a round trip consists of an EV travelling home and back again to work. This duration and round trip is calculated by

$$T_{ECA} = E_{ECA}/P_l \quad (3.4)$$

$$E_{ECA} = E_{trips} - B_{SOC} \quad (3.5)$$

$$E_{trips} = D_t \times E_{cons} \times (n_{trips}) \quad (3.6)$$

where T_{ECA} is the essential charge amount time, E_{ECA} is the essential charge amount, P_l is the low power charger level, E_{trips} is the energy used in completing a round trip, B_{SOC} is the current SOC, D_t is the travel distance, E_{cons} is the energy consumption of the EV and n_{trips} is the number of trips considered essential. When charging at work, the number of trips considered essential is two, while if an EV has to charge at home, this number will be set equal to one. The system after calculating the priority for each EV parked then performs a cumulative sum of all the chargers requesting to be active, in the order of their urgency. It then compares this cumulative sum to the amount of available energy. Chargers with the highest priority will be made active up until the max threshold is reached. In the case that the cumulative sum does not exceed the amount of available energy, the system will calculate how many EVs can charge at the higher power level without exceeding the limit. EVs with the highest priority will be charged at the higher power level. A cumulative sum is performed and compared against the peak demand limit. At this stage, the system will allow all the requested chargers to be active.

3.2.2. Solar PV simulation

The solar PV generation is modelled with pvlib Python, which uses historic weather data to simulate the generated AC output power. pvlib Python was ported from PVLlib MATLAB [59], which was developed by Sandia National Laboratories (Sandia) as an open source PV modelling environment [60]. We used per-minute weather data from a South African weather station ² that includes solar radiation, wind speed and ambient temperature for a year. The Sandia PV Array Performance Model calculates the cell and module temperature, which provides a more accurate PV model, as the PV modules' performance is largely affected by temperature [61]. We use the six-parameter single-diode model developed by the California Energy Commission [62] to calculate the module's DC output. The Sandia Inverter model simulates the AC power conversion by using King's empirical model [63].

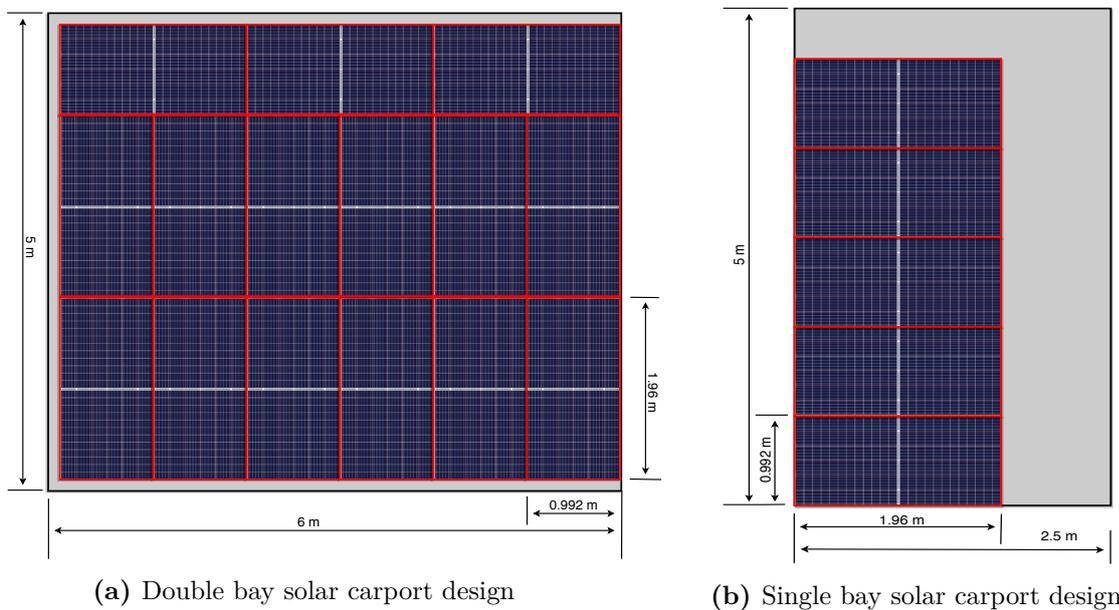


Figure 3.8: Two solar PV carport designs providing shade for one or two EVs.

The simulation requires the number of EVs in the investigated fleet as an input. Based on this input, it calculates the number of PV modules and inverters used. This number is determined by allocating a ratio of five PV modules to one carport, and a maximum of two carports to one inverter. A ratio of five PV modules to a single carport was decided after investigating two different options. Both options, shown in Figure 3.8, take into account the size of the PV modules chosen along with the average size of a parking space being between 12 to 15 m² [43, 45]. The first design, shown in Figure 3.8a, considers a carport design for two vehicles that is 6 m wide by 5 m long, allocating 15 m² per parking space. This design can fit up to 15 PV modules in total over two parking spaces with minimal space wasted, creating a ratio of 7.5 PV modules to a single carport. The first design makes

²Stellenbosch Weather Station: <http://weather.sun.ac.za/>

use of almost all the roof space but can lead to higher overhead costs due to the use of more PV modules. To reduce the cost of the PV system by reducing the overall size, while being capable of sufficiently reducing grid energy consumption when charging, the second option is explored. Figure 3.8b shows this second option. It is designed as a modular single bay carport with dimensions of 2.5 m x 5 m for a total of 12.5 m². This design adheres to the standard parking space mentioned above, while housing 5 PV modules per parking space. The PV module and inverter manufacturer specifications used are listed in Table 3.1.

3.3. Chapter summary

This chapter discusses the perspectives pertaining to the experimental setup, along with the simulation structure expanding on each of its models. The first section describes the three perspectives proposed for the experiments with their relevant details. Each perspective explains the charging scenarios tested and the metrics used in their evaluation. Also, the second perspective describes the procedure taken to clean an incomplete dataset important for the relevant experiments, and the third perspective describes the new simulation design to determine the number of EVs to exceed the grid's installed capacity. The second section explains in detail the EV and PV simulation. The EV simulation starts with describing the designed mobility and battery model and ends with a detailed description of the charging types. It is in this section that the uncontrolled work and controlled smart charging strategy are presented. Following the EV simulation, the PV simulation explains the procedure taken, along with the design choices and relevant parameters.

CHAPTER 4

RESULTS

This chapter presents the findings from both experiments with their corresponding metrics described in Chapter 3. The first section discusses the results of uncontrolled charging compared to ICE vehicles. In the following section, the controlled smart charging strategy applied to multiple scenarios is evaluated against a base case of the uncontrolled work-only scenario.

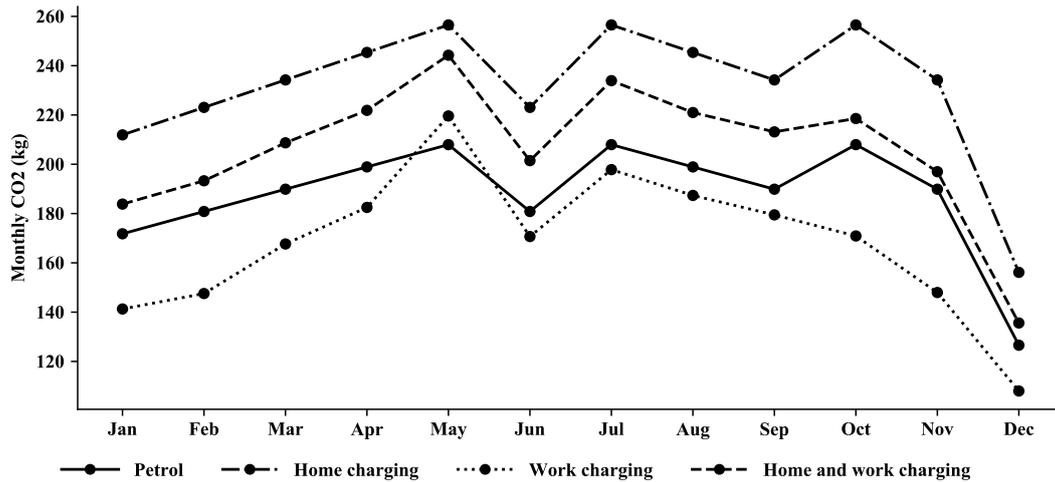
4.1. Uncontrolled charging

This section examines the results from the first experiment, which investigates the uncontrolled charging from the three perspectives discussed in Chapter 3. When discussing the uncontrolled charging scenarios throughout this section, the term uncontrolled is omitted as a simplification as this section does not contain the controlled smart charging strategy discussed in Section 4.2. It is an excerpt from the following journal article: Three shades of green: Perspectives on at-work charging of electric vehicles using photovoltaic carports.

