Smart Charging Strategies for Electric Vehicles utilising Non-dispatchable Renewable Electricity Generation

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The pessimist complains about the wind;

The optimist expects it to change;

The realist adjusts the sails.

William Arthur Ward

Abstract

Access to an inexpensive and reliable supply of energy is critical for the success of modern civilisation. Since the beginning of the Industrial Revolution in the mid 18th century, fossil fuels have enabled great advances across many aspects of society, which have increased the standard of living for many. Unfortunately, dwindling supplies and greenhouse gas emissions resulting from their use means that the continued utilisation of these fuels—particularly for electricity generation and transportation—is simply not sustainable.

Present-day electricity systems are built around the premise that generation is flexible and controllable, while load—generally speaking—is not. This leads to dispatch models where generation is scheduled to meet load, plus some additional capacity to accommodate forecast errors and potential equipment failure. Many renewable generation technologies, such as wind and solar photovoltaics, are non-dispatchable and cannot be scheduled to produce electricity on-demand. Successfully utilising these energy sources therefore requires flexibility in other parts of the system.

Electric Vehicles (EVs) produce no tailpipe emissions, and can be charged at any location with an electricity supply; at home, work, supermarket, or dedicated charging facilities. Because driving times tend to coincide with existing peak electricity demand, EV charging will occur at times of already high electricity demand if not controlled. Fortunately, there is substantial flexibility over the timing of charging, which can be exploited to minimise adverse impacts on electricity grids. Additional benefits are realised when energy is allowed to flow from the vehicle's battery back into the electricity grid; a concept known as vehicle-to-grid (V2G).

Through the development of a simulation based on future energy scenarios in New Zealand, the research presented in this thesis evaluates the extent to which the flexibility of EV charging may be exploited to support high levels of non-dispatchable renewable electricity generation. Several EV charging strategies are introduced and evaluated across a range of metrics with wind penetration levels ranging between 10% and 50% on an annual energy basis. With a V2G-enabled fleet consisting of one million vehicles (25% of New Zealand's projected light vehicle fleet size in 2030), it is found that EV charging is sufficiently flexible to the extent that electricity generation does not need to follow daily variations in load. The EV fleet is capable of meeting the power and ramping requirements of the electricity grid, in addition to its own transportation needs, so long as sufficient energy is generated within a few days of its consumption. Such flexibility is expected to greatly assist the future expansion of non-dispatchable renewable electricity generation in New Zealand.

Acknowledgements

As it comes time to acknowledge those who have helped immensely with the completion of this thesis, it becomes clear that the cliché line “I could not have done it without you” is firmly rooted in reality.

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To the University of Waikato; your financial support has been invaluable throughout this endeavour, for which I am very grateful.

To the Department of Computer Science; thank you for providing the opportunities to publish research and attend conferences. These experiences have been both motivating and insightful. The endless supply of coffee from the tea room is also greatly appreciated.

To the friends and family who have provided an ample supply of distractions; thank you. You may now safely ask how the thesis is going.

And finally, to my parents Alan and Helen; I am forever grateful for your immense and unwavering support over the years.

Contents

List of Figures

List of Tables

Abbreviations

BEV	Battery Electric Vehicle
CCS	Carbon Capture and Storage
CDE	Carbon Dioxide Equivalent
CSP	Concentrated Solar Power
DER	Distributed Energy Resource
DG	Distributed Generation
DR	Demand-Response
DSM	Demand-Side Management
EV	Electric Vehicle
GHG	Greenhouse Gas
HEMS	Home Energy Management System
HEV	Hybrid Electric Vehicle
ICEV	Internal Combustion Engine Vehicle
PHES	Pumped Hydroelectric Storage
PHEV	Plug-in Hybrid Electric Vehicle
PV	Photovoltaics
SOC	State of Charge

TOU Time-of-Use

V2G Vehicle-to-Grid

V2H Vehicle-to-Home

V2P Vehicle-to-Premises

V2V Vehicle-to-Vehicle

VKT Vehicle Kilometers Travelled

Nomenclature

Ancillary Services

Services provided to electric power transmission, including scheduling and dispatch, reactive power and voltage control, loss compensation, load following, system protection, and energy imbalance services (Federal Energy Regulatory Commission, 2014).

Journey

The travel of a vehicle between a starting point and a final destination. This may include one or more trips.

Peak Energy

The amount of energy generated by peak generation sources over a period of time.

Peak Power

The maximum power observed during a period of time.

Spillage

The amount of energy that was not utilised due to lack of demand and storage, over a period of time.

Trip

A single movement of a vehicle, between switching the engine on and turning it off.

Wind Penetration

The proportion of energy derived from wind generation sources over a period of time.

1 Introduction

Anthropogenic climate change has been a major point of discussion in recent years, with predictions of catastrophic and widespread consequences if drastic measures are not taken to reduce Greenhouse Gas (GHG) emissions in the near future (IPCC, 2014a). The negative effects of climate change have been known for some time, and many countries have committed to reducing GHG emissions with the signing of the Kyoto Protocol in 1997 (United Nations, 1998), and the later signing of the Paris Agreement (United Nations, 2015).

The majority of GHG emissions worldwide arise from the transportation, electricity generation, and agricultural industries (IPCC, 2013), all of which are crucial for modern society. Although there have been attempts to reduce the environmental impacts resulting from agriculture, it is considered difficult and costly to achieve significant reductions of GHG emissions. Hence, the transportation and electricity generation industries have been identified as having the most potential to assist with meeting GHG emission targets (IPCC, 2014b).

Fossil fuels have satisfied global energy demands for over a century, but in addition to GHG emissions resulting from their use, there are also concerns about dwindling supplies and political instability in hydrocarbon-exporting countries (Yergin, 2006; Umbach, 2010). In 2012, fossil fuels provided 86.5% of the global primary energy requirements, with the remainder (13.5%) coming from renewable sources (IPCC, 2014b). Many countries aim to be more self-reliant with respect to energy, in order to become more resilient against volatile international markets (Umbach, 2010). Renewable energy sources have received a lot of attention for meeting these needs, as their many advantages include inexpensive (or free) fuel, an inherently secure indigenous supply of primary energy, and low lifetime environmental impacts (Jacobson, 2009).

While renewable energy sources offer great potential for addressing climate change and energy security concerns, these sources introduce challenges of their own. In an electricity system, generation must closely match load at all times. Traditionally, this balance is maintained by controlling the output of generators to meet the instantaneous load, with minor contributions from demand-side measures to reduce load during peak times (Boyle, 2007). In effect, this assumes that generation can be easily controlled, while load is considered to be largely inflexible.

Many of the “new” renewable energy sources, for example wind and solar Photovoltaics (PV), are non-dispatchable. That is, they cannot generate electricity on-demand, and in many cases their output cannot be predicted far in advance. Nuclear power is also seen as a promising technology for meeting future energy needs, but although its output is reliable and predictable, it is not responsive to changes in load and therefore also requires flexibility elsewhere in the electricity grid in order to maintain balance (MacKay, 2009). Because of these characteristics, any large-scale deployment of renewable generation will require additional measures that challenge the traditional balancing mechanisms used by electricity system operators (Ancell, Abbott, Palmer, Tinkley and Samarasinghe, 2005). The three options available for achieving this include the use of highly-dispatchable “backup” generation capacity, energy storage systems, and/or Demand-Side Management (DSM).

Another technology expected to play a major role in reducing global GHG emissions is the Electric Vehicle (EV) (Mason, Page and Williamson, 2010a; Vivid Economics and Energy Centre and University of Auckland Business School, 2012; MacKay, 2009). These vehicles may be partially or fully powered by electricity, in the case of Plug-in Hybrid Electric Vehicles (PHEVs) and Battery Electric Vehicles (BEVs) respectively, which have the advantage of greatly reduced GHG emissions and energy requirements compared to conventional Internal Combustion Engine Vehicles (ICEVs) (Duvall, Knipping and Alexander, 2007).

In order to avoid overloading electricity networks during peak load periods, it is widely accepted that the charging of electric vehicles must be controlled in some manner (Clover, 2013; Putrus, Suwanapingkarl, Johnston, Bentley and Narayana, 2009; Shortt and O’Malley, 2014). However, there is considerable potential to exploit the flexibility of EV charging to not only minimise the load impacts of the vehicles themselves, but to also share the burden of keeping electricity generation and load in balance and hence ease the integration of non-dispatchable generation.

1.1 Research Questions

With the widespread deployment of EVs and non-dispatchable electricity generation, traditional characteristics of generation and load will change. Generators will become less able to produce electricity on-demand, while load will become more flexible and able to adapt to changes in supply. This suggests that some or all of the responsibility for maintaining the balance between generation and load could move away from the traditional generation-side approach (i.e. generating electricity when it is needed), and towards the demand-side (i.e. using electricity when it is available).

Kempton and Letendre (1997) identified the potential for utilising the distributed electricity storage capacity of an EV fleet by allowing bidirectional energy flows between a vehicle's battery and the electricity grid; this is known as Vehicle-to-Grid (V2G). V2G enables the use of an EV fleet to buffer the variability of non-dispatchable generation, and to reduce peak load by storing off-peak energy close to where it will ultimately be consumed.

These observations give rise to the question of how to best manage the charging and/or V2G capabilities of a large EV fleet, particularly in an environment with a high penetration of non-dispatchable electricity generation.

The fundamental research question to be addressed in this thesis is:

> ***To what extent can the flexibility of charging electric vehicles be exploited to support the integration of non-dispatchable electricity generation in New Zealand?***

To answer this broad question, several more specific questions need to be addressed:

1. What are the potential energy demands and usage patterns of an electrified light vehicle fleet?
2. What are the generation characteristics of existing and proposed wind farms?
3. What are the necessary parameters of an energy storage system for buffering variability in high wind generation environments?
4. What EV charging strategies are effective, and how successfully can their adoption support the expansion of both renewable electricity generation and EVs?

1.2 Methodology

The research questions are largely aimed at future scenarios, which require substantial investment in new infrastructure as well as public acceptance of new technologies. Because EVs have not yet been deployed in significant numbers, performing real experiments at the scale required is not feasible. Instead, computer simulation becomes the de facto tool for exploring such questions.

Given the unique combination of low population density, plentiful renewable energy resources, geographic isolation, and one of the highest per-capita private vehicle ownership rates in the world, New Zealand offers an ideal setting for a case study involving large-scale wind penetration and EV deployment. The research is thus based on future energy scenarios relating to New Zealand, however the techniques used in this work may be applied to other parts of the world where suitable data exist.

There are many important engineering and economic challenges that must be addressed before the simulated scenarios can be implemented in the real world, including the deployment of ubiquitous smart grid technology, support for bidirectional power flows in distribution networks, and the adoption of suitable market structures. These issues are not addressed in this research; rather, the focus is on evaluating the potential performance of high-level strategies for managing variability in large-scale non-dispatchable generation, and coordinating the charging of a large number of EVs.

1.3 Thesis Structure

Chapter 2 outlines the general context of the research, including the primary motivations and a summary of the technologies expected to play an important role in the transition away from fossil fuels. It presents the argument that increasing the proportion of non-dispatchable generation and EVs is an essential step towards reducing fossil fuel dependence, and hence it is important to address the challenges presented by these technologies.

Chapter 3 provides an overview of studies related to the integration of non-dispatchable electricity generation, and the various approaches used to coordinate the charging of large numbers of EVs which may include V2G capabilities.

Chapter 4 describes the simulation software developed during the course of the research, including the data and models used to simulate future energy scenarios in New Zealand.

Chapter 5 explores the variability characteristics of wind generation and electricity load in New Zealand, and establishes the necessary performance requirements of a dedicated energy storage system which is capable of maintaining balance between generation and load at varying levels of wind penetration.

Chapter 6 introduces the definition of an EV charging strategy, and outlines the information that can be used to influence charging decisions. It then describes a selection of charging strategies, and identifies a number of key metrics for evaluating the performance of any given strategy.

Chapter 7 presents the results obtained from simulating a range of future energy scenarios in New Zealand.

Chapter 8 revisits the research questions, draws conclusions about the primary findings, and identifies directions for future work.

1.4 Contributions

The research presented in this thesis makes the following original contributions:

- A review of GHG sources and technologies for reducing emissions, particularly in the New Zealand context.
- A review of New Zealand's energy consumption, the present electricity and transportation industries, and future direction these industries are likely to take with respect to the government's energy strategy.
- A review of literature concerning the integration of non-dispatchable renewable electricity generation into electricity grids, and charging approaches for electric vehicles.
- An agent-based simulation framework for evaluating the relative effectiveness of electric vehicle charging strategies across a range of metrics.
- The introduction of several decentralised smart charging strategies for electric vehicles, with an evaluation of their performance.
- The identification of issues related to using an electric vehicle fleet for increasing the utilisation of non-dispatchable electricity generation sources, and a discussion of directions that future work could take.

1.4.1 Publications

Monigatti, P., Apperley, M., Rogers, B. (2014). Smart Energy Interfaces for Electric Vehicles. In *Proceedings of the International Conference on Advanced Visual Interfaces*. Como, Italy: ACM. doi:10.1145/2598153.2602229

Monigatti, P., Apperley, M., Rogers, B. (2012). Improved grid integration of intermittent electricity generation using electric vehicles for storage: A simulation study. In *Third International Green Computing Conference*, IGCC '12, pp. 1–10. San Jose, USA: IEEE. doi:10.1109/IGCC.2012.6322267

Monigatti, P., Apperley, M., Rogers, B. (2011). Visualising present and past: a meter with a flexible pointer. In *Proceedings of the 12th Annual Conference of the New Zealand Chapter of the ACM Special Interest Group on Computer-Human Interaction*, CHINZ '11, pp. 97–100. Hamilton, New Zealand: ACM. doi:10.1145/2000756.2000769

Rist, T., Wendzel, S., Masoodian, M., Monigatti, P., André, E. (2011). Creating awareness for efficient energy use in smart homes. In Feuerstein, G., Ritter, W. (Eds.), *Zusammenfassung der Beiträge zum Usability Day IX: Intelligent Wohnen*, pp. 162–168. Dornbirn, Austria

Monigatti, P., Apperley, M., Rogers, B. (2010). Power and energy visualization for the micro-management of household electricity consumption. In *Proceedings of the International Conference on Advanced Visual Interfaces*, AVI '10, pp. 325–328. Roma, Italy: ACM. doi:10.1145/1842993.1843052

1.4.2 Unpublished Works

Monigatti, P. (2015). Smart charging strategies for electric vehicles: A simulation approach. Presented at University of Waikato Sustainability Symposium, Hamilton, New Zealand

Monigatti, P. (2012). Potential Impact of Electric Vehicles as Grid Storage. Presented at New Zealand Wind Energy Association Conference (NZWEA), Hamilton, New Zealand

Monigatti, P. (2011). Detecting Grid Events. Presented at IEEE Instrumentation and Measurement Society, New Zealand Chapter, Workshop on Smart Sensors, Measurement and Instrumentation, Auckland, New Zealand

2 Background

As a small and isolated country in the South Pacific with a population of approximately 4.4 million (Statistics New Zealand, 2011) and high private vehicle ownership, New Zealand offers an ideal case study for a future energy scenario consisting of a large proportion of non-dispatchable renewable generation and widespread electric vehicle deployment.

The total primary energy supply in New Zealand was 38.2% renewable in 2013, the third highest percentage in the OECD behind Norway and Iceland (Ministry of Business, Innovation and Employment, 2014). A primary reason for this figure is the high proportion of electricity generated from renewable sources, which totalled 75% in 2013 (Ministry of Business, Innovation and Employment, 2014); a figure that the government wants to increase to 90% by 2025 provided that security of supply is not compromised (Ministry of Economic Development, 2011). New Zealand has significant untapped renewable resources, including over 100 TW h per year of wind potential (Kelly, 2011); more than twice New Zealand's annual electricity consumption in 2013 (Ministry of Business, Innovation and Employment, 2014).

On the other hand, New Zealand's primary source of energy in the transportation sector is largely derived from imported oil, leaving the country vulnerable to international disruptions to supplies (Ministry of Economic Development, 2011). Road transport is responsible for 37.6% of the national energy use annually, and contributes 16% to the country's GHG emissions (Ministry for the Environment, 2014). The electrification of transport is seen as an important step to reducing GHG emissions in New Zealand and around the world (Vivid Economics and Energy Centre and University of Auckland Business School, 2012).

While New Zealand's impact on global GHG emissions is minimal, the lessons learnt here are relevant worldwide. The energy and environmental challenges are definitely not unique to New Zealand, as many countries around the world face similar challenges. It is therefore important to understand not only how these challenges relate to New Zealand, but also how a case study in New Zealand relates to the rest of the world. Pure Advantage (2012) states that New Zealand could, as part of its Green Growth strategy, "develop new clean-tech export niches by anticipating what will be in demand as other countries evolve their economies. This includes exporting replicable solutions (knowledge, technology, products and services) developed by addressing challenges in our own back yard."

This chapter describes the motivation and context for the research presented in this thesis, by identifying the issues to be addressed, the technologies that are expected to contribute to a future with a secure energy supply and minimal GHG emissions, and how the planned research fits into the New Zealand's energy strategy.

2.1 Greenhouse Gas Emissions

The latest Assessment Report from the Intergovernmental Panel on Climate Change (IPCC) highlights a wide range of risks associated with climate change, including insecurity of food supplies, damage from extreme weather events, and insufficient access to drinking water (IPCC, 2014a). Furthermore, it is extremely likely that human activity is the primary driver of climate change through the emission of GHGs (IPCC, 2013). Even if GHG emissions are stopped immediately, the impacts of climate change will continue to be felt for many centuries (IPCC, 2013).

While some climate change is inevitable, it is possible to minimise risk through a substantial reduction of GHG emissions. This will require a wide range of changes to both technologies and human behaviour, to be outlined in section 2.1.2 (IPCC, 2014b).

2.1.1 Sources

As shown in figure 2.1, the world's largest emitter of GHGs was China in 2011, followed by the United States, European Union and India, with the fastest growth of emissions occurring in developing countries (IPCC, 2014b).

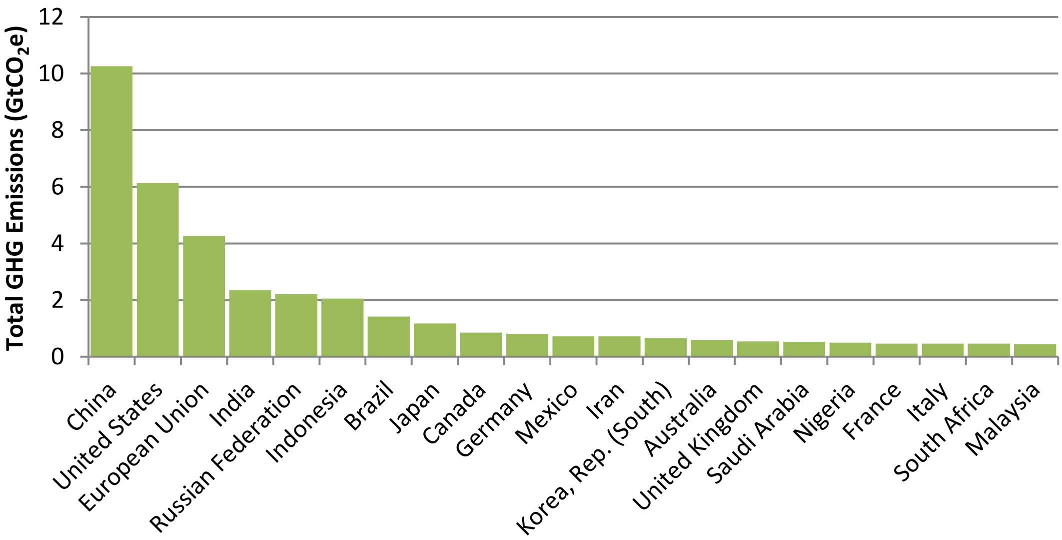


Figure 2.1: GHG emissions of top 20 countries in 2011 (WRI, 2014). New Zealand would be ranked 85th, with total emissions of 53 $MtCO_2e$.

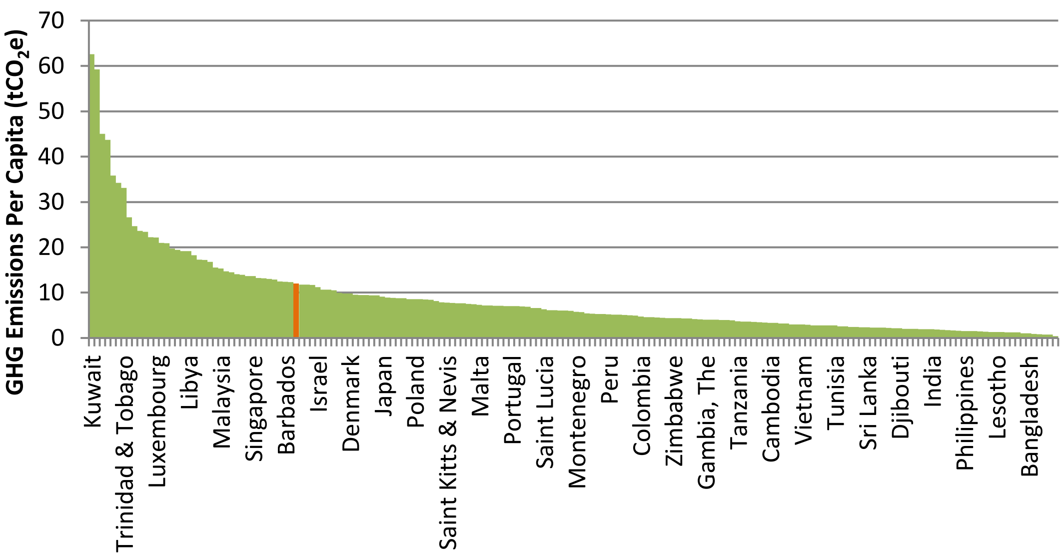


Figure 2.2: GHG emissions per capita by country in 2011 (WRI, 2014). New Zealand highlighted in 39th place.

As a relatively small country, New Zealand is not considered to be a large contributor to overall emissions, ranking at 85th place in 2011.

On a per-capita basis (figure 2.2), New Zealand ranks in 39th place, or roughly average for an OECD nation. However, the composition of those emissions is rather different. Figure 2.3 shows the breakdown of GHG emissions by industry for the world, OECD, and New Zealand.

Worldwide, the major source of GHG emissions are related to energy, primarily from electricity generation and transportation industries. In 2010, the energy supply sector emissions amounted to 35% of global GHG emissions, and without mitigation the emissions from this sector are expected to increase (IPCC, 2014b). Road transport is also a significant source of emissions, at 10.2% (IPCC, 2014b). OECD countries tend to have a higher proportion of emissions from transportation, with a relatively smaller proportion from agriculture and manufacturing compared to world averages.

New Zealand, on the other hand, has a much smaller proportion of GHG emissions from the electricity sector, which is a consequence of its high proportion of renewable generation. Instead, agriculture is the predominant source of GHGs—46.1% in 2011—mainly in the form of methane from ruminant digestion. The emissions from dairy cattle and sheep in New Zealand have been identified as the largest key category in 2011, with emissions from the energy sector coming in second at 42.2%, including 16% from road transportation—of which 63% was from the light private vehicle fleet (Ministry for the Environment, 2014; Concept Consulting Group Ltd, 2012).

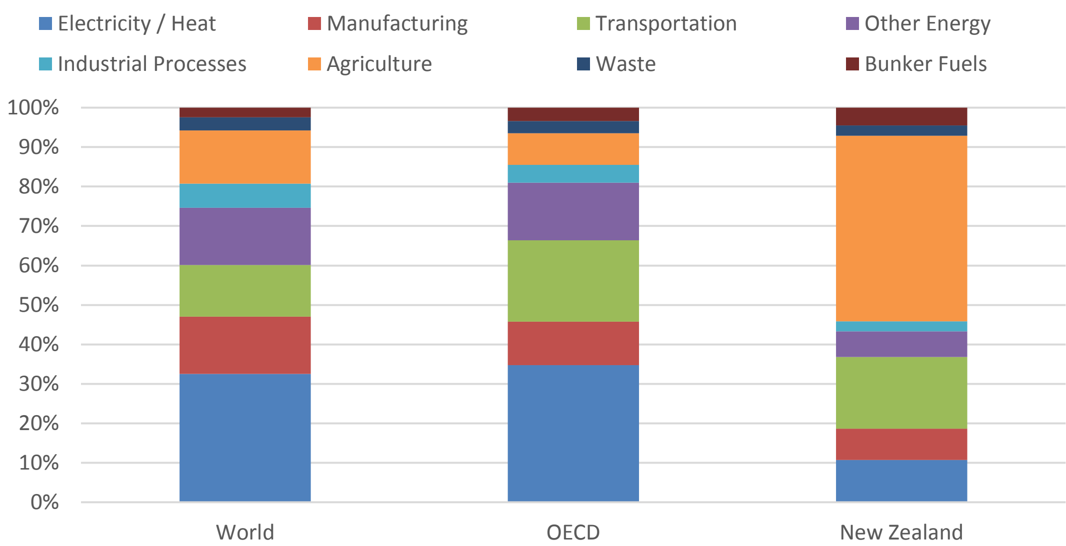


Figure 2.3: GHG emissions by industry (WRI, 2014).

2.1.2 Mitigation

The IPCC (2014b) states that the necessary "deep cuts in emissions will require a diverse portfolio of policies, institutions, and technologies as well as changes in human behaviour and consumption patterns", with high evidence and high agreement among researchers. The report goes on to say that what is most appropriate will vary by country, but almost universally the decarbonisation of electricity supplies will be an important aspect towards minimising GHG emissions, as will the electrification of transportation and heating/cooling (IPCC, 2014b).

Approaches to mitigating GHG emissions fall into four main categories: the move towards low-carbon energy sources, increased energy efficiency (including conservation), the use of carbon sinks, and climate engineering. These categories cover fundamental changes in technologies and human behaviour. The question of which approaches are most effective remains uncertain (IPCC, 2014b).

Since the majority of GHG emissions in New Zealand are from the agricultural sector, and electricity generation is largely from renewable sources already, mitigation of emissions will be costly—no technology currently exists to address methane emissions from agriculture (Pure Advantage, 2012).

Housing standards in New Zealand are seen as a problem; poor insulation leads to increased use of heating, or cold indoor temperatures that can potentially lead to health problems. This has led the government to subsidise retrofitting older houses with better insulation, and introduce stricter regulations for new buildings (Pure Advantage, 2012). In addition, New Zealand has the third highest rate of car ownership in the world, with Pure Advantage (2012) citing low fuel excise taxes and inadequate public transport infrastructure as primary reasons for this—only 2.5%[1] of all trips were made by public transport (Ministry of Transport, 2011).

> ***"Renewable energy technologies appear to hold great promise, but like all major sources of energy they also come with an array of concerns. Many renewable sources of electricity are variable and intermittent, which can make them difficult to integrate into electric grids at scale."***
>
> ***IPCC (2014b)***

[1] Includes work-related travel, but excludes travel as a "professional driver" (involving the transport of goods or people) while driving—for example—a courier, taxi, or bus.

Road transportation contributes significantly towards New Zealand's GHG profile; moving towards alternative fuels such as locally-produced biofuel and electricity may play a significant role in reducing overall emissions (Pure Advantage, 2012). It has been noted that, unless powered by renewable electricity, the widespread deployment of EVs will merely shift emissions from the tailpipe to power stations (MacKay, 2009). This concern is unfounded, however; even when the most emissive form of generation is used (i.e. traditional coal), total emissions would still be lower than from a fleet of ICEVs (Duvall et al., 2007). Shifting emissions from many small internal combustion engines to few large electricity generation plants also enables the use of Carbon Capture and Storage (CCS) technologies, which wouldn't otherwise be feasible (Gibbins and Chalmers, 2008).

2.2 Energy

Inexpensive and reliable access to energy is an essential part of a strong economy (Yergin, 2006). Since the invention of the steam engine in 1781, the majority of energy has been derived from fossil fuels—mainly coal and oil (International Energy Agency, 2014)—with renewable sources contributing 13.5% of the planet's total primary energy supply in 2012 (IPCC, 2014b).

While the problem of global climate change is inextricably related to the consumption of fossil fuels, there are other important challenges too: limited energy reserves, political instability in major oil-exporting countries, vulnerability to international price shocks, and non-GHG pollution (Yergin, 2006; Ministry of Economic Development, 2011). Such concerns have led to increased interest in moving away from traditional fossil fuels and towards renewable energy sources and other alternatives such as nuclear, biofuels, and coal with CCS, aka "sustainable coal" (Ministry of Economic Development, 2011; IPCC, 2014b; MacKay, 2009).

2.2.1 Primary Supply

Globally, renewable energy contributes 21% towards electricity generation, and only 13.5%[2] of the total primary energy supply in 2012—the remainder made up of oil (31.4%), coal (29%), natural gas (21.3%), and nuclear (4.8%) in 2012 (International Energy Agency, 2014). Wind and solar PV deployments are

[2]When nuclear is classified as non-renewable

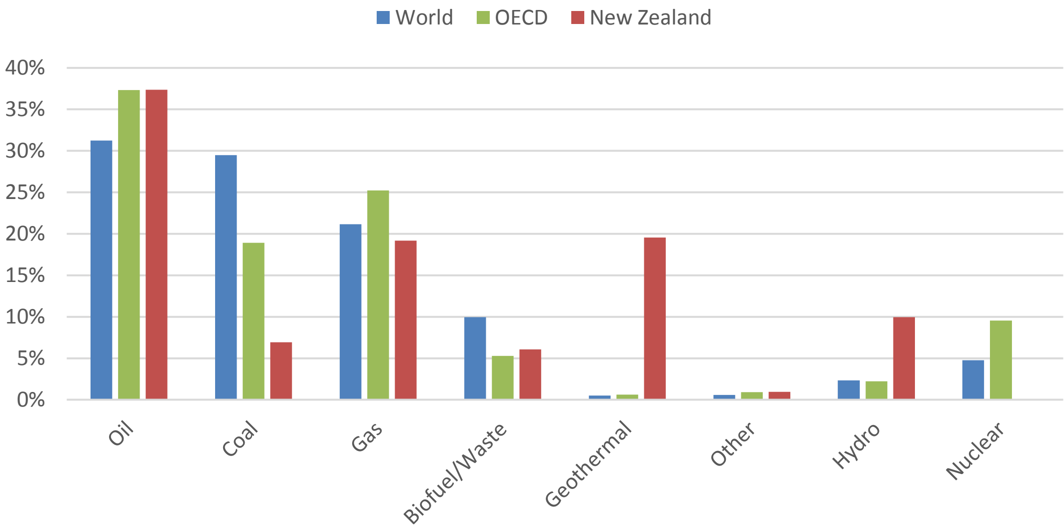


Figure 2.4: Primary energy supply in 2012. Data sourced from the IEA.

rapidly expanding, with significant potential to increase the penetration of renewables. However, these sources—being variable in nature—are likely to increase costs of ensuring a reliable electricity supply at high penetration levels (IPCC, 2014b).

Figure 2.4 shows the total primary energy supply for the world, OECD, and New Zealand. The values quoted in this figure are the sum of local production and imports, less exports. It is important to note that these values do not take into account the level of "usable energy"; that is, this figure does not show the useful energy obtained from each source. For example, New Zealand's high proportion of geothermal energy does not reflect the fact that only around 15% is transformed into electricity (the rest is lost as heat), while 100% of hydroelectric generation is deemed to be usable (Ministry of Business, Innovation and Employment, 2014).

New Zealand is on par with the OECD average for the proportion of energy from oil, which is mainly attributed to transportation. A substantial proportion of New Zealand's electricity is derived from hydroelectric and geothermal sources, at around 57% and 16% of total electricity generation in 2014, respectively (Ministry of Business, Innovation and Employment, 2014). There are currently no nuclear power stations in New Zealand due to the country's nuclear-free stance.

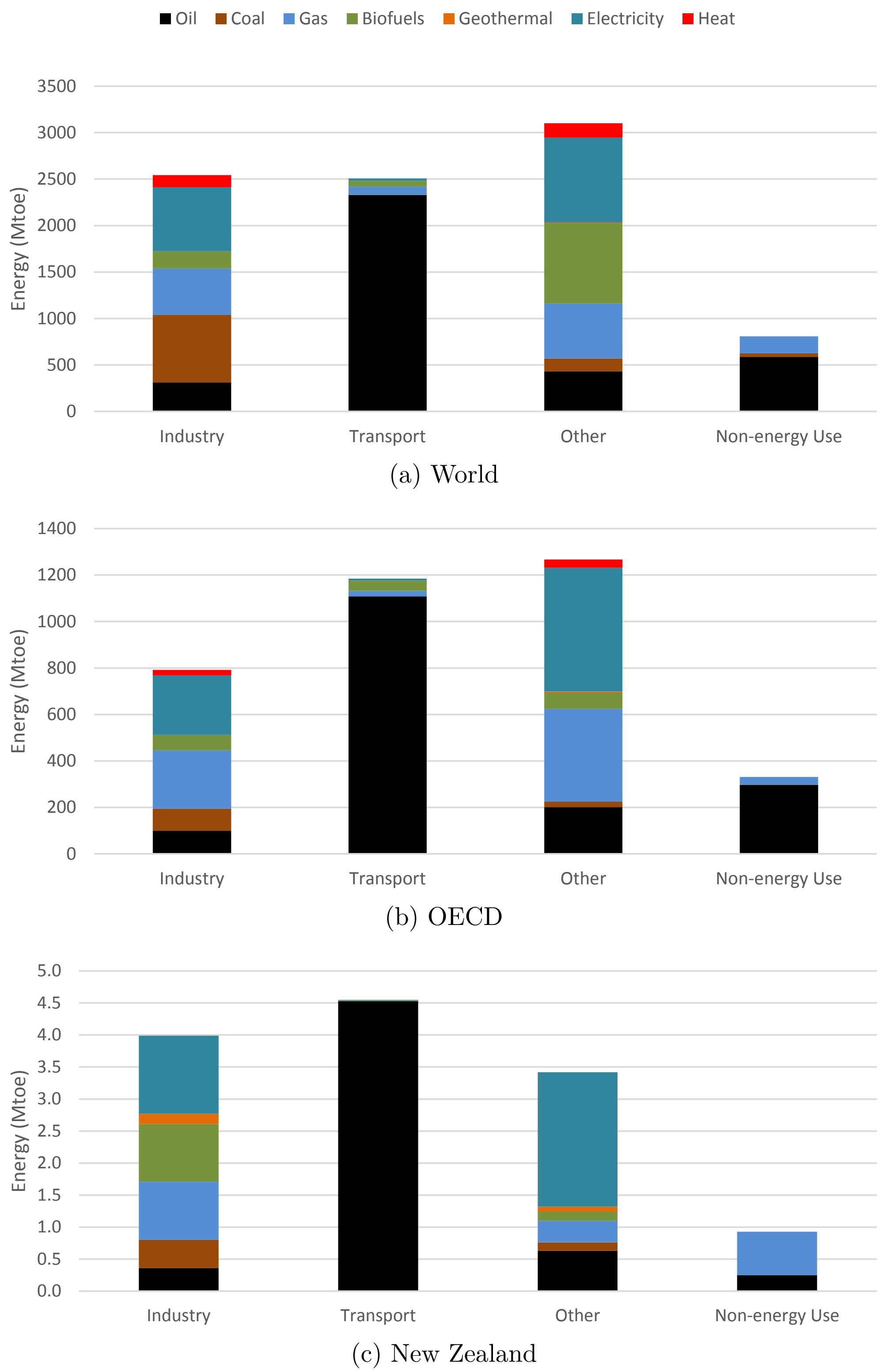


Figure 2.5: Energy end use in 2012, as millions of tonnes of oil equivalent. Data sourced from the IEA.

2.2.2 End Use

Figure 2.5 shows the use of energy by type and sector, for the world, OECD, and New Zealand. The electricity portion of these charts are not directly comparable, since the primary energy source used in electricity generation varies in composition by category.

Transportation makes up a significant portion of energy consumption, almost exclusively from fossil fuels—namely oil. Within the transportation sector, the energy for road transport powered by oil amounts to 71.4%, 84.4%, and 90.1% of all transport energy needs for the world, OECD, and New Zealand, respectively.

Energy consumption in the industrial sector is comprised of a variety of sources; New Zealand's proportion of renewable energy exceeds both world and OECD averages. In New Zealand, the largest industries by energy consumption include non-ferrous metals (electricity) and wood/wood products (biofuels and waste).

The "other" category includes residential and commercial consumption, as well as agriculture. Globally, the residential sector is responsible for 66.5% of the "other" category, and 23.1% of overall consumption, followed by commerce/public services at 23.1% of the category and 8.0% overall. In New Zealand, with the residential sector is responsible for 42.9% of the category (11.4% overall), while commerce/public services follows at 33.8% of the category and 9.0% overall.

These figures show that, around the world, transportation is responsible for a significant portion of fossil fuel consumption. In New Zealand, 81% of annual oil consumption is used in the transportation sector, totalling 60% of the country's overall consumption of energy from non-renewable sources in 2013 (Ministry of Business, Innovation and Employment, 2014).

2.2.3 Energy Security

Maintaining a secure supply of energy is a priority for ensuring economic stability and prosperity (Ministry of Economic Development, 2011); many countries aim to reduce their vulnerability to energy security threats by increasing indigenous production of fossil fuels, and diversifying primary energy sources (Yergin, 2006).

Renewable energy is naturally resistant to these concerns. Fuel is abundant and cheap (or free), and in most cases is produced domestically. However, because of the non-dispatchable nature of many of the new renewable energy sources, it is likely to be expensive for these sources to completely replace existing generation infrastructure (Concept Consulting Group Ltd, 2012).

In electricity generation, what constitutes a secure supply depends on the timescale in question. In the short term, maintaining supply relies on having sufficient infrastructure in place to accommodate changes in the power imbalance between generation and load, for example the loss of a generating unit or an unexpected increase/decrease in load. This is referred to as ramping, and is managed through a combination of spinning reserves and interruptible load. On a slightly longer timescale, the primary concern is having sufficient generation capacity available to cover instantaneous load. In the long term (months to years), the concern is of having sufficient energy available to meet all demand. A regular threat to New Zealand's energy security is that of "dry years", where inflows into hydroelectric lakes are lower than usual and hence the energy available is limited.

Many forms of renewable electricity generation do not contribute to security of supply over short time scales, as their output cannot respond to changes in load, nor can their output be relied upon to be available when needed. Because of this, an additional megawatt of wind generation will not simply replace a megawatt of dispatchable fossil-fuelled generation. Non-dispatchable generation sources do, however, contribute to energy security over the long term. The amount of energy expected from these sources over a long time periods is very predictable, while short-term availability is not. This is in contrast with fossil-fuelled generation where short-term output is controllable (therefore predictable), while long-term fuel availability is not. Variable renewable generation sources can thus be thought of as a source of energy over long time periods, rather than a short-term source of power (Boyle, 2007).

Electric vehicles have considerable potential to improve energy security in New Zealand, by reducing the country's exposure to volatile oil markets and instead using electricity produced locally from renewable sources (Concept Consulting Group Ltd, 2012). If the charging of EVs is carefully managed—especially when V2G is considered—these vehicles may also contribute to the security of electricity supplies by using their storage capacity to buffer short term variability in electricity generation and load.

A review by Jacobson (2009) concluded that a combination of wind generation EVs held the most promise across a range of categories related to climate change, pollution, and energy security.

2.3 Renewable Energy Technologies

Renewable energy is obtained from sources that are continually replenished by nature, includeing solar PV, wind, hydroelectricity, biomass, geothermal, and tidal generation (Ellabban, Abu-Rub and Blaabjerg, 2014). While renewable energy has been used in its various forms for many millennia, today it only plays a minor role in the world's energy supply (section 2.2). In future, the use of renewable energy is expected to expand dramatically; most prominently in electricity generation, heating, and transportation.

This section provides an overview of the main technologies that are expected to play a role in future energy scenarios.

2.3.1 Electricity Generation

Electricity is considered to be a high grade of energy; that is to say, it has valuable properties such as being readily convertible into other forms of energy (e.g. heat, light, motion) and transmitted quickly over long distances.

Table 2.1: Current and technical potential for renewable electricity generation.

Technology	Cost	World ($PW\,h\,yr^{-1}$)		NZ ($TW\,h\,yr^{-1}$)	
	($NZD/MW h)	Potential	Current	Potential	Current
Solar PV	570–2490†	<3000	0.0114	?	0.0
CSP	303‡	1.05–7.8	0.0004	?	0.0
Wind	60–120†	410	0.173	127.37	2.19
Geothermal	60‡	0.57–1.21	0.0576	11.98	6.79
Hydroelectric	79–126*	<16.5	2.840	34.6	24.09
Marine	450–520†	4.58	0.0005664	2.91§	0.0
Nuclear	94–130†	<4.1–122	2.630	N/A	0.0
Coal-CCS	184‡	<11	0.0	?	0.0

World data: Jacobson (2009)
NZ data: Kelly (2011); Ministry of Business, Innovation and Employment (2014)
* Kelly (2011)
† IPENZ (2010)
‡ U.S. Energy Information Administration (2014), using 1 USD = 0.80 NZD
§ Power Projects Limited (2008)

Low grade energy, such as heat, lacks these properties (MacKay, 2009). Of course, conversion between high-grade and low-grade energy is possible, with inevitable losses during the conversion process. For this reason, renewable electricity generation is likely to be more important than other forms of renewable energy, for example solar-thermal and biofuels (Jacobson, 2009).

Table 2.1 shows the different types of renewable electricity generation, including the annual energy currently derived from these sources and the technical potential. The current world renewable electricity production relates to 2005 (except wind and solar PV—2007). For reference, the global electricity generation that year was 18.24 PW h (Jacobson, 2009). New Zealand figures relate to the year 2012, and total generation that year was 42.9 TW h. It must be noted that the numbers presented in this table vary widely in terms of accuracy and relevance; the numbers for established technologies such as hydroelectric and nuclear are considered to be reliable, compared to emerging technologies (e.g. marine, coal with CCS) which are more speculative in nature. It is clear, however, that significant untapped potential exists in variable generation sources, namely solar, wind, and to a lesser extent, marine.

