THE UNIVERSITY OF MELBOURNE

Comprehensive techno-economic modelling of alternative/complementary storage options

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Report for C4NET

Project Consortium

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Executive Summary

This report presented a comprehensive bottom-up methodology for creating high-granularity energy demand profiles in Victoria, encompassing a diverse range of Consumer Energy Resources (CERs) including Battery Energy Storage Systems (BESS), EVs, and controllable thermal loads such as domestic hot water (DHW) and heating and cooling demands, referred to as building fabric related storage (BFRS). The profile development process captures the diversity of demand by accounting for network type, geographic location, and seasonal variability. These detailed demand profiles formed the basis for three case studies designed to evaluate the techno-economic impacts of increasing levels of CER coordination.

The first case study, employing a single-bus model, assesses the full potential of CER coordination in an unconstrained environment. Results demonstrated the substantial capability of CERs to reduce peak demand. BESS emerged as the most impactful technology in flattening the load profile and minimising peak demand. BFRS and DHW loads provided effective peak reduction, particularly during winter days, while EVs contributed to peak reduction across all considered typical days. Coordinated deployment of all CERs delivered the greatest benefits by enabling greater self-consumption of solar generation and flattening of peak demand. This results in substantial peak demand reductions of 11.5% during summer peak days and an even more pronounced reduction of 19.3% during winter peak days in 2050.

The second case study introduces subtransmission network constraints, offering a more realistic assessment of CER coordination. While network limitations introduced complexities like line congestion and PV curtailment, CER coordination still reduced peak demand by 6% in summer peak and 13% in winter peak days for a rural subtransmission network. Notably, coordinated operation helped mitigate line overloading, underscoring the importance of considering network constraints in CER coordination strategies.

The third case study explores integration of market price signals into CER coordination in a rural subtransmission network, revealing a trade-off between leveraging market benefits and increased line overloading. While price-driven CER coordination maximised energy arbitrage by shifting load from high- to low-price periods and generation from low- to high-price, this alignment exacerbated line congestion, highlighting the need to balance economic incentives with technical constraints.

Another important takeaway from this work is the critical role of advanced models that account for network constraints while maintaining computational tractability. In this report, the increased network granularity given by the inclusion of subtransmission networks adds complexity to the optimisation problem and reveals existing limitations that are not observed in unconstrained models. These new limitations show the potential of CER coordination to offer cost-effective alternatives to traditional infrastructure upgrades. The granularity shown in this report could be further increased to include medium voltage (MV) and low voltage (LV) networks following a similar methodology as the one developed in this report. A higher network granularity could shed lights on the specific challenges in MV-LV networks with high CER penetration, providing insight into operational bottlenecks at MV-LV levels. These insights would reveal the potential of the CER coordination to the subtransmission system.

Glossary of Terms / Abbreviations

AEMO	Australian Energy Market Operator
BESS	Battery Energy Storage Systems
BFRS	Building fabric related storage
CBTS	Cranbourne Terminal Station
CER	Consumer Energy Resources
DER	Distributed Energy Resources
DHW	Domestic Hot Water
DNSP	Distribution Network Service Provider
DR	Demand Response
ERTS	East Rowville Terminal Station
ESP	Enhanced Systems planning
EV	Electric Vehicles
GNTS-MBTS	Glenrowan Terminal Station and Mount Beauty Terminal Station
ISP	Integrated System Planning
LV	Low Voltage
MV	Medium voltage
Pu	per unit
TOU	Time-of-use
V2G	Vehicle-to-Grid
V2H	Vehicle-to-Home
WP	Work Package

1 Project Overview

This report corresponds to *Milestone 1*, a literature review of distribution network storage for the Work Package 2.10 (WP2.10), *"Comprehensive techno-economic modelling of alternative/complementary storage options"*. WP2.10 will ultimately assess the interactions of different storage options to determine how they can enhance system flexibility and support optimal network operation and planning.

1.1 Background

As Australia transitions towards a cleaner, more sustainable energy future, storage systems play an increasingly important role in the energy system. Storage systems provide economic benefits such as energy arbitrage by storing electricity from periods of low-cost production (often coinciding with high renewable generation) and releasing it during higher cost hours (often coinciding with peak demand periods). This energy arbitrage thus helps reduce energy curtailment while improving system reliability. The rapid expansion of renewable energy sources is increasing the price differential between low-cost and high-cost periods, which makes storage solutions increasingly attractive to stakeholders, driving an accelerated deployment of storage across all grid levels, from transmission to distribution networks.

In Australia, the Australian Energy Market Operator (AEMO) projects that distribution-connected storage will experience the highest long-term penetration, contributing several gigawatts of capacity to the grid, as shown in Figure 1. However, current projections often overlook the potential contributions of emerging storage technologies such as electric vehicles (EVs) and thermal storage devices, including building fabric-related thermal storage in buildings, and domestic hot water storage in tanks.

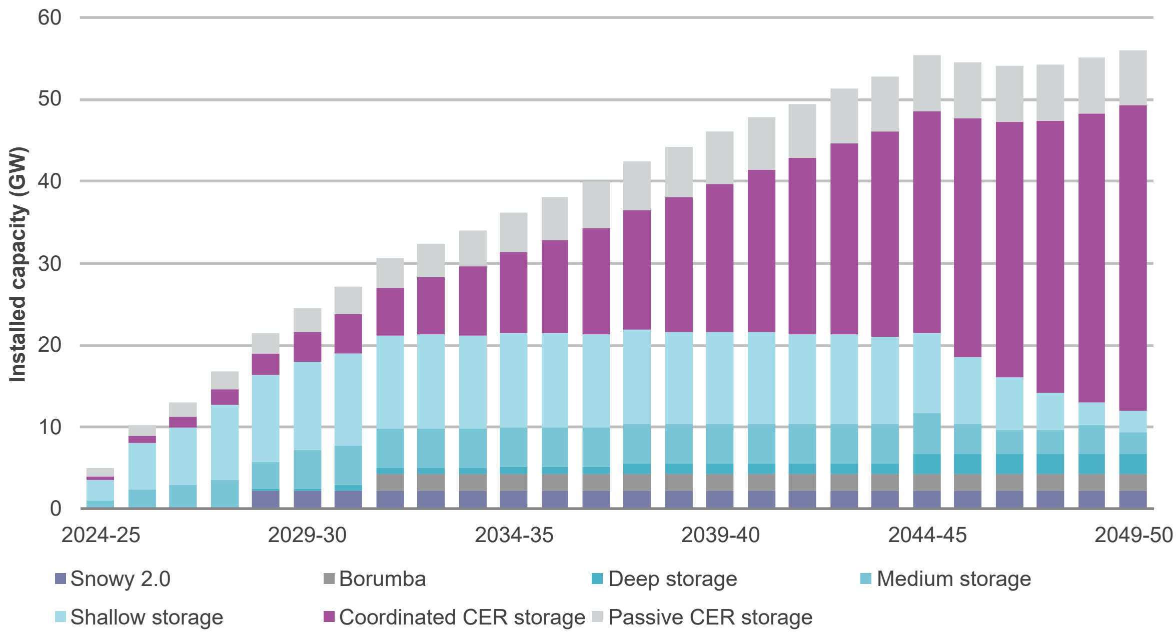

Figure 1 Forecasts of storage Installed capacity in the ISP, NEM (2024-25 to 2049-50) [1]

Figure 2 illustrates the classification of distribution network storage technologies within the broader system of existing storage devices. This figure illustrates the individual contributions of various storage technologies, which typically operates for minutes to hours, with power capacities ranging from kilowatts to megawatts. The orange area in the figure represents an example of the expected envelope resulting from the aggregation of these technologies when connected within a single distribution network. Coordinating storage across multiple distribution networks for transmission-level applications could unlock a substantial storage capacity in the order of gigawatts/gigawatthours.