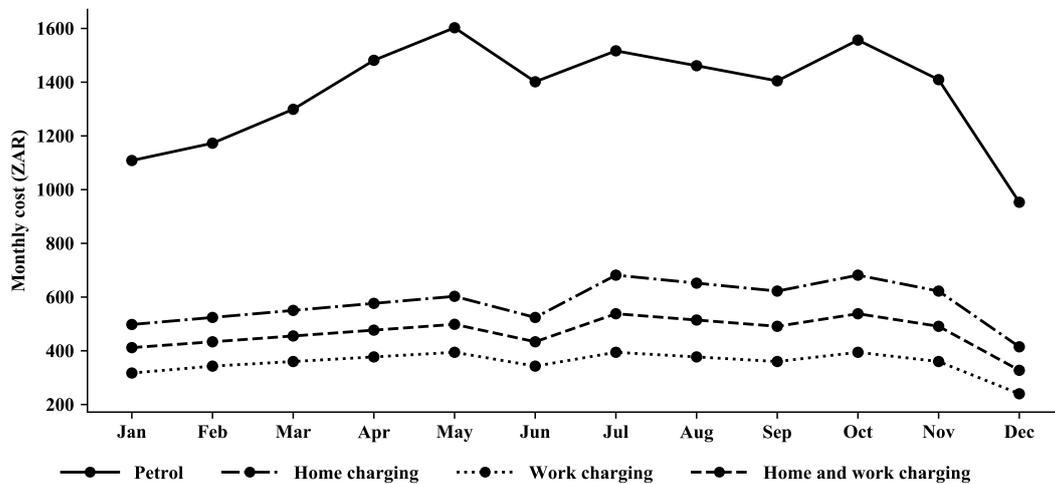
4.1.1. Perspective 1: EV owner with one vehicle

Figure 4.1 shows the owner's perspective for each month of the year. These results are presented in absolute terms, to enable comparison with the petrol vehicle scenario. Figure 4.1a shows the carbon footprint in kg per month for the four scenarios, directly reflecting the energy used in each. We find that switching from a petrol vehicle to a charge-at-home EV substantially increases the owner's CO₂ footprint. This startling finding is due to the coal dependent electricity generation in South Africa. This result can be rationalized by considering a simple example. Compare a Volkswagen Polo that gets 6.3 L/100km to a Nissan Leaf which gets 16.6 kWh/100 km. Assuming both vehicle travel 100km and we utilize the emission intensity rates provided in Table 3.1 (2.3 kg CO₂/L and 954 kg CO₂/MWh), the Polo would generate 14.49 kg of CO₂ whereas the Leaf would generate 15.84 kg. The yearly aggregate, shown in Table 4.1, is a 23% increase, from 2251 to 2777 kg CO₂ per year. In fact, this is also the case for charging at both work and home, which results an annual increase of 10% despite the presence of PV augmentation at the workplace. It is only when work-place only charging is used that the carbon footprint

reduces by 11% due to the high PV augmentation. The only exception is the month of May, during which charging only at work results in a slightly higher footprint than that of using a petrol vehicle - 220 kg versus 208 kg. This occurs in May because of the PV energy generated during this month's charging hours is significantly less than the others. Thereby, requiring more grid energy in to charge the EV (expanded on in Section 4.2.2). It is, however, trivial to avoid this exception by also including May in the winter charging schedule.



(a) Monthly carbon footprint



(b) Financial costs per year

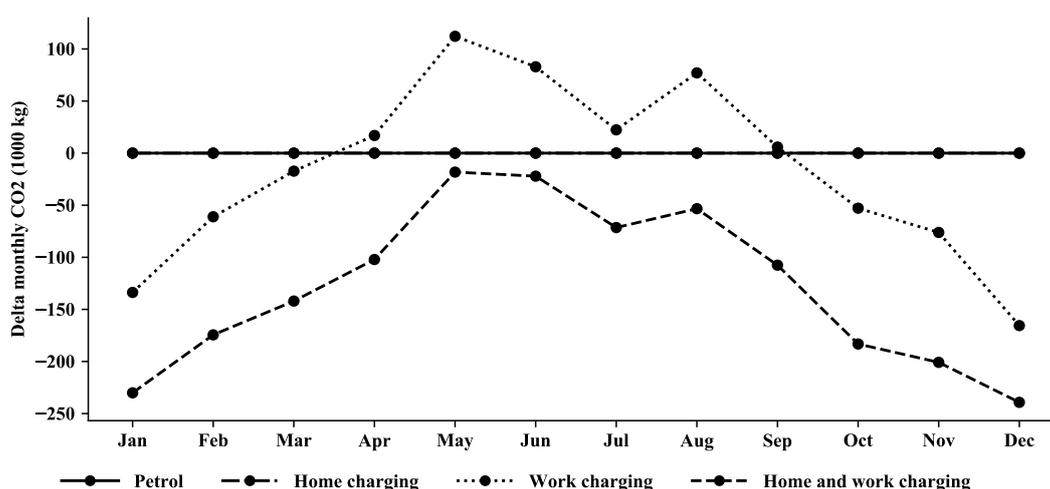
Figure 4.1: A visualisation of the impacts of a petrol and EV vehicle from a vehicle owner's perspective.

Figure 4.1b shows the resulting financial impact on the owner for the same period. It is clearly more expensive to refuel a petrol vehicle than to charge an EV, and it is cheaper to charge an EV at work than at home. This is why charging at both work and home is the second cheapest option. It can be concluded, from both carbon footprint and financial aspects, that charging an EV only at work is by far the best option.

Note that energy plots are not explicitly shown for the three perspectives, as they are equivalent to the carbon footprint plots provided, with the exception that petrol vehicles do not contribute to any electrical energy usage.

4.1.2. Perspective 2: Large employer with 1000 EVs and 1000 carports

Figure 4.2 presents the results from an employer perspective for the four scenarios. These results are provided relative to the baseline case, since the absolute results will differ for each employer. Figure 4.2a shows the difference in carbon footprint from the measured baseline of the employer's buildings. There is no impact from the employer's perspective for either petrol vehicles (the baseline case and status quo) or EVs charging only at home. EVs charging only at work with augmented solar generation produce resultant negative CO₂ emissions for the sunny months of the year, September to March. When these EVs are allowed to also charge at home, the resulting carbon footprint is negative throughout the entire year. This is because EVs charging at both locations will charge less at work, allowing more of the energy generated from the PV system to be fed back into the buildings and reducing the employer's overall grid energy usage. The results in Table 4.1 show that both scenarios on a yearly aggregate are net negative, with the combined work-and-home charging scenario producing a reduction of 1.5 million kg of CO₂. In terms of the employer's carbon footprint, EVs that also charge at home are the best option.

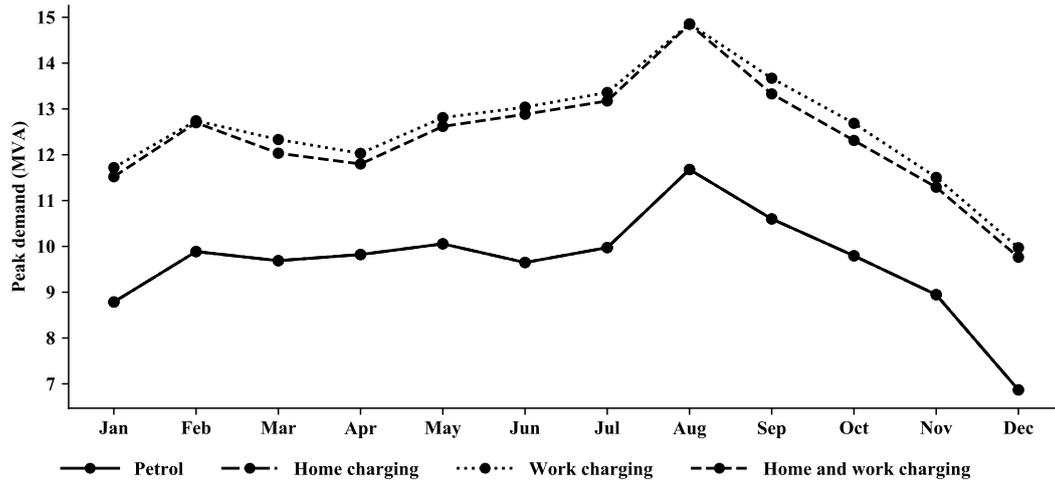


(a) Monthly carbon footprint

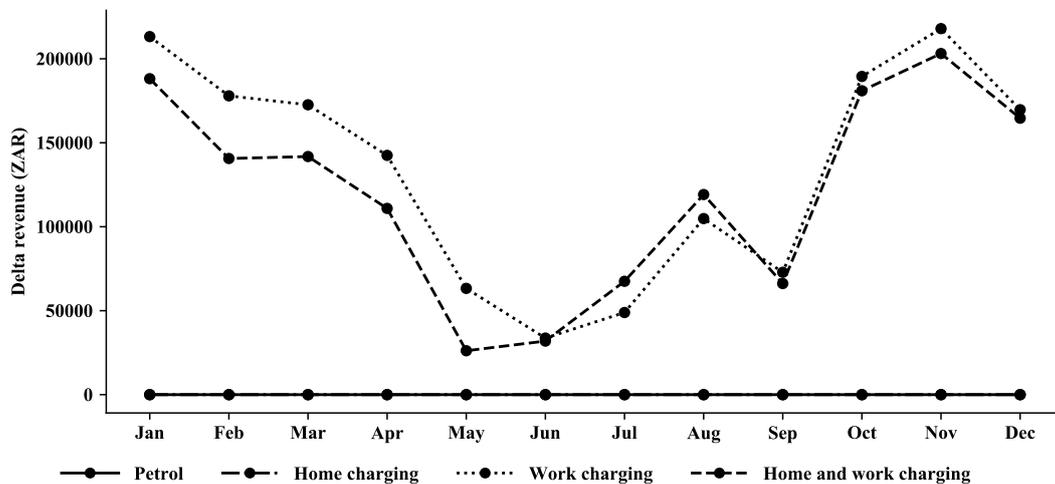
Figure 4.2: An illustration of the impacts of work and work-and-home charging from the perspective of an employer.