Solar

Solar electricity generation comes in two forms; PV, which converts sunlight directly into electricity, and Concentrated Solar Power (CSP), which uses mirrors to concentrate solar radiation and generate heat as an intermediate step. There is a great deal of solar energy available, significantly exceeding global electricity requirements (Jacobson, 2009); however, as with many renewable energy resources, the availability of power is not controllable. Solar PV deployment has increased dramatically in recent years, but its current contribution to electricity supplies worldwide remains minimal.

Solar PV converts sunlight directly to electricity, with no inherent storage. The electrical output from PV varies on a daily cycle, peaking at solar noon, and is affected by local weather conditions. The other form of generation, CSP, uses solar energy to heat a fluid that, in turn, drives a heat engine to generate electricity. Because of inherent thermal energy storage in this system, CSP generators can produce electricity at night (Jacobson, 2009).

In New Zealand, current levels of solar electricity generation are minimal. Although New Zealand's potential is similar or better than many other countries, solar is not expected to be economically viable before at least 2020 except in niche markets such as off-grid installations (IT Power Australia Pty Ltd and Southern Perspectives Ltd, 2009).

Wind

Harnessing energy from wind is not a new phenomenon, but the use of wind turbines to generate electricity is a much more recent development. The first grid-scale wind turbine was built in 1931; a 100 kW machine that operated reliably for 11 years (Hau and von Renouard, 2013, pp. 31-32). In New Zealand, the first large wind turbine was installed near Wellington in 1993. This turbine is rated at 250 kW, and operates with a capacity factor of up to 50% (Power Projects Limited, 2008; Mason, Page and Williamson, 2010b).

The use of wind turbines for electricity generation is considered to be a relatively mature technology, with costs being economically competitive with other sources of electricity. Since a significant majority of wind energy potential remains untapped in New Zealand and around the world, the proportion of total primary energy derived from wind is expected to increase dramatically in coming years (Jacobson, 2009; Kelly, 2011).

The output from wind farms can vary significantly over short time periods, creating stability problems in electricity grids with high levels of wind penetration. Managing this variability is an active area of research, to which this thesis also contributes.

Geothermal

Geothermal power plants utilise naturally heated water and steam from beneath Earth's surface to generate electricity. Except for binary systems, some of the geothermal fluid—which contains water vapour, CO_2, NO, SO_2, and H_2S—is released into the atmosphere, while approximately 70% is reinjected back into the ground (Jacobson, 2009). Binary plants use a closed system that returns all geothermal fluid back underground, making their emissions negligible (Jacobson, 2009).

Because geothermal energy is not affected by weather conditions or time of day, it is well suited to providing consistent base-load electricity with capacity factors approaching 100%, but load-following is also possible (Jacobson, 2009).

New Zealand is considered to be a leader in geothermal electricity generation, having installed the world's first generation plant (Wairakei) in 1958, and in 2010 had derived 17% of its electricity supply from geothermal sources (Vivid Economics and Energy Centre and University of Auckland Business School, 2012). Geothermal generation is expected to expand in New Zealand by 2025 (Ministry of Economic Development, 2011).

Hydroelectric

Of all renewable electricity sources, hydroelectric generation is currently the most widely deployed, supplying 17.4% of global electricity in 2005 (Jacobson, 2009). The majority of hydroelectric generation extracts energy from water falling from an artificial lake, created by flooding an area of land upstream of a dam, while the other variety of hydroelectric generation—run-of-the-river—does not use a dam or flood upstream land.

Hydroelectric generation (excluding run-of-the-river) is well suited to providing peak power by storing water behind the dam during off-peak hours, and releasing it when needed. In addition, base generation is usually provided in order to maintain minimum river flows. New Zealand's hydroelectric system provides up to 4.4 TW h of storage capacity, which is sufficient for approximately 34 days of electricity demand in winter (Mason et al., 2010b). While often seen as a dispatchable source of electricity, hydroelectric availability is limited by rainfall. Low inflows into hydroelectric lakes over long periods ("dry years") have created electricity shortages in New Zealand on several occasions (Mason et al., 2010b).

Because hydroelectric generation is well established, opportunities for new developments are likely to be expensive and face opposition (Mason et al., 2010b).

Marine

Marine electricity generation extracts energy from the motion of water in oceans, caused by tides or waves. Tidal generation provides a predictable but intermittent output that coincides with tidal currents, using turbines mounted underwater, while wave generation utilises floating devices to convert the rise and fall of waves into electricity, offering a less predictable output than tidal generation (Jacobson, 2009). Currently, marine electricity generation is a minor source of energy with limited potential compared to other renewable options.

Nuclear

The question of whether nuclear energy is renewable or not is subject to debate (MacKay, 2009), but it is included here for completeness. Globally, nuclear generation provides slightly less energy than hydroelectric, and is the only other major source of energy among arguably renewable options at present.

Since nuclear generation is dispatchable with a consistent and predictable output, it is likely to remain an important source of energy around the world. However, it is unlikely to form part of New Zealand's future electricity system because of the country's nuclear-free stance, availability of less expensive alternatives, safety concerns, among other issues (IPENZ, 2010).

Coal with CCS

Classifying coal-fired generation as renewable is questionable, but due to the importance of coal in today's energy systems, it is likely to remain in use for some time (MacKay, 2009). The introduction of CCS is expected to allow the continued use of coal-fired generation, while also meeting GHG reduction targets (IPCC, 2014b).

Coal electricity generation plants with CCS utilise additional equipment to capture CO_2 from the emissions stream, and inject it underground for permanent storage. A review by Page, Mason and Williamson (2008) states that coal (with CCS) is, at best, a transitional technology to deliver electricity while other renewable sources are developed. The review concludes that CCS will not help New Zealand meet its GHG reduction targets, and is therefore not relevant to the country's future energy needs.

Summary

There are a range of renewable electricity generation technologies, most of which are variable and non-dispatchable in nature. Solar electricity generation is rapidly expanding in some countries, but is not expected to be economically viable in New Zealand for some years. Instead, wind and geothermal generation plants are expected to make up the majority of new developments in New Zealand.

2.3.2 Biofuels

Biofuels are derived from organic matter—such as corn or waste from forestry—that can exist in solid, liquid, and gaseous forms (Jacobson, 2009). Applications can include electricity generation in thermal plants, liquid fuels for use in transportation, or direct use in heating applications.

As discussed in section 2.2, road transportation uses a significant proportion of total primary energy, and is responsible for the majority of global oil consumption. The use of biofuels to replace oil has been suggested as one solution to both energy security concerns and GHG emissions, but is not seen as a suitable long-term solution; biofuel crops compete with food crops, generate non-GHG emissions when burned, and may have negative impacts on the land used for growing (Jacobson, 2009).

While the production of biofuels represents an economic opportunity for New Zealand, investment in biofuels for passenger vehicles is only likely to amount to 14% of total investment, with the remainder going towards electric and hybrid vehicles (Vivid Economics and Energy Centre and University of Auckland Business School, 2012).

2.4 Electric Vehicle Technology

Electric vehicles have significant potential to reduce both GHG emissions and reliance on energy from fossil fuel sources, and are expected to play an important role in meeting future transportation needs (Mason et al., 2010a; Duvall et al., 2007; Vivid Economics and Energy Centre and University of Auckland Business School, 2012). Currently, electric vehicles have not met mainstream acceptance because of high capital costs, long “refuelling” periods and limited range relative to ICEVs, and concerns about electricity infrastructure requirements (Clover, 2013; Putrus et al., 2009). This section explores the current state of EV technology, trends, and concerns.

2.4.1 Emissions

Tailpipe emissions from EVs are zero, effectively making these vehicles a very clean form of transportation. However, emissions do occur elsewhere as a result of EV use—including from electricity generation used for charging, and energy used for the manufacture and disposal of the vehicle.

While some have raised questions about the net effect of charging electric vehicles from fossil-fuelled electricity generation (MacKay, 2009), overall emissions are lower than ICEVs even when using the most CO_2 intensive source of electricity; coal without CCS (Duvall et al., 2007). A study based on the electricity system in the United States (Samaras and Meisterling, 2008) found that the life cycle GHG emissions from the use of PHEVs is slightly lower per kilometre than that of conventional vehicles, even with carbon-intensive electricity generation. When low-carbon generation is used, a reduction of 60% is expected.

There are other advantages of concentrating emissions to large centralised electricity generators, such as enabling the use of CCS technologies that are infeasible to use in many small, mobile CO_2 sources (Hadley and Tsvetkova, 2009), and moving non-GHG emissions away from populated areas (Kintner-Meyer, 2007).

2.4.2 Energy Storage

Many of the criticisms of EVs can be directly attributed to their energy storage system, such as high purchase cost, long recharging periods, and limited range. Because of this, much research has focussed on different methods of efficiently storing energy for mobile use. Storage systems for EVs fall into four main categories; batteries, ultracapacitors, hydrogen fuel cells, and hybrid systems.

Table 2.2 shows the main present-day energy storage technologies for electric vehicles. Batteries, primarily lithium-based chemistries, are the dominant form of storage device, while hydrogen fuel cells are not yet commercially competitive, costing around five times an equivalent ICEV (Khaligh and Li, 2010).

Batteries currently have the highest specific energy of the storage technologies, and are well suited to storing bulk energy for transportation use. However, they suffer degradation through repeated charging and discharging cycles, and have limited power handling ability. Ultracapacitors offer complementary advantages, with much higher power handling ability and very low degradation with repeated charge/discharge cycles, but have a very low energy storage capacity.

Table 2.2: Comparison of EV energy storage technologies.

Technology	$\mathrm{W\,h\,kg^{-1}}$†	$\mathrm{W\,kg^{-1}}$†	Roundtrip Efficiency†	Lifespan‡
Battery	35 to 175	407 to 1044	0.87 to 0.96	1000 cycles
Ultracapacitor	4.2 to 12	981 to 2569	0.94 to 0.99	10–12 years
Hydrogen	40*‡	-	0.17 to 0.25§	10k–40k hours

* Excluding container and fuel cell

† Burke and Miller (2011)
‡ Khaligh and Li (2010)
§ Yilanci, Dincer and Ozturk (2009)

2.4.3 Charging Considerations

The best method for charging electric vehicles remains an open question, with different approaches offering varying degrees of convenience, charging times, driving range, and infrastructure requirements. The main proposals are discussed below.

Domestic Charging

EVs may be charged at residential settings, with a 5 kW connection being feasible in New Zealand homes, or 2 kW with no modification to existing wiring, provided that not all households charge vehicles at the same time. It is expected that 85% of all charging requirements can be met during overnight hours at homes, while the other 15% of charging will occur sporadically throughout the day (Duncan, Halliburton, Heffernan, Hardie, Watson and Coates, 2010).

It is widely agreed that domestic charging will need to be controlled, because otherwise peak charging demand will coincide with existing electricity peak demand, resulting in severe strain on generation, transmission, and distribution infrastructure (Clover, 2013; Putrus et al., 2009; Shortt and O'Malley, 2014; Aunedi, Woolf, Bilton and Strbac, 2014).

While domestic charging is convenient for most vehicle travel, it is not well suited to longer trips away from home or cases where a fast charge is required.

Public Charging Stations

Public charging stations utilise high power connections to minimise the time spent charging an EV, which is important for enabling multi-stage journeys that exceed the range of a single battery charge. The nature of fast charging stations will require high power on-demand—likely during daytime hours—leaving little opportunity to control charging rates. However, since the majority of vehicles don't travel long distances on any given day (Ministry of Transport, 2011), the demand for fast charging is not likely to be significant if other, less imperative charging methods are available. A case study in London during 2013–2014 confirmed that on average, only a minority of the total energy consumed by an EV was sourced via public charging stations (Aunedi et al., 2014).

Botsford and Szczepanek (2009) notes the psychological benefits of having a fast charging infrastructure available. Following the deployment of a single fast charger in a Tokyo Electric Power Company service area, EV drivers began venturing farther from their base—even though the fast charger was not well utilised. The knowledge that they could quickly charge their vehicles during the day, if necessary, meant that drivers were more willing to return home with a lower State of Charge (SOC) than they would otherwise be comfortable with.

Battery Swap

Battery swapping combines the advantages of fast "refuelling" times for EVs, and the flexibility of charging batteries off-line when low-cost electricity is available. Because of the weight of typical EV batteries, swapping stations must necessarily use robots to perform the swapping. For this to be feasible, EV batteries must be standardised and easily accessible across a range of vehicle manufacturers and models (Mak, Rong and Shen, 2013).

Hydrogen

EVs powered by hydrogen fuel cells have promised significant potential, including zero tailpipe GHG emissions and fast refuelling times. Hydrogen can produced by electrolysis of water using off-peak electricity, either in large centralised facilities or on-site at refuelling stations, which can then be stored for later use in mobile or stationary applications.

The system-level efficiency for hydrogen-powered EVs is much lower than for BEVs, at only 26% vs 72% respectively (Page and Krumdieck, 2009). In addition, the synthesis and distribution of hydrogen will require substantial infrastructure, a further barrier to widespread adoption of hydrogen as an energy storage medium for EVs.

Plug-in Hybrid

PHEVs offer a compromise between ICEVs and BEVs, including a traditional gasoline or diesel engine, electric motor, and small battery. Since most vehicles travel a short distance in a typical day (Ministry of Transport, 2011), the bulk of travel can be done using electrical energy. For longer trips, or situations where fast refuelling is needed, the vehicle can instead use its combustion engine for propulsion. Typical all-electric range for PHEVs are expected to be between 30 and 100 kilometres (Hadley and Tsvetkova, 2009).

There are two forms of hybrid vehicle; series and parallel. Series hybrid-electric vehicles (also known as "range-extended electric vehicles") utilise a solely electric drivetrain, with an internal combustion engine configured as a generator to charge the vehicle's battery while driving, and thus extending its range. In a parallel hybrid-electric vehicle, both the internal combustion engine and the electric motor have a direct connection to the wheels.

2.5 New Zealand's Electricity Sector

New Zealand's electricity sector is dominated by a small number of companies; 5 major generation companies (contributing a combined 92% of annual production), 29 distribution companies, eight major electricity retailers (Ministry of Business, Innovation and Employment, 2014), and one national transmission network which is operated by state-owned enterprise Transpower.

The transmission network is comprised of two synchronous AC grids—one on each major island—which are connected via a 350 kV HVDC cable. Energy flows primarily from generation in the South Island to population centres in the North Island, except when hydroelectric resources in the South Island need to be conserved during dry periods (Transpower, 2014).

2.5.1 Generation

New Zealand's electricity network had 9.6 GW of installed generation capacity in December 2014, which produced 42.2 TW h over the calendar year. This is illustrated by source in Figure 2.6. Renewable sources contributed 75% of this energy (Ministry of Business, Innovation and Employment, 2014), a figure that the government wishes to increase to 90% by 2025 provided that security of supply can be maintained (Ministry of Economic Development, 2011).

A large proportion of the current generation fleet is hydroelectric (55%), primarily based in the South Island, while the proportions of both geothermal and wind generation have been increasing in recent years—comprising 10.1% and 6.6% of installed capacity, respectively, in December 2014 (Ministry of Business, Innovation and Employment, 2014). Looking forwards, geothermal and wind generation are being touted as having the most potential to assist meeting the 90% renewable electricity goal (Ministry of Economic Development, 2011).

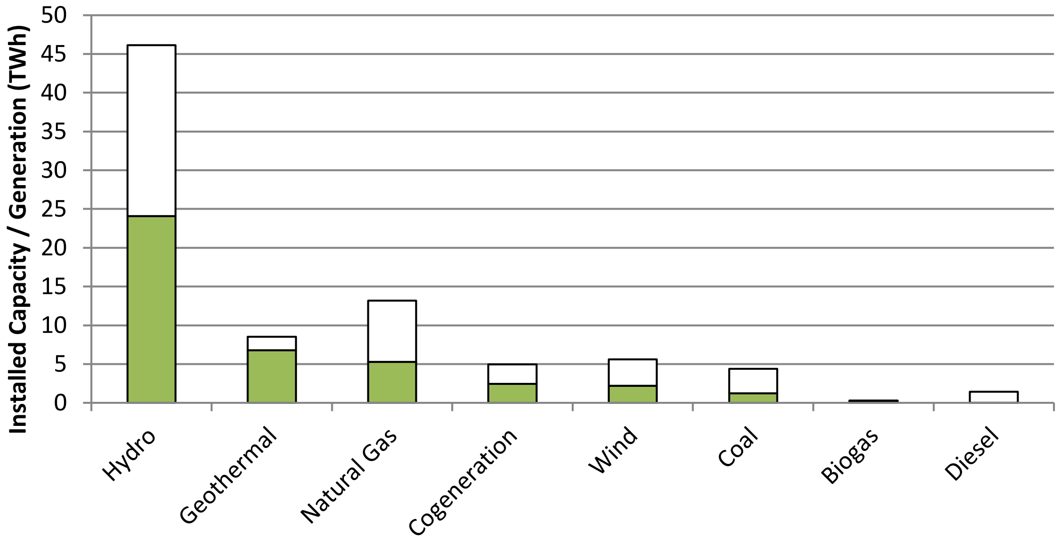
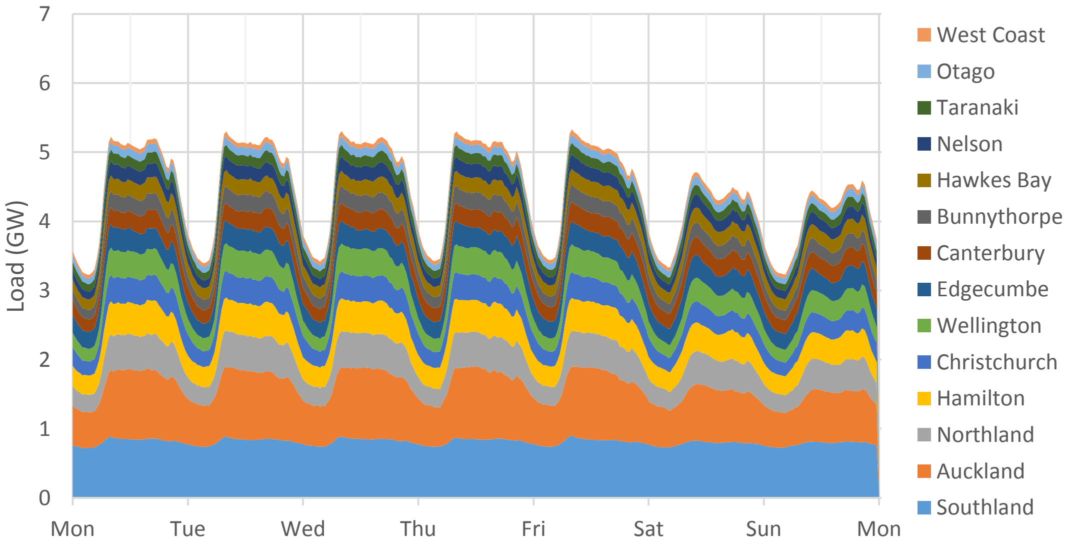


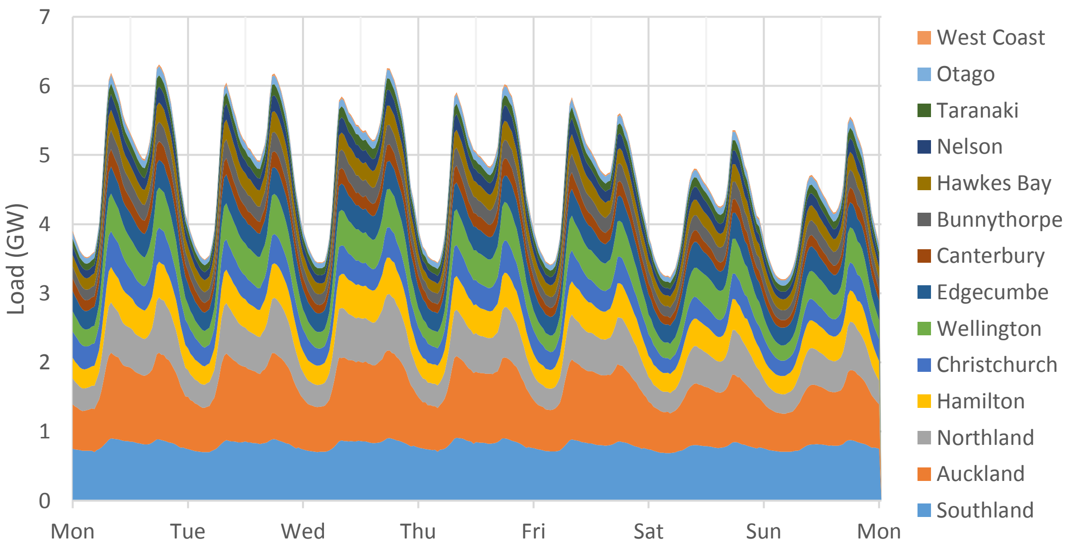
Figure 2.6: New Zealand generation and installed capacity by source in 2014. Data from the Ministry of Business, Innovation and Employment (2014).

Because of New Zealand's reliance on hydroelectricity, periods of low rainfall have the potential to cause electricity shortages (Nair, Naik, Chakrabarti and Goodwin, 2012). While new wind generation is expected to help preserve water and reduce the impact of dry periods, Bull (2010) has shown a potential correlation between periods with low rainfall and periods with low average wind speeds, implying that dry years may also be calm years. As a result, Bull recommends reducing the assumed ability for wind energy to displace hydroelectric energy by 10%, to avoid compromising security of supply.

The majority (98%) of electricity generated during the 2014 calendar year was from large generators with a capacity in excess of 10 MW (Ministry of Business, Innovation and Employment, 2014). Similar to most other countries, the current deployment of Distributed Generation (DG)—small generators on the order of 10 kW—is limited. The widespread deployment of DG will require significant changes in existing infrastructure to support bidirectional energy flows while maintaining protection mechanisms and power quality (Nair and Zhang, 2009), but distribution network operators have already begun to make these changes (Puljic, 2013).



(a) Summer (week ending 24 February 2013).



(b) Winter (week ending 7 July 2013).

Figure 2.7: Typical New Zealand load profiles in summer and winter. Data from Transpower (2013).

2.5.2 Load

The total energy consumption for the 2014 calendar was 39.2 TW h, after accounting for transmission and distribution losses. This corresponds to an average load of 4.5 GW over the course of the year. Figure 2.7 shows typical weekly demand curves for the country's load centres, illustrating the difference between load characteristics in summer and winter. Morning and evening peaks are clearly pronounced during winter, as a result of increased heating and lighting load compared to that during the summer months. While the population of the Southland region is less than 100 000 people, its electricity demand is substantial because of a large aluminium smelter[3].

As shown in figure 2.8, growth in annual consumption has been flat since 2006 across the residential and commercial sectors, while a slight decrease in industrial consumption has been largely cancelled by an increase from the agricultural sector. Despite observing no significant change in demand for eight years, Transpower (2014) expects growth to resume at a rate of 1.2% per year until 2029.

In addition to an increase in overall electricity consumed, concern has been raised that peak load will grow more rapidly than average load (Strbac, Pudjianto, Djapic, Aunedi, Stanojevic, Castro, Ortega, Telfar, Tucker, Corney and

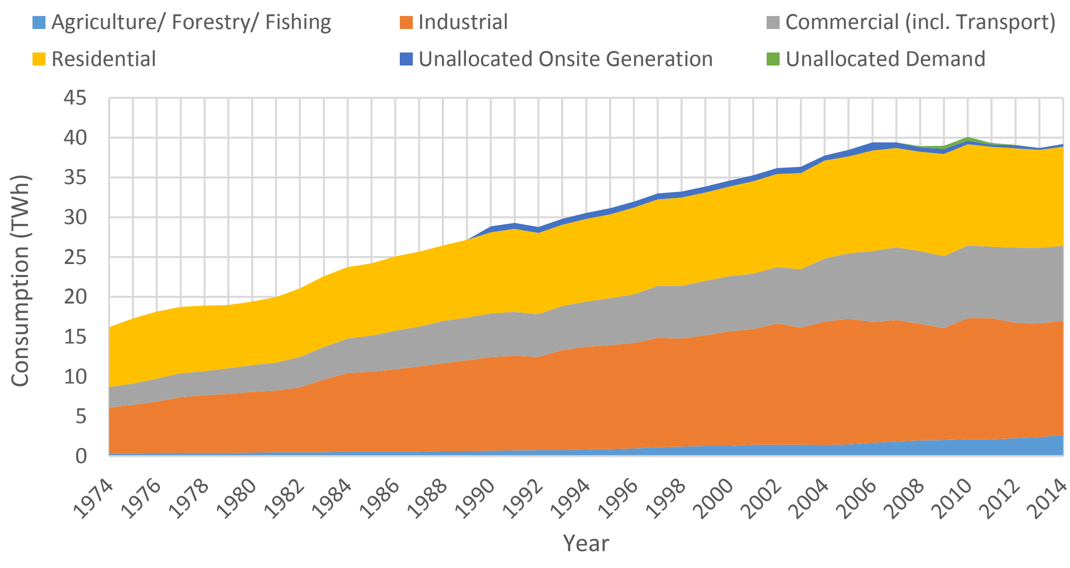


Figure 2.8: New Zealand annual electricity consumption by sector. Data from Ministry of Business, Innovation and Employment (2014).

[3]The Tiwai Point Aluminium Smelter is responsible for approximately 17% of New Zealand's electricity consumption (Bertram and Clover, 2010)

Mcdonald, 2012). This is because the primary drivers of new load—namely heat pumps and EVs—will likely draw electricity from the grid at times of already high demand in mornings and evenings if not controlled. This increased peak-to-average ratio will be costly to accommodate in the existing electricity system, and hence there is a strong case for the deployment of "smart grid" technology to assist with demand management (Strbac et al., 2012).

2.5.3 Storage

As of 2015, New Zealand does not have any large-scale electricity storage systems beyond the inherent storage capacity in the hydroelectric system. The maximum capacity for all hydro lakes combined is approximately 4.2 TW h, of which the vast majority (85%) is in the South Island (Opus International Consultants Limited, 2010). Only Lakes Taupo and Waikaremoana are situated in the North Island.

Figure 2.9 shows the daily storage levels of all major lakes over the 20-year period between 1990 and 2010, calculated as a function of the minimum and maximum permitted water levels, and the efficiency of all downstream generation. During the same period, aggregate inflows into the hydroelectric system averaged approximately 2.1 TW h per month, with a range from 0.984 TW h to 5.34 TW h (Opus International Consultants Limited, 2011).

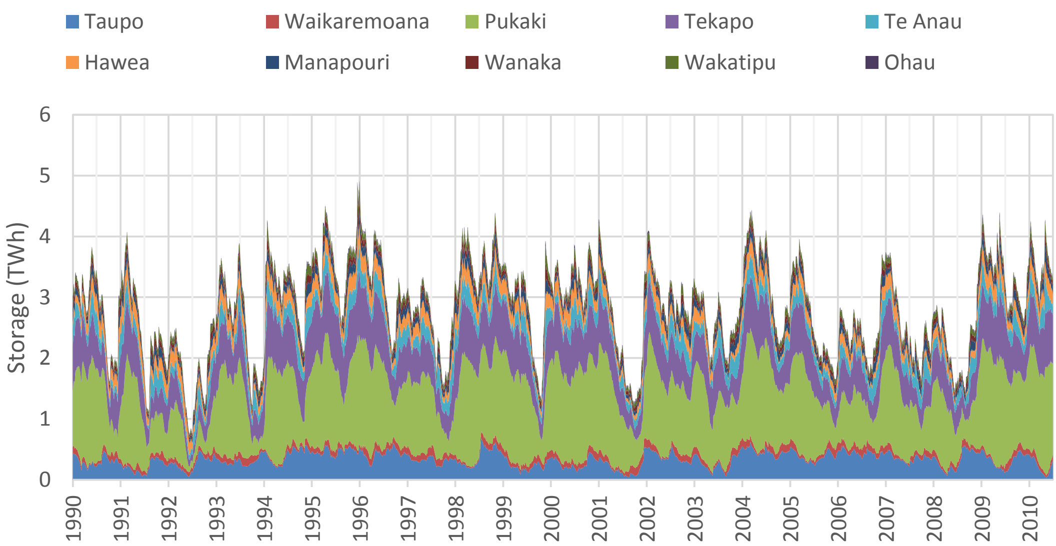


Figure 2.9: New Zealand's hydroelectric energy storage, 1990–2010. Data from Opus International Consultants Limited (2010).

Bardsley (2005) has proposed that the storage potential could be significantly improved with the addition of a Pumped Hydroelectric Storage (PHES) scheme in the Onslow-Manorburn depression in the South Island, which could add an additional storage capacity of up to 10.2 TW h. This scheme is intended to provide long-term storage on a seasonal to multi-year basis to enhance energy security during dry years.

2.5.4 Scheduling and Dispatch

New Zealand operates a security constrained economic dispatch system for ensuring that generation meets load at all times. Ancell (2007) summarises the process as follows:

- Generators submit energy and reserves offers for the day ahead.
- Purchasers submit load bids.
- The System Operator runs processes to produce schedules of cleared generation (energy and reserves) required to meet the forecast load.
- Generators and Purchasers can revise their offers and bids until two hours before dispatch.

Bids are specified to cover a half-hour trading period, while dispatch actions occur at five-minute intervals. In addition to ensuring that scheduled generation is sufficient to meet forecast load, reserves are included to provide redundant generation in the event of an unexpected outage. The magnitude of reserve generation is dictated by the largest unit on the grid, which is 300 MW in the North Island, and 130 MW in the South Island (Ancell, 2007). Frequency keeping is another important aspect of maintaining balance, and is tendered outside the energy and reserves market (Nair et al., 2012). Current requirements for frequency keeping include band of ±50 MW and an ability to change output at a rate of 10 MW min^{-1} (Ancell et al., 2005).

There is some concern that the current approach to managing the dispatch and frequency-keeping process is not sufficient to support variable generation sources; for example, Ancell et al. (2005) identifies that with 800 MW of wind capacity, generation output could change at rates in excess of 40 MW min^{-1}—much greater than the minimum rate required of frequency keeping stations. Because bids are required to be finalised two hours before the time of dispatch, errors in wind generation forecast may be significant enough to exceed the ±50 MW frequency-keeping band; expanding this band to ±75 MW would likely add costs of $2M per month (Ancell et al., 2005).

2.6 New Zealand's Vehicle Fleet

Similar to many OECD countries, the dominant form of transportation in New Zealand is the light passenger vehicle (OECD, 2013). The country ranks highest in the OECD for vehicle ownership per capita, at 82 vehicles per 100 inhabitants, and fourth in terms of passenger vehicles per capita, at 64 vehicles per 100 inhabitants (OECD, 2013). As mentioned previously in this chapter, transportation is responsible for a sizeable proportion of non-agricultural GHG emissions, and the majority (81%) of oil consumption in New Zealand (Ministry of Business, Innovation and Employment, 2014)).

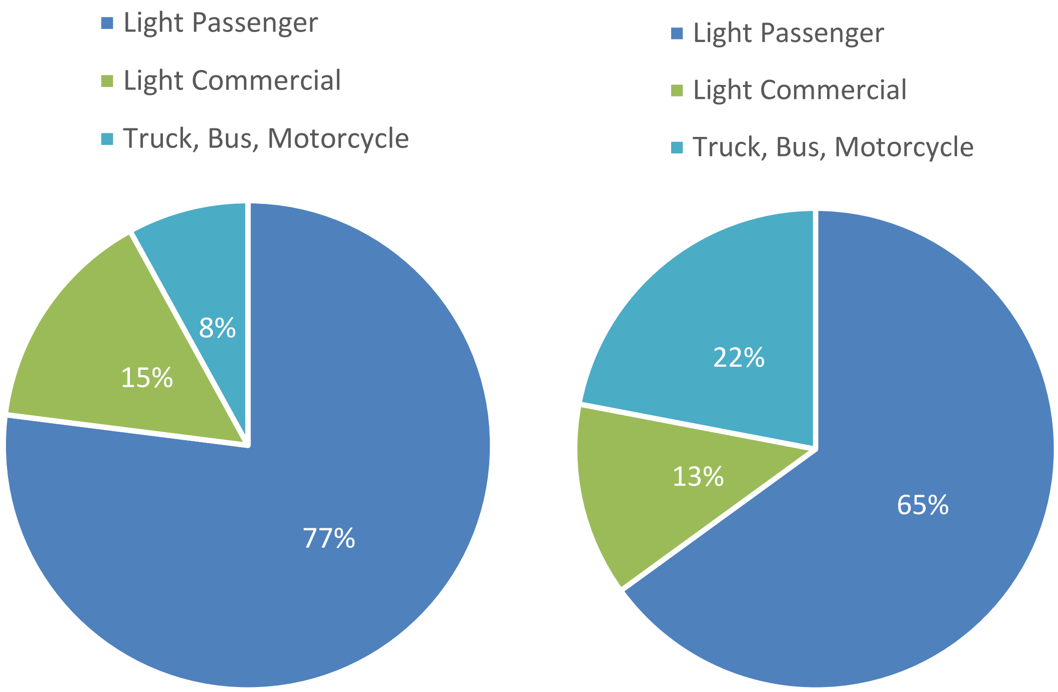
Within the transportation sector, the light private fleet is the largest consumer of petrol (94%), and a smaller amount of diesel (18%), while also being responsible for 64.8% of transport-related GHG emissions (Ministry of Transport, 2014). Thus, moving the light private vehicle fleet from oil-based fuel to electricity would have significant potential to address both energy and GHG concerns in New Zealand.

2.6.1 Composition

New Zealand had 2.7 million light passenger vehicles in 2013, which contributed 77% of all road distance travelled during the year prior, while light commercial vehicles contributed a further 15% of total distance travelled. The remaining 8% of travel was by motorcycle, heavy truck (over 3500 kg), and bus (Ministry of Transport, 2014).

The average age of light vehicles in the fleet is has been gradually increasing since 2000, from 11.75 years to 13.25 years in 2013, with the average age of vehicles leaving the fleet being 20 years for petrol vehicles and 18 years for diesel. Average fuel efficiencies and GHG emissions per km have improved between 2005 and 2013, from 9.58 l/100km to 7.97 l/100km and from 220 $\mathrm{g\,km^{-1}}$ to 183 $\mathrm{g\,km^{-1}}$, respectively (Ministry of Transport, 2014).

EV penetration in New Zealand is currently very low, with only 108 vehicles registered for road use in December 2013, while PHEV penetration was higher at 764 vehicles (Ministry of Transport, 2014).



(a) Distance travelled (b) GHG emissions

Figure 2.10: New Zealand's vehicle fleet in 2012 (Ministry of Transport, 2014).

2.6.2 Vehicle Use

A household travel survey (Ministry of Transport, 2011) conducted between 2007 and 2010 indicates that driving is the most prevalent form of transportation in New Zealand, occupying two-thirds of travel time, while travelling as a passenger, walking, cycling, public transport, and motorcycling make up the remaining third. On average, private vehicles are in use for 3.3% of the time, and the average distance driven per day is 28 km spread over three trips. Males drive 12 000 km per year on average, while females drive 8000 km. The majority of trips (66%) did not carry any passengers.

Of all road travel, the light private vehicle fleet is responsible for the majority of both aggregate distance travelled, and GHG emissions as shown in figure 2.10. This tends to suggest that reductions to GHG emissions from this mode of transportation will have significant potential to reduce GHG emissions across all road transportation in New Zealand.

2.6.3 Predicted Uptake of Electric Vehicles

For EVs to be beneficial to reducing the consumption of fossil fuels and emission of GHGs at a national level, they must be deployed in sufficient numbers. A study by Clover (2013) evaluates the expected uptake of electric vehicles between 2012 and 2030, including the split between general purpose EVs, city EVs (those with limited range and/or top speed), PHEVs, and ICEVs. By 2030, the number of EVs in New Zealand is estimated to range between 1.4 and 1.8 million, with 54% to 61% of those being PHEVs.

Clover (2013) also notes that general-purpose EVs would be the least popular type of EVs, comprising a maximum of 20.2% of the electric fleet in 2030 if battery prices were to drop significantly from current levels. Primary reasons for this choice being unpopular include high purchase cost and limited driving range. The study does not, however, investigate potential V2G revenue as a way to offset high battery costs. While not conclusive, several studies indicate that these revenues may be significant (Han and Han, 2013; Kempton and Tomić, 2005a), and from a grid perspective, the net cost of providing energy to a V2G-enabled vehicle fleet could potentially be negative (Concept Consulting Group Ltd, 2012).

2.7 New Zealand's Energy Strategy

New Zealand's energy strategy (Ministry of Economic Development, 2011) specifies the goal to "Make the most of our energy potential", which is divided into four priorities and subdivided into 12 areas of focus, as shown in figure 2.11. Many of these focus areas are closely related; in particular, increasing the proportion of renewable electricity generation and moving towards an electrified vehicle fleet covers all four priorities.

Much of the Energy Strategy is based on the assumptions that have been presented earlier in this chapter, namely that a) GHGs will become increasingly factored into world markets, b) technological advances will continue in the electricity and transportation sectors, and c) the price of oil will continue to rise and become more volatile.

Perhaps the most important target specified in the Energy Strategy is a 90% renewable electricity system by 2025, providing that security of supply is not compromised. This is expected to be achieved through a combination of new wind farms and geothermal generation plants.

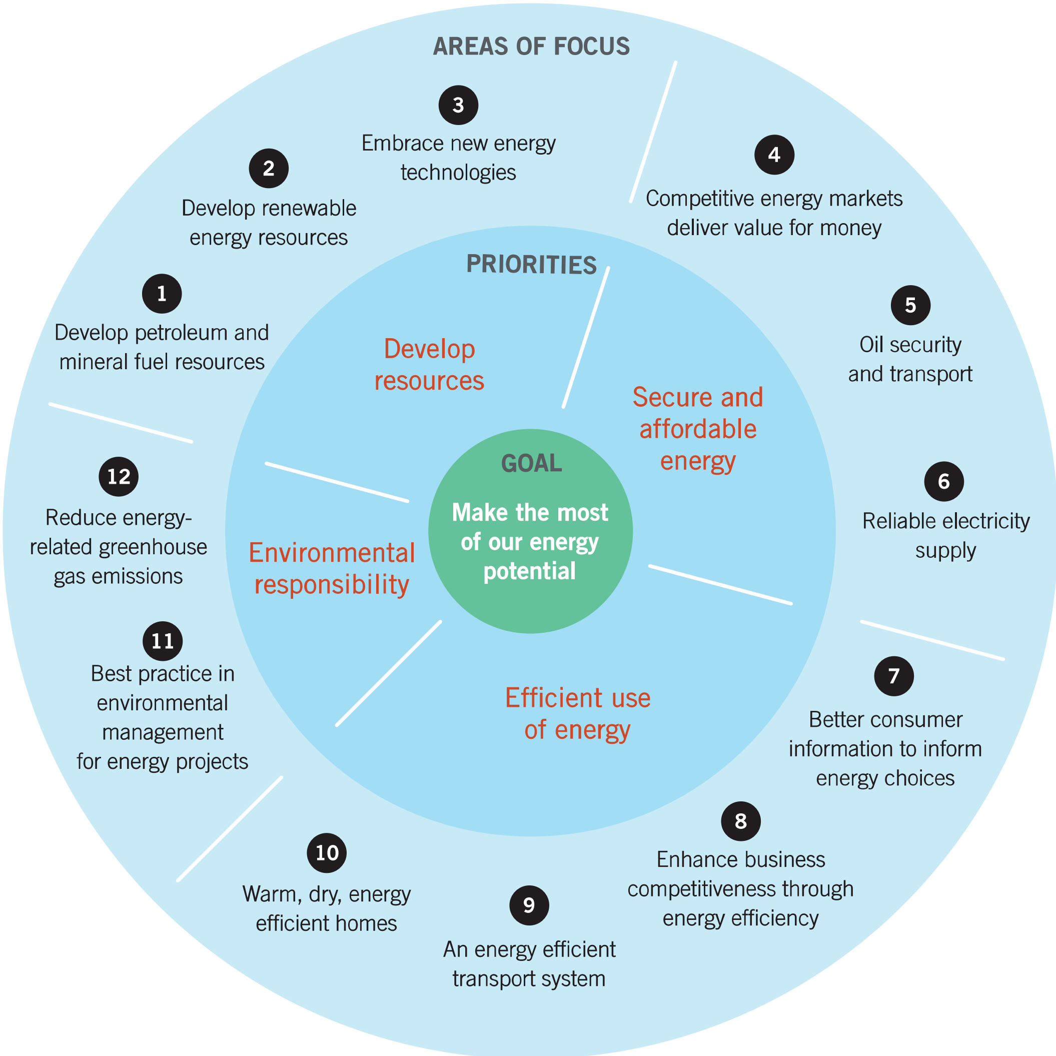


Figure 2.11: New Zealand's energy goals. Reproduced from the New Zealand Energy Strategy document (Ministry of Economic Development, 2011).

The following subsections provide an overview of the energy strategy, including the relevance to this research. Unless stated otherwise, claims made in this section relate specifically to the energy strategy document published by the Ministry of Economic Development (2011).

2.7.1 Develop Resources

The first priority in the Energy Strategy is to develop resources, including petroleum/mineral fuel, renewable energy, and new "green" technologies.

The development of indigenous petroleum and coal does not contribute to the reduction of fossil fuel consumption or GHG emissions, but is seen as important because of its contribution to energy security and reduced exposure to the volatility of international markets; fossil fuels will continue to be an indispensable part of New Zealand's primary energy supply for the foreseeable future.

The second and third focus areas are of more relevance to the research in this thesis—to develop renewable energy sources, and to embrace new technologies. Renewable electricity generation is seen as the main priority, although other technologies are also included such as direct use of geothermal energy, production of biofuels, and technologies that may not exist yet. The government will provide support for the adoption of renewable energy, through market incentives and removal of unnecessary regulatory barriers.

The renewable energy sources expected to have the most impact in coming years are wind and geothermal, although a diverse range of other technologies—for example tidal and solar—are expected to contribute to a secure supply by reducing reliance on a single technology.

The Energy Strategy supports new technologies, such as using electric vehicle batteries for grid-scale energy storage, as well as a number of other energy storage and "smart grid" technologies if shown to be commercially viable. Specifically, the government is in support of research and development in these areas to determine whether they have any relevance in New Zealand's energy future.