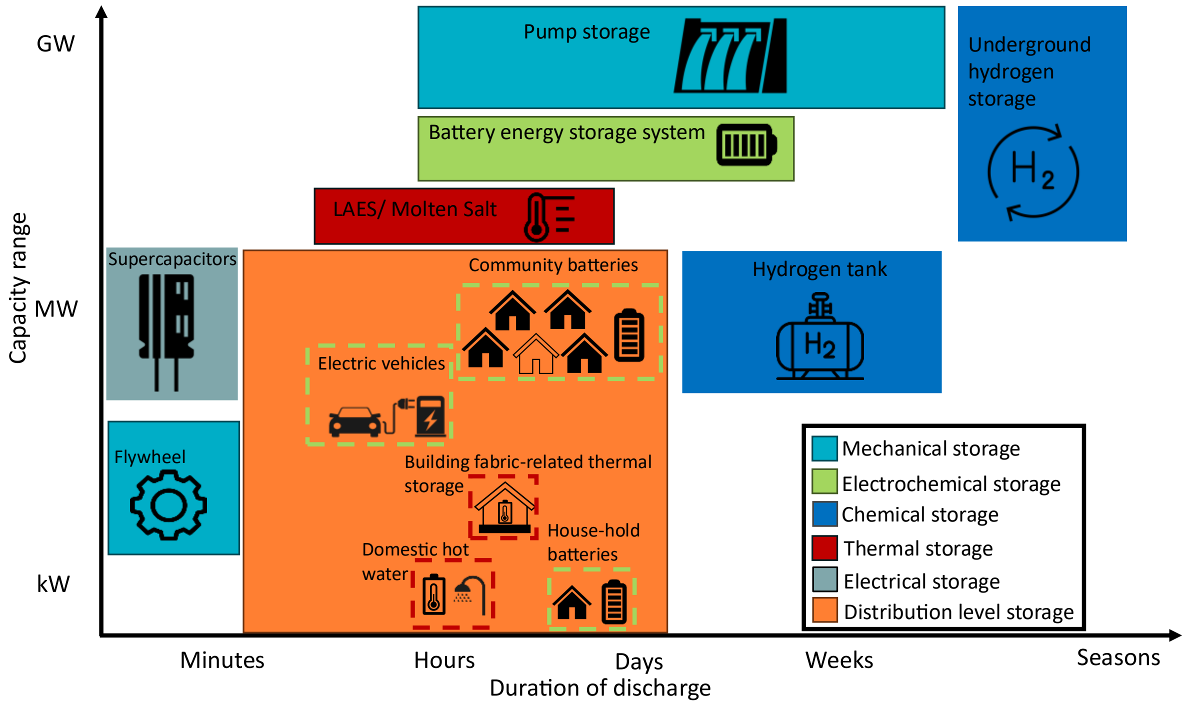

Figure 2 Type of storage classified with different duration and capacity

The orchestration of these diverse storage technologies is fundamental to enable greater integration of renewable energy sources. In distribution networks, these storage technologies may help to reduce network congestion, lower peak demand, and postpone costly infrastructure investments. In the long term, distributed storage will be crucial in the transition to a new, more flexible, power system where energy can flow both ways between transmission and distribution networks.

1.2 Aims and Objectives

WP2.10 “Comprehensive modelling of alternative/complementary storage options”, as part of C4NET Enhanced Systems Planning (ESP), aims to:

- Provide a techno-economic assessment of the benefits brought by multiple storage options (household and community batteries, EV storage and thermal storage) considering different sensitivities.
- Assess the impact of various storage model and scenario parameters on the networks, further informing scenario developments of different stakeholders (storage support to mitigate the impact of 100% solar penetration, storage

support for different sizes and mix of constrained/unconstrained export/import scenarios, cumulative impact of EV penetration.)

WP2.10 should provide a better understanding of the role of different storage options in the network. Providing insights to the Victorian and Australian government about potential cost savings through the effective utilisation of storage resources.

1.3 Key Milestones

The key milestones of this work package, and the corresponding contents are further detailed bellow.

Milestone 1: Literature Review (January 2025)

Report with overview of different storage options (household batteries, electric vehicles, thermal storage, community batteries) at distribution level.

Milestone 2: Modelling and techno-economic assessment (March 2025)

A detailed presentation highlighting the different modelling approaches employed to assess the optimal mix of storage options in different scenarios.

Milestone 3: Evaluation of different flexibility provision options (March 2025)

A detailed presentation showcasing multi-parametric aggregated profiles to inform planning at different level, carried out with a bottom-up approach.

Milestone 4: Final Report (March 2025)

A final report presenting the findings of WP 2.10, including a summary of inputs, assumptions, as well as results from case studies.

2 Methodology

The methodology has three steps, which are summarised in Figure 3. The first step is input data creation, which employs a bottom-up profile generation approach. This step involves creating demand profiles for different technologies within distribution network and, where applicable, obtaining their storage potential. Commercial and residential load profiles are derived from historical data (these loads include lighting, cooking loads, etc); household battery demand projections are obtained from AEMO's forecasts; and demand profiles for EVs, DHW, and heating/cooling are generated using relevant models. Notably, only residential and commercial loads do not offer storage capabilities. The remaining technologies provide storage in different ways: household batteries act as conventional batteries, EVs offer time-varying storage for upstream network support, DHW enables load shifting, and heating/cooling demands provide load reduction to decrease peak demand.

The second step involves simulating distribution network models under two conditions. The first case examines a non-coordinated CER case, where storage is modelled as a fixed demand profile. In this case, DHW and heating/cooling loads cannot be shifted or reduced. Similarly, EVs follow a fixed charging profile, and household batteries operate on predefined charging and discharging schedules that reflect uncoordinated behaviour. This baseline analysis helps to understand system needs without any storage coordination. The second case investigates a coordinated CER case, which analyses the CER coordination impact on the peak demand, line overloading and other metrics. It is important to mention that in both cases the system aims to minimise peak demand, network imports, line overloading, and voltage deviation.

The simulation results from the second step inform the third step, which focuses on evaluating the value of storage in subtransmission networks. In this step, the non-coordinated CER case helps to identify emerging network constraints, while the coordinated CER case highlights the benefits of storage in optimising grid utilisation, enhancing voltage levels, and mitigating line overloading. Furthermore, this step offers valuable insights into the interactions between various storage technologies.

While this methodology is applied to subtransmission networks, its framework has the potential to be extended to analyse finer network granularities, encompassing MV and LV systems. This would allow for a comprehensive determination of the technoeconomic challenges and benefits arising from CER coordination at both the medium and low voltage levels.

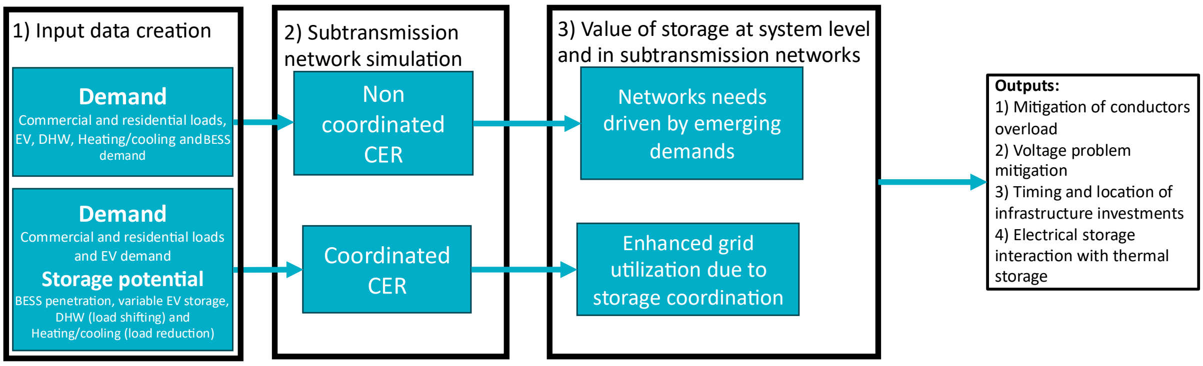

Figure 3 Methodology

3 Bottom-up profile creation

Aggregated profiles were created for typical days across three seasons (shoulder, summer, and winter), four network types (urban, suburban, short rural, and long rural), and four locations (Ballarat, Melbourne, Shepparton, and Traralgon). The commercial profile remained consistent across all seasons, networks, and locations. Residential load and household battery profiles varied by season. Electric vehicle (EV) profiles varied by network type. Heating/cooling and domestic hot water (DHW) demands varied by location, network type, and season. Further details on how these inputs influence each technology's demand will be discussed in the following sections. Moreover, appendix 8.1 includes the seasonal variations of PV profiles.

3.1 Residential and commercial loads

Figure 4 shows the seasonal average daily load profiles for low-voltage (LV) customers. These values were derived from real measurements in other C4NET projects [2]. The profiles demonstrate a peak demand during the winter season, followed by summer and shoulder seasons. These profiles assume 50% electrification of cooling and 30% electrification of heating demand [2]. Unlike residential demand, which varies per season, this work includes a commercial demand profile that represents loads connected to both MV and LV networks. This commercial demand is illustrated in Figure 5 as a single hourly daily per-unit (pu) profile, based on outputs from other C4NET projects [2].

