RouteZero: user guide and knowledge sharing report

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1. Introduction

The goal for RouteZero was to be a broadly accessible tool that provides insights into the feasibility of electrifying bus routes around Australia. It is a web application tool developed by the Battery Storage and Grid Integration Program at the Australian National University (ANU). The tool's development was funded by the Australian Renewable Energy Agency (ARENA) as part of the Next Generation Electric Bus Depot project (ARENA, 2021) led by Zenobe and Transgrid. This project is the first large-scale deployment of electric buses in Australia, with 40 electric buses rolled out into the Transit Systems fleet. These buses operate out of the Leichhardt depot in Sydney, NSW.

The types of questions that RouteZero aims to answer can be broken into two broad categories: energy requirements of routes and depot charging infrastructure. For RouteZero to answer these questions required the development of two models. The first is a data-driven model aimed at answering questions about the energy requirements of routes. This model is based on performance data of the electric buses operating out of Leichhardt. The second is a depot charging optimisation model that answers questions related to the required depot charging infrastructure. These two models are linked as the output from the first model informs the inputs to the second.

This report consists of two parts. Part I is a user guide for the web application tool. It describes the web application tool, its inputs and functionality. It provides examples of using the tool and the types of insights gained from the results. Part II is a technical description of the RouteZero tool. It describes the data set and the modelling methodology used in developing the tool. Including the technical details of the two models and the assumptions made while developing them. Additionally, a case study is provided demonstrating some of the insights the models can give about the feasibility of electrifying various bus routes.

1.1 Terminology: route, trip, and timetable

Throughout this report, the following definitions are used for a *bus route*, a *bus trip*, and a *trip timetable*. A *bus route* is defined as a sequence of bus stops and the path taken between them. A bus might do the same route several times a day or week and multiple buses might be on the same route at the same time. A bus route is what we think of if we were to say that "Newcastle West to University via Carrington" route is not a very direct route between Newcastle West and Carrington.

A *bus trip* is a single occurrence of a bus undertaking a given route. It has a specific start and end time. This is what saying "the 9:11am Monday bus from Newcastle West to University" would be referring to. Each trip on a route is considered to have different energy requirements as the bus may encounter different traffic and weather conditions as well as having a different number of passengers.

A *trip timetable* is defined as the schedule of trips that occur on a route or a collection of routes. It is what a member of the public would use when they check what times they can catch a bus from stop A to stop B. Importantly, a trip timetable provides no information about which bus is operating which trips/routes. Likewise, it does not provide information about the sequence of trips a bus is undertaking or about when a bus would return or depart the depot.

Part I
User Guide

This part of the report provides a guide to using the RouteZero web application tool. It describes the questions the tool can answer, the steps involved, the inputs and parameters, and the results obtained. Lastly, it gives a couple of examples of using the tool.

2. Quick start

Here, a quick run through of using RouteZero with default settings is given for the bus routes in the ACT. RouteZero is broken into three steps: route selection, energy usage predictions, and depot charging optimization. To get started open the tool at `https://routezero.cecs.anu.edu.au/` and follow the steps below:

Step 1: GTFS file and route selection

In this step we will choose the GTFS file source and the routes to be considered:

1. select data source, we will use 'ACT' for this example,
2. select 'Transport Canberra' for the agency,
3. click 'All routes' and then 'Next'.

For the selected routes the busiest week is selected and the scheduled trips extracted from the GTFS data to be used in the following two steps.

Step 2: Predicting electricity usage on routes

In this step, we will use the default parameters and get predictions of the energy consumption on the selected routes:

1. Settings can be used to change the bus battery capacity, the bus maximum charging power, the dead-running (%), and the peak passengers expected. For this example, leave all settings as their default value.
2. Click 'predict route energy usage'.

This will produce a summary of the energy requirements by the routes (see Figure 2.1) and an interactive map of the routes and their energy requirement (see Figure 2.2). The energy requirements summary includes two graphs. The 'buses on routes' graph shows the number of buses required throughout the week to service all scheduled trips on the selected routes. We can see that the tool identified we need at least 225 buses to service this route (maximum from the buses on route graph). Step 3 uses this number as part of the depot charging optimisation. The 'Total energy required on active routes' graph shows the energy required across all the buses to service the scheduled trips throughout the week.

The interactive map (example given in Figure 2.2) shows the routes and their energy usage. Hovering over one of the routes will bring up a tooltip showing the key parameters that are used to predict energy consumption. There are also two dropdown inputs allowing the time window and output used for colour coding to be changed. A bus trip on a route will use different energy depending on the time of day as the temperature and traffic conditions will be different. So changing the selected time window will affect the displayed results. The routes can be colour coded based on the 'energy/km' or 'total energy'. Finally, a CSV file summarising the route parameters and the predicted energy usage broken into time windows can be downloaded by clicking 'Download CSV'.

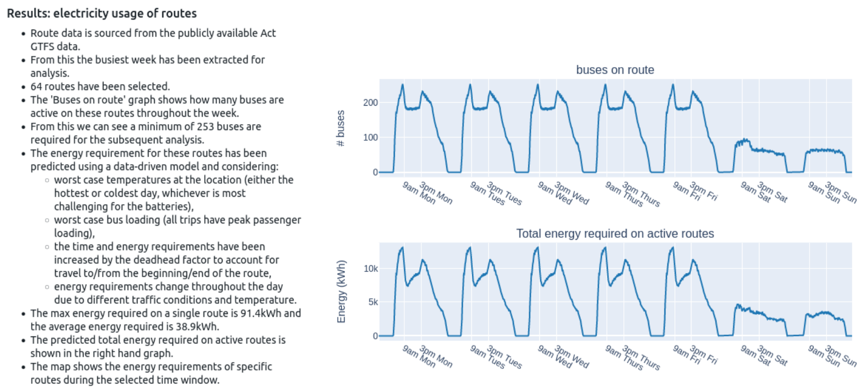

Figure 2.1: Quickstart step two example of energy requirements summary.

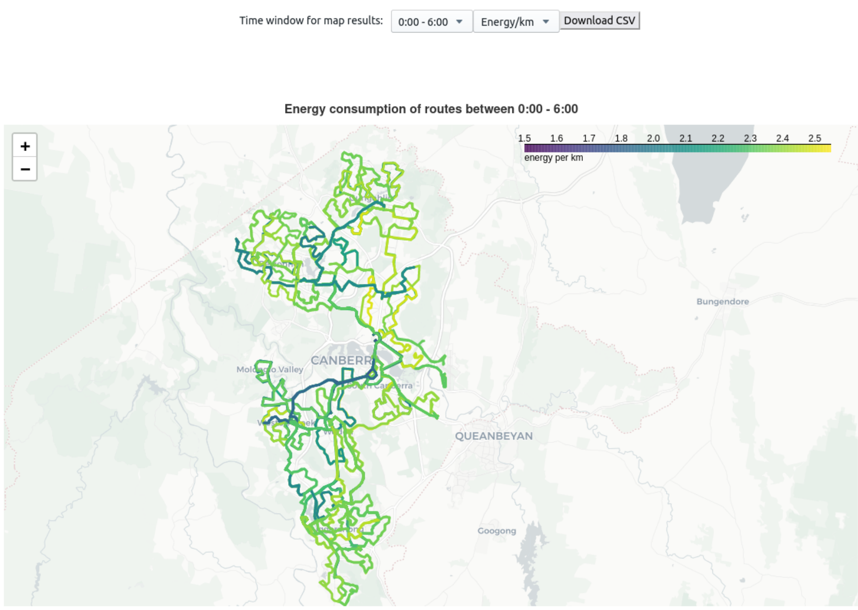

Figure 2.2: Quick start step two example of interactive map.

Step 3: Optimise charging at depot

In this step, the default options will again be used and the total charging profile at the depot optimised assuming that all selected routes are operated by buses from one depot:

1. Settings can be used to change the number of buses, the on-site battery parameters, charger power, and allowed charging windows. For this example, leave all settings as their default.
2. Click 'optimise charging' (this may take a few minutes).

The optimisation finds the profile that minimises the peak power required from the grid while ensuring the bus fleet can meet the energy requirements of the scheduled trips. Once completed, it outputs a summary of the results and several graphs of the optimisation result throughout the week (see Figure 2.3). From top to bottom the graphs show: the power used for charging the buses at the depot; the combined state of charge of the bus fleet; the daily energy used and charged; and, lastly, the number of bus chargers in use.

The results show that the peak demand on the grid to meet the energy requirements of the 64 selected routes operated by 253 buses is 10 MW. A total of 35 chargers were needed. The default chosen set the initial charge to 90% and the end charge is required to be 90%. The selected reserve capacity of 20% is maintained throughout the week.

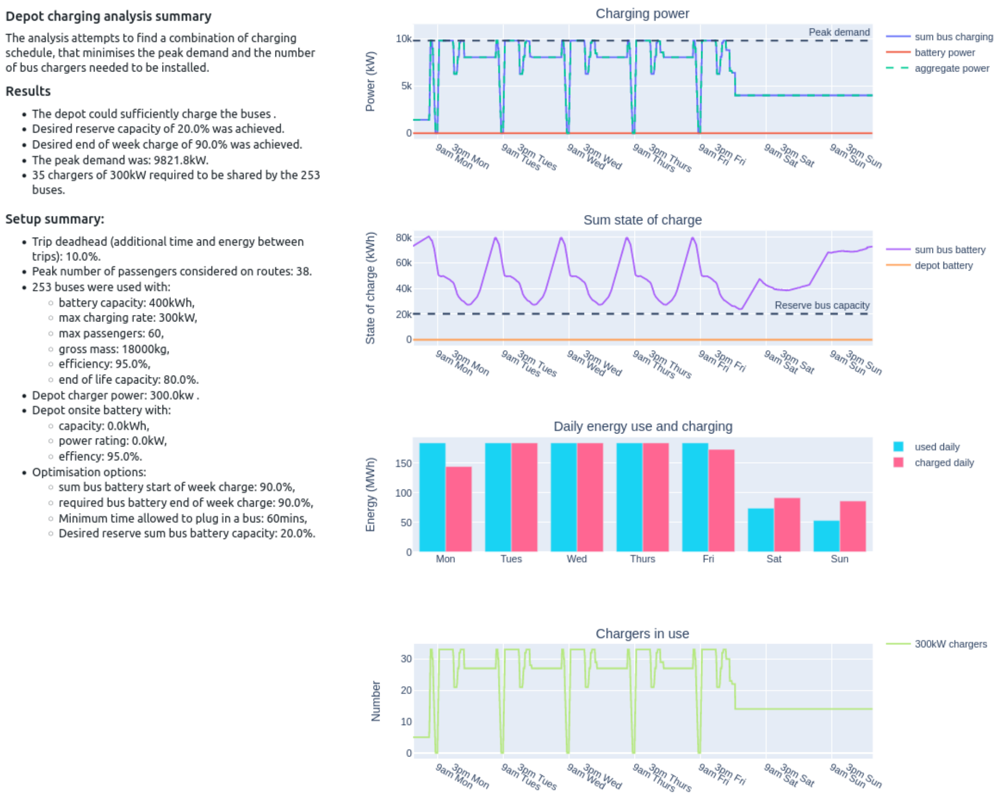

Figure 2.3: Quick start step 3 example output: optimisation summary and profiles.

A detailed description of all parameters and options is given in the following sections.

3. RouteZero webapp overview

The RouteZero web application tool was created to provide insights to a range of users about the feasibility of electrifying bus routes around Australia. The web application is found at `https://routezero.cecs.anu.edu.au/`. The types of questions it can answer can be broken into two broad categories: energy requirements of routes and depot charging infrastructure. These two categories correspond to the two models developed during the project: a data-driven electric bus energy consumption model and a depot charging optimisation model. These questions could include “What routes are most efficient for electric buses to operate?”, “how many buses are needed?”, “how many chargers are needed?”, “what difference does an on-site battery have?”, and “what is the peak power demand on the electricity grid?”.

The tool is broken into three steps outlined below. In each step, calculations and optimisations are made following a ”worst-case” methodology. For example, this worst-case considers the busiest week on the selected routes, peak passenger loading on all trips, and the worst probable temperatures for the buses to operate under at that location. The “worst-case” operating conditions are considered to ensure the routes can be operated even in these conditions.

The rest of this section outlines how each step works and the questions that it can answer. For a quick guide on getting started using the tool see the Quick Start Section 2. A more detailed description of the inputs, parameters and options is then given in Section 4. A description of the outputs and results in Section 5). Finally, several more examples of using RouteZero are given in Section 6.

Step 1: GTFS file and route selection

In step one of RouteZero, the user can select bus routes to be analysed. The bus routes available for selection and the information about them is sourced from publicly available Google Transit Feed Specification (GTFS) files. Table 3.1 gives the files and their sources. After routes are selected, the scheduled trips for the busiest week are extracted and used for steps two and three.

Step 2: Predicting electricity usage on routes

In step two of RouteZero, the data-driven electric bus energy consumption model is used to make predictions of the energy required by an electric bus to perform a trip on a given route based on: average speed, trip distance, average gradient, number of passengers, temperature, number of stops per kilometer, and the buses starting state of charge. For the technical details of this model please refer to Section 9. The outputs from this model can be used to answer the questions:

- How much energy (kWh) is required by an electric bus to undertake a trip on a specified bus route?
- Which routes are more efficient ($\mathrm{kW\,h\,km^{-1}}$) for electric buses?
- What are the total energy requirements (kWh) of a fleet of electric buses servicing the scheduled trips on a selection of bus routes?