The development of renewable resources, including the storage and so-called "smart grid" technologies necessary to support their integration into the electricity grid, is seen as vital part of meeting the 90% renewable electricity target by 2025.

2.7.2 Secure and Affordable Energy

Secure and affordable access to energy is considered to be vital in supporting economic growth and well-being. New Zealand relies on imported oil for half of its primary energy supply, and almost all transportation requirements. This leaves the country vulnerable to volatile international oil markets. Beyond increasing indigenous oil production, the diversification of fuel for transportation and increasing the efficiency of vehicles will help to ensure a secure, affordable energy supply.

A reliable electricity system is defined as having enough generation capacity to supply peak load, having a diversity of sources to provide enough energy in the long term (taking into account variability in, for example, hydro inflows and wind), and having infrastructure in place to deliver electricity from the source to the end user with minimal losses. The Energy Strategy also includes a provision for demand-side technologies such as distributed generation and demand-side load management systems.

Since EVs can be charged from a range of primary energy sources, and are much more efficient than ICEVs, they potentially offer a significant contribution towards a secure and affordable energy supply in New Zealand. Being a net consumer of energy, EVs cannot contribute directly towards energy security goals; however, the flexibility offered by smart charging and V2G could enable better utilisation of non-dispatchable electricity sources that would otherwise be difficult to accommodate.

2.7.3 Efficient Use of Energy

The third Energy Strategy priority is the efficient use of energy. This priority is targeted across a range of areas, for example providing better information to consumers about different options for purchasing various forms of energy, using smart meters and other technologies to help identify inefficient energy use, or offering programmes that encourage better home insulation.

Transportation has been identified as an area with significant potential to improve efficiency, including better public transport, the promotion of walking and cycling in urban areas, and encouragement to increase the uptake of fuel-efficient vehicles. The strategy also states that the government will support the entry of alternative transport fuels into the national fleet, including EVs.

2.7.4 Environmental Responsibility

The final priority is environmental responsibility, which covers GHG emissions, non-GHG emissions, fresh water management, and an improved consenting process under the Resource Management Act 1991.

Within the energy sector, GHG emissions are dominated by transport (44%) and electricity generation (19%). The government has a target of reducing GHG emissions across all sectors to 50% below 1990 levels by 2050, and is willing to commit to between 10% and 20% below 1990 levels by 2020. Steps towards achieving these targets include the New Zealand Emissions Trading Scheme (NZ ETS), and support for greater investment in renewable energy, efficiency, and conservation.

2.8 Smart Grid

The concept of a “Smart Grid” relates to the fusion of traditional electricity transmission networks, and ubiquitous communication networks that together form a large distributed computing platform (Farhangi, 2010; Amin and Wollenberg, 2005). This will enable faster reaction to electrical faults, fine-grained monitoring of network performance, and advanced energy flow management as the electrical network topology moves away from the traditional model of few large dispatchable generators and a large number of “dumb” consumers, to one with many small non-dispatchable generators, “smart” consumers that can react to changing supply conditions, and large-scale distributed energy storage devices (Farhangi, 2010). At a fundamental level, the smart grid will be the enabling technology for making the most efficient use of existing infrastructure, and reducing the investment needed to meet future electricity needs (Farhangi, 2010).

While the exact form of the smart grid is not yet clear, Farhangi (2010) suggests a layered approach similar to that used in the current internet. At the lower levels, sensors, actuators and communication links will be ubiquitous, while upper levels will be responsible for implementing features such as managing distributed generation, storage, and Demand-Response (DR). Ultimately, the smart grid would be a network of interconnected microgrids without the centralised control that is a feature of traditional electricity grids. Similarly, Amin and Wollenberg (2005) envisions the smart grid being comprised of many independent “agents”, each containing sensors to measure information about their own state, and having communication links with other agents to share state information and cooperate as a distributed computing platform.

Ramchurn, Vytelingum, Rogers and Jennings (2012) state that the smart grid will be radically different from current electricity grids, and support bidirectional flows of both data and energy between all parties so that variable generation may be incorporated at scale. In addition to the technical and engineering challenges, the smart grid is expected to interact with end users directly through user interfaces, and indirectly through the application of machine learning techniques to analyse behavioural patterns. The data collected through this interaction will be used to optimise grid operations to ensure that all energy demands are met (Ramchurn et al., 2012).

2.9 Cyber Security

With the increasing utilisation of networked computers in the smart grid and smart vehicles, it is essential to ensure that these systems are secure against cyber attacks.

McDaniel and McLaughlin (2009) identify a number of risks associated with attacks on smart meters, ranging from gaining the ability to manipulate electricity usage data and hence enabling the theft of energy, through to launching distributed denial-of-service attacks and disabling a critical component of the smart grid. Since utilities will rely on smart meters to collect information such as available capacity and potential problems in the network, and to control load during times of peak demand, these types of attacks have the potential to disrupt or physically harm critical infrastructure at a local or national level (McDaniel and McLaughlin, 2009).

The parallel roll-out of smart vehicle technology also exposes similar risks. Newer vehicles are equipped with increasingly sophisticated systems to enhance safety and efficiency, for example the ability to share warnings about dangerous road conditions with other vehicles. Abuse of this technology has the potential to cause a wide range of problems, including disruption of traffic flows by falsely advertising dangerous road conditions (Raya, Papadimitratos and Hubaux, 2006), remote locking of vehicles until a ransom is paid, theft by remotely unlocking a vehicle, and at the extreme end of the scale, sabotage by remotely instructing a vehicle to aggressively apply brakes to induce a loss of control (Zhang, Antunes and Aggarwal, 2014).

Zhang et al. (2014) suggest that traditional approaches for protecting against malware is impractical to implement within vehicles because of limited onboard processing power and the long lifespan of vehicles compared to traditional computers. They propose that communication traffic with a vehicle should be routed through cloud computing resources, where it will be analysed for the presence of malware. For attack vectors other than wireless communication, for example removable media connected to a vehicle's entertainment system, a limited form of local analysis can be performed; if anything suspicious is found, it should be uploaded to the cloud for further analysis (Zhang et al., 2014). This approach may also be relevant to help secure smart grid infrastructure to protect against tampering with smart meters through their wireless interfaces or local infrared communication ports.

Although the security aspects related to the smart grid and vehicle systems are not a focus in this thesis, it is acknowledged that these issues exist, and that maintaining a high level of security is vital to ensure the acceptance and success of smart grid and smart vehicle technology.

2.10 Social Barriers

A lot of research into the adoption of EVs and smart grid technologies tends to focus on the technical aspects related to their use, although their social acceptance is crucially important if these technologies are to be successful (Sovacool and Hirsh, 2009). Barriers to adoption may include opposition to new and unproven technologies caused by a poor understanding of the performance characteristics of electric vehicles (Sovacool and Hirsh, 2009) to concerns related to the privacy and security risks created as a result of large-scale data collection of electricity demand and vehicle travel (McDaniel and McLaughlin, 2009; Simmhan, Kumbhare, Cao and Prasanna, 2011b).

The extensive collection and analysis of data is fundamental to the operation of a smart grid, to allow accurate load forecasting, respond to disturbances, and provide detailed information to consumers (Simmhan et al., 2011b). Unfortunately, there is significant potential for this information to be used (or misused) for purposes other than the reliable supply of electricity. For example, non-intrusive load monitoring by smart meters can reveal detailed behavioural patterns about occupants of a household such as the times the home is occupied, whether a stove or microwave is used for cooking, how often clothes are washed, when a TV is being watched, and sleeping patterns (Cavoukian, Polonetsky and Wolf, 2010; McLaughlin, McDaniel and Aiello, 2011; McDaniel and McLaughlin, 2009). This information could prove to be commercially valuable for purposes such as targeted advertising (Cavoukian et al., 2010).

EVs and other mobile appliances may consume electricity at multiple locations such as home, work, or public charging stations. This may expose snapshots of the vehicle's location for the purposes of billing and controlling charging rates, and hence reveal personal information that could be exploited for purposes other than delivering energy to the vehicle (Cavoukian et al., 2010). Privacy issues related to vehicle use are not unique to EVs and smart grid—some insurance companies offer a discount in exchange for recording driving habits with a GPS logger. To preserve privacy, this record might contain only speed/distance data without location; however, it may be possible to recover location information by combining the distance record with publicly-available mapping data, and hence reconstruct the movements of the vehicle (Gao, Firner, Sugrim, Kaiser-Pendergrast, Yang and Lindqvist, 2014).

The widespread collection and analysis of data is a fundamental part of smart grids and smart transportation systems in the future. This proliferation of data must be carefully managed to protect the privacy of those involved; Cavoukian et al. (2010) argues that privacy should be built into the smart grid. These issues are beyond the scope of the research presented in this thesis, but are nonetheless important to consider. Assumptions are made in later chapters about the willingness of consumers to participate in smart grid and V2G schemes, to make data available for commercial use, and to adapt driving/charging behaviours that may differ substantially from today's patterns.

2.11 Summary

There is little doubt that most, if not all, countries will move towards reducing their GHG emissions, as well as their dependence on fossil fuels. The widespread deployment of non-dispatchable renewable electricity generation and EVs is thought to be critical in meeting these goals; however, the success of these technologies will require significant flexibility in the operation of electricity grids. Strategies for managing this flexibility are therefore an important area of research.

This chapter has provided motivation for a case study involving the widespread deployment of EV and wind generation in New Zealand, including an overview of the characteristics of the major technologies likely to be involved in a future energy scenario. The following chapter discusses research related to the widespread deployment of EVs and non-dispatchable electricity generation, and establishes the course of research to be discussed in the remainder of this thesis.

3 Related Work

Two of the technologies expected to have the most impact in reducing GHG emissions and fossil fuels dependence are Electric Vehicles (EVs) and renewable electricity generation; wind turbines in particular. The widespread deployment of these technologies will challenge the traditional operation of electricity grids, by introducing greater uncertainty and short-term variability in electricity generation, while also necessitating the coordination of EV charging to prevent overloading electrical transmission and distribution infrastructure.

Managing variability and peak load in electricity systems is not a new challenge; however, when faced with a high proportion of non-dispatchable generation and a large number of synchronised high-power loads (e.g. EVs), continuing to manage variability by utilising highly dispatchable generation will become prohibitively expensive (Chardon, Almén, Lewis, Stromback and Château, 2008). Alternative approaches, such as DR and storage, are therefore of increasing interest.

This chapter provides a review of studies related to the large-scale integration of renewable electricity generation, the impacts of EV charging on electricity infrastructure, and strategies for managing and controlling the charging of large numbers of EVs.

3.1 Integration of Non-dispatchable Generation

The management of variability is an essential element in any electricity system; a fundamental requirement being to maintain the balance between generation and load at all times. Over short periods (seconds to minutes), generators must be able to quickly *ramp* their output up or down to match changes in load, while over the mid term (minutes to hours) generators must provide sufficient *power* to cover load. Over longer periods (months to years), generators must be able to deliver sufficient *energy* to cover total demand. Maintaining this balance is usually achieved by adjusting the mechanical inputs to generators in response to any observed mismatch between generation and load (Backhaus and Chertkov, 2013). This approach becomes less feasible with high levels of non-dispatchable generation, which has led to many studies searching for flexibility in other parts of the system.

With renewable generation, the effects of variability are seen across a wide range of time scales. For example, power output from solar PV can rapidly change in response to passing cloud, while nightfall will reduce its power generation capacity to zero. In addition, sunlight hours in temperate areas vary on a seasonal basis, resulting in more energy production during summer months, and less during winter. On the other hand, hydroelectric generation (with reservoir) can provide fast ramping and reliable power output in the short to mid term, but may suffer from long-term energy shortages during extended periods of low rainfall (Suomalainen, Pritchard, Sharp, Yuan and Zakeri, 2015; Mason et al., 2010b). In that situation, other more expensive energy sources must be used to preserve water in the hydro system (Suomalainen et al., 2015).

When the penetration of wind generation in an electricity system is low, its variability is dominated by natural variations in load and therefore can be accommodated using traditional methods without much difficulty (DeCarolis and Keith, 2005). Depending on the particular electricity system, additional measures become necessary to maintain short-term balance when non-dispatchable generation exceeds 10 to 20%. This is not to say, however, that a small amount of non-dispatchable generation has no additional balancing costs associated with it, nor that exceeding the aforementioned threshold will cause a rapid increase in costs. DeCarolis and Keith (2005) argues that while a small amount of wind generation can be accommodated without increased balancing requirements, it comes at a cost of reduced reliability. Furthermore, the variability introduced by wind will increase in proportion to the wind penetration level, and hence the balancing costs will scale linearly with the amount of wind generation in the system (DeCarolis and Keith, 2005).

A discussion of techniques that may be used for managing variability in an electricity system—namely load-following generation, demand-response, and energy storage—is included in the following sections.

3.1.1 Load-following Generation

Since present-day electricity grids manage variability primarily on the supply side, many studies related to renewable generation integration focus on increasing supply-side flexibility to compensate for the variable output of non-dispatchable generation sources. The costs of providing this compensation are tightly related to the existing flexibility in a particular electricity system; for example, electricity systems with high levels of inflexible nuclear and coal generation will face higher costs than systems that are dominated by more flexible sources such as hydroelectricity (Strbac, Aunedi, Pudjianto, Teng, Djapic, Druce, Carmel and Borkowski, 2015).

The effort required to accommodate a new non-dispatchable generation resource largely depends on its output characteristics, particularly in relation to other generation sources, and also to load. When planning a new wind generation sites, for example, it is beneficial to choose a site with an expected output profile that is negatively correlated with the generation profiles of other sources, and positively correlated with load (Suomalainen et al., 2015).

Inflows into existing hydroelectric generation systems in New Zealand are dominated by spring/summer snow melt in the South Island, and winter rainfall in the North Island. Because the South Island hydro system is much larger in terms of storage and power capacity, and because demand is generally higher in winter, it is beneficial for new non-dispatchable generation to have a complementary output profile in order to maintain an energy balance at a seasonal level (Suomalainen et al., 2015). By investigating the correlations between historical hydroelectric lake levels, wind speed, electricity prices, and electricity load, Suomalainen et al. (2015) found that the best suited wind farm sites are likely to be in Southland, since average wind speeds there are high when hydroelectric lake levels are low. Unfortunately, Southland is a considerable distance from New Zealand's main load centres in the North Island (Suomalainen et al., 2015).

Ideal sites for renewable electricity generation are often far from load centres for other reasons as well. For example, wind farms are most effective in windy areas, solar PV performs best when located in areas with plentiful sunlight, and hydroelectric generation (including PHES) is constrained to sites with suitable geography. This necessitates long transmission distances, resulting in increased losses, congestion, and power quality issues—particularly during times of high load (Suomalainen et al., 2015; Klimstra, 2014; Abeyratne, 2007; Strbac et al., 2015).

Distributed Generation (DG) is often said to offer the advantages of reduced transmission and distribution losses, as well as lower peak net demand, by the simple observation that this form of generation is located physically close to the point of consumption (Nair and Jing, 2013). However, local weather conditions can strongly influence all local generators simultaneously, which can cause power quality issues. Klimstra (2014) explains that when local generators are producing a significant amount of power, other more expensive dispatchable generators will be forced offline. As a result, the remaining generators with load-following capability will likely be far from the point of consumption. This will negatively influence local power quality and security of supply, and also increase transmission losses. Alternatively, DG can be curtailed so that local dispatchable generation can continue to operate, but this approach—by definition—results in significant energy spillage (Strbac et al., 2015; Liu, Hu, Lund and Chen, 2013).

At times when DG is producing very little output, sufficient generation capacity must be available elsewhere in the system to cover load. This could be local dispatchable generation, or geographically distant non-dispatchable generation that is currently experiencing more favourable weather conditions. As an example, distributed solar PV will not generate electricity during New Zealand's highest load periods—typically winter evenings when space heating, cooking, and lighting loads are present (Transpower, 2013). This suggests that non-dispatchable DG, on its own, does little to reduce peak loads (Miller, Hwang, Lemon, Read and Wood, 2015).

Fripp (2011) investigates GHG emissions from natural gas generation when used to back up the uncertainty introduced by large-scale wind deployment, using historical wind speed data to estimate the level of dispatchable spinning and non-spinning reserves needed to accommodate short-term forecasting errors in wind generation in the United States. With wind farms spread over an area with a diameter of more than 500 km, it was found that the use of natural gas for accommodating errors in wind forecasts would undo about 6% of the GHG savings expected from the use of wind generation. This study assumes a simplified power system with an installed capacity of dispatchable generation equal to at least that of wind generation, and only includes GHG emissions resulting from accommodating *errors* in wind forecasts—it does not include emissions from dispatchable generation scheduled when wind forecasts are insufficient to cover load. It also does not address the energy lost when wind generation exceeds load, which will become significant at high wind penetration levels (Franco and Salza, 2011). In any case, the use of natural gas to balance fluctuations in wind output is likely to be expensive and should be avoided as much as possible (Franco and Salza, 2011).

3.1.2 Demand Response

Demand-Response (DR) is described as the ability to "...shift demand from one moment in time to another without noticeably affecting the quality of service" (Tindemans, Trovato and Strbac, 2015), which effectively allows some appliances to act as virtual energy storage devices. The primary goal of DR is to adapt demand to match supply conditions, for example by reducing load during peak demand periods (peak shaving), smoothing load profiles to reduce the need to start and stop generation units (Simmhan, Aman, Cao, Giakkoupis, Kumbhare, Zhou, Paul, Fern, Sharma and Prasanna, 2011a), and providing reserve services for covering unexpected losses in generation capacity (Tindemans et al., 2015). Appliances that are well suited to providing DR services include those which have inherent energy storage, such as heating/cooling appliances and EVs, or which provide flexibility over the timing of their use, for example dishwashers and clothes driers.

A recent study by Tindemans et al. (2015) explored the potential for thermostatic appliances to act as primary and secondary reserves in power systems. The study involved simulating up to 100 000 refrigerators, each of which implemented a distributed algorithm for controlling aggregate load in response to a trigger—for example, a particular time of day, or an under-frequency event. The temperature of any individual appliance was not allowed to stray beyond a typical deadband, meaning the expected quality of service provided by the refrigerators was never compromised. Under these conditions, the aggregate refrigeration load was able to drop to 50% within 10 seconds of observing a trigger condition, and remain at 75% of nominal load for up to 30 minutes. Earlier work has demonstrated similar findings (Kupzog, 2008), while local studies have shown that up to 50 MW of regulation potential may be provided by grid-aware thermostatic appliances in New Zealand (Alzaanin, 2014; Strbac et al., 2012).

DR has the potential to significantly offset energy costs; for example, Aikema and Simmonds (2012) has shown that data centres in the United States can participate in the regulation and operating reserve markets by dynamically modifying server workloads in response to electricity supply conditions, including the ability to temporarily suspend a proportion of servers during grid contingencies. While data centre operators must still pay for energy consumed by the facility, payments received for offering such flexibility can reduce net energy costs to zero with only a minor decrease in data centre performance (Aikema and Simmonds, 2012).

New Zealand currently has a wide deployment of ripple control for water heating, an elementary form of DR, and in recent years many electricity distribution and retail companies have begun rolling out smart meters to consumers. These meters have the potential to support more sophisticated DR options in future, including fine-grained control of anticipated loads such as EVs, heat pumps, and smart appliances (Strbac et al., 2012; Puljic, 2013).

3.1.3 Energy Storage

While both DR and load-following generation both offer a substantial contribution towards maintaining balance in an electricity system, those approaches alone are not sufficient when a high proportion of non-dispatchable electricity generation is considered (Strbac et al., 2012). Energy storage is therefore necessary to absorb surplus generation from non-dispatchable sources, and to cover generation shortages during periods of high demand and/or low generation output (Black and Strbac, 2006).

Storage within an electricity system may take a number of different forms, from large-scale centralised storage facilities such as Pumped Hydroelectric Storage (PHES), to highly-distributed storage units deployed in residential homes (Apperley, Monigatti and Suppers, 2015) or even integrated into small appliances; for example, batteries in laptop computers (Morisawa, 2007).

In addition to topology considerations, storage systems are required to hold energy over a wide range of time scales to compensate for variability in generation and load; from near-instantaneous fluctuations in power imbalance, through to seasonal and multi-year variations in energy supply and demand (Mason, Page and Williamson, 2013). These requirements determine the necessary performance metrics of the storage systems in question, in terms of responsiveness to changes in power, absolute power input and output, and total energy storage capacity. In the present-day electricity system in New Zealand, for example, very rapid changes in generation and load—time scales up to several seconds—are smoothed by the inertia of rotating machinery such as generators and turbines, which is extremely responsive but has very little energy storage capacity. Much slower changes—measured in months to years—are often smoothed by water stored in hydroelectric lakes, which have a very large energy storage capacity, but a slow response time.

Centralised Storage

Storage in New Zealand is currently dominated by the combined 4.2 TW h capacity of its hydroelectric reservoirs, with no PHES capability. The energy contained in these reservoirs must operate within a number of constraints including minimum and maximum allowable lake levels, river flow rates, generation and transmission capacity—all of which may vary with time (Opus International Consultants Limited, 2010). In addition, much of the storage capacity is required to buffer the variable inflows into the hydroelectric system itself from rainfall and snow melt, so the effective storage capacity available for other purposes, such as facilitating the integration of non-dispatchable generation sources, will be less than the aggregate capacity of the lakes.

Studies by Mason et al. (2010a,b) have investigated the potential for 100% renewable electricity generation in New Zealand, exploiting the existing hydroelectric storage capacity. Models used in these studies were based on historical generation, load, hydro inflow, and wind speed time-series data, combined with parameters such as generation capacity by plant type and permissible lake storage levels. All hydroelectric systems were aggregated into a single virtual reservoir, with its behaviour dictated by historical observations of peak power output and ramping rates. After replacing fossil fuel generation with new renewable generation, it was found that increased wind penetration would result in larger and more frequent power deficits, and increased hydro spillage.

A later study by Mason et al. (2013) aimed to minimise energy spillage by preemptively switching off geothermal generation when spillage was expected, and mitigated power deficits using a 1.5 GW PHES scheme with a storage capacity of 368 GW h and a utilisation factor of only 0.76%. The authors conclude that a 100% renewable electricity system could provide a secure electricity supply over the 6-year study period, but suggest that alternative methods to address power deficits should be considered.

While centralised energy storage has been shown to provide sufficient energy and power capabilities to support a 100% renewable electricity system in New Zealand, the transmission and distribution network impacts are less clear. For reasons discussed in section 3.1.1, centralised storage is likely to be located far from load centres, and hence suffer from congestion in the transmission network during peak load periods.

Distributed Storage

The use of distributed storage can reduce peak loading of transmission and distribution infrastructure by placing energy storage appliances physically close to load. These appliances are typically modular and scalable, which include large units on the order of several hundred[1] kW h for installation within dis-

[1] Tesla Powerpack

tribution networks, and smaller units on the order of ones[2] to tens[3] of kW h for installation in residential and commercial buildings.

Since peak loading is typically a short-lived phenomena, occurring twice daily and lasting up to several hours (Transpower, 2013), distributed storage capacity does not need to be particularly large to realise its benefits. Indeed, it has been noted that present-day distributed storage technologies become prohibitively expensive when energy must be held for more than a few days, and are therefore not appropriate for seasonal balancing (Klimstra, 2014, pp. 120).

Studies related to distributed storage typically investigate its applications in conjunction with distributed generation. For example, a study by Mason (2015) estimated the storage requirements for small islanded electricity systems in six locations across New Zealand, using a simulation approach over a one-year period. This study utilised hourly electricity load, solar insolation and wind speed data, and simulated an energy storage system with a round-trip efficiency of 81%. Generation was sized such that annual energy production matched annual load, plus an additional allowance to compensate for storage losses. It was found that solar PV required up to three times more storage capacity than wind generation—approximately four months of average load—to maintain balance over the study period. This is mainly attributed to higher demand over winter, and higher solar PV output during summer. Wind generation was observed to be more stable than solar PV over the simulated year, although considerable short-term variability was also present.

To address the large storage requirements for integrating distributed generation, the *grid-lite* concept (Apperley et al., 2015) includes a lightweight connection to a wider electricity grid to provide any balancing needs that cannot be met by local storage. In contrast to net-zero energy balance systems, *grid-lite* imposes a power limit on the grid connection which is typically much less than the peak demand of the building. Experiments by Apperley et al. (2015) focussed on a single residential household, with solar PV sized to provide net-zero energy balance over a one-year study period. Local storage capacity was sized to hold 24 hours of average load, while the grid connection was limited to approximately 20% of peak load. The study found that even without a predictive control system, violations of the grid connection limit were rare.

Although distributed storage is not suitable for long-term balancing, its application for smoothing short-term variability is compelling. Rasmussen, Andresen and Greiner (2012), for example, found that adding efficient short-term

[2] Enphase AC Battery
[3] Tesla Powerwall

storage to a system with inefficient long-term storage greatly improved the efficiency of the overall system.

3.1.4 Discussion

Maintaining balance between electricity generation and load is not a new challenge, but it is expected to become progressively more difficult as non-dispatchable generation and high-powered synchronised loads such as EVs become more prevalent. Large dispatchable generators have traditionally been responsible for maintaining this balance, but DR and storage technologies are expected to play an increasingly important role in future.

New non-dispatchable generation technologies and sites should be chosen such that their output profiles are positively correlated with load, and negatively correlated with other non-dispatchable generation, so that long-term storage requirements are minimised. As a result, it is likely that new generation will be a considerable distance from load centres, resulting in long transmission distances and constraints during high load periods. Distributed generation technologies such as solar PV typically do not reduce peak load, since their output is often poorly correlated with load.

By exploiting the flexibility of some electrical loads, DR technologies have significant potential to compensate for the short-term variability introduced by non-dispatchable generation sources, at a relatively low cost. However, DR has limited ability to provide flexibility over the longer term.

To address the shortcomings of load-following generation and DR technologies, both long and short term storage are likely to be necessary. While large centralised reservoirs are well suited to providing long-term energy storage, they are likely to be situated in remote locations and hence limited in their ability to balance short-term variability and mitigate transmission constraints during peak load periods. Distributed storage offers the complementary advantage of being well-placed for covering short-term peaks in demand, but present-day technology becomes prohibitively expensive when energy must be stored for more than a few days.

A *grid-lite* approach supports a combination of centralised and distributed storage to be used together, in order to realise the benefits of each; large energy storage capacity for long-term energy balancing, and highly-responsive short-term storage for smoothing peak load and variability of non-dispatchable generation. Since this combination places short-term storage physically close to load, transmission and distribution constraints are minimised.

To summarise, many of the studies related to non-dispatchable renewable electricity generation use a simulation approach, based on historical data where available. Primary research themes are based on predictions that electricity generation will become more variable in future as more non-dispatchable sources are introduced, while load will become more flexible through the further adoption of DR technologies. Storage is also expected to become increasingly important, with large centralised facilities providing long-term energy storage, and small distributed storage appliances performing short-term balancing in order to minimise transmission and distribution constraints.

3.2 Electric Vehicle Charging Strategies

With a significant proportion of EVs deployed in an electricity system, there is strong agreement among researchers that their charging must be coordinated or controlled in some manner (Aunedi et al., 2014; Clement, Haesen and Driesen, 2009; Clover, 2013; De Hoog, Thomas, Muenzel, Jayasuriya, Alpcan, Brazil and Mareels, 2013; González Vayá, Galus, Waraich and Andersson, 2012; González Vayá and Andersson, 2012; Habib, Kamran and Rashid, 2015; Lopes, Soares and Almeida, 2009; Putrus et al., 2009; Schuller, Flath and Gottwalt, 2015; Waraich, Galus, Dobler, Balmer, Andersson and Axhausen, 2013). Without coordination, EV charging is likely to occur during times of already high electricity load, and hence require excessive investment in additional generation, transmission, and distribution infrastructure.

While there is little doubt that widespread adoption of EVs necessitates the use of strategies to coordinate their charging, the ultimate form that these strategies will take remains an open question (Waraich et al., 2013). A charging strategy must ensure that EV drivers are able to use their vehicles when needed, while also minimising adverse impacts on electrical infrastructure—particularly during peak load periods. Such strategies could range from simple timer-based approaches that begin charging vehicles at a particular time of day, to more complex strategies that continuously adapt charging rates in response to observed changes in generation and load.

Studies have found that with appropriate charging strategies, EVs are not a significant burden on electricity systems; in fact, their presence offers significant benefits such as increasing baseload utilisation (Shortt and O'Malley, 2009, 2014), increasing direct use of non-dispatchable renewable generation (Franco and Salza, 2011), and enabling a higher proportion of renewable generation than would otherwise be feasible (Schuller et al., 2015). The benefits are further realised when energy is permitted to flow from vehicles back into the electricity grid, which effectively allows an EV fleet to function as a distributed energy resource. This concept, known as Vehicle-to-Grid (V2G), was first introduced by Kempton and Letendre (1997).

Tuttle and Baldick (2012) predicts that the charging behaviours of EVs will evolve over time, starting with a simple charge-only approach and developing to a point where large numbers of EVs coordinate their charging to minimise stress on infrastructure and maximise the utilisation of renewable generation sources.

This section provides an overview of research related to EV charging strategies. These strategies have been categorised into three broad classes: *simple*, which do not consider grid state; *smart*, which optimise charging rates according electricity supply and demand; and *bidirectional*, which are *smart* charging strategies that additionally allow energy to be retrieved from EV batteries for grid balancing purposes.

3.2.1 Simulation Approaches

EV driving patterns are expected to be substantially the same as traditional ICEV driving patterns, and therefore models derived from existing mobility surveys can be used to simulate EV movements (Kristoffersen, Capion and Meibom, 2011; Nunes, Farias and Brito, 2015; Schuller et al., 2015). Based on this assumption, and considering efficiencies of current-generation EVs, the resulting increase in annual electricity demand is expected to be minimal in many countries—typically around 8 to 19% with 60 to 100% electrification of the light vehicle fleet (Duncan et al., 2010; Nunes et al., 2015).

Duncan et al. (2010) calculates that each EV in New Zealand will require approximately 2.1 MW h of electricity per year, or 6 kW h per day. The battery capacity of a present-day EV is typically much greater than its average daily energy consumption, which suggests that charging load can be largely decoupled from driving patterns if regular charging opportunities are available.

Studies of EV charging strategies often use an agent-based simulation using EV behaviour and electrical models, combined with historical electricity generation and load data where available (Carvalho, Sousa and Ventim Neves, 2013; Waraich et al., 2013; Alvaro, Gonzalez, Fraile-Ardanuy, Knapen and Janssens, 2013). This approach allows the performance of charging strategies to be evaluated and compared across a range of parameters, such as peak charging load, utilisation of non-dispatchable renewable generation, and battery degradation where bidirectional energy flows are permitted.

3.2.2 Simple Charging Strategies

First generation EVs are likely to support only simple charging strategies, which typically assume that electricity is available on-demand but may also include the ability to utilise off-peak electricity during preset charging windows (Tuttle and Baldick, 2012). Because electricity demand varies predictably on a diurnal cycle, a simple timer-based approach can increase off-peak utilisation of generation and transmission infrastructure with minimal investment in new smart grid technologies.

The simplest possible charging strategy is often referred to as “dumb”, “as fast as possible”, “uncontrolled”, or “greedy”. An EV using this strategy will begin charging at its fastest possible rate immediately after being connected to a charger. Studies have found that the charging load profile created by this strategy tends to align with existing high-load periods, which is most pronounced during evenings (Waraich et al., 2013; Shortt and O’Malley, 2009). While only a small proportion of charging activity occurs overnight when electricity load is typically lowest, the use of chargers at multiple locations during the day—for example at home, work, and other commercial areas—can reduce the evening charging peak by approximately 30% (Weiller, 2011).

Overnight charging strategies attempt to improve the load profile by moving the bulk of EV charging load into off-peak periods, either by following a fixed schedule, or by reacting to coarse pricing signals. These strategies typically require that each EV is fully charged by the start of the next day, with supplementary charging used during daytime hours where necessary (Waraich et al., 2013; Alvaro et al., 2013; Mason, 2014).

Pricing signals can potentially synchronise the onset of EV charging load, where a significant number of vehicles begin charging at the beginning of a low tariff period. This rapid onset may cause a peak which is twice that seen with uncontrolled charging, which emphasises that charging strategies must not synchronise the behaviour of large numbers of vehicles (Waraich et al., 2013; Alvaro et al., 2013).

Carvalho et al. (2013) investigates the effects of a fixed overnight charging strategy on wind penetration levels that can be accommodated in the Portuguese electricity system, with a maximum of 1% curtailment on an annual energy basis. The start of the charging period is normally distributed around 22:00 each night, with a standard deviation of 1 h and a charging power of 3.3 kW. This study found that wind penetration is restricted to 21% with no EVs present in the system, rising to 40% with full electrification of the light vehicle fleet, following an almost-linear relationship between these variables.

3.2.3 Smart Charging Strategies

Second generation EVs are expected to adopt charging strategies that coordinate the charging behaviour of large numbers of vehicles, allowing the aggregate charging load to closely follow the availability of renewable electricity generation while avoiding peak load periods (Tuttle and Baldick, 2012). In addition, these vehicles may participate in the ancillary services market to provide functionality such as limited up/down regulation to generate revenue for EV owners (Tuttle and Baldick, 2012). The charging strategies that enable these behaviours rely on smart grid technologies to provide the necessary information and control capabilities.

Smart charging strategies fall into two broad categories: *centralised*, whereby charging actions are dictated by a central authority that optimises charging load across a large number of EVs, and *decentralised*, where each EV acts as an autonomous agent and performs charging decisions independently based on aggregate information shared between agents.

The flexibility afforded by these charging strategies relies on EVs being grid-connected for much longer than is strictly necessary to meet transportation requirements. Waraich et al. (2013) proposes financial incentives for EV owners to leave their vehicles connected to the grid for as long as possible, while also rewarding the accurate prediction of the upcoming use of the vehicle so that charging can be planned accordingly. Kristoffersen et al. (2011) assumes that all EVs will be grid-connected while not in use, while Nunes et al. (2015) uses a more conservative estimate that 70% of parked cars will be grid connected. The former assumption will tend to overestimate the flexibility offered by an EV fleet, but is nonetheless useful in establishing an upper bound of EV availability and hence the potential merits of smart charging strategies.

Centralised Smart Charging

Centralised charging involves the use of an *aggregator* or *charging service provider* to calculate individual charging schedules for a large number of EVs, such that the aggregate charging load closely follows a desired profile. These schedules must obey a number of constraints, including those associated with individual vehicles such as driving patterns and maximum charging rates, and those related to transmission and distribution capabilities.

The optimisation goal varies among studies, including the desire to minimise EV charging costs (Kristoffersen et al., 2011), to minimise energy spillage from non-dispatchable generation sources (Nunes et al., 2015), and to follow load profiles specified by other participants in the electricity market, such as retailers, to avoid overloading transmission and distribution networks (Sundstrom and Binding, 2012). Regardless of how the goal is specified, a common theme is to meet the energy needs of each EV at the lowest overall cost, and within the physical constraints of the electricity system.

All smart charging strategies utilise knowledge about when a particular EV will be connected to the grid, and its energy requirements. This information may be specified by vehicle owners (Waraich et al., 2013), or predicted by the charging service provider based on the full historical trip data obtained from all participating EVs, which does raise privacy concerns (see section 2.10). Once the energy requirements and grid connection schedules for each EV are known, charging strategies may attempt to meet those requirements precisely (Sundstrom and Binding, 2012), or aim to fully charge all EVs by the following morning (Kristoffersen et al., 2011; Waraich et al., 2013).

Charging schedules are typically planned in advance, and optimised over a 24-hour period divided into fixed charging slots of 15 minutes (Sundstrom and Binding, 2012) to one hour (Kristoffersen et al., 2011). Schuller et al. (2015) uses an optimisation horizon of both 24 hours and one week, finding that the longer horizon resulted in greater utilisation of non-dispatchable generation, assuming that travel and generation forecasts over this period are accurate. This approach is not conducive to changes in EV energy and/or timing requirements between the planning and execution of charging schedules; any deviation from the original plan will almost certainly result in a suboptimal load profile. Sundstrom and Binding (2012) suggests rerunning the optimisation process in light of revised requirements, but it is unknown whether this will be practical.

Centralised charging strategies are effective at integrating EVs into electricity systems with little overall impact; Kristoffersen et al. (2011), for example, found that peak load did not increase with 25% electrification of Denmark's light vehicle fleet, while average and minimum load increased by 5% and 10% respectively. In the same scenario, approximately 74% of charging occurred at night while non-EV load is typically at its lowest.

When a significant level of solar PV is considered as part of the generation mix, Nunes et al. (2015) has shown that EV charging primarily occurs during daytime hours. With 100% electrification of the light vehicle fleet in Portugal, smart charging enables solar PV penetration of up to 34% at less than 1% curtailment; without any EVs in the system, curtailment rises to 3% at only 25% solar PV penetration (Nunes et al., 2015). Assuming that the solar panels are installed locally, daytime charging will not increase peak loading of transmission and distribution networks.

The strategies described in this section have been shown to be effective at minimising charging costs, however the approach of scheduling EV charging over a fixed future period of time does limit the ability for an EV fleet to compensate for errors in generation forecasts and unexpected electricity outages in real time. While the schedules calculated by an aggregator or charging service provider might be effective based on the assumptions and forecasts used in the calculation, real-world performance in the presence of deviations from these predictions is likely to be suboptimal. The centralised nature of these strategies may also face opposition by customers who do not want to lose control of when their EV is able to charge, owing to the real or perceived loss of spontaneity imposed by the aggregator once charging schedules have been finalised (Ma, Callaway and Hiskens, 2010).

Decentralised Smart Charging

Decentralised charging does not rely on a centralised authority to calculate optimal charging schedules; instead, all vehicles perform charging decisions independently with the goal of meeting their own transportation needs at the lowest cost (Ma et al., 2010; Ahn, Li and Peng, 2011). The decentralised approach is expected to be more acceptable to customers than centralised charging, since they retain full control of their vehicle's charging behaviour.

While simple price-based charging strategies may create unintended load peaks during low tariff periods (section 3.2.2), decentralised smart charging strategies require that each EV coordinate its charging schedule with other grid-connected vehicles such that the aggregate EV load profile approaches a global optimum (Ma et al., 2010; Ahn et al., 2011). Indeed, Ma et al. (2010) demonstrates that a Nash equilibrium exists, so an EV acting in its own self interest tends to also act in the best interests of the entire EV fleet.

Ma et al. (2010) uses an iterative approach to negotiate charging schedules, whereby each grid-connected EV proposes a charging profile based on advertised electricity prices for a future 24-hour period, which it then submits to an aggregator. The aggregator uses this information to recalculate its electricity load forecast, and then broadcasts updated electricity prices to all grid-connected vehicles. Each vehicle may choose to update its charging schedule in light of this new information, and this process repeats until no further changes are needed.

The iterative negotiation technique used by Ma et al. (2010) has several benefits for EV owners over centralised strategies, including the privacy advantage gained by not requiring driving patterns to be shared with a third party, and the retention of control by allowing charging to occur at suboptimal times of day—albeit at a higher cost to the vehicle owner—in the interest of convenience. While this study does not simulate driving behaviours, it found that charging activity occurred exclusively during overnight hours when it could reasonably be assumed that a majority of vehicles would be at home.

Ahn et al. (2011) evaluates the potential for EVs to participate in grid frequency regulation in addition to the load shifting goal of the studies mentioned previously. The proposed charging strategy involves optimising aggregate grid load over a 24-hour period, broken into 10-minute blocks, which is negotiated in a decentralised manner. Rather than an iterative approach, Ahn et al. (2011) requires each EV to calculate its own charging profile based on its proportional contribution to the collective energy requirements of the EV fleet. The aggregator is responsible for collecting this information, including forecasts of generation and non-EV load, and distributing it to all EVs. Charging power calculations are configured such that vehicles with a lower SOC or a shorter time to departure are charged at a higher rate than other vehicles, in order to ensure that charging targets are met.

Each EV simulated in Ahn et al. (2011) also implements frequency droop control, which operates on a much shorter time scale than load shifting—10 seconds and 10 minutes respectively. A participating EV will increase or reduce its scheduled charging power in response to an observed deviation from nominal grid frequency; the magnitude of this response is determined by the total number of grid-connected vehicles, which is broadcast by the aggregator at regular intervals. Frequency regulation offered in this manner is a net-zero energy service, so it does not impact the load shifting performance of the charging strategy, nor does it increase battery degradation. However, this service can only be offered while the vehicle is charging, which generally occurs during low-demand periods.

Ahn et al. (2011) concludes that the decentralised approach described in the study achieves near-optimal performance—within 0.1% of a centralised linear programming solution—while also reducing reliance on frequency regulation units by 75% with an EV penetration of 25%.

Hybrid Smart Charging

Tindemans et al. (2015) discusses a DR technique that combines aspects of both centralised and decentralised control, whereby a centralised authority provides DR-capable appliances with a target hourly or daily response profile, but allows those appliances to perform short-term decisions autonomously based on global signals such as grid frequency. This reduces the necessity of reliable and low-latency communications networks while retaining the benefits of centralised control, and could easily be adapted to control EV charging.

3.2.4 Bidirectional Charging Strategies

The smart charging strategies discussed thus far have addressed several important aspects related to the integration of EVs into electricity systems, which exploit the inherent flexibility of their charging to minimise peak load, maximise the utilisation of off-peak electricity generation, and optionally provide a frequency regulation service during charging. These strategies require that energy flows exclusively from grid to vehicle, which limits the potential of utilising EV batteries as a distributed energy resource.

Third and subsequent generations of EV are expected to support bidirectional charging strategies, which allow energy to be retrieved from an EV battery for use outside of the vehicle (Tuttle and Baldick, 2012). Several variants of this concept exist, which differ by scope and level of coordination required. The simplest such strategy is known as Vehicle-to-Home (V2H), where a single vehicle provides load shifting and/or backup power to a single household, but requires that the net load of the home does not become negative. Vehicle-to-Premises (V2P) involves multiple vehicles working together to provide similar services to a commercial premises, again requiring that net load does not become negative. Vehicle-to-Grid (V2G), on the other hand, allows energy from an EV battery to flow beyond the home or premises through a net-metered grid connection, and hence offers more flexibility than both V2H and V2P (Tuttle and Baldick, 2012).