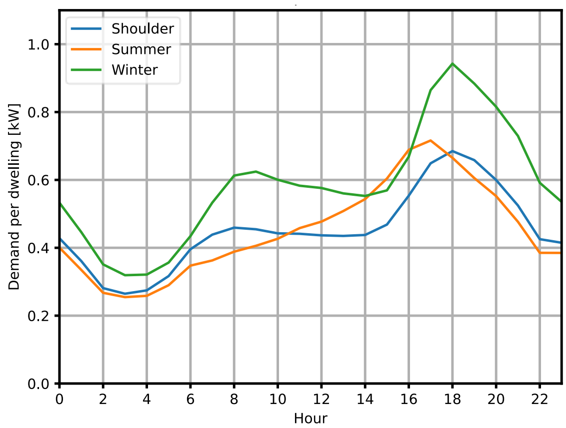

Figure 4 Residential load

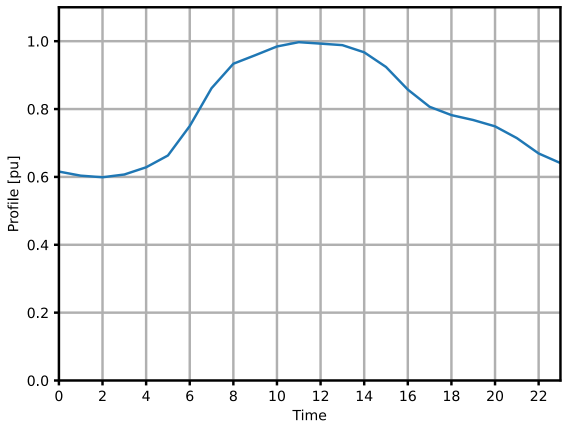

Figure 5 Commercial load

3.2 Household batteries

In 2023, Australia had over 250,000 household batteries referred to as Battery Energy Storage Systems (BESS). According to the latest ISP forecasts, the NEM will require at least 32 GW/522 GWh of storage capacity by 2034-35 and 56 GW/660 GWh by 2049-50 (see Figure 1 and [3]). Victoria is projected to experience a notable surge in household battery deployments. Figure 6 illustrates this trend, showing that the cumulative number of installed batteries will reach approximately one million by 2050, corresponding to a total capacity of 9.3 GW/18.3 GWh [2]. The average size of household BESS is assumed to increase progressively by C4net projects [2], from 5.2 kW/11 kWh in 2025, reaching 7.5 kW/15 kWh by 2040 and 9.5 kW/18 kWh by 2050.

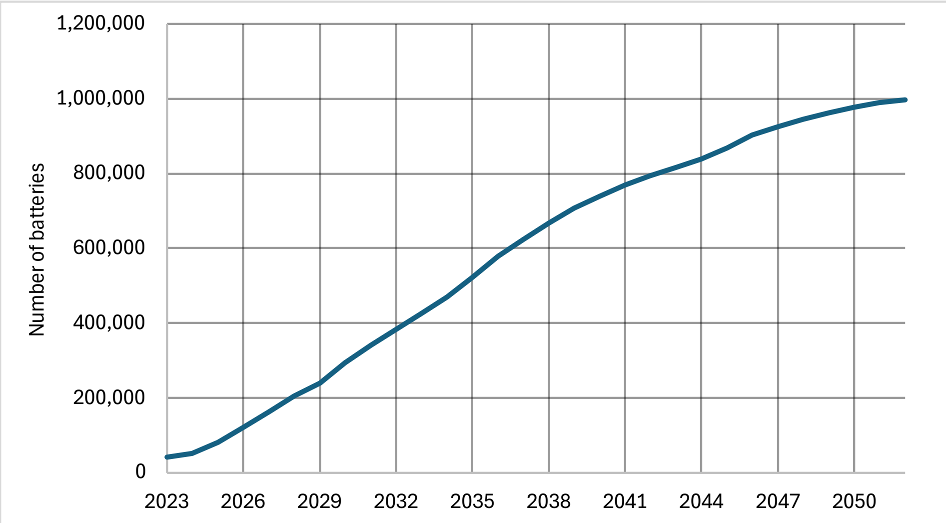

Figure 6 Number of batteries project in Victoria by C4NET projects [2]

AEMO forecasts that household batteries will follow a charging and discharging pattern, with charging occurring during solar hours and discharging during the evening and early morning [3]. Figure 7 illustrates this behaviour, displaying the seasonal charging and discharging profiles per battery based on data from the ISP [3]. The data is categorised into three seasons: shoulder (autumn and spring), summer, and winter. Additionally, Figure 8 presents the projected maximum charging and discharging power per year in Victoria, highlighting the potential benefits of effectively managing these devices.

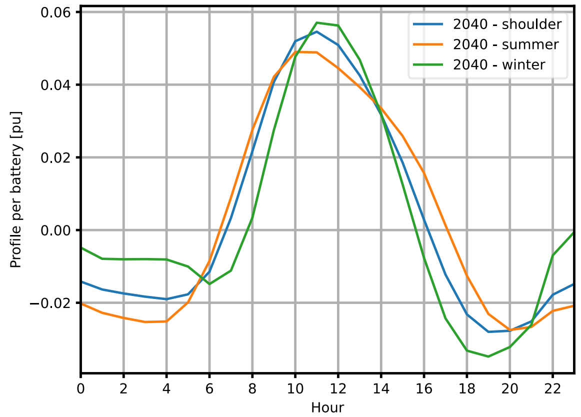

Figure 7 Profile per battery based on data from [3]

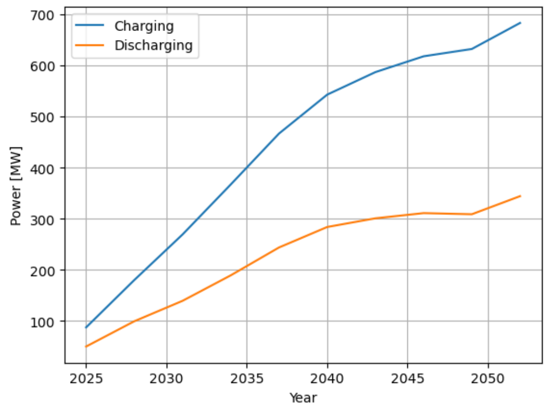

Figure 8 Maximum charging/discharging aggregated power for household batteries in Victoria based on data from [3]

3.3 Electric vehicles

The anticipated widespread adoption of Electric Vehicles (EVs) will not only increase electricity demand but also create a significant opportunity to utilise additional storage within distribution networks. This section details the input data used to generate EV storage availability profiles, focusing on the input data for battery size, charger capacity, charging patterns, arriving/departing times and commuting distance. The modelled power and storage values per vehicle shown in this section were obtained using the tool developed in [4].

3.3.1 EV battery size

Battery size is a crucial factor in EV modelling. Larger batteries require less frequent charging. Consequently, the average daily percentage of battery connected to the network varies with battery size, as shown in Figure 9. While larger batteries show a lower average percentage of connected battery, they offer greater storage capacity. For example, a 10 kWh battery averages 60% connection at 00:00, providing 6 kWh, whereas a 130 kWh battery averages 20% connection, providing 26 kWh.

Figure 10 shows the penetration of electric vehicles in Victoria highlighting the different EV sizes expected in the future [3], with large vehicles being the most prevalent, followed by medium and small cars. Figure 11 illustrates the average demand projected by AEMO for the different EV size for the unscheduled type of user, the figure is made with data available in [3]. This figure shows the correlation between vehicle size and demand, with large vehicles exhibiting the highest average demand, followed by medium and small vehicles. Additionally, Figure 12 provides a histogram of existing EV models [5]. Based on this data, battery sizes have been defined as 30 kWh for small vehicles, 80 kWh for medium vehicles, and 125 kWh for large vehicles.

