Potential for electric vehicle adoption in Australia

by

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MASTER OF RESEARCH

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Abstract

Transport is expected to become electrified in coming decades, bringing new challenges and opportunities for commuters and electricity distributors. This thesis presents analysis of Household Travel Survey (2014/15) and Journey to Work (2011) census datasets from the New South Wales (NSW) with the aim of;

(i) investigating whether electric vehicles (EVs) could meet the daily commuting needs, and
(ii) quantifying the potential impact of EVs on the electricity distribution grid as a function of location and time.

It was found that 87% of commuter vehicle trips could be provided using affordable EVs and that the resulting electricity demand would increase by more than 10% in only 9 out of 35 local government areas (LGAs) in NSW, Australia. We also quantified the potential spatiotemporal electric energy available for vehicle-to-grid services.

It was found that greenhouse gas emissions across NSW would reduce by 26% $CO_{2(eq)}$ even if all EVs were recharged from non-renewable coal-fired power plants, due to greater efficiency of EVs. The results demonstrated the potential for wide-scale adoption of EVs in Australia. Lastly, to facilitate analysis and prediction of key variables, the travel data was modelled using regression trees (RTs) and artificial neural networks (ANNs).

Statement of Candidature

I certify that the work presented in this thesis has not previously been submitted for a degree nor has it been submitted as part of the requirement for a degree to any other university or institution other than Macquarie University.

I also certify that this thesis is an original piece of research and it has been written by me. Any help and assistance that I have received in my research work and preparation of this thesis itself have been appropriately acknowledged.

Sohaib

Sohaib Rafique

April 24, 2017

Acknowledgement

First and foremost, I would like to express my profound gratitude to my supervisor Professor Graham E. Town for his continuous encouragement, support and guidance throughout my research. He stood by me whenever I encountered any difficulties during my research.

I sincerely appreciate the financial support from Macquarie University for awarding me the Research Training Pathway (RTP) scholarship.

I would also like to thank 'Transport Performance and Analytics, Transport for NSW', for providing NSW Household Travel Survey (HTS) 2014/15 data for comprehensive analysis.

With the deepest love, I would appreciate the patience and compassion of my wife and kids, who have always been there with me during all the ups and downs of my life. My wife has always been there to support and encourage me. Words may not recompense for her contributions in my life.

I would thank my father, brother, sister and brother-in-law for their help, encouragement and assistance. It is a pity my mother passed away in 2008 and did not see this day. At least she lived long enough to know that I would get here. Her wisdom, compassion and love are deep within me and provide a lifelong inspiration.

Finally, I must express my deepest gratitude to Allah for HIS countless blessings.

This thesis is dedicated to my beloved ***'Mother'***

(may Allah grant her best place in paradise - Ameen)

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Chapter 1

Introduction

1.1 Background

It is expected that transport will become electrified in coming decades, bringing new benefits, challenges and opportunities [1]. Global sales of EVs increased by 70% in 2015 compared to 2014, with over half a million EVs being sold worldwide in 2015. EVs stock has been growing since 2010. Seven countries have reached over 1% EVs market share in 2015. The national EV sales are forecast to reach 276,800 vehicles per annum by 2036 **Fig. 1.1-1**. As a result, total vehicles on the road are forecasted to reach over 2.85 million by 2036 [2]. These growth trends are expected to be supported by declining trends in battery prices, increasing battery energy densities and the increasing viability of home-storage and charging options [3].

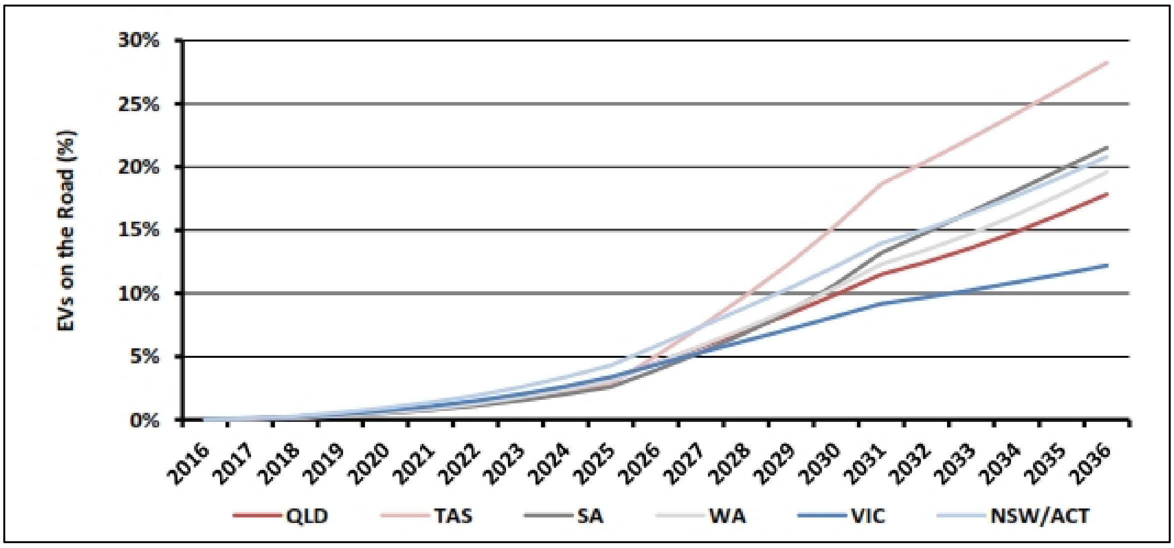

Fig. 1.1-1. EV Uptake by Region [2]

In this thesis, we show that the introduction of electric vehicles (EVs) will be beneficial for both, the environment and the individuals. As EVs displace internal combustion engine vehicles (ICEVs), the expected benefits of electrification include reduction in GHG emissions, decrease in fuel oil consumption, lower operation & maintenance costs, and opportunities to use the associated battery energy storage systems (BESSs) for participation in an energy market through V2X (here 'V' refers to vehicle and 'X' refers to grid, infrastructure, another vehicle, etc.) energy transfers [1].

Range anxiety is usually assumed to be one of the main factors hindering the uptake of EVs [4]. Other than up-front costs, the other potential concerns are lack of infrastructure and the impact of EVs on the electricity distribution system [1]. However, analysis of real travel data shows that such concerns are largely unfounded for most vehicle commutes within cities, provided the EVs are recharged nightly. For example, a study of commutes across the United States (US) estimated that 87% of vehicle-days could be provided by existing affordable EVs [5].

We have analyzed two different sources of datasets (i.e. NSW Household Travel Survey data (2014/15) [6, 7] and Journey to Work (2011) Census data [8]) for four diverse regions at different scales depicting similar results, also the results were similar to a study conducted for major states across US [5]. Our analysis showed that majority of the vehicle commutes in the State of NSW could be provided by affordable EVs. We have estimated the potential impact of EVs on the electricity distribution grid in terms of anticipated rise in electric energy demand during different times of the day. The average SOC distribution of the EVs at key times during the day was also mapped within the resolution of the available data. Considering the importance of the spatiotemporal availability of EVs we have developed and compared two models for predicting location wise availability of EVs during different times of the day. Additionally, we have also estimated the possible reduction in GHG emissions due to the greater efficiency of EVs relative to ICEVs.

1.2 Literature Review

Electric vehicles are emerging as a promising solution for better environment accompanied by various challenges and opportunities. In recent years, research around the globe was done to monitor and analyse various sources of vehicle travel data to identify driving patterns and travel needs, so that feasibility for EV adoption could be evaluated. Studies were conducted based on the travel surveys to analyse the driving patterns to obtain detailed driving requirements and charging/discharging availability of EVs [9, 10]. These studies mainly focused on availability and unavailability of EVs for power grid integration during different times of the day, without evaluating the potential impact of EV recharging on the power grid. Another study analysed vehicle data from GPS devices installed in 76 representative vehicles to predict load profiles and determine driving & parking patterns [11]. Although the data was collected from practical sources but it was very limited to represent the population. Also, the potential impact on the existing power grid was not evaluated.

Charging behaviour of EVs would play an important role in determining the spatiotemporal load profiles and opportunities for V2X operations. An analysis on charging patterns in Western Australia show that 55% of the charging events occur at business and home locations, while only 33% of EV charging was carried out at charging stations [12]. The analysis indicated the occurrence of the charging events but did not evaluate the impact on the power grid.

One of the expected challenges after the adoption of EVs would be the increase in electric energy demand along with spatiotemporal dynamics of moving EVs [13]. Research has been conducted to model the spatiotemporal electric energy demand of EVs [14-17]. This was analysed based on simulations, not using the real data. and the impact on the power grid was also not evaluated. A research analysed the impact of EV charging on voltage levels and not on the existing network capacity [18]. Another challenge with the adoption of EVs would be the dynamic behaviour of the load and/or energy source. Prediction of spatiotemporal availability of EVs with their SOC is very important for effective management of power distribution. Research has been conducted to forecast the spatiotemporal availability, charging demand, respective load profiles and peak shaving potential of EVs [19-26]. However, the impact on existing power grid was not analysed using real travel data. Research has also been done to model stochastic mobility and the plug-in probability of a fleet of EVs [27]. The issue of impact on the power grid due to additional load of EV recharging has been analysed by most researchers but due to lack of available data for EV recharging and driving patterns, different approaches were used to analyse the issue. Very little research has used the household travel survey data to identify increased demand in potential problem areas.

One of the aspects of EVs as moving loads in the power system is when a vehicle is charged at a weaker node of the network and may lead to adverse impacts [28]. The research explored one of the network constraints (i.e.; minimum required voltage) at the distribution level and demonstrated that the physical locations of the individual load in the network play a significant role in determining voltage stability throughout the network. The analysis showed that the addition of a single load at a weaker point of the network could have an equivalent impact as considerably greater number of loads added to stronger locations of the network. This research focused on the after effects of spatiotemporal recharging of EVs on the power distribution network using a small network. The research did not present methodology to identify regions with potential high electric energy demand.

Widespread adoption of EVs is anticipated in Australia over the next 30 years. Research has been done to project spatial uptake of EVs and forecast market share of EV's, PHEV's, HEV's and ICEV's [29]. This study anticipated the spatial uptake of EVs and demonstrated the potential rise in spatiotemporal electric energy demand in the state of Victoria. The analysis and modelling were based on census data. It did not identify specific regions which were vulnerable to an excess rise in electric energy demand. On the other hand, research has also been done to address policy & infrastructure issues and encourage the uptake of EVs [30].

EVs compared to ICEVs are not available on roads in good numbers for real-time data analysis. Due to limitations of available data for precise analysis on EV driving and charging patterns, an effort was done to create a test dataset for Plug-in Hybrid Electric Vehicle (PHEV) based on 536 GPS-equipped taxi vehicles [31]. The research also identified the possibilities for vehicle-to-grid opportunities. Since the dataset was very limited in numbers, therefore the sample size could not be considered representative of the population.

Much research has been done to analyze the impact of EVs on the power grid, the spatiotemporal uptake of EVs and predicting the availability of EVs for recharging. There are still gaps in the existing research mainly due to unavailability of the adequate dataset of EVs for precise analysis. The aim of this paper is to minimize this gap by analyzing the available travel data.

1.3 Research Framework & Objectives

This '**Master of Research**' has been carried out in the Sustainable Energy Systems Engineering (SESE) group of the Department of Engineering, Faculty of Science and Engineering at Macquarie University, Sydney, Australia. This is a **ten-month** research effort starting in July 2016. Based on Macquarie University guidelines, the main body of the thesis should be between **50 to 55** pages. The work was funded by Research Training Pathway Scholarship (RTP) award.

The thesis aims to accomplish the following objectives;

i. Analyse widespread potential for EVs adoption in Australia by analysing household travel survey and census datasets.

ii. Quantify the spatiotemporal rise in electric energy demand and opportunities of electric energy available for V2X operations due to the presence of EVs in the network.
iii. Evaluate the aggregated reduction in GHG emissions for an average weekday and weekend day.
iv. Develop and compare models for the spatiotemporal distribution of vehicles.

1.4 Research Contributions

The main contributions of this thesis are;

i. One of the most commonly assumed problem in EVs is its limited range [4]. Our analysis shows that range limitation of EV should not be the barrier for its adoption based on daily commuting needs.
ii. This research quantified the spatiotemporal impact of EV charging on power distribution grid. The analysis also highlighted areas which require attention due to rise in electric energy demand because of EV charging.
iii. We have developed and compared two techniques to model the spatiotemporal distribution of vehicles. The model provides compact organisation of measured dataset. This will help in estimating the spatial and temporal electric energy required and/or available, planning of charging infrastructure and developing the electric energy management strategies for EVs.
iv. We have mapped the average SOC distribution of the EVs at key times during the day, indicating the maximum net load (for recharging) and/or available electric energy (for V2X services) across NSW.
v. This analysis also evaluated the reduction in GHG emissions due to electrification of transportation.

1.5 Thesis Overview

The thesis consists of five chapters, including this introduction and a final conclusion. The remaining three chapters are organised as follows: In Chapter 2, we have discussed the results evaluated from the analysis of NSW travel survey and census data. Using realistic assumptions regarding EV battery capacity and the availability of domestic charging, we have determined the ability of EVs to meet daily commuting needs, spatial and temporal distribution of electric energy stored in EV batteries (i.e.

available for V2X) and estimated the reduction in GHG emissions. The results of this work were presented in the following publication:

• Rafique, S. and G. Town, "Potential for EVs adoption in Australia". International Journal of Sustainable Transportation, Taylor & Francis, 2017 (under review)

In Chapter 3, we have evaluated the spatial and temporal distribution of electric energy required for EV recharging and potential impact on the power distribution grid, using the results from the analysis in Chapter 2. The potential rise in electric energy demand was compared with average electric energy consumption of respective LGAs. The results helped in identifying regions where aggregated EV charging could cause serious disturbances in power distribution network. The results of this work are to be presented as following publication:

• Rafique, S. and G. Town, "The impact of electric vehicles on electricity distribution in New South Wales, Australia" (under preparation)

Modelling the spatiotemporal distribution of EV is necessary to estimate the potential impact of EVs on the electricity distribution system and plan the roll out and charging facilities. In Chapter-4, we have developed two models for estimating the spatiotemporal distribution of vehicles and compared the results. By estimating the spatiotemporal distribution of vehicles, we will be able to calculate the spatiotemporal electric energy requirement and availability for EVs.

Chapter 2

Data Analysis

2.1 Introduction

The limited driving range of EVs is generally assumed to be the fear factor in adopting EVs [4]. The other potential concerns are lack of infrastructure and the impact of EVs on the electricity distribution system [1]. However, analysis of real travel data shows that these concerns are not realistic for the majority of the vehicle commutes within cities. For example, a study of vehicle commutes across the United States (US) estimated that 87% of vehicle-days could be provided by existing affordable EVs [5].

The vehicle commute data for four regions at different scales in NSW, Australia were analysed. The datasets were extracted from two different sources (i.e. NSW Household Travel Survey data (2014/15) [6] and Journey to Work (2011) Census data [8]). The comparison cross-validated the statistics at different levels (i.e. region size and population density), yet producing similar results. The results were also similar to a study conducted for major states across US [5]. The first dataset of 20 suburbs in South-Western Sydney (Bankstown area) and the second dataset for Sydney Inner City were retrieved from Journey to Work (2011) data tables [8], based on a five-yearly census of population and housing, conducted by the Australian Bureau of Statistics (ABS). The third and fourth dataset for the Statistical Areas Level-3 (SA3s) and Local Government Areas (LGAs) of NSW were extracted from the NSW Household Travel Surveys (HTS) 2014/15 [6, 7].

Our analysis showed that majority of the vehicle commutes in the state of NSW could be provided by affordable EVs. We have estimated the spatiotemporal rise in electric energy demand due to potential recharging of EVs. Alternatively, we have also calculated the spatiotemporal electric energy available for V2X (here 'V' refers to the vehicle and 'X' refers to the grid, infrastructure, another vehicle, etc.) operations. The average SoC distribution of the EVs at key times during the day was also mapped within the resolution of the available data. Additionally, we have also estimated the possible reduction in GHG emissions due to the greater efficiency of EVs relative to ICEVs.

2.2 Methodology

The datasets were tabulated and key electric energy indicators (i.e. the rate of electric energy consumption in Wh/km, charging capacity in km/hr, the rate of $CO_{2(eq)}$ emissions in gm/km) were calculated and compared with similar estimations in other studies. A brief schematic block diagram of the methodology is presented in **Fig. 2.2-1**. These factors were used to calculate the electric energy consumption per trip (kWh/km), overall electric energy requirements (kWh), electric energy available (kWh), recharge duration required per trip (hrs), SOC after trip completion, electric energy densities (kWh/km^2) during different times of the day at different locations, thus estimating spatiotemporal electric energy needs and opportunities. Spatiotemporal and aggregated $CO_{2(eq)}$ emission reductions were also calculated, keeping in view indirect GHG emissions caused by charging of EVs through coal-fired power plants.

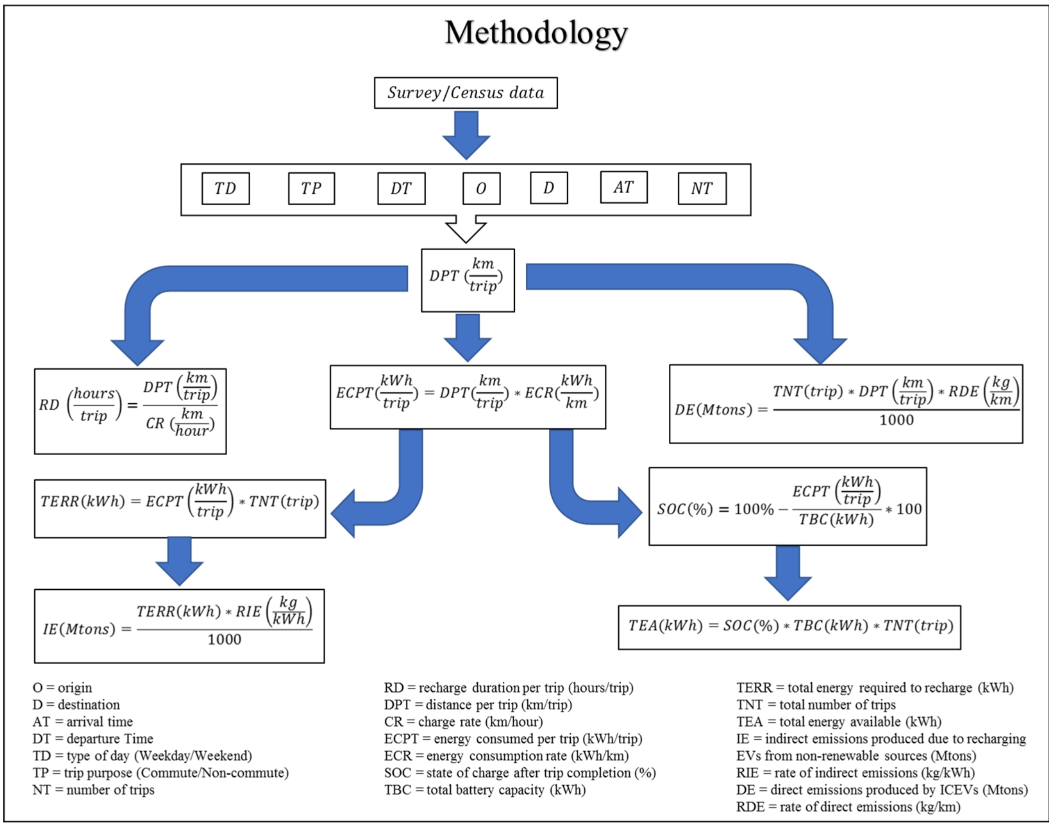

Fig. 2.2-1. Systematic block diagram of energy parameter calculations

2.3 Assumptions

The datasets were analysed using some conservative assumptions to extract realistic information. Two types of assumptions were made, the first associated with data limitations and the second for performance parameters.

2.3.1 Assumptions - data limitations

To avoid having an extremely large number of data points and due to privacy restrictions of identifying individuals in the ABS data, the following assumptions were made;

i. only one-way trips were considered, as evident in the travel survey dataset that great majority of vehicle trips (i.e. 82% of the weekday and 94% of the weekend trips) were non-commute as shown in **Fig. 2.4-13** & **Fig. 2.4-14**.

ii. only vehicle trips less than 30 ~ 40 km were considered so that the vehicle returns to its origin without intermediate recharging. 87% of the total weekday and weekend day vehicle trips were less than 35 km (**Fig. 2.4-15**) in 50 LGAs of NSW averaging 15.7 km/trip for weekday and 15.3 km/trip for a weekend day which was consistent with Australia's average commuting distance i.e. 15.6 km/trip [32].

iii. travel distance <u>between</u> the regions (i.e. suburbs, SA3s and LGAs) were based on Google map driving distances from the centre of origin region to centre of destination region. This assumption is appropriate as the average calculated distance was consistent with published average commuting distance for Australia i.e. 15.6 km/trip [32].

iv. travel distance <u>within</u> the regions (i.e. suburbs, SA3s and LGAs) were based on radial distances from the centre to the boundary of the region, then evaluating the road distance using 'road distance to air distance factor. This assumption is appropriate as the average calculated distance was consistent with published average commuting distance for Australia i.e. 15.6 km/trip [32].

v. electric energy consumption due to the difference in height between origin and destination was negligible as the differences in elevation between the analyzed regions extracted from Google maps were negligible.

vi. the vehicle type for all trips was a personal passenger car as the datasets used were based on passenger cars.

vii. for the purpose of this analysis the number of passengers was not considered as the weight of the passengers is usually negligible compared to weight of the vehicle.

viii. it is assumed that vehicles are recharged nightly. This assumption is appropriate mainly becuase;

   a. it is simple & easy
   b. it is good for battery life to make-up the discharged energy in small states rather than recharging from minimum energy levels
   c. no additional charging infrastructure required in the regions

2.3.2 Assumptions – performance parameters

The actual dataset represents average weekday and weekend day trips conducted by ICEVs in NSW. However, for analysis purposes, it was assumed that all these vehicle trips were conducted by Nissan Leaf (2011-15) with a rated battery capacity of 24 kWh and a useful battery capacity of 19.2 kWh (i.e. 80% depth of discharge). The Nissan Leaf (2011-15) had a maximum range of 135 km [27] on a full charge based on EPA cycle. However, for realistic calculations, the maximum distance travel range was taken as 120 km (75 miles) [5] on a full charge. It is expected that all the vehicles were recharged using 220 V 15 A 3.0 kW Level-1 (L-1) chargers with 10% current losses. The average rate of GHG emissions for ICEVs was 261 gm/km $CO_{2(eq)}$ [33]. Indirect GHG emission factor for consumption of purchased electricity from a coal-fired plant for NSW was 0.86 kg/kWh $CO_{2(eq)}$ [34].

It follows that;

i. The electric energy consumption rate for a passenger car is 0.12 kWh/km to 0.18 kWh/km [30]. We have calculated 0.16 kWh/km as the electric energy consumption rate of the battery.

ii. The charging rate was calculated to be 15 km/hr which was comparable to the charging rate used by [11] and defined as the distance that could be travelled (in km) after charging for 1 hour.

A brief comparison of EVs and ICEVs is presented in **Table 2.3-1**. The comparison is based on five years lease cost and 75000 miles travel distance in five years for both type of cars [35]. The table compares key figures only.

Parameters	ICEV	EV
efficiency	30 miles per gallon	3.80 miles per kWh
fuel cost	3.00 $ per gallon	0.15 $ per kWh
fuel consumption for 75000 miles	2,500 gallons	19740 kWh
total fuel cost	7,500 $	2960 $
maintenance cost	400 $ per year	100 $ per year
maintenance cost for 5 years	2,000 $	500 $
GHG emissions	417 gm per mile	860 gm per kWh
total GHG emissions	31.28 Mtons	16.98 Mtons

Table 2.3-1. Comparison of EVs and ICEVs

2.4 Results

Travel data for four different regions within NSW were analyzed for trip distance (km), electric energy consumed per trip (kWh/trip), SOC distribution during 24 hrs of the day, recharge duration (at 3.0 kW), electric energy densities (kWh/km^2) and reduction in GHG emissions ($CO_{2(eq)}$). The latter results were presented in the following sections for each region.

2.4.1 South Western Sydney (Bankstown Areas)

The census data of journey to work (2011) [8] was analysed and results were mapped dynamically using MS-Excel. As an example, the spatial distribution of in-going vehicles trips was presented in **Fig. 2.4-1**. Alternatively, this dynamic map could demonstrate the spatial distribution of electric energy available for V2X operations, electric energy required for recharging EV batteries, average SOC distributed in the region and the estimated duration required to recharge an EV battery.

Trips of these 20 suburbs were classified into two categories. The in-going trips, conducted by residents of other suburbs who travel to these suburbs for work. The outbound trips, conducted by residents of these suburbs who travel to other suburbs for work.

Detailed analysis shows that 77% in-going and 63% outbound trips were conducted using vehicles. The average trip length of 85% in-going and 90% outbound vehicle trips was less than 30 km and an average electric energy consumption per trip was 2.6 kWh. These vehicle trips were well within the range of currently available electric vehicles such as the Nissan Leaf (2011-15).

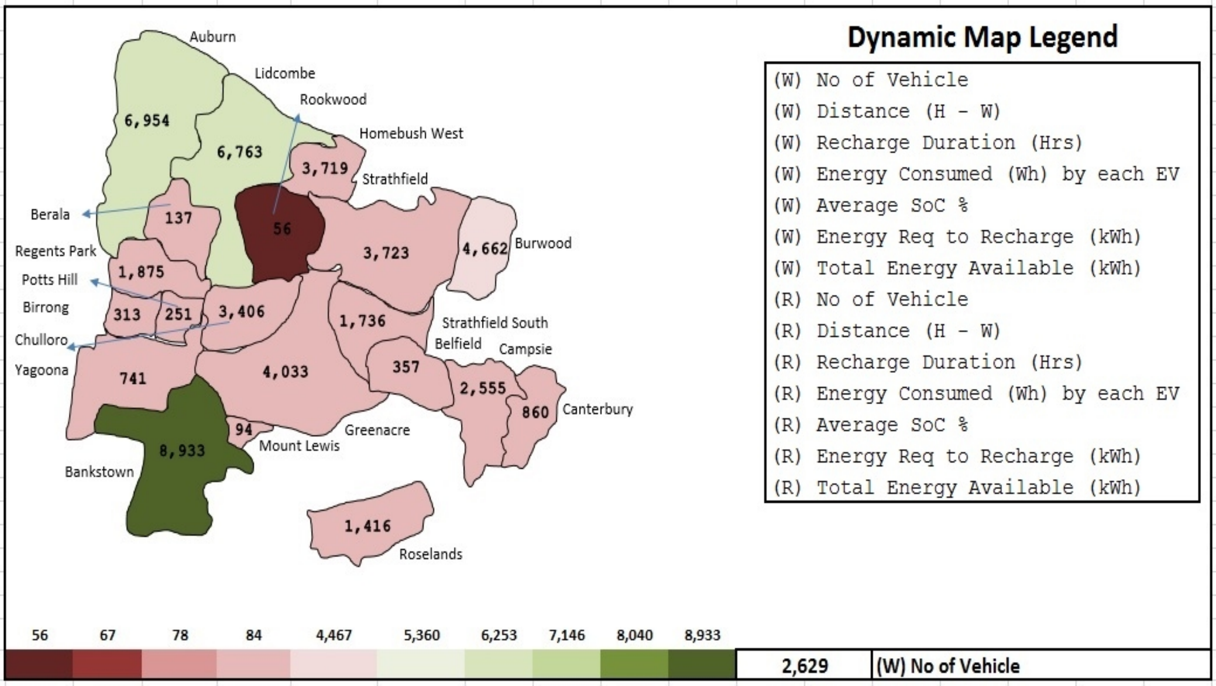

Fig. 2.4-1. Example of MS-Excel based dynamic map of Bankstown area indicating spatial distribution of in-going number of vehicles

The estimated aggregated electric energy remaining in the in-going vehicles could exceed 1.1 GWh which could be used for V2X electric energy transfer operations. Alternatively, the aggregated increase in electric energy demand per day would reach 102 MWh. The outbound vehicles were dispersed in 50 different suburbs and the assessed aggregated electric energy remaining in the outbound vehicles would be around 0.88 GWh for V2X electric energy transfer operations.