The cost of adding bidirectional energy capability to an EV may be negligible, since the same power electronics that deliver energy to the vehicle's motor can also be used to deliver energy back into the home, premises, or grid (Kempton, Udo, Huber, Komara, Letendre, Baker, Brunner and Pearre, 2008; Botsford and Szczepanek, 2009). Similarly, the cost of distribution network upgrades to support bidirectional energy flows should not be attributed entirely to V2G, since this same equipment is necessary to support DG; indeed, its deployment has already begun (section 2.5.1). Likewise, the communications infrastructure necessary for coordinating a large-scale V2G deployment is also needed for unidirectional smart charging, and therefore no additional communications investment is required.

Many researchers have rejected the concept of bidirectional charging strategies on the basis of high incremental costs, primarily attributed to EV battery degradation when using present-day technologies (Weiller, 2011; Kristoffersen et al., 2011), while others have found substantial benefits for their use in high-value applications such as operating reserves, frequency regulation, and peak shaving (Kempton and Letendre, 1997; Kiviluoma and Meibom, 2011; Han and Han, 2013; van der Kam and van Sark, 2015).

While studies typically assume that battery degradation is solely a function of energy throughput, Ribberink, Darcovich and Pincet (2015) demonstrates that degradation depends on a range of parameters including time since manufacture, charging and discharging currents, and the SOC around which the charging/discharging activity occurs. This study concludes that shallow battery cycling near a medium SOC at a low to moderate power level is best in terms of degradation, and that the negative impacts of bidirectional charging are similar to that of aggressive driving habits and thus are not prohibitive to its deployment.

Vehicle to Home

V2H is a system that uses an EV battery to reduce household energy costs, which is primarily achieved by reducing peak load of the home and/or increasing self-consumption of locally-generated electricity. Its main advantage over more complex V2G systems is that it can be deployed without changes to the infrastructure and business models used in the wider electrical grid (Haines, McGordon, Jennings and Butcher, 2009).

Haines et al. (2009) presents a V2H study comprising a single house and EV, with the goal of limiting the peak net load of the house/vehicle system. The EV has a 26.5 kW h battery with a charging power of 3 kW and round-trip efficiency of 81%, while the home has a peak load of 10 kW and an average load of 420 W. This study assumes that the EV is only charged at home, and requires that its battery SOC at the end of the day is not less than it was at the beginning, in order to ensure that the V2H strategy is sustainable over multiple days.

The V2H strategy used in Haines et al. (2009) is very similar to that of *grid-lite* (section 3.1.3); a power limit is set for the grid connection, and V2H is used to cover any household load in excess of that limit where possible. The study found that V2H implemented in this manner successfully reduced peak load to 3262 W when the EV was used for a 30 mile round trip commute, and the power limit was set to 300 W excluding EV charging load. In this scenario, less than 1% of the vehicle's SOC was used for peak shaving since those peaks were short-lived. The study also found that V2H was not appropriate when the EV was used for an 80 mile commute, but noted that these distances are rare.

Since the charging strategy used in Haines et al. (2009) bases decisions solely on measured household load, its performance from a wider grid perspective is unlikely to be optimal. The authors note that the EV would charge opportunistically during evening hours when local demand drops below the threshold, even though wider electricity load is typically highest during this period. Other V2H studies avoid this problem by instead responding to pricing signals, which minimises the total energy costs of the home while also reducing load during high-tariff periods (Nakada, Nakano and Akizuki, 2015).

Vehicle to Premises

V2P expands on the V2H concept by utilising multiple vehicles connected to a commercial building, which may be owned by a number of different parties. Like V2H, the primary goals of V2P include minimising total energy costs through decreasing peak load and/or increasing self-consumption of locally-generated electricity.

Gamallo and Fraile-Ardanuy (2012) introduces the concept of a “Stochastic Aggregated Battery (SAB)”, which adds an additional control layer between the vehicles and building. This layer is responsible for coordinating the charging and discharging of individual vehicles, and presents a single virtual battery to the building’s energy management system. Naturally, the characteristics of the virtual battery—such as total storage capacity, SOC, and power capability—will vary over time as vehicles arrive and depart from the system. Each EV owner can specify acceptable charging/discharging prices, minimum and maximum allowable SOC, and connection times, which the SAB uses to distribute power demands among all connected vehicles to achieve the lowest overall energy cost. This system was evaluated via simulation, based on a real 70-worker office building in Madrid and seven heterogeneous present-day EVs. The results indicate that the SAB is capable of reducing overall energy costs to the building while also delivering a small profit to individual EV owners.

A later study by van der Kam and van Sark (2015) investigates the application of V2P within a microgrid containing an office building, three households, two EVs, a $31\,\mathrm{kW_p}$ solar PV installation, and an export-capable connection to a wider electricity grid. A centralised control approach is used, with the aim of increasing self-consumption of locally-generated electricity by issuing V2P dispatch instructions in realtime. Electricity sources and loads are prioritised depending on availability: uncontrollable load is first met by PV, then

V2P, and finally by the grid when necessary. Similarly, any PV output that exceeds uncontrollable load will first be used for charging EVs, and any remaining excess will be exported to the grid. The simulation found that the self-consumption of 49% without V2P could reach 62 to 87% with V2P, while EV energy throughput could increase by up to 400%.

Vehicle to Grid

First introduced by Kempton and Letendre (1997), V2G provides a superset of functionality beyond V2H and V2P by allowing energy to flow from a home or premises into the wider electricity grid. While the V2G concept was introduced prior to both V2H and V2P, its widespread deployment is unlikely to precede those systems (Tuttle and Baldick, 2012). This is primarily attributed to the greater need for coordination between multiple parties, who may have conflicting needs. Research suggests that V2G will find the most value in the regulation and spinning reserve markets, where payments are received for availability and total energy throughput is low; the costs of providing these services are therefore likely to be minimal (Kempton and Tomić, 2005b; Kiviluoma and Meibom, 2011). Another application of V2G is peak shaving, applied across a wider area than V2H and V2P, which may be cost effective at up to one hour per day (Zhuk, Zeigarnik, Buzoverov, Sheindlin and Kucherov, 2015).

The benefits arising from V2G apply to the wider electricity market, while its costs are bourne primarily by vehicle owners—both in terms of travel inconvenience and battery degradation—so suitable economic and business models must be developed. Kempton and Tomić (2005b) suggests that an electricity retailer could purchase V2G power directly from its customers, or alternatively a third party could offer free battery replacements to EV owners in exchange for V2G services.

The value of V2G is dependent on the vehicle's location within the distribution network, and is higher in areas with capacity constraints (Kempton and Letendre, 1997). V2G-capable vehicles in constrained areas of distribution networks can potentially reduce peak load, and also serve as a form of energy conveyance that operates in parallel with traditional distribution lines, for example by charging at work and later injecting that energy at home to cover evening load (Waraich et al., 2013).

Studies have found that the effectiveness of V2G depends on vehicles being connected to the grid for substantially longer than is strictly needed for charging purposes; for example, Mason (2014) found that using V2G to cover evening peak load in a residential area was counterproductive when only overnight charging was available. This emphasises the importance of having charging facilities in multiple locations, such as home and work.

Vehicle to Vehicle

Vehicle-to-Vehicle (V2V) describes the concept where energy from one EV flows into the battery of another, which would typically occur when the energy requirements of the latter are more urgent than that of the former (Alvaro, Gonzalez, Gamallo, Fraile-Ardanuy and Knapen, 2014). While V2V energy flows are likely to occur with any V2P or V2G charging strategy, Alvaro et al. (2014) introduces a peer-to-peer energy exchange market where vehicles can directly negotiate and transfer energy between one another, independently of a wider electric grid. This is motivated by the observation that 80% of vehicles can exceed their own energy needs from a low-cost overnight charge, while the remaining 20% must be charged at a higher cost during the day to meet travel requirements.

When implemented as a V2P strategy, V2V enables fast charging during peak load periods without substantially increasing the building's net load, assuming that other EVs are capable of supplying energy at a lower cost than the grid. Alvaro et al. (2014) found that this system achieved a 40% reduction in the cost of daytime charging for energy buyers, while also achieving a modest profit for sellers.

3.2.5 Discussion

Charging strategies, whether simple or smart, must ensure that sufficient energy is delivered to EVs in a timely manner, in order to avoid compromising the mobility of their drivers. Uncontrolled charging is the best approach to achieve this goal, but is not feasibile to deploy on a large scale. Simple approaches—such as overnight or dual-tariff charging—are able to mitigate the negative effects of uncontrolled charging to some extent, without requiring substantial changes to grid operations.

Smart charging strategies enable fine-grained control over the aggregate charging load profile of an EV fleet, and can be implemented in a centralised or decentralised fashion; the latter ensures that EV owners retain control over their vehicle's charging behaviour, and is therefore more likely to be accepted by consumers. These charging strategies also enable EVs to participate in electricity regulation markets, which assists the integration of non-dispatchable renewable electricity generation. However, these strategies are dependent on communication networks connecting vehicles and coordination facilities—typically known as aggregators—which is a potential barrier to their adoption. The benefits of smart charging can be extended by allowing bidirectional energy flows between EVs and the grid, which enable increased self-consumption of locally-generated electricity, reduced peak loads, extended EV participation in operating reserves and regulation markets, and lower overall electricity prices.

Regardless of which charging strategy is employed, there are many benefits of providing charging facilities at multiple locations and leaving EVs connected to the grid whenever possible. Long connection times enable greater flexibility for smart charging strategies, resulting in better charging schedules than would be possible with reduced connection times. Uncontrolled charging also benefits from extended connection times by spreading individual EV charging loads over a longer period, and hence reducing the aggregate charging load of the fleet. EV owners should therefore be encouraged to connect their vehicles to chargers as often as possible.

3.3 Trip Prediction and User Interfaces

Smart charging strategies, whether unidirectional or bidirectional, require knowledge of when a vehicle will be used next, and how far it must travel, so that charging targets can be met in a grid-friendly fashion. This knowledge is likely to be derived from a combination of assumptions, learnt travel patterns, and direct input from the driver. The balance between these information sources represents a trade-off between the vehicle's ability to complete unplanned trips, driver convenience, the level of flexibility offered to the grid, and charging costs.

A framework for calculating charging targets could be described as follows:

1. Unplanned trips will always be shorter than a preset distance.
2. Regular commuting patterns are expected to continue into the future.
3. Any trips longer than the preset minimum range (point 1), and are not part of a regular commuting pattern (point 2), will be specified in advance by the driver.

From this information, a charging strategy can: a) calculate the minimum battery SOC to be maintained at all times; b) automatically accommodate regular driving patterns without violating the minimum allowable SOC; and c) accommodate longer non-routine trips when given sufficient advance notice.

Drivers will be able to tune the above parameters according to preferences and travel requirements (Kempton and Letendre, 1997); for example, a rural driver might specify a longer minimum range for unplanned trips than a city driver, while someone who favours convenience over charging costs might simply set the minimum range to the full capacity of the vehicle and hence nullify the benefits of smart charging. Alternatively, Kempton and Tomić (2005b) suggests that suitable values could be learnt by collecting a few weeks of trip data while employing a *greedy* charging strategy, before migrating to a smart charging strategy once typical trip distances and patterns have been established.

A driver must inform their vehicle of any non-routine travel, since this cannot be predicted from past behaviours. The user interface for doing so could range from a simple "override" button that would instruct the vehicle to use a *greedy* charging for the following 24-hour period (Kempton and Tomić, 2005b), through to user interfaces that allow precise trip distances and departure times to be specified (Kempton and Letendre, 1997; Monigatti, Apperley and Rogers, 2014). The latter option allows the use of smart charging to prepare the vehicle for a long trip, and therefore allows that trip to be completed at a potentially lower cost than a simple override button.

3.4 Summary

Future electricity systems are likely to include a higher proportion of non-dispatchable generation, flexible load, and distributed energy resources than present-day systems, and will likely operate in an increasingly decentralised fashion. New non-dispatchable generation is most economically competitive when built at scale and located in areas where their fuel sources are abundant, such as windy mountain ranges for wind farms or areas with plentiful sunlight for solar PV, while energy storage is most effective when situated near the point of consumption in order to minimise transmission constraints. However, the cost of distributed energy storage is prohibitive when energy must be stored for more than a few days, so bulk energy storage for seasonal balancing must be performed by large centralised facilities such as hydroelectric lakes. This architecture mirrors recent developments in edge computing; urgent energy demands are serviced by local storage, while longer-term energy and storage requirements are serviced indirectly by large centralised facilities that benefit from economies of scale.

To accommodate a large-scale deployment of EVs, electrical infrastructure must necessarily incorporate mechanisms to control charging behaviour. Because of the significant energy storage capacity of EVs, these control mechanisms allow an EV fleet to function as both a flexible load and a distributed energy resource at a very low capacity cost compared to dedicated energy storage facilities, although incremental costs are expected to be higher. Studies that explore the implications of smart charging strategies typically use an agent-based simulation approach, with models based on a combination of historical data and and travel surveys.

This chapter has presented an overview of research related to the integration of non-dispatchable electricity generation and EV charging strategies, which will be built upon in the following chapters in order to evaluate the implications of these technologies in a New Zealand context.

4 Simulation and Modelling

Previous chapters have provided the motivation and context for the research, and established the need for simulation tools to assist with the exploration of future electricity and transportation scenarios.

This chapter begins by establishing the requirements for the simulation software, and follows with a description of the software structure. Subsequent sections describe the statistical models, data sources, and the implementation details of the software.

4.1 Overview

In a future energy scenario with high penetration of non-dispatchable electricity generation and EVs, it is essential to ensure that the system maintains an acceptable standard of reliability. A simulation approach has been chosen to evaluate a wide range of scenarios, and explore the interactions between electricity generation, load, and the requirements of an EV fleet. This will allow comparisons between different EV charging strategies across a range of metrics, including how much—if any—dispatchable generation capacity is required to ensure that electricity demand is met at all times.

Chapter 3 has established the case for the implementation of V2G, and thus it is important to evaluate the benefits of bidirectional power flows in a New Zealand context. With increasing levels of non-dispatchable generation and flexible load, it is inevitable that some responsibility for maintaining real-time balance between generation and load will shift to the demand side.

The simulation therefore must be able to simulate many important aspects of New Zealand's electricity and transportation sectors, along with a number of different EV charging strategies, to evaluate how effectively renewable energy sources can replace existing dispatchable generation while continuing to meet present electricity consumption patterns as well as the new demands introduced by an electrified vehicle fleet.

4.2 Requirements

To establish the requirements of the simulation, let's begin by revisiting the primary research questions.

1. What are the potential energy demands and usage patterns of an electrified light vehicle fleet?
2. What are the generation characteristics of existing and proposed wind farms?
3. What are the necessary parameters of an energy storage system for buffering variability in high wind generation environments?
4. What EV charging strategies are effective, and how successfully can their adoption support the expansion of both renewable electricity generation and EVs?

Answering these questions requires a few features in the simulation software. Firstly, a range of input parameters need to be taken into account, including data related to electricity generation and load, vehicle fleet size, and models for the behaviour and electrical characteristics of an EV. The simulation must take these inputs, and produce output in a form that is useful for further analysis; for example, the instantaneous energy balance once all generation and load sources are considered, including the EV fleet, over the entire simulation period. The details of inputs, outputs, and models used in the simulation are described in the following sections, while an overall data flow representation is shown in figure 4.1.

4.2.1 Inputs

Several models are required to address the first research question. Firstly, a model of an EV is needed for the simulation, with representative characteristics such as battery capacity, maximum charging rate, and energy efficiency. In addition, a behavioural model is necessary to accurately simulate the usage patterns of the vehicle. These models together establish the energy require-

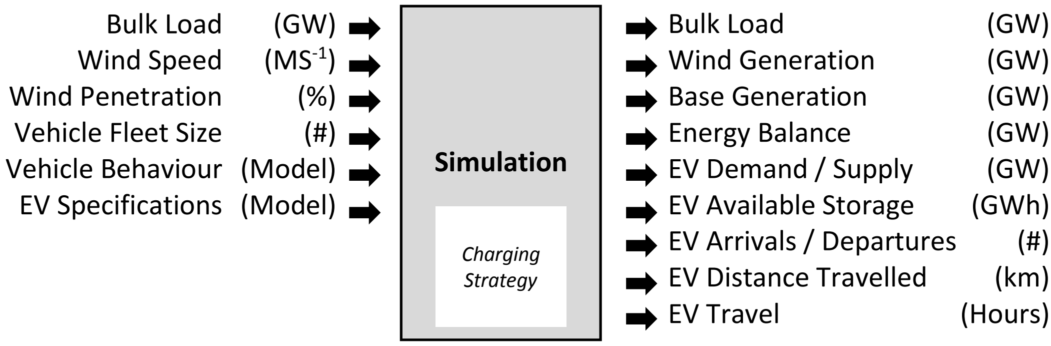


Figure 4.1: Simulation data flows.

ments for an individual vehicle, including both the amount of energy needed and the times of day where opportunities for charging are available. The final model needed for the first research question is that of the adoption rates of EVs to establish a likely fleet size in a future (simulated) year.

The second research question requires an accurate model of large-scale non-dispatchable renewable generation, for which this thesis focusses on wind[1]. Real wind speed data for current and potential future wind farm sites are readily available, which include variability over a range of time scales from short-term (minutes) to seasonal variations—both of which are relevant to the research. The final input to the simulation is wind penetration, which specifies the energy to be generated from wind farms over the simulation period as a fraction of total generation.

4.2.2 Outputs

The purpose of the simulation is to evaluate the energy requirements of an EV fleet, and the performance characteristics for a range of charging strategies. Thus, the output of the simulation needs to enable the analysis of these characteristics.

The simulation itself should perform basic summary calculations during and at the termination of a scenario run, for example the total energy consumed from peak generation sources over the year for the scenario under test; however, the bulk of the detailed analysis is to be performed after a simulation run has completed, using the resulting time series data. An example is shown in figure 4.1. These data are to be output for every simulation tick, including the instantaneous power for all loads and generation sources, the aggregate

[1]In many countries, including New Zealand, wind is predicted to be the fastest growing source of renewable energy

capacity and stored energy of the EV fleet, and the vehicle movements that occurred during the last tick window: total number of arrivals and departures, aggregate distance travelled, and total time the EV fleet spent travelling.

The output described above must necessarily be aggregated for all EVs in the simulated fleet, since recording the individual state of a large number of EVs over the simulation period will result in an extremely large volume of data. However, it may be useful to evaluate the performance of a charging strategy from the perspective of an individual vehicle, such as average state-of-charge. In this case, additional probes may be included during a simulation run, which will add another output column describing the values seen by the probe. This is useful for reviewing the charging decisions made by a particular strategy in the context of a single EVs.

An in-depth discussion of charging strategies is included in chapter 6.

4.2.3 Computational Performance

The challenge of maintaining power balance in the short term and also evaluating the performance of electric vehicle charging strategies over the long term requires the simulation software to run at fine time scales over a significant period of time, and effectively manage a realistic number of EVs. For the purposes of this research, the requirement is set at one million vehicles over the course of one year, at five-minute resolution. This allows sufficient detail to investigate future energy scenarios in New Zealand.

Since a primary goal of the simulation is to enable the exploration of various scenarios, the simulation software must maintain a modular design to allow the easy addition of different models, for example new types of generation, DR technologies, and energy storage devices other than EVs. These models may be implemented in any way necessary, subject to the computation efficiency requirements stated above, but must have a well-defined “connection” to the electricity grid in terms of energy and information flows. These requirements are described fully in section 4.3.

The final two research questions may be addressed by comparing a potentially large number of simulated scenarios with different parameters, so for performance reasons it is useful to be able to simulate each scenario in parallel.

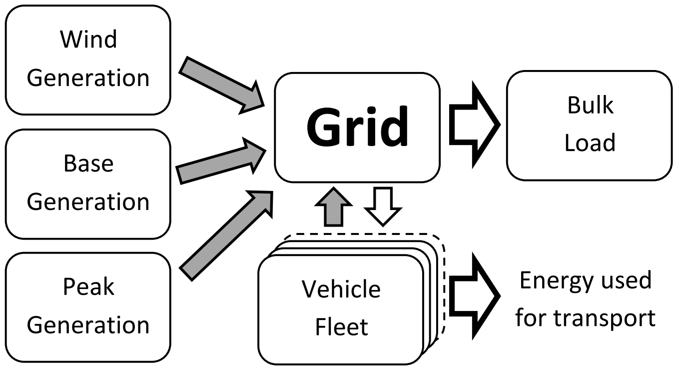


Figure 4.2: Simulation energy flows.

4.3 Software Structure

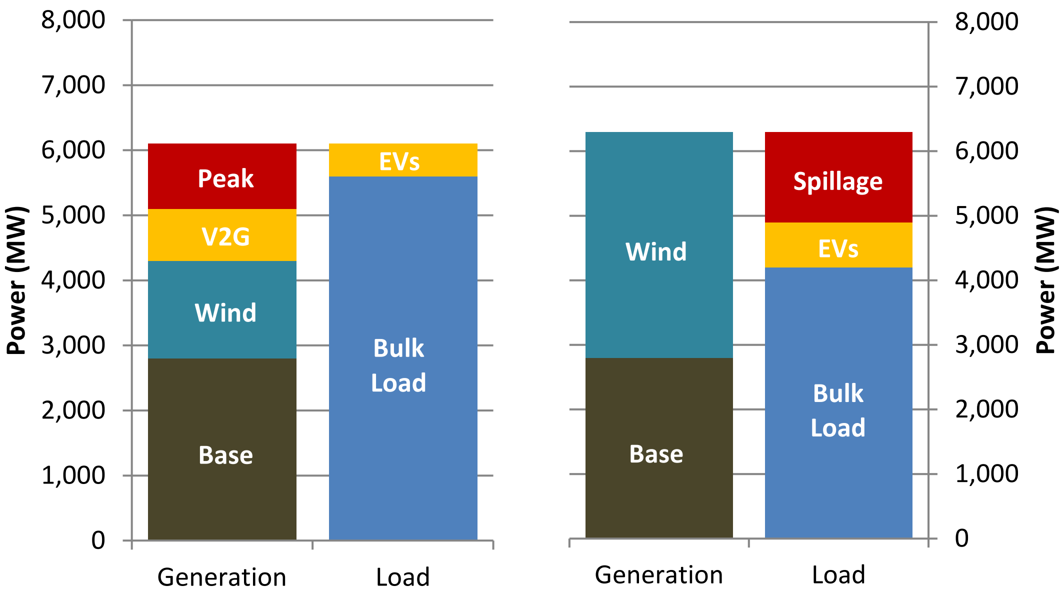
The current form of the simulation software is aimed at investigating the system-wide implications of the introduction of EVs and expansion of renewable generation, and therefore grid topology constraints have been left to future work.

Figure 4.2 provides a general overview of simulated energy flows within software. On the left are generation sources that only deliver power into the grid, while the loads on the right only consume power. The vehicle fleet allows energy flows in both directions. The components of this model, and the data on which they are based, are described in the following sections.

For the purposes of this research, the "grid" refers to a single-point connection between generation sources and loads, since grid topology considerations are not presently taken into account.

The simulated generation consists of a fixed base level with seasonal variation, plus variable wind and peak generation (see section 4.5). This is similar to the approach used by Inage (2010), but differs in that wind generation is based on real wind-speed data rather than a statistical model. The only generation source that varies in response to changes in load is peak generation.

The EV fleet is given priority for maintaining the balance between generation and load, while peak generation fills in any shortfall that cannot be met by the fleet. This approach covers scenarios that may or may not include V2G capability; without V2G, peak generation is always used to cover generation shortages. Similarly, any surplus of generation is first offered to the EV fleet,



(a) Generation shortage (b) Generation surplus

Figure 4.3: Simulated energy balance with V2G for both deficit and surplus situations.

and any energy that cannot be stored or consumed is counted as spillage, as shown in figure 4.3.

While it is useful to illustrate the differences between peak generation and spillage—and between V2G and EV charging—each can be seen as analogous. For example, a negative peak generation requirement is identical to spillage, while a negative EV charging rate is the same as V2G. Peak generation and spillage cannot occur at the same time, but it is possible for the EV fleet to be both a source of electricity and a consumer at the same time. This happens during generation shortages when some vehicles urgently need charging for an upcoming trip, while others have surplus energy available; details to be described in section 6.3.

4.3.1 Tick Interval

Five minutes has been chosen as the simulation tick interval for the experiments presented in this research, since it represents the highest temporal resolution available in the input datasets. However, it is possible to dynamically change the tick interval during the course of a simulation run if, for example, extra resolution is required around some exceptional event such as a major generation outage. This approach allows detailed investigation of such events, without sacrificing performance during other time periods within a simulation run.

Linear interpolation is used to calculate intermediate values for datasets that don't match the chosen tick interval, and vehicles are allowed to arrive and depart at any time including between simulation ticks. When a vehicle is scheduled to depart between ticks, the energy transferred to/from the EVs battery is calculated as the fraction of the tick interval in which the vehicle was connected to the grid, multiplied the charging/discharging power selected by the vehicle's charging strategy. Similarly, since power is chosen only at the beginning of each tick interval, it is quite possible that an EV battery will charge beyond its full capacity, or be depleted below its minimum allowable level, by the time the next charging decision is made. To correct this, a check is performed to detect when this will happen, and the requested power level will be scaled by an amount that will prevent the issue.

4.3.2 State Information

The state information maintained by the simulation can be divided into two categories—global information that is accessible anywhere within the simulation, and the internal state of individual models. The variables that represent simulation state are listed in tables 4.1 (the grid state) and 4.2 (the state of an individual EV).

Table 4.1: Variables representing grid state.

Symbol	Explanation	Unit
st	Current simulation date and time	*timestamp*
t	Simulation tick number	-
ϵ	Tick interval	*timespan*
B	Base generation	W
L	Bulk load	W
W	Wind generation	W
E_{AV}	Energy available in the EV fleet	J
E_R	Energy required to fully charge the EV fleet	J
L_{EV}	Imperative EV charging load	W
S	Surplus generation	W

Global State

The first group of global information (table 4.1) refers to the state of the simulation itself, namely the simulated date and time, tick number, and tick interval. These are initialised at the beginning of a simulation run, and normally increase monotonically throughout the scenario run.

The second group of global information is based on the aggregate state of the models within. For example, *base generation* is the combined power output of all base generation models, while *surplus generation* is the total generation less the total load. These values are aggregated and recorded on each tick, but are not available to models until the following tick. This means that all grid-state information will be five minutes old by the time it is available to the EV fleet, and hence mismatches in generation and load are inevitable even when the EV fleet is capable of providing perfect balance. A shorter tick interval will reduce the potential mismatch, assuming that load and generation changes are less over shorter periods.

The rationale behind delaying the availability of information is to reflect a real implementation. The process of collecting, aggregating, and disseminating these values in a real smart grid will not be instantaneous, and hence the entities within the smart grid must necessarily base any calculations on information that has been delayed. In a real implementation, it may be possible to combine this aggregate information with real-time measurements of grid frequency in order to have a more up-to-date estimate of global state, and hence the real-time requirement for this class of information is eased (Kupzog, 2008).

Internal State

Certain models within the simulation are required to maintain their own internal state, the most significant example being the EV model. The upper section of table 4.2 shows the variables contained within the EV model that specify the parameters set at the start of the simulation, for example battery capacity, maximum charging and discharging rates, and efficiency. These do not change over the course of a scenario run.

The dynamic variables within the EV model are shown in the lower section of table 4.2. The current state of charge is updated on each tick, which is calculated from the tick duration and the charging/discharging power that was chosen on the previous tick using the vehicle's selected charging strategy.

Table 4.2: Variables representing individual EV state.

Symbol	Explanation	Unit
Q_{MAX}	Maximum battery capacity	J
Q_{MIN}	Minimum allowable state of charge	J
P_{MAX}	Maximum charge power	W
P_{MIN}	Minimum charge (i.e. discharge) power	W
η	Battery-to-wheel efficiency	$\mathrm{J\,m^{-1}}$
q	Current state of charge	J
p	Current charge/discharge power	W
Q_1	Battery charge required by time T1	J
T_1	Time of next departure of an EV	*timestamp*
D_1	Distance of the next trip	m
V_1	Average speed of the next trip	$\mathrm{m\,s^{-1}}$

The variables related to the upcoming use of the vehicle, most importantly the charging target specified by Q_1 and T_1, are updated when a vehicle returns from a trip and do not change until completing the following trip. Further details of the EV model are discussed in section 4.7, while the operation of charging strategies is discussed in chapter 6.

The wind generation model does not maintain any internal state, since its power output is simply a function of instantaneous wind speed. Similarly, the base generation model only follows seasonal averages and is not influenced by other factors. In future, other generation models may keep track of internal state, for example the amount of water stored in hydroelectric lakes.

Aggregation

On each simulation tick, all simulation models first update their state, and then global state variables are recalculated. Each model is queried for its latest state, which is added to the relevant global state variables.

The calculation of the energy available within the EV fleet, E_{AV_t}, is shown in equation 4.1. This is the sum across all EVs connected to the grid, based on how much energy each vehicle currently has stored in excess to its own requirements. The result is the amount of energy that is available for grid management purposes.

On the other hand, equation 4.2 shows the calculation for the unused capacity within the batteries of all grid-connected EVs; that is, the amount of energy that the EV fleet is able to store. This capacity is available for providing down regulation.

Imperative EV charging load, shown in equation 4.3, is simply the aggregate power draw by all grid-connected EVs that are in the imperative charging mode, i.e. charging that must be considered as inflexible load. A full description of EV charging modes is included in section 6.3.

Finally, the calculation of surplus generation is the sum of all generation sources (base and wind), less electricity demand of both the bulk load model (section 6.3) and the aggregate imperative charging demands of the EV fleet. This value is negative when load exceeds demand.

$$E_{AV_t} = \sum_{i=1}^{n} q_i - \max\left\{Q_{MIN_i}, Q_{1_i} - P_{MAX} \times (T_{1_i} - st)\right\} \tag{4.1}$$

$$E_{R_t} = \sum_{i=1}^{n} Q_{MAX_i} - q_i \tag{4.2}$$

$$L_{EV_t} = \sum_{i=1}^{n} p_i, \forall \text{ev} \in Imperative \tag{4.3}$$

$$S_t = B_t + W_t - (L_t + L_{EV_t}) \tag{4.4}$$

4.3.3 Initial Setup

At the beginning of the simulation, the state is typically unsettled; the entire EV fleet might have empty batteries, for example. This is addressed by running the simulation for a (simulated) day before the intended start time, allowing state to settle down, which is a similar approach to that used by Dallinger, Krampe and Wietschel (2011) and De Hoog et al. (2013).

This approach was chosen, rather than simply specifying a typical SOC for each EV, since what is “typical” varies between charging strategies. Some strategies tend to maintain battery SOC near full capacity, while others maintain a much lower level. If the initial value was incorrect, all EVs will simultaneously attempt to rectify the situation, which will create demands on the grid and generation that are not realistic. By running the simulation for a period before the intended start time, these extreme values are not recorded and hence do not influence the results.

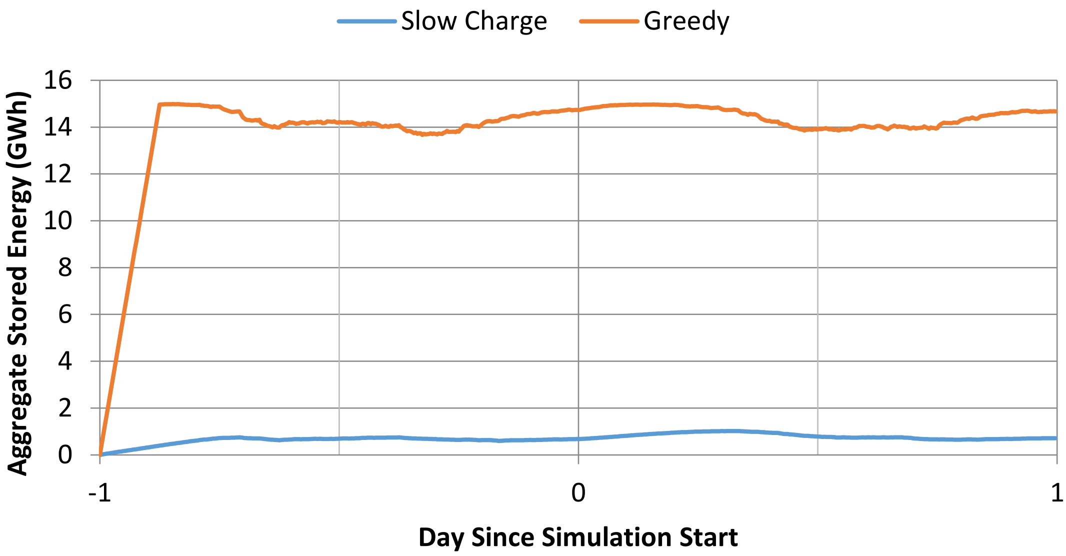


Figure 4.4: Simulation SOC start-up behaviour for two distinct charging strategies.

The start-up period is shown in figure 4.4, for two distinct charging strategies; slow charge, and greedy. These strategies will be described in more detail in chapter 6; they represent the extreme cases where *slow* maintains a minimal SOC while *greedy* attempts to maintain this level at close to a full charge. The example shows the aggregate stored energy in fleet of a million EVs, each with a 15 kW h battery. The state settles down well within the 1-day start-up period.

4.4 Generic Models

Many of the models within the simulation share similar characteristics. For example, electricity load and wind speed both consist of time series data, while several models associated with vehicle behaviour rely on the sampling of probability distributions. The generic model classes are described here, while specific details of each model are included in upcoming sections.

4.4.1 Entity

For the purposes of simulation, an *entity* refers to anything that connects to the grid. This provides a standard interface for any model that generates, stores, or consumes electricity. An *entity* only supports three functions: connecting to the grid, disconnecting from the grid, and retrieving the instantaneous power of that entity.

The value of instantaneous power returned by an *entity* is typically specified by its underlying model. A positive value indicates that energy is flowing from the entity into the grid, while a negative value indicates the reverse.

4.4.2 Replay Model

The *replay* model is an abstract subclass of *entity*, and provides a means of reading time-series data from CSV files. This data is then stored in memory in a form that supports efficient lookups by timestamp at each simulation tick—essentially “replaying” the data during the simulation period. If no entry exists at a given timestamp, the *replay* model is responsible for interpolating between the nearest two data points.

The *replay* model does not parse the input files itself, since it is often useful for underlying models to customise this if necessary. For example, modelling a wind farm requires converting raw data (wind speed) into a meaningful form for the model (power output). Thus, the *replay* model asks the underlying model to parse each line from a file into a timestamp-value pair, which it then stores ready for lookup.

When instantaneous power is retrieved from the *replay* model, it simply looks up the appropriate value—interpolating where necessary—and returns it. Underlying models can override this behaviour if necessary, for example in models that must maintain internal state.

4.4.3 Probability Distribution Model

The *distribution* model provides a standard way of reading a cumulative distribution function from file, and allowing efficient sampling of that distribution during a simulation run. This model is structured in a similar way to the *replay* model, where the underlying model is required to parse each line from the input file.

Once the probability distribution is stored in memory, the *distribution* model allows efficient random sampling of that distribution. This model is primarily used for generating non-uniform random numbers, for example when producing trip distances for vehicle travel.

4.5 Electricity Generation

For the purposes of testing the performance of charging strategies (to be introduced in chapter 6), models of electricity generation are required. One of the metrics being tested in this research is how well each charging strategy performs at maintaining balance between electricity generation and load. To assist with this analysis, an extreme generation scenario is considered that consists only of base and wind generation, neither of which attempt to follow the variability of load. Peak generation is only called upon when load exceeds the sum of base and wind generation, and after the contributions from V2G are considered, if available.

4.5.1 Base Generation

Base generation provides a consistent power output to meet the energy needs of consumers. These generators are typically efficient, but do not respond to rapid changes in load. Therefore, they are well suited for running constantly over long time periods.

In the simulation, the base generation model provides a consistent power output that only varies over a seasonal time scale. At any particular instant, the power output of the model, B_t, is specified as the average load over a three-month window, less the expected contribution from wind energy. The ratio

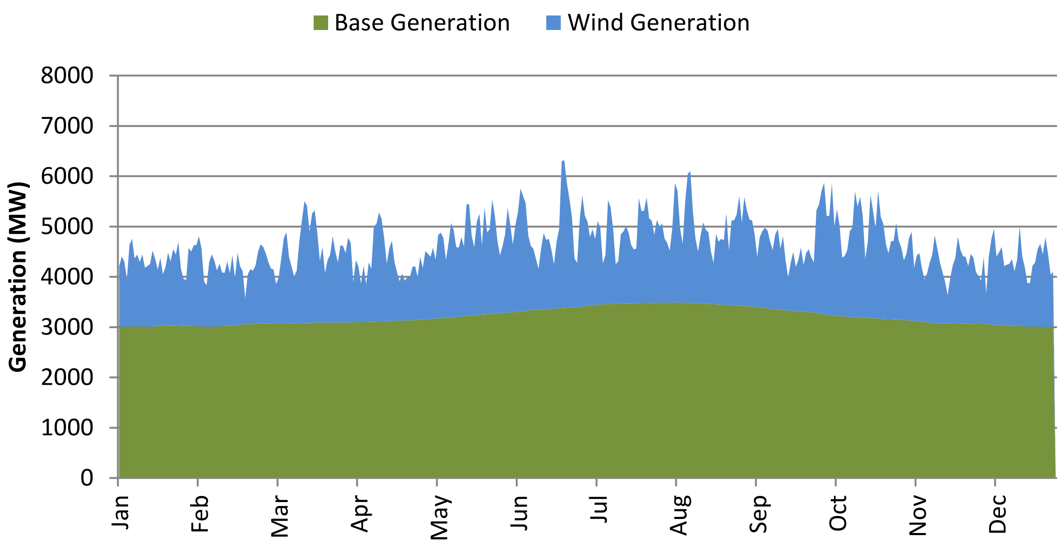


Figure 4.5: Simulated annual generation profile at 30% wind penetration.

between base and wind generation is determined by the wind penetration level, which is a simulation input. For example, at a 30% level of wind penetration, base generation output is set to the power level required to contribute the remaining 70% of energy consumed. This is illustrated in figure 4.5.

In a real electricity system, there are a variety of base generation sources such as hydro, geothermal, coal and nuclear, each with different characteristics in terms of responsiveness to changes in load, energy storage capability, and fuel costs. The system operator must dispatch generation appropriately to ensure an acceptable balance between maintaining a secure electricity supply and cost.

As discussed in section 3.1.4, large-scale centralised storage is expected to be utilised for seasonal balancing of generation and load, while distributed storage will be used for short-term balancing since it is ideally situated close to load centres. The model described here serves as an approximation of such a system, assuming that base generation will be dispatched to follow average—rather than instantaneous—load. An evaluation of the full interaction between centralised and distributed energy storage has been left to future work.

4.5.2 Wind Generation

As described in section 2.5.1, wind energy is predicted to comprise a significant proportion of New Zealand's future generation portfolio. It is therefore vital to model the potential output of current and future wind farms, driven by real wind speed data.

The resolution and time period covered by the data is critical, since different time scales present different challenges for a system operator. Over short time periods, change in power output ("ramping") is the most significant concern for maintaining frequency stability, while over the mid term the absolute power output must be sufficient to cover demand. Over seasonal time scales, the total energy output is most important—especially so in countries like New Zealand, which are adversely affected by "dry years" because of a significant reliance on hydroelectricity.

A synthetic wind speed dataset for 15 current and potential wind farm sites in New Zealand is available, as described by Turner, Zheng, Gordon, Uddstrom, Tait, Pearson, De Vos, Sterk, Carey-Smith and Moore (2009). This dataset consists of time series wind speed data at 10-minute intervals over several years; however, for commercial reasons the wind speeds for each site are disguised either by normalisation, or by not revealing mast heights or co-ordinates. For the purpose of simulation, this is not a major concern since the variation in wind speed is more important than its absolute value.

The relationship between wind speed and power output is approximately linear once factors such as turbine characteristics and farm layout are taken into account (Bull, 2010; Jacobson, 2009). To map wind speed to a power output, the speed at which the wind farm produces its full output must first be calculated. According to the New Zealand Wind Energy Association (2011), New Zealand wind farms have an average capacity factor of 40%. Since the average synthetic wind speed for 2007 was $9.44\,\mathrm{m\,s^{-1}}$, the nameplate power output will be achieved at wind speeds of approximately $23\,\mathrm{ms^{-1}}$ or above. The formula to map wind speed to power output is therefore:

$$W_t = \frac{\text{wind speed}[t] \times \text{capacity factor}}{\text{average wind speed}} \times \text{nameplate capacity} \tag{4.5}$$

Since the current incarnation of the simulation does not include issues related to grid topology, data for all 15 wind farm sites are averaged to create one large virtual wind farm. Wind speed data for the year 2007 were used, since this is the most recent complete year in the dataset.

The nameplate capacity of the simulated wind farm is set according to average load and the wind penetration level being tested, as specified in equation 4.6.

$$\text{nameplate capacity} = \frac{\text{average load} \times \text{wind penetration}}{\text{capacity factor}} \tag{4.6}$$

4.5.3 Peak Generation and Spillage

The peak generation model is ultimately responsible for maintaining the balance between generation and load, after the contributions of the EV fleet are considered. It is the only model that has access to the real-time state of the grid, and simply sets its output to the level necessary to bring the power imbalance to zero. This power level—which may be negative at times of excess generation—is written to the output file directly at each simulation tick. Peak generation can therefore be considered as an output of the simulation rather than a model within it.