Figure 4.2b shows the historic monthly peak demands ("Petrol" & "Home charging") and the new peak demands from the charging scenarios. When EVs also charge at home, the

4.1. Uncontrolled charging



(b) Monthly peak demand



(c) Annual change in revenue

Figure 4.2: (continued)

monthly peak demand is smaller than that for EVs charging only at work. The difference between the two new peaks is in the order of a few hundred kVA. For an employer wanting to provide EV charging but concerned about the peak demand increasing, work-and-home EV charging is the best fitting scenario. Figure 4.2c shows the financial impact on the employer. The employer is able to make a larger net revenue from EV owners charging only at work, with the exception of the months of July and August. As shown in the figure, the profit from work-and-home EV charging follows the work-only charging. The yearly aggregate results in Table 4.1 show that charging EVs only at work yields 12% more revenue.

Table 4.1: Simulation results in yearly aggregates

Perspective	Metrics	Petrol	Home	Work	Work & home	Unit
Owner (absolute)	CO ₂	2,251	2,777	2,021	2,472	kg
	costs	16,368	6,951	4,262	5,611	ZAR
Employer (relative)	CO ₂	0	0	-189,000	-1,545,000	kg
	revenue	0	0	1,607,000	1,441,000	ZAR
Grid (absolute)	CO ₂	2,209,642	2,725,665	-185,422	-179,743	10 ³ kg

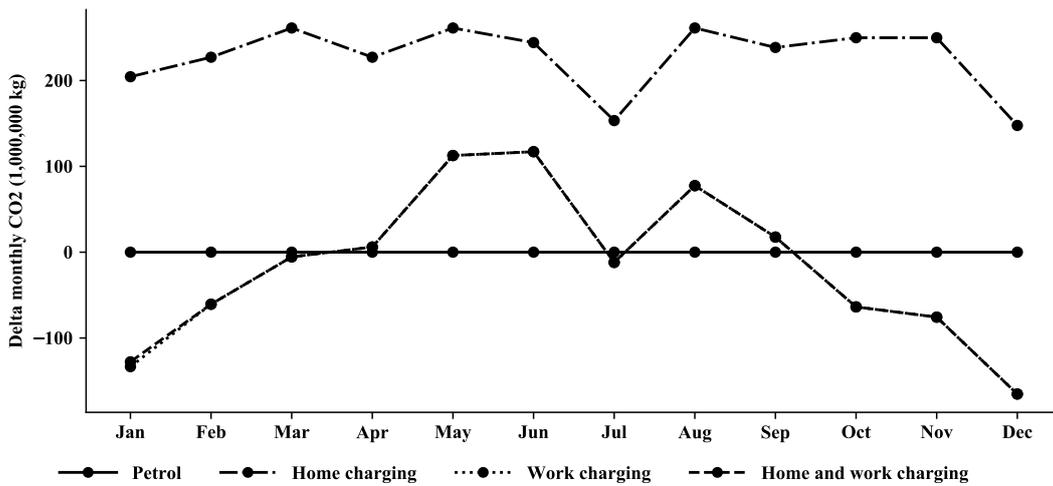
4.1.3. Perspective 3: The constrained coal-dependent grid with 1 million EVs and 1 million carports

Figure 4.3 shows the impact from the grid’s perspective. These results are presented as absolutes. Figure 4.3a shows the grid’s carbon footprint and demonstrates that charging EVs at home produces the biggest carbon footprint, while both work-only and work-and-home charging produces the smallest. This is because we consider that all the energy produced from the PV carports will reduce the total grid energy required.

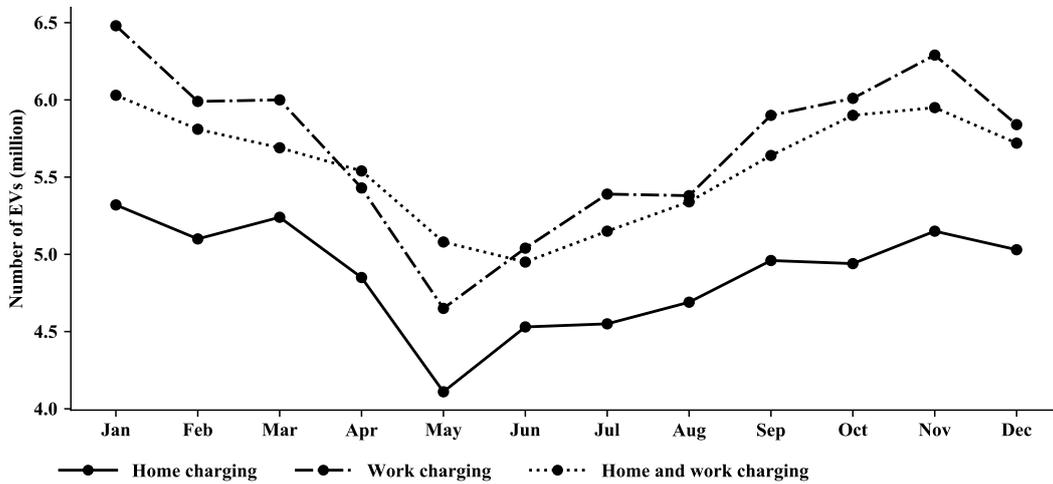
Figure 4.3b shows the number of EVs required to exceed the grid’s capacity in the different EV charging scenarios. This is especially important, given South Africa’s fragile utility. The grid’s capacity is exceeded with the addition of 4.11 million vehicles (an estimated 37% of the total fleet) charging only at home in May. It takes 5.32 million vehicles charging only at home to exceed the grid capacity in this scenario’s best-case month of January (which happens to be when Eskom resumed load shedding in 2020, even with virtually no electric vehicles in the country). Work-and-home charging performs slightly better - it takes 4.65 million and 6.48 million vehicles to break the grid in May and January respectively. In the best-case scenario, charging only at work, the grid can sustain between 4.95 million and 6.03 million vehicles throughout the year.

Figure 4.3c and Figure 4.3d show daily demand profiles for a summer and a winter month respectively. A morning and an evening peak are apparent above the historic profile. The morning peaks in these plots are from the work-only and work-and-home-charging scenarios, while the evening peaks are associated with the home-only charging scenarios. As shown in these figures, work-and-home EV charging contributes to both peaks; however, the duration of these peaks is much shorter than those in the other scenarios. Figure 4.3d shows how, in the winter based charging schedule used to avoid peak times, EVs begin charging only after 9am. Home-only EV charging contributes to the largest overall demand in a day, which is in the evening. The morning peak that occurs in both months is followed by a dip, which is a result of the energy supplied by the PV systems. This dip reveals an opportunity to balance EV charging across the day by spreading out their charging towards the afternoon, to make use of as much available PV energy as possible, and reduce these morning peaks further.

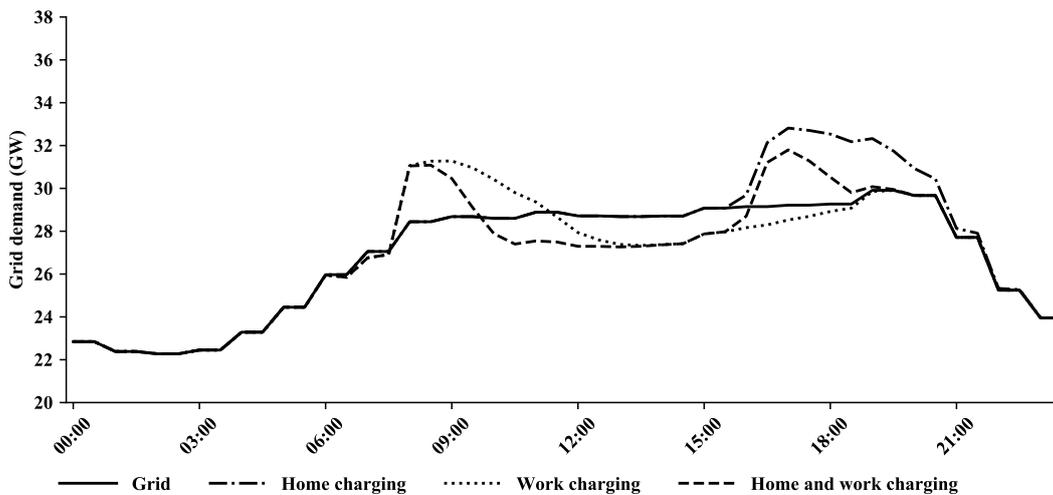
4.1. Uncontrolled charging



(a) Monthly carbon footprint



(b) EVs required to exceed the grid's capacity



(c) January daily profile

Figure 4.3: A depiction of the impacts of uncontrolled charging from the grid perspective.