The energy consumption predictions are based on the following inputs:

Table 3.1: GTFS file sources.

GTFS file	Source	Last updated
Greater Sydney	https://opendata.transport.nsw.gov.au/dataset/timetables-complete-gtfs	04/06/2022
Vic Metro Buses	https://discover.data.vic.gov.au/dataset/ptv-timetable-and-geographic-information-2015-gtfs	06/01/2022
Vic Regional Buses	https://discover.data.vic.gov.au/dataset/ptv-timetable-and-geographic-information-2015-gtfs	06/01/2022
ACT	https://www.transport.act.gov.au/contact-us/information-for-developers	08/04/2022
Tas Burnie	https://www.metrotas.com.au/community/gtfs/	18/05/2022
Tas Hobart	https://www.metrotas.com.au/community/gtfs/	18/05/2022
Tas Launceston	https://www.metrotas.com.au/community/gtfs/	18/05/2022
Darwin	https://dipl.nt.gov.au/data/bus-timetable-data-and-geographic-information	23/04/2022
Alice Springs	https://dipl.nt.gov.au/data/bus-timetable-data-and-geographic-information	23/04/2022
Perth	https://www.transperth.wa.gov.au/About/Spatial-Data-Access	23/06/2022
Adelaide	https://data.sa.gov.au/data/dataset/https-gtfs-adelaidemetro-com-au	30/10/2021
Brisbane	https://www.data.qld.gov.au/dataset/general-transit-feed-specification-gtfs-seq	08/07/2019

- average speed,
- average gradient,
- number of bus stops per kilometer,
- number of passengers,
- temperature,
- starting state of charge.

The hottest and coldest temperature likely to be experienced at that time and location are considered with the worst temperature for the battery being chosen, the passenger information is expected from the user, the gradient information is calculated from the NASA SRTM elevation data (Farr et al., 2007), and the rest of the inputs are calculated from the GTFS data. The predicted energy requirements are then passed to step three.

To complete this step select the appropriate route and bus options and click “Predict route energy usage”. For more details on the inputs and outputs see Section 4 and 5. Before discussing step three, a brief discussion on the limitations of the data-driven energy consumption model is given below.

Data-driven energy consumption model limitations

The electric bus energy consumption model was developed using performance data from buses operating as part of the project. The performance data corresponds to buses operating in Sydney's inner west and as such several variables within the data had limited ranges and the majority of trips have:

- a moderate temperature between 7 °C and 26 °C,
- a relatively flat average gradient between -1.8% and 1.8%,
- a higher stop per kilometer ratio > 2,
- a lower average speed $< 30\,\mathrm{km\,h^{-1}}$.

While the developed data-driven model has been fit to the trends exhibited in the dataset, application to routes that have conditions outside these ranges is extrapolation and less confidence should be placed in the results.

Some examples of routes that fall outside these conditions are:

- routes in locations that experience very hot temperatures such as Darwin,
- routes in locations that experience very cold temperatures such as Hobart or Canberra,
- very hilly or mountainous routes for instance in some parts of Hobart,
- rural routes with a low number of stops per kilometer.

For more details on the data set used for model development see Section 8.

Step 3: Optimise charging at depot

In step three of RouteZero, the depot charging optimisation model determines the total charging power profile at the depot that minimises the peak demand on the grid while ensuring that the electric bus fleet has enough energy to service the scheduled trips. For the technical details of this model please refer to Section 10. This model can be used to answer questions including:

- What is the peak load that charging the electric buses will place on the grid connection?
- How many buses are required to service the timetabled trips on the selected routes?
- How many electric bus chargers are required?
- What impact does the addition of an on-site depot battery have?
- What impact does restricting the times of day that the buses can be charged have?

The optimisation model considers that all selected routes are operated from a single depot by the user-specified number of buses and does not consider additional charging locations. It treats the bus fleet battery capacity as a whole and finds the charging power required at the depot so that the bus fleet can meet the energy requirements of the selected routes. This approach was chosen to make the most of the available route and trip information.

To get started choose the desired depot and optimisation settings and click "optimise charging". The inputs and outputs are described in greater detail in Sections 4 and 5. A brief description of the modelling assumptions made is given below.

Depot charging optimisation model assumptions

The GTFS data from which route and trip information are obtained contain no information about individual buses. That is, from the GTFS data we do not know what sequence of trips an individual bus needs to operate. Given this limitation, it is not possible to know the energy use of an individual bus and consequently, it is not possible to determine the charging schedule of a single bus. Some key assumptions are listed below and more details can be found in Section 10.2.

- The time and energy required for a bus to get to the start of a trip and return from a trip are, on average, covered by the dead running factor. This is an additional percentage of the trip time and required energy.
- No single bus trip uses more energy than the maximum bus battery capacity. This can be checked beforehand using the outputs of step 2.
- The aggregate state of charge methodology means we assume the available charge is perfectly distributed across the buses required for trips. That is, if we have a combined 100 kWh state of charge available and five trips each needing 20 kWh, then it is assumed five buses have 20 kWh each rather than one bus having 100 kWh.
- Changing which bus is connected to a charger takes minimal time.
- That there is a minimum time a bus can be plugged in to charge. Beyond this time, the buses charging can be rotated as much as needed.
- That the bus operator would be willing to let the combined state of charge run down on busier days and charge up on less busy days.

4. Description of inputs, parameters, and options

The web application tool is broken into three steps with each step allowing the user to choose different options or parameters. Descriptions of the inputs, options and parameters are given in the corresponding step below.

Step 1

The inputs and options for step 1 are described in the table below.

Name	Description	Default value
Select GTFS source	The GTFS file from which routes can be selected. The options are described in Table 3.1.	None
Select Agency	If the GTFS file contains routes operated by multiple agencies, then a specific agency can be selected here to filter the available routes.	None
Select Routes	Allows the user to select multiple routes from the GTFS file that they are interested in. Note that for the charging optimisation all selected routes will be considered as operated by buses from the same depot.	None
Advanced options	A tick box to enable 'advanced options' in steps two and three.	False

Step 2

In step two, the user can choose parameters and options for the selected routes and the buses to be considered. These are described in the table below.

Name	Description	Default value
Route options:		
Dead-running (%)	An additional percentage of time and energy allocated to all trips to, on average, account for the buses travelling between trips, from the depot, and back to the depot. For example, with 10% dead-running a trip scheduled in the GTFS data to take 20 minutes and use 10 kWh would be extended to take 22 minutes and use 11 kWh, with the time extension applied by starting and finishing the trip 1 minute earlier.	10%
Peak passengers	The peak passengers that might be expected across all selected routes. Following the worst-case methodology where we want to ensure the scheduled trips can be managed even in the worst conditions, this peak value will be used for all trips. However, it should be noted that the energy consumption is less sensitive to the number of passengers than to other parameters (see Section 9).	38
Bus parameters:		
Battery capacity (kWh)	The battery capacity of each bus.	400 kWh
Charging power (kW)	The maximum allowed charging power of the buses.	300 kW
Charging efficiency	(Advanced option) The efficiency of charging the buses. For example, with the default value of 0.95, charging at 100 kWh for 1 hour will increase the buses charge by 95 kWh. Note that any discharging efficiency is factored into the energy consumption model.	0.95
End of life capacity (%)	(Advanced option) The battery capacity at the end of the batteries service life. Battery capacity typically decreases over the life of the battery and so for the worst-case methodology this decreased capacity is considered.	90%

Step 3

In step three, the user can choose options for the depot infrastructure and the charging optimisation. These are described in the table below.

Name	Description	Default value
Depot options:		
Max charger power (kW)	The maximum rated power of the chargers. The optimisation will find the minimum number of chargers required to meet the energy requirements of the scheduled trips.	300 kW
On-site battery capacity (kWh)	The capacity of an on-site battery to be considered (if any). This battery is used by the optimisation to offset peak demand on the grid by charging when there are no buses available to charge or the buses are not allowed to charge.	0 kWh
On-site battery power (kW)	The rated power of the on-site battery (if any) to charge and discharge.	0 kW
On-site battery efficiency	(Advanced option). The charging and discharging efficiency of the on-site depot battery (if any).	0.95
Number of buses	The number of buses to be used to service the scheduled trips. All buses are considered to be charged at the same depot. The minimum value is calculated from the 'buses on route' graph output of step two.	
Optimisation options:		
Min plugin time (min)	The minimum amount of time to connect a bus to a charger before rotating to charge a different bus. If this time is set to 60 minutes and charging is allowed for 8 hours overnight, then this means a maximum of 8 different buses could be plugged into the one charger during the night.	60 min
Start of week charge (%)	The percentage charge that the buses and on-site battery start the week with.	90%
End of week charge (%)	The required percentage charge that the buses and on-site battery must end the week with.	90%
Bus reserve capacity (%)	The percentage of the combined capacity of all buses to keep in reserve throughout the week.	20%
Allowed charging times	Tick boxes to enable or disable bus charging during particular hours of the day.	all

5. Description of results and outputs

The web application outputs results for the user during steps two and three — there are no outputs from step one. These outputs are described below in the corresponding sections.

Step 2

Step two produces predictions of energy requirements for the trips scheduled on the selected routes. The results provided to the user are described in the table below.

Name	Description
Electricity usage summary	Summarises the predicted energy requirements of the selected routes and their timetabled trips. Gives the maximum and average energy usage of the routes and the minimum number of buses required to operate the timetabled routes.
Buses on route graph	Displays the number of buses required on scheduled trips throughout the week taking into account the dead-running (%).
Energy required on active routes graph	Displays the combined predicted energy requirements of all the timetabled trips throughout the week. This energy requirement is used as an input to the charging optimisation in step three.
Interactive energy consumption map	Shows a map of the selected routes coloured by their predicted energy consumption. The colouring can be based on either the energy usage per kilometer or the total energy usage. The results are shown for a given time window which can be changed by the user. The same route may have a different predicted energy usage at different times of the day due to different temperature and traffic conditions (impacting average speed). Hovering over a route will bring up a tooltip that shows the parameters impacting its predicted energy usage. Note, if there are no active trips on the route during a particular time window then that route will not be displayed.
Downloadable CSV	A CSV summarising the predicted energy usage on the selected routes can be downloaded. The route parameters affecting the prediction are included and the results are broken into time windows.

Step 3

Step three optimises the charging power at the depot to minimise the peak demand on the grid while ensuring the energy requirements of the timetabled trips can be met. The results provided to the user are described in the table below.

Name	Description
Depot charging analysis summary	Summarises the options chosen that affect the optimisation and the results. Gives the peak demand, the number of chargers required and reports on whether it was feasible to meet the energy requirements of the timetabled trips with the given setup. If it was not feasible some suggestions to modify the setup are given.
Charging power graph	Displays the combined bus charging power, the on-site battery power, and the aggregate power required from the grid. The peak power required from the grid is shown — minimizing this peak demand is the primary objective of the optimization.
State of charge graph	Displays the combined state of charge for all buses and the state of charge for the on-site battery. The input 'State of week charge (%)' controls the starting point, while the 'Bus reserve capacity (%)' and 'End of week charge (%)' constrain the optimisation. If a feasible solution to the charging that satisfies these constraints cannot be found then the closest solution is shown (even if this gives a negative state of charge values). If no feasible solution is found, this is highlighted in the analysis summary and changes to the setup are suggested.
Daily energy use and charging chart	Displays the total energy used and charged across all buses each day.
Chargers in use	Displays the number of chargers that are in use throughout the week. The optimisation attempts to minimise the total number of chargers needed as a secondary objective. The number of chargers that can be used at any given time is impacted by the number of buses that would be at the depot, the min plugin time, and the allowed charging time windows. Warning: because the schedule of individual buses is not known, the chargers in use graph is indicative only.

6. Examples

This section provides three examples that demonstrate how the RouteZero tool can be used, as well as how changing the setup can impact the results.

6.1 Example 1: Impact of an on-site battery on charging power

In this example, 40 routes were selected from the Greater Sydney GTFS feed for the Newcastle Region. The example demonstrates the impact that adding an on-site depot battery can have on the peak demand when the buses are restricted to only charging overnight (between 7am and 7pm). Initially, no on-site battery is included for the optimisation and the peak demand is determined before adding a 10 MW h on-site battery and comparing the results. The selected routes, inputs, and options for all steps are shown in Figure 6.1. Note that 130 buses with 480 kWh battery capacity were used to ensure sufficient combined battery capacity to service all scheduled routes during the daytime without recharging.