Peak generation and spillage are shown graphically in figure 4.6. With no assistance from the EV fleet, the burden of maintaining balance is entirely placed upon peak generators. If—by coincidence—the grid is perfectly balanced, the

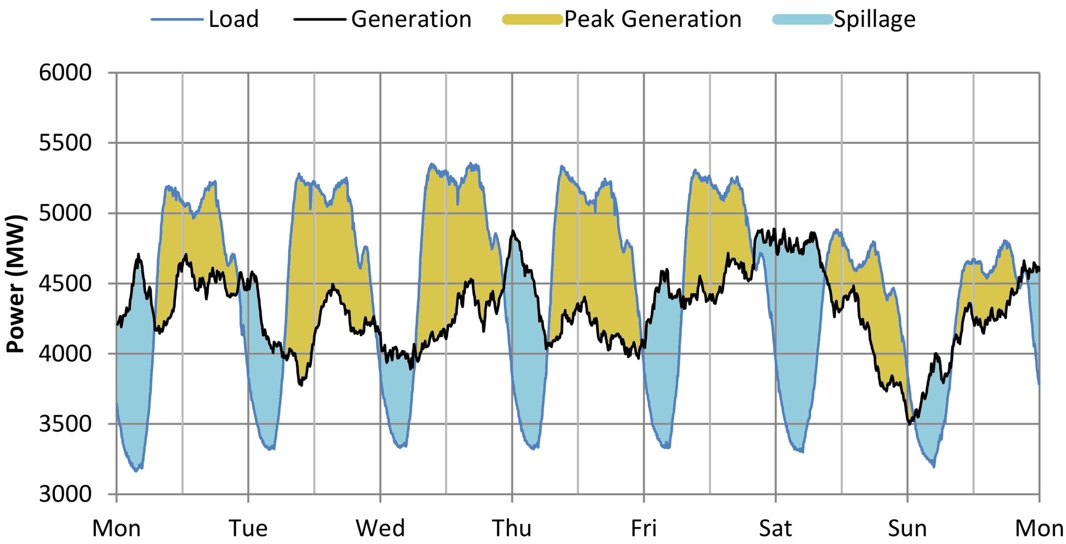


Figure 4.6: Example of peak generation and spillage.

peak generation requirement is zero. For all other times, either the input from peak generators is required, or spillage is recorded.

Peak generators are required to be highly responsive and dispatchable, since they must match their output against load for the grid to remain in balance. In many countries, these generators typically burn fossil fuels and are less efficient than base generators (Black and Strbac, 2006), leading to a goal of minimising their use. Furthermore, the provision of back-up capacity to cover intermittency in wind and other renewables constitutes a significant inefficiency in overall grid system design. In the New Zealand situation, peak generation is itself commonly derived from renewable sources—principally hydroelectric—however it remains an important goal to reduce the use of peak generation where possible in order to ease transmission constraints, and to minimise spillage by fully utilising wind generation when available.

4.6 Bulk Load

In the simulation, bulk load comprises all existing electricity demand, to provide a baseline for electricity consumption patterns over a range of time scales. It is essential to model electricity consumption in order to see the interactions between "normal" electricity consumption and the additional load introduced by the electric vehicle fleet. This is achieved by "playing back" zone load data

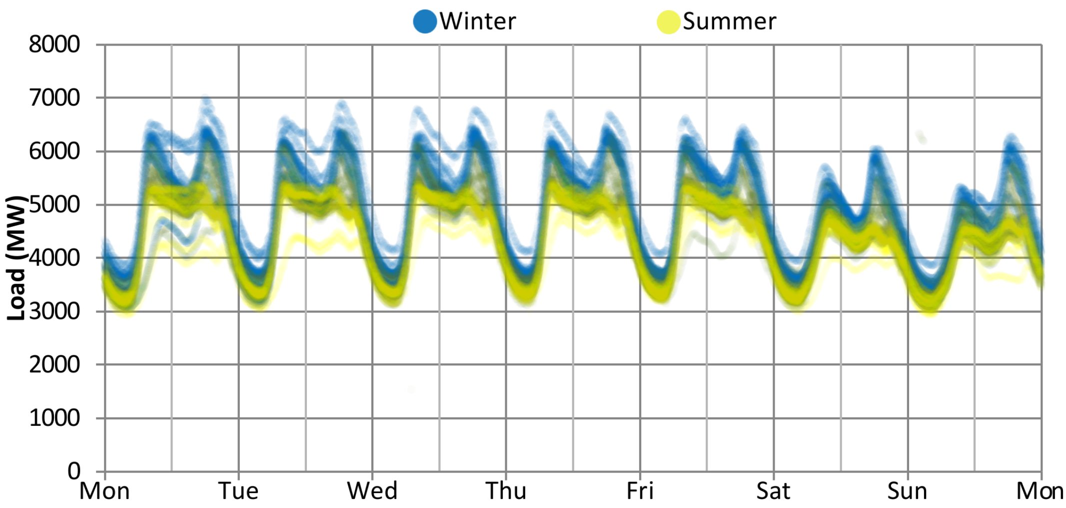


Figure 4.7: New Zealand weekly load curve in 2011.

for the year 2011[2], obtained from Transpower (2013), New Zealand's transmission network operator.

The zone load dataset contains both real and reactive power for all grid exit points in New Zealand at five-minute intervals. At this stage, the simulation utilizes only the aggregate real power for the whole country, disregarding grid topology.

Figure 4.7 shows the national load curve for 2011. All 52 weeks are shown, coloured by season. During the winter, cooler temperatures and fewer sunlight hours mean that the morning and evening peaks are higher and more pronounced than in summer, where the daytime load is relatively flat. Although demand follows a reasonably consistent pattern within seasons, the effects of several unusual events are visible as faint traces outside the normal consumption patterns. The exceptionally high winter load that is most pronounced during the working week is the result of unusually cold weather in July and August, while the unusually low demand events correspond to holiday periods, including Christmas/New Year, ANZAC and Queen's Birthday weekends, and the day after the 2011 Rugby World Cup final.

[2]The data between 02:00 and 03:00 on April 3 were corrupt, likely due to a daylight saving bug, and were hence removed. In addition, the data for 07:00 on April 20 was also corrupt and hence removed. The interpolation built into the simulation will fill in the blanks.

4.7 Vehicle Fleet

There are two main aspects to the vehicle model in the simulation; (i), the vehicle behaviour model that determines the timing and energy use of trips made by a vehicle, and (ii), the electrical model, which dictates charging and discharging (V2G) rates when connected to the grid. Together, these models establish both the energy consumed by the vehicle, and the times at which the vehicle is available for charging.

4.7.1 Behaviour Model

An important part of the simulation is to accurately model the times of day vehicles are in use, and how far they travel. These factors influence both the energy requirements of the vehicles, and the times at which they may be connected to the grid. The New Zealand Household Travel Survey (Ministry of Transport, 2011) invited people from 4600 households to record all of their travel over a two-day period; the results from this survey have been used to build statistical models for vehicle behaviour.

In this research, “trip” refers to a single vehicle movement, between starting the vehicle and stopping it, while a “journey” refers to travel between two

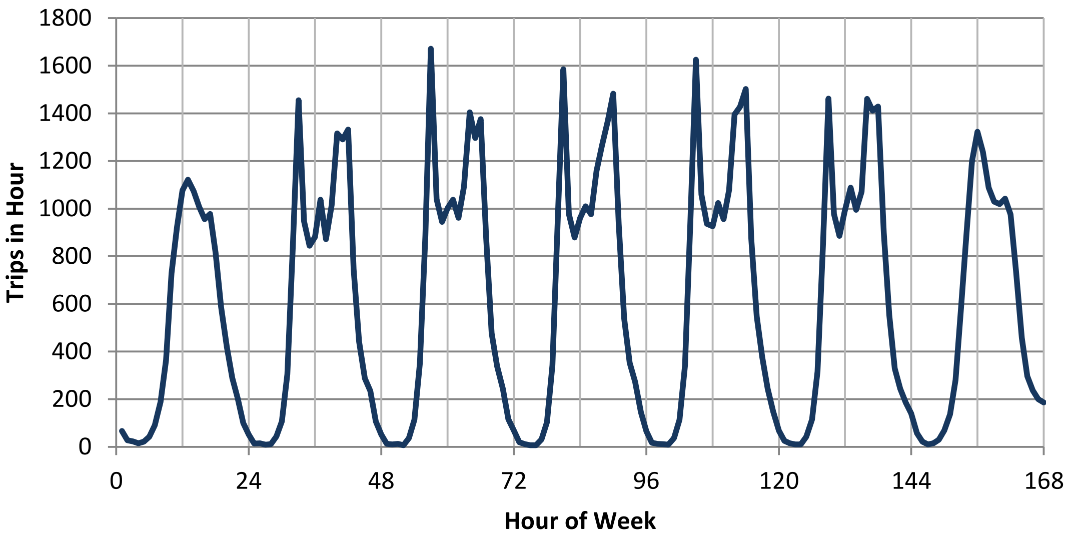


Figure 4.8: Weekly distribution of vehicle trips, starting Sunday. Data from Ministry of Transport (2011).

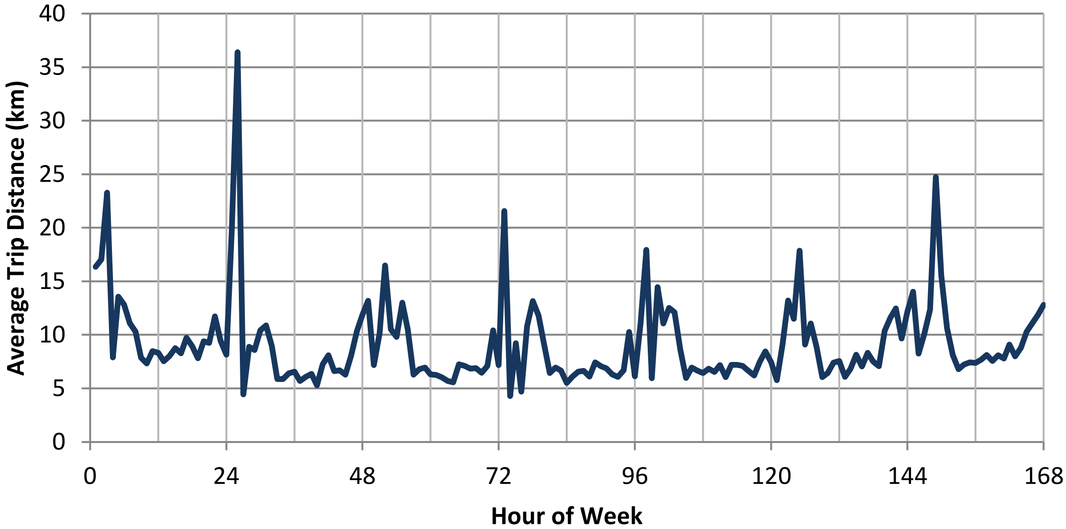


Figure 4.9: Average trip distance by hour of week, starting Sunday. Data from Ministry of Transport (2011).

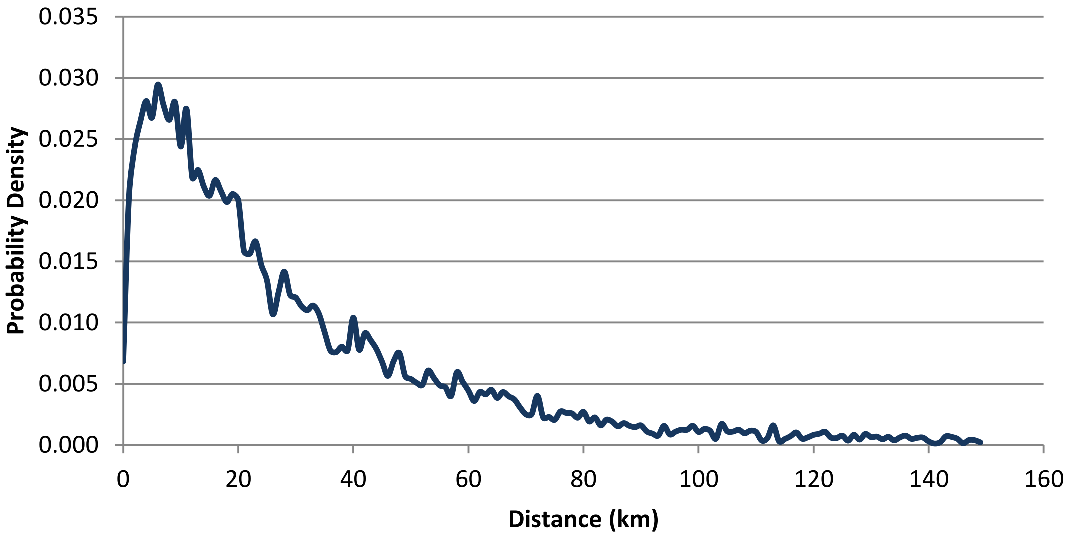


Figure 4.10: Normalised trip distance distribution. Data from Ministry of Transport (2011).

points, which may include multiple “trips”. For each vehicle in the simulation, a sequence of upcoming trips is stored. The description of each trip includes a time of departure, a distance to be travelled, and the average speed for that trip. At the conclusion of a trip, the EV reconnects to the grid and will remain connected until its next departure. All trips for the simulation period can be generated at the beginning of a scenario run, or dynamically during runtime to reduce memory requirements.

To generate the next trip’s time of departure, the cumulative distribution function derived from figure 4.8 is sampled 22 times, since this is, on average, the number of trips made each week (Ministry of Transport, 2011). The sample that is immediately after the current simulation time is used as the time of next departure, wrapping back to the start of the next week if necessary.

Once the departure time has been established, a mean trip distance is taken from the distribution shown in figure 4.9, which is then modified to provide an individual trip distance as follows: A random sample is taken from a distribution of trip distance per day, which has been normalized to have a mean of one, as shown in figure 4.10. The average trip distance from figure 4.9 is then multiplied by this value and becomes the distance of the next trip.

Finally, the average speed for all trips is simply chosen to be $36\,\mathrm{km\,h^{-1}}$, a figure obtained by the distribution of daily travel distance per vehicle (Ministry of Transport, 2011).

If a trip is not possible, either because its distance is greater than the range of the vehicle, or the charging strategy failed to adequately provide for it, the vehicle will not depart. Instead, the failure is noted and the vehicle will remain connected to the grid until the scheduled departure time of the following trip.

Table 4.3: Static vehicle characteristics.

Parameter	Value	Unit
Maximum battery capacity	50	kW h
Minimum allowable state of charge	1	kW h
Maximum charge power	5	kW
Minimum charge (i.e. discharge) power	-5	kW
Battery-to-wheel efficiency	110	$\mathrm{W\,h\,km^{-1}}$
Grid-battery-grid Round Trip Efficiency	100	%

4.7.2 Electrical Model

The electrical model of an EV includes parameters such as battery capacity, maximum charging and V2G rates, upper and lower SOC limits, efficiency, and perhaps most importantly, a charging controller that implements a particular charging strategy (chapter 6).

The vehicle parameters chosen to be representative of a typical BEV are shown in table 4.3, while charging and discharging rates are considered typical values for domestic electricity connections in New Zealand (Duncan et al., 2010; Concept Consulting Group Ltd, 2012). These parameters are represented in SI base units within the simulation, but are shown here in units that are more commonly encountered when discussing EV characteristics. Table 4.2 more formally describes these parameters.

The charging strategy implemented by an EV is responsible for choosing a suitable charging (or V2G) rate to ensure that the energy requirements of the EV are met. This is achieved using a decentralised charging model, whereby each EV makes its own decisions about charging and V2G rates based on information from multiple sources, as illustrated in figure 4.11. Some parameters are measured by the EV itself, while others are acquired from a communications network (section 4.3.2). A charging strategy is not required to utilise all available information; for example, an unsophisticated strategy might be to simply charge at the maximum allowable rate until a full SOC is reached, while a smart strategy could make use of all information to provide ancillary

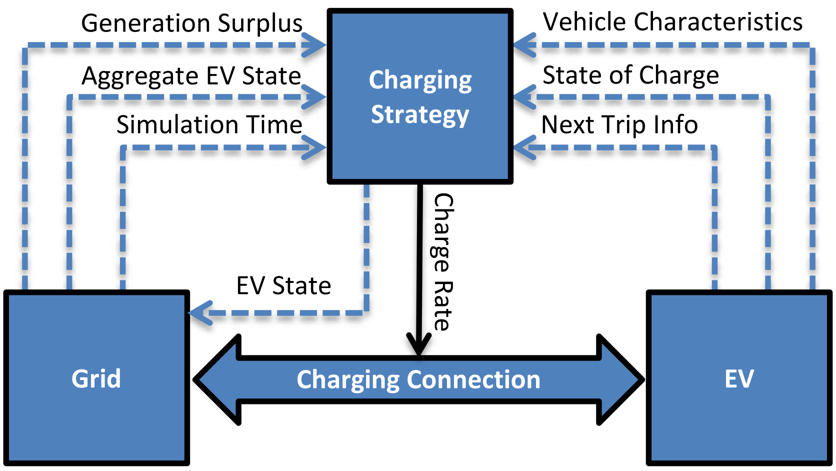


Figure 4.11: EV electrical model.

services to the grid. A full discussion of charging strategies is the focus of chapter 6.

In the simulation, batteries are not modelled for a particular technology; rather, they are treated as a simple “box of energy”. This decision was made on the basis that the most common energy storage technology in coming years is uncertain. Many technologies have potential—for example lithium ion batteries, fuel cells, and super capacitors—which may be combined in hybrid systems to exploit the advantages of each (Khaligh and Li, 2010). Although there are differences in the behaviour of these different technologies, most notably SOC-dependent charging rates and efficiency, these differences are not expected to significantly affect results.

A grid-battery-grid round-trip efficiency of 100% is used, which differs from typical values of between 80 to 90% seen in other V2G-related studies (Kristoffersen et al., 2011; Mason, 2014; Nunes et al., 2015). Energy losses resulting from conversion processes are inevitable and important to consider—especially in studies at the scale of a single vehicle or residential area—but doing so in isolation will not accurately characterise the wider efficiency gains achieved elsewhere in the system. Transmission and distribution network losses, for example, average approximately 7% in New Zealand (Ministry of Business, Innovation and Employment, 2014), and are influenced by many parameters including net load and transmission distances (Nair and Zhang, 2009); similar or greater losses are observed when partly-loaded thermal generation is used to balance load (Kim, 2004). The complex interplay between these factors, among others, is difficult to evaluate without accurate and detailed models for all parts of the system. Instead, the assumption is made that V2G conversion losses will be approximately offset by efficiency gains elsewhere in the system, and hence the effective grid-battery-grid efficiency is set to 100%.

4.8 Simulation Operation

For each tick of the simulation, the state of the internal models is updated, and all global state variables are recalculated. For electricity generation and load models, changes in state can only occur at the time of a tick, while EVs may depart on a trip—or arrive back from a trip—at any time.

The steps followed at each simulation tick can be summarised as follows:

1. For each vehicle that has departed since the previous tick, disconnect it from the grid.

2. For each vehicle that has returned from travelling since the previous tick, update its battery state and reconnect it to the grid.

3. Update values for wind generation, base generation, and bulk load from their respective models.

4. For each connected EV, recalculate its charging/discharging rate using its chosen charging strategy.

5. Recalculate the global state of the grid, including power imbalance and aggregate EV fleet metrics.

6. Record the current state of the simulation, including generation outputs, load, vehicle arrivals and departures, the aggregate charge state of the EV fleet, and other parameters.

This process begins shortly before the start of the simulation period (see section 4.3.3), and continues until the scenario run is complete.

4.9 Cluster Implementation

The analysis in this research compares large numbers of different scenarios to evaluate the performance of charging strategies with varying levels of wind penetration, EV fleet size, among other parameters. The simulation software can run on a standard personal computer, but much greater performance can be achieved by running many scenarios in parallel and analysing the output once all scenario runs are complete. Hence, the software has been adapted to run on Symphony[3], a cluster computer at the University of Waikato.

Figure 4.12 shows the structure of a distributed simulation run containing multiple scenarios. Each of the independent variables (e.g. charging strategy,

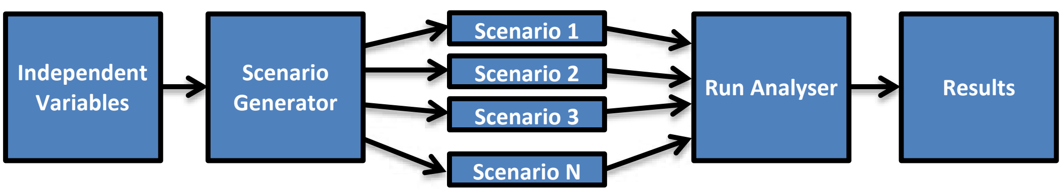


Figure 4.12: Cluster Implementation.

[3]http://symphony.waikato.ac.nz/

wind penetration, EV fleet size, EV battery size) are specified as discrete values, and a script (the scenario generator) combines all possible combinations of these variables to create a list of scenarios to be tested. This list is then submitted to the cluster computer using the TORQUE Resource Manager[4], which dispatches each scenario run to a dedicated processor within the cluster.

After all scenario runs have completed, the run analyser combines the intermediate results from each run and generates the final results for further analysis.

4.10 Summary

In order to evaluate the implications of the widespread deployment of EVs and wind generation in New Zealand, there are a number of capabilities that a simulation needs to support. This chapter began by establishing those requirements—namely the inputs, outputs, and performance—and then presented the software design and formulation of the models that will be used in the case study.

The models for electricity generation, load, and vehicle travel each extend generic models that process either time-series or probability distribution data from the relevant files. Each simulated EV performs its own charging decisions using information about its own state, the state of the grid, and aggregate state of all other grid-connected vehicles.

[4]http://www.adaptivecomputing.com/products/open-source/torque/

5 Balancing Variability

This chapter explores the variability of wind speed and electricity load, and establishes the performance requirements for the hypothetical energy storage system needed to keep the electricity grid in balance over a simulated year. It does not intended to provide realistic figures for New Zealand's electricity system; rather, the intention is to establish best-case performance characteristics of an ideal energy storage system under the constraints of the simulation software and generation profile.

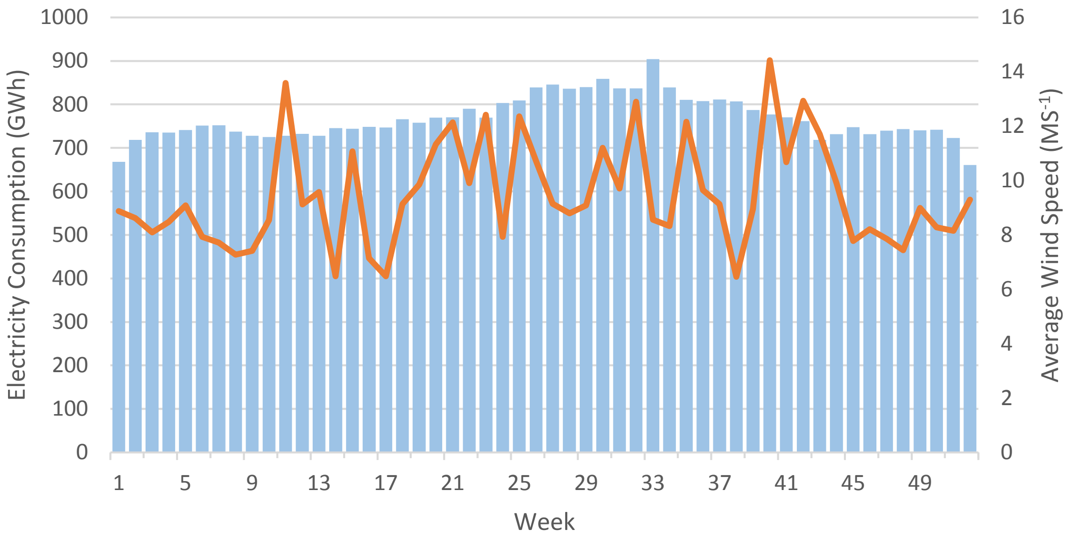


Figure 5.1: Average weekly wind speed and electricity consumption. Data from Turner et al. (2009) and Transpower (2013) respectively.

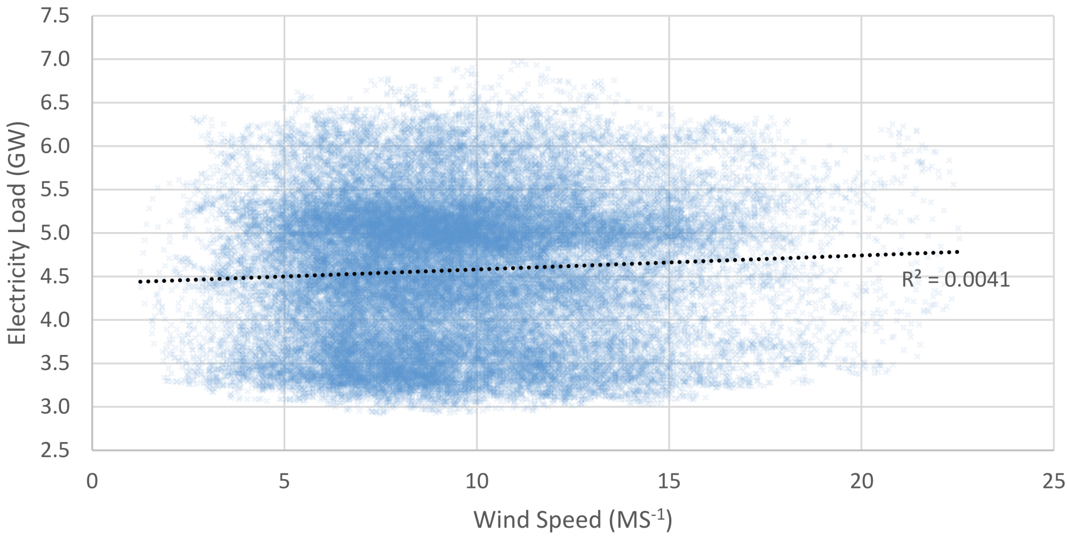


Figure 5.2: Instantaneous wind speed vs electricity load, sampled at 10-minute intervals over one year. Data from Turner et al. (2009) and Transpower (2013) respectively.

5.1 Variability of Load and Wind

The first aspect addresses the variability of the electricity load, wind speed, and the temporal relationship between the two. If these quantities were perfectly correlated, and assuming that the energy generated was equal to the energy consumed throughout the year, then no energy storage would be required.

Figure 5.1 shows average weekly wind speed (line chart) overlaid onto the weekly electricity consumption, from the beginning of January through to the end of December. In terms of weekly load, more energy is delivered to consumers over the winter months, while the weeks of lowest demand occurs over the Christmas and New Year holiday period. The average wind speed, however, is higher during Autumn and Spring. The relationship between energy consumption and average wind speed is not strong at this time scale, implying that storage is required to balance supply and demand over multi-week periods.

The correlation between instantaneous wind speed and electricity is also very weak, as shown in figure 5.2. This indicates that short-term energy storage is very important if wind were used as the sole source of electricity generation.

5.2 Storage Requirements

This section examines the performance required of the energy storage system needed to supply New Zealand's present-day electricity needs from the generation profile described in section 4.5; that is, an inflexible base generation profile that follows seasonal trends in load, plus a fixed level of wind generation that is scaled to meet the remainder of energy needs over the simulated year.

Three aspects of the storage system are considered: its total energy storage capacity, maximum power input and output, and maximum ramp rate. These factors are evaluated by their effects on the storage system's ability to maintain balance between generation and load, which is stated in terms of the demands placed upon peak generation: total peak energy used and spilled, peak power input and output, and maximum observed ramp rates.

As described in section 4.3.2, it is not possible to maintain a perfect balance between generation and load at all times. Some level of peak generation and spillage is to be expected, even with an ideal energy storage system.

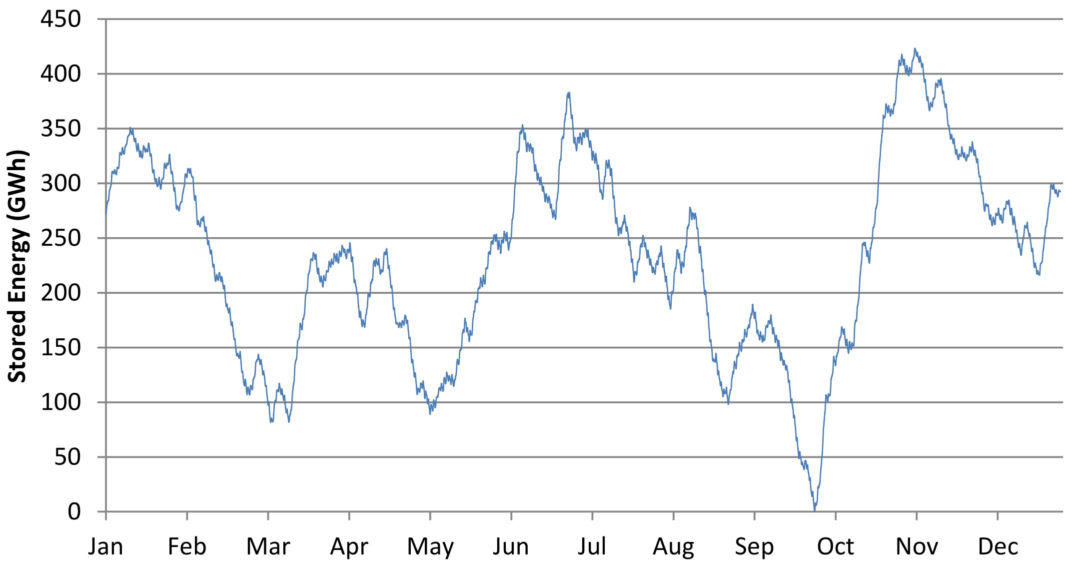


Figure 5.3: Ideal stored energy for 2011 (30% wind).

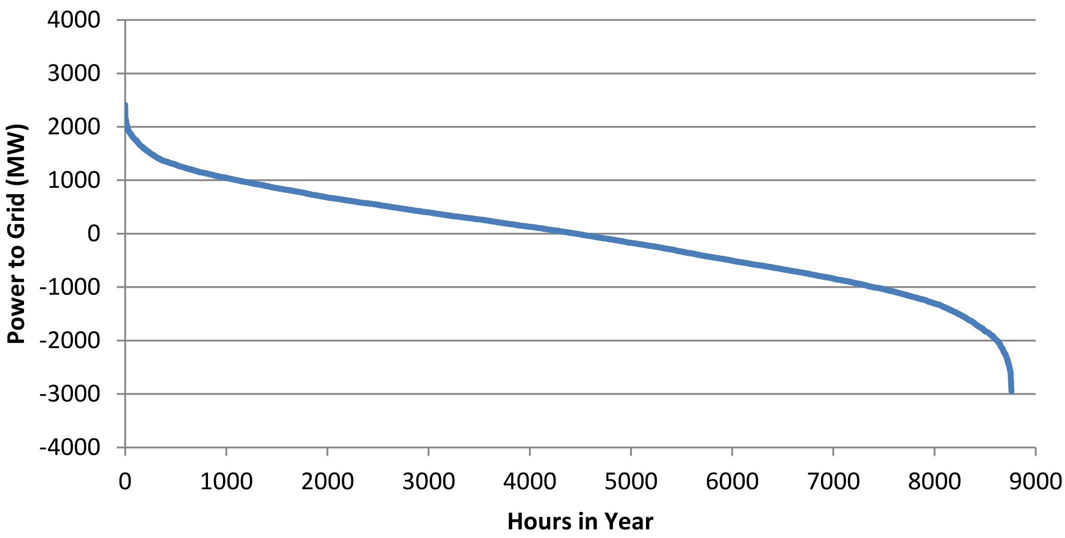


Figure 5.4: Ideal storage power-duration curve for 2011 (30% wind).

5.2.1 Baseline Performance

This section evaluates the utilisation of an ideal energy storage system in terms of total stored energy, and power input/output levels over the course of a simulated year. An ideal system has infinite energy storage capacity, no limits on power input/output, and unlimited ramp rates.

Figure 5.3 shows the total stored energy over the simulated year, with the minimum observed level normalised to zero. The effects of higher-than-average wind speed during autumn and spring are apparent, as is a steady decline in stored energy over the course of winter when demand is higher. The maximum observed capacity of 423 GW h implies that having a total storage system larger than this is not likely to contribute any significant savings in peak generation or spillage, although extra capacity will contribute towards increased energy security.

The duration curve of power into and out of the energy storage system is shown in figure 5.4. Overall, a connection capacity of ±3 GW between the energy storage system and the grid is sufficient to prevent bottlenecks, and a capacity of half that value (i.e. ±1.5 GW) is sufficient to provide for more than 90% of the year.

Using this ideal energy storage system, the total energy requirement from peak generation sources over the year was 134 GW h, or approximately 0.3% of total demand. Because the generation has been sized to provide exactly the amount of energy consumed over the year, energy spillage over the year is also 134 GW h.

5.2.2 Energy

The first parameter to be evaluated is energy storage capacity. The simulation was configured to run scenarios with storage capacity ranging from zero to 1 TW h in 10 GW h steps, with the peak generation and energy spillage recorded for each step. Figure 5.5 shows that with no storage available, both peak generation and spillage are approximately 3 TW h per year, or 7% of total demand.

When storage capacity is increased, the peak generation requirement and spillage both decrease rapidly. Significant savings are realised with a capacity of 100 GW h, which is approximately equivalent to the average daily consumption of 119 GW h. As expected, additional capacity beyond approximately 400 GW h had negligible impact on peak generation and spillage.

5.2.3 Power

The second parameter of interest is the capacity of the connection between the energy storage system and the electricity grid. Figure 5.6 shows that a connection capacity of approximately ±1.5 GW reduces peak generation and spillage considerably, and doubling that capacity achieves relatively little benefit. This is to be expected, given the power-duration curve required of the ideal energy storage system shown in figure 5.4.

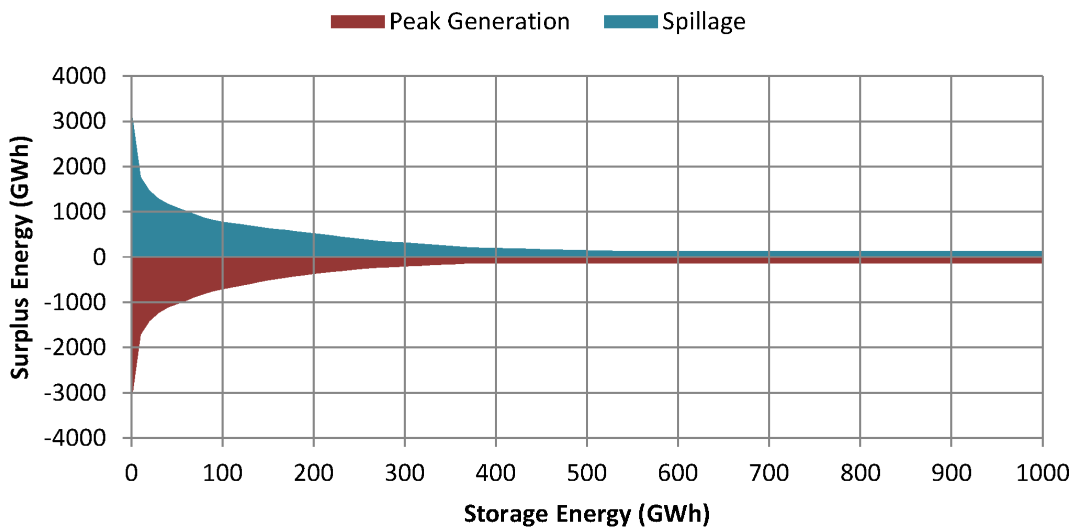


Figure 5.5: Storage capacity vs peak generation and spillage (30% wind).

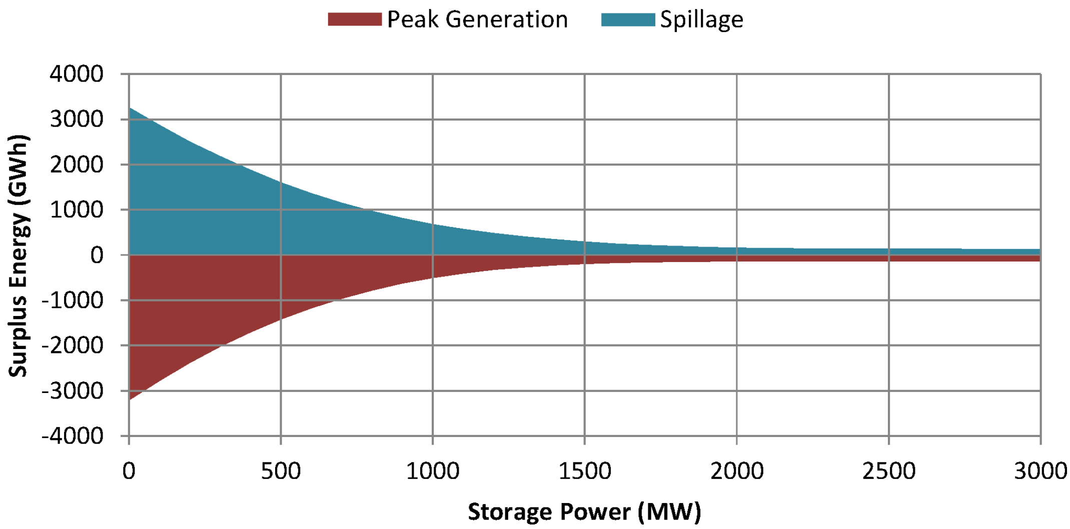


Figure 5.6: Storage power I/O vs peak generation and spillage (30% wind).

It must be noted, however, that the ability to cover peak load is an essential requirement of an electricity grid. Therefore, although a higher capacity grid connection achieves little benefit in terms of the energy used from other generation sources, the additional capacity is still necessary.

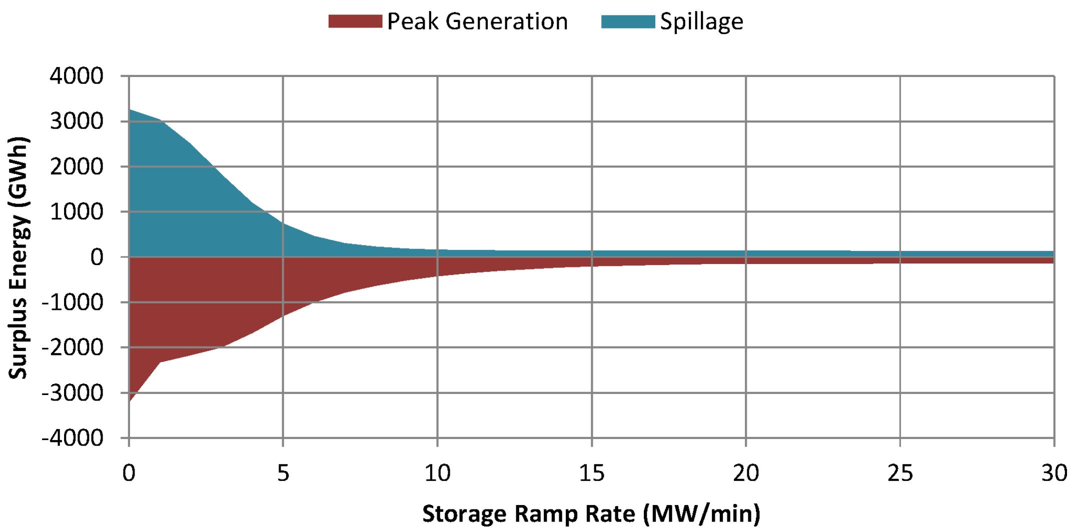


Figure 5.7: Ramp rate vs peak generation and spillage (30% wind).

5.2.4 Ramp Rate

The final parameter of interest is the ramp rate of the energy storage system; that is, the rate at which the system can change its output power. Figure 5.7 suggests that a ramp rate of $20\,\mathrm{MW\,min^{-1}}$ is sufficient in an environment with 30% wind; approximately double the present frequency-keeping requirement in New Zealand (section 2.5.4). In situations where the ramping ability of the storage system is insufficient, peak generation or spillage must be employed to maintain balance while the storage system responds.

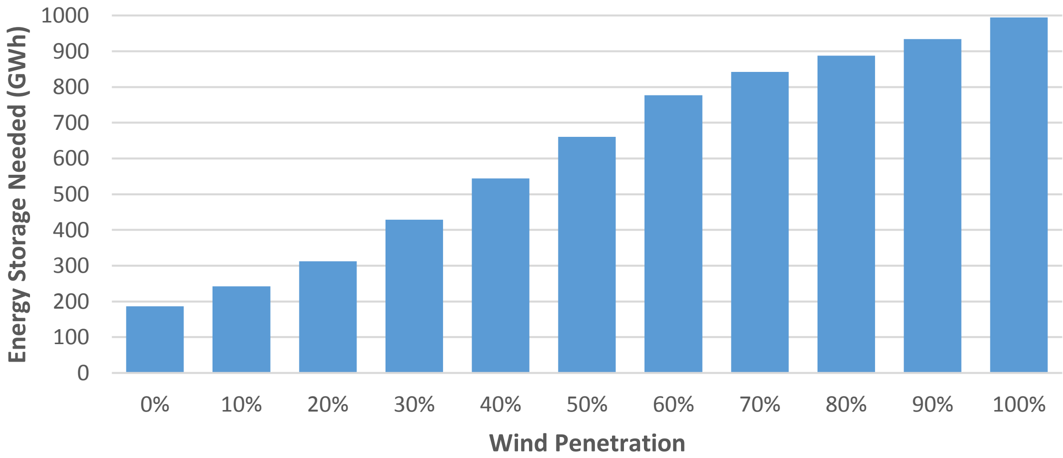
The asymmetry between the peak generation requirement and spillage is a consequence of load and generation characteristics. In situations where the energy storage system must increase its output, the average rate required is $5.81\,\mathrm{MW\,min^{-1}}$, versus an average down ramping rate of $5.66\,\mathrm{MW\,min^{-1}}$.