(d) June daily profile

Figure 4.3: (continued)

4.1.4. Summary

These results show that from a vehicle owner's perspective it is significantly more expensive to refuel a petrol vehicle than it is to charge an electric vehicle, and that electric vehicle owners are able to save the most by charging their vehicles at work. For South Africa, carbon emissions from charging the vehicles increase beyond those of a petrol vehicle in almost every case, except when the vehicles are charged solely at work, making the most use of solar energy.

From the employer's perspective, at-work charging scenarios have an annual net positive revenue and a negative carbon impact. The financial benefit is larger when employees charge only at work. The overall carbon emission footprint is smaller when employees also charge vehicles at home, as less charging takes place at work, allowing excess solar energy to be fed back into the building.

As in the other two perspectives, the grid is put under the most pressure from electric vehicles charging only at home. The carbon footprint is higher, and the energy capacity of the grid is exceeded with the addition of 4.11 million of these vehicles. The projected daily demand profile shows a morning peak when vehicles are charged at work and an evening peak when they are charged at home. When the vehicles are charged at home and at work, the duration of the peaks is shorter. These findings suggest the need to investigate how to balance electric vehicle charging times further and reduce these peaks.

4.2. Controlled smart charging

This section presents the results from the second experiment. It serves as a comparison of the controlled smart charging strategy explained in Section 3.2.1, with various load

limits applied against the uncontrolled work-only charging strategy. In this experiment, we consider the following controlled load limits: 0.5, 0.65, 0.8 and 0.95 kW/EV. These load limits are much lower than the load from uncontrolled charging, which can either be 3.68 or 6.67 kW/EV. The results are split into two parts; (1) incomplete trips, and (2) metrics previously considered for a large employer with 1000 EVs and 1000 carports.

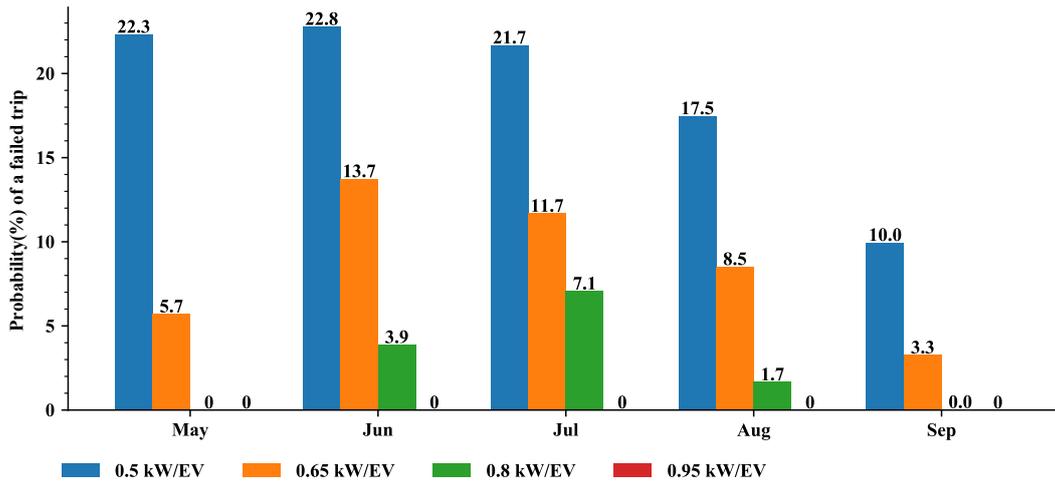
4.2.1. Incomplete trips

Figure 4.4 and Figure 4.5 present the failed and one-way trips recorded by the simulation respectively. Only months from May to September are shown, as there were no incomplete trips in the other months. This is due to these trips being largely impacted by the amount of solar energy available, and occur more frequently in months with less sunshine. Both figures exclude the uncontrolled charging strategy, as it always fully charges vehicles thereby never having failed or one-way trips. It serves as a baseline, like petrol vehicles in Section 4.1.

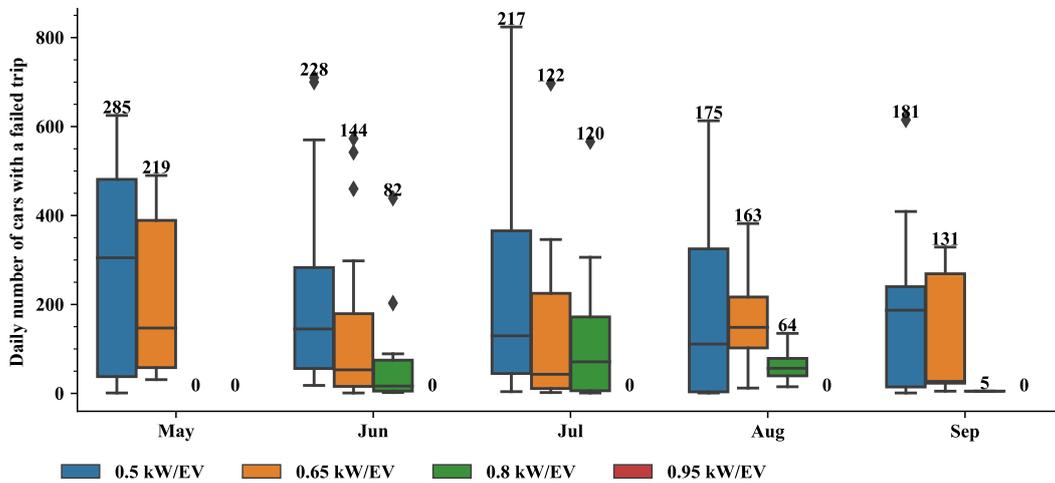
Figure 4.4a shows the probability of an EV trip failing for the various charging limits. As seen in the figure, as the load limit increases the probability of failed trips decreases. The daily probability peaks at 22.8% in June when a 0.5 kW/EV charging limit is applied, whereas for the 0.65 kW/EV limit the June peak is found to be 13.7%. Increasing the limit to 0.8 kW/EV results in significant reductions, such as a maximum probability of 7.1% and a probability of less than 0% for the months of May and September. The 0.95 kW/EV charging limit has the best results, maintaining a 0% probability of failed trips throughout the year.

The distribution of EVs in the fleet with failed trips can be seen in Figure 4.4b. A monthly average of the number of failed trips in the fleet is also plotted on the figure. Similarly to the trend seen in the failed trips probability plot, the daily number of EVs experiencing failed trips decreases significantly as the load limit increases. On the worst day in July, the number of EVs that couldn't complete their journey decreases from 824 to 346 when the limit increases from 0.5 to 0.65 kW/EV. Increasing the limit to 0.8 kW/EV reduces the average number of failed trips significantly, with the largest reduction seen in May and September with as little as 0 and 5 trips respectively. As expected, there are no failed trips when applying the 0.95 kW/EV limit.

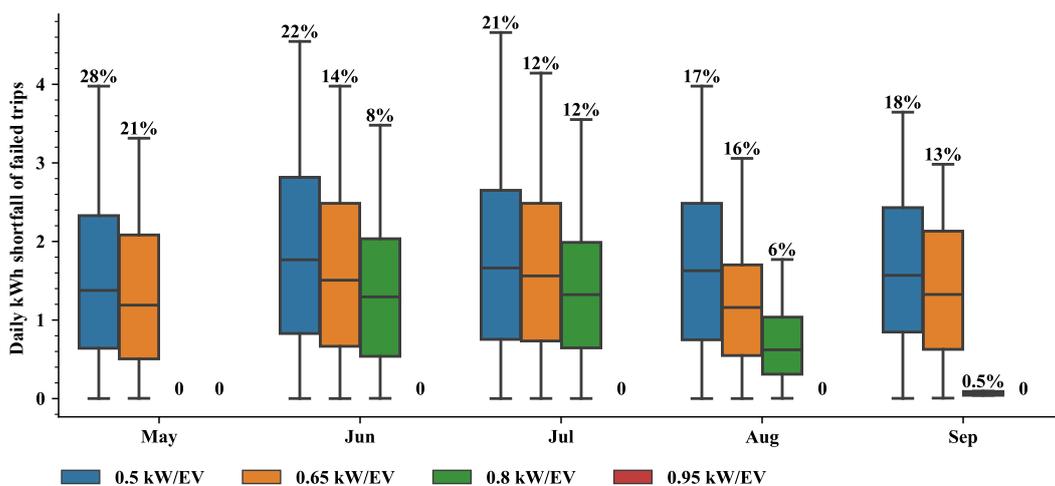
Figure 4.4c shows the kWh shortfall of the trips shown in Figure 4.4b, along with an average percentage of the number of failed trips in the fleet. A 0.5 kW/EV charging limit results in less than a quarter (21.7%) of the fleet having incomplete trips on days with failed trips. These trips failed because batteries were not sufficiently charged, on average they lacked between 0.75 to 2.55 kWh. As the charging limit is increased the kWh shortfall is reduced. Notably, the 0.8 kW/EV limit leads to a smaller kWh shortfall ranging from 0.5 to 1.9 kWh, whereas the 0.95 kW/EV limit has no shortfall.