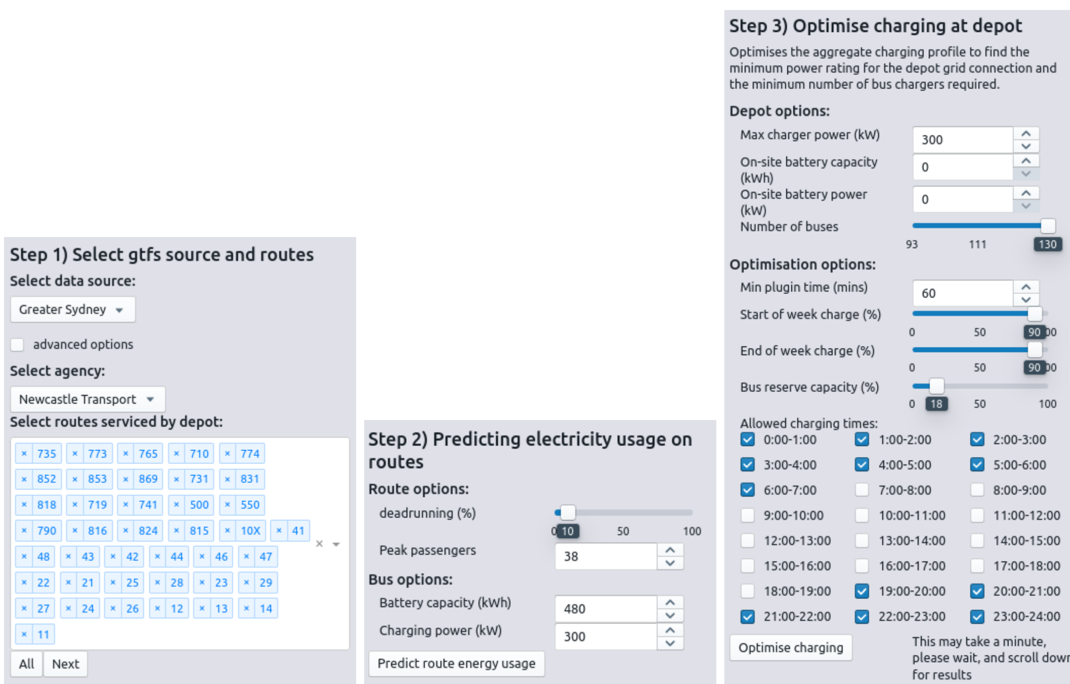

Figure 6.1: Example 2 selected routes, inputs, options for all steps. (Right) Step 3 inputs show the case without an on-site battery.

Step 2 outputs the predicted energy requirements of all trips timetabled on the selected routes for the busiest week. Figure 6.2 shows the output 'buses on route' and 'total energy requirement of active routes' graph from which we can see that a maximum of 93 buses are required to be on trips at any given time and that all weekdays have roughly the same energy requirements. Therefore a minimum of 93 buses are required to service the timetabled trips, where more may be necessary depending on the energy and charging requirements.

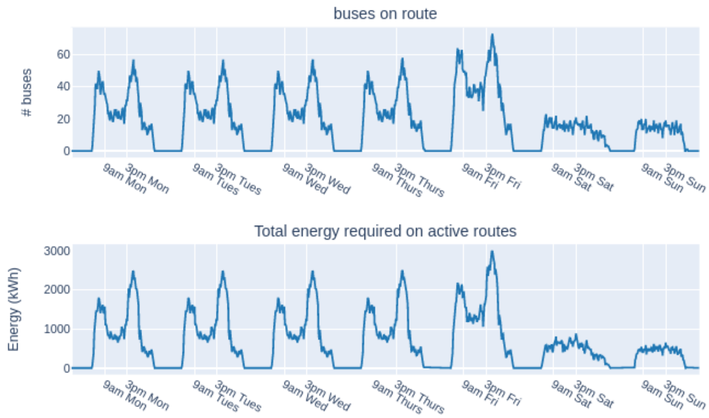

Figure 6.2: Example 1 output from step 2 — buses on route and total energy requirement of active routes.

This step also provides an interactive map showing the routes active during a given time window and their energy requirements — see Figure 6.3.

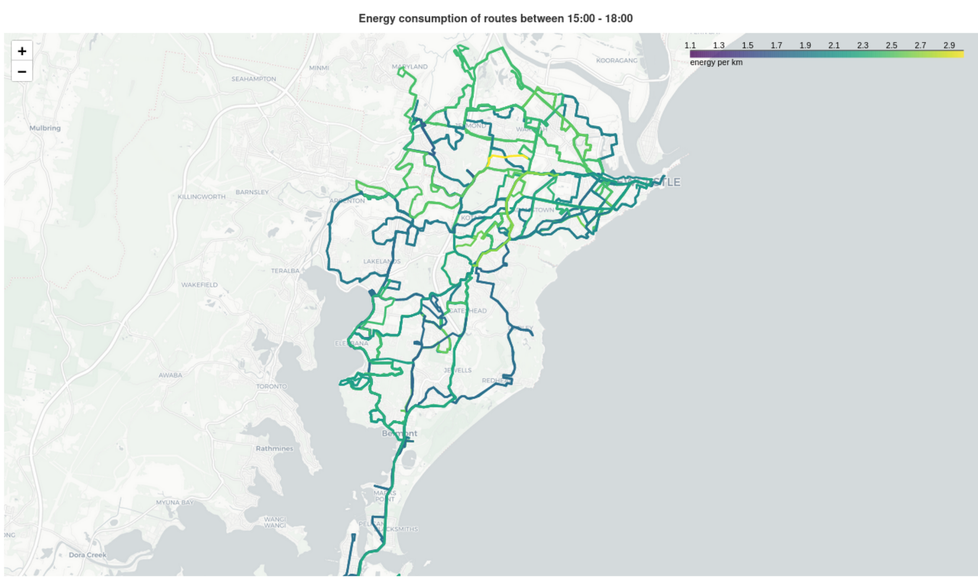

Figure 6.3: Example 2 interactive map from step 2. Energy consumption per kilometer of active routes between 3pm and 6pm.

Step 3 runs the depot charging optimisation. The optimisation is run for two cases: without an on-site depot battery and with a 10 MW h on-site depot battery. The results are shown in Figure 6.4. Without the battery, the peak demand on the grid is 3773 kW. Adding the on-site battery reduces the peak demand to 3001 kW by having the on-site battery charge during the day when the buses are not allowed to charge and then using this to offset the charging power of the buses overnight.

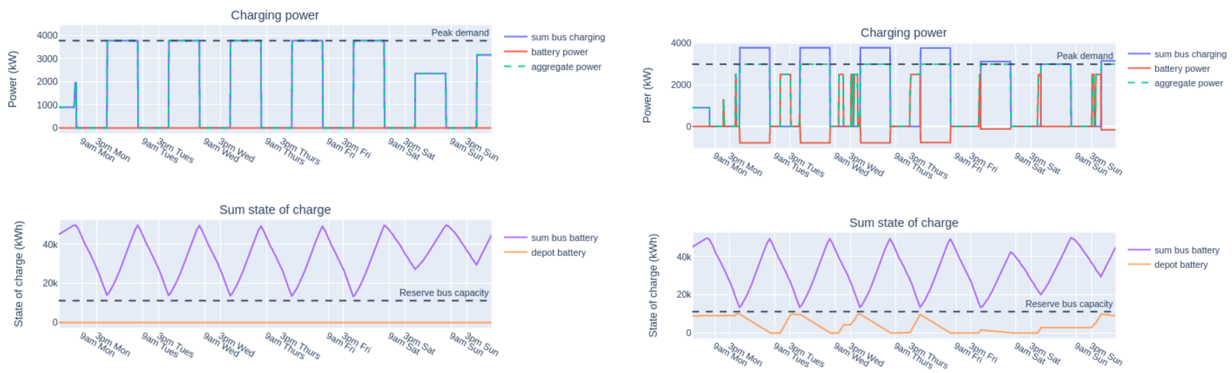

Figure 6.4: Example 1 charging power and state of charge graphs output from step 3. (Left) No on-site depot battery. (Right) 10 MW h on-site depot battery.

6.2 Example 2: Impact of adjusting allowed bus charging times

In this example, all routes from the Darwin GTFS file are selected which includes routes in Darwin and Palmerston. The example shows the impact of restricting when the buses are allowed to charge. Initially it considers that charging is only allowed between 7 pm and 7 am before relaxing this to include the off-peak period between 10 am and 3 pm. It also sets that buses must be plugged in to charge for a minimum of 4 hours before rotating charging. The selected routes, inputs, and options for all steps are shown in Figure 6.5.

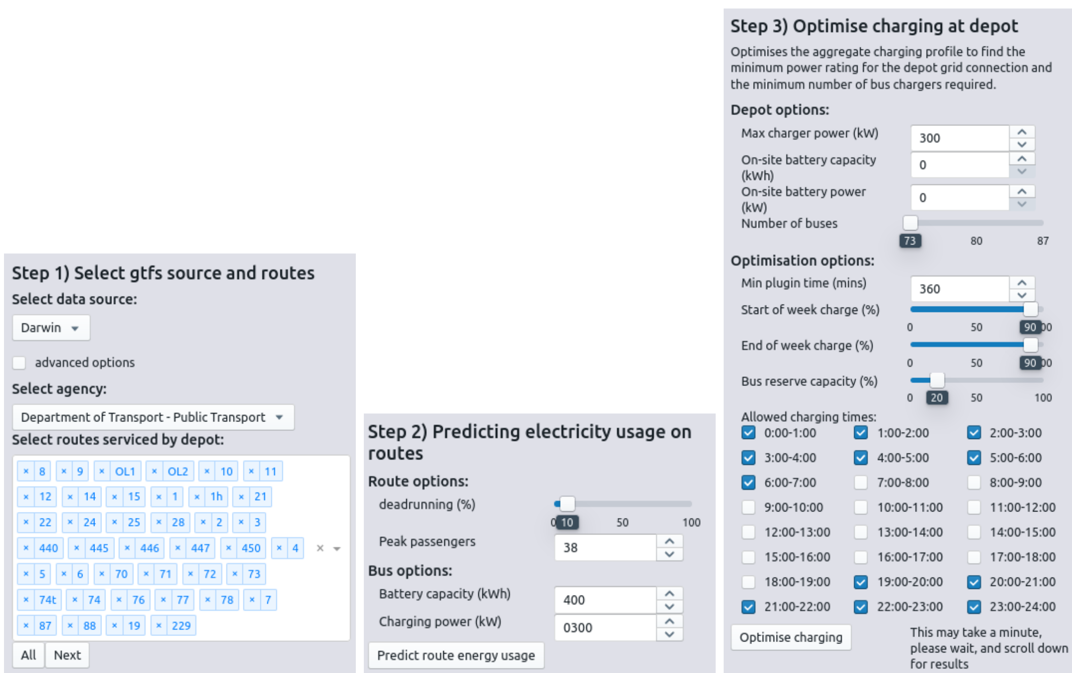

Figure 6.5: Example 2 selected routes, inputs, options for all steps.

Step 2 outputs the predicted energy requirements of all trips timetabled on the selected routes for the busiest week. Figure 6.6 shows the output 'buses on route' and 'total energy requirement of active routes' graph from which we can see that a minimum of 73 buses are required (also stated in the summary text) and that Friday has the largest energy requirement on the buses.

This step also provides an interactive map which shows the routes active during a given time window and their energy requirements — see Figure 6.7.

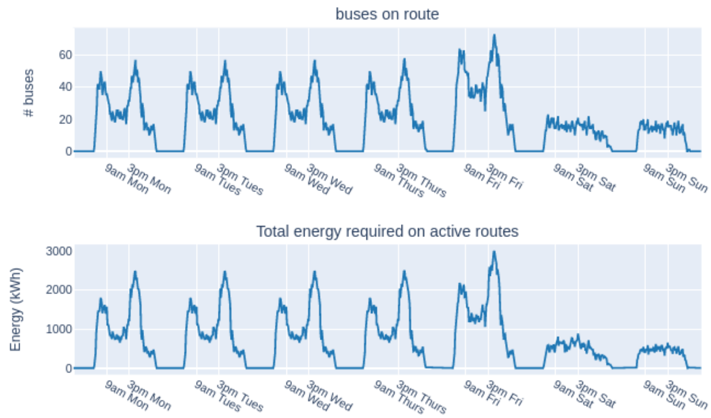

Figure 6.6: Example 2 output from step 2 — buses on route and total energy requirement of active routes.

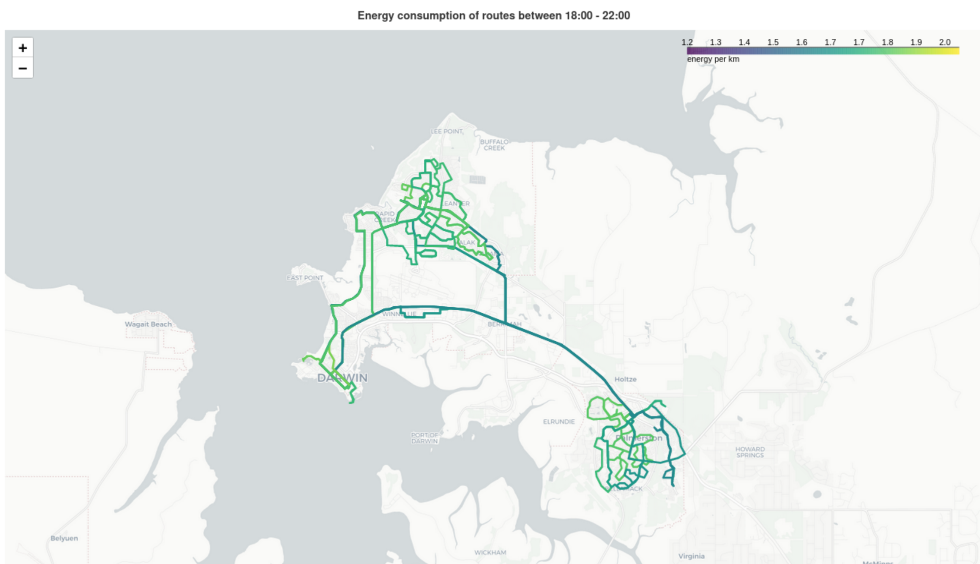

Figure 6.7: Example 2 interactive map from step 2. Energy consumption per kilometer of active routes between 6 pm and 10 pm.