2.4.2 Sydney Inner City

Statistics show that more than 0.4 million people work in Sydney Inner City and only 95,000 workers (i.e. 23% of the total workers) use the vehicle to commute. 83,000 workers (i.e. 88% of the vehicle commuters) commute less than 40 km (**Fig. 2.4-2**) which is well within the range of currently available EVs.

The average commute distance for 88% of the vehicle trips was 21 km with an average electric energy consumption per trip of 3.3 kWh. An estimated 1.75 GWh electric energy would be available for V2X electric energy transfer operations. Alternatively, if these vehicles were recharged after their first trip then the electric energy demand in Sydney Inner City would rise by 0.2 GWh per day. On average 83% of the vehicles had more than 75% SOC when they arrive at Sydney Inner City (**Fig. 2.4-3**). Statistics clearly show that there is a good potential of replacing ICEVs with currently available EVs based on travel requirements.

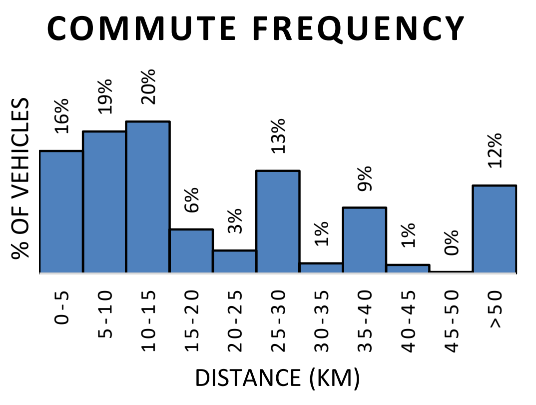

Fig. 2.4-2. Frequency of Distance travelled per trip

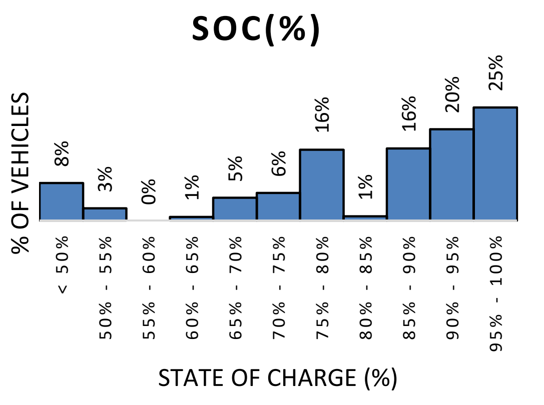

Fig. 2.4-3. Estimated SOC of vehicles after trip completion

2.4.3 Statistical Areas Level-3 (SA3) NSW

From the NSW Household Travel Survey 2014/15 data [6], on average there were 10.9 Million vehicle trips on a weekday and 8.8 Million vehicle trips on a weekend day in 57 SA3 areas of NSW. 88% vehicle trips were less than 30 km (**Fig. 2.4-4**) and could be provided by currently available EVs. The calculated average recharge duration for 88% of EVs was less than 2 hours using L-1 chargers (**Fig. 2.4-5**).

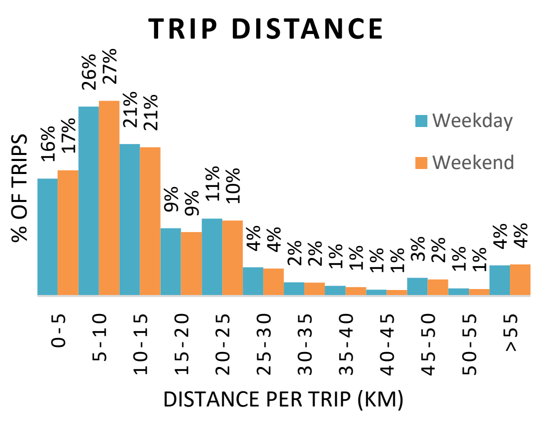

Fig. 2.4-4. Distance travelled per trip for average weekday (blue) and weekend day (orange) trips

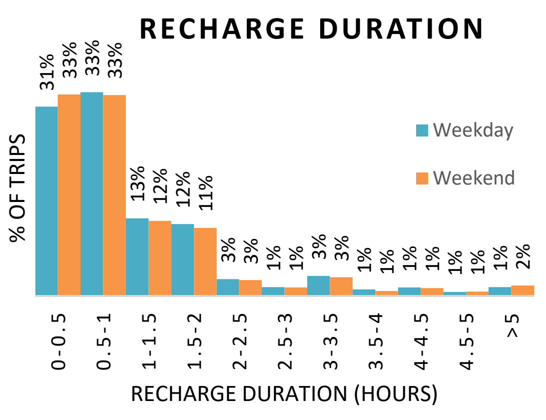

Fig. 2.4-5. Calculated recharge duration per trip for average weekday (blue) and weekend day (orange) trips

Calculations also show that an EV would retain more than 70% SOC at the end of 92% of the vehicle trips (**Fig. 2.4-6**). It was calculated that 84% of the vehicles would require less than 4 kWh per trip to recharge using an L-1 charger (**Fig. 2.4-7**).

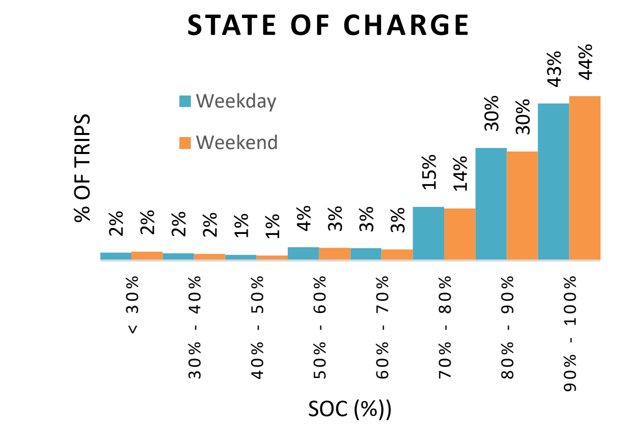

Fig. 2.4-6. Estimated SOC of vehicles after trip completion for average weekday (blue) and weekend day (orange) trips

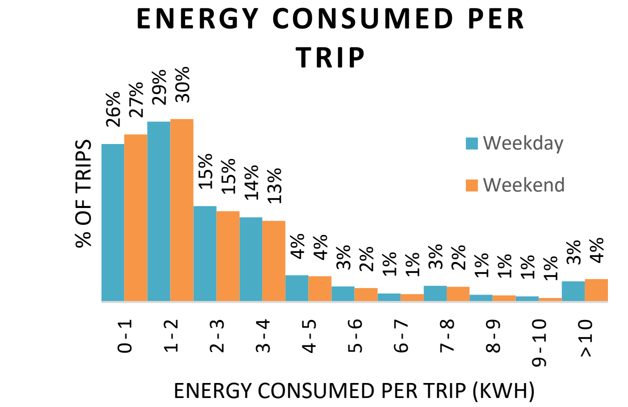

Fig. 2.4-7. Estimated electric energy consumed per trip to recharge for average weekday (blue) and weekend day (orange) trips

There was a strong correlation between population density (people/km^2) and trip concentration (trips/km^2). Data show that trip concentration is higher in densely populated areas (**Fig. 2.4-8**).

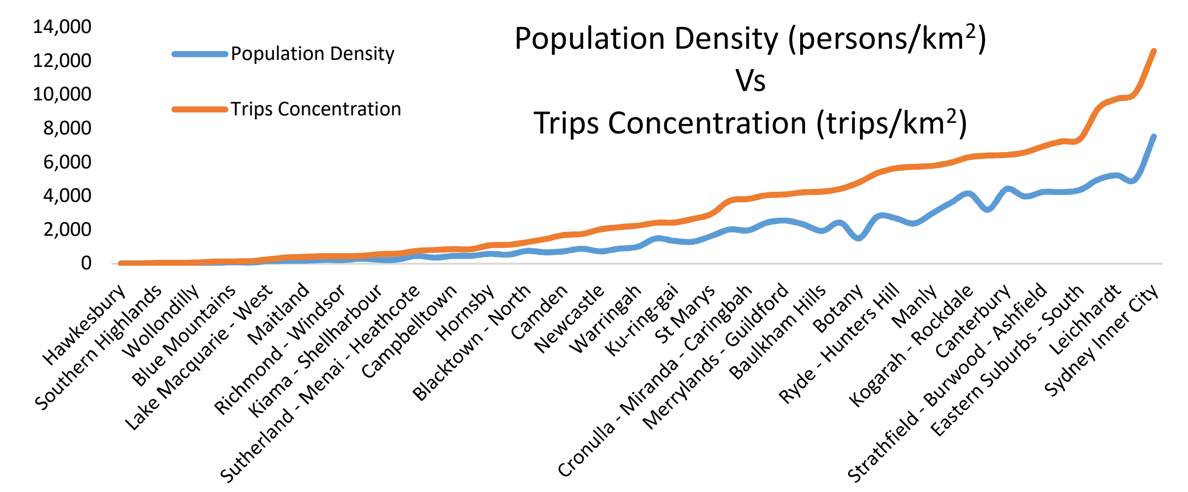

Fig. 2.4-8. Relation between Population Density (persons/km^2) and Trips Concentration (trips/km^2)

The arrival times of the 10.9 million vehicle trips (**Fig. 2.4-9**) on an average weekday and 8.8 million vehicle trips (**Fig. 2.4-10**) on an average weekend day, show that there was a margin of 10 hours for EVs to recharge during night time (i.e. from 9 PM in the evening to 6 AM in the morning). More than 86% of the weekday trips and 88% of the weekend day trips use electric energy that could be recharged in less than 3 hours on average, using an L-1 charger (**Fig. 2.4-5**). Even if the EVs were recharged nightly, there was sufficient time to be fully charged.

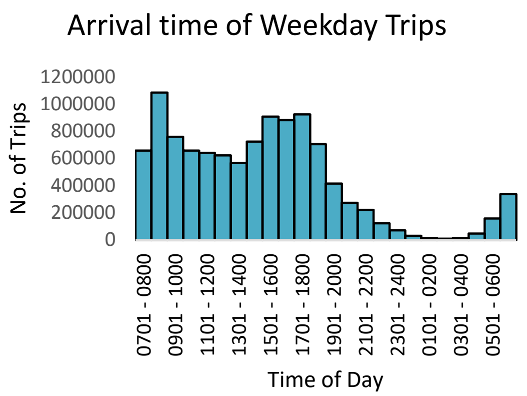

Fig. 2.4-9. Arrival times of 10.9 Million trips on an average weekday

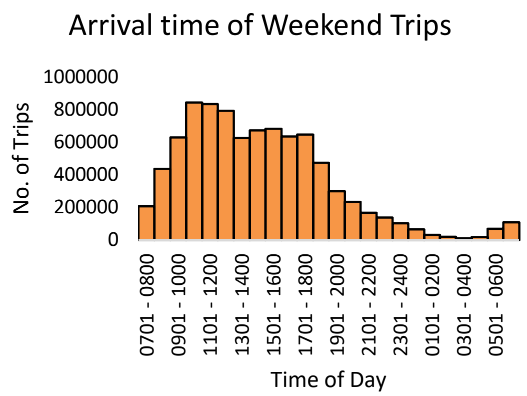

Fig. 2.4-10. Arrival times of 8.8 Million trips on an average weekend

The spatiotemporal energy distribution is important for grid operators to manage the energy required to recharge EVs as a function of location and time. It also helps the grid operators to avoid the electricity distribution hot spots. The spatiotemporal energy density (kWh/km^2) available for V2X operations in NSW was calculated based on the number of trips completed (**Fig. 2.4-11**). It could be estimated that **Fig. 2.4-11** represents the minimum local energy densities available at 09:00 AM, as the vehicles which are garaged and/or parked are not considered in the analysis. The **Fig. 2.4-11** shows that energy density available is concentrated around Sydney Inner City due to;

i. the destination for majority of the trips is Sydney Inner City and its nearby surrounding regions
ii. the land area of Sydney Inner City and its nearby surrounding regions is smaller compared to regions which are further away from Sydney Inner City therefore the energy density is higher
iii. the trip lengths are shorter for vehicle trips whose destination is Sydney Inner City and its nearby surrounding regions therefore more number of vehicles are expected to retain high state of charge after trip completion

On the contrary, the energy density (kWh/km^2) required for recharging EVs was also at its peak at 09:00 AM (**Fig. 2.4-12**) because the energy densities were evaluated based on number of trips completion, and majority of the trips were completed at 9AM. Hence, it could be inferred that many EVs which require recharge and/or charge transfer are expected to be located close to each other and energy transfer between vehicles can take place without overloading the electric power grid.

It is evident that electric energy available for V2X operations is much higher than the electric energy required to recharge EVs. It is also evident from the maps presented in **Fig. 2.4-11** & **Fig. 2.4-12** that the demand of energy required for charging EVs could easily be met by the energy available with EVs present in the nearby areas (e.g. energy transfer between vehicles via the electricity distribution network). This would redistribute charge among the vehicles. This may be useful during the peak load times of the power grid (i.e. where no additional generation capacity is needed).

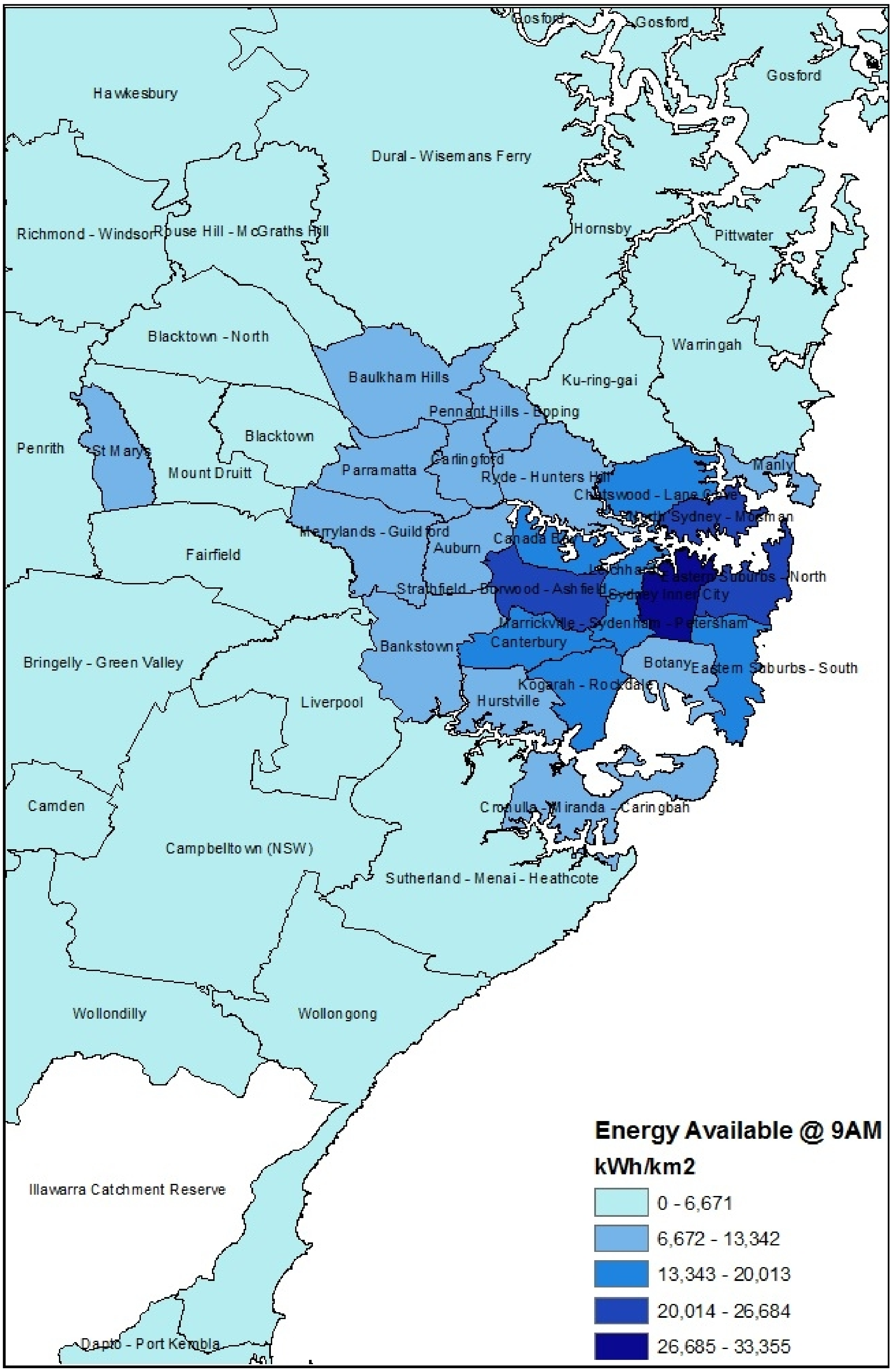

Fig. 2.4-11. Estimated electric energy concentration (kWh/km^2) available @ 9:00 AM

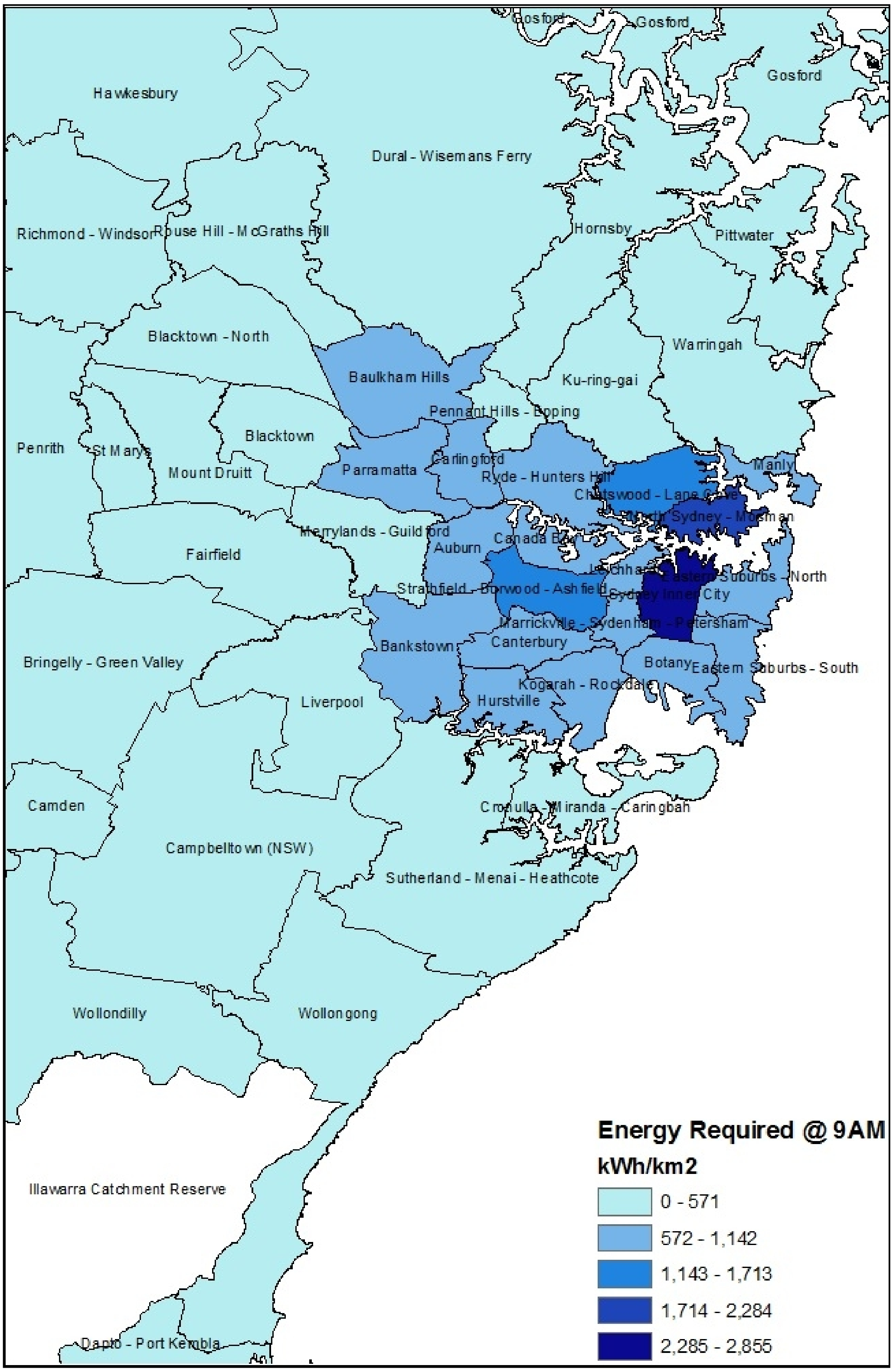

Fig. 2.4-12. Estimated electric energy concentration (kWh/km^2) required @ 9:00 AM

2.4.4 Local Government Areas (LGAs) NSW

Aggregated vehicle trips for an average weekday were 11.1 Million and 8.6Million for an average weekend day in 56 LGAs of NSW, extracted from the NSW Household Travel Survey 2014/15 data [7]. 2.0 Million vehicle trips (**Fig. 2.4-13**) for an average weekday and 0.5 Million vehicle trips (**Fig. 2.4-14**) for an average weekend day were categorised as a commute (i.e. home to work and back). Trip length of 87% of the total weekday and weekend day vehicle trips were less than 35 km (**Fig. 2.4-15**) in 50 out of 56 LGAs in NSW. Whereas, 82% of the weekday commute vehicle trips and 81% of the weekend commute vehicle trips, travel similar distance per trip (**Fig. 2.4-16**). This show that based on trip lengths, these conventional vehicle trips could potentially be replaced with affordable electric vehicle trips.

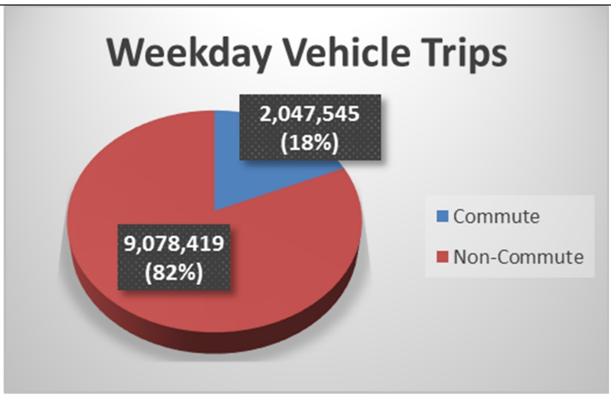

Fig. 2.4-13. Weekday vehicle trips categories

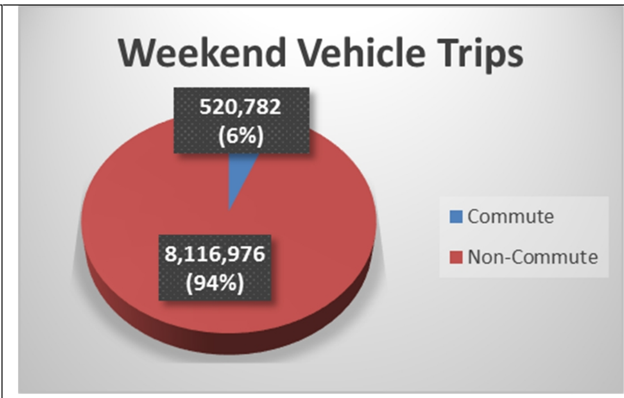

Fig. 2.4-14. Weekend vehicle trips categories

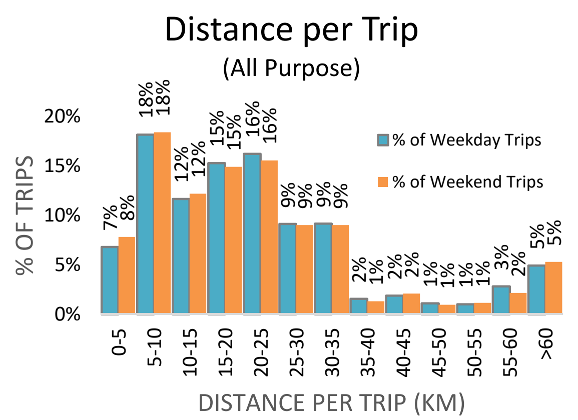

Fig. 2.4-15. Distance travelled per trip for an average weekday and weekend day (all trips)

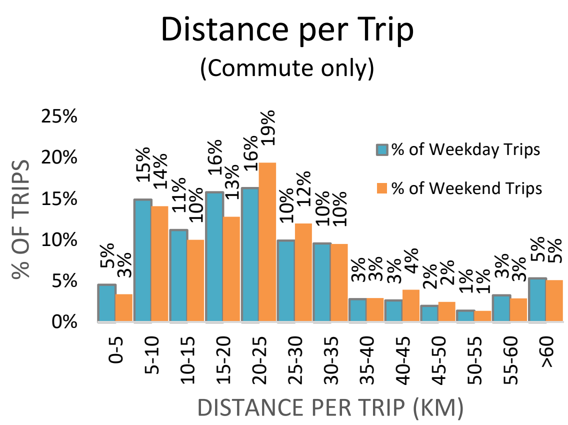

Fig. 2.4-16. Distance travelled per trip for an average weekday and weekend day (commutes)

The average recharge duration for 90% of the total (**Fig. 2.4-17**) and 88% of the commute (**Fig. 2.4-18**) vehicle trips for an average weekday and weekend day were less than 3 hours using L-1 chargers.

It was estimated that more than 90% of the total (**Fig. 2.4-19**) and 88% of the commute (**Fig. 2.4-20**) vehicle trips for an average weekday and weekend day consume less than 30% of the total battery capacity per trip.