(a) Probability of a failed trip



(b) Distribution of cars with a failed trip and the monthly average of the failed trips numerically expressed above each whisker



(c) Distribution of shortfall (kWh) and the percentage of failed trips numerically expressed above each whisker

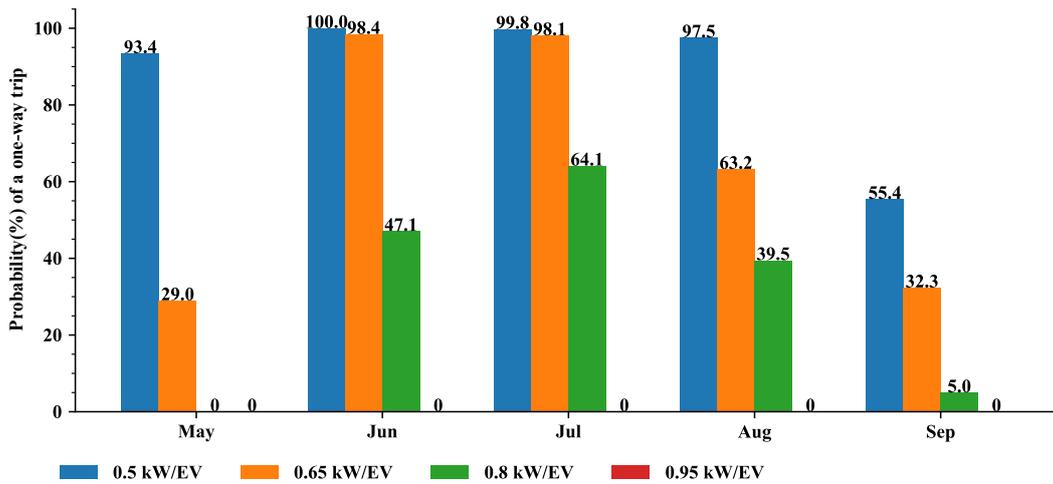
Figure 4.4: An illustration of the failed trips experienced by a fleet of 1000 EVs due to insufficient charging.

Figure 4.5a shows the probability of a EV requiring home charging. EVs charge at home if they cannot successfully complete the next trip to work with their current SOC. The probability of this happening decreases as the charging limit is eased and allows EVs to charge more at work. A higher probability is seen in the winter months as solar energy generation decreases. A strict charging limit of 0.5 kW/EV almost guarantees that EVs will require daily home charging from May to August, whereas in September the probability of it drops close to 50%. This large drop in September also occurs for the other limits. Aside from September, advantages from increasing the limit to 0.65 kW/EV are easily noticeable in May and August, with a probability decrease of 64.4 and 34.3% respectively. Applying the increased limit of 0.8 kW/EV has a positive affect seen across all months, with the best case being no EVs making use of home charging during the month of May. As it is seen with the dead event occurrence, the 0.95 kW/EV charging limit allows EVs to sufficiently charge at work throughout the year, removing the necessity for home charging.

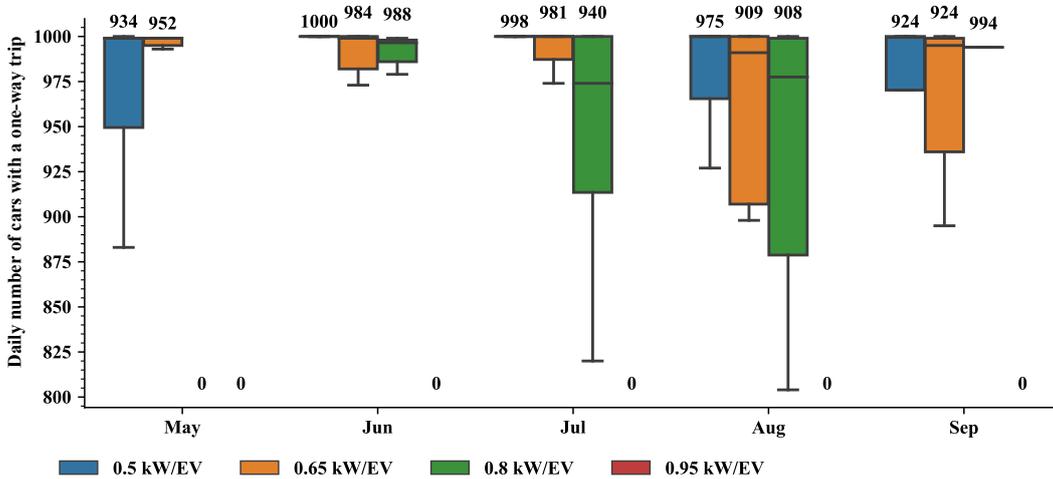
Figure 4.5b shows the distribution of EVs in the fleet only able to make a one-way trip for the recorded days, and the average per month. The distribution of EVs not being able to complete a round trip ranges from 800 to 1000 EVs, showing that when a one-way trip occurs it occurs for the majority of the fleet. A charging limit of 0.8 kW/EV has a larger variation than the stricter limits, specifically in July and August. In this case a larger variation is a good thing, as it shows that for a portion of those recorded days there is a reduction of one-way trips.

Figure 4.5c shows the distribution of home energy used in kWh for the trips shown in Figure 4.5b, along with the average percentage of EVs with a SOC only capable of making a one-way trip. When limiting charging at work to 0.5 kW/EV, EVs require significantly more charging at home, with some requiring more than 8 kWh. As charging restrictions are eased, the amount of home charging decreases greatly. EVs on average charge between 0.5 to 1.6 kWh less at home when the work charging limit increases from 0.5 to 0.8 kW/EV.

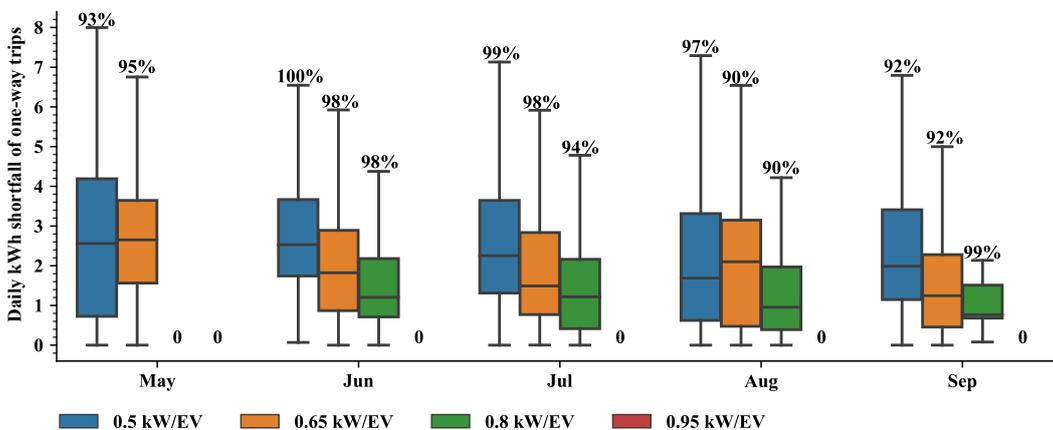
Figure 4.5d shows for the relevant months, the monthly average carbon footprint of an EV charging at home due to a SOC to low to complete a round trip, directly reflecting the amount of energy used at home per vehicle. As previously seen above, home charging which only begins at 0.8 kW/EV, increases the more work charging is limited, thereby also leading to increased CO₂ emissions attached to the EV owner. EVs with work charging limited to 0.8 kW/EV have home charging associated emissions from June to August, with minimal emissions in September. The stricter charging limits have notably higher emissions and begin as early as May. Yearly aggregates of these emissions are in Table 4.2. They reveal that an EV owner's carbon footprint increases by 63% when a charging restriction increases from 0.8 to 0.65 kW/EV.



(a) Probability of an EV requiring home charging to complete a round trip

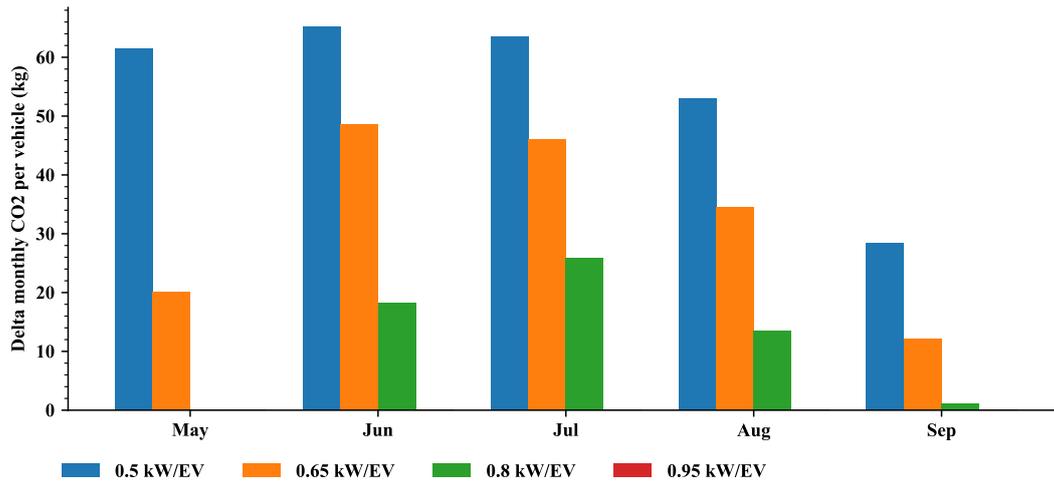


(b) Distribution of cars charging at home to be able to travel to work and the average occurrence numerically expressed above each whisker



(c) Distribution of amount charged (kWh) and the percentage of EVs home charging numerically expressed above each whisker

Figure 4.5: A visualisation of the required home charging for a fleet of 1000 EVs to complete a round trip.