Step 3 runs the depot charging optimisation. Initially, when charging is only allowed overnight between 7 pm and 7 am, the optimisation reports that it cannot sufficiently charge the buses to meet the energy requirements (state of charge goes negative) let alone maintain the reserve bus battery capacity of 20% — see Figure 6.8 (Left). Looking at the state of charge change during the day on Friday which starts full at 7 am and falls below the reserve by 7 pm, we can deduce that the combined capacity of the 73 buses is not enough to meet the energy requirements of all trips on this day without additional charging. There are three probable solutions to this: increase the number of buses, increase the battery capacity of the existing buses, and allow charging at additional times. Figure 6.8(Right) demonstrates the result of additionally allowing charging during the off-peak times of 10 am–3 pm and shows that the reserve is now maintained. For this case, the peak demand on the grid is 3134 kW and 39 chargers are required.

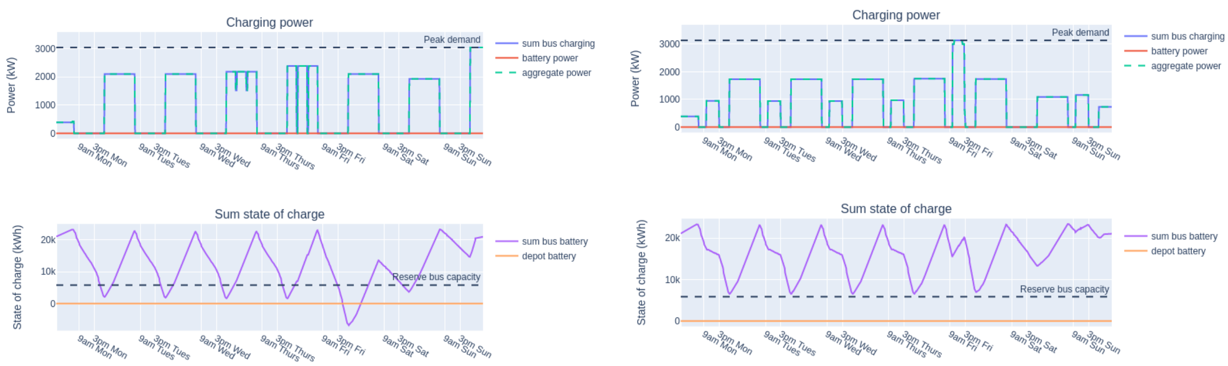

Figure 6.8: Example 2 charging power and state of charge graphs output from step 3. (Left) Charging only allowed overnight. (Right) Charging also allowed from 10am till 3pm.

6.3 Example 3: Advanced options

In this example, all metropolitan routes from the Launceston Tasmania GTFS file are selected. This example shows how the advanced options can be changed — specifically the charging efficiencies and the end-of-life battery capacity. The selected routes, inputs, and options for all steps are shown in Figure 6.9.

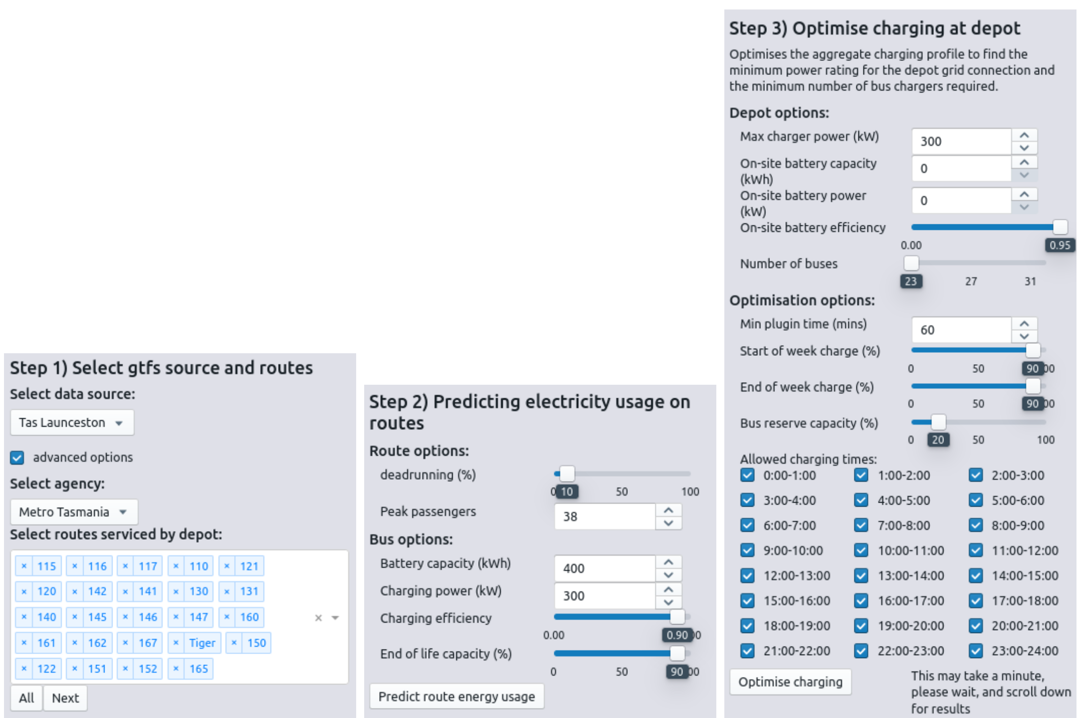

Figure 6.9: Example 3 selected routes, inputs, and options for all steps. Note, in the first step 'advanced options' has been selected allowing the bus charging efficiency to be reduced to 0.9 and the end-of-life capacity increased to 90% in step 2.

Step 2 outputs the predicted energy requirements of all trips timetabled on the selected routes for the busiest week. Figure 6.10 shows the output 'buses on route' and 'total energy requirement of active routes' graph from which we can see that a minimum of 73 buses are required (also stated in the summary text) and that Friday has the largest energy requirement on the buses.

This step also provides an interactive map which shows the routes active during a given time window and

Figure 6.10: Example 3 output from step 2 — buses on route and total energy requirement of active routes.

their energy requirements — see Figure 6.11.

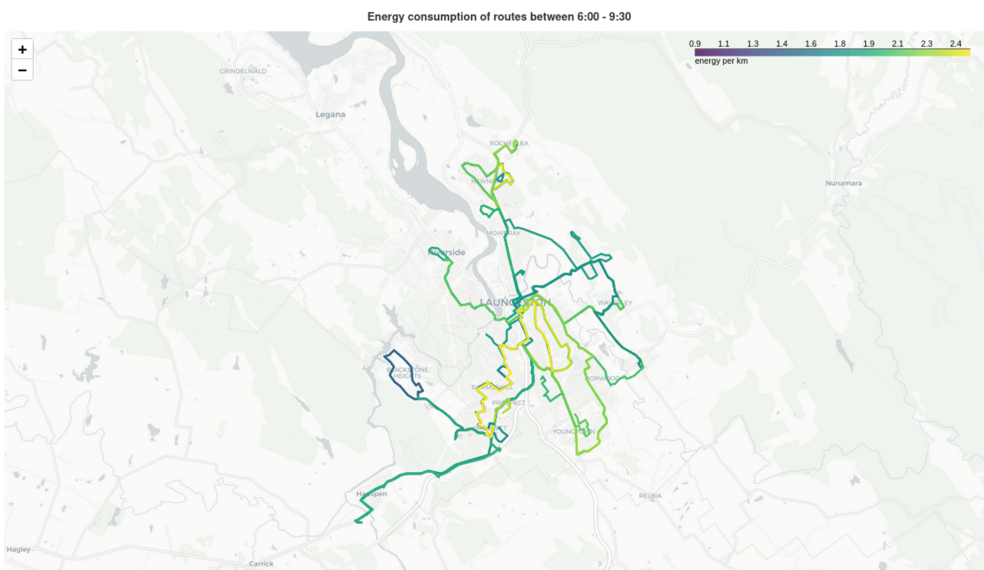

Figure 6.11: Example 3 interactive map from step 2. Energy consumption per kilometer of active routes between 3 pm and 6 pm.

Step 3 runs the depot charging optimisation. The resulting charging power and state of charge graphs are shown in Figure 6.12. For the setup used, the peak demand is 571 kW, and two chargers are required.

Figure 6.12: Example 3 charging power and state of charge graphs output from step 3.

Part II
Technical description of RouteZero tool

This part of the report shares the technical details of the project. It describes the data obtained, the modelling methodology taken, and the models developed. Lastly, it includes a case study that demonstrates possible insights that the project can provide about the feasibility of electrifying various bus routes.

7. Overview and methodology

The goal of this project was to develop a broadly accessible tool that can provide users insights into:

A) the feasibility of electrifying Australian bus routes,

B) the charging infrastructure required at the bus depot.

Our tool provides these insights by allowing users to predict the energy required by electric buses on user-specified routes, and determine for a selection of routes to be operated by electric buses the total charging power required from the grid, the number of bus chargers required, and impact of an on-site battery. Two models were developed to achieve this:

- a data-driven electric bus energy consumption model described in Section 9,
- a depot charging optimisation model described in Section 10.

Figure 7.1 illustrates how these models fit together and the different processes of training and use.

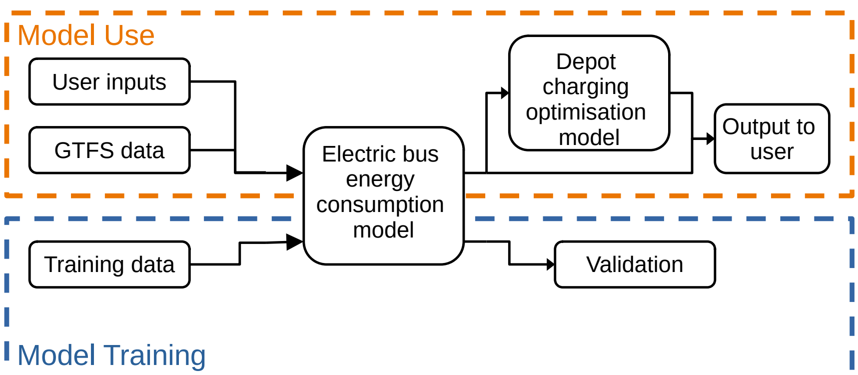

Figure 7.1: Illustration of how the two developed models fit together and the different processes of training compared to producing outputs for a user.

The required inputs have been chosen so that the final tool would be broadly accessible and applicable to as many routes as possible. It is important to distinguish between data available for model training and the data available when making predictions. The data available for model training was provided from an electric bus trial on a small selection of routes in Sydney's inner west and is described in greater detail in Section 8. To apply the model to other routes, a source of data containing parameters of these routes was needed and publicly accessible GTFS data — described in Section 8.6 — was chosen. Aligning the information available for both model development and model use was a driving factor behind many modelling decisions made. To narrow down the choice of inputs a review of the factors relevant to predicting energy consumption was undertaken.

7.1 Review of inputs for predicting energy consumption

The approach taken is to develop a data-driven model that requires as inputs only information that is available to potential end-users. This excludes models requiring high-resolution instantaneous speed and acceleration data such as the work in Chen et al. (2021) or the physics-based models presented in Hjelkrem et al. (2021); Moniot (2017); Basma et al. (2020). Instead, we consider data-driven models (Li et al., 2021; Abdelaty et al., 2021; Abdelaty and Mohamed, 2021) (e.g. linear regression and regression trees) that use lower fidelity information about a route — for example, average speed and gradient.

With this in mind, a literature review and informal interviews were conducted to determine the most relevant factors for predicting energy consumption. The following lower fidelity data is significant for predicting energy usage of electric busses (Abdelaty and Mohamed, 2021; Abdelaty et al., 2021; Chen et al., 2021; Hjelkrem et al., 2021; Li et al., 2021):

- terrain — average road gradient;
- driver aggressiveness — the magnitudes of accelerations and declarations;
- temperature — this has a significant impact on the energy consumption due to auxiliary systems i.e. air-conditioning and battery cooling/heating, as well as battery performance;
- passenger loading — this nominally makes up 20% of the vehicle gross mass affecting energy required for driving and also impacting air-conditioning energy consumption;
- number of stops — captured as average per kilometer;
- average speed — this also gives some indication of traffic;
- initial state of battery charge (SoCi);
- road condition — wet or dry, paved or unpaved etc;
- vehicle mass.

The majority, but not all, of this information was included in the data available for this project and a description of the final data set used for training is given in Section 8.