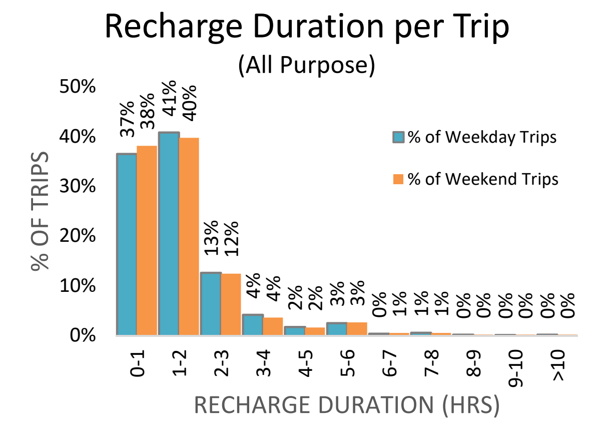

Fig. 2.4-17. Calculated recharge duration per trip for an average weekday and weekend day (all trips)

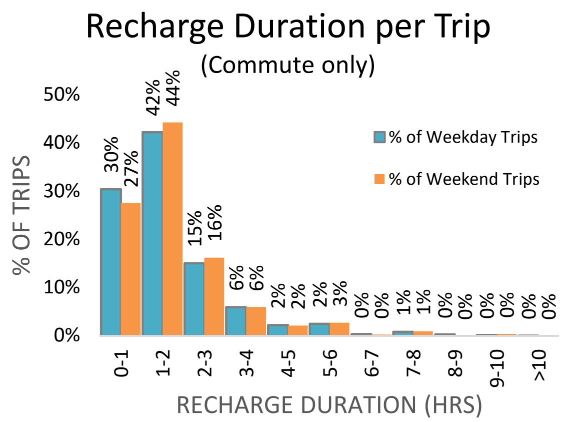

Fig. 2.4-18. Calculated recharge duration per trip for an average weekday and weekend day (commutes)

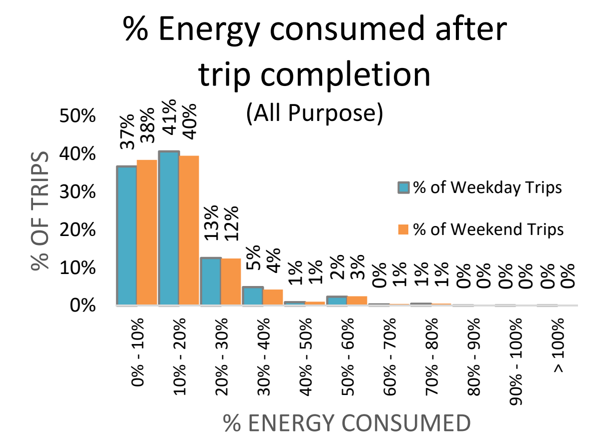

Fig. 2.4-19. Estimated % electric energy consumption per trip for an average weekday and weekend day (all trips)

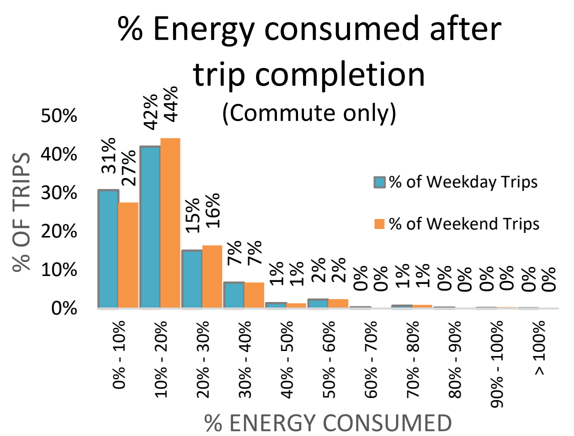

Fig. 2.4-20. Estimated % electric energy consumption per trip for an average weekday and weekend day (commutes)

The analysis for commute trips (i.e. home to work and back) show that for 82% of the total weekday commute vehicle trips (i.e. trip length less than 35 km/trip), total electric energy required to recharge the EVs after completing round trip, was less than 10 GWh/day, whereas electric energy available for V2X operations was 23 GWh/day (considering the depth of discharge to be 80%). Similarly, for 81% of the total weekend commute vehicle trips, the total electric energy required to recharge the EVs after completing round trip, was less than 3 GWh/day, whereas electric energy available for V2X operations was 6 GWh/day.

The arrival times of the 11.1 Million vehicle trips on an average weekday (**Fig. 2.4-21**) and 8.8 Million vehicle trips on an average weekend (**Fig. 2.4-22**) show that there is a margin of 10 hours to recharge during night time (i.e. from 9 PM in the evening to 6 AM in the morning). Which is sufficient to recharge an electric vehicle battery, since more than 90% of the weekday and weekend day vehicle trips use electric energy that could be recharged in less than 3 hours using an L-1 charger (**Fig. 2.4-17**).

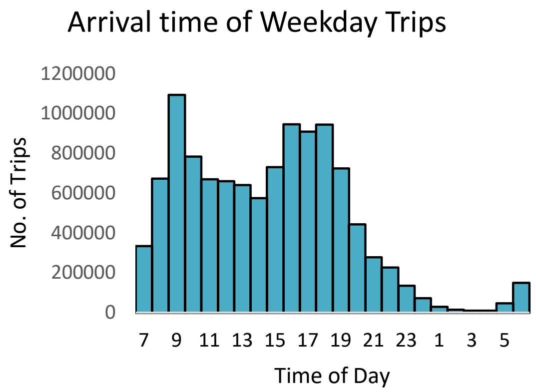

Fig. 2.4-21. Arrival times of 11.1 Million trips on an average weekday

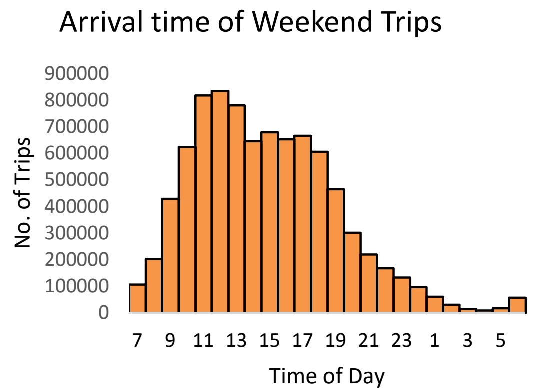

Fig. 2.4-22. Arrival times of 8.6 Million trips on an average weekend

2.4.5 Reduction in fuel depletion and GHG emissions

Fossil fuels are the source of 82% (**Fig. 2.4-23**) of the world's energy supply and are responsible for 99% (**Fig. 2.4-24**) of the greenhouse gas (GHG) emissions [36]. The transport sector consumes about 64% (**Fig. 2.4-25**) of the global oil supply [36] and causes about 23% (**Fig. 2.4-26**) energy-related GHG emissions [37].

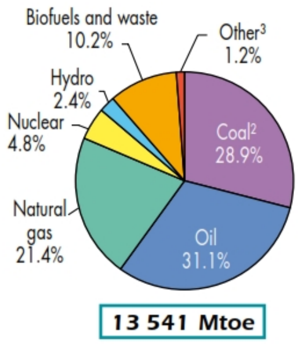

Fig. 2.4-23. World total primary energy supply (1971 to 2013) by fuel type [36]

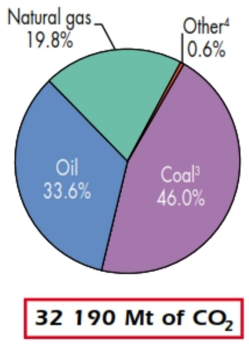

Fig. 2.4-24. World CO_2 emissions from fuel combustion by fuel type (1971 to 2013) [36]

In 2011/12 total emissions in Australia were 543.6 Mtons $CO_{2(eq)}$, where NSW accounted for 148.9 Mtons $CO_{2(eq)}$ (i.e. 27.4% of the total GHG emissions in Australia) [38]. The transport sector in

Australia was responsible for 90.2 Mtons $CO_{2(eq)}$ emissions, where NSW accounted for 26.4 Mtons $CO_{2(eq)}$ (i.e. 29.3% of the GHG emissions from Transport sector in Australia) [38].

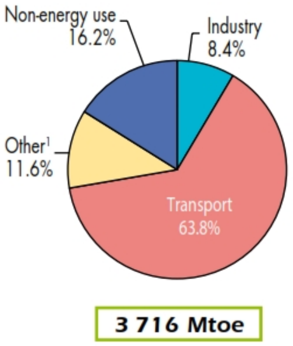

Fig. 2.4-25. Total oil consumption by sector (1971 to 2013) [36]

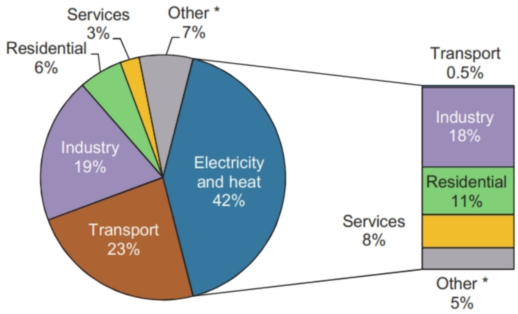

Fig. 2.4-26. World CO_2 emissions from fuel combustion by sector in 2014 [37]

The GHG emissions can be broadly categorised into two major types; 'Direct' and 'Indirect' emissions. 'Direct emissions are produced from sources within the boundary of an organisation and as a result of that organisation's activities' and 'Indirect emissions are emissions generated in the wider economy as a consequence of an organisation's activities (particularly from its demand for goods and services), but which are physically produced by the activities of another organisation' [34]. EVs do not contribute to direct GHG emissions, they produce indirect emissions through the consumption of electricity.

There can be various scenarios for evaluating the reduction in GHG emissions due to the adoption of EVs. We have evaluated the reduction in GHG emissions using two scenarios. Both scenarios were evaluated based on vehicle trips in 50 LGAs of NSW.

2.4.5.1 Case - I

When EVs were recharged using renewable sources (the wind, solar etc.). In this case, EVs would not contribute to indirect emissions. Therefore, 56% of NSW transport sector GHG emissions (compared with emissions in 2011/12) would be reduced if 87% of the vehicle trips were conducted by EVs in 50 LGAs of NSW.

2.4.5.2 Case - II

When EVs were recharged using electricity generated from coal-fired power plants, EVs would contribute in indirect emissions. Therefore, 26% of NSW transport sector GHG emissions (compared with emissions in 2011/12) would be reduced if 87% of the vehicle trips were conducted by EVs in 50 LGAs of NSW.

The results of both cases discussed above are compared to reported GHG emissions of NSW (2011/12) and presented in **Fig. 2.4-27**.

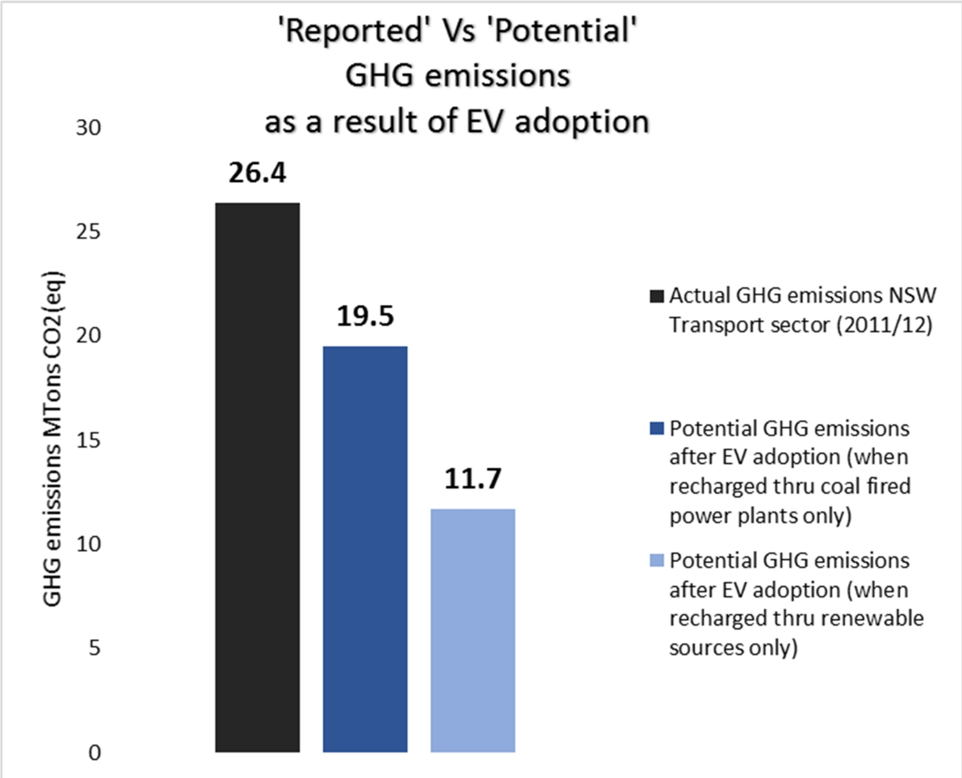

Fig. 2.4-27. Comparison of 'Reported' & 'Potential' GHG emissions as a result of EV adoption

2.5 Conclusion

Four different sources of datasets representing diverse ranges of boundary divisions were thoroughly analysed to quantify the possible adoption of EVs in Australia and its respective outcomes in terms of V2X opportunities and reduction in GHG emissions. Under realistic assumptions (i.e. mid-range battery capacity, home charging) the analysis of Journey to Work (2011) data tables [8] and NSW Household Travel Survey (HTS) 2014/15 [6, 7] show that more than 87% of daily vehicle trips across NSW were less than 35 km. This range could readily be provided by currently available EVs.

If 87% ICEV trips across NSW were conducted by an average EV, it would potentially result in more than 200 GWh of aggregated electric energy available for V2X electric energy transfer operations for an average weekday across 50 LGAs of NSW. Alternatively, EVs would impact the existing power infrastructure in terms of increased load. The aggregated rise in the electric energy demand would be

26 GWh across during an average weekday. Detailed analysis of the spatiotemporal rise in electric energy demand is conducted in Chapter-3.

Mapping the spatiotemporal distribution of the average SOC of vehicles showed that concentration of electric energy (kWh/km^2) was higher in densely populated areas. It was evaluated that the electric energy available for V2X operations was much higher than the electric energy required to recharge EVs. Therefore, transfer of electric energy from EV to other infrastructure and/or vehicle (V2X) via grid could effectively fulfil the additional electric energy demand. Hence, power grid could be managed during peak electric energy demand.

The pattern of arrival times of vehicle trips show that vehicles were parked at home for about 10 hours overnight, this duration was sufficient to recharge EVs which were used for commuting needs during the day. More than 90% of the weekday and weekend day trips across NSW, require less than 3 hours to recharge using L-1 chargers.

Lastly, it was calculated that even if all EVs were recharged from non-renewable coal-fired power plants, the greater efficiency of EVs would result in a reduction of 26% $CO_{2(eq)}$ across NSW (compared to GHG emissions from transport sector across NSW in 2011/12). This chapter demonstrates the potential for widespread adoption of EVs in Australia.

Chapter 3

Grid Impact

3.1 Introduction

The transport sector is expected to become increasingly electrified in coming years, bringing new benefits, challenges and opportunities [1]. The electric vehicle (EV) stock has been growing since 2010 and sales of EVs increased by 70% in 2015 compared to 2014 globally, with over half a million EVs being sold worldwide in 2015. The growth trend in EV sales is likely to accelerate with the declining cost of batteries [5], increasing battery energy densities, and the increasing viability of home-storage and charging options [3].

One of the consequences of the widespread adoption of EVs will be an increase in electricity demand, hence there is potential to overload electric power distribution networks, especially if a large proportion of EV charging is rapid and/or unscheduled [19]. The data available on EV usage and impact is relatively sparse, however existing travel data for internal combustion engine vehicles (ICEVs) may be used to indicate the expected impacts of EVs assuming vehicle usage remains unchanged. Here we have evaluated the spatiotemporal aggregated rise in electricity demand based on the NSW Household Travel Surveys (HTS) 2014/15 [7] dataset. Although the survey data was based on ICEVs, we have used it with some careful assumptions to infer useful conclusions about the potential impact of EVs on the electric power grid.

We have estimated the potential spatiotemporal rise in electric energy demand across 50 Local Government Areas (LGAs) of New South Wales (NSW). It was found that 87% of the total vehicle trips, 82% of the weekday commute vehicle trips and 81% of the weekend commute vehicle trips were less than 35 km/trip. Our estimations for the spatiotemporal rise in electric energy demand assumed that all vehicle trips were conducted using EVs with trip lengths less than 35 km/trip. The potential electric energy demand of these LGAs was compared with average electric energy consumption across respective LGAs. The electricity consumption data was retrieved from customer billing data in Ausgrid's network [39]. Data of only 35 out of 50 LGAs was compared since services to other LGAs were provided by different service providers and electricity consumption data was not available. Additionally, a potential solution for the rise in electric energy demand is presented in terms of the available state of charge (SOC) with EV batteries after round trip completion. This electric energy could be used for V2X energy transfer operations.

3.2 Analysis

NSW Household Travel Surveys (HTS) 2014/15 [7] dataset show that there were 11.1 million and 8.6 million vehicle trips for an average weekday and weekend day respectively in 56 LGAs of NSW. The purpose of 2.0 million (i.e. 18% of total weekday vehicle trips) and 0.5 million (i.e. 6% of total weekend vehicle trips) vehicle trips for an average weekday and weekend day respectively was commute (i.e. home to work and back). The average trip length of 87% of total vehicle trips was 15.7 km/trip and 15.3 km/trip for an average weekday and weekend day respectively, which was consistent with Australia's average commuting distance i.e. 15.6 km [32].

In this chapter, the analysis is presented for two scenarios, the potential spatiotemporal rise in electric energy demand during an average week for (i) all-purpose (i.e. commute and non-commute) vehicle trips and (ii) commute vehicle trips. The aggregated electric energy consumption was calculated for vehicle trips with trip lengths less than 35 km/trip. We have considered the vehicle trips with one side trip length of less than 35 km/trip due to following reasons;

i. 87% of the total weekday and weekend day vehicle trips were less than 35 km
ii. 82% weekday commute vehicle trips were less than 35 km/trip
iii. 81% weekend day commute vehicle trips were less than 35 km/trip
iv. We have assumed the Nissan Leaf (2011-15) with full charge distance travel range of 120 km. Considering 35 km for one side trip, means 70 km for full commute trip with 50 km range still available after completing the round trip without requiring intermediate recharging.

After presenting both scenarios, a detailed analysis was conducted to evaluate the potential spatiotemporal rise in electric energy demand for scenario two (i.e. commute vehicle trips only). The spatiotemporal aggregated electric energy available for V2X opportunities across LGAs of NSW were also estimated and the results were presented in the respective sections.

3.2.1 Scenario-1 (all purpose vehicle trips)

In scenario-1, the potential rise in spatiotemporal electric energy demand for all-purpose (i.e. commute and non-commute) vehicle trips during an average weekday and weekend day was evaluated. **Fig. 3.2-1** summarised the rise in electric energy demand at different times of the day in 50 LGAs of NSW during **(a)** an average weekday and **(b)** average weekend day. The figures represent aggregated electric energy demand at respective destinations after the trip completion. The aggregated electric energy required to recharge EVs after completing the trip were summarised in **Table 3.2-3** & **Table 3.2-4**.

The aggregated electric energy required to recharge the EVs were evaluated based on one side trips since the detailed spatial information for non-commute vehicle trips was not available. It is clear from **Fig. 3.2-1** that there were many trips conducted during the weekday and weekend day. When we consider all-purpose (i.e. commute and non-commute) vehicle trips, then it is difficult to estimate recharging of EVs during the day time. Therefore, based on the availability of EVs for all-purpose vehicle trips, it could be assumed that EVs would be recharged overnight only.

The rise in electric energy demand due to EV recharging is dependent on the driving and recharging patterns. Autonomous vehicles (AVs) are expected to change the way we travel. This new technology will potentially impact personal travel in areas which include safety, congestion, and travel behaviour. It is expected that vehicle miles travel will increase by 20% compared to non-AVs travel at 10% market penetration rate of AVs [40]. This implies that electric energy management of autonomous EV fleets would be more predictable compared to non-AVs. Therefore, it would be easy to predict the availability of vehicles for charging and discharging operations (where discharging of vehicles refers to V2X operations).

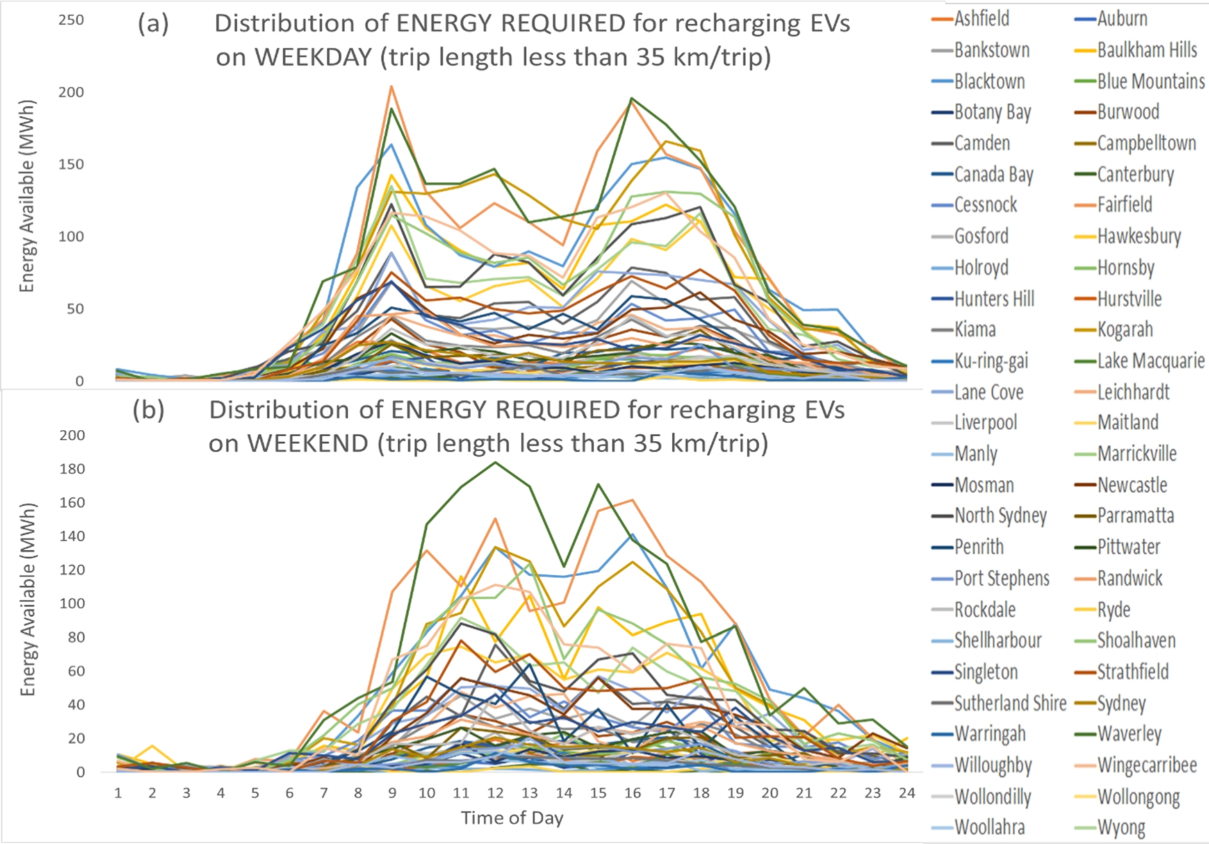

Fig. 3.2-1. Spatiotemporal rise in electricity demand during **(a)** an average weekday **(b)** average weekend day due to recharging of EVs for all-purpose vehicle trips

Spatiotemporal distribution of aggregated ***ENERGY REQUIRED*** (MWh) to recharge EVs for ***WEEKDAY*** (all purpose trips ≤ 35 km/trip)