(d) Carbon footprint of home charging

Figure 4.5: (continued)

4.2.2. Large employer with 1000 EVs and 1000 carports

Figure 4.6 and Figure 4.7 present the findings of the charging strategies from the perspective of an employer. These findings are measured relative to the employer's previous electricity consumption.

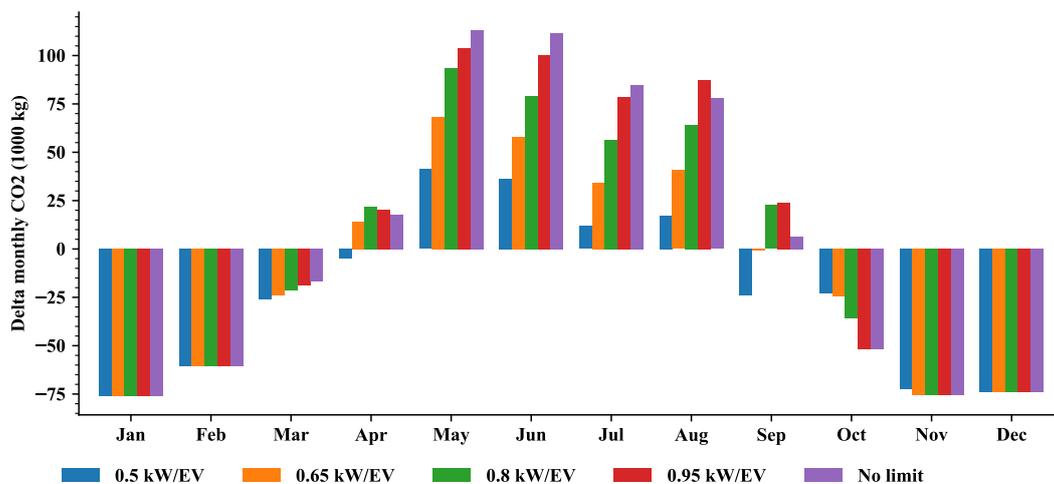
Figure 4.6a portrays the carbon footprint for the employer with the various charging limits applied. The carbon footprint is largely impacted by the PV output. This is shown by the sunny months of the year having negative emissions. On months with more sunshine, namely October to March, the strategies perform similarly. It's in and around the winter months, specifically May to August, that the large differences are seen. A trend seen throughout the year is that as the charging limit becomes more restrictive, the amount of CO₂ increases. It's also seen that the 0.95 kW/EV charging limit performs similarly to the no limit work-only charging strategy. None of the strategies are able to have a continuously negative impact for each month of the year. However if one looks at the yearly CO₂ totals found in Table 4.2, charging strategy restrictions of 0.8 kW/EV and higher result in a net negative. A 0.5 kW/EV charging limit has by the most reductions in CO₂ emissions, which is twice as much as the 0.65 kW/EV limit.

Table 4.2: Smart charging simulation results in yearly aggregates

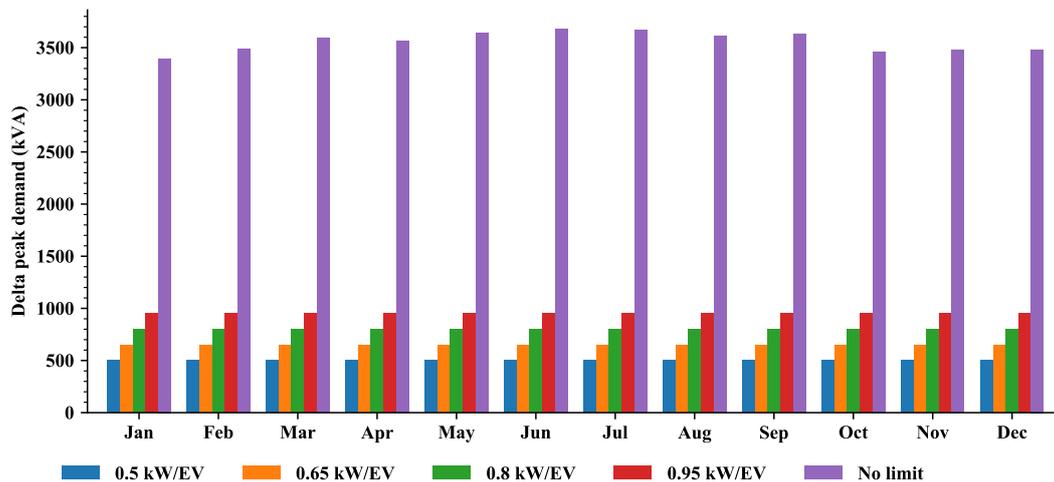
Metrics	Charging limit (kW/EV)					Unit
	0.5	0.65	0.8	0.95	None	
Home CO ₂	272	161	59	0	0	kg/EV
Work CO ₂	-254	-120	-6	57	57	10 ³ kg
Revenue	3,288,262	3,205,127	3,113,950	3,003,165	1,284,505	ZAR

Figure 4.6b shows the monthly peak demand in kVA. The fleet utilizing a uncontrolled work-only charging results in a delta monthly peak demand of 3500 kVA throughout the

year. As expected, the load limit strategies have a peak demand that is proportional to their largest allowed limit. With a fleet of 1000 EVs, a peak demand of 500 kVA is seen throughout the year with a strategy of 0.5 kW/EV implemented. Out of all the limits investigated, this limit having the smallest increase in peak demand is ideal for an employer concerned with peak demand. These results further show that there are options and possible personal adjustments available to employers concerned with increased peak demands from EV charging. It allows them to not cancel out EV charging due to peak demands increasing, but to be able to provide charging while maintaining the peak induced from EV chargers.



(a) Monthly carbon footprint

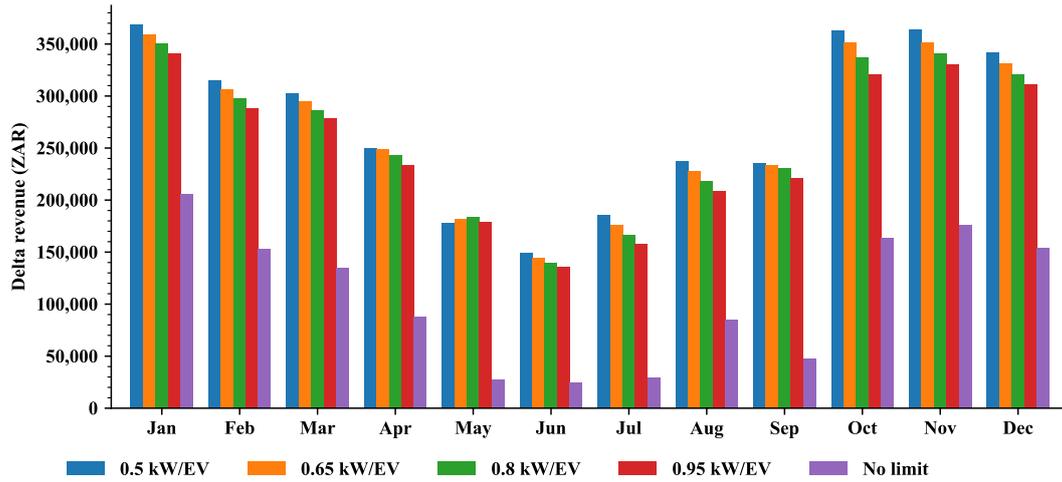


(b) Monthly peak demand

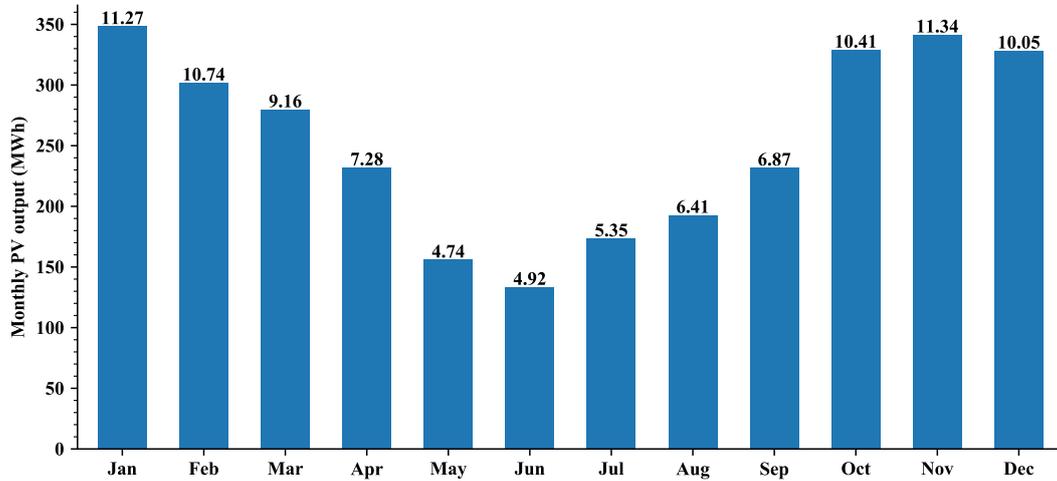
Figure 4.6: An illustration of the impacts of controlled and uncontrolled charging from the perspective of the employer.