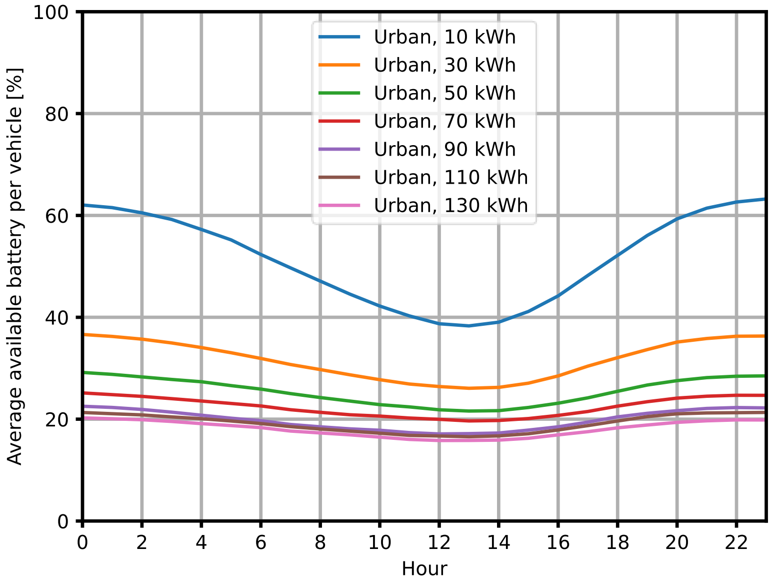

Figure 9 Average available battery per vehicle in an urban network – Unscheduled users

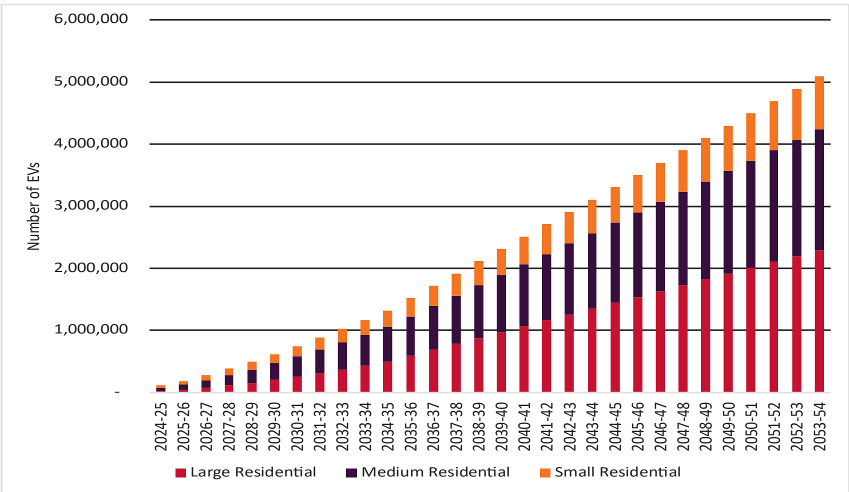

Figure 10 Number of EVs per year and type [6]

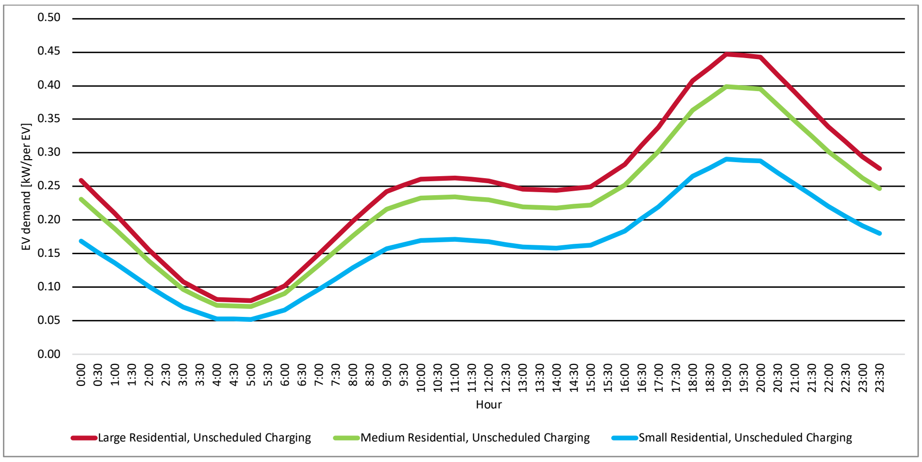

Figure 11 Average electric vehicles demand profile for unscheduled charging behaviour and vehicle size [1]

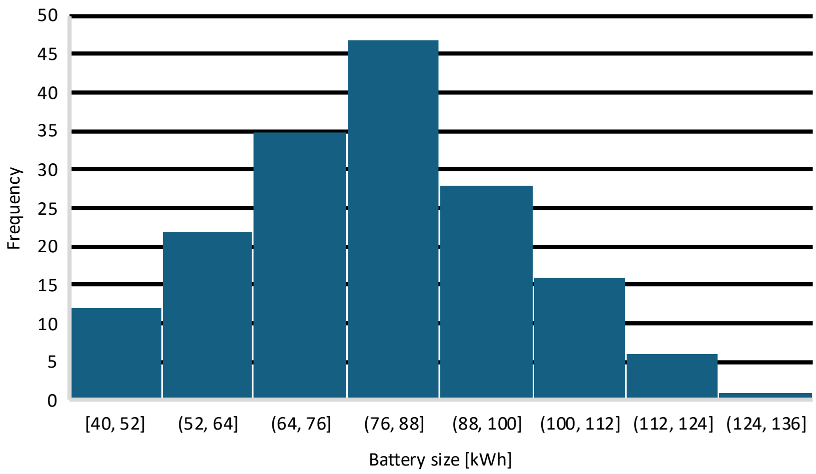

Figure 12 Histogram of battery size of existing vehicles in Australia

3.3.2 Charger size

Figure 13 based on C4NET project data [2], shows Australia's projected charger penetration. Currently, 2.3 kW chargers are the most prevalent, with 80% penetration, but this is projected to decrease to 36% in the long term. Conversely, 3.7 kW chargers are expected to increase from their current levels to approximately 44% penetration, becoming the most common type. While 7.4 kW chargers currently have low penetration, they are projected to reach 20% by 2052-53.

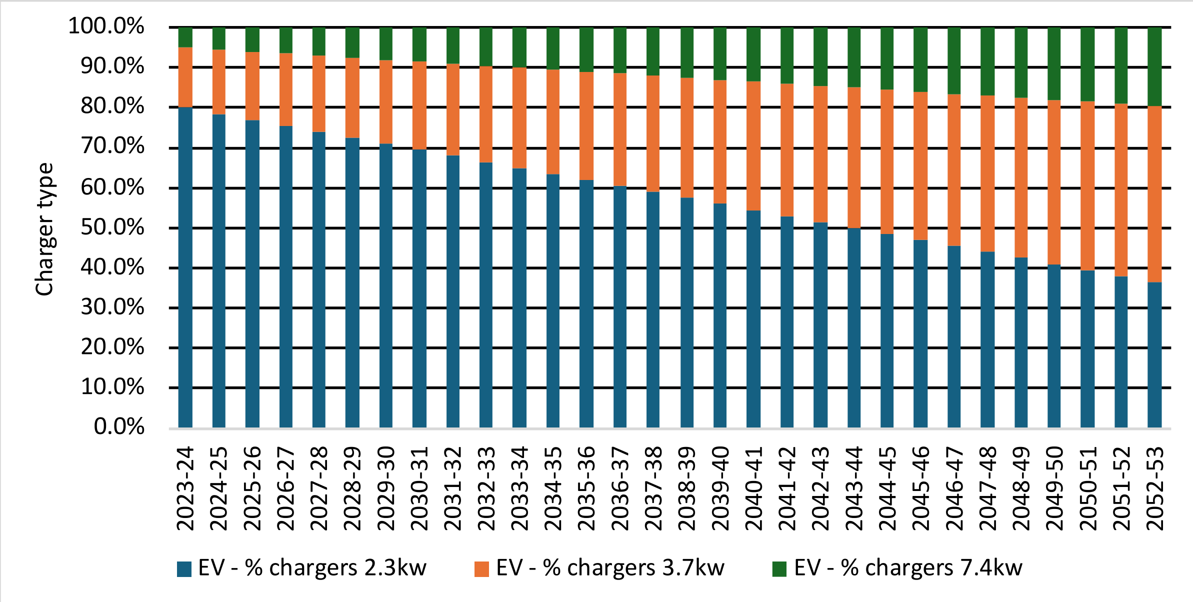

Figure 13 Charger type projections by C4NET

3.3.3 Charging behaviours

Figure 14 illustrates the two dominant EV charging behaviours projected by AEMO: unscheduled charging and public charging (see Appendix 8.2 for more details about the EV profiles popularity and comparison with real EV profiles). Unscheduled charging is primarily driven by user lifestyle choices rather than cost reduction, typically occurring at residential locations. In contrast, public charging requires dedicated infrastructure to support high-power charging and is expected to connect to medium-voltage networks [7].

Figure 15 illustrates how the charging types are represented in a distribution network, showing medium and low voltage levels. Residential connections for low-voltage EVs typically range from 0 to 2 per dwelling. On the other hand, public charging stations, located in medium-voltage networks, support simultaneous connections for multiple EVs. The spatial distribution of storage resources impacts storage availability and accessibility across both medium and low voltage network.