LGA	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Total
Wollongong	7.5	0.0	1.0	5.2	8.5	10.0	69.0	78.9	188.5	136.7	136.7	146.7	109.9	114.0	118.7	195.8	177.9	152.4	120.7	61.9	39.0	35.8	21.2	10.7	1947
Gosford	2.3	1.9	0.0	3.4	7.3	23.5	42.2	88.5	204.2	131.2	106.0	123.2	110.3	94.2	158.9	193.3	156.9	147.4	103.8	71.8	37.0	32.4	24.0	5.1	1869
Lake Macquarie	1.8	0.8	0.8	2.2	3.1	13.4	47.7	78.2	131.0	129.7	134.5	143.2	128.8	112.2	105.3	138.6	166.0	159.4	101.4	57.9	36.2	35.1	14.4	5.0	1747
Blacktown	8.3	4.4	1.9	0.0	7.9	23.1	41.1	133.9	163.5	108.2	87.2	79.1	89.9	79.5	121.3	150.2	154.7	146.7	115.9	63.4	49.1	49.5	20.8	9.1	1709
Wyong	1.2	0.8	0.9	0.9	4.8	26.0	48.4	77.0	116.6	113.9	104.3	88.6	86.9	71.8	113.3	120.6	130.4	103.8	85.6	42.9	25.2	19.9	10.8	8.7	1403
Baulkham Hills	1.9	0.0	0.0	0.0	0.0	7.6	32.2	74.7	142.6	106.4	90.6	79.4	81.9	63.9	107.9	110.5	122.0	110.7	72.0	70.6	39.0	36.9	12.7	7.6	1371
Sutherland Shire	3.5	3.2	0.0	0.0	4.1	9.9	29.2	68.7	114.9	102.2	88.9	82.0	85.4	66.6	82.3	127.7	130.9	129.8	113.4	55.1	34.7	15.3	10.2	9.0	1367
Penrith	2.9	0.6	0.9	1.3	9.1	20.7	25.8	69.1	122.5	65.2	65.3	87.8	82.1	59.4	85.3	108.7	112.8	120.5	66.7	54.5	24.2	27.6	15.5	4.5	1233
Newcastle	1.3	1.7	1.3	2.6	0.0	22.5	39.2	84.6	134.8	71.0	68.1	70.7	72.0	59.1	77.1	95.9	93.3	116.1	65.6	36.1	32.0	22.5	11.7	11.3	1191
Hornsby	2.3	0.6	0.7	0.0	0.9	6.2	23.9	58.7	107.6	66.2	55.4	65.6	70.2	51.3	70.9	98.4	90.8	111.0	68.3	50.2	34.9	19.7	13.0	7.1	1074
Liverpool	5.4	0.0	0.5	0.0	8.5	11.2	34.1	38.1	88.4	46.1	39.2	42.6	51.2	51.0	75.9	74.6	73.3	70.0	67.0	42.4	21.4	25.0	10.9	8.2	885
Campbelltown	4.5	1.7	0.8	3.5	9.6	15.3	28.2	48.7	88.9	46.0	43.5	54.0	54.9	39.8	54.8	78.6	75.0	56.5	58.0	28.0	17.6	12.2	12.3	6.8	839
Warringah	2.4	0.3	2.1	0.9	0.0	7.9	13.5	41.7	75.2	55.8	57.8	49.9	47.1	48.8	61.8	72.5	64.0	77.2	62.7	31.8	15.1	12.7	13.1	8.9	823
Parramatta	3.2	0.8	0.0	0.7	3.2	9.1	22.6	57.2	68.4	50.1	32.3	26.1	32.3	29.4	33.2	49.6	50.8	61.3	42.6	34.4	18.9	20.2	15.8	9.3	671
Bankstown	1.6	1.8	4.0	0.8	2.9	14.8	22.0	33.7	68.2	48.9	37.1	36.0	37.9	32.7	42.2	69.4	53.8	48.9	35.5	26.3	14.8	13.0	7.3	6.4	660
Port Stephens	1.3	1.3	0.0	0.0	1.2	1.4	24.9	33.2	51.0	46.1	41.5	47.2	36.1	46.6	35.8	58.9	56.5	42.8	29.2	14.4	16.8	9.3	7.6	0.0	603
Fairfield	6.4	1.2	0.3	1.1	3.2	10.3	19.4	37.0	69.4	42.4	31.7	35.0	26.1	33.3	33.4	53.6	42.2	43.6	49.5	20.6	19.7	9.6	6.5	4.4	600
Sydney	2.5	0.3	0.4	2.0	2.5	23.0	36.2	55.9	68.7	44.9	39.2	28.6	26.4	25.3	29.0	21.4	22.8	31.9	26.1	20.1	16.0	7.7	8.0	3.0	542
Ryde	2.1	1.2	0.3	0.5	1.0	3.7	15.5	45.1	46.4	48.5	32.5	24.3	26.2	23.7	25.1	29.7	24.8	28.7	28.3	14.6	12.8	11.2	5.1	3.2	454
Maitland	0.0	0.0	0.7	0.0	0.8	5.9	10.1	16.2	45.9	38.0	31.4	31.9	26.1	25.7	40.4	46.0	35.8	37.0	26.2	13.1	12.5	3.1	2.1	2.5	451
Ku-ring-gai	2.5	1.4	0.6	0.2	0.0	1.6	11.4	30.7	45.0	28.1	24.7	23.5	24.8	19.1	30.8	42.6	30.5	38.4	36.5	18.1	11.0	12.7	5.1	4.6	444
Camden	1.2	0.0	0.0	0.4	0.7	2.4	9.6	24.6	42.9	25.4	20.1	9.1	12.8	10.4	28.6	35.9	30.9	38.2	27.8	15.0	10.4	8.9	3.4	0.4	359
Shellharbour	0.0	0.8	0.0	0.0	1.0	2.4	4.3	16.7	36.3	25.4	24.1	17.3	17.5	16.1	26.9	44.9	31.3	32.5	23.3	12.1	7.9	5.6	3.8	1.6	352
Randwick	1.6	0.2	0.0	0.7	0.4	5.5	13.3	15.6	33.2	20.4	22.9	20.6	14.7	15.6	17.6	19.6	27.2	25.4	19.5	17.8	7.3	5.2	5.7	1.9	312
Pittwater	0.5	1.1	0.0	0.0	0.2	0.6	7.5	10.1	25.5	16.6	17.7	18.4	17.5	13.7	21.1	22.3	26.8	35.4	19.5	13.7	3.7	5.7	4.1	1.7	283
Auburn	1.2	0.6	0.0	0.5	5.5	9.0	12.7	27.1	27.3	21.3	13.1	9.3	14.0	12.1	16.5	18.0	17.9	22.8	15.1	16.3	5.2	8.9	3.8	0.8	279
Canterbury	0.0	0.3	1.0	1.2	0.7	3.6	8.4	14.7	20.9	18.2	11.2	16.6	9.8	19.6	20.1	24.8	21.8	23.1	22.1	10.8	7.9	3.2	4.1	4.5	269
Holroyd	0.4	0.0	0.9	0.1	3.1	5.5	9.6	16.9	28.8	13.4	9.5	13.0	12.1	10.8	17.0	21.2	15.8	17.2	15.3	11.6	9.9	7.5	4.4	1.5	245
Willoughby	1.0	0.0	0.3	0.0	0.8	3.3	10.1	24.8	27.3	21.5	19.0	14.7	19.6	13.4	12.5	12.2	13.8	13.8	15.6	6.1	4.7	3.8	2.8	1.0	242
Botany Bay	0.0	0.0	0.0	0.2	3.9	15.6	10.8	14.6	27.0	11.3	9.3	15.3	11.6	9.9	15.4	15.0	10.6	11.9	11.5	8.0	4.9	6.4	1.8	1.2	216
Hurstville	0.4	0.1	0.2	1.0	0.5	1.2	3.7	12.3	18.8	12.8	12.2	11.6	8.7	7.1	16.4	18.8	17.8	15.9	15.9	14.1	5.2	3.3	3.2	0.6	202
Rockdale	1.2	0.0	0.0	0.4	1.1	3.3	4.2	7.2	17.1	12.1	9.2	11.8	9.1	12.2	12.3	16.6	14.9	25.5	9.4	8.6	7.4	6.3	4.7	2.1	196
North Sydney	0.1	0.0	0.0	0.0	0.0	1.6	7.3	19.1	27.6	17.9	12.3	14.3	9.1	9.3	6.1	10.2	8.7	11.2	12.6	9.7	6.5	4.9	2.5	1.1	192
Canada Bay	0.6	0.1	0.0	0.0	0.2	2.5	7.1	11.0	17.7	11.3	11.0	11.0	10.0	8.8	10.2	12.5	15.0	15.9	16.0	8.5	4.3	4.1	4.5	0.4	183
Manly	0.0	0.0	0.0	0.9	0.0	0.8	5.2	9.2	10.7	13.1	10.8	13.8	5.7	4.9	10.0	19.5	13.4	16.2	17.8	10.0	4.9	0.6	3.3	2.6	174
Marrickville	0.4	1.3	0.1	0.0	0.6	3.7	7.7	10.9	15.8	11.2	7.4	7.9	5.4	9.3	7.1	10.4	11.6	12.5	14.5	10.1	6.7	2.6	1.8	1.2	160
Kiama	0.0	0.0	0.0	0.0	1.0	0.2	4.6	6.1	13.4	16.7	1.7	8.5	9.0	6.6	8.4	13.4	13.8	5.2	8.3	4.3	2.6	1.7	1.3	0.7	128
Kogarah	0.5	0.0	0.1	0.0	0.5	1.0	4.3	8.5	14.0	7.6	8.7	4.9	7.2	6.0	8.4	9.5	8.9	12.6	7.7	7.1	2.6	3.3	1.8	0.5	126
Leichhardt	0.3	0.0	0.1	0.0	1.1	2.6	6.8	7.0	9.6	7.8	4.2	8.2	6.1	5.2	6.4	5.7	7.2	8.8	9.5	5.5	3.0	1.4	2.1	0.5	109
Strathfield	1.0	0.0	0.0	0.0	3.8	1.2	3.0	11.1	15.1	5.8	5.9	5.2	4.1	3.1	6.1	7.2	4.9	8.2	6.5	3.0	2.1	2.3	2.6	0.1	103
Waverley	0.3	0.5	0.0	0.0	0.0	0.4	4.4	8.9	5.8	7.5	4.3	7.0	10.7	4.2	5.5	4.8	6.9	7.2	10.3	3.7	1.3	1.3	0.8	0.5	96
Woollahra	0.0	0.0	0.0	0.0	0.0	0.9	1.5	7.9	9.2	6.1	5.6	5.0	3.1	4.4	4.0	7.4	5.5	10.1	6.7	3.7	2.2	4.9	0.9	0.4	89
Lane Cove	0.1	0.0	0.0	0.0	0.1	3.1	4.7	8.9	7.3	8.7	4.7	3.7	4.0	2.3	4.5	6.1	5.4	6.4	6.1	2.5	3.4	2.7	0.5	0.0	85
Ashfield	0.7	0.1	0.0	0.0	0.0	1.4	1.6	5.2	8.8	2.5	5.1	5.0	3.1	3.2	5.1	4.5	5.6	6.3	7.3	3.2	3.0	1.8	2.4	0.6	76
Burwood	0.0	0.4	0.4	0.0	0.0	1.4	2.5	4.0	9.4	3.4	4.4	3.2	3.1	1.6	5.9	3.7	2.4	4.3	5.1	3.1	2.1	2.1	1.2	1.6	65
Mosman	0.0	0.2	0.0	0.0	0.0	0.8	4.3	3.4	5.5	4.0	5.8	3.5	3.3	4.5	2.0	4.5	3.8	3.6	5.6	2.5	1.5	0.7	0.4	0.1	60
Cessnock	0.0	0.0	0.0	0.0	1.0	1.0	0.4	2.9	2.4	3.7	2.2	4.7	7.2	2.7	5.5	3.1	3.1	2.5	1.7	4.0	0.0	1.0	0.0	0.0	49
Wollondilly	0.7	0.0	0.0	0.0	0.0	0.0	0.4	3.2	1.4	1.8	0.9	1.4	1.6	1.1	0.0	0.0	6.8	4.8	3.3	0.9	0.8	0.7	0.8	2.8	33
Hunters Hill	0.2	0.0	0.0	0.0	0.0	0.1	0.1	2.0	4.0	1.1	1.8	2.3	1.1	1.5	4.0	2.1	2.0	1.8	2.5	1.5	0.5	0.5	0.3	0.1	29
Shoalhaven	0.0	0.0	0.0	0.0	0.0	0.0	0.9	1.0	0.8	0.0	0.0	1.1	0.0	0.0	0.0	0.4	3.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	9

Table 3.2-1. Spatiotemporal rise in electricity demand during an average weekday for all-purpose vehicle trips under 35 km/trip (green-minimum, yellow–medium, red-maximum electricity demand-MWh)

Spatiotemporal distribution of aggregated ***ENERGY REQUIRED*** (MWh) to recharge EVs for ***WEEKEND*** (all purpose trips ≤ 35 km/trip)

LGA	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Total
Wollongong	9.3	2.1	5.4	0.0	5.9	3.8	31.0	43.8	53.7	147.3	169.2	184.0	169.5	121.9	170.9	137.7	123.6	77.4	86.5	33.7	50.0	29.0	31.2	15.1	1702
Gosford	8.5	2.5	2.5	0.0	7.8	6.7	36.2	23.6	107.1	131.6	110.3	150.6	95.4	100.7	155.0	161.7	128.4	112.9	87.8	43.1	21.5	40.0	19.9	2.8	1557
Blacktown	10.3	0.0	5.2	0.0	0.5	10.9	12.3	33.4	59.0	83.1	104.7	133.5	117.0	115.9	119.3	141.2	109.3	61.5	88.3	49.0	44.0	36.2	19.3	10.6	1364
Lake Macquarie	5.3	1.7	3.4	3.2	2.2	5.9	20.2	16.1	39.1	88.0	94.6	133.6	125.2	86.4	110.0	124.7	108.7	83.0	50.2	39.9	21.1	10.4	14.9	12.0	1200
Sutherland Shire	8.6	2.3	0.0	0.0	0.0	7.0	22.0	40.4	50.0	85.4	103.3	103.5	123.5	67.3	96.4	88.2	76.0	56.4	52.5	42.3	16.8	22.9	18.9	7.4	1091
Baulkham Hills	10.4	4.8	2.5	0.0	2.8	5.0	15.7	12.8	39.2	56.3	116.4	77.4	104.7	55.2	97.8	81.3	89.2	93.7	49.1	38.7	31.1	12.8	8.9	20.2	1026
Wyong	2.0	0.0	0.0	1.6	2.6	0.0	14.3	10.3	66.9	75.2	102.4	111.1	106.9	76.0	74.2	59.7	76.4	73.6	29.4	27.8	7.7	6.0	15.1	0.0	939
Newcastle	3.5	1.2	0.0	0.0	6.8	12.8	12.4	28.8	37.4	63.7	91.6	82.2	63.2	65.4	47.0	74.0	59.8	51.1	48.2	29.0	14.1	13.9	16.4	5.7	828
Hornsby	1.5	15.7	0.0	0.0	0.0	2.1	6.1	13.4	49.5	69.7	74.6	65.3	70.1	55.0	61.1	59.2	70.9	61.7	50.0	18.4	20.6	19.1	22.1	11.1	817
Penrith	0.0	5.3	1.9	0.7	0.0	0.0	3.2	13.8	42.0	60.9	88.3	81.6	54.1	47.8	67.0	70.5	45.9	43.4	43.0	25.4	24.5	11.4	11.0	9.0	751
Warringah	3.5	5.5	2.8	0.0	0.0	1.0	6.9	5.8	30.4	41.6	78.1	59.6	70.1	50.0	48.2	49.4	49.8	55.5	20.3	21.2	20.8	8.2	3.6	6.5	639
Liverpool	10.4	1.9	3.3	2.8	2.3	7.8	3.6	16.0	29.1	33.4	50.4	50.9	49.6	36.4	57.1	48.6	35.6	52.3	27.1	34.9	16.6	5.4	13.8	0.2	590
Campbelltown	0.0	5.7	0.0	0.0	1.5	3.9	4.3	5.9	29.1	44.8	33.2	75.6	52.5	37.8	56.5	40.6	41.8	38.8	26.7	14.8	24.2	13.0	9.7	4.8	565
Parramatta	2.2	3.4	0.0	0.6	2.5	3.2	8.8	2.2	21.2	35.3	55.9	50.5	45.6	34.3	56.3	37.4	37.8	38.8	34.1	26.7	13.1	8.6	23.0	14.3	556
Fairfield	5.9	2.5	0.0	0.6	1.1	7.2	9.7	18.6	36.6	36.6	55.6	51.4	32.7	42.1	32.6	26.5	23.6	39.9	17.0	15.3	14.6	17.7	7.6	11.8	507
Bankstown	0.7	3.1	0.0	3.5	0.0	9.4	2.1	10.4	15.3	33.9	45.2	31.7	37.7	31.6	36.7	27.5	43.0	44.9	33.2	14.9	21.4	13.3	7.4	4.2	471
Port Stephens	0.0	0.0	0.0	0.0	0.0	1.0	6.2	12.6	24.3	56.7	46.1	40.6	64.0	18.5	37.5	11.5	40.1	13.6	32.6	17.5	2.8	5.4	5.2	0.0	436
Sydney	1.8	3.6	0.0	2.9	0.9	11.4	9.9	7.8	22.7	28.9	33.5	46.0	29.1	32.3	24.2	29.9	27.1	23.9	38.3	21.1	12.9	14.6	5.9	6.6	435
Maitland	6.5	0.0	0.0	0.0	5.8	0.0	6.1	3.9	23.9	27.9	47.8	38.4	45.1	46.6	18.1	12.2	25.7	29.8	27.1	21.5	9.7	7.6	4.1	7.8	416
Ku-ring-gai	0.7	0.0	0.0	0.0	0.0	0.0	3.4	8.0	16.1	28.2	34.5	26.7	30.1	25.6	26.4	18.0	19.4	28.8	22.6	12.1	9.9	4.7	5.5	6.2	327
Ryde	0.5	0.6	0.8	0.0	1.0	0.0	2.4	6.0	17.9	21.4	31.3	26.7	22.1	16.9	26.5	23.6	26.1	27.3	17.4	12.6	9.8	6.4	4.8	5.0	307
Camden	1.5	0.0	0.0	0.0	0.0	4.8	6.4	5.6	11.0	19.9	34.4	30.5	23.1	33.8	21.2	23.6	29.8	22.0	11.1	12.1	3.5	4.7	2.9	0.9	303
Shellharbour	0.0	0.0	0.0	0.0	0.0	3.0	1.2	6.6	17.0	16.2	17.4	46.7	24.7	16.3	27.1	22.5	27.5	18.6	10.2	8.2	3.8	6.5	0.5	2.8	277
Randwick	0.9	0.0	0.0	0.0	0.0	2.8	1.0	8.5	13.9	19.7	26.5	15.5	21.7	23.8	14.4	19.5	23.5	24.2	9.8	12.7	9.7	2.6	2.9	8.8	262
Pittwater	2.3	0.0	0.0	0.0	0.0	0.5	3.1	8.9	17.9	8.3	26.3	24.0	21.3	13.3	14.7	12.8	20.2	20.9	8.4	9.8	11.4	1.9	1.1	1.9	229
Canterbury	3.0	0.0	0.0	0.0	1.0	3.0	0.2	2.6	7.7	14.6	18.5	16.0	19.6	18.2	16.2	18.9	20.7	16.7	7.3	4.2	10.6	4.2	5.7	4.6	213
Botany Bay	0.3	0.0	0.0	0.0	2.8	5.5	4.9	5.0	11.1	10.6	12.3	16.0	14.5	11.9	10.9	19.5	14.3	11.6	6.2	11.3	3.8	6.2	1.5	5.6	186
Holroyd	0.0	1.5	0.7	0.0	0.8	3.1	0.2	4.1	1.7	11.2	13.9	23.6	9.9	14.6	16.3	3.2	13.4	19.9	10.7	8.3	3.8	2.6	5.6	6.0	175
Rockdale	0.3	0.2	0.0	0.0	0.0	3.3	2.6	3.5	4.9	6.6	13.4	14.2	16.8	14.2	15.2	12.0	13.8	16.8	12.5	5.1	6.2	4.8	1.8	4.9	173
Willoughby	0.0	0.4	0.0	0.0	0.0	0.0	1.0	4.0	13.5	8.9	14.8	20.6	16.2	14.9	15.6	14.3	11.8	14.4	6.1	8.2	3.4	0.9	1.6	1.8	172
Auburn	0.0	3.9	0.3	3.8	0.0	1.9	3.0	5.7	9.7	7.5	13.7	19.2	13.2	17.6	15.9	6.7	10.8	8.7	9.9	1.5	3.7	3.9	5.4	1.6	167
Canada Bay	2.8	0.0	0.0	0.0	0.7	1.4	6.0	2.1	9.9	9.3	15.1	15.7	11.7	10.5	9.4	13.4	20.0	8.6	11.1	5.0	4.7	5.0	1.0	1.3	165
Hurstville	6.2	1.3	0.0	0.0	0.0	1.0	0.7	3.3	4.6	9.8	12.6	10.0	13.5	22.7	10.7	11.8	18.4	14.3	7.1	2.0	0.6	1.1	3.6	3.3	159
Kiama	0.0	0.0	0.0	0.0	0.0	1.6	4.6	2.0	4.1	6.2	17.6	15.3	21.5	9.1	2.5	12.2	25.5	10.8	0.0	1.1	2.5	2.8	0.0	0.0	140
Marrickville	1.5	0.0	1.3	0.0	0.0	0.3	0.0	2.4	3.7	8.8	11.7	11.9	13.6	9.5	13.4	11.4	14.2	4.7	7.9	8.3	6.0	1.2	4.4	0.7	137
North Sydney	2.9	1.4	0.0	0.0	0.0	0.0	1.3	5.9	3.8	4.8	17.0	6.3	13.5	9.2	12.2	13.1	8.6	9.3	6.9	7.3	3.6	0.0	2.4	2.9	132
Manly	0.0	1.7	0.0	0.0	0.0	0.0	1.6	1.8	13.6	11.2	12.7	13.2	9.7	6.0	7.4	11.9	12.4	4.2	10.3	5.8	0.4	3.1	0.2	0.4	128
Strathfield	1.7	0.0	0.0	0.0	0.0	0.5	7.7	3.7	9.7	5.7	11.3	11.8	8.9	8.6	8.1	4.1	7.5	0.6	1.6	2.9	0.3	2.6	3.8	0.6	102
Woollahra	0.6	0.3	0.3	0.0	0.0	0.0	0.0	4.5	2.5	6.1	5.9	9.4	20.0	6.0	5.2	5.1	5.1	12.7	7.7	3.5	2.8	0.8	1.6	0.0	100
Kogarah	2.6	1.7	1.6	0.0	0.8	0.4	0.1	2.4	1.2	3.6	6.9	7.4	10.6	7.4	4.1	9.1	7.9	7.4	4.2	4.5	1.6	3.6	0.4	0.6	90
Waverley	1.0	0.0	0.0	0.0	0.0	0.0	0.8	2.1	2.0	7.3	6.4	9.0	8.8	8.2	8.1	8.1	6.7	4.9	3.8	3.0	2.1	1.1	0.4	1.4	85
Leichhardt	0.0	0.0	0.0	0.0	0.2	0.2	2.4	2.1	4.4	3.0	5.2	10.8	5.8	4.5	6.6	2.8	10.4	5.3	4.8	2.2	2.7	0.9	1.1	2.8	78
Burwood	0.6	0.0	0.0	0.0	0.0	0.0	0.0	1.2	3.1	4.7	11.2	5.2	8.5	2.6	9.6	2.7	3.4	5.7	2.1	0.0	4.0	1.1	0.4	1.4	68
Lane Cove	0.3	0.0	0.0	0.0	0.0	0.0	1.0	0.9	4.3	4.3	3.2	9.4	6.6	11.8	2.1	2.4	5.1	3.9	4.3	1.0	3.3	0.2	1.5	0.2	66
Mosman	1.8	0.6	0.0	0.0	0.0	0.0	0.0	2.8	2.5	6.1	7.2	7.1	6.0	5.7	3.0	4.2	4.0	7.4	2.1	1.1	0.3	1.3	0.2	0.7	64
Ashfield	0.0	0.8	0.0	0.0	0.0	0.0	0.7	2.6	3.9	2.3	6.1	4.8	9.6	2.5	3.9	4.4	2.9	4.7	6.0	1.3	0.5	0.0	0.7	4.8	63
Wollondilly	0.0	0.0	0.0	0.0	0.0	1.7	0.0	2.0	2.3	0.0	2.1	11.4	5.9	3.6	4.3	1.7	2.2	4.2	0.0	0.0	0.0	2.0	0.0	3.9	47
Hunters Hill	0.0	0.0	0.0	0.0	0.0	0.0	0.5	1.4	0.0	2.5	2.1	2.1	1.4	0.7	1.4	3.0	5.9	3.6	1.4	1.5	1.3	0.0	0.0	0.0	29
Cessnock	0.0	0.0	2.8	0.0	0.0	1.7	0.0	0.0	0.0	0.9	0.0	2.5	4.5	4.9	0.0	1.7	0.0	0.8	0.0	0.0	0.0	0.0	6.1	0.0	26
Shoalhaven	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.6	0.0	0.0	0.0	2.3	3.6	0.0	0.0	0.0	0.0	2.0	0.0	0.0	0.0	0.0	0.0	0.0	12

Table 3.2-2. Spatiotemporal rise in electricity demand during an average weekend day for all-purpose vehicle trips under 35 km/trip (green-minimum, yellow–medium, red-maximum electricity demand-MWh)

3.2.2 Scenario-2 (commute vehicle trips only)

In scenario-2, the potential rise in spatiotemporal electric energy demand for commute vehicle trips during an average weekday and weekend day was evaluated. Due to limitations of the spatial information about vehicle trips following assumptions were made in addition to EV specifications assumed in Chapter-2;

i. Vehicle trips with the purpose of travel – commute (i.e. to work and back) were considered because spatial information of all non-commute vehicle trips was not available

ii. Vehicle trips with one side travel distance less than 35 km/trip were considered so that all EVs would return home without needing an intermediate recharge

3.2.2.1 Electric energy required

We have evaluated the aggregated rise in electric energy demand across 50 LGAs of NSW during key times of the day. **Fig. 3.2-2** summarised the rise in electric energy demand at different times of the day in 50 LGAs of NSW during **(a)** an average weekday and **(b)** average weekend day. The figures represent aggregated electric energy demand at respective destinations after the trip completion. The aggregated electric energy required to recharge after completing the trip were summarised in **Table 3.2-3** & **Table 3.2-4**.

Fig. 3.2-2 (a) shows that there were two clear peaks when trips were conducted during the weekday. Therefore, it could be evaluated that for weekday commute vehicle trips, EVs could potentially be recharged during the day when they were parked at work (provided a charging facility is available at the workplace). **Fig. 3.2-2 (b)** shows the electric energy demand for weekend commute trips. It is clear from the comparison of electric energy demands for weekday and weekend day that there is a specific pattern of vehicle trips for the weekday commute vehicle trips. Whereas, there is no specific pattern for weekend commute trips.