Figure 4.6c shows the financial impact of the charging limits investigated monthly. It has a similar trend to the one seen in Figure 4.6d. From May to September, there is drastically less revenue than the other months. This shows that charging revenue is largely

4.2. Controlled smart charging



(c) Annual change in revenue for the employer

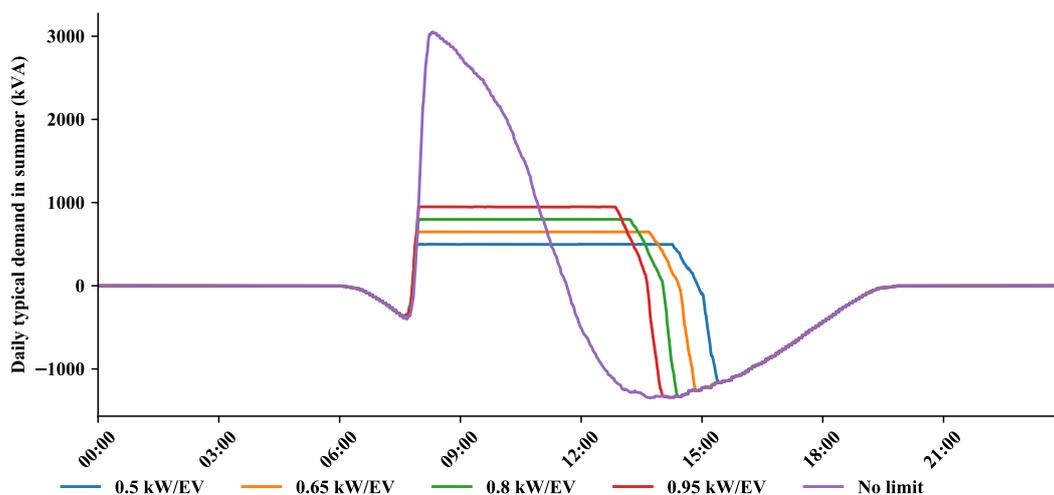


(d) Monthly PV output

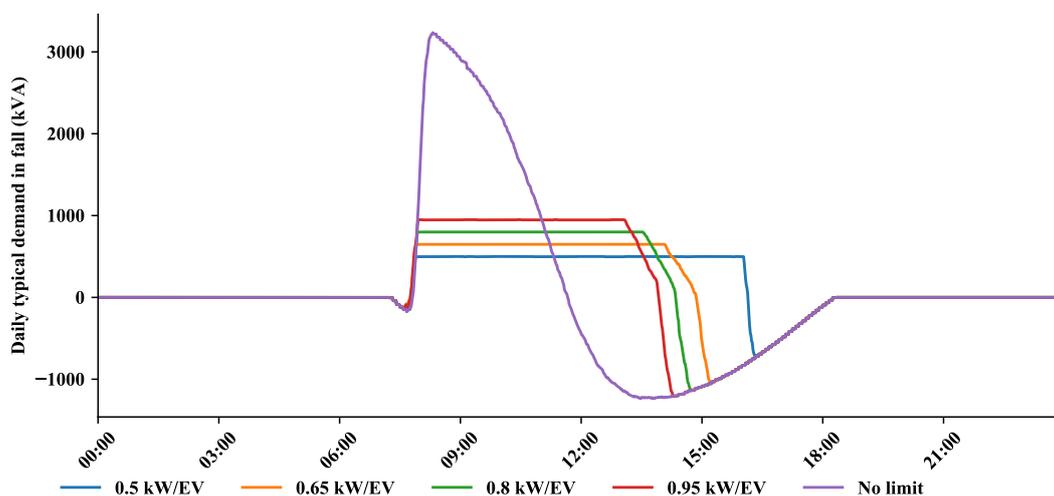
Figure 4.6: (continued)

dependent on the amount of available renewable energy. The revenue is also impacted by the peak demand charge. This is shown by the large increase of revenue when an employer switches from uncontrolled to controlled EV charging, and from the revenue increasing with the more restricted the charging load limits become. The increase in revenue is due to the monthly electric bill decreasing as the peak demand decreases. A charging load limit of 0.5 kW/EV renders the most revenue monthly, followed by 0.65, 0.8, 0.95 kW/EV and lastly the uncontrolled charging strategy. The exception to this is in May with a charging limit of 0.8 kW/EV generating the most revenue. Changes in the revenue across the various load limits are marginal compared to uncontrolled charging. The yearly aggregate results in Table 4.2 shows that revenue only increases by 7% with the load limit changing from 0.95 to 0.5 kW/EV. However, switching from uncontrolled charging to controlled charging with a load limit of 0.95 kW/EV yield 57% more revenue. These results show the advantages of switching over to a controlled charging strategy.

Figure 4.6d shows the monthly output of the PV system in MWh, along with the daily average written above it. It is apparent when viewing this figure, that the period of May to September has significantly lower energy produced, whereas from October to March there is a large amount produced. There is a 57% difference in the average amount of daily PV energy produced from June to November. The reductions in solar energy throughout May to September lead to less EV charging allowed, higher carbon emissions, reduced revenue and provide a feasible explanation for the occurrence of the failed and one-way trips seen above.



(a) Summer

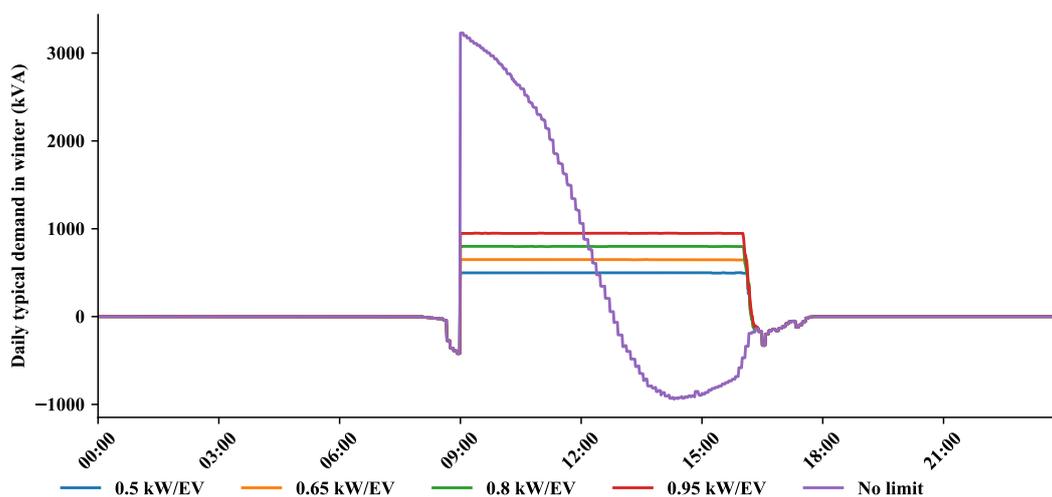


(b) Fall

Figure 4.7: The daily typical demand of controlled and uncontrolled charging for a fleet of 1000 EVs for four seasons.

Figure 4.7 portrays how the daily typical demand profile changes across each season. Figures 4.7a to 4.7d each show a typical day in January, April, July or October representing summer, fall, winter and spring respectively. It is seen in all of these figures, that the controlled charging strategies not only reach their respective peak load limits but maintain

them for the majority of the working hours. The controlled charging strategy is the opposite. It has a large morning peak demand, which after the demand drastically decreases, leaving the majority of the afternoon not utilized. The PV system feeds back any excess energy into the employer's buildings, creating the dip seen in the demand profile. Figure 4.7c shows that the reduction of renewable energy available in winter increases the duration of EV charging for the limit-based strategies. This reduction combined with the winter-based charging schedule, which delays charging up until 9am, causes charging to occur up until the end of a workday. The relationship of work charging and available PV energy also applies to the other seasons, however, due to more PV energy being available, it creates visible changes to the charging duration for the various load limits. The duration increases as the load limit becomes more restrictive, leading to EVs charging for longer, the 0.5 kW/EV limit requiring the longest period to charge versus 0.95 kW/EV being the shortest. Comparing Figure 4.7a to the other three, it is seen that EVs finish charging earlier in summer, followed by spring, fall and finally winter.