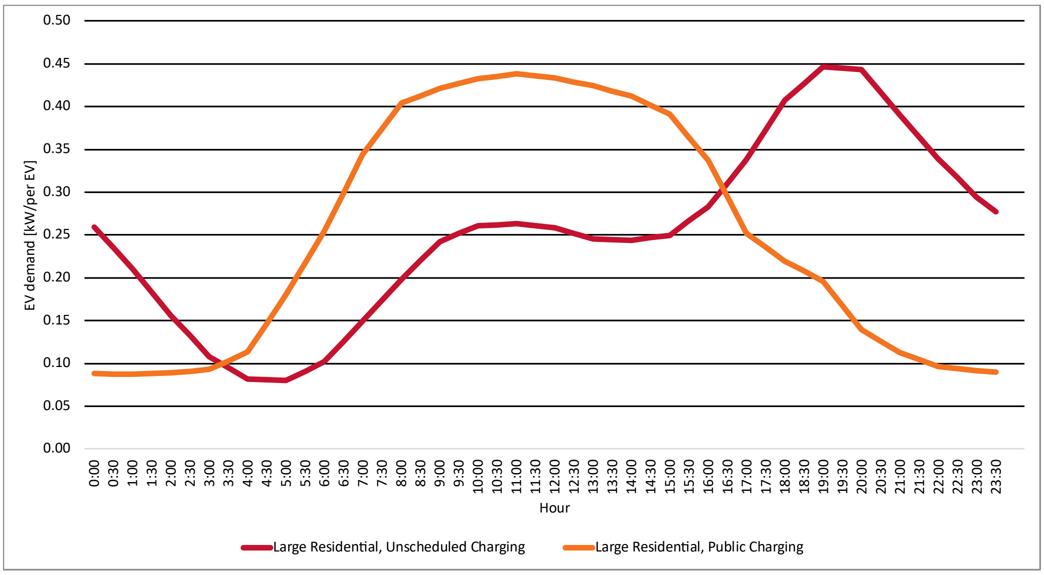

Figure 14 Unscheduled and public charging behaviour expected by AEMO

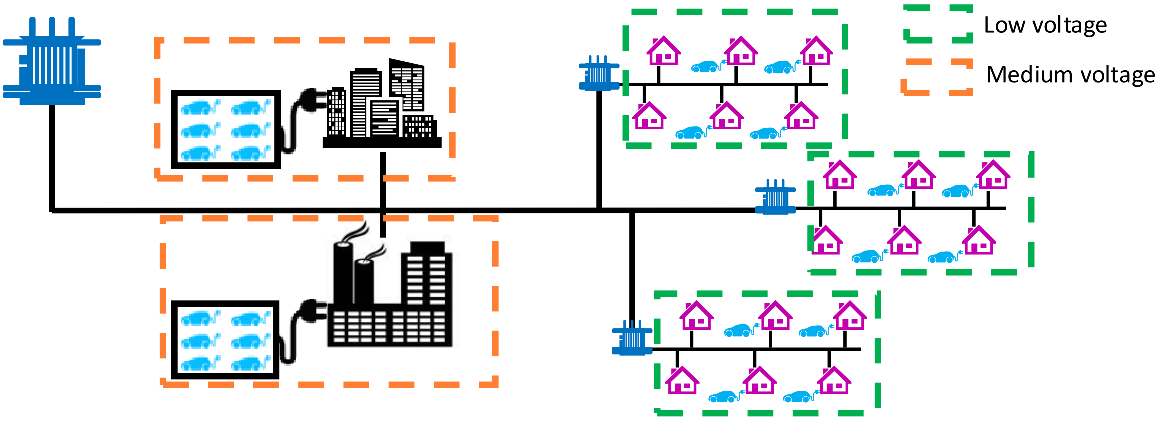

Figure 15 Medium voltage and low voltage users

3.3.4 Arriving and departing time

Figure 16 and Figure 17 illustrate the arrival and departure times for unscheduled (residential) EV charging users and public EV charging users, respectively. These temporal parameters facilitate the replication of AEMO's anticipated EV profiles through the generation of randomised EV simulations.

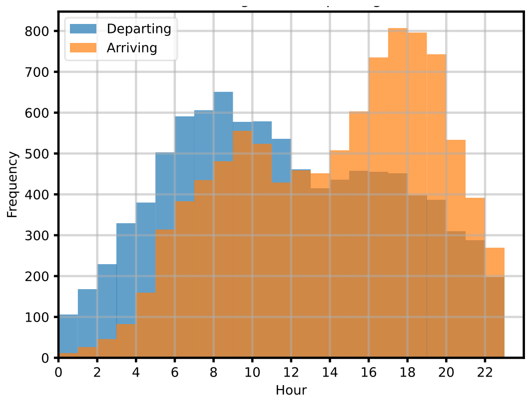

Figure 16 Arriving and departing time for unscheduled users

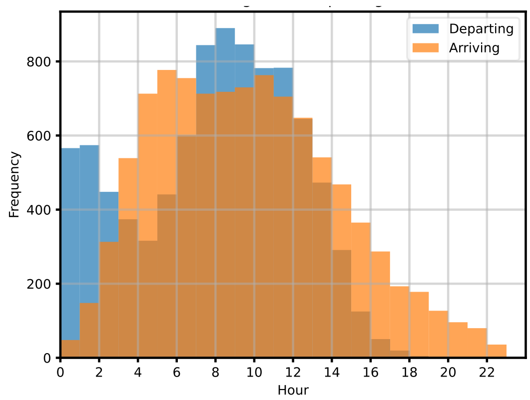

Figure 17 Arriving and departing time for public users

3.3.5 Commuting distance

Figure 18 (created for this report based on census data from [8]) illustrates the inverse correlation between commuting distance to work and population density within Victoria. The figure demonstrates that residents of densely populated areas tend to exhibit shorter daily commutes compared to those residing in sparsely populated areas, who typically travel longer distances. Based on density metrics, postcodes were classified into CBD, Urban, Suburban, Rural Short, and Rural Long, as depicted in Figure 19. The average commuting distances for each of these network classifications were subsequently calculated, and the results are presented in Table 1, which highlights that the average commuting distance in urban areas is approximately half that of rural areas.

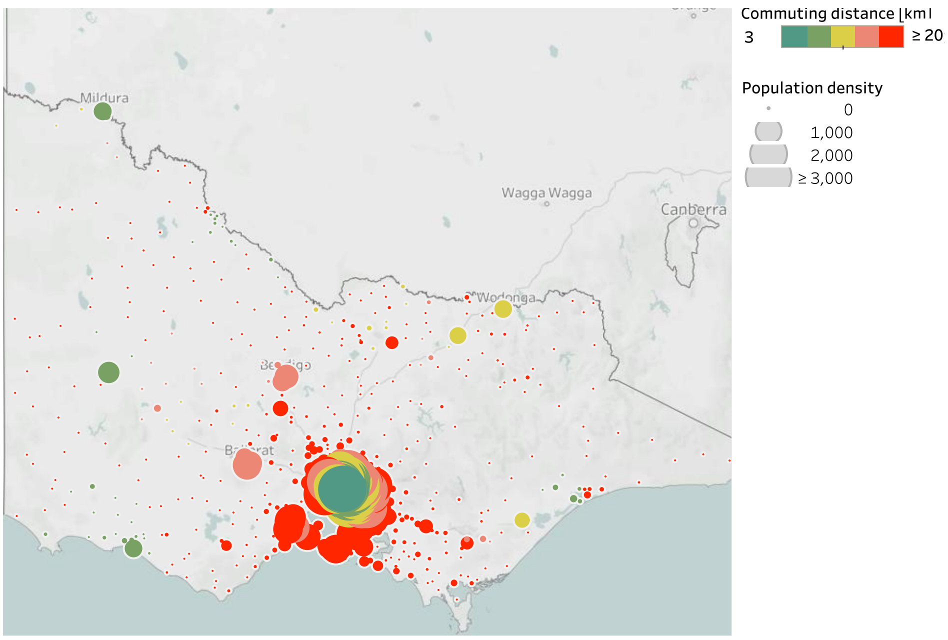

Figure 18 Commuting distance to work and density per postcode based on [8]