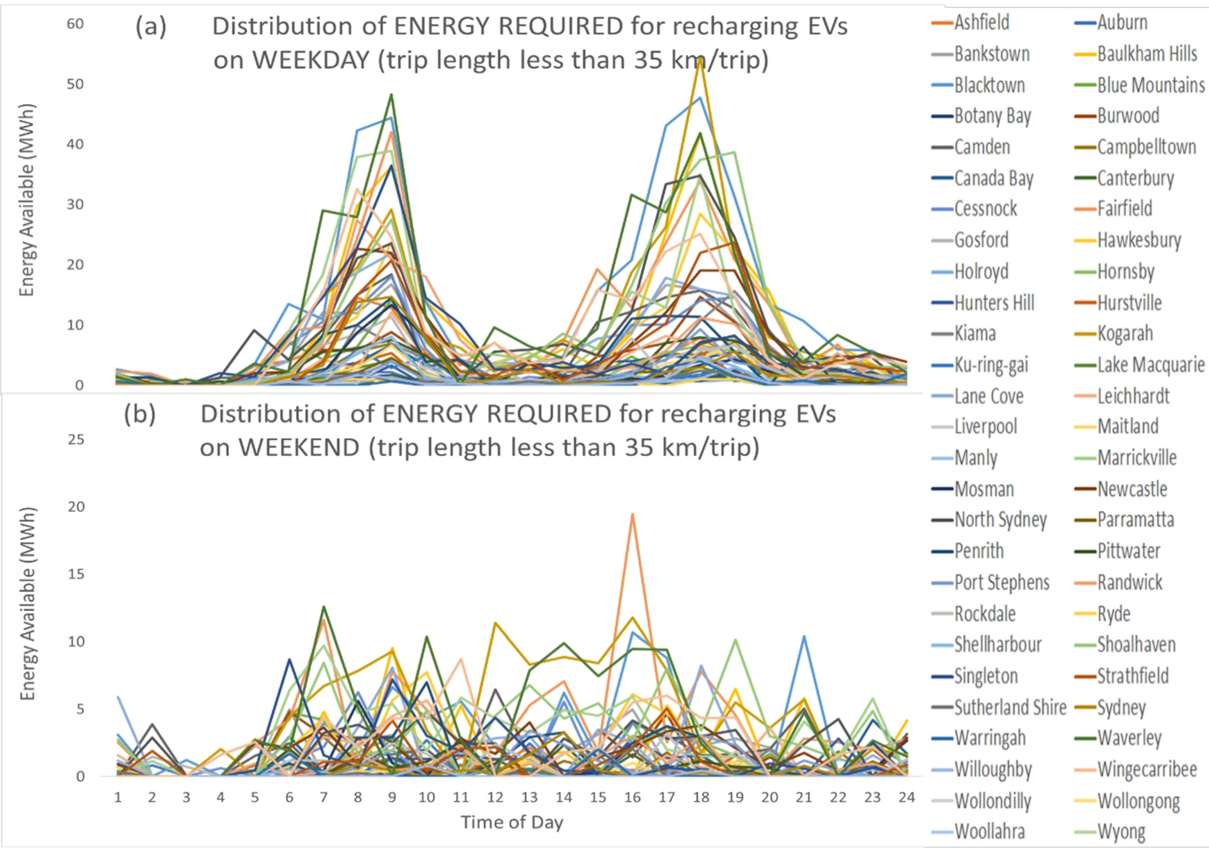

Fig. 3.2-2. Spatiotemporal rise in electricity demand during **(a)** an average weekday **(b)** average weekend day due to recharging of EVs for commute vehicle trips

Spatiotemporal distribution of aggregated ***ENERGY REQUIRED*** (MWh) to recharge EVs for ***WEEKDAY*** (commute trips ≤ 35 km/trip)

LGA	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Total
Blacktown	2.6	1.6	0.0	0.0	3.4	13.5	11.0	42.3	44.5	13.9	4.2	2.9	3.4	4.8	15.6	20.8	43.1	47.7	31.3	13.5	10.7	5.9	5.8	2.8	345
Wollongong	1.4	0.0	1.0	0.0	3.6	2.3	29.0	27.9	48.3	11.4	0.0	9.6	6.6	4.5	9.4	31.6	28.7	41.9	22.0	5.0	3.8	8.4	5.4	2.3	304
Gosford	2.3	1.9	0.0	0.0	2.3	9.0	9.7	24.4	42.1	11.0	3.3	7.1	2.4	7.2	19.3	12.9	23.6	33.9	20.8	13.4	3.0	6.8	1.2	1.6	259
Lake Macquarie	1.8	0.0	0.0	0.0	0.0	8.0	14.7	19.5	29.1	8.2	6.3	2.2	4.7	7.6	4.8	18.8	26.2	54.6	21.4	7.9	5.6	4.2	3.5	1.6	251
Sutherland Shire	1.9	0.0	0.0	0.0	0.5	2.0	7.6	18.7	27.5	8.1	5.1	5.1	4.3	8.6	6.0	16.5	30.2	37.4	38.7	13.6	4.4	3.8	3.0	3.0	246
Baulkham Hills	0.0	0.0	0.0	0.0	0.0	1.9	9.4	29.7	36.3	13.9	8.5	3.2	3.2	6.0	3.0	8.6	25.2	41.6	22.8	15.6	3.5	6.5	3.6	0.1	243
Penrith	1.6	0.0	0.0	1.3	9.1	4.2	9.2	21.1	23.6	7.7	0.8	5.6	5.9	6.8	5.0	12.1	33.4	34.8	24.6	8.9	3.8	4.8	4.6	0.0	229
Newcastle	0.7	0.6	0.0	0.5	0.0	8.9	18.4	37.9	38.9	7.1	2.4	3.4	5.4	2.0	6.2	15.5	12.8	35.0	12.1	3.9	2.1	1.9	1.7	0.5	218
Wyong	0.0	0.0	0.0	0.0	0.0	7.2	15.3	32.6	24.5	8.8	4.8	7.0	3.7	4.2	15.9	14.1	22.2	25.1	14.7	4.1	1.1	3.6	4.6	3.3	217
Hornsby	1.0	0.0	0.0	0.0	0.1	1.8	7.8	11.4	23.8	8.4	1.9	3.7	5.4	3.3	2.3	9.3	13.0	28.4	22.0	14.3	3.9	3.6	3.2	0.0	169
Liverpool	2.1	0.0	0.0	0.0	1.9	4.1	15.6	18.7	21.8	3.1	2.1	3.7	3.7	4.6	7.7	8.8	17.8	15.9	14.8	5.3	4.2	1.3	5.2	3.1	166
Parramatta	1.8	0.4	0.0	0.0	2.0	2.2	8.3	22.6	21.9	11.4	4.0	0.1	3.6	1.2	1.5	7.0	12.1	19.0	19.0	8.6	2.7	4.0	5.5	3.9	163
Sydney	0.0	0.0	0.0	2.0	1.4	8.2	14.6	22.8	36.4	14.5	10.2	2.6	2.6	3.9	1.9	3.6	1.9	7.1	8.2	3.7	3.1	2.6	1.2	0.0	153
Campbelltown	1.0	1.0	0.2	1.2	1.4	2.3	8.0	15.0	18.4	3.0	4.1	1.2	2.3	1.7	10.5	12.2	14.6	15.7	12.7	5.8	1.4	2.5	2.8	3.1	142
Warringah	0.4	0.0	0.0	0.0	0.0	0.0	3.9	14.9	20.7	8.5	2.3	1.5	4.0	0.8	3.4	6.4	10.3	22.0	23.7	6.1	2.6	4.2	3.0	2.2	141
Ryde	0.4	0.0	0.0	0.0	0.3	1.3	7.3	27.4	20.9	18.0	7.5	2.6	2.1	2.6	2.3	3.0	5.7	11.2	10.1	4.3	1.1	5.3	1.1	0.2	135
Bankstown	0.9	0.0	0.0	0.0	1.9	4.0	12.1	12.0	16.7	7.4	1.6	1.2	0.3	1.5	2.3	9.8	16.6	15.9	10.7	6.1	2.1	3.0	0.8	0.3	127
Fairfield	1.9	0.0	0.0	0.1	0.7	6.7	10.6	12.7	18.1	6.0	0.5	0.0	1.4	1.1	2.9	10.0	10.1	14.1	14.6	6.6	1.8	0.8	3.3	0.0	124
Port Stephens	1.3	1.3	0.0	0.0	1.2	0.0	8.4	10.0	14.5	3.9	4.2	0.0	3.8	2.9	3.3	11.1	11.5	11.4	5.6	0.0	6.4	0.0	0.0	0.0	101
Ku-ring-gai	0.0	0.6	0.6	0.0	0.0	0.2	0.7	10.0	6.9	4.4	4.2	1.0	2.6	2.3	2.7	2.9	4.2	10.6	15.6	9.3	1.7	2.0	1.6	1.2	85
Camden	0.0	0.0	0.0	0.4	0.7	1.8	5.9	5.8	8.8	5.0	0.9	1.7	0.4	0.4	4.8	5.8	7.0	14.7	10.5	2.8	2.0	2.4	0.0	0.4	82
Auburn	0.9	0.0	0.0	0.0	3.2	4.1	6.2	14.5	12.9	5.4	2.2	0.3	0.5	2.1	2.9	3.3	5.0	7.9	4.5	3.4	0.6	0.6	0.0	0.0	80
Randwick	1.3	0.0	0.0	0.7	0.0	2.2	5.5	6.2	7.6	4.9	1.2	0.2	0.3	2.7	1.8	1.3	7.0	8.0	7.4	5.2	1.7	1.5	2.2	0.0	69
Holroyd	0.0	0.0	0.0	0.0	1.7	2.5	6.7	8.5	11.3	2.2	0.0	3.0	0.5	0.3	0.9	2.4	4.3	6.2	4.5	4.0	1.5	4.1	2.4	0.0	67
Maitland	0.0	0.0	0.7	0.0	0.8	0.9	4.4	2.7	12.1	4.5	2.0	0.3	0.0	0.7	2.5	5.5	8.2	6.6	4.1	3.0	1.2	1.3	1.3	0.7	64
Willoughby	0.5	0.0	0.0	0.0	0.0	1.4	3.3	13.8	14.7	8.0	0.4	1.0	2.7	0.3	0.4	0.3	2.2	2.9	5.6	1.5	1.7	1.6	0.9	0.4	64
Botany Bay	0.0	0.0	0.0	0.0	2.4	7.1	4.3	6.4	14.2	3.9	0.0	1.7	0.5	0.9	1.4	4.8	1.8	4.9	1.8	1.2	1.8	0.0	0.3	0.9	60
North Sydney	0.0	0.0	0.0	0.0	0.0	0.5	2.0	8.8	13.3	8.0	1.2	1.0	0.3	1.4	0.5	1.0	1.6	3.4	4.3	2.3	1.5	0.4	0.4	0.5	52
Shellharbour	0.0	0.0	0.0	0.0	0.0	0.7	0.5	5.6	7.9	1.2	0.6	0.7	0.9	0.9	1.9	7.8	1.6	5.7	6.6	2.8	0.6	1.7	1.8	0.7	50
Canterbury	0.0	0.0	0.0	0.5	0.0	1.3	2.6	3.8	6.7	3.3	0.0	1.2	0.0	1.0	3.9	4.0	4.9	4.4	5.6	4.6	0.1	0.3	1.5	0.4	50
Canada Bay	0.1	0.0	0.0	0.0	0.2	1.5	2.4	5.6	6.9	2.0	0.5	0.1	0.7	1.6	0.9	0.9	5.3	5.1	7.1	1.5	1.4	1.3	0.2	0.1	46
Hurstville	0.0	0.0	0.2	0.2	0.2	0.0	0.5	3.7	5.3	0.3	0.6	1.6	0.4	0.6	0.8	3.5	5.4	6.6	5.7	6.0	0.7	0.5	1.2	0.3	44
Rockdale	0.5	0.0	0.0	0.0	1.0	1.4	1.6	1.5	3.9	0.9	1.4	0.4	0.4	0.6	1.1	2.0	4.3	9.3	3.9	2.9	1.2	1.4	1.6	1.7	43
Marrickville	0.0	1.3	0.0	0.0	0.2	1.8	1.9	2.9	6.6	1.8	0.3	0.3	0.1	1.3	0.2	1.3	3.6	4.4	6.9	1.5	0.7	0.4	0.3	0.0	38
Pittwater	0.0	0.4	0.0	0.0	0.0	0.3	1.5	2.1	4.6	1.1	0.4	0.7	0.6	0.6	0.5	2.2	2.2	6.9	8.3	2.7	0.6	0.9	0.3	0.8	38
Strathfield	0.5	0.0	0.0	0.0	0.7	0.0	2.0	5.2	8.1	1.2	0.4	0.8	0.2	0.0	0.6	1.6	0.8	4.8	3.2	0.3	0.5	0.2	0.0	0.0	31
Manly	0.0	0.0	0.0	0.4	0.0	0.0	0.4	0.5	4.0	2.9	0.7	0.0	0.2	0.8	1.5	2.0	2.2	4.0	7.9	0.8	1.3	0.2	0.2	0.6	31
Kogarah	0.5	0.0	0.0	0.0	0.0	0.3	0.5	3.8	5.4	0.6	0.5	0.4	0.1	0.1	0.4	1.5	1.1	5.6	1.8	2.0	0.7	0.8	0.0	0.0	26
Lane Cove	0.1	0.0	0.0	0.0	0.0	1.0	0.9	6.0	2.9	4.7	0.8	0.0	0.3	0.0	0.4	0.1	1.0	1.8	2.9	0.9	1.1	0.7	0.0	0.0	26
Leichhardt	0.0	0.0	0.0	0.0	0.6	0.3	1.3	2.9	4.2	1.5	0.0	1.4	0.2	0.3	0.4	0.1	1.2	3.1	1.3	2.4	0.0	0.0	0.0	0.2	21
Ashfield	0.0	0.0	0.0	0.0	0.0	1.3	1.0	2.2	2.2	0.2	0.8	0.1	0.2	0.2	1.0	0.3	1.6	1.3	4.7	1.4	0.1	0.4	1.5	0.3	21
Waverley	0.1	0.0	0.0	0.0	0.0	0.2	0.6	2.1	0.6	0.6	0.0	0.0	0.7	0.1	0.7	0.7	1.1	2.4	1.9	0.5	0.8	0.0	0.0	0.0	13
Woollahra	0.0	0.0	0.0	0.0	0.0	0.6	0.1	1.7	1.2	0.2	0.3	0.0	0.0	0.0	0.2	0.4	1.2	4.5	1.9	0.4	0.0	0.0	0.0	0.2	13
Wollondilly	0.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.0	4.0	1.5	0.0	0.8	0.0	0.0	1.9	13
Cessnock	0.0	0.0	0.0	0.0	0.0	1.0	0.4	0.0	1.7	0.8	0.0	1.0	0.8	0.9	0.0	1.0	1.1	2.5	0.7	0.8	0.0	0.0	0.0	0.0	13
Mosman	0.0	0.0	0.0	0.0	0.0	0.0	2.1	1.0	1.0	0.3	0.0	0.0	0.3	0.8	0.1	0.4	0.6	1.2	3.0	1.0	0.1	0.5	0.0	0.0	12
Kiama	0.0	0.0	0.0	0.0	0.0	0.2	0.7	0.8	3.3	0.0	0.0	0.0	0.0	1.9	0.0	0.0	1.4	0.7	1.9	0.0	0.0	0.0	0.5	0.7	12
Burwood	0.0	0.0	0.0	0.0	0.0	0.0	0.3	1.2	1.7	0.5	0.5	0.3	0.0	0.0	0.1	0.3	0.3	1.0	2.4	0.0	0.9	0.1	0.0	1.5	11
Shoalhaven	0.0	0.0	0.0	0.0	0.0	0.0	0.9	1.0	0.8	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	5
Hunters Hill	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.5	1.4	0.0	0.0	0.1	0.1	0.0	0.0	0.3	0.6	0.7	0.9	0.0	0.1	0.0	0.0	0.0	5

Table 3.2-3. Spatiotemporal rise in electricity demand during an average weekday for vehicle commute trips under 35 km/trip (green-minimum, yellow–medium, red-maximum electricity demand-MWh)

Spatiotemporal distribution of aggregated ***ENERGY REQUIRED*** (MWh) to recharge EVs for ***WEEKEND*** (commute trips ≤ 35 km/trip)

LGA	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Total
Lake Macquarie	0.0	0.0	0.0	2.0	0.0	4.4	6.7	7.8	9.3	3.5	0.0	11.4	8.3	8.9	8.4	11.8	7.9	1.8	5.5	3.6	5.7	0.0	2.0	1.6	111
Gosford	2.5	0.0	0.0	0.0	2.5	4.2	11.6	0.0	7.8	4.9	2.5	1.7	5.3	7.1	1.8	19.5	2.5	7.8	4.5	0.0	2.8	2.5	2.0	2.8	96
Wollongong	0.0	0.0	0.0	0.0	2.7	1.9	12.6	5.1	0.0	10.4	2.7	0.0	7.9	9.9	7.4	9.5	9.4	2.4	0.0	0.0	4.7	0.0	2.7	1.5	91
Sutherland Shire	2.7	0.0	0.0	0.0	0.0	2.9	8.4	1.6	2.0	4.9	0.0	4.5	6.8	4.3	5.4	2.7	8.0	3.4	10.1	3.0	2.2	1.2	4.9	0.0	79
Newcastle	0.0	1.2	0.0	0.0	0.0	6.4	9.7	4.7	5.4	1.9	5.9	4.3	3.2	4.9	4.5	5.9	2.0	1.5	1.4	0.0	4.1	1.5	5.8	0.0	74
Blacktown	3.1	0.0	1.2	0.0	0.5	0.0	3.9	2.1	6.6	4.3	5.6	2.2	0.0	6.2	1.2	10.7	8.8	0.0	0.0	0.0	10.4	0.0	2.5	0.9	70
Wyong	0.0	0.0	0.0	1.6	2.6	0.0	4.4	2.1	4.3	4.3	8.7	0.0	0.0	1.8	2.1	5.5	6.0	4.3	4.4	0.0	0.0	1.6	2.2	0.0	56
Baulkham Hills	0.0	0.0	0.0	0.0	2.8	0.0	4.8	0.0	9.5	0.0	5.2	0.0	1.6	1.8	0.0	0.0	5.2	1.3	6.5	0.0	5.8	0.0	0.0	4.1	49
Liverpool	5.9	0.0	0.0	0.0	2.3	0.9	0.0	3.6	8.1	0.0	2.0	2.8	3.0	0.0	3.5	2.5	0.0	8.2	2.4	0.0	0.7	0.0	1.6	0.2	48
Penrith	0.0	2.9	0.0	0.0	0.0	0.0	3.2	3.8	2.5	4.8	2.4	2.5	0.0	2.8	1.4	4.1	2.8	3.0	3.5	0.0	2.4	4.3	0.0	0.0	46
Campbelltown	0.0	3.9	0.0	0.0	1.5	2.5	0.0	1.6	1.7	2.0	0.0	6.5	1.5	0.0	0.0	2.9	3.1	1.6	1.7	2.0	5.0	0.0	0.0	3.2	40
Parramatta	0.9	0.0	0.0	0.0	2.5	2.1	3.6	0.8	2.4	0.2	2.8	1.7	4.0	0.0	1.4	2.2	3.4	3.8	2.1	0.7	1.8	0.4	0.0	2.9	40
Hornsby	0.0	0.0	0.0	0.0	0.0	2.1	4.4	0.0	5.7	7.7	1.6	0.0	1.1	0.0	2.0	6.1	4.7	2.5	0.9	0.0	0.0	0.0	0.0	0.0	39
Bankstown	0.7	0.0	0.0	0.0	0.0	5.0	0.0	2.8	3.1	0.7	0.8	1.3	0.0	1.7	3.1	5.0	0.8	2.3	2.8	2.1	0.3	1.3	0.8	0.0	34
Sydney	0.0	0.0	0.0	0.0	0.4	8.7	1.6	0.7	7.2	3.0	1.9	4.4	1.8	0.4	0.3	0.0	0.7	0.4	0.0	1.0	0.6	0.0	0.7	0.0	34
Port Stephens	0.0	0.0	0.0	0.0	0.0	1.0	0.0	2.9	2.9	7.0	0.0	1.0	2.9	3.3	0.0	2.5	3.7	2.9	0.0	0.0	0.0	0.0	2.5	0.0	32
Maitland	1.6	0.0	0.0	0.0	2.4	0.0	2.9	2.4	4.5	5.7	2.1	0.0	1.5	0.0	2.0	0.0	1.6	0.7	0.6	3.6	0.0	0.0	0.6	0.0	32
Fairfield	1.0	0.0	0.0	0.6	0.0	1.2	2.2	6.2	1.1	0.2	1.9	0.0	0.0	5.5	0.0	4.0	2.9	2.6	1.5	0.0	0.0	0.0	0.0	1.1	32
Camden	0.0	0.0	0.0	0.0	0.0	4.8	3.0	2.9	0.0	1.1	2.5	0.0	1.8	0.0	3.5	1.4	4.7	0.0	0.0	1.4	0.0	0.0	2.0	0.0	29
Warringah	0.0	1.9	0.0	0.0	0.0	0.0	1.1	1.1	4.1	0.4	2.1	2.2	0.0	0.0	0.9	2.2	5.0	1.1	0.0	0.0	0.0	0.0	0.0	0.9	23
Botany Bay	0.0	0.0	0.0	0.0	0.0	4.8	4.2	0.5	2.8	0.0	0.0	0.0	0.6	0.0	0.0	4.0	0.0	1.5	0.0	1.7	0.0	0.0	0.0	0.4	20
Rockdale	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.6	2.0	0.0	0.0	0.6	3.4	2.4	1.2	0.4	0.0	3.1	2.3	0.0	1.2	0.4	0.0	0.0	18
Shellharbour	0.0	0.0	0.0	0.0	0.0	1.2	1.2	0.9	2.5	1.7	0.0	2.4	1.2	0.0	2.2	0.0	3.2	0.0	0.0	0.0	0.0	0.0	0.0	1.3	18
Ryde	0.0	0.0	0.0	0.0	1.0	0.0	0.4	1.6	0.4	0.7	2.3	0.0	0.9	0.0	1.5	3.0	1.0	3.0	0.0	0.0	0.0	0.5	1.0	0.0	17
Kiama	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.3	1.3	1.6	1.3	1.3	0.0	0.0	2.7	1.4	1.6	0.0	0.0	0.0	2.8	0.0	0.0	15
Hurstville	0.4	0.0	0.0	0.0	0.0	0.9	0.0	2.3	0.0	0.0	0.0	0.0	0.0	0.0	0.4	2.1	3.7	2.5	1.5	0.0	0.0	0.0	0.0	0.0	14
North Sydney	0.0	0.0	0.0	0.0	0.0	0.0	0.4	5.6	1.0	0.0	2.9	0.0	0.0	0.0	0.3	0.0	0.0	0.4	0.0	0.0	0.0	0.0	0.5	2.7	14
Canterbury	0.0	0.0	0.0	0.0	0.0	3.0	0.2	0.2	1.3	0.6	0.0	0.0	0.0	0.0	0.6	0.0	0.2	0.6	0.4	0.3	0.6	0.0	4.2	1.7	14
Auburn	0.0	0.0	0.0	0.0	0.0	0.0	0.8	1.8	2.9	0.0	1.5	0.9	2.1	0.0	0.0	0.5	0.0	0.3	0.7	0.0	0.0	0.0	0.7	0.0	12
Canada Bay	0.0	0.0	0.0	0.0	0.0	0.6	2.9	0.7	1.4	0.0	0.0	0.0	0.0	1.2	0.5	0.0	1.8	0.0	0.2	0.0	0.0	1.8	0.0	0.5	12
Randwick	0.0	0.0	0.0	0.0	0.0	2.0	0.0	1.7	0.6	1.1	2.6	0.0	0.0	0.0	0.0	0.0	0.7	1.1	0.7	0.6	0.0	0.0	0.0	0.0	11
Holroyd	0.0	1.5	0.7	0.0	0.0	1.9	0.0	1.1	0.0	0.0	0.0	0.0	0.2	0.0	0.1	0.3	0.0	0.2	1.1	1.9	0.0	0.3	0.0	0.6	10
Willoughby	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.9	0.4	0.0	0.5	0.4	1.6	3.3	0.5	0.0	0.0	0.3	0.0	0.0	0.8	0.0	0.0	0.3	9
Ku-ring-gai	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.6	0.0	0.7	0.8	0.0	0.0	0.0	1.5	0.0	0.0	0.0	0.0	2.0	0.0	0.0	0.0	0.7	7
Pittwater	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.3	0.6	0.6	0.0	1.3	0.0	0.0	0.0	0.0	0.6	1.2	0.6	0.0	0.0	0.0	1.1	0.0	7
Marrickville	0.7	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.4	0.9	0.0	0.0	1.4	0.0	0.0	1.0	0.0	0.0	1.1	0.0	0.0	0.0	0.0	0.0	6
Kogarah	0.0	0.0	0.0	0.0	0.8	0.0	0.1	0.2	0.0	0.0	0.8	0.7	0.0	0.0	0.0	0.0	0.4	0.0	1.5	0.0	0.2	0.0	0.0	0.0	5
Lane Cove	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.7	0.0	0.0	0.4	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.3	0.0	0.8	0.2	5
Cessnock	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.3	0.0	1.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4
Manly	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.1	0.0	0.0	0.0	1.9	0.0	0.0	0.0	0.0	0.0	4
Wollondilly	0.0	0.0	0.0	0.0	0.0	1.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4
Ashfield	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.4	0.0	0.0	0.0	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4
Waverley	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.9	0.0	0.0	0.0	0.0	0.0	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3
Strathfield	1.2	0.0	0.0	0.0	0.0	0.5	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.6	0.0	0.0	0.0	0.0	0.0	0.5	0.0	3
Burwood	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.9	0.0	0.2	0.0	0.0	0.0	0.0	0.3	2
Leichhardt	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.6	0.0	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.0	0.0	0.0	1
Woollahra	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.0	0.0	0.0	1
Mosman	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1
Hunters Hill	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.0	0.0	1
Shoalhaven	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0

Table 3.2-4. Spatiotemporal rise in electricity demand during an average weekend day for vehicle commute trips under 35 km/trip (green-minimum, yellow–medium, red-maximum electricity demand-MWh)

Table 3.2-5 show a comparison between the aggregated rise in electric energy demand, average electric energy consumption and population density across 35 LGAs of NSW. The aggregated rise in electric energy demand was calculated based on recharging of EVs after completion of round trip vehicle commute for average weekday and weekend day. The analysis identified 09 LGAs where the rise in electric energy demand would increase by more than 10% of current electric energy consumption. Based on the analysis of 35 LGAs it could be inferred that if 82% of the weekday and 81% of the weekend vehicle commute trips were conducted using commonly available EVs, then there would be an aggregated increase in electric energy demand per day of 8% compared to current electric energy consumption.

S.No.	LGA	Population Density	ACTUAL CONSUMPTION	Commute Energy Req			
				Weekday	Weekend	Weighted Avg	perc(%) of consumption
		people/sq.km	MWh/day	MWh/day	MWh/day	MWh/day	%
1	LAKE MACQUARIE	304	2,328	501	221	421	18%
2	GOSFORD	179	2,456	518	193	425	17%
3	PORT STEPHENS	78	980	202	65	163	17%
4	WYONG	209	2,087	434	112	342	16%
5	NEWCASTLE	833	2,243	436	149	354	16%
6	HORNSBY	354	1,843	337	77	263	14%
7	BOTANY BAY	1,914	808	121	41	98	12%
8	MAITLAND	179	956	127	64	109	11%
9	WARRINGAH	994	1,894	282	46	214	11%
10	RYDE	2,686	2,219	269	35	202	9%
11	KU-RING-GAI	1,342	1,433	171	15	126	9%
12	MANLY	2,983	541	61	8	46	9%
13	HURSTVILLE	3,644	911	89	28	71	8%
14	PITTWATER	669	756	75	14	58	8%
15	ASHFIELD	5,258	425	41	7	32	7%
16	ROCKDALE	3,667	965	86	35	72	7%
17	BANKSTOWN	2,485	2,789	255	69	202	7%
18	LANE COVE	3,171	547	51	9	39	7%
19	STRATHFIELD	2,679	657	63	7	47	7%
20	RANDWICK	3,793	1,558	138	22	105	7%
21	CANADA BAY	4,025	1,085	91	23	72	7%
22	AUBURN	2,395	1,888	161	24	122	6%
23	CANTERBURY	4,323	1,293	100	28	79	6%
24	KOGARAH	3,789	669	52	9	40	6%
25	WILLOUGHBY	3,172	1,639	127	18	96	6%
26	NORTH SYDNEY	6,374	1,490	105	28	83	6%
27	MARRICKVILLE	4,911	1,038	76	12	57	6%
28	MOSMAN	3,393	379	25	2	18	5%
29	LEICHHARDT	5,274	656	43	3	31	5%
30	HUNTERS HILL	2,431	193	10	1	7	4%
31	BURWOOD	4,795	523	22	4	17	3%
32	CESSNOCK	27	733	25	8	20	3%
33	SYDNEY	6,858	9,915	305	67	237	2%
34	WAVERLEY	7,432	915	26	7	21	2%
35	WOOLLAHRA	4,589	848	26	3	19	2%

Table 3.2-5. Comparison of actual electricity consumption and rise in electricity demand due to EV recharging for all commute trips less than 35 km/trip

Fig. 3.2-3 show the relation between the rise in electric energy demand and population density. It is clear by comparing **Fig. 3.2-3 (a)** & **(b)** that rise in electric energy demand was higher in regions where population density is low. This is because people travel large distances for the commute (i.e. home to work and back) using private vehicles since public train networks are limited in regions with low population density. The average commute distance in 09 LGAs (highlighted in **Table 3.2-5**) was 24.3 km/trip for weekday and 24.2 km/trip for the weekend day. Whereas, the average commute distance in other 41 LGAs was 15.9 km/trip during a weekday and 15.2 km/trip for an average weekend day.