5.3 Effects of Wind Penetration

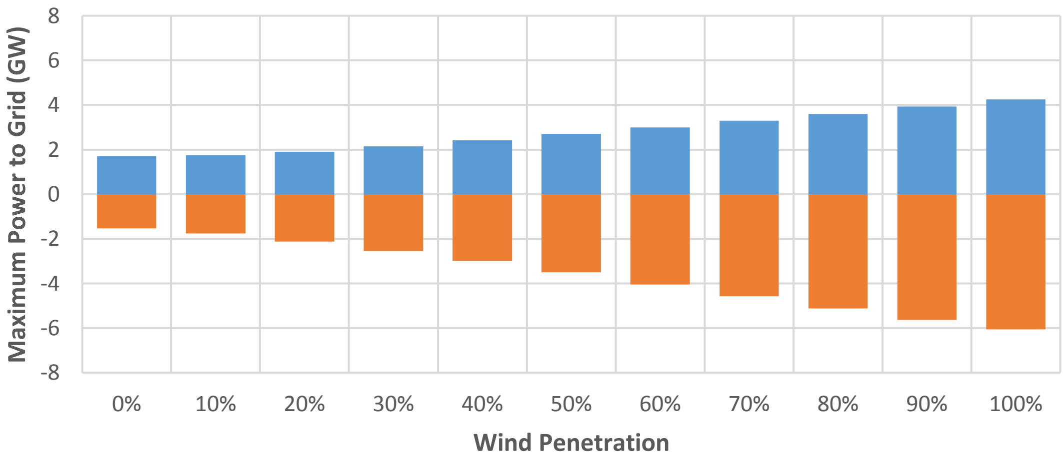
This chapter thus far has evaluated the energy storage performance requirements with a fixed 30% wind penetration, with no short-term load-following generation, and with New Zealand's present-day electricity demand. This section briefly looks at how the performance requirements change as a function of wind penetration, from 0% to 100% in 10% steps.

Figure 5.8 shows how the three main storage system characteristics—energy capacity, connection capacity, and ramp rates—vary as a function of wind penetration. The total energy storage capacity (figure 5.8a) rises more than five-fold as wind penetration increases from zero to 100%. On a seasonal basis, periods of high wind generation and periods of high electricity demand do not coincide. Therefore, energy must be stored in the interim, which may be several months or more as indicated in figure 5.3. As a larger proportion of energy is derived from wind, this effect is magnified and thus the total energy storage requirements will increase.

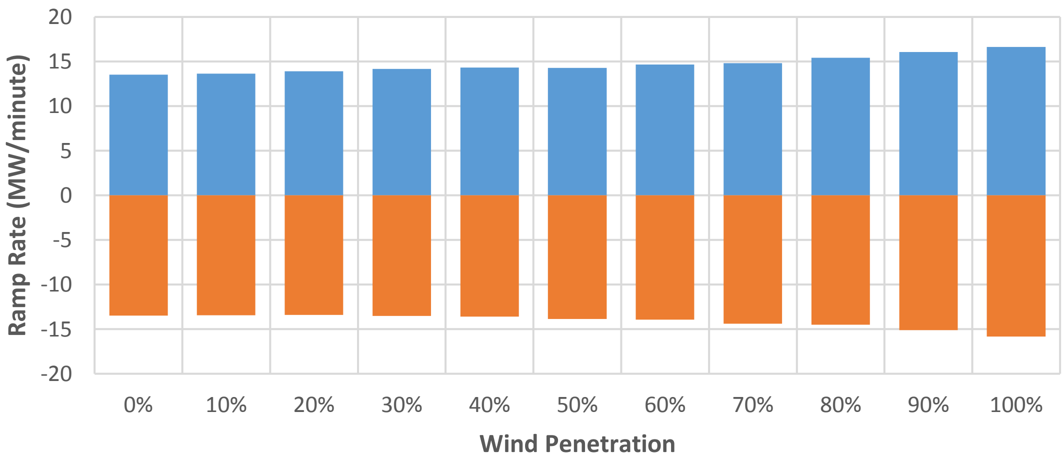
Over shorter time scales on the order of a day, the grid connection capacity is often the limiting factor of the energy storage system. Because wind generation can be very low at times of high electricity load, the energy storage system must be able to immediately make up the difference in order to prevent load shedding. On the other hand, when wind output is high during times of low demand, the energy storage system must be able to absorb the excess energy to prevent spillage. Figure 5.8b shows that the peak power required of the



(a) Energy capacity required.



(b) Connection capacity required (99.9th percentile).



(c) Ramp rate required (99.9th percentile).

Figure 5.8: Energy storage requirements by wind penetration.

energy storage system roughly doubles as wind penetration increases from zero to 100% for energy flows from the storage system to the grid, and increases more than three-fold for energy flows from the grid to storage system.

Finally, although ramp rate requirements do increase as wind penetration increases, figure 5.8c shows that this effect is not significant.

5.4 Summary

The correlation between wind speed and electricity load is poor, and thus some form of energy storage is necessary to ensure that electricity generation matches load at all times. This chapter has investigated three requirements of such a storage system in terms of its energy capacity, grid connection capacity, and ramping ability.

A small amount of peak generation and energy spillage is unavoidable—even with an ideal energy storage system—because the simulation software does not allow an energy storage system to respond instantly to changes in generation and load. This effect is very small, however, at approximately 0.3% of total electricity demand over the simulation period.

The level of peak generation and spillage is affected by the less-than-ideal characteristics of the energy storage system, including its finite storage capacity, limited grid connection capacity, and limited ramping ability.

Finally, the demands of all three characteristics increase as the proportion of wind generation in the system increases.

6 Charging Strategies

This chapter introduces the charging strategies that will be evaluated in the following chapter. It begins with the definition of an EV charging strategy, and specifies the information that may be used to influence charging decisions. Next, a number of charging strategies are described, some of which include secondary goals that go beyond simply charging the vehicle. Finally, the criteria used to evaluate the performance of a charging strategy is discussed.

In this research, charging decisions are made by each individual vehicle whilst connected to the grid, using information about the current state of electricity generation, electricity load, and the aggregate state of other connected vehicles. The primary purpose of an EV is to provide transportation, so it follows that the primary goal of a charging strategy is to ensure that a sufficient SOC is achieved prior to an EV departing on its next trip. Other goals, such as providing ancillary services to the grid, are secondary.

6.1 Definition of a Charging Strategy

At an abstract level, the role of a charging strategy is to choose the rate at which an EV draws electricity from the grid. This rate can be continuously

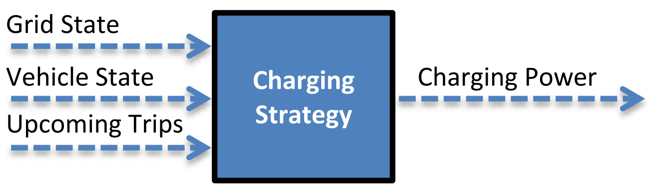


Figure 6.1: Charging strategy block diagram.

variable, and may be negative where bidirectional flows are supported. From a simulation point of view, the charging strategy is responsible for answering the following question at each simulation tick:

> ***Given the current state of the grid, the state of the vehicle's battery, and plans for upcoming trips, what should the vehicle's power draw be during the next tick interval?***

There are certain goals expected of a charging strategy, the most important being that the EV achieves a sufficient state of charge by the time it is due to depart on its next trip. One way to achieve this is to always answer "the maximum rate possible" (the *greedy* strategy); however, this approach imposes severe stress on electrical infrastructure, as explained in section 3.2.

Secondary goals for a charging strategy could include reducing charging rates during times of high electricity demand, returning electricity back into the grid to cover generation shortages, or providing load-matching services. For this to be possible, the charging strategy will require access to information on which to base its decision when setting the charging rate. The information is divided into three main categories; the state of the grid, the state of the EV, and the upcoming usage of the EV (see figure 6.1). This is described in more detail in section 6.1.2.

6.1.1 Function

The primary aim of a charging strategy is to attain a SOC of at least the charging target Q_1 by the time of next departure T_1, by choosing an appropriate charging or discharging rate p at each simulation tick, based on the state of the EV (see table 4.2 on page 75). The calculation of Q_1 is explained in section 6.2.

As shown in figure 6.2, an EV may have some residual stored energy (Q_0) when reconnected to the grid at time T_0. Assuming that the primary goal of meeting Q_1 at time T_1 will be achieved, the SOC must remain within the shaded area at all times. This area is defined by maximum charging (P_{MAX}) and discharging (P_{MIN}) rates, as well as the maximum (Q_{MAX}) and minimum (Q_{MIN}) allowable SOC of the vehicle.

Each charging strategy is free to choose its path between T_0 and T_1, for which it may utilise outside information in order to achieve a secondary goal, such as minimising peak loads or supporting intermittent generation sources. A charging strategy does not necessarily utilise all information available to it; for

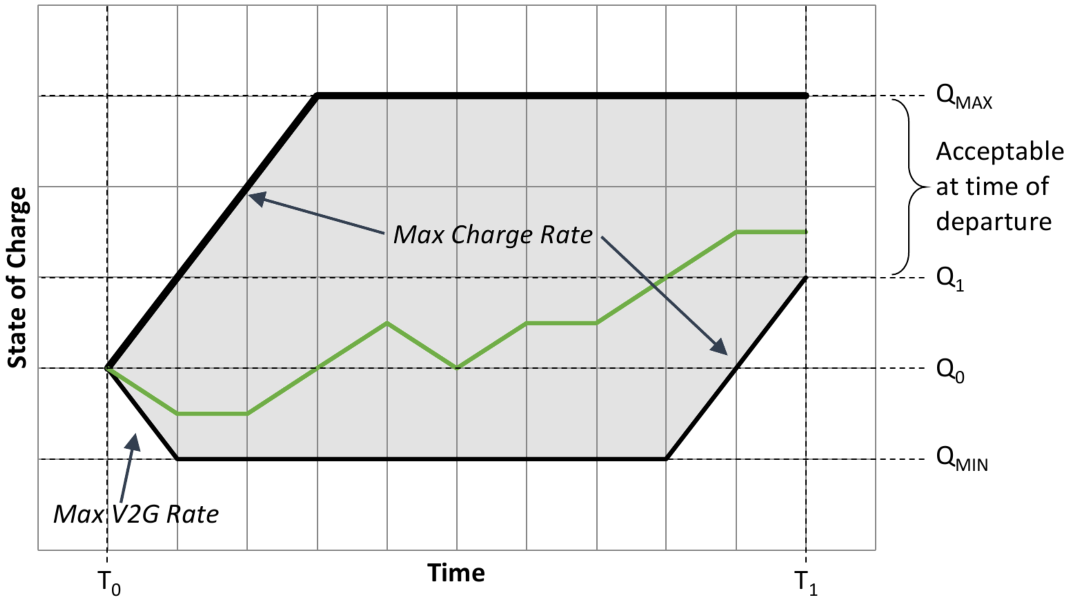


Figure 6.2: Function of a charging strategy. The vehicle should strive to meet the charging target Q_1 at the time of next departure T_1. How this is achieved is up to the charging strategy, but the SOC must remain within the grey area.

example, the *greedy* approach simply specifies the maximum possible power (P_{MAX}) until the battery is fully charged.

Several charging strategies include the secondary goal of supporting the grid whenever possible. Provided that the vehicle's SOC will not stray outside the predefined area, a charging strategy may choose to return energy to the grid during generation shortages (up regulation, or V2G), or charge at a variable rate in response to available generation (down regulation). If bidirectional energy flows are not supported, the SOC cannot decrease while the vehicle is connected to the grid.

6.1.2 Information for Decision Making

With few exceptions, charging strategies rely on information from three primary sources in order to make sensible charging decisions: the grid (current generation, load, and aggregate state of the EV fleet), the vehicle (SOC, vehicle efficiency), and the vehicle's driver (upcoming trips). The variables made available to an individual EV are shown in tables 4.1 and 4.2 on pages 73 and 75 respectively.

Charging strategies do not necessarily make use of all available information; for example, the basic strategies described in section 6.4.1 do not require any input from the driver about upcoming trips. When more information is available, an EV can offer more battery capacity for grid management purposes. However, the trade-off is an increased chance that the EV won't have a sufficient SOC to complete a subsequent trip.

6.1.3 Prediction of Future Journeys

This chapter thus far has hinted that some charging strategies either require information about upcoming usage of a vehicle, or perform better with access to this information. Of course, this raises the question: *where will information about future use of a vehicle come from?*

A number of approaches may be used, which fall into two main categories: have the driver specify this information in advance, or attempt to learn typical usage patterns for a particular driver based on past observations. A combination of the two may prove best, since there will always be trips that are out of the ordinary and do not lie within what is considered "normal". A full discussion of these approaches is included in section 3.3.

In this research, it is assumed that charging strategies have access to perfect information about upcoming trips. An evaluation of how the charging strategies perform with less-than-perfect information has been left to future work.

6.2 Charging Targets

With the exception of traditional charging strategies, such as *greedy*, *overnight*, and *valley-fill* (to be described in section 6.4.1), all charging strategies considered in this research aim to meet a charging target, Q_1, by the time of the vehicle's next departure, T_1. At the very least, Q_1 should cover the requirements of the next trip. If this is not achieved, the vehicle might be unable to complete the trip as planned.

It must be noted that charging targets specify the *minimum* state-of-charge to be achieved by the time of next departure. A charging strategy may exceed this amount, and the strategies that utilise surplus electricity generation are likely to do so. In addition, Q_1 is normally overestimated so that a failure to meet it does not necessarily mean that the next trip cannot be completed. If, however, the state-of-charge at time T_1 is less than the energy that will be used during the trip, the simulation treats that trip as one which cannot be completed, and hence a failure is recorded.

Three possible approaches to calculating Q_1 are described below.

6.2.1 Full Charge

The most simple method is to aim for a full charge at the time of next departure, namely:

$$Q_1 = Q_{MAX} \tag{6.1}$$

By using this method—referred to as *full-charge*—a driver only has to specify when the vehicle is needed next. One benefit of this method is that the battery SOC, q, is likely to remain near full capacity on average, except where a driver has indicated that the vehicle won't be used for a long period of time. This means that the vehicle is likely to be capable of completing unplanned trips. However, this method does suffer from the potential to unnecessarily draw energy from the grid at inopportune times.

6.2.2 Naïve

At the other end of the spectrum, Q_1 can be set to cover only the energy requirement of the next trip. This requires knowledge of when—and how far—that trip will be. This *naïve* method leaves more battery capacity available to support the grid, but is less tolerant of unplanned trips. It also fails to allow for multiple trips that are separated by insufficient charging windows (illustrated in figure 6.4), since the maximum charging power P_{MAX} might be insufficient to transfer the necessary energy within the time available.

The charging target calculation for this method is:

$$Q_1 = \min\{D_1.\eta.M, Q_{MAX}\} \tag{6.2}$$

where D_1 is the distance of the next trip, η is the battery-to-wheel efficiency of the vehicle, and M is a safety margin set to 1.2.

```
for (i = Trips.Length - 1; i > 0; i--)
{
        CurrentTrip = Trips[i];
        PrevTrip = Trips[i - 1];

        EnergyNeeded = CurrentTrip.Distance *
           VehicleEfficiency;

        ChargePotential = (CurrentTrip.Start -
           PrevTrip.Finish) * MaxPower;

        ResidualEnergy = MinEnergy[i] + EnergyNeeded -
            ChargePotential;

        if (ResidualEnergy < 0)
                ResidualEnergy = 0;

        MinEnergy[i-1] = ResidualEnergy;
}
```

Figure 6.3: Look-ahead algorithm for calculating charging targets.

6.2.3 Look-Ahead

The third method, *look-ahead*, addresses the issue of multiple trips occurring with limited intermediate charging windows. It requires a knowledge of a sequence of upcoming trips, which may be difficult to obtain. However, including this case allows for the evaluation of charging strategies when perfect information is available.

The *look-ahead* method examines a sequence of upcoming trips rather than only the next trip. In cases where insufficient time exists between trips to charge for a second trip, the amount of the shortage will be added to the charging target for the first trip. This ensures that, upon return from the first trip, there will be sufficient charge remaining in the EV battery to allow the charging target for the second trip to be met. The look-ahead period used in the simulation is 10 trips, which corresponds to approximately three days.

Figure 6.3 describes the *look-ahead* algorithm, which works backwards from the final trip in the look-ahead sequence. At each step, the algorithm adds the energy needed by the present trip and subtracts the charging potential during the period following the end of the previous trip. **Trips** is an array of future trips ordered by time of departure (earliest first), while **MinEnergy** is an array of values specifying the amount of energy required, excluding that needed by the next trip, to successfully complete the whole sequence of trips. If these values exceed the available battery capacity at any point, the vehicle will be unable to complete the sequence as planned. **MinEnergy** is the same length as the **Trips** array, with all values initialised to zero.

After running the algorithm, the first element in the **MinEnergy** array contains the energy required in excess to that needed by the first trip in the sequence, in order to successfully complete the full sequence of trips. Hence, when using the look-ahead approach, Q_1 is set to be the sum of energy required for the first trip in the sequence, and the amount calculated in **MinEnergy[0]**.

6.2.4 Summary

Figure 6.4 shows the behaviour of the three methods for calculating Q_1. For the purposes of illustration, the numbers are notional and no units are given. The maximum charging rate is one unit of energy per unit of time, and the energy consumption during trips is the same. The maximum battery capacity is 6 units. Negative-sloping (shaded) sections of the graph are a result of

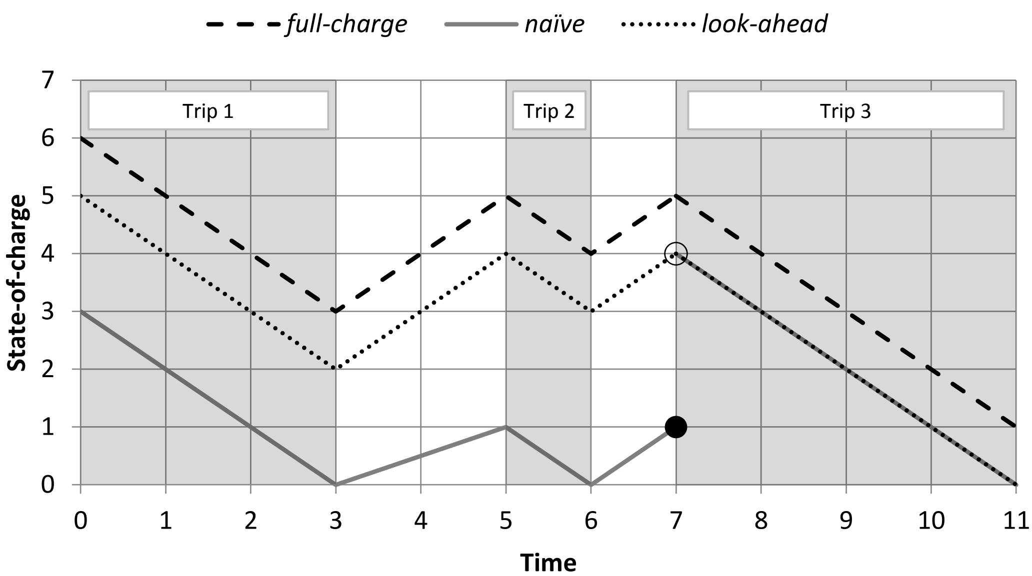


Figure 6.4: Calculating charging targets for a sequence of three trips. Both the *full-charge* and *look-ahead* methods meet the requirements for the sequence, while the *naïve* method fails at time 7.

the vehicle using energy during trips, while positive slopes illustrate charging periods. Three trips are shown, starting at time 0, 5 and 7.

The lower line indicates the minimum energy necessary when planning only for the next trip in the sequence (the *naïve* method), where each trip is allowed to finish with an empty battery. The upper line indicates the maximum energy possible when aiming for a full charge at each departure (the *full-charge* method). The dotted intermediate line indicates the minimum charge that will allow the vehicle to complete all trips successfully, without exceeding the maximum charge rate, as calculated using the *look-ahead* method.

When using the *naïve* method, the third trip would probably not be possible—unless the charging strategy happened to utilise surplus generation—since the charging rate required between time 6 and 7 is greater than the allowable limit. The *full-charge* method does not reach its charging target for trips two and three, but the trips are able to be completed because this method overestimates energy required. At the end of the *look-ahead* period–three trips in this example—the stored energy is allowed to reach zero.

6.3 Charging Modes

When connected to the grid, an EV can be in one of four modes that determine its charging behaviour. Table 6.1 shows the three boolean variables that represent the state of the vehicle and grid, and the four boolean expressions used to determine the charging mode.

F is true only when the EV is fully charged and cannot accept any more energy from the grid, while **P** is true when the EV is capable of supplying energy back

Table 6.1: Variables used to determine charging mode.

Symbol	Explanation
F	The vehicle is fully charged
N	The grid has a shortage of generation
P	The vehicle is able to supply energy to the grid
Mode A	Idle, when: $(\overline{P} \wedge F) \vee (F \wedge \overline{N})$
Mode B	Flexible charging, when: $P \wedge \overline{F} \wedge \overline{N}$
Mode C	Imperative charging, when: $\overline{P} \wedge \overline{F}$
Mode D	V2G, when: $P \wedge N$

to the grid without compromising its ability to meet charging targets. **N** is true when grid load exceeds generation output.

In mode **A**, the net power into the EV will be zero; that is, there is no energy flowing into or out from the vehicle. This occurs when there is a surplus of generation but the battery is already full, or the battery is full but the vehicle is unable to provide any energy back to the grid.

In mode **B**, there is a surplus of generation, the battery is not full, but the vehicle is able to provide energy back to the grid. This last point refers to the fact that the EV *can* provide energy back to the grid, implying that it currently has more energy than the lower limit shown in figure 6.2. In this mode, the rate of charging varies in response to the magnitude of the surplus to ensure that total generation and load stay in balance.

In mode **C**, the EV draws energy from the grid regardless of other requirements. This mode is selected when the vehicle must charge urgently in order to stay within the limits shown in figure 6.2, or if the charging strategy does not implement modes **B** or **D**.

In mode **D**, there is a shortage of generation, and the vehicle is able to provide energy back to the grid. This is the V2G mode, where the power into the vehicle becomes negative and hence energy flows from the EV back into the grid. The power varies according to the magnitude of the shortage to ensure that total generation and load stay in balance.

A given charging strategy will not necessarily support all four modes, but at a minimum modes **A** and at least one of **B** or **C** are necessary.

6.4 Charging Strategies

This section describes the charging strategies that will be evaluated in chapter 7. These strategies are divided into three classes—traditional, target-based, and smart.

The purpose of each strategy is described, including its modes of operation and the information it requires to make charging decisions, while typical behaviours are illustrated in figures 6.5, 6.6, and 6.7. In each figure, the range that each charging strategy must remain within is indicated by black lines, which is constrained by the maximum and minimum allowable charge levels (Q_{MAX} and Q_{MIN}), as well as the maximum allowable charging and V2G power (P_{MAX} and P_{MIN}).

6.4.1 Traditional Charging Strategies

The traditional charging strategies are simple in their operation, and require no notice of upcoming trips. Of the three strategies presented here, the first two only support charging modes **A** and **C**, where the idle mode is selected when the battery is full or outside the conditions imposed by the strategy (i.e. daytime for *overnight*), and imperative charging is used otherwise. The third strategy, *valley-fill*, supports mode **B** instead of mode **C**, since the charging rate is based on aggregate grid load.

Since traditional charging strategies do not attempt to meet a charging target (T_1 and Q_1), this is not shown in figure 6.5.

Greedy

This strategy is often referred to as uncontrolled charging. Once an EV is connected to the grid, it will charge at its maximum rate in mode **C** until its battery is full, at which point it will switch to idle mode (**A**), as shown in figure 6.5a.

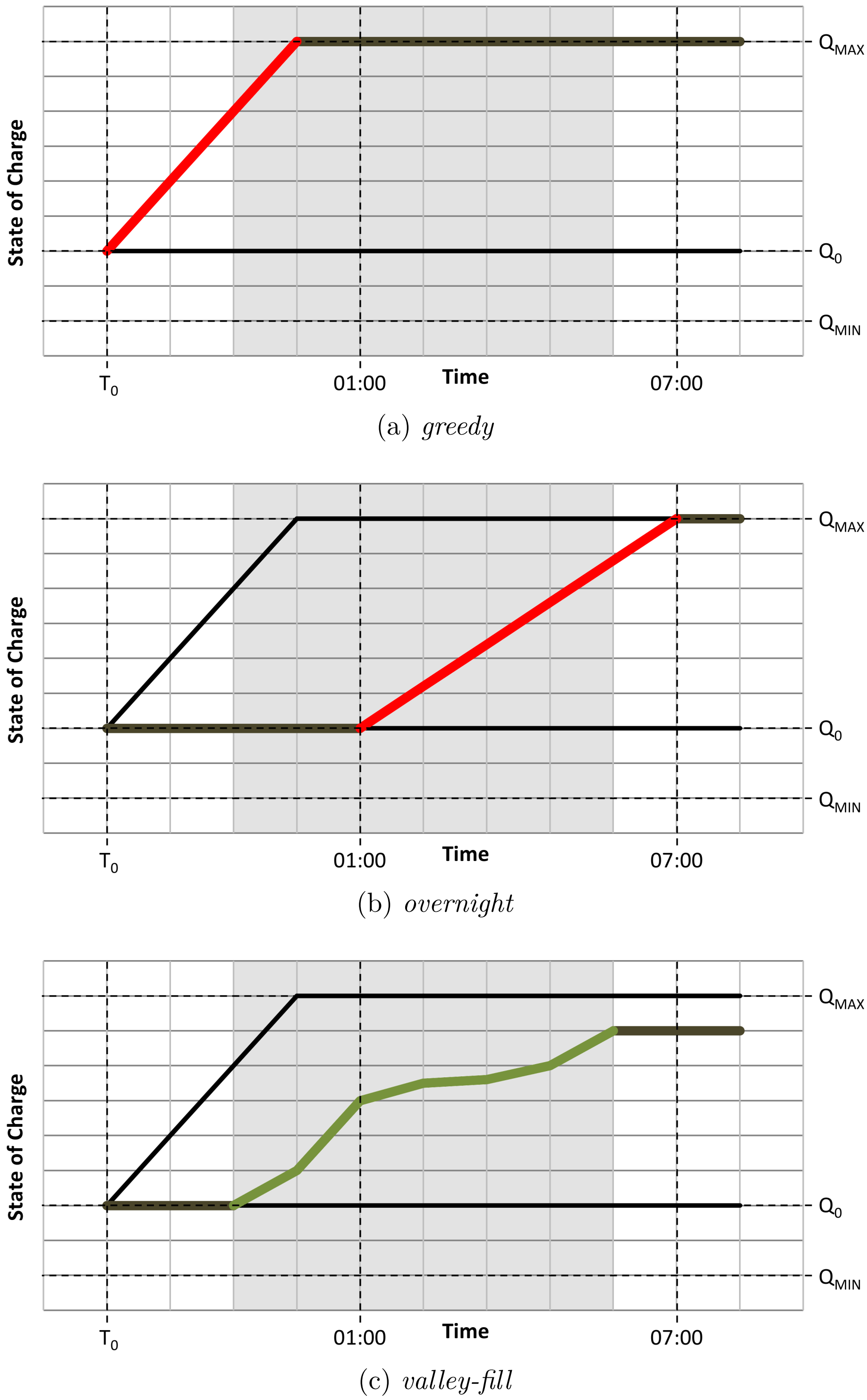
This strategy offers the best possible performance in terms of meeting the energy requirements of the vehicle, but is generally accepted to be expensive or infeasible to use on a large scale (Clover, 2013; Putrus et al., 2009; Shortt and O'Malley, 2014).

Overnight

Vehicles using the *overnight* strategy will charge during the night, which is defined as being between the hours of 01:00 and 07:00 in this research. Between these hours, EVs charge in mode **C** at the minimum rate necessary to obtain a full charge by the end of that period, as shown in figure 6.5b. Outside of this period, the vehicle remains in mode **A**.

Valley Fill

Based on an idea similar to the *overnight* strategy, the *valley-fill* strategy attempts to make use of surplus generation capacity during off-peak periods. Rather than relying on time-of-day to signal when this occurs, *valley-fill* uses the magnitude of all non-EV load, and charges when this drops below a set



(a) *greedy*

(b) *overnight*

(c) *valley-fill*

Figure 6.5: Typical behaviours of traditional charging strategies. Charging modes: **A**: Brown, **B**: Green, **C**: Red. The shaded area indicates that electricity demand is below a preset threshold.

threshold. This strategy has also been a focus of several studies, for example Ma et al. (2010); Denholm and Short (2006).

An EV utilising this strategy will remain in mode **A** while electricity load is above the preset threshold, and will enter mode **B** when load drops below it. This is illustrated in figure 6.5c.

When in mode **B**, charging power is calculated using equation 6.3. Each vehicle using the *valley-fill* strategy calculates its charging power so that the total load is raised up to the threshold amount; in effect, "filling the valley". Vehicles with less stored energy will charge at a higher rate than those nearing a full charge.

$$P_{IN_t} = (threshold - L_{t-1} - L_{EV_{t-1}}) \times \frac{Q_{MAX} - q_t}{E_{R_{t-1}}} \tag{6.3}$$

6.4.2 Target-based Charging Strategies

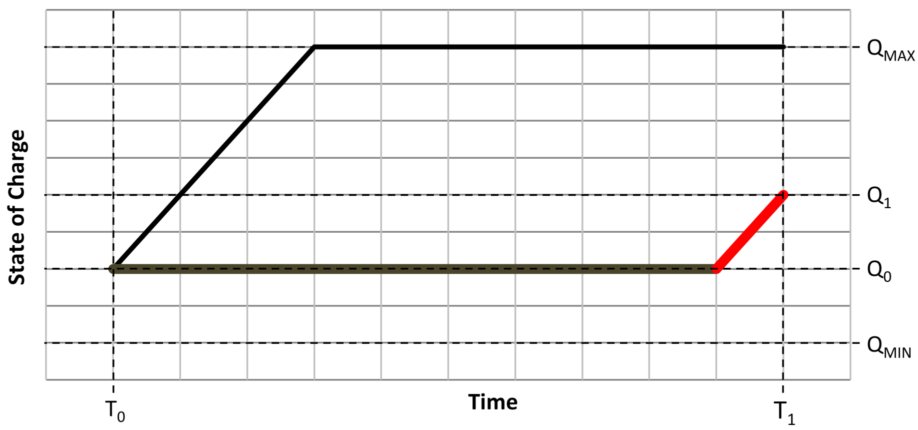
The next two charging strategies aim to reach the charging target Q_1 by the time of next departure T_1, as described in section 6.2. The strategies presented here only support modes **A** and **C**, and unlike the traditional charging strategies, target-based strategies do not take into account time-of-day or grid state, hence these factors are not shown in figure 6.6.

Lazy

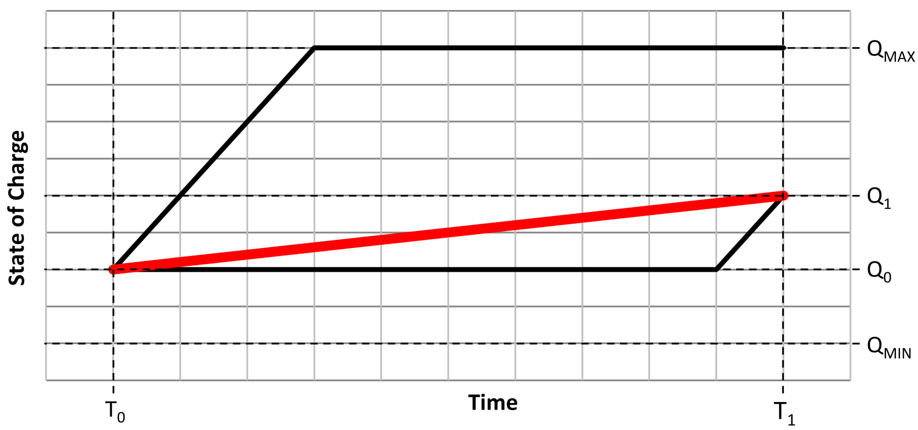
Vehicles using the *lazy* charging strategy do not charge immediately when connected to the grid, but instead wait in mode **A** as long as possible before switching to mode **C** and charging at the maximum rate in order to meet the charging target. This can be seen as a "just-in-time" approach, as shown in figure 6.6a.

Slow

When connected to the grid, EVs using the *slow* charging strategy will charge in mode **C** at the minimum rate needed to meet the charging target, illustrated in figure 6.6b. This attempts to keep power demands low by spreading the required energy transfer over the longest possible period of time.



(a) *lazy*



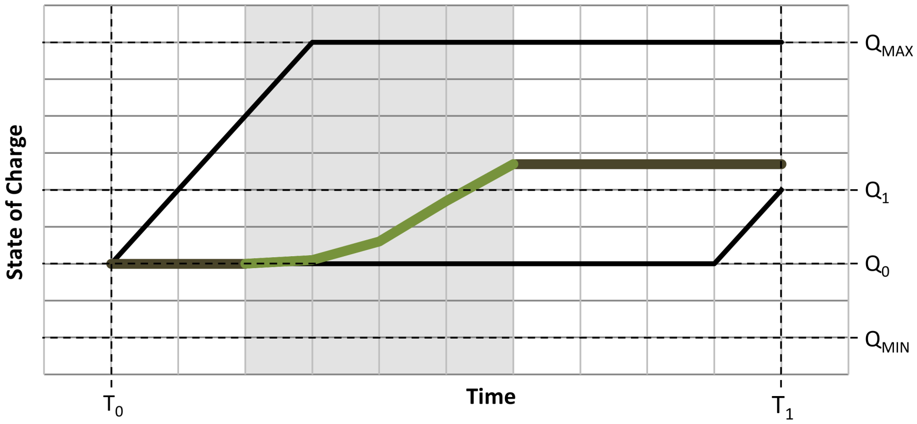
(b) *slow*

Figure 6.6: Typical behaviours of target-based charging strategies. Charging modes: **A**: Brown, **C**: Red.

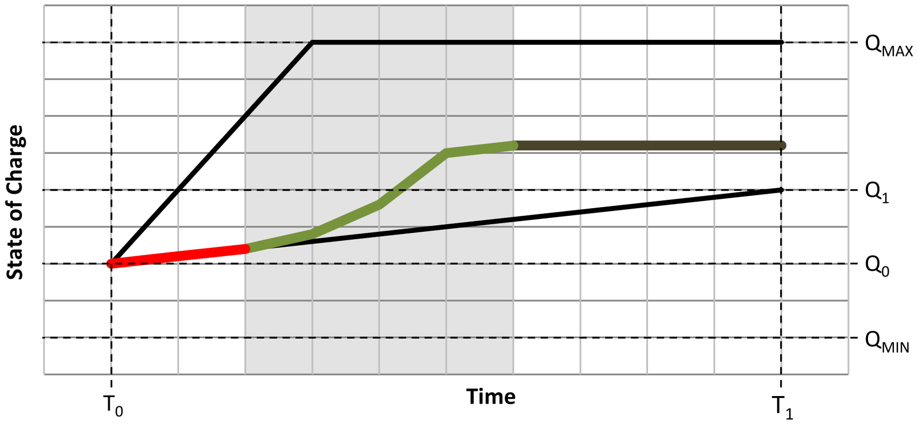
6.4.3 Smart Charging Strategies

The "smart" charging strategies take into account the current state of the grid when making charging decisions, and attempt to minimise their own impacts on the grid while also providing ancillary services where possible. Of these, only one—the *co-op* strategy—supports bidirectional energy flows.

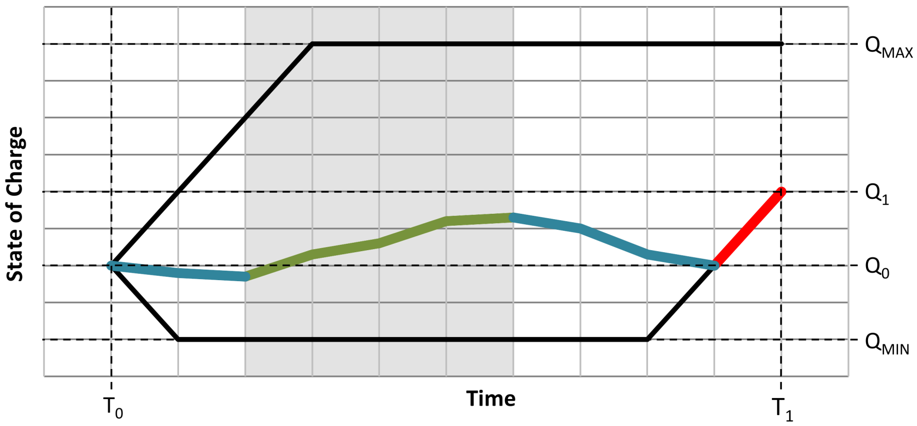
Like the target-based charging strategies, smart charging strategies also aim to meet a charging target. During times of surplus electricity generation, indicated by the shaded area in figure 6.7, an EV using a smart charging strategy will utilise mode **B** unless its battery is already fully charged. At all other times, it is assumed that the grid has a shortage of generation and hence



(a) *lazy+*



(b) *slow+*



(c) *co-op*

Figure 6.7: Typical behaviours of smart charging strategies. Charging modes: **A**: Brown, **B**: Green, **C**: Red, **D**: Blue. The shaded area indicates surplus generation.

an EV will not charge unless it is necessary in order to meet the charging target.

Lazy+

As an extension of the *lazy* charging strategy, *lazy+* will charge during its “waiting” period when surplus generation is available; that is, when total generation exceeds bulk load plus any imperative EV charging load. Mode **B** is used if the vehicle is not already fully charged, which provides a “down” regulation service. Each vehicle calculates its own charging power based on the aggregate state of the EV fleet; the calculation itself is described in section 6.5.1.

An EV waits as long as possible in the hope that surplus generation will become available before its next departure. If this does not happen, however, the vehicle will eventually switch to the imperative charging mode (**C**) in order to meet its charging target. The example shown in figure 6.7a does not require a last-minute imperative charge, since the target Q_1 had already been met during a generation surplus.

Slow+

The *slow+* strategy follows a similar rationale to that used in *lazy+*. When connected to the grid, an EV using this strategy will begin charging in mode **C** at the minimum rate needed to meet its charging target, but will switch to mode **B** and increase its charging rate when surplus generation is available, as shown in figure 6.7b. Like *lazy+*, this also provides a “down” regulation service during times of surplus generation, but avoids the possibility of a last-minute spike in charging power before departing on a trip.

Co-op

The *co-op* charging strategy provides full V2G capability, supporting all four charging modes. It operates in a similar manner to the *lazy+* strategy, where a last-minute imperative charge is used to ensure that an adequate SOC is attained by the time of next departure, and a “down” regulation service is provided during times of surplus generation.

The primary difference between *co-op* and *lazy+* is the provision of “up” regulation during generation shortages (mode **D**). In this situation, a calculation is performed (section 6.5.2) where the charging power becomes negative, and hence energy flows from the EV back into the grid.

The decision to enter V2G mode is based on whether enough time is available to bring the battery back up to a sufficient level before the next departure, i.e. the battery SOC will remain within the acceptable limits shown in figure 6.7c. The calculation for the lower limit at time st is shown in equation 6.4.

$$q_{lower} = \max\left\{Q_{MIN}, Q_1 - P_{MAX} \times (T_1 - (st + \epsilon)\right\} \tag{6.4}$$

If the present level of energy stored in the battery (q) exceeds q_{lower}, then the EV is able to contribute energy back to the grid. Because each vehicle performs this calculation independently, it is possible for energy to flow from one vehicle to another during generation shortages (i.e. V2V), when some EVs charge in mode **C** while others discharge in mode **D**.

6.5 Calculation of Charging and V2G Power

Once a charging mode is selected, an appropriate charging (or V2G) power must be calculated. Each EV performs this calculation independently, but may utilise aggregate state information from other vehicles and/or generation and load. In the simulation, these calculations are performed at each tick. The symbols used in calculations are described in tables 4.1 and 4.2 on pages 73 and 75 respectively.

For mode **A**, the charging power is simply zero, while in mode **C** this is set to a fixed rate according to the charging strategy—most commonly the maximum charging rate, P_{MAX}. Modes **B** and **D** are explained below.

6.5.1 Flexible Charging

For flexible charging (mode **B**), vehicles with a high SOC are charged at a lower rate than those which are nearer to empty, according to equation 6.5.

$$P_{IN_t} = S_{t-1} \times \frac{Q_{MAX} - q_t}{E_{R_{t-1}}} \tag{6.5}$$

Notice that the grid-state values used in the calculation are from the previous simulation tick, $t - 1$, while the vehicle state value is for the current time t.

This reflects a real situation, where the process of aggregating and distributing grid-state information is expected to take some time, while vehicle state can be known instantaneously.

Also note that the equation may produce charging power levels well in excess of the vehicle's maximum charging power P_{MAX}; for example, consider the case where only one vehicle is connected to the grid. This calculation will attempt to absorb the entire generation surplus, which is unlikely to be a realistic demand for a single EV. P_{IN} must therefore be limited to P_{MAX}.

6.5.2 Flexible Discharging

Following a similar approach as the calculation of charging power, the discharging power calculation (mode **D**) also aims to evenly distribute the aggregate stored energy between vehicles. EVs that are near a full SOC are discharged at a higher rate than those which are nearly empty, according to equation 6.6.

$$P_{OUT_t} = S_{t-1} \times \frac{q_t - q_{lower}}{E_{AV_{t-1}}} \tag{6.6}$$

As above, the power level calculated by this equation must be limited to remain within the capabilities of the vehicle and grid connection.

6.6 Performance Evaluation

When evaluating the overall performance of an EV charging strategy, there is no simple way to conclude that one is "better" than another. In this research, a number of factors are considered, some of which conflict with others. These characteristics are outlined in table 6.2, and are described below in further detail.

6.6.1 Peak Energy

Peak energy is defined as the total amount of energy consumed from peak generation sources over the simulation period, in GW h. A goal is to minimise this as much as possible, although some level of peak energy will certainly be required (see section 5.2).

Table 6.2: Evaluation metrics for charging strategy performance.

Parameter	Unit
Peak Energy Required	GW h
Spillage Energy	GW h
Peak Power	MW
Peak Ramp Rate	$\mathrm{MW\,min^{-1}}$
Reserve Availability	MW
Interruptible Load Availability	MW
Information Requirements	*list*
Failed Trip Departures	% of total trips
Battery Degradation	% of energy throughput for travel
Average Battery SOC	% of full capacity

6.6.2 Spillage Energy

Spillage, also measured in GW h, refers to energy that could have been utilised, but was not. This occurs when generation potential exceeds demand, and no storage is available to store the excess; this energy is necessarily wasted. Spillage can take many forms, including water flowing through a hydroelectric spillway, curtailed energy in wind farms, or unused sunlight in solar installations. Again, a goal is to minimise this figure, although some spillage is inevitable.