8. Description of the training data

To develop a data-driven predictive model for electric bus energy consumption a training dataset of bus trips was required. Where for each trip the input (independent) and output (dependent) parameters wishing to be modelled are recorded. The required data was collated from several sources: Zenobe, Transport for NSW, and publicly available temperature and weather data. The collected data corresponds to the battery electric bus trial at the Leichhardt bus depot in Sydney's inner west as part of the Next Generation Electric Bus Depot Project (ARENA, 2021). The data from these sources were cleaned, combined, and processed to give the following information about each trip undertaken by a bus on a route:

- average gradient (%),
- average number of passengers,
- number of stops per kilometer,
- average speed (km/hour),
- starting battery state of charge (%),
- temperature (degrees Celsius),
- energy consumption per kilometer (kWh/km),
- distance (km),

This final data set contains no information about road condition, driver aggressiveness, and vehicle mass. As such, these variables were excluded from the modelling. Road condition was excluded as all the modelling data was collected in Sydney's inner west and so a range of different road conditions would not be present. The reasons to exclude vehicle mass and driver aggressiveness are explained in Section 8.1.

8.1 Bus data from Zenobe

Zenobe provided one-minute resolution data recorded from each bus' operations containing:

- bus id,
- date and time stamp,
- GPS location,
- odometer reading (km),
- state of charge (integer %),

The data for each bus was on average 33% complete (i.e. we had on average 10 weeks duration worth of data per bus) with the worst being 7.7% and the best being 40.3%. The majority of the incomplete records were due to missing GPS locations. Note that the battery state of charge is recorded in integer percent and for the buses used this equates to increments of either 3.68 kW or 4.22 kWh. The time resolution of the Odometer data was not granular enough to calculate accurate acceleration and deceleration and given that this information would not be available to the end-user for predictions it was decided to exclude accelerations (driver aggressiveness) from the modelling.

The data was recorded from two types of electric buses: the BYD Gemilang D9RA, and the Yutong E12. The relevant specifications for these buses are summarized in Table 8.1. With data from only two different types of buses and both buses having the same gross vehicle mass, it was decided to exclude vehicle mass from the modelling.

Table 8.1: Bus specifications relevant to the modelling.

Bus	Gross Vehicle Mass (kg)	Battery capacity (kWh)
BYD Gemilang D9RA	18000	368
Yutong E12	18000	422

8.2 Route and passenger data from Transport for NSW

Transport for NSW provided data relating to each bus stop on route for the buses. For each bus stop the following information was available:

- bus id,
- date,
- direction (inbound or outbound),
- sequence number (what number stop it is on the route),
- route short name,
- actual arrive time,
- actual depart time,
- number of passengers upon departing the stop.

Note that there are often several route variants with the same route short name. Hence, knowing the route's short name doesn't fully identify which route the bus was on.

8.3 Publicly available temperature and elevation data

The data provided by Zenobe and Transport for NSW needed to be augmented with temperature and elevation information. Hourly temperature data for several weather stations in Sydney was recorded and tagged by date and time. Elevation data was sourced from the NASA SRTM altitude data (Farr et al., 2007) which can be referenced by GPS location.

Where hourly temperature data was not available, the minimum and maximum temperature for the day were used to scale a representative hourly temperature profile and temperatures from this scaled profile were then used. This was necessary for 3 weeks in June. The representative temperature profile was calculated from the average of the existing data and is shown in Figure 8.1.

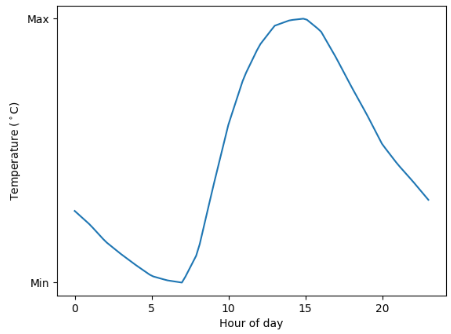

Figure 8.1: Representative temperature profile over a day.

8.4 Data processing and cleaning

The data from each source need to be combined into a single dataset of trips. The following steps were taken to process and clean the data.

1. The bus operating data was combined with the bus specifications to calculate the state of charge in kWh.
2. Temperature information was added to the bus data based on the date and time.
3. Elevation data was added to the bus data based on the GPS locations.
4. The per stop information from Transport for NSW was aggregated to give the following information about each trip made by a bus:
   - bus id,
   - average passengers,
   - route short name,
   - trip start date and time,
   - trip end date and time.
   - number of stops
5. This trip data was then matched to segments of the bus data based on the bus ids and the date and time. The following information could then be computed and added to the trip information:
   - average gradient (%),
   - GPS path,
   - average temperature (°C),
   - trip distance (km),
   - stops per kilometer,
   - energy consumed (kWh),
   - energy consumption per kilometer ($\mathrm{kW\,h\,km^{-1}}$).
6. All trips with missing information were removed.
7. Comparison with GTFS route data:

- the GPS path was compared with each of the GTFS route shapes corresponding to the route short name and where no close enough match was found the trip was removed from the database,
- the distance travelled was compared to the GTFS route distance information and where the difference was greater than 3000 m the trip was removed.

8. The data were manually inspected to remove any obvious outliers.
9. Lastly, information not required for the modelling was removed.

8.5 Summary statistics and analysis

After processing, the final dataset spanned the time-frame from 6$^{\text{th}}$ of of January 2022 till the 31$^{\text{st}}$ of August 2022 and consisted of 10459 trips on 42 different routes by 33 different buses. Table 8.2 summarizes the variables contained in the dataset and the distribution of the variables in the dataset is shown in Figure 8.2.

Table 8.2: Dataset summary.

Variable	Description (units)	Mean	Minimum	Maximum
SOC_i	Trip start state of charge (%)	89.1	25.0	100.0
g	Average gradient (%)	0.1	-2.0	2.0
T	Average temperature on trip (°C)	17.6	5.0	28.8
s/km	Number of bus stops per kilometer on the route	3.1	1.3	6.6
v	Average speed on the trip ($\text{km}\,\text{h}^{-1}$)	17.6	3.6	37.7
p	Average number of passengers on the trip	6.1	0.0	40.1
ec/km	Average energy consumption per kilometer on the trip ($\text{kW}\,\text{h}\,\text{km}^{-1}$)	1.06	0.33	2.74

It can be seen that several of the input variables cover only a limited range. The majority of trips have:

- a moderate temperature between 7 °C and 26 °C,
- a relatively flat average gradient between -1.8% and 1.8%,
- a higher stop per kilometer ratio > 2,
- a lower average speed $< 30\,\text{km}\,\text{h}^{-1}$.

These limited ranges are in line with the time of year the data was collected and the location and types of routes it corresponds to—Sydney's inner west.

While the developed data-driven model has been fit to the trends exhibited in the dataset, application to routes that have conditions outside these ranges is extrapolation and less confidence should be placed in the results.

Some examples of routes that fall outside these conditions are:

- routes in locations that experience very hot temperatures such as Darwin,
- routes in locations that experience very cold temperatures such as Hobart or Canberra,
- very hilly or mountainous routes for instance in some parts of Hobart,
- rural routes with a low number of stops per kilometer.

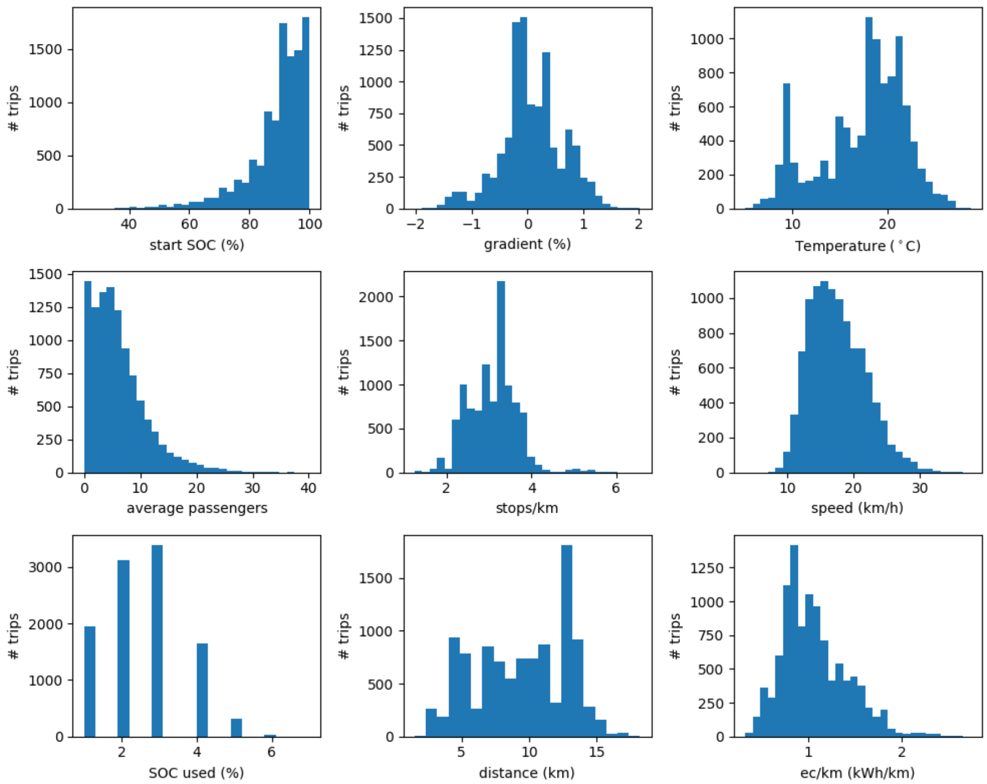

Figure 8.2: Distributions of the dataset variables. Both the dependent (output) and independent (input) variables are shown. Also shown is the distribution of percent state of charge used on trips and trip distance from which the energy consumption per kilometer is calculated.

The state of charge information being provided as whole integer percentages has a significant negative impact on the data quality due to the loss of precision. This loss of precision creates uncertainty about the actual state of charge used on a trip. For example, a recorded state of charge used of 5% corresponds to an actual state of charge used between 4.5% and 5.5%. This is equivalent to uncertainty of ± 1.84 kWh for the BYD Gemilang D9RA and ± 2.11 kWh for the Yutong E12. As shown in Figure 8.2 most of the trips use between one and five percent state of charge. Hence the loss of precision equates to a relative error between $\pm 50\%$ and $\pm 10\%$ with the error being worse for trips taken on shorter routes that use less battery capacity.

It is also possible to compute the approximate standard deviation of the error on the measured energy consumption per kilometer that this equates to. Recognizing that this quantification error has a uniform distribution, we can convert the kWh error range into a per kilometer value for each trip and calculate the variance of the possible distribution. The result is that the $\mathrm{kW\,h\,km^{-1}}$ errors have an average standard deviation of 0.279. Note that this is the measurement standard deviation not the standard deviation of predictions made by our trained model. The standard deviations made by our trained model are illustrated in the sensitivity plots (Figure 9.2) given in Section 9.

8.6 Data source for end-user outputs

Static General Transit Feed Specification (GTFS) files are used as the primary source of data when producing outputs for an end-user. Files containing information about a large number of routes within Australia are freely available online for each state and territory. A summary of the contained data relevant to the modelling is given below. Those interested can find a detailed description of the data in the online reference documentation (Google, 2022).

For each bus route the GTFS files give the following information:

- the trips schedule on this route,
- a list of stops belonging to the route and their locations,
- the arrival and departure time of each bus stop on a trip,
- The stops along the route and their locations,
- A GPS path for the route.

Added to this is temperature and elevation information obtained from public sources as described in Section 8.3, and passenger information provided by the end-user.

From this, the inputs required for the electric bus energy consumption model (see Section 9) are calculated allowing predictions of energy consumption to be made. A schedule of trips for a selection of routes can also be extracted which is used in the depot charging optimisation model (see Section 10).

9. Electric bus energy consumption model

A Bayesian linear regression model is fit to the modelling data. We choose a linear regression model because of its ease of interpretation, lower dependence on large amounts of data when compared to non-parametric models such as random forests and neural networks, and greater ability to extrapolate outside the training data. A Bayesian approach is used to fit the model as it quantifies the uncertainty in the parameter values. This allows a confidence interval to be placed on the predictions.

The linear regression model can be represented as

$$\mathrm{ec/km} = c_0 + c_1 \mathrm{s/km} + c_2 g + c_3 T + c_4 v + c_5 p + c_6 \mathrm{SOC}_i + c_7 I_{>97\%}(\mathrm{SOC}_i) + c_8 T^2 + e \tag{9.1}$$

where e is an error term that is approximated as zero-mean Gaussian and $I_{>97\%}$ is an indicator function that indicates if a trip is started with a close to full battery:

$$I_{>97\%}(\mathrm{SOC}_i) = \begin{cases} 1 & \mathrm{SOC}_i > 97\%, \\ 0 & \text{otherwise.} \end{cases} \tag{9.2}$$

Several variable transforms have been included: temperature squared, and a battery close to full indicator. These account for the following patterns.

Energy consumption by auxiliary systems (air conditioning and battery management) has an approximately quadratic relationship with the external temperature (Abdelaty and Mohamed, 2021). Figure 9.1 shows that ec/km as a function of SOC_i has a clear negative trend—batteries are more efficient at higher capacity—with the exception that at close to 100% initial state of charge the trips have a much higher energy consumption. This is explained by Abdelaty and Mohamed (2021) as a result of less ability to regeneratively brake if the battery is already close to full. To model this the indicator function, $I_{>97\%}$ is used.