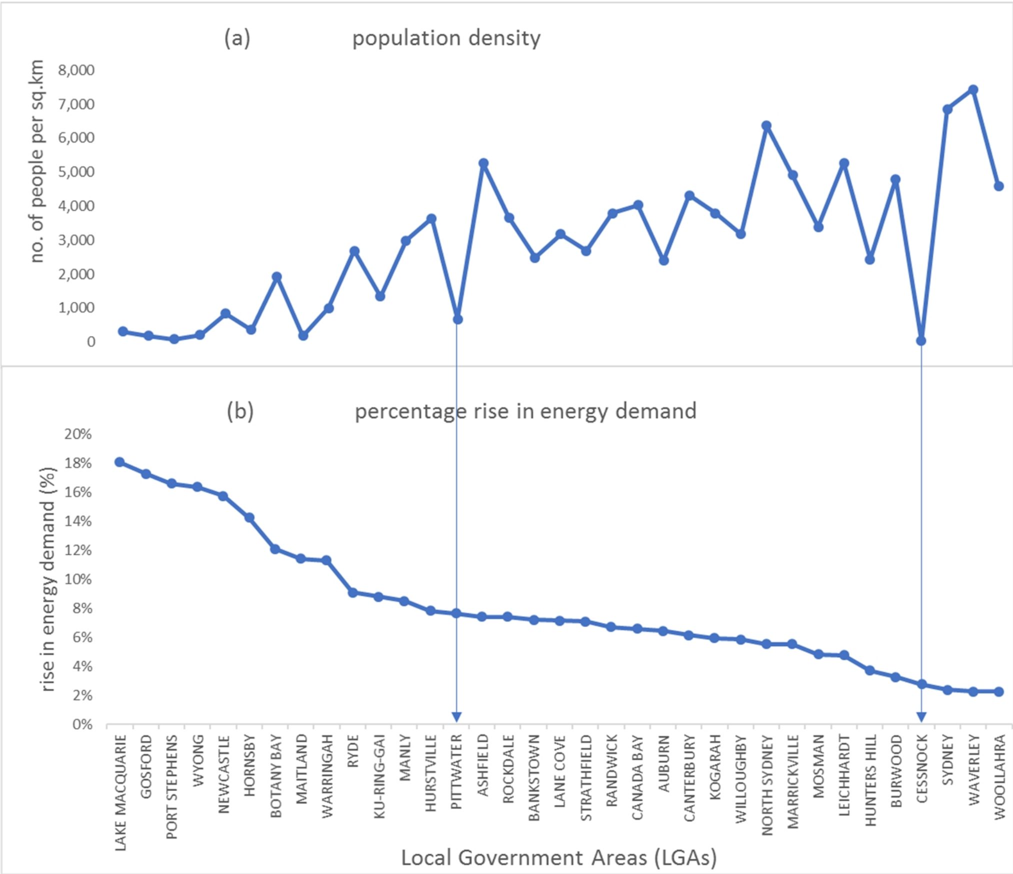

Fig. 3.2-3. (a) region-wise population density **(b)** region-wise rise in electricity demand as percentage of average electricity consumption

Cessnock (an LGA) appeared as an exception, which contradicts with the above estimations. Here, the population density and potential rise in energy demand due to recharging of EVs, both were low. The reason being, we have only considered vehicle trips with trip length less than 35 km/trip. Whereas, the length of average vehicle commute trip to Cessnock was 46.6 km/trip for a weekday and 44.6 km/trip for a weekend day. Only 15% of the total weekday commute vehicle trips were less than 35 km/trip with an average of 25.9 km/trip. Whereas 16% of the total weekend commute vehicle trips were less than 35 km/trip with an average of 25.9 km/trip, the majority of the trips were excluded from analysis.

Similarly, Pittwater (an LGA) do not follow the above-established relation between the rise in energy demand and population density. Here, the population density is low but rise in energy demand was high. The dataset shows that 88% of the weekday and 100% of the weekend vehicle commute trips were less than 35 km/trip. The average trip length for all vehicle commute trips to Pittwater was 21.6 km/trip on a weekday and 13.4 km/trip on a weekend. Despite having low population density, the majority of the trips were conducted in nearby regions, unlike other local government areas which have low population density and travel far distances for the commute.

It could be evaluated that the potential rise in electric energy in 09 out of 35 LGAs would exceed 10% of the current electric energy consumption for 82% of weekday and 81% of weekend commute vehicles trips (trip lengths less than 35 km/trip) if these trips were conducted with commonly available EVs (highlighted in **Table 3.2-5**).

3.2.2.2 Electric energy available

Besides charge scheduling, peak shaving and/or upgrading the electric power network, one of the potential solutions for increased electric energy demand could be the utilisation of available electric energy in terms of remaining SOC of EV batteries. The available electric energy could be transferred to nearby EVs and/or the power grid, using the available electric power distribution infrastructure. Based on similar analysis and assumptions, we have estimated the amount of electric energy available for V2X operations.

We have estimated the aggregated electric energy available across 50 LGAs of NSW during key times of the day. **Fig. 3.2-4** summarised the potential spatiotemporal electric energy available for V2X operations during **(a)** an average weekday and **(b)** average weekend day. The figures represent aggregated electric energy available at respective destinations after the trip completion. Specific details of the summarised graphs in **Fig. 3.2-4** were presented in **Table 3.2-6** & **Table 3.2-7** for aggregated spatiotemporal electric energy available during an average weekday and weekend day respectively. The spatiotemporal aggregated values of electric energy available in respective LGAs were calculated based on following considerations,

i. EV batteries would not discharge below 20% SOC
ii. Available electric energy was calculated after considering energy consumption of round trip by EVs (trip lengths less than 35 km/trip)

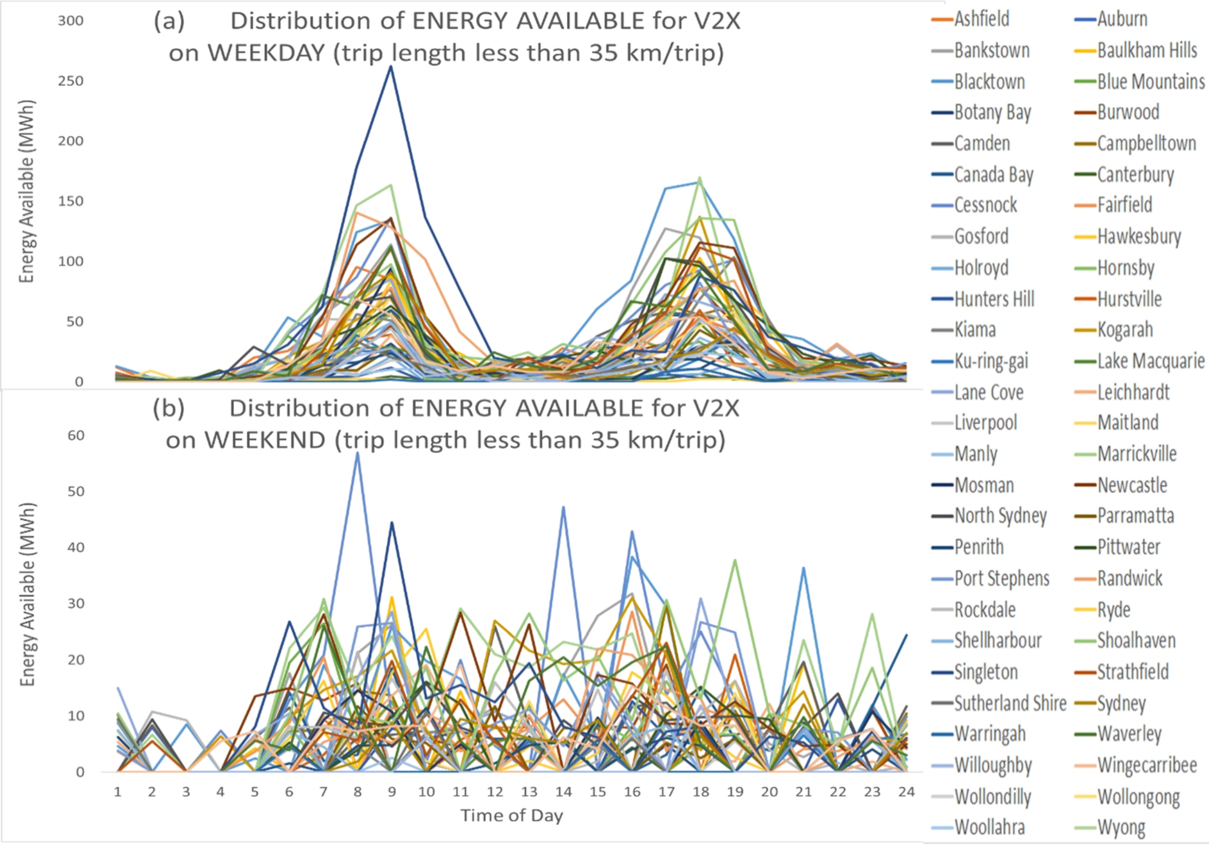

Fig. 3.2-4. Spatiotemporal electricity available during **(a)** an average weekday **(b)** average weekend day for V2X operations of commute vehicle trips

Spatiotemporal distribution of aggregated ***ENERGY AVAILABLE*** (MWh) for V2X on ***WEEKDAY*** (commute trips ≤ 35 km/trip)

LGA	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Total
Blacktown	12.8	4.0	0.0	0.0	11.7	53.4	37.4	124.2	134.4	52.0	12.1	14.1	14.2	24.3	60.4	84.0	160.3	165.5	118.6	41.4	35.4	18.8	24.0	8.7	1212
Sydney	0.0	0.0	0.0	7.2	15.3	30.8	62.3	178.1	262.2	136.7	77.1	20.1	14.4	22.5	11.3	26.0	24.5	87.9	76.2	37.2	28.2	18.9	14.6	0.0	1152
Newcastle	3.9	3.7	0.0	3.0	0.0	41.7	72.9	146.6	163.4	34.5	11.4	16.2	24.6	8.0	17.5	67.4	61.6	169.6	65.3	18.9	12.3	11.3	9.7	3.1	967
Parramatta	5.3	1.9	0.0	0.8	4.4	7.9	53.6	113.6	135.7	54.3	20.0	1.5	20.5	10.0	10.8	47.6	68.1	115.5	111.2	47.0	19.5	17.9	18.7	13.2	899
Sutherland Shire	4.2	0.0	0.0	0.0	1.9	8.1	27.3	76.0	97.6	30.9	20.7	18.0	14.9	31.3	25.9	64.1	107.8	135.9	134.4	44.4	17.3	14.0	9.4	11.1	895
Ryde	4.6	0.0	0.0	0.0	2.5	3.2	34.9	140.4	128.4	101.6	41.8	16.0	17.4	12.4	19.2	22.9	56.4	76.7	84.0	30.6	9.8	31.9	11.1	2.2	848
Fairfield	2.8	0.0	0.0	1.2	4.5	40.0	62.5	87.2	136.3	36.2	4.3	0.0	6.6	9.3	28.8	53.7	80.2	92.7	101.4	45.3	16.1	9.4	15.6	0.0	834
Bankstown	6.5	0.0	0.0	0.0	10.8	19.9	55.0	76.3	114.0	38.8	10.4	11.2	3.5	9.0	8.1	74.9	127.2	119.9	62.3	31.4	7.4	20.4	5.4	1.6	814
Warringah	2.6	0.0	0.0	0.0	0.0	0.0	25.1	70.0	110.4	45.3	9.3	8.7	20.2	5.5	15.0	38.6	56.7	111.5	101.3	23.6	8.7	15.3	10.5	11.8	690
Penrith	5.2	0.0	0.0	2.0	28.9	14.0	28.0	66.3	70.5	23.3	2.7	16.9	19.3	21.1	15.6	36.6	102.5	99.4	68.8	27.8	9.5	13.8	13.9	0.0	686
Wollongong	2.9	0.0	2.0	0.0	8.9	4.7	72.1	61.4	112.2	26.3	0.0	24.5	13.5	9.2	19.4	66.7	62.5	90.8	50.4	10.3	8.6	18.6	11.1	4.7	681
Liverpool	6.0	0.0	0.0	0.0	11.6	19.5	69.9	70.4	85.2	14.4	9.1	13.4	19.6	22.0	37.1	33.0	72.8	66.5	57.0	17.9	15.1	6.3	19.7	12.5	679
Randwick	2.1	0.0	0.0	9.5	0.0	10.9	34.3	45.0	62.8	39.0	16.7	3.5	3.7	20.9	26.1	16.6	102.5	95.9	67.8	46.7	23.5	14.5	21.8	0.0	664
Lake Macquarie	4.7	0.0	0.0	0.0	0.0	21.1	33.8	51.7	68.8	21.1	15.6	5.1	10.8	19.3	11.0	44.2	65.7	137.0	51.6	18.1	13.3	9.9	7.6	3.4	614
Auburn	12.2	0.0	0.0	0.0	20.0	25.7	47.8	95.5	85.3	46.2	13.5	2.3	4.5	27.9	18.2	37.5	26.6	53.3	42.2	30.2	8.3	9.8	0.0	0.0	607
Baulkham Hills	0.0	0.0	0.0	0.0	0.0	5.3	17.1	64.7	88.1	33.0	23.7	7.8	10.5	16.8	7.2	22.6	57.4	102.7	56.7	41.0	7.2	14.4	9.2	0.4	586
Hornsby	1.6	0.0	0.0	0.0	0.6	5.6	24.7	35.6	83.7	29.3	5.7	13.2	17.6	10.9	7.1	32.8	45.6	99.7	75.6	50.1	16.5	11.5	10.1	0.0	577
Campbelltown	3.8	4.1	0.4	2.0	5.2	10.6	31.6	64.8	76.5	12.3	16.7	5.8	9.2	6.7	37.6	50.5	58.1	54.9	49.3	21.4	5.8	6.9	11.4	12.6	558
Holroyd	0.0	0.0	0.0	0.0	13.9	18.7	52.3	51.3	70.4	23.1	0.0	15.6	2.2	4.2	7.7	26.0	48.0	57.8	49.4	23.8	10.5	29.7	8.1	0.0	513
Ku-ring-gai	0.0	1.5	1.9	0.0	0.0	2.7	3.3	56.3	50.8	28.8	15.3	5.0	10.6	16.3	7.4	23.5	25.4	68.4	103.7	51.9	7.4	9.7	6.6	4.0	501
Wyong	0.0	0.0	0.0	0.0	0.0	13.7	33.9	68.9	55.4	17.8	9.2	13.3	8.1	8.5	32.8	30.3	51.0	53.8	32.4	7.8	2.6	7.0	10.9	9.3	467
Canada Bay	4.5	0.0	0.0	0.0	4.3	9.3	20.8	30.3	59.1	24.8	3.2	3.3	4.2	16.8	10.6	21.5	63.8	55.6	62.8	19.8	9.8	12.2	4.3	4.3	445
Gosford	3.4	2.8	0.0	0.0	4.3	15.7	18.3	42.0	78.3	17.6	4.9	10.4	3.5	13.8	29.2	21.6	45.1	57.9	33.5	19.7	5.5	10.0	1.7	2.4	442
Hurstville	0.0	0.0	3.6	3.6	3.6	0.0	6.2	41.7	55.5	2.5	1.9	11.0	9.4	9.2	5.4	37.9	52.8	76.8	58.4	27.4	14.8	4.6	4.8	5.1	436
Canterbury	0.0	0.0	0.0	3.8	0.0	10.8	22.9	41.7	59.7	36.0	0.0	4.4	0.0	8.0	26.7	31.3	55.9	53.8	28.5	23.8	3.8	3.5	9.5	4.2	428
Willoughby	3.2	0.0	0.0	0.0	0.0	5.8	14.4	70.4	90.5	54.6	5.5	9.8	10.6	3.5	2.7	6.8	19.9	25.3	44.8	21.4	6.1	12.4	5.4	8.9	422
Camden	0.0	0.0	0.0	3.1	3.9	7.6	26.9	24.3	46.4	19.8	4.7	7.5	2.4	2.3	20.6	24.8	31.7	77.7	48.5	18.3	7.6	9.1	0.0	2.3	389
Rockdale	2.4	0.0	0.0	0.0	8.1	8.4	17.2	21.7	49.3	9.3	17.3	2.4	6.1	6.8	9.4	15.9	32.7	82.3	34.0	24.9	6.8	10.6	7.3	15.7	388
Botany Bay	0.0	0.0	0.0	0.0	6.9	38.2	19.6	44.7	72.0	28.4	0.0	3.7	7.2	12.3	10.1	36.6	27.7	33.2	13.9	6.3	10.7	0.0	0.7	8.9	381
Marrickville	0.0	9.3	0.0	0.0	1.0	18.5	12.4	32.4	70.6	16.4	5.3	3.0	1.0	8.9	5.5	13.2	29.2	46.5	58.1	11.9	11.0	12.8	7.7	0.0	375
North Sydney	0.0	0.0	0.0	0.0	0.0	3.1	13.5	45.5	94.1	36.1	5.2	7.2	7.5	12.4	2.3	1.7	17.5	29.8	33.0	12.7	8.0	7.4	4.8	6.4	348
Kogarah	7.5	0.0	0.0	0.0	0.0	2.3	6.3	34.4	39.3	7.4	5.7	4.0	3.1	3.7	5.9	24.7	17.4	59.7	15.2	14.1	10.2	3.4	0.0	0.0	264
Shellharbour	0.0	0.0	0.0	0.0	0.0	2.7	3.6	25.1	44.1	8.5	3.4	2.7	3.6	5.9	10.7	40.7	7.5	30.0	30.8	12.4	4.3	7.3	10.3	4.5	258
Strathfield	3.0	0.0	0.0	0.0	1.9	0.0	19.2	33.5	48.9	14.7	7.0	10.0	3.4	0.0	5.6	20.2	6.9	36.4	24.6	3.3	5.0	7.8	0.0	0.0	251
Waverley	4.5	0.0	0.0	0.0	0.0	4.5	4.3	33.5	20.4	13.5	0.0	0.0	15.6	4.0	6.7	13.0	16.0	27.9	40.2	10.1	12.3	0.0	0.0	0.0	226
Leichhardt	0.0	0.0	0.0	0.0	2.2	2.0	8.7	28.1	29.0	20.6	0.0	6.0	6.1	6.0	2.8	3.1	13.6	48.7	22.4	18.9	0.0	0.0	0.0	4.0	222
Ashfield	0.0	0.0	0.0	0.0	0.0	3.4	7.6	25.5	25.7	3.4	3.9	4.1	5.7	6.1	7.9	8.9	32.0	19.4	37.2	6.9	2.6	6.5	9.2	2.1	218
Maitland	0.0	0.0	2.3	0.0	2.9	2.9	12.9	8.3	38.5	14.3	6.9	0.9	0.0	2.4	8.4	17.4	25.9	22.4	13.9	9.5	4.2	4.5	4.5	2.4	205
Woollahra	0.0	0.0	0.0	0.0	0.0	3.4	4.0	21.6	28.1	4.8	7.7	0.0	0.0	0.0	5.3	9.5	16.4	51.3	38.9	7.4	0.0	0.0	0.0	4.5	203
Pittwater	0.0	1.9	0.0	0.0	0.0	1.3	9.8	9.4	27.9	7.8	3.8	3.5	3.8	5.3	4.8	12.0	11.0	43.1	27.6	13.0	3.4	4.7	2.6	1.9	199
Lane Cove	2.3	0.0	0.0	0.0	0.0	6.8	2.0	39.0	23.0	21.4	2.3	0.0	2.5	0.0	6.7	3.3	6.7	19.4	40.8	9.3	4.6	3.6	0.0	0.0	194
Manly	0.0	0.0	0.0	2.8	0.0	0.0	10.0	5.2	17.7	17.4	2.2	0.0	4.3	6.2	10.3	11.0	11.7	22.2	40.7	7.3	3.3	5.2	4.3	2.8	185
Port Stephens	2.1	2.1	0.0	0.0	2.0	0.0	13.7	16.3	23.7	6.4	6.9	0.0	6.2	4.7	5.4	18.0	18.7	18.6	9.1	0.0	10.4	0.0	0.0	0.0	164
Burwood	0.0	0.0	0.0	0.0	0.0	0.0	2.5	15.0	31.7	7.6	3.0	3.2	0.0	1.6	2.9	12.1	9.4	10.5	26.4	0.0	7.0	2.6	0.0	7.1	143
Mosman	0.0	0.0	0.0	0.0	0.0	0.0	9.8	6.3	10.4	10.9	0.0	0.0	5.9	4.3	3.2	10.2	13.3	24.6	21.7	4.9	3.2	2.2	0.0	0.0	131
Hunters Hill	0.0	0.0	0.0	0.0	0.0	1.4	1.8	5.2	20.9	0.0	0.0	3.0	2.2	0.0	0.0	4.3	5.3	6.5	15.3	0.0	0.9	0.0	0.0	0.0	67
Kiama	0.0	0.0	0.0	0.0	0.0	1.1	4.0	4.7	11.9	0.0	0.0	0.0	0.0	8.8	0.0	0.0	6.6	3.3	4.4	0.0	0.0	0.0	2.5	3.3	50
Wollondilly	1.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	8.5	11.1	4.3	0.0	2.3	0.0	0.0	5.3	35
Cessnock	0.0	0.0	0.0	0.0	0.0	2.8	0.9	0.0	4.5	2.1	0.0	2.6	2.2	2.3	0.0	2.6	2.8	6.5	1.9	2.1	0.0	0.0	0.0	0.0	33
Shoalhaven	0.0	0.0	0.0	0.0	0.0	0.0	2.1	2.4	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.9	0.0	2.4	2.4	0.0	0.0	0.0	0.0	0.0	12

Table 3.2-6. Spatiotemporal electricity available during an average weekday for vehicle commute trips under 35 km/trip (red-minimum, yellow–medium, green-maximum electricity available-MWh)

Spatiotemporal distribution of aggregated ***ENERGY AVAILABLE*** (MWh) for V2X on ***WEEKEND*** (commute trips ≤ 35 km/trip)

LGA	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Total
Newcastle	0.0	6.6	0.0	0.0	0.0	22.1	29.3	14.9	24.2	11.1	29.2	21.0	18.6	23.3	21.9	24.7	6.3	4.7	8.4	0.0	23.5	4.6	28.1	0.0	323
Sutherland Shire	10.5	0.0	0.0	0.0	0.0	10.0	30.8	10.1	8.7	18.6	0.0	17.3	28.2	16.4	20.7	9.2	30.7	13.0	37.8	10.4	8.4	4.8	18.6	0.0	304
Fairfield	8.7	0.0	0.0	7.4	0.0	12.8	20.8	57.0	9.8	1.7	20.0	0.0	0.0	47.3	0.0	42.9	13.7	25.0	13.0	0.0	0.0	0.0	0.0	9.8	290
Lake Macquarie	0.0	0.0	0.0	6.4	0.0	9.7	14.6	17.0	21.7	7.5	0.0	26.9	21.7	19.3	20.0	31.0	20.9	3.9	11.9	7.8	14.4	0.0	6.4	5.1	266
Blacktown	4.7	0.0	8.5	0.0	2.4	0.0	19.1	7.9	26.0	19.9	16.6	4.7	0.0	17.5	5.9	38.3	29.5	0.0	0.0	0.0	36.4	0.0	11.9	2.2	251
Parramatta	10.2	0.0	0.0	0.0	13.5	15.0	28.1	10.4	4.5	10.2	28.4	9.1	26.3	0.0	17.3	15.8	8.6	8.5	12.5	7.7	4.6	4.8	0.0	4.9	240
Bankstown	9.2	0.0	0.0	0.0	0.0	17.6	0.0	21.2	26.2	6.8	8.3	11.5	0.0	17.2	27.8	31.8	8.3	4.8	13.7	5.1	2.7	6.0	7.7	0.0	226
Sydney	0.0	0.0	0.0	0.0	8.1	26.8	11.4	7.3	44.5	13.1	15.5	12.4	19.4	8.1	6.1	0.0	7.2	8.1	0.0	6.3	5.2	0.0	7.2	0.0	207
Wollongong	0.0	0.0	0.0	0.0	5.6	3.9	26.0	10.6	0.0	22.3	5.5	0.0	16.3	20.5	15.4	19.6	22.4	5.0	0.0	0.0	9.8	0.0	5.5	3.0	191
Liverpool	15.0	0.0	0.0	0.0	6.6	10.4	0.0	16.7	28.5	0.0	8.3	10.8	8.2	0.0	17.8	8.5	0.0	30.9	9.8	0.0	8.1	0.0	6.4	0.8	187
Rockdale	3.8	0.0	0.0	0.0	0.0	0.0	0.0	25.9	26.6	0.0	0.0	8.7	11.2	4.6	16.7	7.0	0.0	26.7	24.8	0.0	7.7	7.0	0.0	0.0	171
Gosford	3.7	0.0	0.0	0.0	3.6	8.8	20.5	0.0	11.4	10.9	3.7	5.0	7.8	13.0	5.4	28.6	3.7	11.4	9.3	0.0	4.1	3.7	5.8	4.1	164
Campbelltown	0.0	8.3	0.0	0.0	6.1	11.5	0.0	6.3	6.6	7.4	0.0	25.9	8.2	0.0	0.0	11.6	12.4	6.3	6.6	8.1	19.6	0.0	0.0	11.7	157
Penrith	0.0	9.4	0.0	0.0	0.0	0.0	10.6	8.9	8.3	15.8	7.9	5.8	0.0	9.2	4.7	13.6	9.2	9.8	9.9	0.0	7.9	14.0	0.0	0.0	145
Ryde	0.0	0.0	0.0	0.0	6.3	0.0	5.3	7.6	5.2	10.5	7.5	0.0	10.2	0.0	22.0	20.9	14.6	13.1	0.0	0.0	0.0	2.6	6.3	0.0	132
Wyong	0.0	0.0	0.0	5.5	7.3	0.0	8.4	7.3	8.2	8.3	19.1	0.0	0.0	6.1	4.1	15.3	11.5	8.3	8.4	0.0	0.0	5.5	7.6	0.0	131
Baulkham Hills	0.0	0.0	0.0	0.0	4.2	0.0	7.2	0.0	31.1	0.0	14.4	0.0	4.7	5.4	0.0	0.0	10.5	4.4	16.2	0.0	19.3	0.0	0.0	9.2	127
Canterbury	0.0	0.0	0.0	0.0	0.0	14.1	1.9	3.1	18.6	1.8	0.0	0.0	0.0	0.0	8.6	0.0	3.1	15.0	6.0	3.8	8.8	0.0	11.7	24.4	121
Camden	0.0	0.0	0.0	0.0	0.0	15.0	12.7	15.9	0.0	5.9	4.4	0.0	9.9	0.0	8.3	7.9	19.2	0.0	0.0	7.8	0.0	0.0	11.1	0.0	118
Hornsby	0.0	0.0	0.0	0.0	0.0	6.1	16.3	0.0	17.7	25.5	4.8	0.0	2.0	0.0	3.4	17.8	13.6	7.3	2.6	0.0	0.0	0.0	0.0	0.0	117
Canada Bay	0.0	0.0	0.0	0.0	0.0	7.2	7.5	14.5	13.7	0.0	0.0	0.0	0.0	7.8	7.8	0.0	29.8	0.0	10.9	0.0	0.0	5.4	0.0	10.4	115
Warringah	0.0	5.5	0.0	0.0	0.0	0.0	7.1	5.6	19.8	2.9	13.0	5.4	0.0	0.0	5.8	13.4	23.0	7.1	0.0	0.0	0.0	0.0	0.0	5.8	115
Shellharbour	0.0	0.0	0.0	0.0	0.0	8.0	8.0	6.1	16.6	6.5	0.0	16.0	8.0	0.0	14.7	0.0	18.1	0.0	0.0	0.0	0.0	0.0	0.0	8.6	111
Botany Bay	0.0	0.0	0.0	0.0	0.0	19.5	26.5	6.0	12.6	0.0	0.0	0.0	12.1	0.0	0.0	8.2	0.0	4.8	0.0	10.3	0.0	0.0	0.0	8.3	108
Maitland	5.3	0.0	0.0	0.0	6.1	0.0	9.9	7.4	13.6	19.1	7.2	0.0	5.0	0.0	6.8	0.0	5.3	2.4	1.9	12.2	0.0	0.0	1.9	0.0	104
Holroyd	0.0	10.8	9.2	0.0	0.0	4.2	0.0	21.4	0.0	0.0	0.0	0.0	7.4	0.0	1.9	12.4	0.0	10.2	16.3	3.9	0.0	1.6	0.0	1.1	101
Randwick	0.0	0.0	0.0	0.0	0.0	5.2	0.0	3.9	9.9	16.1	12.1	0.0	0.0	0.0	0.0	0.0	10.2	15.3	10.1	9.4	0.0	0.0	0.0	0.0	92
Kogarah	0.0	0.0	0.0	0.0	6.2	0.0	3.1	9.7	0.0	0.0	5.7	8.6	0.0	0.0	0.0	0.0	21.7	0.0	20.9	0.0	9.7	0.0	0.0	0.0	86
Auburn	0.0	0.0	0.0	0.0	0.0	0.0	9.3	5.1	12.6	0.0	4.2	7.9	7.9	0.0	0.0	7.0	0.0	4.4	10.9	0.0	0.0	0.0	10.9	0.0	80
Willoughby	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.9	8.7	0.0	9.5	8.0	6.0	5.3	9.3	0.0	0.0	6.5	0.0	0.0	12.0	0.0	0.0	7.0	74
North Sydney	0.0	0.0	0.0	0.0	0.0	0.0	9.3	14.5	10.8	0.0	4.9	0.0	0.0	0.0	9.7	0.0	0.0	8.9	0.0	0.0	0.0	0.0	10.8	4.4	73
Hurstville	9.1	0.0	0.0	0.0	0.0	8.2	0.0	10.4	0.0	0.0	0.0	0.0	0.0	0.0	9.1	5.6	16.2	6.6	6.8	0.0	0.0	0.0	0.0	0.0	72
Kiama	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	7.7	5.9	7.2	5.9	5.9	0.0	0.0	12.6	6.3	7.2	0.0	0.0	0.0	13.0	0.0	0.0	72
Marrickville	7.2	0.0	0.0	0.0	0.0	0.0	0.0	8.9	8.9	2.0	0.0	0.0	12.7	0.0	0.0	6.6	0.0	0.0	14.1	0.0	0.0	0.0	0.0	0.0	60
Pittwater	0.0	0.0	0.0	0.0	0.0	0.0	0.0	11.7	5.9	5.2	0.0	11.7	0.0	0.0	0.0	0.0	5.2	2.5	5.9	0.0	0.0	0.0	5.6	0.0	54
Port Stephens	0.0	0.0	0.0	0.0	0.0	1.6	0.0	4.7	4.7	11.4	0.0	1.6	4.7	5.4	0.0	4.0	6.1	4.7	0.0	0.0	0.0	0.0	4.0	0.0	53
Burwood	6.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	10.4	0.0	0.0	0.0	6.3	0.0	0.0	0.0	4.9	0.0	6.3	0.0	0.0	0.0	0.0	6.0	40
Strathfield	7.5	0.0	0.0	0.0	0.0	7.0	4.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	6.4	8.3	0.0	0.0	0.0	0.0	0.0	5.6	0.0	39
Ku-ring-gai	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.5	0.0	7.0	7.6	0.0	0.0	0.0	4.9	0.0	0.0	0.0	0.0	7.5	0.0	0.0	0.0	5.7	37
Lane Cove	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	6.3	0.0	0.0	5.2	0.0	6.7	0.0	0.0	0.0	0.0	0.0	6.6	0.0	5.7	6.7	37
Waverley	9.5	0.0	0.0	0.0	0.0	0.0	0.0	8.2	0.0	10.8	0.0	0.0	0.0	0.0	0.0	6.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	34
Ashfield	0.0	8.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.6	0.0	0.0	0.0	9.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	23
Woollahra	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	6.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	11.9	0.0	0.0	0.0	0.0	0.0	0.0	18
Leichhardt	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.6	6.0	0.0	0.0	0.0	0.0	6.4	0.0	0.0	0.0	0.0	0.0	0.0	18
Manly	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	6.2	0.0	0.0	0.0	5.5	0.0	0.0	0.0	0.0	0.0	12
Cessnock	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	6.2	0.0	4.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	11
Wollondilly	0.0	0.0	0.0	0.0	0.0	4.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	10
Hunters Hill	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	7.3	0.0	0.0	0.0	7
Mosman	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3
Shoalhaven	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0