6.6.3 Peak Power

Peak power is the highest total load observed during the simulation period, specified in MW. Since all infrastructure must be sized to cover the highest load, even if only for a short period, this metric must also be kept to a minimum.

6.6.4 Ramp Rate

Ramp rate describes a rate of change in power, specified as $\mathrm{MW\,min^{-1}}$. High ramp rates can be introduced by intermittent generation sources such as wind, or widespread synchronised load behaviours. Sufficient load-following generation, demand response capacity, and/or energy storage must be available at all times to compensate for these effects, so lower ramp rates are generally preferred.

In this research, ramp rate is specifically described as the rate of change in the imbalance between generation and load, after the net contribution of EV fleet has been taken into account.

6.6.5 Reserve Availability

To ensure a reliable electricity supply, spinning reserves are required to be capable of covering the loss of the single largest generator or transmission line in the grid, without shedding any non-interruptible load. Spinning reserves are typically required to provide their specified power output for up to 30 minutes, or until replacement reserves can be brought online.

In this research, reserve availability is defined as the V2G power output that can be sustained for a 30 minute period by the EV fleet, specified in MW.

6.6.6 Interruptible Load Availability

Interruptible load is a similar concept to reserve availability, however it is implemented as a reduction in load rather than a source of power. In this research, interruptible load refers to the non-essential EV charging, specified in MW, that may be safely interrupted for up to 30 minutes.

6.6.7 Information Requirements

The level of information required by a charging strategy varies from none (in the case of *greedy*) to a wide range of information including near real-time generation and load measurements, aggregate EV battery state, and a sequence of upcoming trips for the vehicle (in the case of the *look-ahead* variant of *co-op*). The effort required to obtain this information must be weighed against the increases in performance that it provides, and hence is considered when comparing the overall performance of charging strategies. See section 6.1.2 for further detail.

6.6.8 Failed Trip Departures

This is the number of trips that were scheduled to take place, but were not possible due to an insufficient SOC at the scheduled time of departure. Obviously, it is in the driver's best interest to keep this metric as low as possible, ideally zero. There are cases where this is not possible, for example when a driver attempts to schedule a long trip that exceeds the range of the vehicle, or a sequence of shorter trips that are separated by insufficient charging windows (see figure 6.4). This metric is expressed as the percentage of failed trip departures relative to the total number of trips scheduled during the simulation period.

6.6.9 Battery Degradation

Bidirectional charging strategies often attract criticism owing to the resulting acceleration of EV battery degradation. In this research, battery degradation is expressed as the percentage of energy that was ultimately used for transportation, out of the total energy entering the battery; the remainder is assumed to have been used for V2G purposes. Unless future battery technology proves to be immune to cycling degradation, this metric should be maximised.

6.6.10 Average State-of-Charge

Charging strategies maintain battery SOC at different levels as a side-effect of their operation. For example, the *greedy* strategy will tend to keep the SOC near full capacity, while *lazy* will keep this level near the minimum.

The average SOC can be used to estimate the charging strategy's ability to accommodate unexpected or unplanned journeys; a higher average is preferable in this regard. Battery degradation, however, is minimised around a medium SOC with present-day battery technologies (Ribberink et al., 2015; van der Kam and van Sark, 2015).

6.7 Summary

This chapter has introduced the role and responsibilities of a charging strategy, described a number of charging strategies, and discussed the metrics to be considered when comparing the performance of a charging strategy.

At a fundamental level, a charging strategy needs to continuously decide on the appropriate power level that an EV should charge at, when provided with information about the grid state, vehicle state, and upcoming usage of the vehicle. The aim of the charging strategy is to ensure that all scheduled trips can be completed, by attaining a sufficient SOC by the time of departure, while also minimising demands placed on electrical infrastructure.

The appropriate SOC to be reached at the time of departure can be calculated in several ways. Firstly, the charging strategy could aim for a full charge by the time of next departure. This will ensure that the vehicle can complete trips, where possible, but only if the time of departure is accurate. Secondly, the charging target could be set to the minimum necessary to complete the next upcoming trip. Since the majority of trips are much shorter than the range of a typical vehicle, this leaves more battery capacity available for grid management purposes. However, difficulties may arise when charging for multiple trips without intermediate charging opportunities. The third method aims to address this shortcoming by looking at a sequence of upcoming trips, and ensuring that the whole sequence can be completed successfully by modifying charging targets where necessary.

When an EV is connected to the grid, it may be in one of four charging modes: idle, flexible charging, flexible discharging, or imperative charging. The mode used will depend upon the state of the grid and vehicle, as well as the upcoming trips that the vehicle must complete. The charging mode determines which calculation is used for setting the charging power.

Charging strategies fall into three main classes: traditional, which don't require significant smart grid infrastructure or interaction with a vehicle's driver; target-based, which attempt to minimise their grid demands by only charging for trips specified by a driver; and smart charging strategies, which rely on information about grid state in order to perform optimally. Of the smart charging strategies, only *co-op* supports the bidirectional energy flows that are necessary for providing "up" regulation, while both *lazy+* and *slow+* support "down" regulation when the vehicle is charging.

The calculation of charging power is performed independently by each vehicle, which may utilise information such as the aggregate state of the grid and other vehicles that are currently connected. These calculations aim to maintain balance between total generation and load, while also establishing an even distribution of energy stored among individual vehicles.

Finally, evaluating the performance of a charging strategy is not trivial; a number of often-conflicting factors must be considered. These factors include concerns for individual drivers, such as the number failed trips and battery degradation, as well as concerns at a system level, such as peak generation requirements and ramping rates.

7 Simulation Results

Previous chapters have described the simulation structure, the requirements of an energy storage system for the New Zealand electricity grid, and introduced a range of charging strategies for electric vehicles. This chapter presents an evaluation of those charging strategies, using a fleet size of one million vehicles, and with wind penetration ranging from 10% to 50% on an annual energy basis.

The responsibility for maintaining instantaneous balance between electricity generation and load lies primarily with the EV fleet. In cases where the EV fleet is unable to achieve this balance, excess energy is either spilled (when generation exceeds load), or generated by highly-dispatchable peak generation. There is no load-following generation, nor any energy storage, elsewhere in the system. For the purposes of establishing best-case performance characteristics, it is assumed that an EV will be connected to the grid at all times while not travelling, and the effective EV charging/discharging efficiency is assumed to be 100% for reasons discussed in section 4.7.2.

The generation model (section 4.5) is configured to provide exactly the energy required by the bulk load model over the simulation period (section 4.6), plus an additional 130 W average power allowance for each EV. The proportion of wind generation to base generation is set according to the wind penetration being evaluated.

Each performance metric (introduced in section 6.6) is presented separately in the following sections, except where it makes more sense to discuss certain combinations of metrics in conjunction; for example, peak generation and spillage.

Unless otherwise stated, the method used for calculating charging targets is *naïve* for *lazy*, *slow*, *lazy+* and *slow+*, while *look-ahead* is used for *co-op* (see section 6.2).

7.1 Peak Energy and Spillage

Figures 7.1 and 7.2 show the annual peak generation requirement and energy spillage, respectively, for each charging strategy. It is important to reiterate that an additional generation allowance of 130 W per EV is included for all scenarios except *No EVs*.

Of particular interest is that using the *greedy* strategy greatly increases the energy required from peak generation sources, while slightly decreasing energy spillage due to the 130 W allowance per vehicle being slightly more than required. Similarly, using the *overnight* and *valley-fill* strategies—which don't take into account generation availability—do not decrease the peak generation requirement; however, spillage is significantly reduced because these strategies primarily utilise electricity during times of low demand. Because *lazy* operates in a similar way to *greedy*, in that a fast charge is performed immediately before using the EV (rather than afterwards), they exhibit similar peak generation and spillage characteristics. The *slow* strategy reduces the peak generation requirement somewhat, because it spreads the load over a longer period, but has little impact on spillage.

The smart charging strategies show a reduction in both peak generation requirements and spillage, suggesting that their energy needs can be almost en-

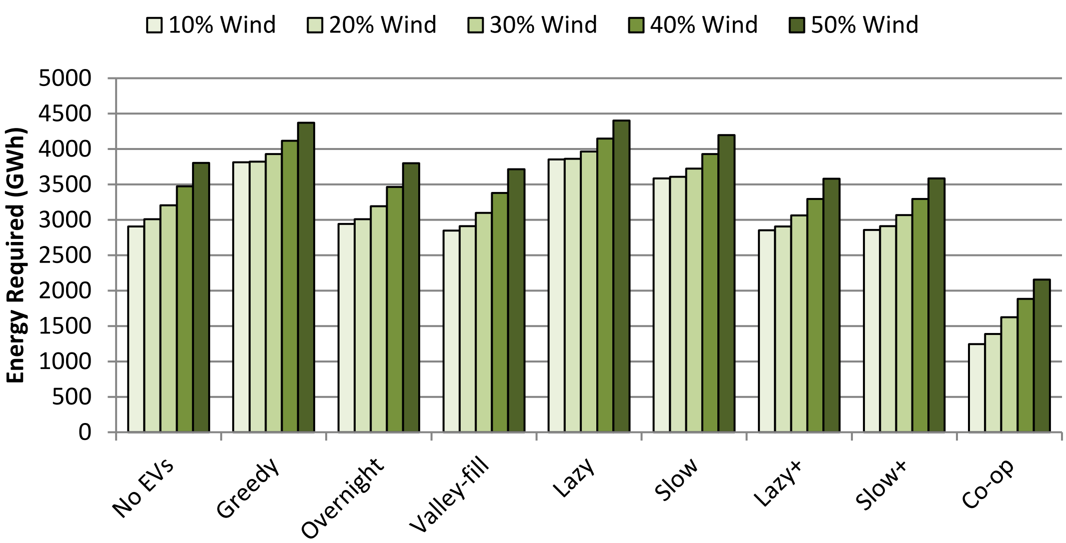


Figure 7.1: Peak generation required for each charging strategy.

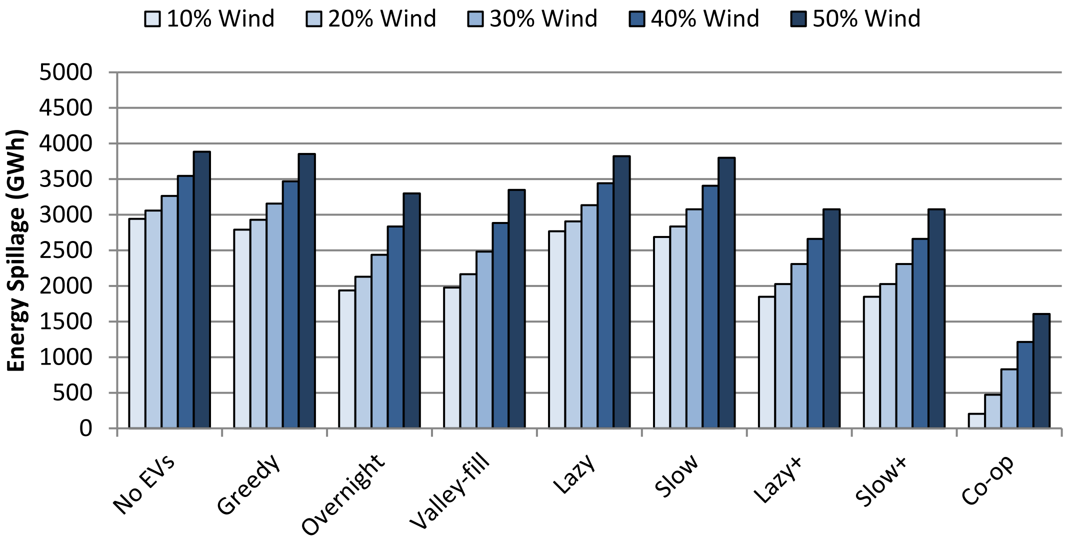


Figure 7.2: Annual energy spillage for each charging strategy.

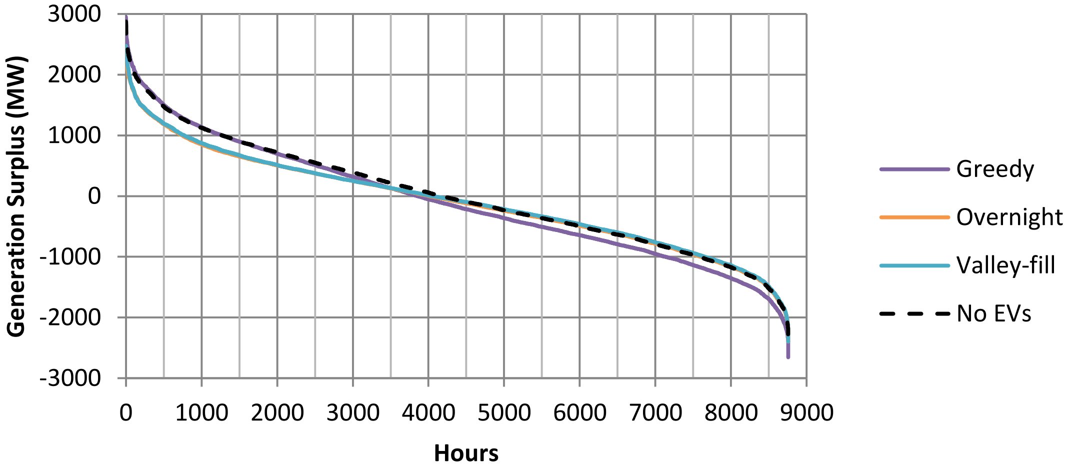
tirely met by non-dispatchable generation sources. Where V2G is supported (the *co-op* strategy), these improvements are dramatic.

However, the overall peak generation and spillage characteristics do not give the full picture of charging strategy performance. The imbalance-duration curves[1] for each charging strategy are shown in figure 7.3, when tested at a 30% wind penetration. The power imbalance between generation and load is shown on the vertical axis, while the horizontal axis shows the number of hours that the imbalance was above the corresponding value during the simulated year. The imbalance is specified as a generation surplus; that is, a positive value indicates that there is more generation than load, which cannot be stored and hence is counted as spillage. Similarly, a negative value indicates a shortage, which must be met by peak generation sources.

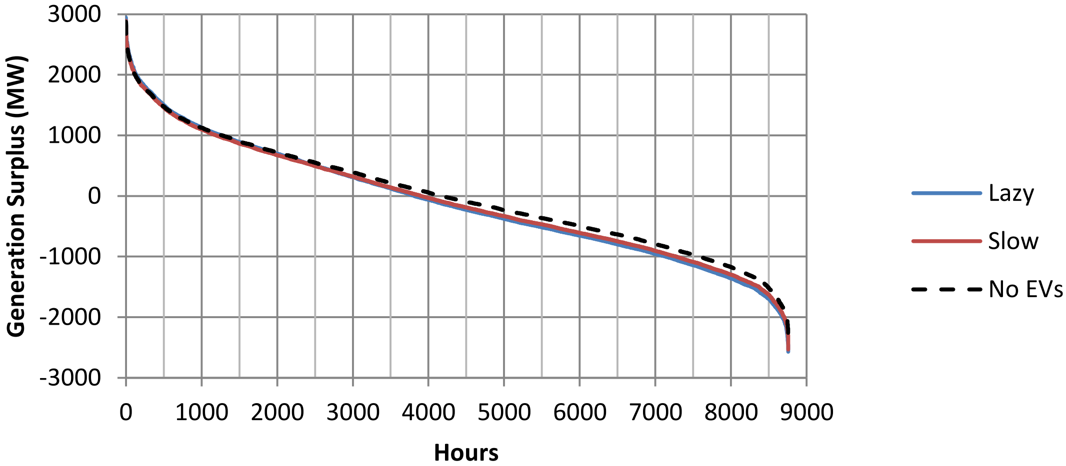
Figure 7.3a shows that EVs utilising the *overnight* and *valley-fill* perform very similarly over the course of the year, and both perform the bulk of their charging during times of surplus generation. Vehicles using the *greedy* strategy, on the other hand, primarily charge during times of already high demand and make little use of surplus generation when it is available.

The next figure, 7.3b, shows that the target-based strategies perform similarly across the year. Both strategies cause an increase in the annual peak, and the bulk of EV charging occurs during generation shortages. The *lazy* strategy is

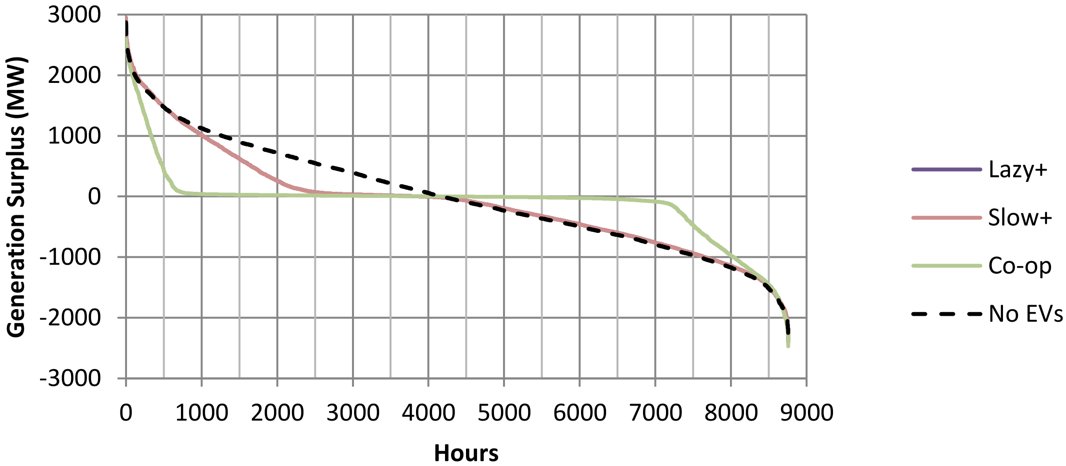
[1]The duration curves presented in this chapter are a generalisation of load-duration curves, which are commonly used in industry (Masters, 2013, pp. 44). These figures are created by down-sampling the raw 5-minute simulation output to one-hourly averages, which are then sorted in descending order and graphed.



(a) Traditional charging strategies



(b) Target-based charging strategies



(c) Smart charging strategies

Figure 7.3: Grid imbalance-duration curves with 30% wind.

slightly worse in this regard, due to its tendency to charge rapidly just before vehicles are used, which coincides with times of high electricity demand.

The final figure, 7.3c, shows an improved situation over both traditional and target-based charging strategies. Both *lazy+* and *slow+* perform identically, since almost all (99.5%) charging occurs in mode **B** when a sufficiently large battery is installed in each EV. Of particular interest is that both *lazy+* and *slow+* perform the bulk of their charging during times of surplus generation, keeping the grid in balance for around 1500 hours of the year. Once V2G is introduced, in the *co-op* strategy, this figure increases significantly; the grid is kept in balance for around 6000 hours of the year using only the EV fleet. Most charging is done during times of surplus generation, while energy is fed back into the grid during times of generation shortages.

7.2 Peak Power

The second performance metric to consider is peak power. This is the highest total load observed during the simulation period, which dictates the level of infrastructure needed to meet load and hence should be kept to a minimum.

As shown in figure 7.4, the *greedy* strategy substantially increases the peak demand, and both target-based strategies also increase the peak by a smaller amount. Those strategies that attempt to charge primarily during off-peak

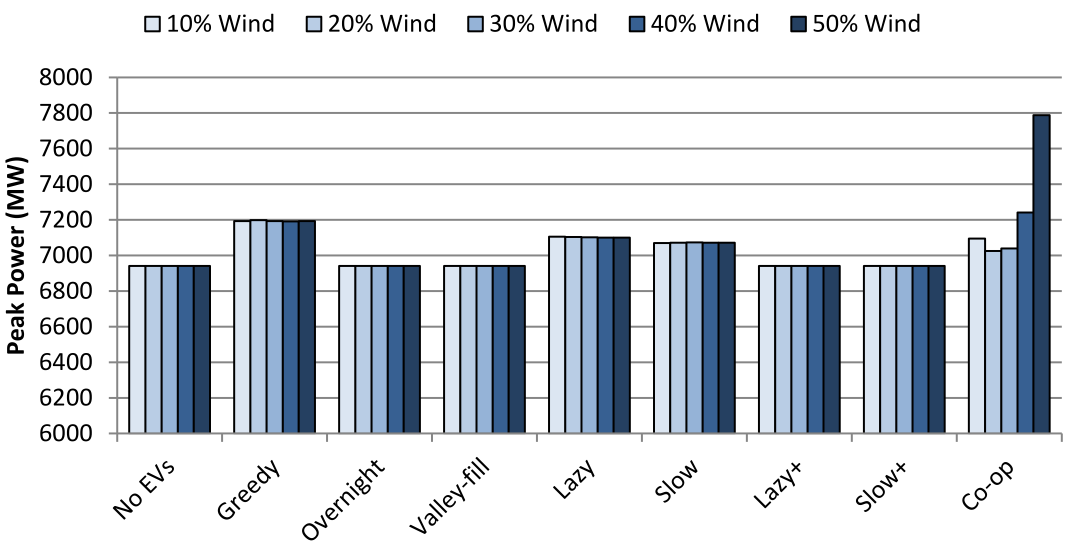
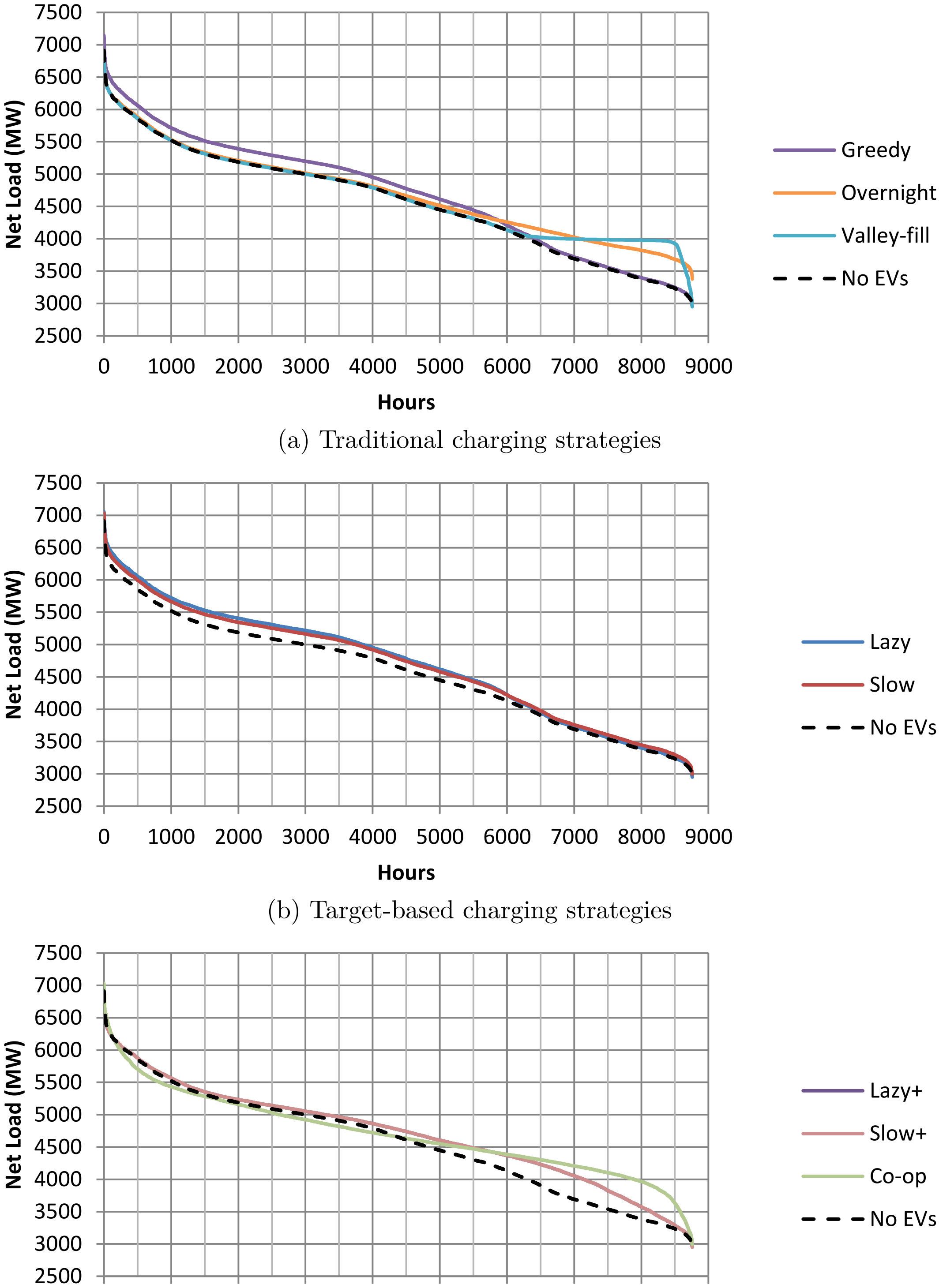


Figure 7.4: Peak power for each charging strategy.



(a) Traditional charging strategies

(b) Target-based charging strategies

(c) Smart charging strategies

Figure 7.5: Load-duration curves with 30% wind.

periods (*overnight*, *valley-fill*, *lazy+*, *slow+*) have minimal impact on peak power, if any. Most interestingly, *co-op* increases the peak power at all wind penetration levels, most significantly at 50%.

Figure 7.5 shows the load-duration curve for each charging strategy. The *greedy* strategy clearly increases the load during higher load periods, while making little use of off-peak energy. Both *overnight* and *valley-fill* show the opposite—minimal impact during high load periods, while most charging occurs during low load periods. The *valley-fill* strategy clearly shows the EV fleet charging when load is below the 4 GW threshold, while *overnight* spreads the charging load over a wider range of load levels.

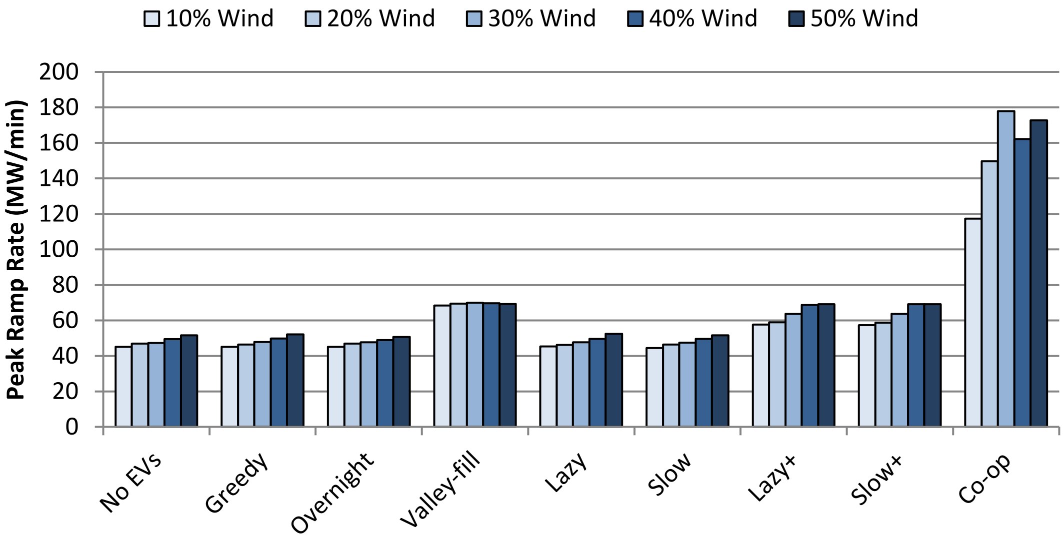
Figure 7.5b show that the target-based strategies tend to concentrate charging during mid-to-high load periods; slightly more pronounced with the *lazy* strategy since the *slow* strategy tends to be less "peaky". Unfortunately, neither of these strategies make use of low load periods.

Finally, the power performance of the smart charging strategies is shown in figure 7.5c. As mentioned in the previous section, both *lazy+* and *slow+* perform almost identically when a sufficiently large battery is installed in each EV, since most charging occurs in mode **B**. This has the effect of utilising electricity during low-demand periods. The *co-op* strategy shows a substantial increase in off-peak power levels, while the aggregate EV charging load during higher demand periods is negative at times. Unfortunately, this strategy does not decrease the overall peak power level, as can be seen to the left of the figure; in fact, the peak power level is increased, if only for a very short period of time.

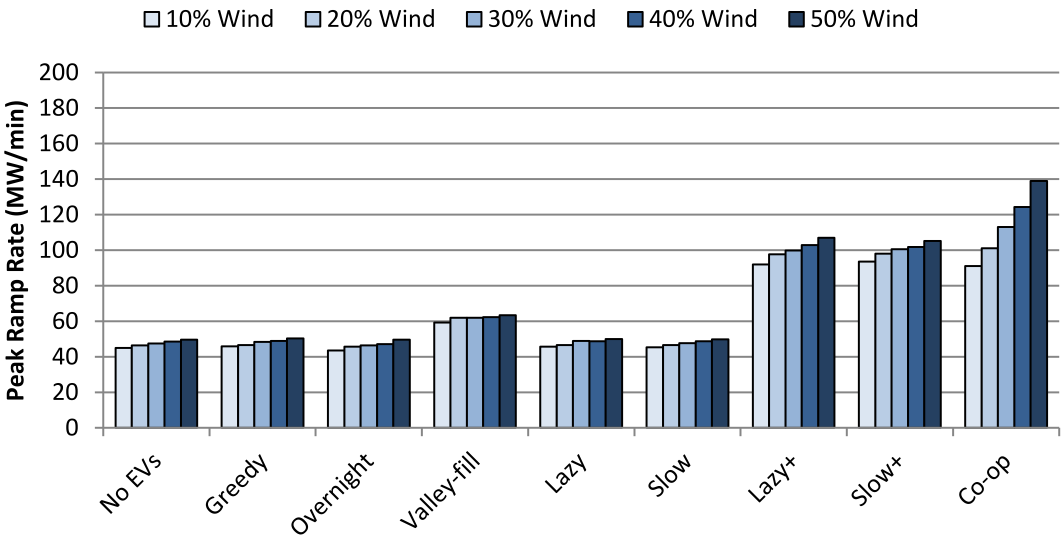
7.3 Ramp Rate

The third metric of charging strategy performance is ramp rates; that is, the rate of change in the imbalance between electricity generation and load. Ideally, this would be kept to a minimum since it is more difficult to compensate for rapid changes in net load (Fripp, 2011; M.Annaswamy and Amin, 2013).

Figure 7.6 shows the maximum ramp rates observed during the simulation period, in both the up and down directions. Ramping up (figure 7.6a) refers to the highest rate of increase in load (or decrease in generation), while ramping down (figure 7.6b) shows the reverse.

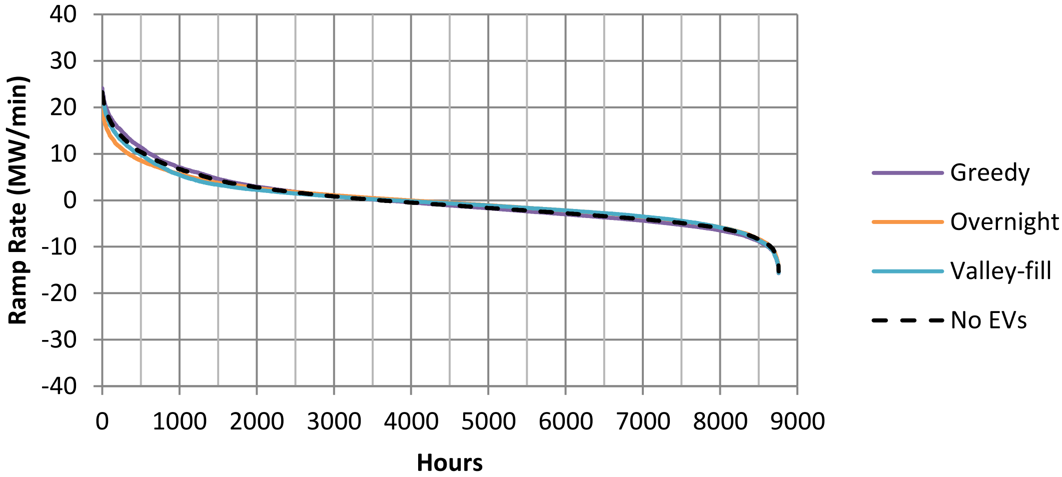


(a) Ramping up

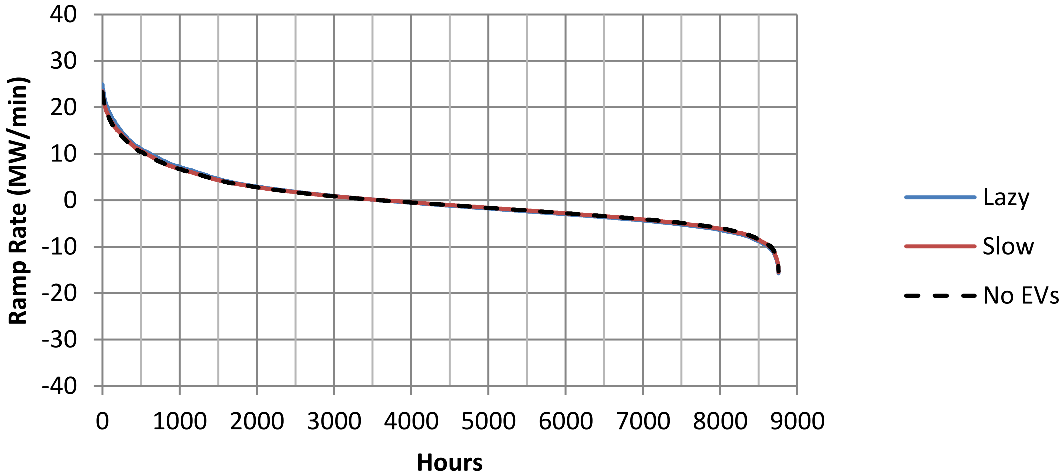


(b) Ramping down

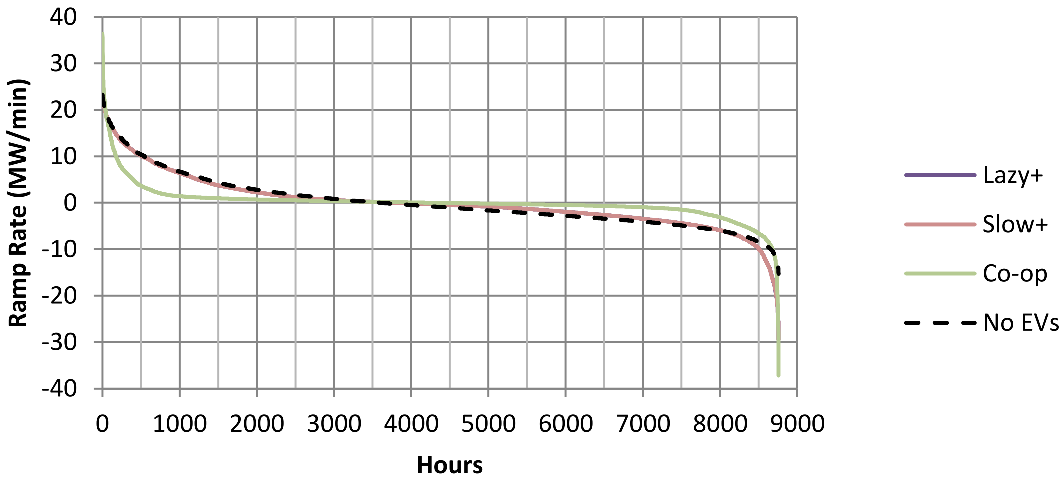
Figure 7.6: Peak ramp rates with 30% wind.



(a) Traditional charging strategies



(b) Target-based charging strategies



(c) Smart charging strategies

Figure 7.7: Ramp-duration curves with 30% wind.

The primary observations of these two graphs is that ramp rates generally increase with increasing wind penetration, and that the charging strategies which utilise grid-state information (*valley-fill*, *lazy+*, *slow+*, *co-op*) introduce greater ramp rates compared to the scenario where no EVs are present. During times of generation shortage, when vehicles utilising the *co-op* strategy are feeding energy back into the grid, eventually the batteries in those vehicles become depleted. At this point, the EV fleet becomes incapable of providing more energy to the grid, which suddenly introduces a large generation deficit and hence a high upwards ramp rate.

On the other hand, vehicles using any smart charging strategy will charge during times of excess generation, essentially bringing total generation and load into balance—a down regulation service. Once the batteries of these vehicles reach full capacity, however, the EV fleet is no longer capable of providing this service and hence a sudden generation surplus is created. Generation sources on the grid must then be able to rapidly curtail their output to keep the grid in balance.

When looking at the hourly averages for ramping rates, in figure 7.7, neither the traditional and target-based charging strategies affect the duration curves much. The smart charging strategies, however, show some interesting effects. The *co-op* strategy keeps ramping rates to very low levels for around 6000 hours of the year, but the extreme cases are much worse than having no EVs on the grid. Both *lazy+* and *slow+* don't affect the upwards ramp rates much, but down ramp rates are higher due to the effect explained earlier.

The discrepancy between the absolute ramping rates in figures 7.6 and 7.7 are an artefact of down-sampling data when generating the duration curves; figure 7.6 shows the maximum observed 5-minute ramp rate during the simulation period, while figure 7.7 shows hourly averages.

7.4 Reserve Availability

Operating reserves must be available at all times to cover unexpected events in the grid, such as higher than normal load levels or the unexpected loss of a generator/transmission line. Reserves are required to be available immediately, and provide their specified power output for a period of 30 minutes, until additional generation can be brought online. An EV fleet is only capable of contributing to reserve availability when V2G is supported, so only the *co-op* strategy is presented here.

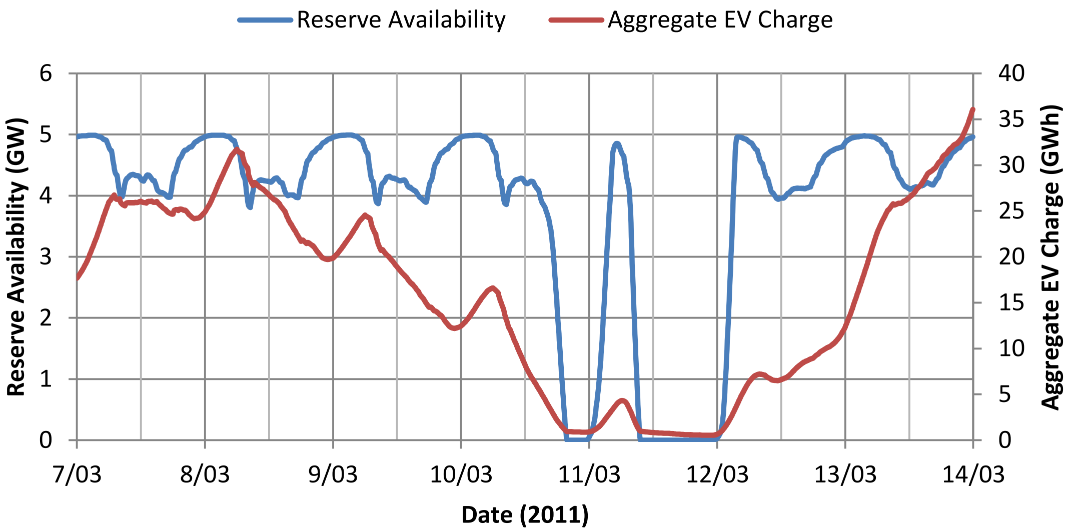


Figure 7.8: An example week showing spinning reserves offered by an EV fleet using the *co-op* charging strategy at 30% wind penetration. Note the net shortage of electricity up until the 12th.

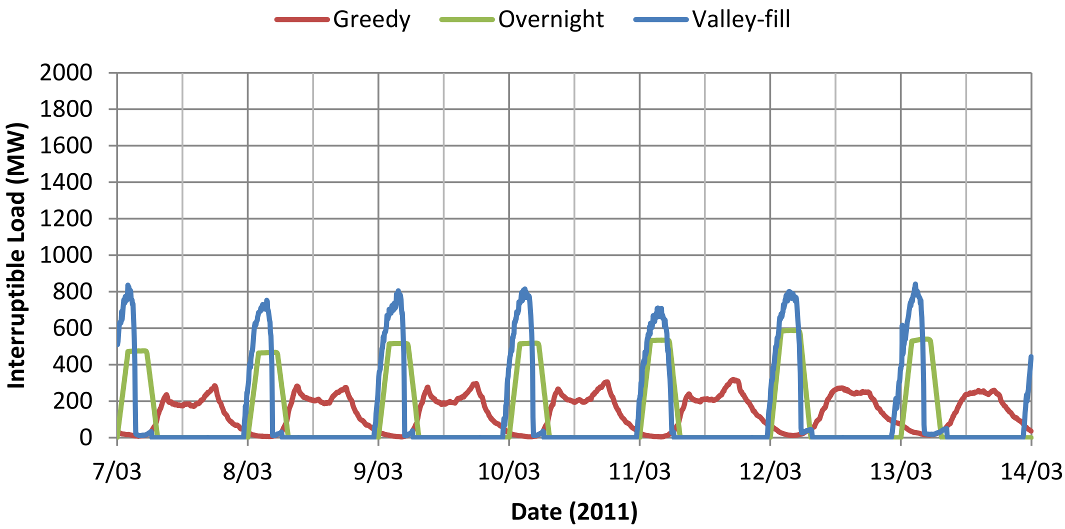
Figure 7.8 shows an example week of reserve availability offered by the EV fleet. This particular week was a period of low wind generation, and as a result the aggregate SOC of the vehicle fleet decreased over the course of the week. The blue line shows that the EV fleet can offer significant reserves for the majority of the time, at between 4 GW and 5 GW for a half-hour period. In New Zealand, this is sufficient to cover the simultaneous failure of nearly all generators in the country.

The reserve availability, for the most part, is limited by the power capacity of the connection between each EV and the grid. This is evident by the fact that reserve availability is largely independent of the aggregate SOC, except where the SOC reaches very low levels.