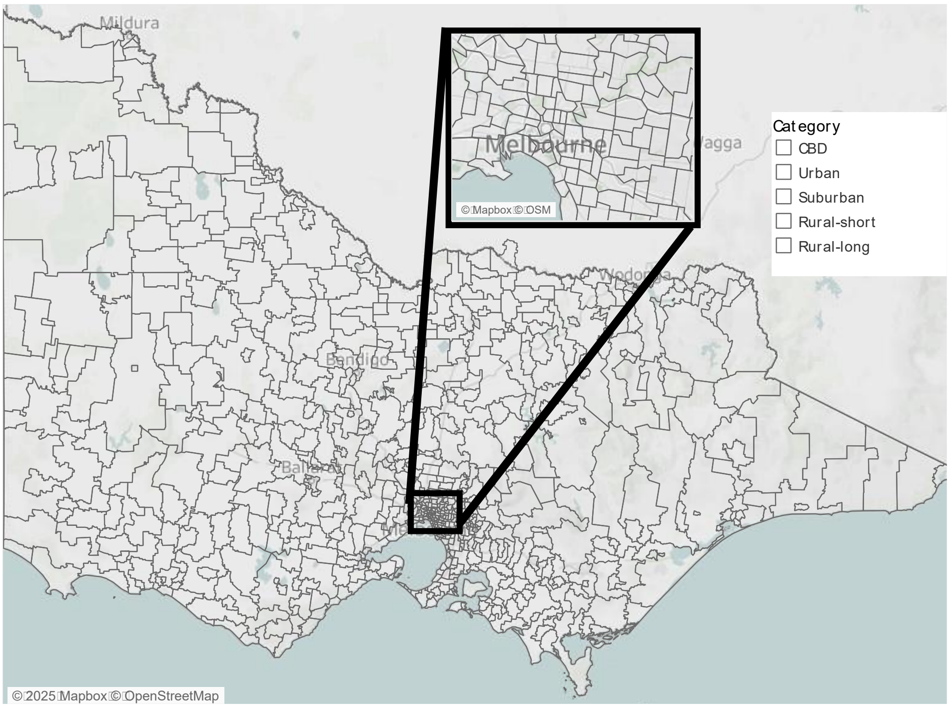

Figure 19 Network type based on density of postcodes

Table 1 Average distance travel per network type

Network type	Average [km]	Standard deviation [km]
CBD	6.51	12.48
Urban	11.75	12.63
Suburban	18.62	19.47
Rural short	22.86	28.74
Rural long	22.91	32.03

According to the findings of [4] and [9], commuting distances are characterised by a lognormal distribution. To ensure consistency with the average distances specified in Table 1, the parameters of the lognormal function were calibrated. This calibration results in the urban and rural EV commuting distance distributions, which are shown in Figure 20 and Figure 21, respectively.

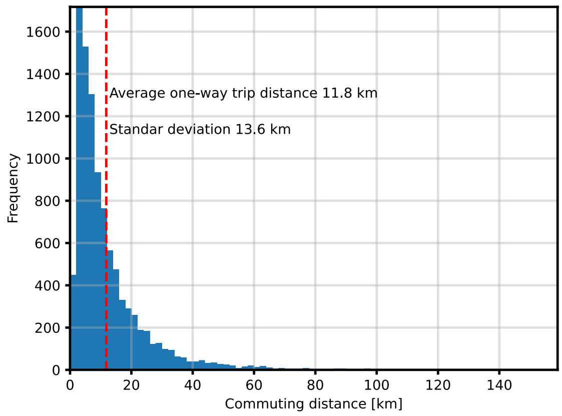

Figure 20 Lognormal distribution of urban vehicles

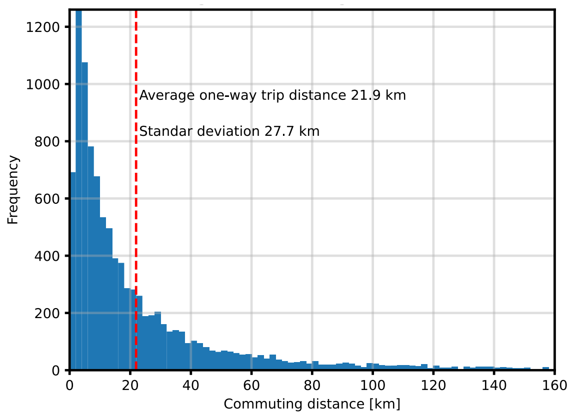

Figure 21 Lognormal distribution of rural short network

The average commuting distance associated with each network type significantly affects the frequency of required charging sessions. As a result, CBD/Urban networks exhibit a lower frequency of weekly charging sessions, while rural networks, characterised by longer commuting distances, necessitate more frequent charging. This relationship is graphically represented in Figure 22.

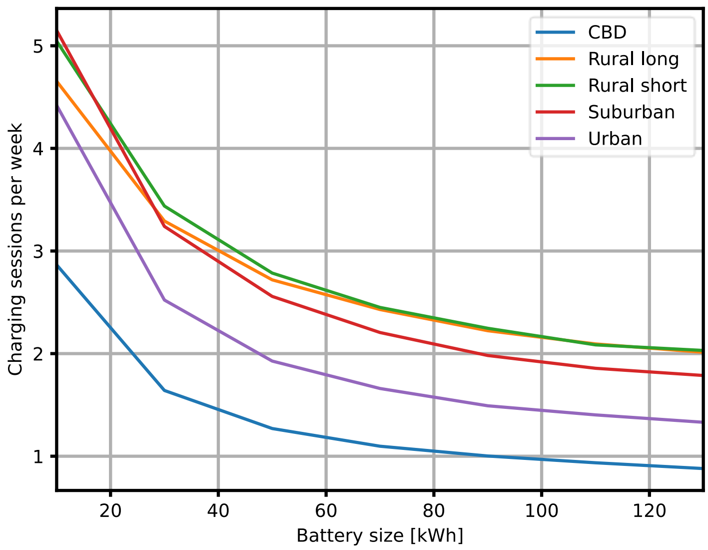

Figure 22 Charging sessions per week for different network types

3.3.6 Resulting profiles

Figure 23 and Figure 24 illustrate the average power consumption per vehicle, derived from the modelling of EV profiles for unscheduled and public users, respectively. Within these figures, the modelled average power consumption is represented by the blue line, the AEMO data by the orange line, and the average maximum connected power (Pmax) given by the EV charger is shown in the green line. Figure 25 and Figure 26 illustrate the average minimum and maximum energy levels per vehicle, which define the storage capacity boundaries.

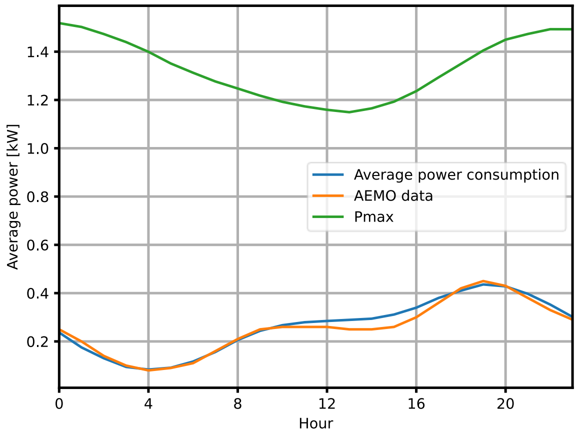

Figure 23 Average profile for Unscheduled users (Charger: 7.4 kW, Battery size: 125 kWh)

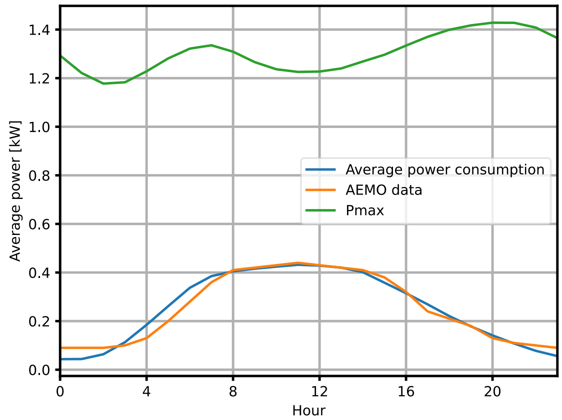

Figure 24 Average profile for public users (Charger: 7.4 kW, Battery size: 125 kWh)

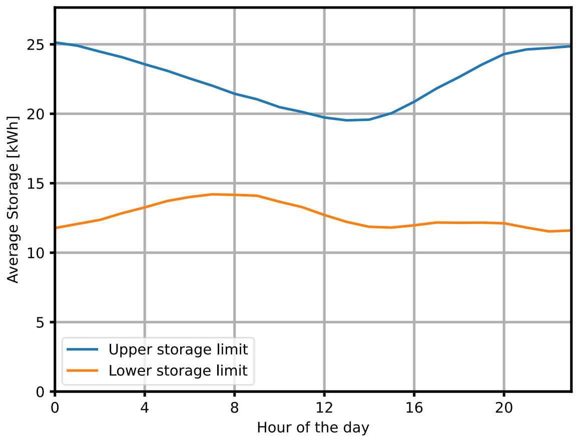

Figure 25 Average minimum and maximum energy for Unscheduled users (Charger: 7.4 kW, Battery size: 125 kWh)