Table 3.2-7. Spatiotemporal electricity available during an average weekend day for vehicle commute trips under 35 km/trip (red-minimum, yellow–medium, green-maximum electricity available-MWh)

Table 3.2-8 present a comparison of aggregated electric energy available and estimated the rise in electric energy demand due to recharging of EVs (for weekday and weekend) with trip length less than 35 km/trip across 50 LGAs of NSW. The estimated rise in electric energy demand due to recharging of EVs was calculated for the round trips. The location-wise aggregated energy available in terms of SOC of EV batteries was evaluated after considering the 80% depth of discharge (i.e. batteries of EV could be discharged up to 20% SOC only). The analysis shows that the rise in energy demand in 48 out of 50 LGAs of NSW could easily be met by the available electric energy of EVs for both weekdays and weekends without any additional load on the power grid. More than 50 MWh/day electric energy could be made available for V2X operations in 43 out of 50 LGAs on a weekday and 23 out of 50 LGAs on weekend day.

S.No.	LGA	Population density	Estimated rise in energy demand		Energy available after commute trips		Diff b/w required & available energy	
			Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
		people/sq.km	MWh/day	MWh/day	MWh/day	MWh/day	MWh/day	MWh/day
1	Sydney	6,858	305	67	1,152	207	846	140
2	Fairfield	1,935	248	64	834	290	586	226
3	Ryde	2,686	269	35	848	132	579	97
4	Parramatta	2,849	326	79	899	240	573	161
5	Bankstown	2,485	255	69	814	226	559	157
6	Newcastle	833	436	149	967	323	531	174
7	Randwick	3,793	138	22	664	92	526	70
8	Blacktown	1,301	691	140	1,212	251	521	111
9	Auburn	2,395	161	24	607	80	446	56
10	Warringah	994	282	46	690	115	408	69
11	Sutherland Shire	660	492	158	895	304	404	146
12	Holroyd	2,590	134	20	513	101	379	81
13	Canada Bay	4,025	91	23	445	115	354	92
14	Liverpool	616	331	95	679	187	348	91
15	Hurstville	3,644	89	28	436	72	347	44
16	Ku-ring-gai	1,342	171	15	501	37	330	22
17	Canterbury	4,323	100	28	428	121	328	93
18	Rockdale	3,667	86	35	388	171	302	135
19	Marrickville	4,911	76	12	375	60	299	49
20	Willoughby	3,172	127	18	422	74	295	56
21	Campbelltown	484	284	81	558	157	274	76
22	Botany Bay	1,914	121	41	381	108	260	67
23	North Sydney	6,374	105	28	348	73	243	46
24	Hornsby	354	337	77	577	117	240	40
25	Penrith	456	458	93	686	145	228	52
26	Camden	290	165	58	389	118	225	60
27	Kogarah	3,789	52	9	264	86	212	76
28	Waverley	7,432	26	7	226	34	200	27
29	Strathfield	2,679	63	7	251	39	189	33
30	Leichhardt	5,274	43	3	222	18	180	15
31	Woollahra	4,589	26	3	203	18	177	15
32	Ashfield	5,258	41	7	218	23	177	16
33	Shellharbour	449	101	35	258	111	157	76
34	Lane Cove	3,171	51	9	194	37	143	28
35	Manly	2,983	61	8	185	12	123	4
36	Pittwater	669	75	14	199	54	123	39
37	Burwood	4,795	22	4	143	40	120	36
38	Lake Macquarie	304	501	221	614	266	113	45
39	Mosman	3,393	25	2	131	3	106	0
40	Baulkham Hills	442	485	98	586	127	101	29
41	Maitland	179	127	64	205	104	78	40
42	Wollongong	295	608	181	681	191	73	10
43	Hunters Hill	2,431	10	1	67	7	57	6
44	Wyong	209	434	112	467	131	33	19
45	Kiama	81	24	30	50	72	26	41
46	Wollondilly	18	25	7	35	10	10	3
47	Cessnock	27	25	8	33	11	8	3
48	Shoalhaven	21	10	0	12	0	2	0
49	Port Stephens	78	202	65	164	53	-37	-12
50	Gosford	179	518	193	442	164	-77	-28

Table 3.2-8. Comparison of aggregated electricity available and estimated rise in electricity demand due to recharging of EVs with trip length less than 35 km/trip

3.3 Conclusion

In this chapter, the potential rise in electricity demand due to recharging of EV batteries was calculated as a function of time and location and compared with existing electricity consumption. The analysis showed that 82% of weekday and 81% of the weekend vehicle commuter trips were for trip lengths less than 35 km/trip, which could easily be provided by an electric vehicle, and that the associated increase in average demand for electricity would be 8% on average over all regions. The results also showed that the rise in demand for electrical energy is likely to be higher in regions where population density is low.

The results show that the rise in electric energy demand is likely to be higher in regions where population density is low. This is because people travel large distances for the commute (i.e. home to work and back) using private vehicles since public train networks are limited in regions with low population density [41]. It was analysed that rise in electric energy demand was higher in 9 LGAs compared to other 41 LGAs due to larger commute distance travels.

Lastly, a potential solution for the rise in electric energy demand is presented in terms of available SOC with EV batteries after round trip completion. This electric energy could be used for V2X energy transfer operations. The analysis also showed that if recharged every night then many commuter vehicles would at most times have a substantial excess of electrical energy stored in their batteries, which could be used for vehicle to grid and other applications. It was calculated that more than 50 MWh/day would be available in 43 out of 50 LGAs on weekdays, or in 23 out of 50 LGAs on weekend days.

Chapter 4

Modelling Vehicle Movement

4.1 Introduction

Modelling the spatial distribution of electric vehicle (EV) specifically location and state of charge (SOC) at a given time is necessary to estimate the potential impact of EVs on the electricity distribution system and plan the roll out and charging facilities. Unmanaged charging could cause demand side management issues such as increased power losses, phase imbalances and power quality problems, as well as overloading and degradation of transformers. The modelling of spatiotemporal distribution of EVs with their state of charge (SOC) is important for;

i. estimating the impact of dynamic load and/or dispersed electric energy sources on the electric power infrastructure in terms of overloading, unpredicted peaks in the power demand, power quality issues and V2X (here 'V' refers to vehicle and 'X' refers to grid, infrastructure, another vehicle, etc.) operations management.
ii. planning the locations of charging infrastructure based on electricity demand
iii. developing electric energy management strategies

The modelling of data provides simple and compact organisation of measured dataset. In this chapter, we have modelled the raw data using two techniques (i.e. Regression Tree (RT) and Artificial Neural Network (ANN)) for estimating the spatiotemporal distribution of vehicles and compared the results. By estimating the spatiotemporal distribution of vehicles, we will be able to calculate the spatiotemporal electric energy requirement and availability for EVs by processing the data as in

Chapter-3. The techniques were implemented on household travel survey data using MATLAB for two scenarios;

i. Weekday commute trips
ii. Weekday non-commute trips

4.2 Modelling Techniques

The data was processed to estimate the spatiotemporal distribution of the vehicles. Models were compared using statistical methods to evaluate the efficiency. Two techniques (i.e. RT and ANN) were used to develop models for two scenarios (i.e. 'weekday commute' and 'weekday non-commute' vehicle trips). This resulted in four cases for spatiotemporal distribution of vehicles.

i. 'weekday commute' vehicle trips using RT
ii. 'weekday commute' vehicle trips using ANN
iii. 'weekday non-commute' vehicle trips using RT
iv. 'weekday non-commute' vehicle trips using ANN

4.2.1 Datasets & Assumptions

Aggregated vehicle trips for an average weekday in 56 LGAs of NSW were 11.1 million and for an average weekend were 8.6 million, extracted from the NSW Household Travel Survey 2014/15 data [7]. 2.0 million vehicle trips for an average weekday and 0.5 million vehicle trips for an average weekend day were categorised as commute trips (i.e. home to work and back). Whereas, 9.1 million vehicle trips for an average weekday and 8.1 million vehicle trips for an average weekend day were categorised as non-commute trips. The travel patterns for weekday and weekend, commute and non-commute vehicle trips are plotted in **Fig. 4.2-1**.

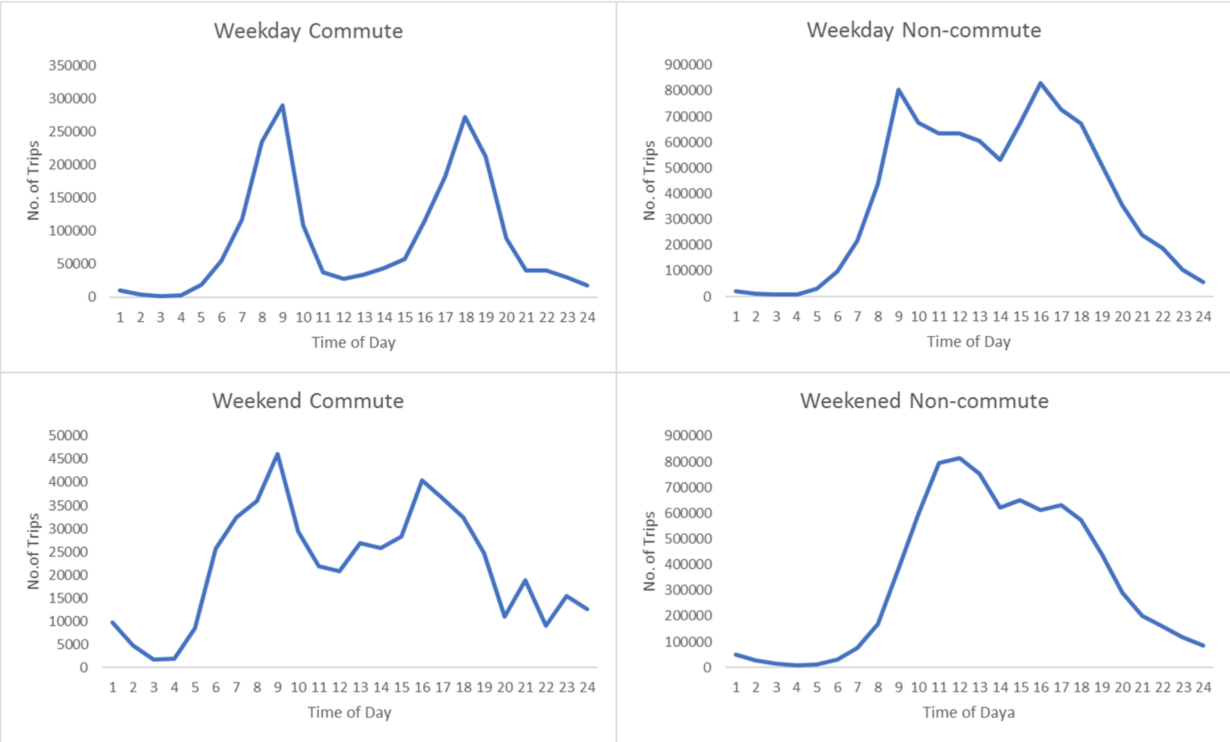

Fig. 4.2-1. Vehicle travel patterns

There were five input variables 'X' (also known as predictors, features, or attributes) and one target variable 'Y' (also known as a response) for all four cases. These input variables are available from the raw dataset (household travel survey data). The target 'Y' was 'number of trips' and the five input predictors 'X' were;

1. Origin
2. Depart Time
3. Destination
4. Arrive Time
5. Distance per trip

4.2.2 Performance Measurement

The accuracy of the models is measured using following statistical parameters. In all equations,

A = actual value

F = forecasted value

n = number of periods

t = specific time

4.2.2.1 Bias

Bias is a measure of general tendency or direction of error. It is a consistent deviation from the mean in one direction (high or low). The lower value of Bias represents a good model. It is calculated using equation (1) as follows;

$$B \quad = \frac{\sum(A-F)}{n} ----------e \ \ (1)$$

4.2.2.2 Mean Absolute Deviation

The mean absolute deviation (MAD) is a measure of dispersion. A measure of by how much the values in the data set are likely to differ from their mean. The lower value of MAD represents a good model. It is calculated using equation (2) as follows;

$$M \quad = \frac{\sum_{i=1}^{n}|Ai-Fi|}{n} --------e \ \ (2)$$

4.2.2.3 Tracking Signal

Tracking Signal (TS) is used to determine the larger deviation (in both plus and minus) of error in the model. The lower value of TS represents a good model. It is calculated using equation (3) as follows;

$$T \ = \frac{\sum(A-F)}{M} -----------e \ \ (3)$$

4.2.2.4 Mean Squared Error

The Mean Squared Error (MSE) is a measure of how close a fitted line is to data points. The lower value of MSE represents a good model. It is calculated using equation (4) as follows;

$$M \quad = \frac{\sum_{i=1}^{n}(Ai-Fi)^2}{n} --------e \ \ (4)$$

4.2.2.5 Root Mean Squared Error

Root Mean Squared Error (RMSE) represents the sample standard deviation of the differences between predicted values and observed values. The lower value of RMSE represents a good model. It is calculated using equation (5) as follows.

$$R \quad = \sqrt{M} \quad ----------- e \quad (5)$$

4.2.2.6 Mean Absolute Percentage Error

Mean Absolute Percentage Error (MAPE) is a measure of the accuracy of a model in statistics. It expresses the accuracy as a percentage. The lower value of MAPE represents a good model. It is calculated using equation (6) as follows;

$$M \quad = \frac{100}{n} \sum_{i=1}^{n} \frac{|Ai - Fi|}{A} ---- e \quad (6)$$

4.2.3 Regression Tree

Decision trees can be categorised as 'Classification trees' and 'Regression trees'. Classification trees give responses that are discrete (e.g. true or false). Regression trees give numeric responses. Regression is a data mining technique of predicting the value of a target based on one or more predictors (categorical or numerical) [42]. Decision tree builds regression models in the form of a tree structure. It breaks down a dataset into smaller and further smaller subsets while developing an associated decision tree incrementally at the same time. The result is a tree with decision and leaf nodes. A decision node has two or more branches with each branch representing values for the tested attributes. Leaf node represents a decision on the numerical target [43].

We used the Regression Tree (RT) because preparing data, making predictions, representation of information and selection of predictor variables are fast, easy and reliable. The predictor variables can be of any type (numeric, categorical, etc.). The trees are insensitive to outliers and missing data in the predictor variables can be adjusted by using surrogates. The hierarchical structure of a tree ensures that the response to one input variable depends on values of inputs which are higher in the tree, therefore, interactions between predictors are modelled automatically [44].

4.2.3.1 Algorithm

The core algorithm for building decision trees is called ID3 (Iterative Dichotomiser 3) invented by J.R. Quinlan. This employs a top-down, greedy search through the space of possible branches with no backtracking. The ID3 algorithm uses Standard Deviation Reduction to construct a decision tree for regression [43].

A decision tree is built top-down from a root node involving the data partitioning into subsets of similar values. Standard deviation is used to calculate the homogeneity of a numerical sample. The standard deviation is zero for the numerical sample which is completely homogeneous [43].

The reduction of standard deviation is based on the decrease in standard deviation after a dataset is split on an attribute. The main task of constructing a decision tree is to find the attribute that returns the maximum reduction of standard deviation (i.e., the most homogeneous branches) [43]. Following are the steps of standard deviation reduction;

1. The standard deviation of the target is calculated.
2. The dataset is then split into the different attributes.
3. The standard deviation for each branch is calculated.
4. The resulting standard deviation is subtracted from the standard deviation before the split. The result is the standard deviation reduction.
5. The attribute with the maximum standard deviation reduction is chosen for the decision node.
6. Dataset is divided based on the values of the selected attribute.
7. The branch set with standard deviation more than '0' needs further splitting.
8. The process is run recursively on the non-leaf branches until all data is processed.
9. When the number of instances is more than one at a leaf node, the average is calculated as the final value for the target.

4.2.3.2 Model Implementation

A model using Regression Tree was developed with MATLAB function 'fitrtree'. The syntax "tree = fitrtree(X,Y)" returns a regression tree based on the input variables 'X' and output 'Y'. The "tree" is a binary tree where each branching node is split based on the values of a column of 'X'. The model takes the spatiotemporal inputs 'X' and predicts the expected number of vehicle trips 'Y'.

4.2.3.3 Performance Analysis

The results of Regression Tree models for two scenarios ('weekday commute' and 'weekday non-commute' vehicle trips) were tabulated in **Table 4.2-1**.

Regression Tree (RT)		
Description	Weekday Commutes	Weekday Non-commutes
No. of Trips	2,047,545	9,078,417
No. of Inputs (predictor)	5	5
No. of Outputs (response)	1	1
Bias	2E-14	1E-14
Mean Absolute Deviation (MAD)	129	305
Tracking Signal (TS)	9E-13	5E-13
Mean Squared Error (MSE)	73,969	771,744
Root Mean Square Error (RMSE)	272	878
Mean Absolute Percentage Error (MAPE)	46%	49%

Table 4.2-1. Statistical analysis of Regression Tree models for 'weekday commute' and ‘weekday non-commute’ vehicle trips

The analysis shows that the MAD, MSE, RMSE and MAPE for ‘weekday commute’ vehicle trips were lower compared to similar parameters for ‘weekday non-commute’ vehicle trips. This implies that RT model for ‘weekday commute’ vehicle trips was better than the RT model for ‘weekday non-commute’ vehicle trips. Also, Bias and TS for both scenarios are extremely low, almost approaching zero. This implies that RT models for both scenarios are unbiased.

A Scatter plot of ‘target’ and ‘predicted’ vehicle trips for ‘weekday commute’ and ‘weekday non-commute’ vehicle trips was presented in **Fig. 4.2-2** & **Fig. 4.2-3**. The comparison of scattered plots shows that the RT model for ‘weekday non-commute’ trips was more accurate compared to RT model for ‘weekday commute’ trips.

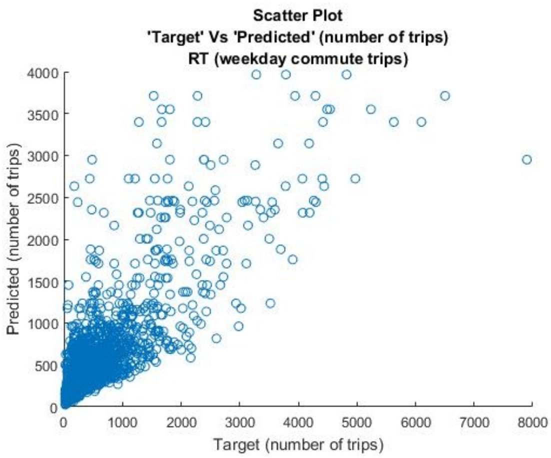

Fig. 4.2-2. RT Scatter plot of 'Target' Vs 'Predicted' no. of trips for 'weekday commute'

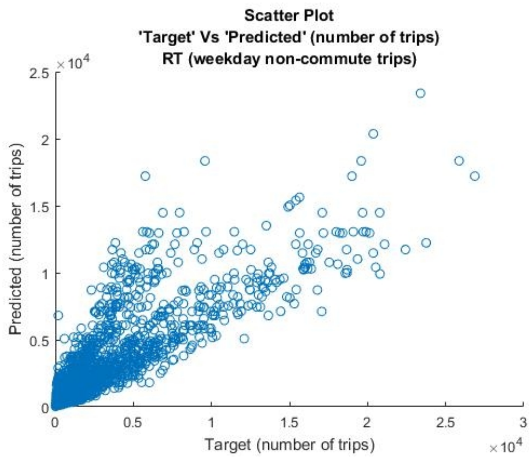

Fig. 4.2-3. RT Scatter plot of 'Target' Vs 'Predicted' no. of trips for 'weekday non-commute'

4.2.4 Neural Networks

An Artificial Neutral Network (ANN) is a system which is analogous to the biological neural network, such as the brain. It is comprised of a network of artificial neurons (also known as "nodes"). These nodes are connected to each other. A value is assigned to each connection based on their strength, with higher values indicating a strong connection. There are three types of neurons in an ANN; input nodes, hidden nodes and output nodes (**Fig. 4.2-4**) [45].

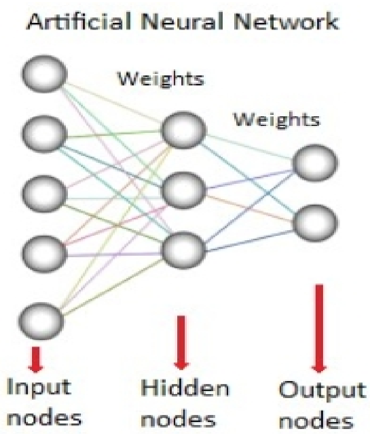

Fig. 4.2-4. Types of neurons in Neural Network

The fundamental building block for the neural network is the perceptron. It receives inputs, sums those inputs, checks the result and produces an output. It is used to classify linearly separable classes. The perceptron consists of weights, the summation processor, and an activation function.

The inputs and connection weights are typically real values. Within each node's design, there is a built-in transfer function. The transfer function translates the input signals to output signals. It uses a threshold to produce an output. **Fig. 4.2-5** shows various activation/transfer functions which are used for training the network. Due to the differentiable property of the log-sigmoid and tan-sigmoid functions, these are commonly used in back-propagation algorithms.

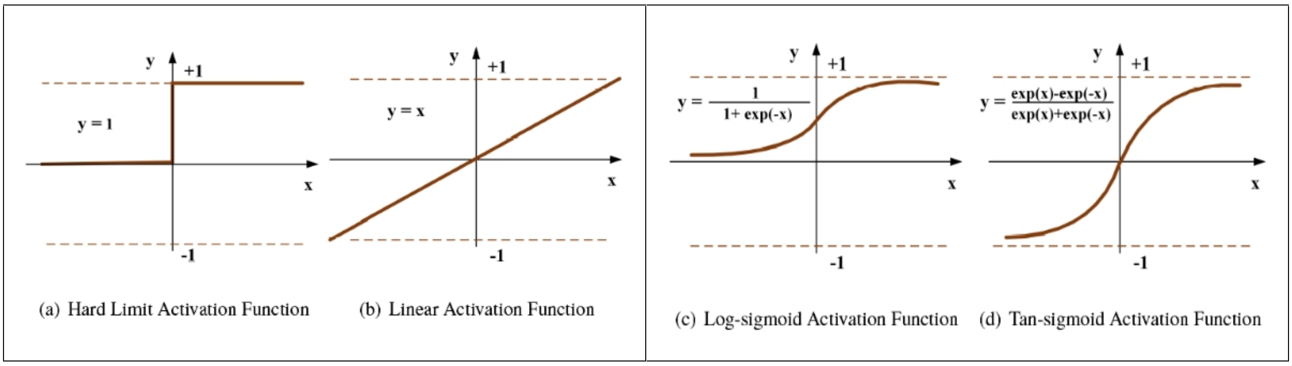

Fig. 4.2-5. Examples of Activation/Transfer Functions [46]

ANN is good at fitting functions. We have used ANN models because they require less formal statistical training to develop. ANN models can implicitly detect complex nonlinear relationships between independent and dependent variables. They can detect all possible interactions between predictor variables [47].