The data set was split 80/20 into training and validation sets. The model parameters were fit to the training data using Bayesian linear regression (Box and Tiao, 2011). Briefly, given output $\mathbf{y} \in \mathbb{R}^n$, inputs $\mathbf{X} \in \mathbb{R}^{n \times p}$, model parameters $\boldsymbol{\theta} \in \mathbb{R}^p$ with a zero-mean Gaussian prior such that

$$\mathbf{y} = \mathbf{X}\theta + e, \tag{9.3}$$

where e is zero-mean Gaussian with covariance $\mathbf{\Sigma}$, then the parameters will have posterior mean and variance given by

$$\begin{aligned} \mathbb{E}[\boldsymbol{\theta}|\mathbf{y}] &= (\mathbf{X}^\mathsf{T}\mathbf{\Sigma}^{-1}\mathbf{X} + \mathbf{\Sigma}_p^{-1})^{-1} X^\mathsf{T}\mathbf{y}, \\ \mathbb{V}[\boldsymbol{\theta}|\mathbf{y}] &= (\mathbf{X}^\mathsf{T}\mathbf{\Sigma}^{-1}\mathbf{X} + \mathbf{\Sigma}_p^{-1})^{-1}, \end{aligned} \tag{9.4}$$

where $\mathbf{\Sigma}_p$ is the prior covariance of the parameters.

This was used to fit our linear regression model with a large prior covariance placed on the parameters to represent no prior knowledge and the measurement variances calculated as discussed in Section 8.5. The resulting parameter means and 95% confidence intervals are given in Table 9.1. The model was validated by making predictions on the validation set and calculating the prediction error, which had a weighted mean of $5.34 \times 10^{-3}\,\mathrm{kW\,h\,km^{-1}}$ and a standard deviation of $0.278\,\mathrm{kW\,h\,km^{-1}}$.

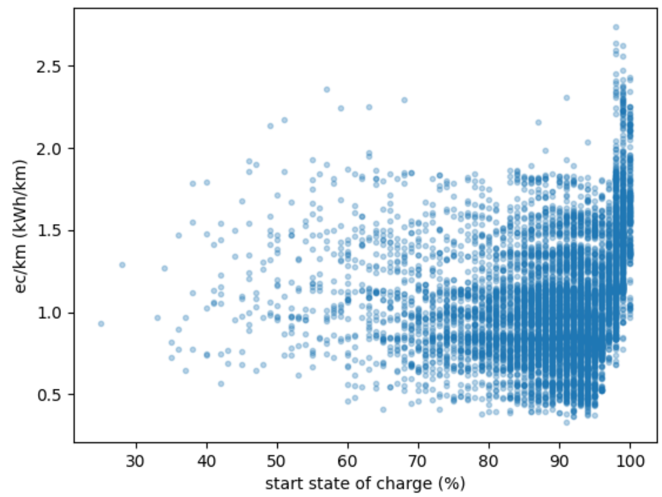

Figure 9.1: Energy consumption per kilometer as a function of battery state of charge at the beginning of a trip as observed in the modelling data.

Given that the error introduced by recording the state of charge in integers has an average standard deviation of approximately 0.279, we can be confident that the trained model is the best that can be achieved given the dataset.

Table 9.1: Model parameters after fitting to the training data.

Parameter	Description	Mean	95% CI
c_0	model constant	1.94	[1.86, 2.02]
c_1	coefficient of s/km	0.046	[0.0353, 0.0567]
c_2	coefficient of g	0.209	[0.197, 0.221]
c_3	coefficient of T	-0.0715	[-0.0782, -0.0648]
c_4	coefficient of v	-0.0157	[-0.017, -0.0143]
c_5	coefficient of p	0.0032	[0.00214, 0.00427]
c_6	coefficient of SOC_i	-0.00319	[-0.0037, -0.00268]
c_7	coefficient of $I_{>97\%}(\mathrm{SOC}_i)$	0.428	[0.414, 0.442]
c_8	coefficient of T^2	0.002	[0.0018, 0.0022]

Sensitivity plots of the predicted energy consumption as a function of a single variable with all other variables set to the data set mean are shown in Figure 9.2. It is observed that temperature, speed, and gradient have the biggest impact on the predicted energy consumption while average passengers has the lowest. The model indicates that:

- Energy consumption increases with the number of stops per kilometer. Intuitively, stopping more often should be less energy efficient, and high values for this parameter would also indicate a route in a higher density urban area with more traffic.
- Energy consumption increases with average gradient aligning with intuition that more energy is required to end at a higher elevation while going down the electric buses can use regenerative braking.
- As already discussed, energy consumption is a quadratic function of temperature with the most efficient

point being close to the approximate air conditioning set point.

- Energy consumption decreases with increased average speed. Given that the modelling data corresponds to urban routes with relatively low average speed, the average speed is probably a strong indicator of traffic with higher speeds corresponding to less traffic and therefore greater efficiency. It is probable that at speeds greater than this drag and other effects would start to dominate and this trend may not hold.
- Energy consumption increases with the number of passengers—added mass and air conditioning load—however, it has minimal impact compared to other parameters.
- As already discussed, energy consumption decreases with the start state of charge up until the trips are started almost full at which point the ability to regeneratively brake is limited.
- That for most trips with an energy consumption of around $1\,\mathrm{kW\,h\,km^{-1}}$ the 95% confidence interval is around $\pm 0.05\mathrm{kW\,h\,km^{-1}}$ or roughly $\pm 5\%$.

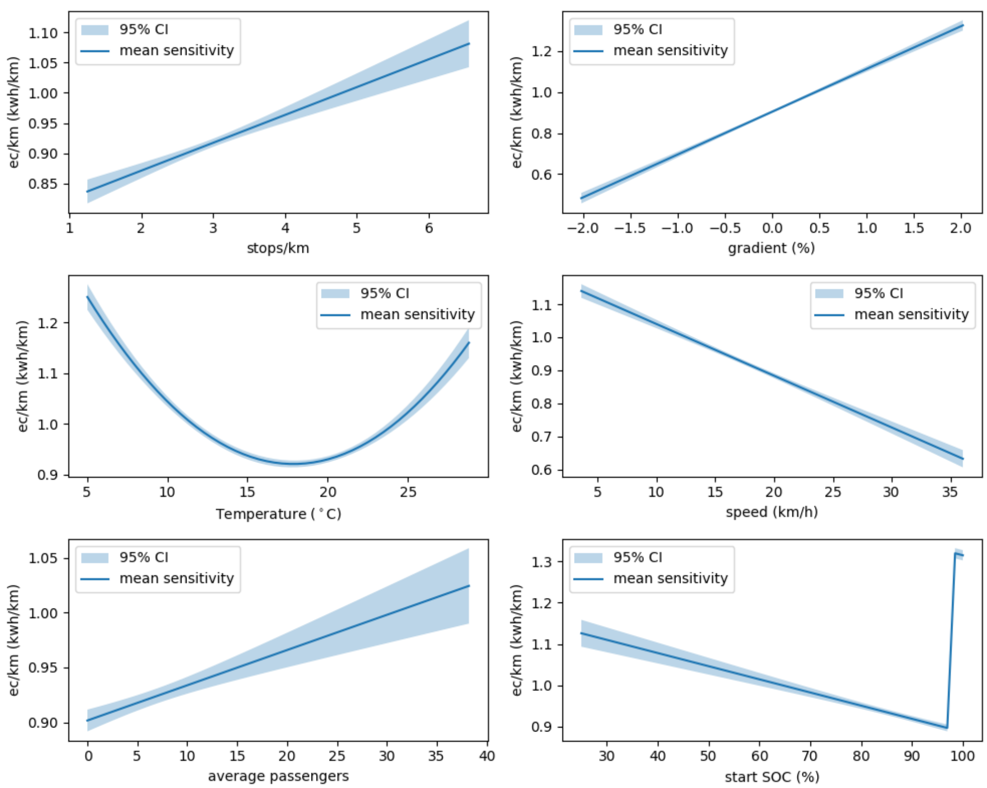

Figure 9.2: Sensitivity of the predicted energy consumption per kilometer as a function of a single input at a time keeping the other inputs held constant at the data set mean.

10. Depot charging optimisation model

A depot charging optimisation model was developed. The objective of the optimization is to determine the maximum power from the grid required by the depot and the minimum number of bus chargers required while ensuring that the buses can be sufficiently charged to service the timetabled trips.

To create a broadly accessible tool, the optimisation problem was formulated such that the required inputs could be calculated from publicly available GTFS data and our electric bus energy consumption model described in Section 9. The GTFS data contains information about each route and the timetabled trips on these routes. However, the GTFS data has no information about which buses would undertake each trip and in what order. Without this information, it is not possible to determine the energy requirements of a single bus. So instead of optimising the charging for each bus, the bus fleet is considered as a whole.

Considering the bus fleet as a whole, the optimisation needs to ensure that the total charging done across all buses is enough to meet the energy requirements of the timetabled trips. This effectively considers the combined battery capacity of all the buses as a single entity. Care is then taken to ensure that:

- the maximum charging power during any time window is proportional to the number of buses not required to be on a trip — equivalent to saying only buses at the depot can be charged;
- the charging done is less than the energy used on trips that have already taken place, i.e we are only recharging the buses after they have used energy on trips.

This approach requires the energy requirements of the timetabled trips to be calculated and this process is described in Section 10.1. Additionally, it makes several assumptions and has several limitations as described in Section 10.2. Finally, the mathematical details of this formulation are given in Section 10.3.

10.1 Energy requirements of timetabled trips

The depot charging optimisation model developed here requires as an input the energy requirements of the timetabled trip. This information is calculated largely from publicly available GTFS data in conjunction with the electric bus energy consumption model developed in Section 9. This process will be summarized in this section and an overview is shown in Figure 10.1. In addition to the GTFS data, a couple of other parameters are required as described in Table 10.1.

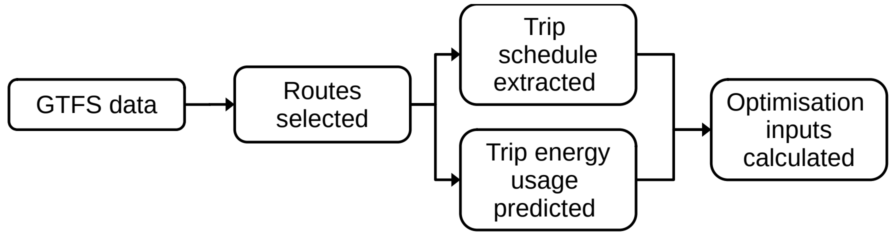

Figure 10.1: Processing of GTFS data to give inputs for the depot charging optimisation model.

The energy requirements are determined by the following process:

Table 10.1: Parameters required to calculate the timetabled trips energy requirements.

Parameter	Description	Source	Value range
Dead-running	The average percentage of additional time required by a bus to operate a trip in addition to the nominal trip duration specified in the timetable. This is used to account for the time taken to go to and from the depot. This factor is also applied to the energy requirements. The default is 10%.	User	0–100%
Passengers	The number of passengers expected on the bus trips.	User	0–Full
Temperature	The maximum and minimum temperature possible on the trip. Taken from historical data for the location and time of each trip and the 1^{st} and 99^{th} percentile are used.	Historical	$^{\circ}C$
Gradient	The average gradient on the trip. The GTFS data contains a GPS path for each route and so the elevation for each point could be added and the average gradient calculated.	NASA SRTM	%
Minimum charge time	The minimum allowed time that a bus can be plugged in to charge for.	User	0–360min

1. A source of GTFS data is chosen.
2. Routes are selected from this GTFS data that the user would wish to service from a depot.
3. Data for each trip on these routes is extracted.
4. The energy required for each trip is predicted;
   (a) trip length, average speed and number of stops per kilometer are calculated from the GTFS data;
   (b) temperature, passenger, and gradient information are added;
   (c) the model in Section 9 is used to predict the energy required;
   (d) the dead running factor is applied to the predicted energy.
5. The trip timetable is extracted from the GTFS data for the busiest week. The duration of each trip is adjusted to account for the dead running factor applied equally to the start and end times. From this, the number of buses required on trips throughout the week can be calculated and an example is shown in Figure 10.2.
6. The schedule and trip energy requirements are combined to give the required energy of trips departing the depot as a function of time throughout the week. This is done by allocating each trip's energy requirement to the time window during which it starts. An example is shown in Figure 10.2. **This is the parameter $\mathbf{E_{R,t}}$ used in the mathematical formulation**.
7. Also needed is the energy used on trips returning to the depot as a function of time throughout the week. This is calculated by allocating each trip's energy requirement to the time window during which it finishes. **This is the parameter $\mathbf{E_{D,t}}$ used in the mathematical formulation**.
8. Lastly, the number of buses available to charge at each time throughout the week is calculated. This is computed as the maximum number of buses minus the buses required on trips. The minimum charge time is enforced by applying a windowed minimum function over the number of available buses. **This is the parameter $\mathbf{N_t}$ used in the mathematical formulation.**

Throughout this process, a worst-case methodology is taken. This aims to ensure that the depot is capable of sufficiently charging the bus fleet even under the worst expected operating conditions. This is achieved by selecting the busiest timetabled week from the GTFS data, considering the location-based temperature range and using the temperature that results in the highest energy requirements, and considering the 95% confidence intervals for the predicted energy consumption.