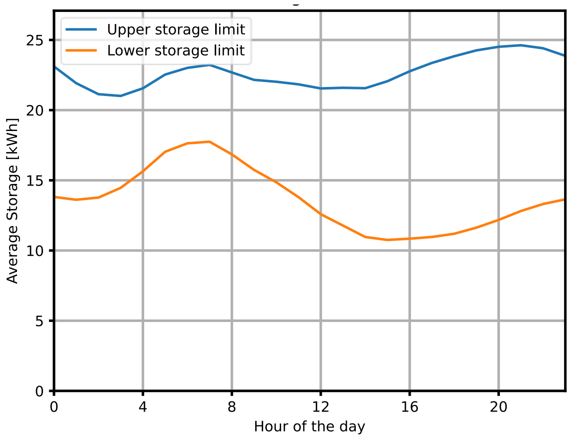

Figure 26 Average minimum and maximum energy for public users (Charger: 7.4 kW, Battery size: 125 kWh)

3.4 Domestic hot water/Heating and cooling profiles

DHW and heating/cooling profiles -which can also be referred to as building fabric related storage (BFRS)- are significantly influenced by location, network type, and season. Location dictates a dwelling's exposure to distinct climate zones, while network type correlates with house types, which vary geographically. Seasonal variations dictate temperature fluctuations and overall weather conditions. This analysis assumes the electrification of DHW heating via heat pumps, consistent with recent National Construction Code updates that have effectively banned electric resistive water heaters systems due to their high carbon emissions [10]. Using the tool developed in [11], and assuming 50% electrification of cooling and 30% of heating in 2023 dwellings, this section presents an accurate model of heating/cooling demand. By enabling its coordination, substantial Demand Response (DR) capacity can be unlocked. Additionally, the tool calculates DHW demand. Enabling the storage potential of DHW can facilitate significant demand shifting, helping to reduce peak demand.

3.4.1 Location

Victoria is divided into three climate zones, as shown in Figure 27 [12]. To model heating and cooling demand, four locations were selected: Ballarat, Melbourne, Shepparton, and Traralgon. Although Traralgon and Melbourne share the same climate zone, both are included to account for potential local variations.

Figure 28 illustrates how heating and cooling demand varies by location. Shepparton experiences the highest cooling demand during summer, whereas Ballarat has the highest heating demand in winter. In contrast, DHW demand remains relatively consistent across locations, with Ballarat showing a slightly higher peak.

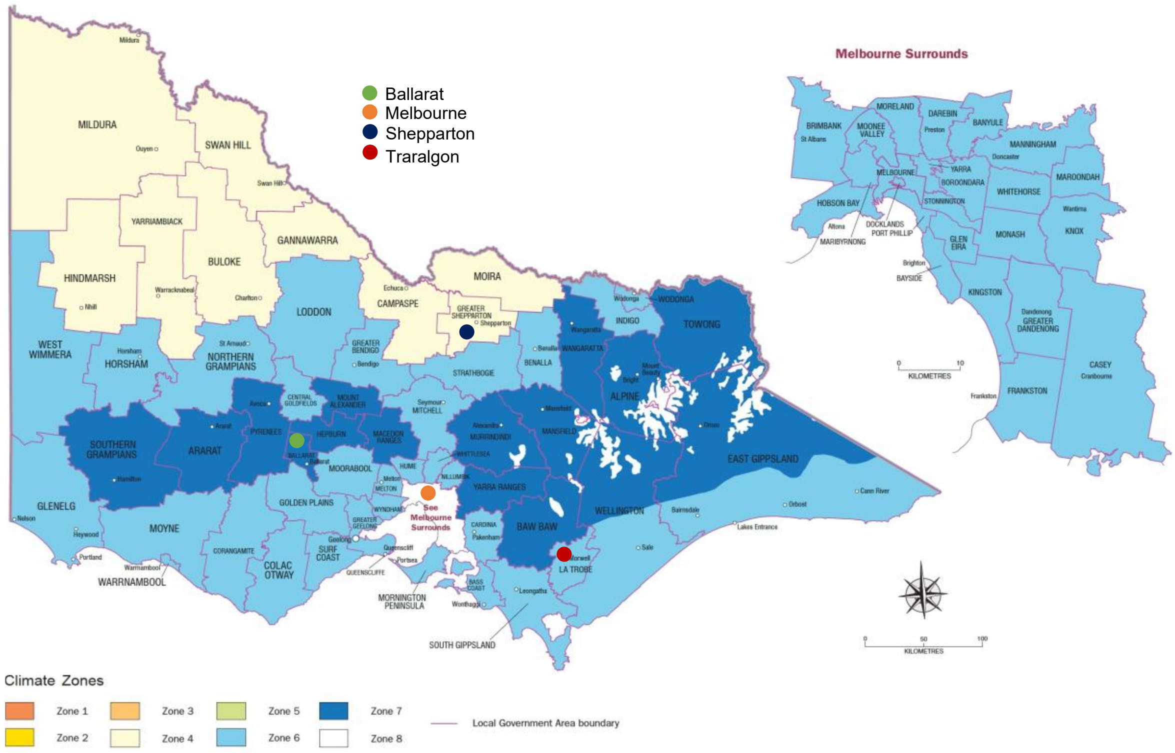

Figure 27 Climate zone map [12]

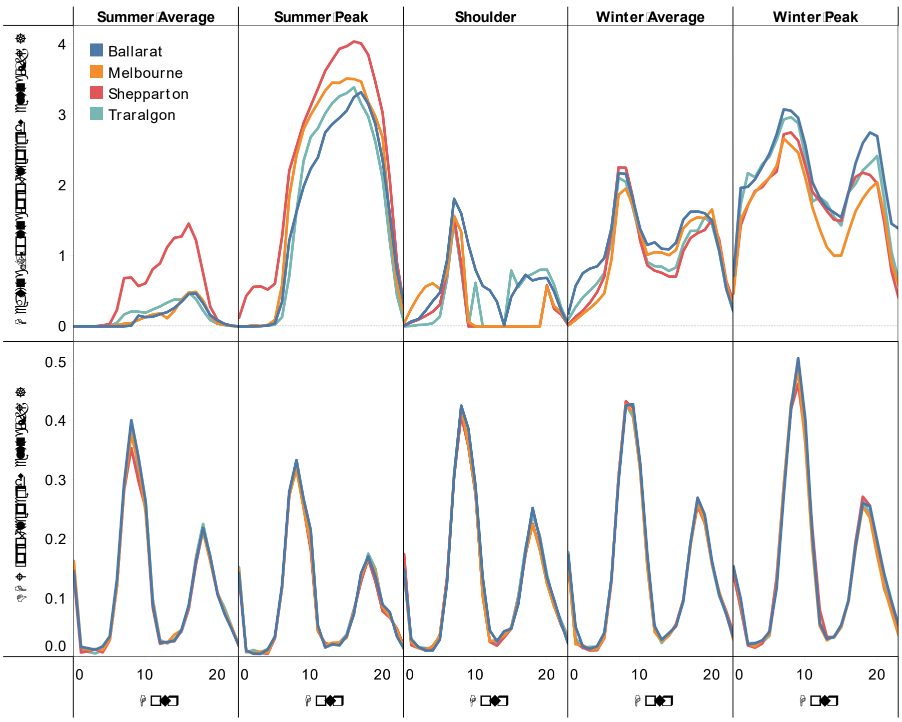

Figure 28 Heating/Cooling and DHW profiles per location

3.4.2 Network type

Heating, cooling, and DHW energy demands are significantly influenced by the building types within a network. Urban areas, characterised by a greater concentration of buildings compared to rural areas, experience significantly different heating/cooling and DHW requirements than rural areas.

In Australia, residential buildings can be classified by type (detached house, semi-detached house, apartment), household size (1 to 4 occupants), and energy efficiency based on construction year (Old: before 1991; Modern: 1992–2006; New: 2007–2011; Efficient: after 2012) [11]. Notably, more energy-efficient buildings require lower-capacity heating and cooling appliances to maintain comfortable indoor conditions, resulting in reduced energy consumption and improved thermal storage capacity. Figure 29, based on 2021 census data [13], illustrates the distribution of separate houses, semi-detached homes, and apartments across different census years from 1991 to 2021. According to C4NET internal project forecasts [2], the number of dwellings in Victoria is expected to rise from approximately 3 million in 2023 to around 4.1 million by 2050. Additionally, older homes are projected to be renovated at a rate of 1.5% per year, transitioning to more energy-efficient structures.

Figure 30 shows the seasonal heating and cooling demand across different network types, highlighting the influence of the different dwelling composition of the networks on energy usage patterns. Rural networks exhibit the highest demand across all seasons, primarily due to a higher penetration of detached homes, which are typically more energy consuming. Urban and suburban networks show lower energy requirements, attributed to a greater penetration of more energy-efficient apartments and semi-detached houses.