4.2.4.1 Algorithm

Basic steps of an ANN were extracted from [45] and are presented (**Fig. 4.2-6**) as follows;

1. The input nodes take in numerical information.
2. This information is presented as activation values and passed throughout the network.
3. Each node is given a number, the higher the number the greater the activation.
4. The activation value is passed from node to node based on the connection strengths (weights), inhibition or excitation, and transfer functions.
5. Each of the nodes sums the activation values it receives and then modifies the value based on its transfer function.
6. The activation flows through the network and hidden layers until it reaches the output nodes.
7. The output nodes then reflect the input as meaningful information.

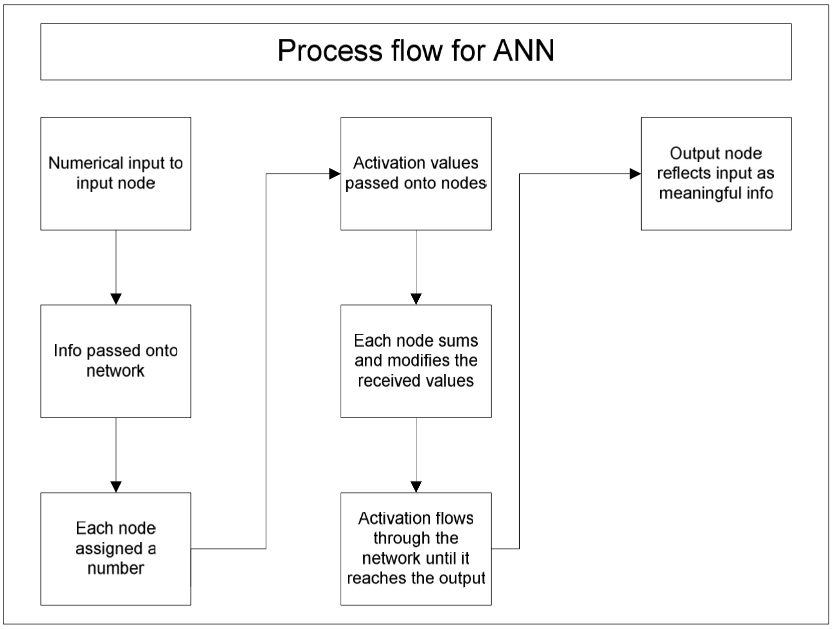

Fig. 4.2-6. Basic process flow for Artificial Neural Network

We have used a supervised two-layer feed-forward network with sigmoid hidden neurons and linear output neuron. It is called supervised because the trained network can produce the desired outputs in response to a set of inputs and allow to see how closely the actual output match the target.

ANN models are generally classified into feed-forward (FF) and feed-back (FB) networks. An FF network is a non-recurrent network which contains inputs, outputs, and hidden layers. It is called FF because the signals can only travel in one direction. We have used an FF network because it is fast and easy. The algorithm for FF network extracted from [45] is presented (**Fig. 4.2-7**) as follows;

1. Input data is passed onto a layer of processing elements where it performs calculations.
2. Each processing element makes its computation based upon a weighted sum of its inputs.
3. The newly calculated values then become the new input values that feed the next layer.
4. This process continues until it has gone through all the layers and determines the output.
5. A threshold transfer function is sometimes used to quantify the output of a neuron in the output layer.

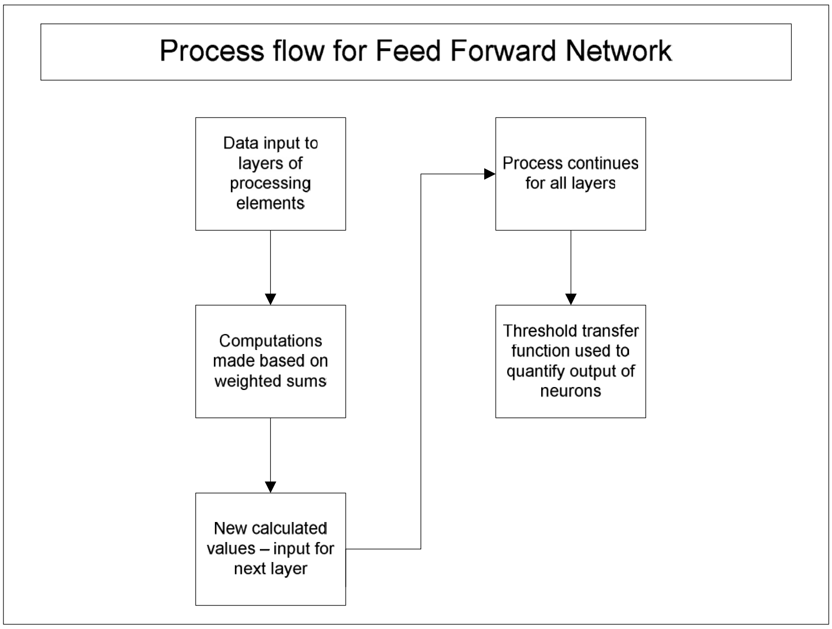

Fig. 4.2-7. Process flow for Feed Forward Network

The network was trained with Levenberg-Marquardt backpropagation algorithm. We have used this algorithm because this algorithm typically requires less time. The algorithm for back-propagation (BP) neural network was extracted from [45]. The backpropagation algorithm is presented (**Fig. 4.2-8**) as follows;

1. A training input pattern is provided to the input layer.
2. The data pattern is then propagated from layer to layer through the network until a pattern is generated in the output layer.
3. If the generated output pattern is different from the target, then errors occur.
4. The errors are calculated and then propagate backwards through the input layer to adjust the weights to get the required output.
5. To minimise the error function, the BP algorithm updates the network weights and biases in the direction in which the negative gradient vector of the error function decreases rapidly.
6. This is made possible by using a sigmoid as the non-linear transfer function. The sigmoid is used because it is differentiable.

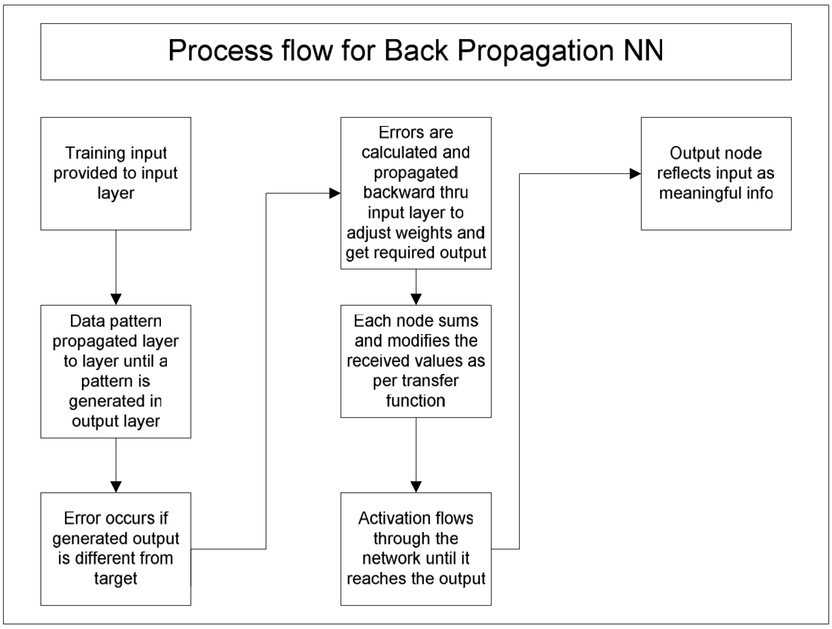

Fig. 4.2-8. Process flow for Back Propagation Neural Nework

4.2.4.2 Model Training

A supervised two-layer feed-forward network with fifty (50) sigmoid hidden neurons and one (1) linear output neuron is used for model training (**Fig. 4.2-9**).

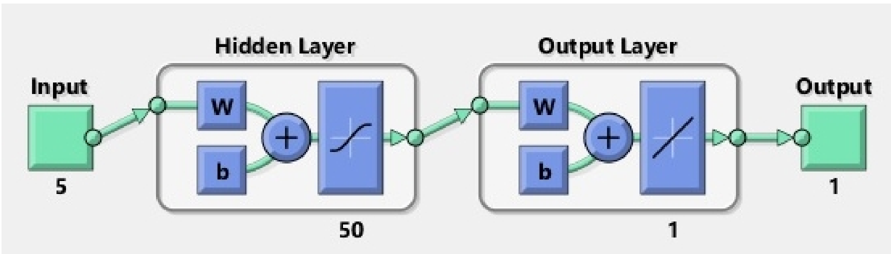

Fig. 4.2-9. Neural Network Architecture for 'weekday commute' and ‘weekday non-commute’ vehicle trips

For both datasets (i.e. ‘weekday commute’ and ‘weekday non-commute’ vehicle trips), data was randomly divided into three categories; ‘training’ (80% of the total data), ‘validation’ (10% of the total data) and ‘testing’ (10% of the total data). The ‘training’ dataset was presented to the network during training, and the network was adjusted according to its errors. The ‘validation’ dataset was used to measure network generalisation, and to halt training when generalisation stops improving. The last dataset ‘testing’ have no effect on training and therefore provides an independent measure of network performance during and after training.

4.2.4.3 Performance Analysis

The results of Artificial Neural Network models for two scenarios (weekday commute and non-commute vehicle trips) were tabulated in **Table 4.2-2**.

Artificial Neural Network (ANN)		
Description	**Weekday Commutes**	**Weekday Non-commutes**
No. of Trips	2,047,545	9,078,417
No. of Neurons	50	50
No. of Inputs (predictor)	5	5
No. of Outputs (response)	1	1
Bias	-1.4	16.2
Mean Absolute Deviation (MAD)	220	673
Tracking Signal (TS)	-37	277
Mean Squared Error (MSE)	142,134	1,642,706
Root Mean Square Error (RMSE)	377	1,282
Mean Absolute Percentage Error (MAPE)	98%	226%

Table 4.2-2. Statistical Analysis of Artificial Neural Network models for 'weekday commute' and 'weekday non-commute' vehicle trips

The analysis shows that the MAD, MSE, RMSE and MAPE for ‘weekday commute’ vehicle trips were lower compared to similar parameters for ‘weekday non-commute’ vehicle trips. This implies that ANN model for ‘weekday commute’ vehicle trips was better than the ANN model for ‘weekday non-commute’ vehicle trips. However, Bias and TS values indicate inappropriate modelling for both scenarios. The negative values of Bias and TS for ‘weekday commute’ vehicle trips model indicate that the actual number of trips were consistently less than the predicted model. And, positive values of Bias and TS for ‘weekday non-commute’ vehicle trips model indicate that the actual number of trips were greater than predicted model.

The frequency distribution of errors for the ANN model for ‘weekday commute’ and ‘weekday non-commute’ vehicle trips was presented in **Fig. 4.2-10** & **Fig. 4.2-11**. The ‘error’ is the difference between desired ‘target’ and ‘output’ of the model. The blue bars represent training data, the green bars represent validation data, and the red bars represent testing data. For a more accurate model of prediction, the error should be zero and/or close to zero. The errors for both the models were much higher. This implies that the model for weekday commute and non-commute vehicle trips could not be accurately modelled by ANN.

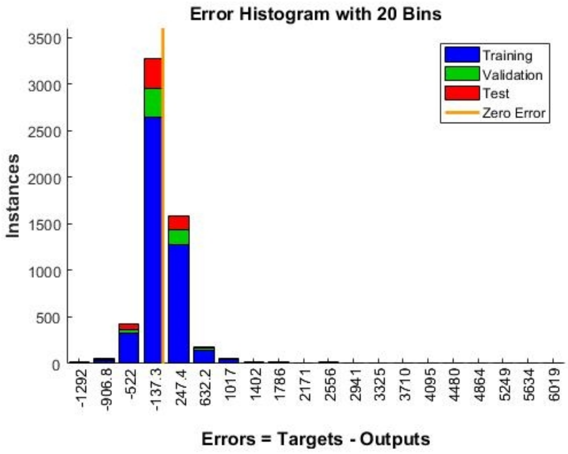

Fig. 4.2-10. Weekday commute trips error frequency distribution using ANN

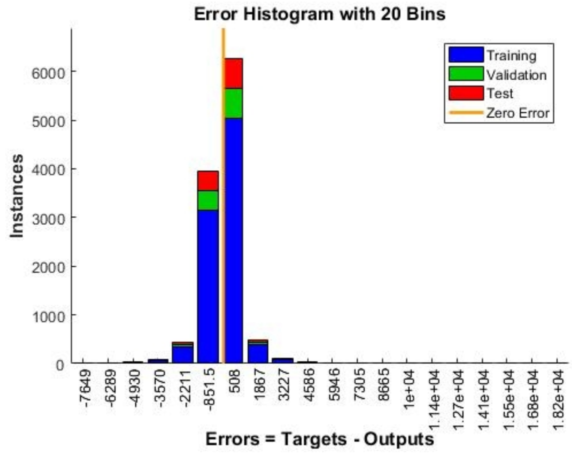

Fig. 4.2-11. Weekday non-commute trips error frequency distribution using ANN

Fig. 4.2-12 represent the scatter plot of ANN model for 'weekday commute' vehicle trips. The figure represents the scatter plot of 'target' (i.e. desired results) against 'output' (i.e. results from the model). The plot did not represent a good model. A good model would be represented when all data points follow the desired target represented by a diagonal line.

Fig. 4.2-13 represent the scatter plot of ANN model for 'weekday non-commute' vehicle trips. The figure represents the scatter plot of 'target' (i.e. desired results) against 'output' (i.e. results from the model). The plot did not represent a good model.

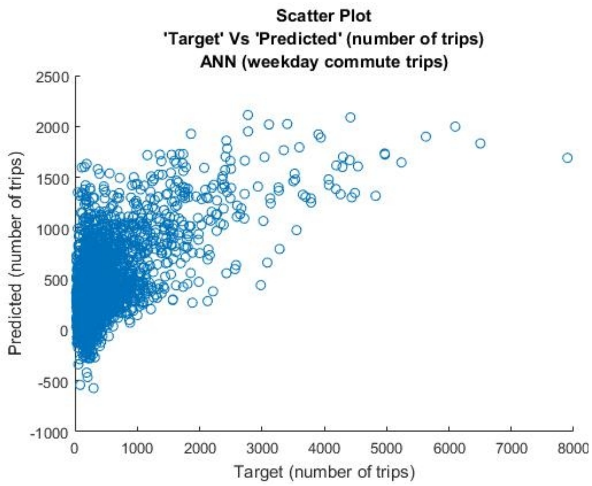

Fig. 4.2-12. ANN Scatter plot of 'Target' Vs 'Predicted' no. of trips for 'weekday commute'

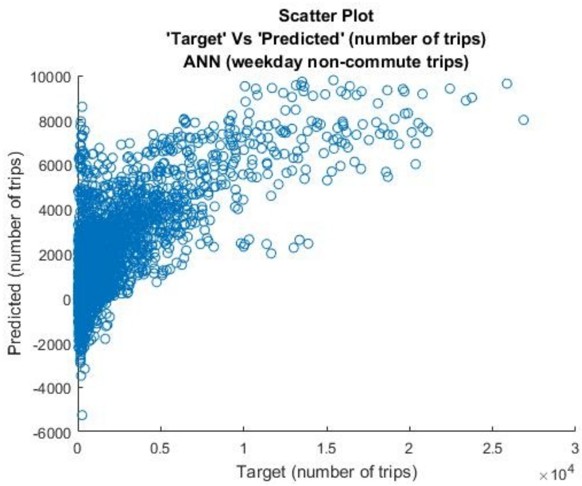

Fig. 4.2-13. ANN Scatter plot of 'Target' Vs 'Predicted' no. of trips for 'weekday non-commute'

4.2.5 Comparison of Modelling Techniques

Two different techniques (i.e. RT and ANN) were used for modelling the spatiotemporal distribution of vehicles in 50 LGAs of NSW. We have compared these techniques for similar datasets (i.e.

'weekday commute' and 'weekday non-commute' vehicle trips). These two models were used because these models provide good pattern recognition for large and complex datasets.

The comparison of RT and ANN techniques to model the spatiotemporal distribution of vehicle trips for 'weekday commute' vehicle trips using same inputs is tabulated in **Table 4.2-3**. The comparison shows that parameters MAD, MSE, RMSE and MAPE were much lower for RT compared to ANN. The Bias value for RT was almost negligible which implies that the model developed for 'weekday commute' vehicle trips using RT was more accurate compared to ANN.

Weekday Commute		
Description	Regression Tree (RT)	Artificial Neural Network (ANN)
No. of Trips	2,047,545	2,047,545
No. of Inputs (predictor)	5	5
No. of Outputs (response)	1	1
Bias	2E-14	-1.4
Mean Absolute Deviation (MAD)	129	220
Tracking Signal (TS)	9E-13	-37
Mean Squared Error (MSE)	73,969	142,134
Root Mean Square Error (RMSE)	272	377
Mean Absolute Percentage Error (MAPE)	46%	98%

Table 4.2-3. Comparison of RT and ANN models for 'weekday commute' vehicle trips

Similarly, the comparison of RT and ANN techniques to model the spatiotemporal distribution of vehicle trips for 'weekday non-commute' vehicle trips using same inputs is tabulated in **Table 4.2-4**.

Weekday Non-Commute		
Description	Regression Tree (RT)	Artificial Neural Network (ANN)
No. of Trips	9,078,417	9,078,417
No. of Inputs (predictor)	5	5
No. of Outputs (response)	1	1
Bias	1E-14	16.2
Mean Absolute Deviation (MAD)	305	673
Tracking Signal (TS)	5E-13	277
Mean Squared Error (MSE)	771,744	1,642,706
Root Mean Square Error (RMSE)	878	1,282
Mean Absolute Percentage Error (MAPE)	49%	226%

Table 4.2-4. Comparison of RT and ANN models for 'weekday non-commute' vehicle trips

The comparison shows that MAD, MSE, RMSE and MAPE was much lower for RT compared to ANN. The Bias value for RT was almost negligible which implies that the model developed for 'weekday non-commute' vehicle trips using RT was more accurate compared to ANN.

Comparing the two models (i.e. RT and NN) for both datasets (i.e. 'weekday commute' and 'weekday non-commute' vehicle trips), it could be evaluated that RT models performed significantly better in modelling the spatiotemporal distribution of vehicles.

4.3 Conclusion

To facilitate analysis and prediction of key variables, the household survey travel data was modelled using regression trees (RTs) and artificial neural networks (ANNs). Four scenarios were developed; two using RT for 'weekday commute and non-commute' vehicle trips and other two using ANN for the same datasets.

The statistical analysis of RT and ANN models for 'weekday commute' vehicle trips show that RT modelled the data more accurately compared to ANN. The statistical parameters MAD, MSE, RMSE and MAPE for the RT model were very low compared to same parameters for the ANN model. Similarly, the results of statistical analysis of RT and ANN models for 'weekday non-commute' vehicle trips were compared. And a comparison of all statistical parameters show that for 'weekday non-commute' vehicle trips also RT modelled more accurately compared to ANN.

It could be concluded that RT models performed significantly better in modelling the spatiotemporal distribution of vehicles compared to ANN models. However, these models could be made more precise by using high-resolution spatial dataset.

Chapter 5

Conclusion & Future Work

5.1 Conclusion

This research quantified the potential of electric vehicles (EVs) adoption and its consequences in Australia. Limited distance travel range of EVs is assumed to be the major hurdle in its adoption. We have analysed household travel survey data for 50 local government areas (LGAs) in New South Wales (NSW), Australia. It was evaluated that 87% of the total vehicle trips were less than 35 km/trip, which could easily be provided by an affordable EV. We conducted a similar analysis for regions with different geographic boundaries (i.e. statistical areas level-3 and suburbs) within NSW, Australia. The results were consistent and these results were also similar to a study conducted for vehicle commutes in the United States [5]. Therefore, it could be established that limited range of EVs would not be a hurdle based on travel needs.

This research also quantified the spatiotemporal impact of EV charging on the electric power grid. The analysis of household travel survey data for 35 LGAs in NSW shows that electricity demand would increase by 8% compared to actual electricity consumption per day when 82% of the weekday commute vehicle trips (i.e. home to work and back) were conducted by EVs. On the contrary, the rise in electric energy demand in 48 out of 50 LGAs of NSW could easily be met by the available electric energy from EV batteries without any additional load on the power grid, while EVs are recharged overnight only.

This research also estimated the potential reduction in greenhouse gas (GHG) emissions. It was calculated that even if all EVs were recharged from non-renewable coal-fired power plants, the greater efficiency of EVs would result in a reduction of 26% $CO_{2(eq)}$ across NSW (compared to GHG emissions from transport sector across NSW in 2011/12). This implies that introduction of EVs could play a significant role in the reduction of GHG emissions.

Lastly, to facilitate analysis and prediction of key variables, the travel data was modelled using regression trees (RTs) and artificial neural networks (ANNs). The model provides compact organisation of measured dataset. The models help in estimating the spatiotemporal distribution of EVs and calculating the impact of dynamic electric load and/or dispersed electric energy sources on the electric power network. On comparing both models, it was found that RT models performed significantly better than ANNs in modelling the travel data.

5.2 Future Work

This research was a macro level analysis of the potential for EV adoption and its consequences in Australia. This research can be extended to the micro-level evaluation of the spatiotemporal impact of EV recharging on the power grids. The evaluation could be detailed down to distribution substation and/or transformer level by estimating the potential spatiotemporal charging and discharging events for EVs. Thus, comparing electric energy demand due to EV recharging and existing electric power grid capacity at higher spatial resolution.

It is expected that in future the fleet of vehicles would be electrified. Therefore, another aspect that could be extended from the existing research is the evaluation of spatiotemporal electric energy demand due to recharging of automated self-driven electric vehicles fleet.

The models developed in this research were based on some assumptions due to limitations of the available dataset. These models could be made more accurate by training with a more refined dataset with higher spatiotemporal resolution.

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Appendix-A (List of Publications)

1. Rafique, S. and G. Town, "Potential for EVs adoption in Australia". International Journal of Sustainable Transportation, Taylor & Francis, 2017 (under review)

2. Rafique, S. and G. Town, "The impact of electric vehicles on electricity distribution in New South Wales, Australia" (under preparation)

Appendix-B (Data Samples)

LGA Sample Data

day_type	purpose	O_LGA11	D_LGA11	d_timeperiod	a_timeperiod	weekday_estimates	weekend_estimates
2.00	2.00	9999	8350	24.00	1.00	#NULL!	465.92
1.00	1.00	8550	8550	24.00	24.00	197.38	#NULL!
1.00	2.00	8550	8550	24.00	24.00	564.89	#NULL!
2.00	2.00	8550	8550	24.00	1.00	#NULL!	202.55
2.00	2.00	8500	8050	24.00	24.00	#NULL!	525.87
1.00	2.00	8500	7200	24.00	1.00	280.99	#NULL!
1.00	1.00	8450	8450	24.00	24.00	477.73	#NULL!
1.00	2.00	8450	8450	24.00	1.00	536.83	#NULL!
1.00	2.00	8450	8450	24.00	24.00	895.82	#NULL!
2.00	2.00	8450	8450	24.00	1.00	#NULL!	751.86
2.00	1.00	8450	8450	24.00	24.00	#NULL!	308.84
2.00	2.00	8450	8450	24.00	24.00	#NULL!	757.47
1.00	2.00	8450	8350	24.00	2.00	214.89	#NULL!
2.00	2.00	8450	5950	24.00	2.00	#NULL!	838.38
1.00	1.00	8450	4400	24.00	24.00	285.17	#NULL!
1.00	2.00	8400	8400	24.00	24.00	335.91	#NULL!
2.00	2.00	8400	4900	24.00	1.00	#NULL!	530.39
1.00	2.00	8350	8350	24.00	24.00	267.71	#NULL!
2.00	2.00	8350	8350	24.00	1.00	#NULL!	558.13
2.00	1.00	8350	8350	24.00	24.00	#NULL!	416.59
1.00	2.00	8350	7150	24.00	1.00	351.16	#NULL!

SA3 Sample Data

day_type	O_SA3_11	D_SA3_11	a_timeperiod	d_timeperiod	weekday2014_estimates	weekend_day2014_estimates
1.00	10201	99999	10.00	8.00	336.85	#NULL!
1.00	10201	99999	18.00	10.00	336.85	#NULL!
2.00	10201	12802	22.00	20.00	#NULL!	655.00
1.00	10201	12801	12.00	10.00	303.68	#NULL!
1.00	10201	12702	8.00	6.00	341.10	#NULL!
2.00	10201	12602	8.00	7.00	#NULL!	702.67
2.00	10201	12602	15.00	14.00	#NULL!	228.22
2.00	10201	12602	20.00	18.00	#NULL!	816.05
1.00	10201	12601	18.00	17.00	166.47	#NULL!
1.00	10201	12601	18.00	18.00	296.88	#NULL!
2.00	10201	12601	14.00	13.00	#NULL!	836.72
1.00	10201	12504	7.00	6.00	1061.03	#NULL!
1.00	10201	12504	8.00	6.00	348.40	#NULL!
2.00	10201	12504	9.00	8.00	#NULL!	749.22
2.00	10201	12504	17.00	16.00	#NULL!	826.74
2.00	10201	12503	10.00	9.00	#NULL!	787.19
2.00	10201	12503	16.00	15.00	#NULL!	730.29
1.00	10201	12501	6.00	5.00	298.73	#NULL!
1.00	10201	12501	9.00	7.00	329.44	#NULL!
2.00	10201	12403	11.00	9.00	#NULL!	1648.91
1.00	10201	12203	6.00	5.00	472.44	#NULL!

Sydney Inner City (Journey to Work) Data Sample

Origin SA3	Origin SA3 ID	Train	Bus	Ferry/Tram	Vehicle driver	Vehicle passenger	Other mode	Walked only	Mode not stated	Worked at Home or Did not go to Work	Total
Goulburn - Yass	10101	18	7	0	30	0	0	15	4	25	99
Queanbeyan	10102	7	0	0	12	0	7	10	0	12	48
Snowy Mountains	10103	6	3	0	13	0	0	4	3	23	52
South Coast	10104	0	0	0	9	0	0	3	0	12	24
Gosford	10201	2849	16	9	625	73	12	50	48	560	4242
Wyong	10202	807	17	9	325	45	9	18	24	199	1453
Bathurst	10301	16	6	3	22	0	0	3	0	26	76
Lachlan Valley	10302	0	0	3	16	0	0	3	0	11	33
Lithgow - Mudgee	10303	11	6	0	35	0	0	4	0	14	70
Orange	10304	0	0	0	29	0	6	4	0	6	45
Clarence Valley	10401	0	3	0	4	3	0	0	3	9	22
Coffs Harbour	10402	6	6	3	17	0	0	10	0	26	68
Broken Hill and Far West	10502	0	0	0	3	3	0	3	3	3	15
Dubbo	10503	4	3	0	15	0	3	9	3	3	40
Lower Hunter	10601	15	9	0	77	3	7	12	0	37	160
Maitland	10602	16	3	0	34	0	0	3	0	6	62
Port Stephens	10603	10	4	3	39	0	0	10	3	9	78
Upper Hunter	10604	0	0	0	13	0	0	3	3	3	22
Dapto - Port Kembla	10701	405	6	0	175	9	3	3	6	79	686
Kiama - Shellharbour	10703	247	17	0	166	3	0	16	6	63	518
Wollongong	10704	1734	34	3	643	33	10	32	32	367	2888
Great Lakes	10801	3	0	3	9	0	0	0	0	15	30