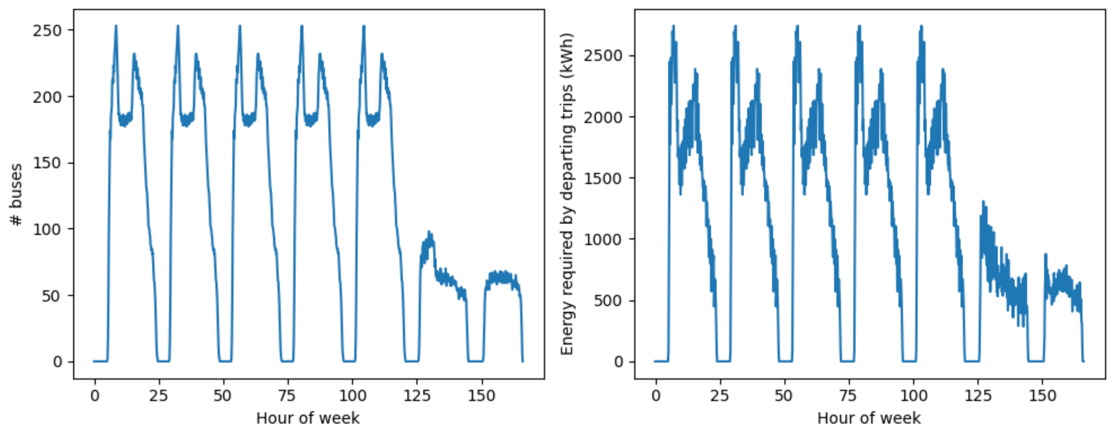

Figure 10.2: Example processed inputs to the optimisation model for 64 routes in the Australian Capital Territory. (Left) Number of buses required on trips throughout the week. (Right) Energy required by trips departing the depot throughout the week. A dead running factor of 10% was used and expected passengers was set to 38 for all routes.

10.2 Assumptions and limitations

The optimisation model makes a number of assumptions listed here:

- The time and energy required for a bus to get to the start of a trip and return from a trip are on average covered by the dead running factor. This is an additional percentage of the trip time and required energy.
- No single bus trip uses more energy than the maximum bus battery capacity. This should be checked beforehand.
- The aggregate state of charge methodology means we assume the available charge is perfectly distributed across the required buses. That is, if we have a combined 100 kWh state of charge available and five trips each needing 20 kWh, then it is assumed five buses have 20 kWh each rather than one bus having 100 kWh.
- Changing which bus is connected to a charger takes minimal time.
- That there is a minimum time a bus can be plugged in to charge. However, the total number of charging rotations is not tracked by the optimisation.
- All routes considered are serviced by buses from the same depot.
- That the bus operator would be willing to let the combined state of charge run down on busier days and charge up on less busy days.

The limitations of this method are listed here:

- Provides no information about the state of charge of individual buses.
- Does not include options for additional charge locations (other than the depot) such as end of trip (turn around point) charging.
- Does not solve the scheduling problem of deciding which bus should undertake which trips and in what sequence — this is outside the scope of the project.

10.3 Mathematical formulation

The objective is to find the charging profile that minimises the required grid connection power and number of chargers while ensuring that the buses are sufficiently charged to service the route timetable. The charging optimisation is formulated as a linear program with the optimisation variables and parameters described in Table 10.2.

Table 10.2: Optimisation variables and parameters

Variable	Description	Parameter/Variable	Domain
t	index over the time window	parameter	$\{1,\ldots,T\}$
x_t	how much the buses are charged at time t in kW	variable	$\mathbb{R}^+$
η_x	bus charging efficiency	parameter	$[0,1]$
s_f	slack variable on the required final state of charge constraint	variable	$\mathbb{R}^+$
s_r	slack variable placed on the reserve battery constraint	variable	$\mathbb{R}^+$
G	grid connection max capacity in kW	variable	$\mathbb{R}^+$
b_t	depot battery charge/discharge power at time t in kW	variable	$[L_b, U_b]$
v_t	auxiliary variable used in implementing depot battery charging efficiency	variable	$\mathbb{R}$
η_b	depot battery charge and discharge efficiency	parameter	$(0,1]$
$E_{R,t}$	energy required by buses departing the depot at time t in kWh	parameter	$\mathbb{R}^+$
$E_{D,t}$	energy used on last trip by buses returning to the depot at time t kWh	parameter	$\mathbb{R}^+$
M	total number of buses	parameter	$\mathbb{I}^+$
N_t	buses at the depot and able to be charged at time t	parameter	$\{0,\ldots,M\}$
N_c	number of bus chargers	variable	$\mathbb{I}^+$
U_x	max charger power in kWh	parameter	$\mathbb{R}^+$
C_s	Initial percentage battery capacity of the buses and on-site battery	parameter	$[0,1]$
C_f	Required percentage final battery capacity of the buses and on-site battery	parameter	$[0,1]$
α	constant for converting from power in kW to energy in kWh	parameter	$\mathbb{R}^+$
B	battery capacity of each bus in kWh	parameter	$\mathbb{R}^+$
D	depot battery capacity in kWh	parameter	$\mathbb{R}^+$
R	combined bus battery capacity to hold in reserve kWh	parameter	$\mathbb{R}^+$
a_t	binary variable indicating whether bus charging at time t is allowed	parameter	$\{0,1\}$
p_0	cost on minimising grid connection max capacity	parameter	$\mathbb{R}^+$
p_1	cost on number of chargers $p_1 << p_0$	parameter	$\mathbb{R}^+$
p_2	cost on charging from grid, stops unnecessary charging $p_2 << p_1$	parameter	$\mathbb{R}^+$
Q	cost on slack variables to ensure constraints are satisfied $Q >> p_0$	parameter	$\mathbb{R}^+$
r_t	auxiliary variable used to regulate change in charging at time t	variable	$\mathbb{R}^+$
L	bus battery end-of-life capacity	parameter	$(0, 1]$
w	the minimum number of time windows that a bus must be plugged in for before rotating	parameter	$\mathbb{I}^+$

The linear program that we wish to optimise is

$$
\begin{aligned}
\theta^* = \underset{\theta}{\text{argmin}} \quad & p_0 G + p_1 N_c + p_2 \sum_{t=1}^{T} (x_t + b_t) + Q s_f + Q s_r + p_2 \sum_{t=1}^{T-1} r_t, \\
s.t. \quad & (10.2) - (10.9)
\end{aligned}
\tag{10.1}
$$

where θ is the set of all optimisation variables, Q is a large cost placed on the slack variables to ensure the constraints will be satisfied if feasible, p_0 is a cost used to minimise the required grid connection capacity,p_1 is a smaller cost placed on the number of chargers. The inclusion of $x_t + b_t$ and r_t in the objective acts similarly to regularising the charging power (i.e. similar to placing a quadratic cost on power) while maintaining the linear nature of the problem. In essence, p_2 is a small cost placed on charging power to prevent unnecessary charging, and the auxiliary variable r_t is included to minimise large changes in the charging power. This is done by including a constraint to ensure it is greater than the absolute difference in charging between two consecutive time steps:

$$
\begin{aligned}
r_t &\geq x_{t+1} - x_t, \qquad \forall t = 1, \ldots T - 1 \\
r_t &\geq -x_{t+1} + x_t \qquad \forall t = 1, \ldots T - 1,
\end{aligned}
\tag{10.2}
$$

Maximum bus charging constraint:

$$
\begin{aligned}
x_t a_t &\leq N_t U_x \qquad t = 1, \ldots T, \\
x_t &\leq a_t U_x N_c \qquad t = 1, \ldots T.
\end{aligned}
\tag{10.3}
$$

Grid connection constraint:

$$
x_t + b_t \leq G \qquad t = 1, \ldots T.
\tag{10.4}
$$

Enforcing that the cumulative charging done is less than the cumulative energy used by buses that have returned to the depot plus the gap between the starting capacity and max capacity. That is, ensuring the state of charge is less than the maximum:

$$
\eta_x \alpha \sum_{i=1}^{t} x_i \leq (1 - C_s) MBL + \sum_{i=1}^{t-1} E_{r,i} \qquad \forall t = 1, \ldots T.
\tag{10.5}
$$

Enforcing that the cumulative charging done is greater than the cumulative energy required by buses that have departed the depot minus the difference between the start state of charge and the reserve. That is, ensuring that the state of charge is above the reserve:

$$
LC_s MB + \eta_x \alpha \sum_{i=1}^{t-1} x_t - \sum_{i=1}^{t} E_{D,i} + s_r \geq R \qquad \forall t = 1, \ldots T,
\tag{10.6}
$$

where the slack variable $s_r \geq 0$ is included to ensure an optimisation solution is reached even if the reserve cannot be achieved.

Enforcing the desired final state of charge is achieved:

$$
LC_s MB + \alpha \eta_x \sum_{t=1}^{T} (x_t - E_{D,t}) + s_f \geq LC_f MB,
\tag{10.7}
$$

where the slack variable $s_f \geq 0$ has been included to ensure that a solution is reached even if the desired final state of charge cannot be achieved.

Minimum plugin time constraint, i.e. enforces that during the specified number of time windows a single charger cannot charge more than the battery capacity of a bus:

$$\alpha\eta_x \sum_{t-w}^{t} x_t \leq N_c B \tag{10.8}$$

Note, that this only approximates the desired constraint as we cannot know how much capacity each bus has used.

Depot battery minimum, maximum and final state of charge constraints

$$v_t \leq \eta_b b_t \qquad \forall t = 1, \dots T, \tag{10.9}$$

$$v_t \leq \frac{1}{\eta_b} b_t \qquad \forall t = 1, \dots T, \tag{10.10}$$

$$C_s D + \alpha \sum_{i=1}^{t} v_i \geq 0, \qquad \forall t = 1, \dots T, \tag{10.11}$$

$$C_s D + \alpha \sum_{i=1}^{t} v_i \leq D, \qquad \forall t = 1, \dots T, \tag{10.12}$$

$$C_s D + \alpha \sum_{t=1}^{T} v_i \geq C_f D, \tag{10.13}$$

where the battery charge and discharge efficiency creates a piecewise linear program and the auxiliary variable v_t has been included to reformulate this as a linear program and avoid introducing any binary variables (Vandenberghe, 2013).

The complete optimisation model describes a linear program that can be solved efficiently using the open source CBC library from COIN-OR (Forrest et al., 2022).

11. Case study

This section presents a case study of asking what is the peak grid power, minimum number of chargers, and minimum number of electric buses required to electrify 40 routes in Newcastle, Australia. It does this for the following scenarios:

A) bus charging allowed at all times of the day and no on-site depot battery;

B) bus charging allowed at all times of the day and a 20 kWh on-site depot battery;

C) bus charging allowed only at night time (6pm till 6am) and no on-site depot battery;

D) bus charging allowed only at night time (6pm till 6am) and a 10 kWh on-site depot battery;

The data source for the case study is the Greater Sydney GTFS file (Transport for NSW, 2022). From this, the 40 busiest routes in Newcastle are selected and the busiest week on these routes is chosen. During this week a total of 6876 trips are scheduled on the selected routes. The parameter values used for the case study are given in Table 11.1.

Table 11.1: Parameter values used in the case study.

Parameter (units)	Value
Dead running (%)	10
Bus charger max power (kW)	150
Bus battery capacity (kWh)	400
Bus charging efficiency (-)	0.95
On-site battery efficiency (-)	0.95
On-site battery max power (kW)	2500
Number of passengers (-)	30
Bus end-of-life battery capacity (%)	80
Minimum charging time (min)	60
Start of week SOC (%)	90
End of week required SOC (%)	90

The number of buses required on routes throughout the week and the predicted energy required throughout the week are shown in Figure 11.1. The maximum number of buses required on route at any given time is 93. This is used as the minimum number of buses in the depot charging optimisation problem.

The results from each scenario are summarised in Table 11.2. The depot power and battery state of charge profiles throughout the week for each scenario are shown in Figures 11.2, 11.3, 11.4 and 11.5. These results show that restricting charging to during the night increases the peak power demand on the grid and increases the number of buses required (comparing scenario B to scenario A). The increase in buses is due to needing

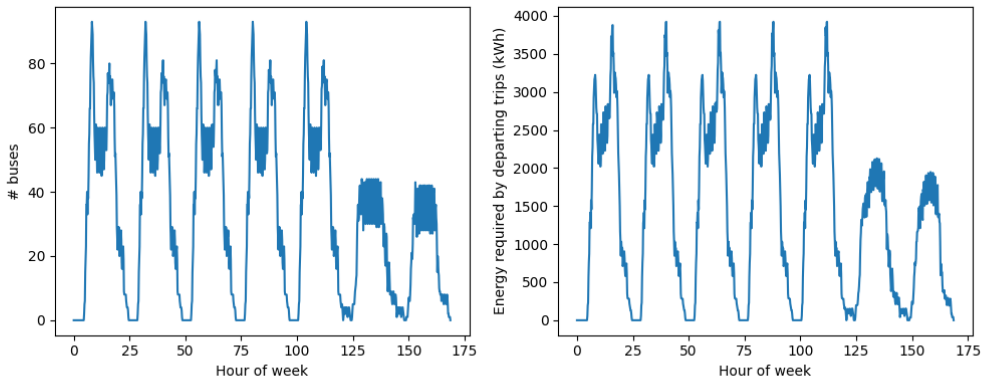

Figure 11.1: (Left) The number of buses on scheduled trips throughout the week. (Right) The predicted energy required across the fleet of buses to operate the scheduled trips throughout the week.

to meet the energy requirements of all scheduled trips during the daytime without recharging and this cannot be achieved with only 93 buses.