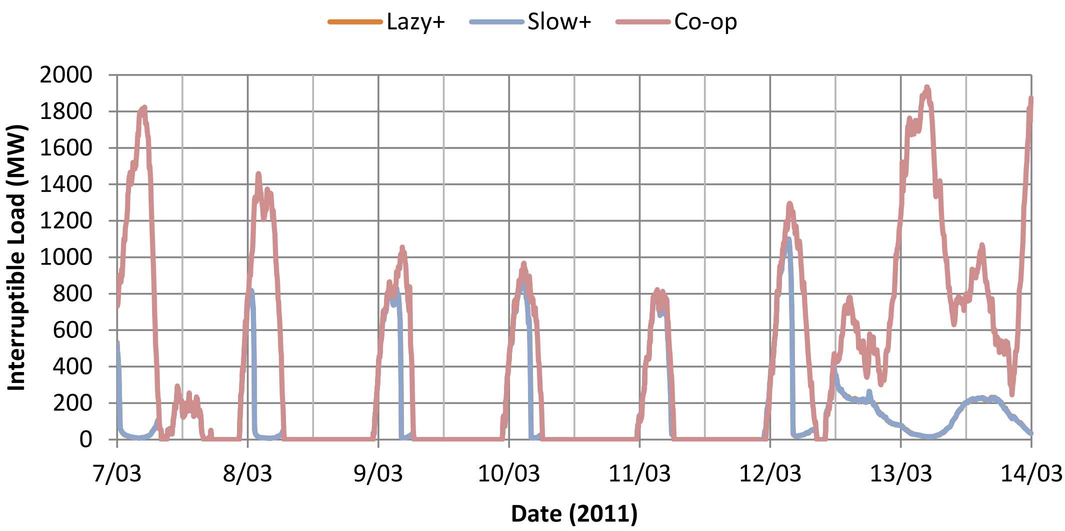
Overall, the EV fleet is capable of providing reserves in excess of 1 GW, sufficient to cover the present reserve requirements in New Zealand, for 78% of the year.

7.5 Interruptible Load Availability

Interruptible load is another form of operating reserve; however, instead of being an offer to provide additional power to the grid, it is an offer to reduce load. Like reserves, the time period is 30 minutes.



(a) Traditional charging strategies



(b) Smart charging strategies

Figure 7.9: Example week of interruptible load availability.

When the EV fleet offers interruptible load, each vehicle calculates how much of its charging power it can cut without compromising its ability to meet charging targets. If the vehicle is scheduled to depart within 30 minutes, no interruptible load is offered; exceptions being *greedy* and *valley-fill*, since these strategies do not have knowledge of upcoming trips. The *overnight* strategy specifies that interruptible load is offered, on the condition that a full charge is achievable by the end of the charging period.

This form of reserve can only be offered while the EV fleet is actively drawing power from the grid; it is therefore limited to off-peak periods in the majority of cases, which is a major disadvantage compared to other forms of reserves. The cost of interrupting load is theoretically less expensive, since it does not cause additional battery degradation in the way that V2G would. However, this is not seen as an advantage because reserves are only used in unexpected circumstances, and therefore the cost of being "available" in both cases is essentially free.

Figure 7.9 shows the interruptible load availability for traditional and smart charging strategies. Most of these, *greedy* being the notable exception, charge primarily at night and therefore can only offer interruptible during night-time hours. The *co-op* strategy offers substantial interruptible load levels for the bulk of this particular weekend (12-13 March), where a large amount of wind generation is available, demand is low, and the aggregate battery SOC is near minimum.

An EV that supports V2G can offer both interruptible load and reserve availability at the same time; it is certainly possible for a vehicle to stop charging, and begin feeding energy back into the grid.

7.6 Information Requirements

For each charging strategy, it is important to consider the information required to make charging decisions. This can range from nothing (in the case of the *greedy* strategy) to comprehensive information about the state of the grid, other connected vehicles, and the upcoming use of the vehicle (*co-op look-ahead*).

These requirements are shown in table 7.1, and are divided into four main categories. The first is time-of-day, which provide both a mechanism for "timer-based" charging (*overnight*), while also enabling the calculation of how much time is available before the vehicle's next departure. The following two

Table 7.1: Information required by each charging strategy.

Strategy	Time	L	G	C	E	A	T	D	S
greedy	-	-	-	-	-	-	-	-	-
overnight	●	-	-	-	-	-	-	-	-
valley-fill	-	●	-	●	●	-	-	-	-
lazy	●	-	-	-	-	-	●	●	-
slow	●	-	-	-	-	-	●	●	-
lazy+	●	●	●	●	●	-	●	●	-
slow+	●	●	●	●	●	-	●	●	-
co-op (*naïve*)	●	●	●	●	●	●	●	●	-
co-op (*full-charge*)	●	●	●	●	●	●	●	-	-
co-op (*look-ahead*)	●	●	●	●	●	●	●	●	●

Symbols:

	Description	Unit
L	Grid load, excluding flexible EV charging	MW
G	Total generation, excluding V2G	MW
C	Connected EV storage capacity	GW h
E	Aggregate energy in the EV fleet	GW h
A	Available energy in the EV fleet	GW h
T	Time of next departure	*time*
D	Distance of next trip	km
S	Sequence of upcoming trips	*array*

classes of information must be obtained via communication networks (see section 4.3.2): the grid state, consisting of near real-time load and generation, and aggregate EV fleet state, consisting of the total storage capacity available, total stored energy, and the energy that is available to feed back into the grid once transportation requirements are taken into account. The final class of information concerns the upcoming use of the vehicle; when it will be used next, how long the next trip will be, and—in the case of *co-op look-ahead*—a sequence of these parameters for a number of upcoming trips. This information would be obtained through machine learning, and/or specification by the driver of the vehicle (section 3.3).

It is difficult to make an objective comparison between charging strategies concerning the level of information they require, since the relative difficulty of obtaining each piece of information is not yet established; nor are they weighed up against the benefits they enable. Such analysis is left to future work.

7.7 Failed Trip Departures

During the course of the simulated year, approximately 1.1×10^9 trips were (or would be) made by the EV fleet of 1×10^6 vehicles. A trip failure is noted when an EV does not have a sufficient SOC to complete a scheduled trip at the time of departure, which can be caused by the trip being beyond the range of the vehicle, insufficient time available between trips to recharge, or the outright failure of a charging strategy to attain a sufficient SOC on time. Apart from installing a larger battery in an EV, nothing can be done for the first cause; the other two are consequences of the charging strategy being used.

Figure 7.10 shows the number of failed trips for each charging strategy and level of wind penetration. Noting the log scale, it is clear that some strategies perform significantly worse than others; in particular, the *valley-fill* strategy fails to provide for approximately 6% of all trips, while both *lazy* and *slow* fail to provide for between 3% and 4% of all trips.

The poor performance of the *valley-fill*, *lazy* and *slow* strategies can be attributed to several factors. First, the *valley-fill* does not attempt to reach any charging targets, and only makes use electricity when total load is below a set threshold. It is of utmost importance to set this threshold at a suitable level to ensure enough energy is delivered to vehicles using this strategy. Both *lazy* and *slow* only attempt to deliver enough energy for the very next trip, implying that an EV finishes each trip with a depleted battery. This leaves the

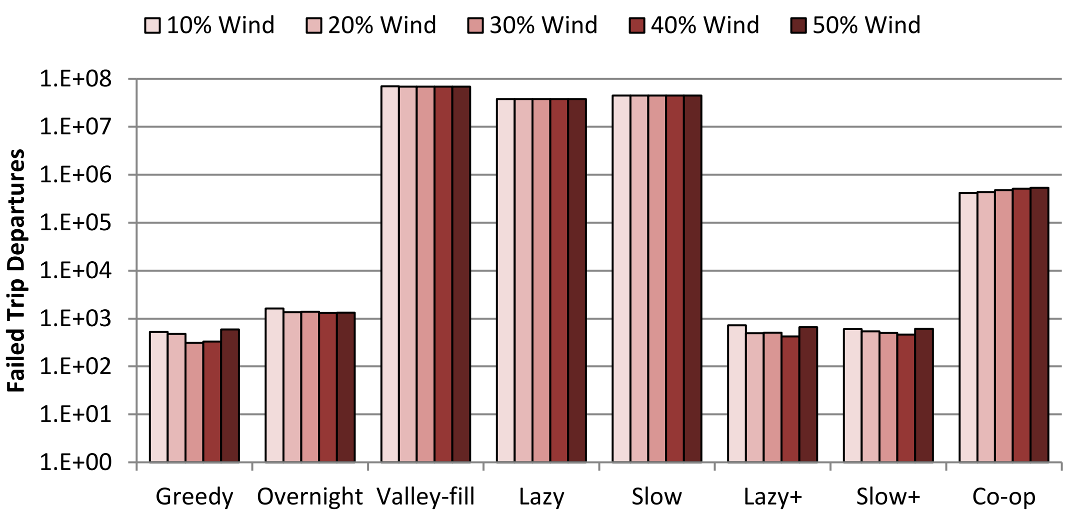


Figure 7.10: Number of failed trips for each charging strategy. Note log scale on the vertical axis.

vehicles vulnerable to having insufficient time to recharge before a subsequent trip.

The *co-op* strategy performs significantly better, only failing to complete one in 2000 trips, while at the same time enabling the EV to provide ancillary services to the grid. Meanwhile, both *lazy+* and *slow+* achieve excellent performance rivalling that of *greedy*, in addition to providing a down-regulation service to the grid while charging.

Vehicles using the *overnight* strategy also achieve excellent performance, since they start each day with a full charge and only a small minority of drivers will travel more than the range of the vehicle in a single day.

7.8 Battery Degradation

A common criticism of the V2G concept is the additional battery degradation introduced by grid requirements, for batteries that typically have a limited number of charge/discharge cycles (Han and Han, 2013). It is therefore important to assess the significance of this degradation, including the proportion of the battery's charge/discharge cycles that were used for transportation verses the proportion used for grid balancing purposes.

Figure 7.11 shows that most strategies attribute 100% of their energy throughput to transportation, which is unsurprising considering that these strategies

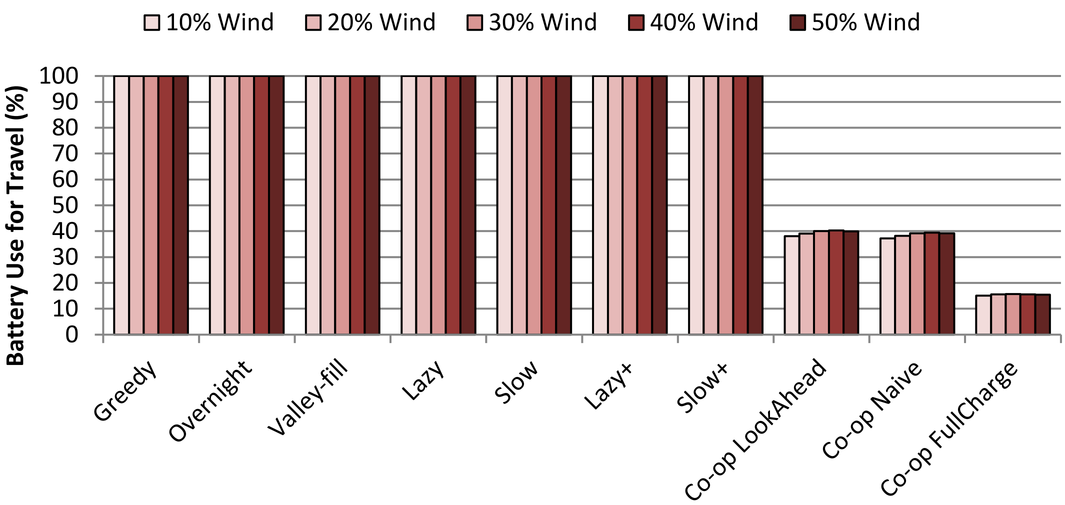


Figure 7.11: Proportion of battery energy throughput attributed to travel.

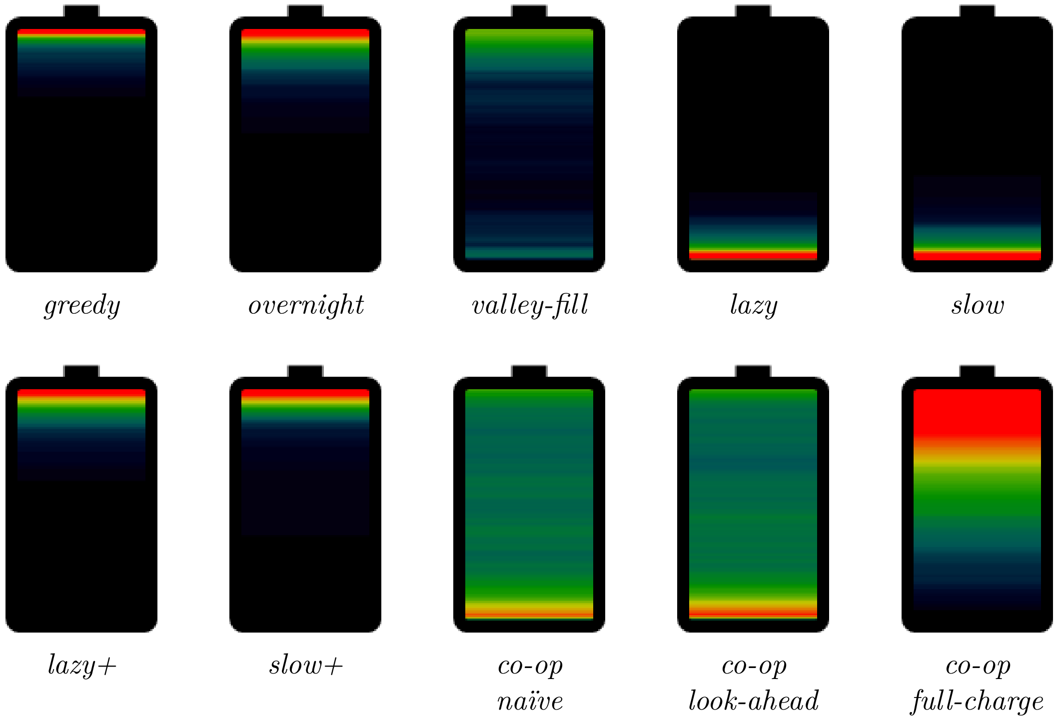


Figure 7.12: Battery wear heatmap for an individual EV.

do not support V2G. However, the three variants of the *co-op* strategy, which differ in the calculation of their charging target (section 6.2), all show a significant increase in throughput attributed to grid management. Interestingly, both *naïve* and *look-ahead* achieve very similar results, while the *full-charge* approach more than halves the energy throughput attributed to transportation.

This suggests that setting charging targets too high will increase battery degradation, caused by increased imperative charging demands as vehicles try to reach a full charge even when this is not necessary to satisfy transportation requirements. This results in more energy flowing between vehicles during times of generation shortages; i.e. vehicles charging in mode **C** (imperative charging) will source a significant portion of their energy from other EVs that are operating in mode **D** (V2G).

Figure 7.12 shows a heatmap visualisation of battery activity as a function of its SOC; a full charge is at the top of the diagrams. When the battery experiences a change in its SOC, that change is highlighted at the appropriate levels. It shows, for example, that the battery of vehicles using the *greedy* strategy will experience mostly shallow discharges near a full SOC, while the *lazy* and *slow* strategies cause shallow cycling near minimum battery capacity.

On the other hand, the three variants of the *co-op* strategy show increased wear across the full range of the battery, with the majority of activity being near minimum capacity (*naïve* and *look-ahead*). Since the *full-charge* method attempts to reach—as the name suggests—a full charge, most of the activity occurs near full capacity.

While not addressed in this research, analysing which regions of a battery's SOC see the most activity could prove to be important; for example, lithium ion batteries exhibit higher rates of self-discharge at a higher SOC, may become permanently damaged by remaining near its minimum SOC (Zimmerman, 2004), and experience the lowest capacity fading with activity around a 40% SOC (Ribberink et al., 2015). Additionally, hybrid energy storage systems consisting of both batteries and ultracapacitors (Khaligh and Li, 2010) may greatly extend battery life when the majority of activity occurs over a small SOC range.

7.9 Average State-of-Charge

The average SOC for the EV fleet over the simulated year is shown for each charging strategy in figure 7.13. The *greedy* strategy maintains this level near 100%, which identifies the upper limit for any charging strategy. The *lazy* strategy, on the other hand, will maintain a low average SOC because the vehicle will only charge at the last minute, to the lowest SOC necessary to

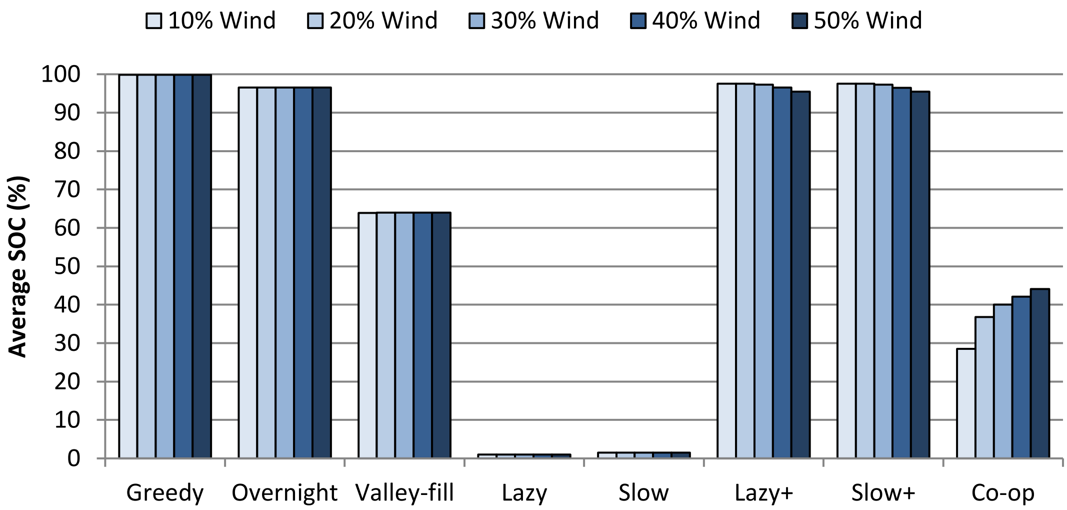
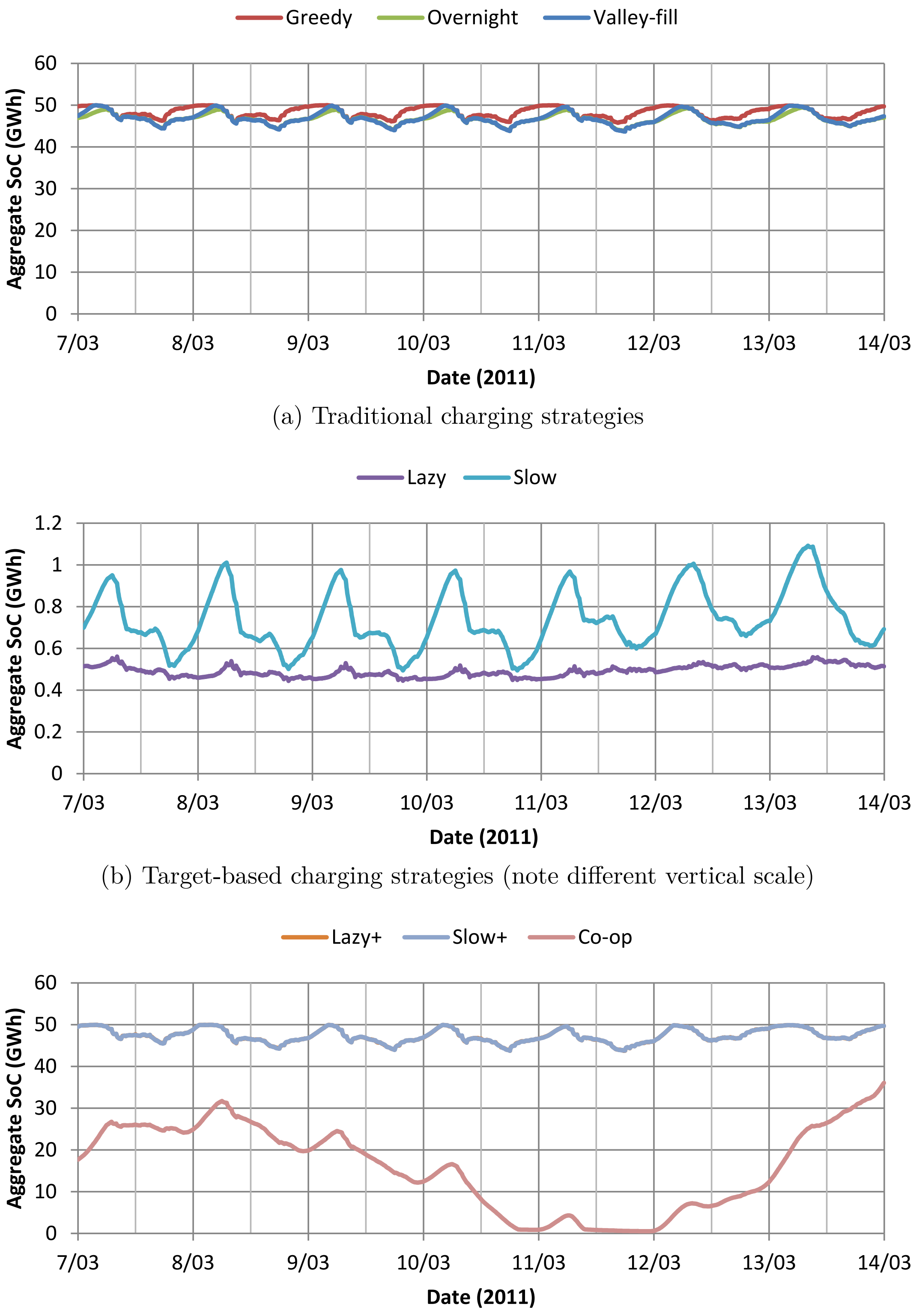


Figure 7.13: Average battery SOC for each charging strategy.



(a) Traditional charging strategies

(b) Target-based charging strategies (note different vertical scale)

(c) Smart charging strategies

Figure 7.14: Example week showing aggregate fleet SOC for each charging strategy.

complete a trip. The average SOC for *lazy* thus identifies the lower limit for any charging strategy.

The *overnight* strategy maintains a high average SOC, since it aims for a full charge at the beginning of each day, while *valley-fill* will only charge when grid load is below a set threshold. Of course, a higher threshold will increase the average SOC for vehicles using this strategy.

The smart charging strategies are the only ones to be affected by wind penetration. Higher wind penetration levels create more variability in electricity generation, which leads to greater fluctuations of aggregate stored energy as the vehicles compensate for imbalances between generation and load. This increased variability tends to push average SOC figures closer to 50%.

Figure 7.14 shows an example week of how the aggregate SOC varies in time. This is the same week shown in figures 7.8 and 7.9, where average load exceeds generation up until the 12$^{\text{th}}$. Noting that the total capacity for the EV fleet is 50 GW h, this shows that the *greedy* strategy maintains very close to a full charge; the grid-connected storage is mainly affected by vehicles disconnecting in order to travel. Both *overnight* and *valley-fill* perform similarly, with *overnight* slightly lagging behind *valley-fill*; this suggests that perhaps the definition of "night" could be adjusted to begin earlier.

The target-based strategies, shown in figure 7.14b, maintain a very low SOC. The *lazy* strategy in particular doesn't show much variation in aggregate level, because an individual vehicle will rapidly charge just before leaving on a trip, at which point it disconnects from the grid. On the other hand, the *slow* strategy requires an EV to charge over a much longer period of time and hence the variation is apparent at grid scale. The highest SOC occurs at around 06:00 before the morning commute on weekdays, and just after 08:00 on weekends, while troughs are observed around 19:00 on all days after the majority of EVs return home with an empty battery.

The smart charging strategies shown in figure 7.14c show that the aggregate SOC for both *lazy+* and *slow+* remains near full capacity, charging mainly at night, while vehicles using the the *co-op* strategy gradually lose energy during the day through V2G, and are unable to fully recover this energy at night because insufficient energy is available. From just before the 11$^{\text{th}}$, the EV fleet is no longer able to offer V2G services, and do not charge beyond what is necessary to cover transportation needs. Once wind energy is available again, from the 12$^{\text{th}}$ onwards, the EVs collectively charge towards full capacity, providing a down-regulation service where possible.

7.10 Discussion

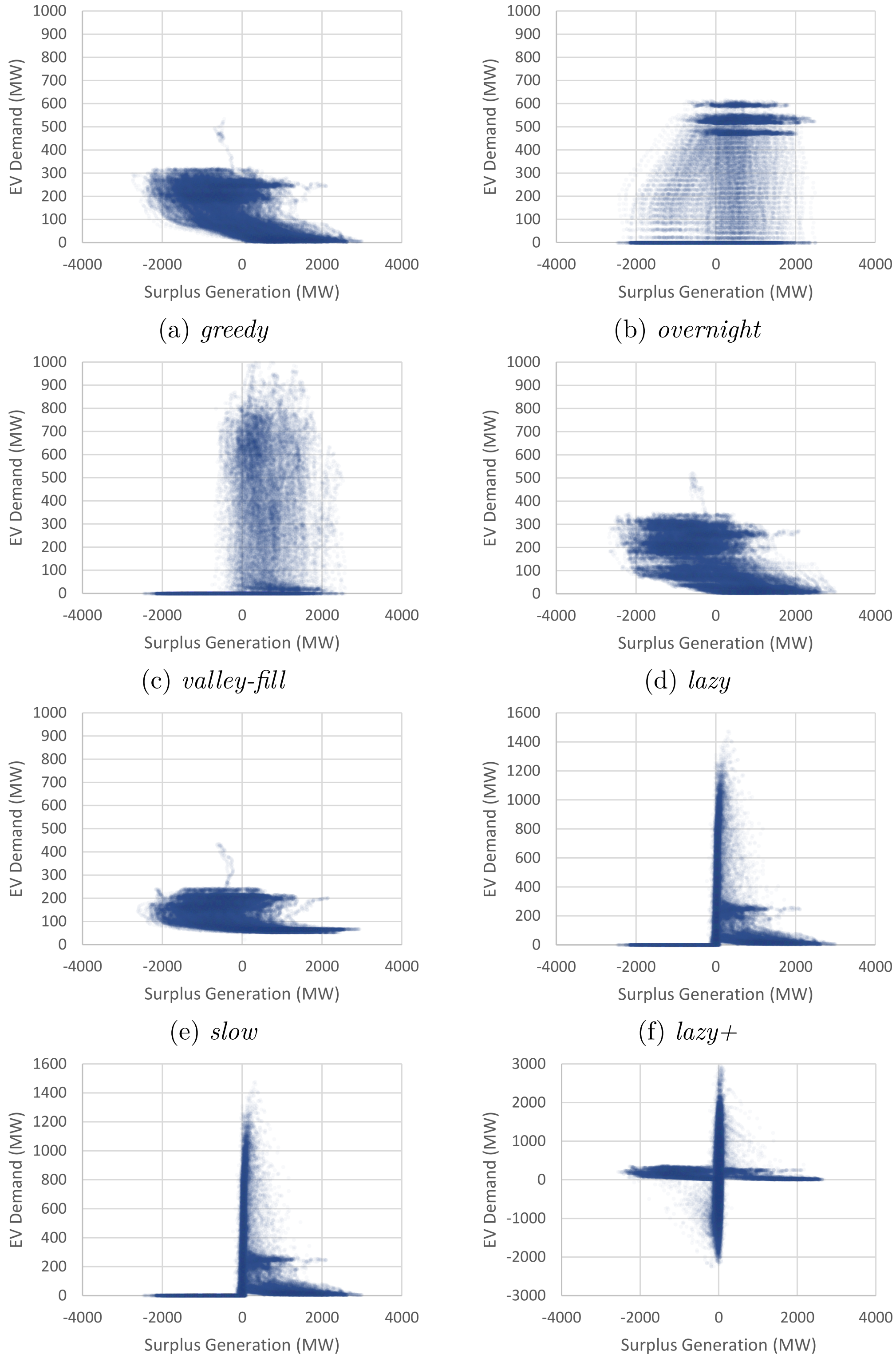
Figure 7.15 shows a summary of charging strategy behaviours in terms of aggregate EV load vs grid imbalance. Note that the vertical axis is different for smart charging strategies due to higher peak charging/discharging rates, and only the *co-op* figure shows the lower two quadrants that represent V2G energy flows.

In the ideal case, all EV charging would occur while surplus generation is zero—i.e. total generation perfectly matches total load, including that of the EV fleet. This can happen either by chance (unlikely), or be achieved by actively controlling EV charging and/or V2G rates. The second most preferred case is the upper-right quadrant, where the EV fleet is charging while surplus generation is available. Spillage is occurring in this quadrant, but at least some of this energy is being captured by the EV fleet. Some charging will inevitably occur in the upper-left quadrant, during times of generation shortage. This is not ideal, since this energy must be provided by highly-dispatchable peak generation sources. The activity in this quadrant should ideally be kept to a minimum.

Where V2G is supported (figure 7.15h), activity in the lower-left quadrant shows that V2G is assisting with the generation shortage but it is not enough to completely cover the shortfall. Any activity in the lower-right quadrant should be avoided, as it does not make sense for the EV fleet to deliver power into a grid that is already experiencing a surplus.

Of the traditional charging strategies, *greedy* shows that the majority of charging activity occurs in the upper-left quadrant, which is clearly not ideal. Both the *overnight* and *valley-fill* strategies move a significant portion of this activity over to the right; however, these strategies do not provide any means to balance generation and load. The distinct levels in figure 7.15b are a result of vehicle usage patterns, with the upper level representing the higher Vehicle Kilometers Travelled (VKT) on Fridays, the middle level includes Tuesday, Wednesday, Thursday, and Saturday, while the lower level corresponds to lower daily VKT on Sunday and Monday (Ministry of Transport, 2011).

The target-based strategies cause the bulk of EV charging to occur during times of generation shortages, similar to the behaviour seen with *greedy*. Because *slow* spreads charging activity over long periods, there is always a minimum charging load present. The *lazy* strategy, on the other hand, causes vehicles to sit idle for a large portion of time before charging at a high rate.



(a) *greedy* (b) *overnight*

(c) *valley-fill* (d) *lazy*

(e) *slow* (f) *lazy+*

(g) *slow+* (h) *co-op*

Figure 7.15: Summary of charging behaviours.

Once smart charging is introduced, there is a clear shift towards charging while the grid is in balance. Both *lazy+* and *slow+* perform the majority of charging while the grid remains in balance, and a lesser portion of charging while spillage is occurring. Very little activity occurs in the upper-left quadrant, which is ideal.

Once V2G is considered (figure 7.15h), the bulk of activity is restricted to the axes—vehicles are either charging/discharging while the grid remains in balance (vertical axis), or remaining idle while the grid is not in balance (horizontal axis). The imperative charging load is apparent in the upper-left quadrant, while almost no activity is present in the lower-right quadrant. The transition between charging modes can be seen as activity passes briefly through the upper-right quadrant; this occurs when vehicles are charging to keep the grid in balance, but transition to idle after reaching a full SOC. The opposite effect occurs in the lower-left quadrant, i.e. vehicles that exhaust their surplus stored energy while discharging into the grid will either become idle, or begin imperative charging if necessary.

Table 7.2 shows a summary of the key performance metrics for all charging strategies tested. The introduction of electric vehicles enable greater utilisation of wind generation capacity, regardless of the charging strategy used, but the greatest gains are realised when using the smart charging strategies—particularly when V2G is supported. Use of the *co-op* strategy reduces both peak generation and spillage by a significant margin relative to the other scenarios. Unfortunately, peak power and ramping requirements are significantly worse, even if only for a small number of hours over the year. This suggests that care must be taken to avoid the conditions that give rise to poor charging strategy performance.

7.11 Summary

This chapter has presented the results of simulating an EV fleet of one million vehicles, across a range of charging strategies, and for wind penetration levels ranging from 10% to 50%. Comparing the "performance" of charging strategies is not trivial; a number of different factors must be considered, and evaluated in terms of contributing towards a specific goal.

Smart charging strategies that do not support bidirectional energy flows are able to reduce both the energy required from peak generation sources and energy spillage when compared with uncontrolled (*greedy*) charging, however most of the benefits can be realised with simple time-based (*overnight*) control.

Table 7.2: Summary of charging strategy performance with 30% wind penetration.

	Total Consumption (GW h)	Transport Consumption (GW h)	Peak Energy (GW h)	Spillage (GW h)	Peak Power (MW)	Peak Ramp Up (MW min^{-1})	Peak Ramp Down (MW min^{-1})	Failed Trips	Wind Utilised	Average SOC
No EVs	40044	0	3207	3265	6940	47	48	0.000%	74%	0%
greedy	41215	1156	3927	3158	7193	48	48	0.000%	75%	99%
overnight	41199	1157	3192	2437	6940	48	46	0.000%	80%	96%
valley-fill	41063	1008	3099	2480	6940	70	62	6.081%	80%	64%
lazy	41276	1038	3964	3132	7102	48	49	3.313%	75%	1%
slow	41093	1030	3726	3078	7073	47	48	3.951%	75%	2%
lazy+	41201	1156	3064	2308	6940	64	100	0.000%	81%	97%
slow+	41206	1157	3067	2306	6941	64	100	0.000%	81%	97%
co-op (naïve)	41199	1118	1584	830	7027	160	113	0.885%	93%	40%
co-op (full-charge)	41236	1156	2239	1448	9094	72	122	0.000%	88%	85%
co-op (look-ahead)	41240	1156	1624	829	7035	178	113	0.042%	93%	40%

When V2G is considered, both peak energy and spillage are significantly reduced over any of the charge-only strategies. With V2G, the balance between generation and load can be maintained solely by the EV fleet for the majority of the simulation period, even when generation is highly variable with high levels of wind penetration.

However, energy is only one factor to consider. The *co-op* strategy does not address peak power concerns; in fact, peak load is actually increased when using this strategy, at all tested levels of wind penetration. These peaks only occur in a very small number of hours over the year, but since infrastructure must be able to handle these peaks, this is still a major concern.

A similar problem exists with ramp rates. While the introduction of an EV fleet using the *co-op* charging strategy does significantly reduce ramp rates for the majority of the year, extreme cases are much worse than having no EV fleet, and worse than if uncontrolled charging were used. Unidirectional smart charging strategies also increase down ramping rates, and have a minimal (but still noticeable) effect on up ramping rates.

Operating reserves can be offered by an EV fleet, as both a power source and as interruptible load. The *co-op* strategy offers a significant level of power that is well in excess of New Zealand's present-day requirements, so long as the aggregate stored energy remains above approximately 5 GW h. Interruptible load can be offered by most charging strategies, which vary in both the power levels offered and times of day available. Since most strategies tend to charge during night-time hours, this is when the highest levels of interruptible load are available. When charging, the EV fleet can likely cover a large portion of New Zealand's operating reserve requirements through interruptible load.

The information required to make charging decisions ranges widely among charging strategies. In general, the best all-round performing strategies require the most comprehensive information, including near-realtime information about generation, load, aggregate EV state, and upcoming vehicle use. The simple *greedy* strategy, on the other hand, requires no information at all.

Keeping the number of failed trips to a minimum is of utmost importance to the successful deployment of EVs. The *greedy* strategy offers the best performance within the limitations of the vehicle's operating parameters, but at the cost of increasing demands placed on electricity networks. The use of smart charging strategies can ease grid demands somewhat, without significantly increasing the number of failed trips.

In terms of battery degradation in a V2G-enabled EV fleet, overestimating how much energy will be needed to complete a trip (*full-charge*) will significantly increase battery degradation, compared to when more accurate estimates are used (*naïve*, *look-ahead*). This suggests the importance of having accurate foresight into the upcoming use of the vehicle. These results also suggest that placing the primary burden of balancing generation and load on the EV fleet causes significant wear on those vehicles' batteries; less than half of the total energy into the battery was ultimately used for transportation in all cases.

The average aggregate SOC of the EV fleet varies considerably across charging strategies, from near full (*greedy*) to almost empty (*lazy*). A higher average SOC means the vehicle is more likely to be able to complete unplanned trips, but less able to provide down-regulation services to the grid.

In summary, this chapter has demonstrated that an EV fleet—coupled with smart charging strategies—can offer significant flexibility for accommodating non-dispatchable electricity generation, particularly when V2G is supported. While the average case performance of these strategies is very good, the extreme cases are often worse than if no EVs were present at all.

8 Summary and Conclusions

This thesis has evaluated the potential for smart charging strategies to assist the growth of wind generation and electric vehicles in New Zealand.

Early chapters have explored the problem space, and have identified both wind generation and electric vehicles as important technologies to help New Zealand—among other countries—meet its obligations for reducing greenhouse gas emissions, and reduce its dependence on fossil fuels. The widespread adoption of wind generation and electric vehicles, however, brings an array of concerns related to their management. Traditional approaches to managing generation, transmission, and distribution become less feasible when dealing with the increased volatility caused by non-dispatchable generation, and higher peak loads introduced by EVs if their charging were to be uncontrolled.

There is significant flexibility in the timing of EV charging, which has inspired research about optimising charging schedules to achieve specific goals. The potential synergies between the flexibility of EV charging and the volatility introduced by non-dispatchable generation have not gone unnoticed; two decades ago, Kempton and Letendre (1997) introduced the concept of Vehicle-to-Grid (V2G), which enables an EV fleet to function as a distributed energy resource.

The primary research question is thus asked:

> ***To what extent can the flexibility of charging electric vehicles be exploited to support the integration of non-dispatchable electricity generation in New Zealand?***

A review of the literature in chapter 3 has put forward the argument that a future electricity system is likely to be more decentralised than today's systems, with an increasing proportion of flexible load, and a larger installed capacity of non-dispatchable generation. This will lead to models where the demand-side will play a more active role in maintaining the balance between generation and load. EVs in particular are well suited to providing short-term balancing services, as they can operate as both a flexible load and a distributed energy resource. Since vehicles are typically located close to load centres, they will not cause transmission constraints when used to cover peak load. The management of large numbers of EVs can be achieved using centralised or decentralised means; the argument is put forward that the latter approach is preferable, and is therefore adopted as the method of choice in this thesis.

Chapter 4 has described the development of simulation software used to explore the research question, including the data and statistical models used for representing future New Zealand energy scenarios. Chapter 5 has explored the necessary performance requirements of a theoretical energy storage system used for managing the variability of generation and load in New Zealand, while chapter 6 introduces decentralised EV charging strategies that aim to address the primary research question.

Finally, the results are presented in chapter 7, which indicate that smart charging strategies—particularly when bidirectional energy flows are supported—have significant potential to support the integration of non-dispatchable electricity generation in New Zealand.

8.1 Findings

Primary findings indicate that an EV fleet consisting of one million vehicles, adopting a V2G-enabled smart charging strategy, and operating in the simulated electricity environment at a wind penetration level of 30%, can:

- Reduce the utilisation of peak generation by more than 50%.
- Reduce energy spillage by 75%.
- Assume the full responsibility of maintaining balance between generation and load for 70% of the year.
- Nullify net ramping rates for 70% of the year.
- Exceed New Zealand's operating reserve requirements in excess of 78% of the year.
- Allow generation and load profiles to be completely uncoupled, so long as sufficient energy is generated within several days of its consumption.

However, these benefits do not come without cost. Primary disadvantages arising from the use of V2G-enabled smart charging strategies include:

- Increased EV battery degradation caused by a 150% increase in energy throughput.
- Slightly increased peak load.
- Peak net ramping rates more than doubled.
- Vehicles required to be grid-connected as often as possible.
- Extensive information about the state of the grid and upcoming vehicle usage is needed.
- The proportion of failed trips increases to approximately 1 in 2500.

These findings indicate that the average-case performance of smart charging strategies is very good, while extreme cases tend to exacerbate the very problems that smart charging intends to solve. While the research presented in this thesis evaluates charging strategy performance in isolation, and assumes that no dispatchable generation or storage exists in the electricity system, this is not intended to represent a realistic future energy scenario; rather, it establishes the *potential* benefits of smart charging when operating in a generation environment with extreme variability.

The poor performance behaviours highlighted above occur when the EV fleet is operating near its upper and lower SOC limits, which suggests that the grid system operator should ensure that these limits are avoided through careful management of dispatchable generation and large-scale centralised energy storage facilities.

With a V2G-enabled EV fleet, it is no longer necessary for generation to precisely follow load, so long as the aggregate SOC of the EV fleet is maintained at an acceptable level. This provides significant flexibility over the scheduling of generation, and opens the possibility for new dispatch models that operate on an energy (rather than power) basis. For example, instead of scheduling generation to match load forecasts, generation could be scheduled to maintain the aggregate SOC of the EV fleet at an acceptable level; the EV fleet will then carry the responsibility for precisely following load in realtime. This model is expected to be robust against forecasting errors in both generation and load, without requiring excessive utilisation of non-EV regulation services.

8.2 Limitations and Future Work

While the results presented in this thesis show promise regarding the applications of smart charging strategies for electric vehicles in New Zealand, there remain many unsolved challenges. Of particular interest are the local and regional effects of arising from the widespread adoption of electric vehicles and non-dispatchable generation, as well as other related technologies including distributed generation and storage.

In addition to wind generation, other sources of renewable electricity are also expected become more common in future, including geothermal, rooftop solar PV, and tidal generation; each of these will likely introduce unique spatial and temporal variability that will need to be managed. Multiple energy storage options also exist, ranging from distributed batteries deployed in homes, to large-scale pumped hydroelectric storage facilities.

The simulation software can be readily extended to include models of these technologies, assuming that suitable data are available. In addition to exploiting the storage capacity of an EV fleet, the simulation could further evaluate the balancing potential of other mechanisms such as domestic electricity load management, and *grid-lite* systems. Accurate modelling of New Zealand's existing hydroelectric systems is also important, including aspects such as the variable nature of inflows, long-term storage potential, compliance with resource consent conditions, and its interactions with EV charging strategies.

In the wider context of renewable energy integration, it is clear that a silver bullet does not exist. With a vast array of competing generation, storage, and demand-side management technologies, and also conflicting priorities of the many stakeholders involved, development of the best solutions is not merely a technical challenge, but an economic one. The research presented in this thesis has explored the potential benefits and drawbacks of smart charging strategies for EVs based on the assumption that their owners are willing and able to participate in such schemes. Future work must develop and evaluate suitable economic models that consider the costs associated with various smart grid technologies, and create economic dispatch models that minimise overall costs while preserving consumer choice and maintaining a secure electricity supply.

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