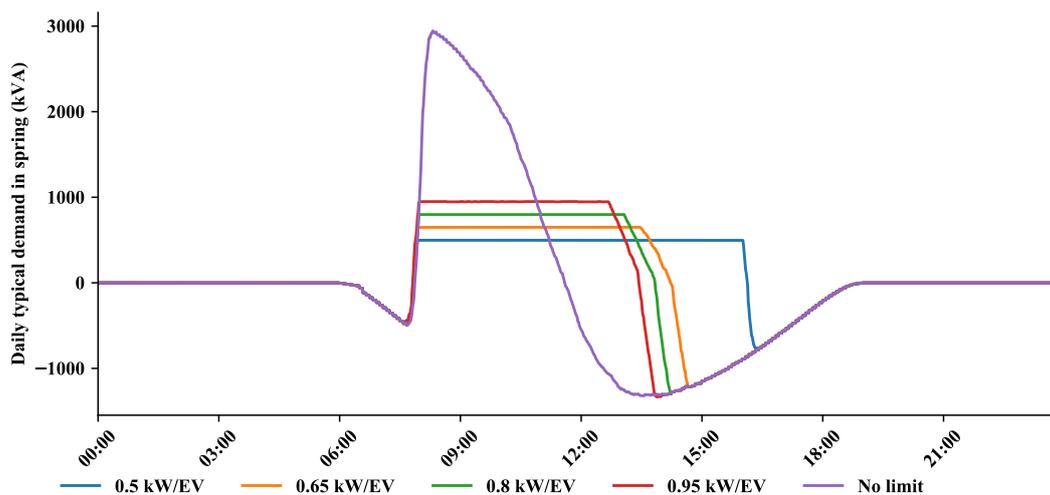


(c) Winter

Figure 4.7: continued

4.2.3. Summary

It can be seen from these results that there is a definite advantage to implementing a controlled smart charging strategy. The employer's annual net revenue increases by more than double when switching to the smart charging strategy proposed. This finding is the case for each of the applied limits. As the load limit applied is made more restrictive, the revenue does increase in minor magnitudes. The opposite is found for the carbon emissions, as there are substantially fewer emissions up until the 0.95 kW/EV limit. At this level of restriction, the carbon emissions are the same as the uncontrolled charging scenario. It makes sense that they would be the same, as this was the one limit tested



(d) Spring

Figure 4.7: continued

that was able to complete every trip without requiring home charging. All the other smart charging scenarios lead to EV users needing to charge at home so they could make their next trip, and times when they could not make their trip back home due to an insufficient charge. As the limit was made more restrictive, these incomplete trips occurred more frequently. A correlation between the monthly solar PV output and the occurrence of these trips, the revenue and carbon emissions is seen.

4.3. Chapter summary

This chapter opened by exploring the results of the uncontrolled charging scenarios of the first experiment. The first experiment compared EVs charging at home, work and both to petrol vehicles from the perspective of a vehicle owner, employer and the grid. The maximum number of charging EVs that the grid is capable of handling is determined for each EV scenario. The section concluded with two EV impacted daily load profiles. The second experiment follows from this with the investigation of the controlled smart charging strategy implemented in various scenarios. They were compared to the uncontrolled work-only charging scenario. This section was broken up into two parts, first looking at the user satisfaction with analysis on failed and one-way trips. The second part covers the large employer perspective metrics with the addition of a monthly PV energy output.

CHAPTER 5

CONCLUSION

This chapter provides a brief overview of the chapters before it, including references to the objectives of Section 1.2, along with recommendations for future work building on this project.

The impacts investigated from the growing population of electric vehicles (EVs) in other countries makes it clear that the arrival of these vehicles must be planned for beforehand. Especially for a country such as South Africa currently with a small population of EVs. If not, their associated carbon footprint will be larger than that of petrol vehicles they replace, defeating the purpose of changing to EVs. Without this planning, they will also placing a large strain on an already struggling grid.

Overall, this project has shown that work-place charging of EVs using photovoltaic (PV) augmented carports, whether it is the sole charging scenario, or if it is combined with home-based charging, has significant benefits, including an overall reduction in total carbon footprint, and an increase in the total number of EVs that can be supported by the grid. A further benefit is the potential income stream generated for the workplace. The real benefits stem from the fact that PV generates in the daytime, and if EVs are at the workplace during the day, then it makes sense for them to be charged there, providing direct and local consumption of the solar-generated electricity, managing an increased overall load on the electricity system from the growth in EV numbers, without the need for increased centralized resources and grid capacity. An increase in these benefits is possible by employing a controlled smart charging strategy. Smart charging has significant potential to make use of more available PV energy throughout the charging EVs, reducing the peak load caused by EVs and increase revenue.

5.1. Thesis summary

This thesis consists of five chapters. **Chapter 1** begins by providing the reader with a broad overview of the context in which the problem statement, solution and its objectives are formulated. It highlights the issue of carbon emissions, EVs and their possible impacts, the South African context, the potential of PV carports with high levels of solar insolation and demand-side management (DSM) strategies as a possible mitigation method.

Chapter 2 is made up of four sections reviewing relevant research categorized by grid effects, load shifting, mobility models and DSM. In the first three sections, the studies discuss issues of carbon emissions, energy usage, load demand and cost. These issues are considered from one, or at most two, of three possible perspectives: residential, commercial or energy supplier. However, none of the studies discusses all of those issues, or considers all three perspectives. Further, none of them takes into account a range of EV penetration, from small to medium, and large. Considering the studies read, EV models generally consist of a mobility and battery model. These models can consist of an aggregate form for an entire fleet of EVs or utilize separate variables for each EV. Mobility models are often based off of probability models sampled from combustion vehicle traffic surveys, more advanced statistical methods or from EV charging data which at this stage is limited. In the reviewed literature, many studies speak of the benefit of supplementing EV charging with solar energy, and some consider this is energy harnessed with PV-equipped carports. Often this is considered for developed countries with low amounts of solar insolation. The fourth section explores the various types of DSM mitigation efforts, along with relevant techniques applied to find an optimal or near-optimal solution. It is in this chapter, that the first research objective is satisfied:

Research objective 1:

A thorough literature study needs to be conducted in order to identify how common EV models are implemented, the possible impacts of EV charging and the methods researchers have attempted to mitigate them.

Chapter 3 covers the design of the experimental setup, along with explanations of the simulation and its models. Section 3.1 discusses the logic of the different experiments. It includes their related boundaries, the perspectives and metrics used in evaluating them. This section concludes with a proposed simulation design to determine the number of charging EVs the grid can maintain. Section 3.2.1 describes in detail the simulation setup in two parts. The first looks at the EV model stating any assumptions made, methodically describing the EV battery and mobility model implemented and presenting the charging strategies considered. Following this, the chapter concludes by providing a detailed explanation of the approach taken to simulate the solar PV, along with the parameters or assumptions made when designing the solar PV carports. This chapter entailing the design of the required simulations and experiments satisfies in part research objectives 2 to 5:

Research objective 2:

To be capable of investigating different fleet perspectives, develop an EV simulator that can model an EV fleet of a chosen size over a requested period. It should incorporate realistic mobility behaviour and battery characteristics. The simulation should output relevant information on a combination of carbon emissions, energy usage, the peak load demand and financial costs/revenue from charging of the fleet.

Research objective 3:

Use a trusted solar PV model to design and model a modular PV carport system. Incorporate this with the EV model to assess any potential benefits to EVs.

Research objective 4:

Adapt the original simulator to be able to determine the maximum fleet size that the grid can support using a given grid capacity and historical grid data.

Research objective 5:

Develop a smart charging algorithm that utilizes a DSM strategy to determine the potential mitigation effects of controlled charging strategies compared to uncontrolled charging strategies.

Chapter 4 discusses the results of the experiments and simulation approaches taken described in Chapter 3. It opens with discussing the results of the first experiment, which investigates the effects of uncontrolled EV charging at home, work and both to petrol vehicles from the perspective of a vehicle owner, employer and the grid. These perspectives in their listed order are comprised of a single EV, 1000 EVs and 1 million EVs. Work-related scenarios utilize solar PV carports to limit the grid energy consumed. In the grid perspective, the maximum number of charging EVs that the grid is capable of handling is determined for each EV charging scenario. The next section discusses the second experiment following on from the findings of the first. These findings conclude that noticeable benefits of solar PV carports are visible, but there is still a need to investigate a controlled charging strategy. The second experiment investigates a controlled smart charging strategy applied to ensure a peak load demand limit is not exceeded for various chosen limits. Smart charging is compared to uncontrolled work-only charging to evaluate its potential benefit from the perspective of the large scale employer. It is evaluated with the same metrics as in the first experiment, with the additional metric of including an evaluation of EV owner satisfaction. This satisfaction is a gauge for the occurrence of failed and one-way trips. Implementing and simulating the proposed models, fulfils the final requirements of the research objectives 2 to 5:

5.2. Suggestions for future work

Since the focus of this project has been on the potential impacts of large scale EV charging in South Africa, it has viewed this solely from an energy perspective. That being the case, only the operational environmental impact of energy consumption is considered, excluding the impact of pre-operational production and shipment and post-operational disposal of EVs. This is a potential area to be investigated, providing a more in-depth environmental assessment.

The investigated EV impacts during this study on energy consumption and peak demand were insightful, answering questions asked while laying the foundation for new

questions. Building on this foundation, one could consider more EV impacts such as voltage or frequency deviations on a residential level.

A smart charging strategy applied with DSM techniques deemed extremely beneficial in reducing the impacts of EV charging. It was able to improve on the results of simple uncontrolled charging that makes use of solar PV carports. It would be interesting to see the smart charging methods applied in a South African context to peak shaving or technology such as V2G.

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