Table 11.2: Summary of case study results for each scenario.

Scenario	Peak grid power (kW)	Number of bus chargers	Number of buses
A	1968	14	93
B	1768	14	93
C	3730	25	150
D	2939	25	150

The results also show that the addition of an on-site depot battery has a greater impact on the peak grid power when charging is restricted to the night. A decrease in peak grid power of 191 kW is observed when charging is allowed at all times (comparing scenario B to A). By comparison, a decrease of 800 kW is observed when charging is only allowed at night (comparing scenario D to C). This can be explained by comparing the profiles in Figures 11.3 and 11.5. When bus charging is only allowed at night there is sufficient time for the on-site battery to be recharged. In contrast, when bus charging times are not restricted there are only short windows during peak trip times when no buses are charging and the on-site depot battery can be charged. These time windows can be seen in the number of bus chargers in use graph and are insufficient to fully recharge the on-site battery. Charging the on-site battery at the same time that all the chargers are in use would increase the peak demand rather than decrease it.

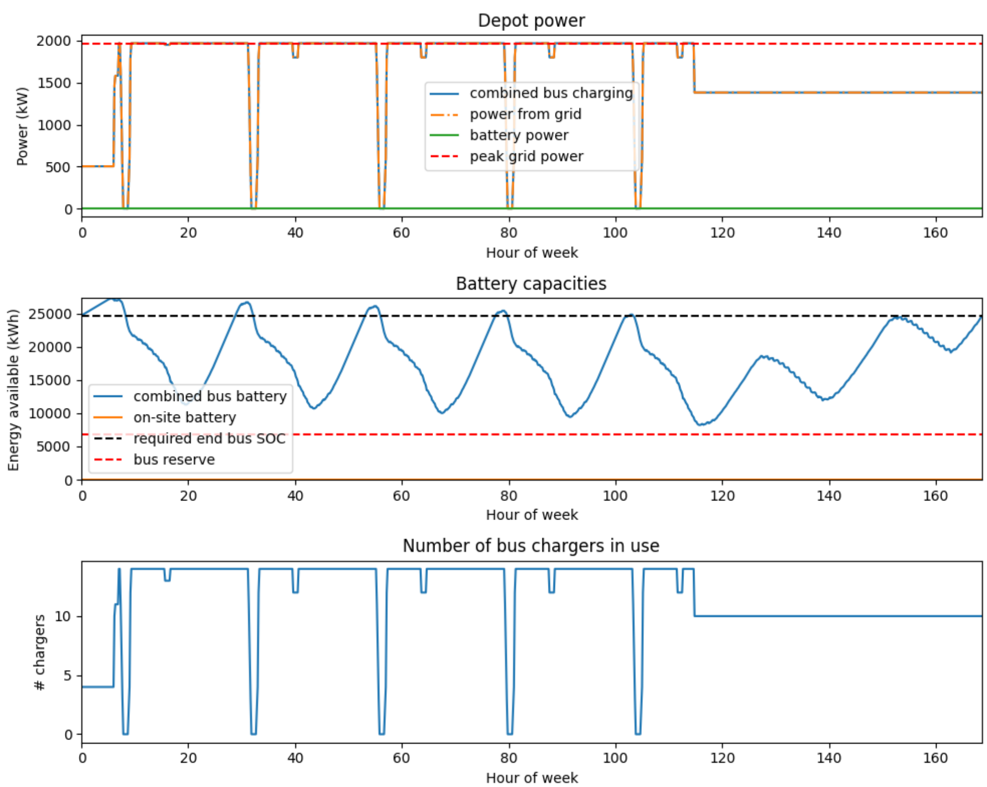

Figure 11.2: Case study results for scenario A: bus charging allowed at all times and no on-site depot battery.

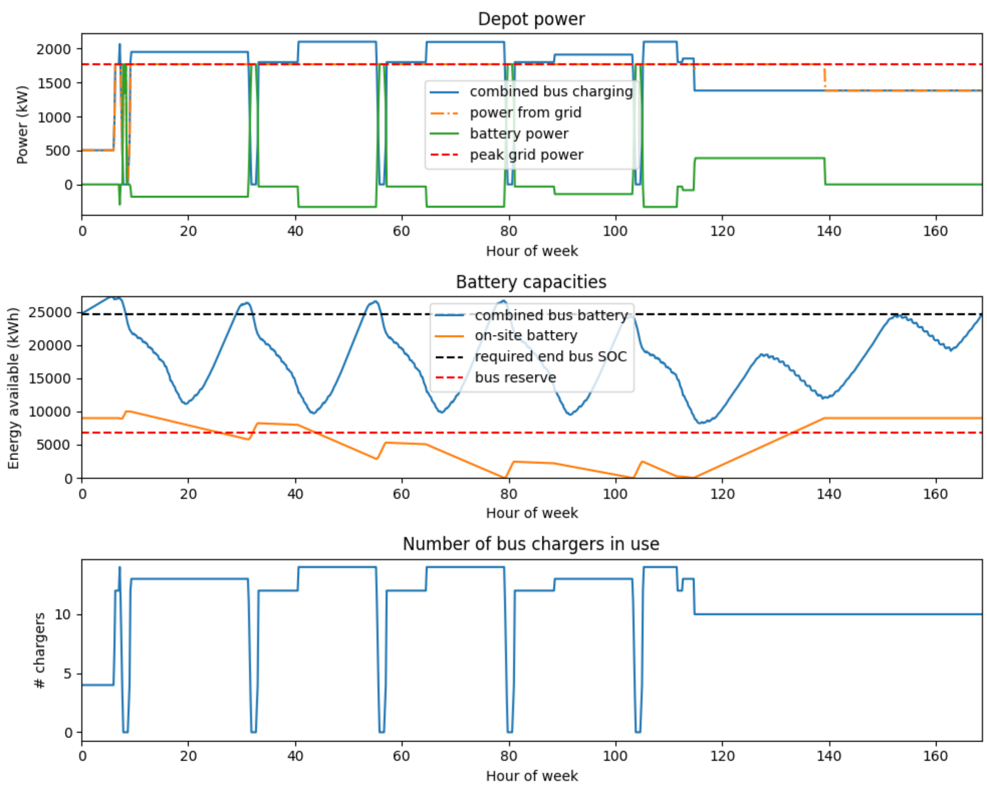

Figure 11.3: Case study results for scenario B: bus charging allowed at all times and a 10 MW h on-site depot battery.

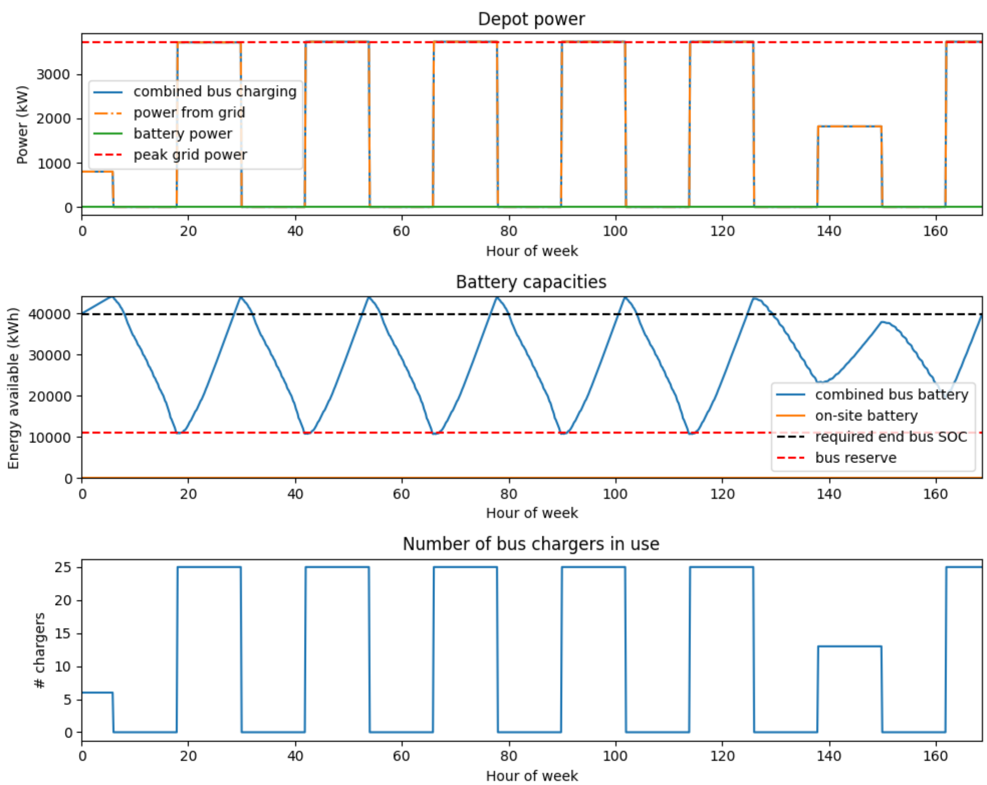

Figure 11.4: Case study results for scenario C: bus charging allowed only between 6pm and 6am and no on-site depot battery.

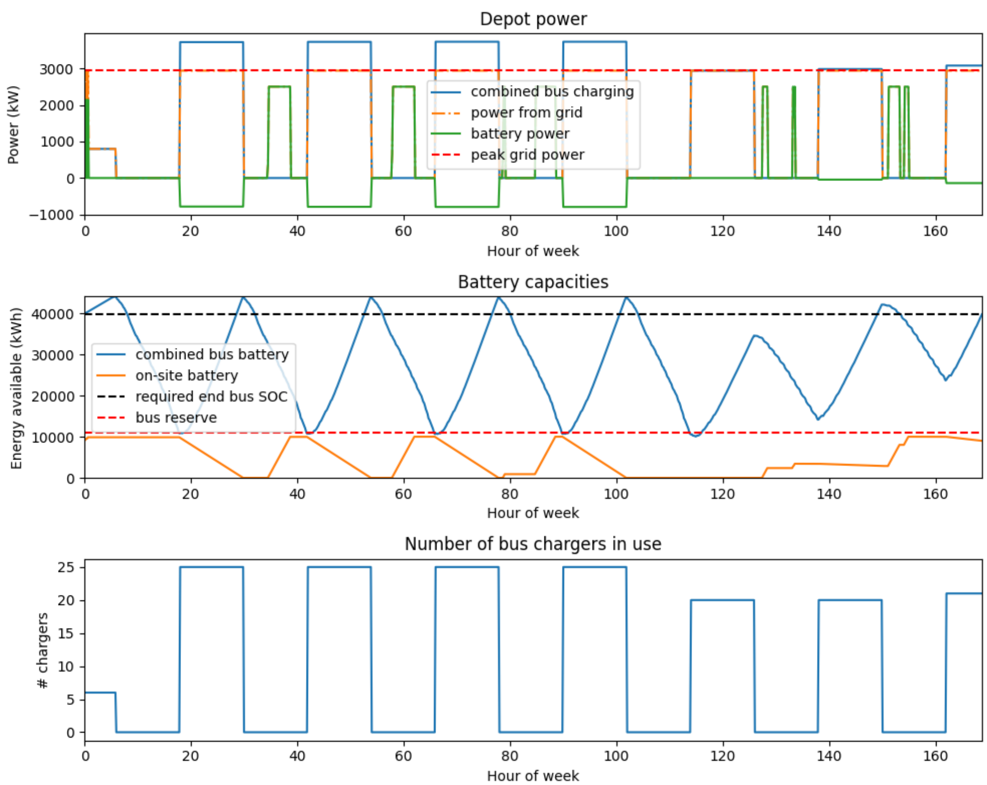

Figure 11.5: Case study results for scenario D: bus charging allowed only between 6pm and 6am and a 10 MW h on-site depot battery.

12. Conclusion

As part of the Next Generation Electric Bus Depot project the RouteZero web application tool has been developed. The goal for RouteZero was to be a broadly accessible tool that provides insights into the feasibility of electrifying bus routes around Australia. RouteZero can be used to answer questions related to the electric bus energy requirements of routes around Australia, and the depot charging requirements and peak power demand on the grid.

Two models were developed as part of RouteZero. The first is a data-driven model for the energy required by an electric bus to undertake a trip on a route taking into account a range of parameters including traffic and weather conditions. This model is based on performance data of the electric buses operating out of Leichhardt. The second model optimises the aggregate charging of the bus fleet to meet the operational demands of the trips timetabled on a selection of routes while minimising the peak demand that the depot places on the electricity network.

The two primary limitations of RouteZero are the restricted variable range in the training data, and the aggregate bus battery modelling approach. The first could be easily addressed by acquiring performance data from electric buses operating in a greater variety of conditions. Fixing the second is not possible without access to the scheduling information of individual buses which is unlikely to be available to a wide range of users. However, providing that the dead running factor is chosen appropriately, it is believed that for a reasonable size bus fleet the results would closely approximate the power requirements at the depot. The exception would be the case of only a small number of buses operating a couple of routes in which case the schedule of individual buses would have a far greater impact on the power requirements.

There are several possible future extensions to this work that could increase its impact. These include: including a measure of decarbonisation by modelling diesel bus fuel consumption on routes, using the knowledge and experience gained from this project to create a similar tool for truck routes, and using RouteZero to assess whether increased electric bus usage would have lower or higher demands on the electricity grid compared to increasing use of private electric vehicles.

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