In contrast to the heating and cooling demand, DHW demand remains relatively stable. This consistency is attributed to the use of heat pumps with hot water tanks, which produce similar demand profiles for different dwelling types. Consequently, DHW presents only slight variations, such as a marginally higher peak observed in urban areas.

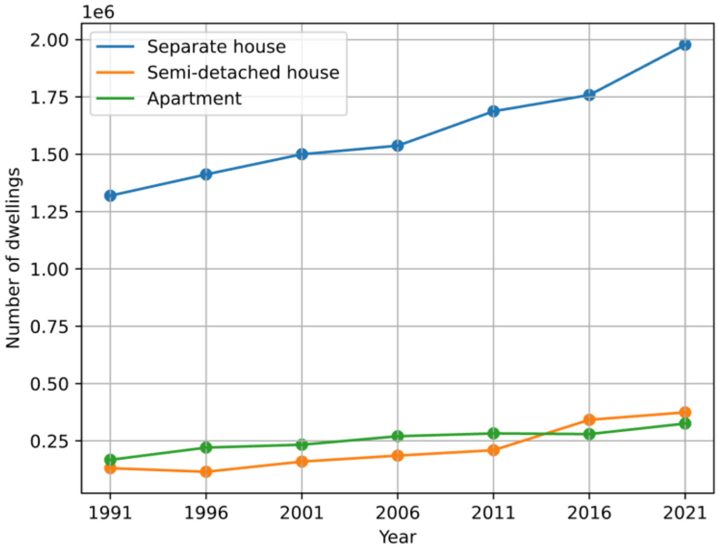

Figure 29 Type of dwellings in Victoria per year

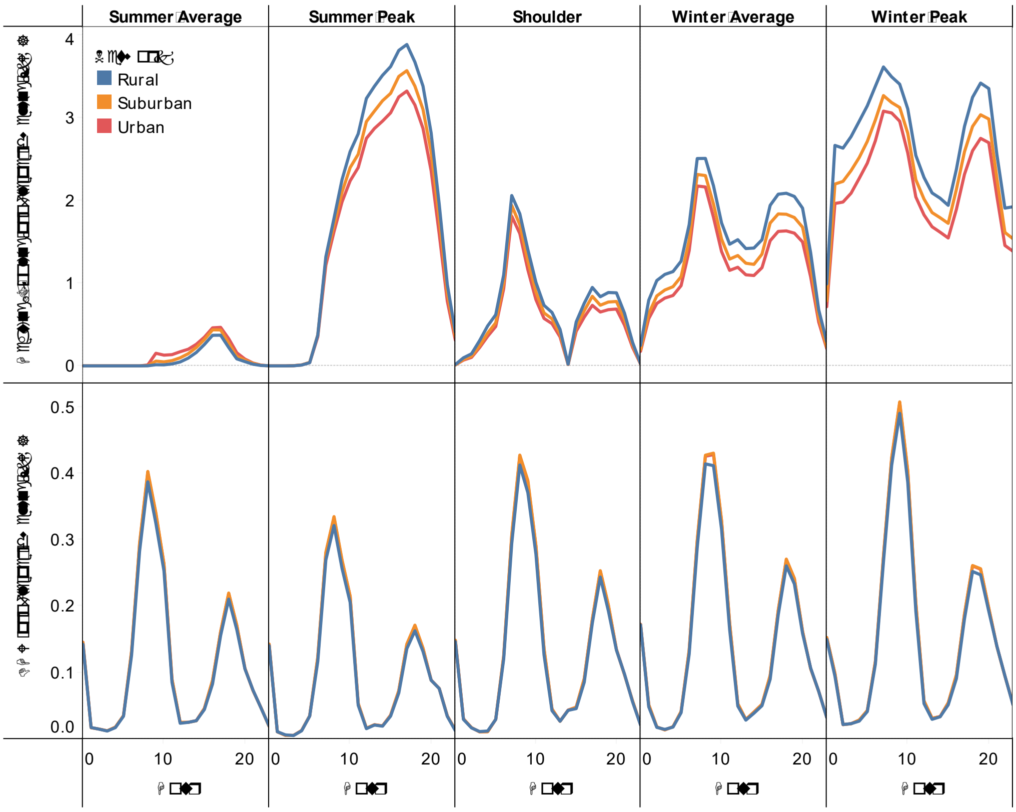

Figure 30 Heating/Cooling and DHW profiles network type impact

3.4.3 Seasons

Figure 31 illustrates the impact of weather on DHW and Heating/Cooling demand. For Heating/Cooling, summer profiles show an increase in demand starting during solar hours, peaking around 5 PM, and then decreasing through evening and night. In contrast, winter and shoulder profiles exhibit two daily peaks: one in the morning (7-8 AM) and another in the evening (4-8 PM). The DHW profile follows a similar pattern across seasons, with morning and evening peaks, but varies in energy consumption. Summer profiles exhibit the lowest energy requirements, correlating with higher temperatures, while winter profiles show the highest energy demand.

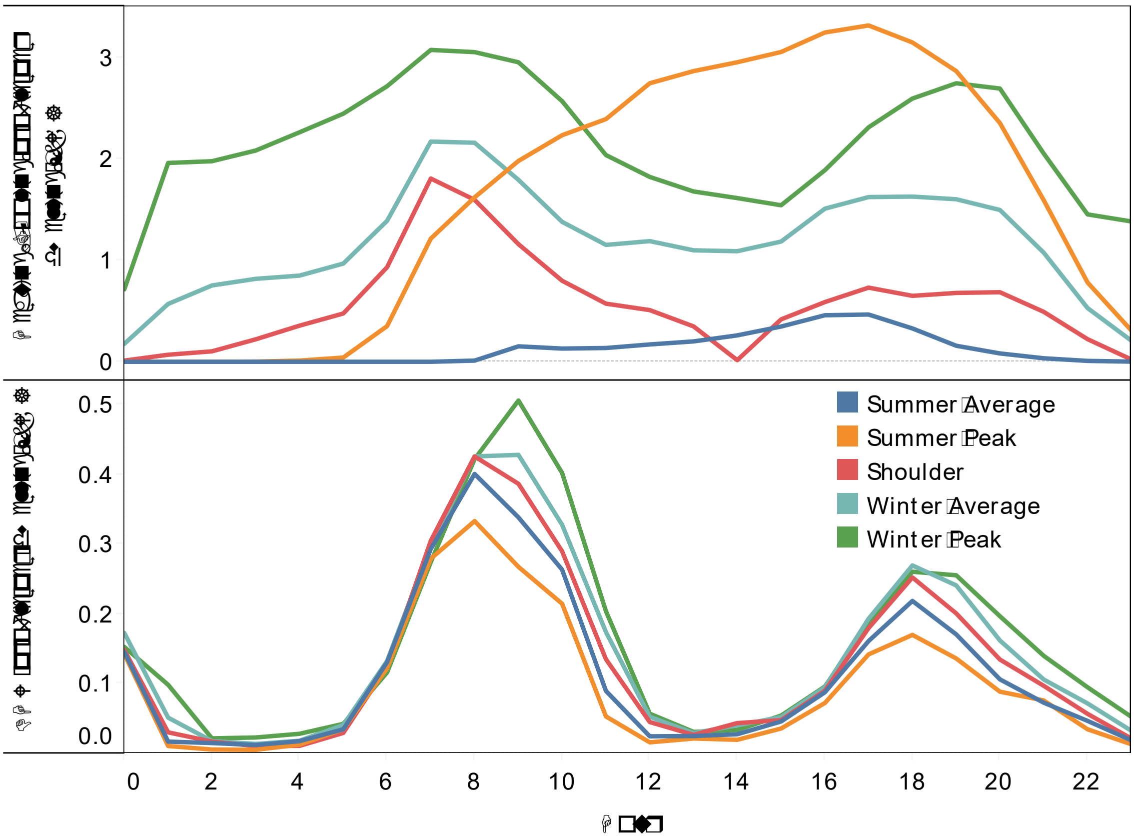

Figure 31 Average heating/cooling and DHW profiles per season

3.5 Aggregated profile

Figures 32 and 33 show the aggregated energy profiles for Victoria in 2040 and 2050, encompassing all network types, locations, seasons, and technologies. The blue area represents BESS, the only technology discharging power to the system. The red area indicates DHW demand, and orange represents Heating/Cooling demand. DHW energy requirements are comparable to Heating/Cooling only during shoulder and summer average days. In contrast, Heating/Cooling demand significantly exceeds DHW demand during winter and summer peak days. The plot also includes commercial loads connected to MV/LV networks (purple), residential loads (yellow), and EV demand (light teal) at the top of the figure. Furthermore, Figure 34 shows the total aggregated profile and the total PV generation in distribution networks without including the operation of batteries to highlight the comparison of the resources.

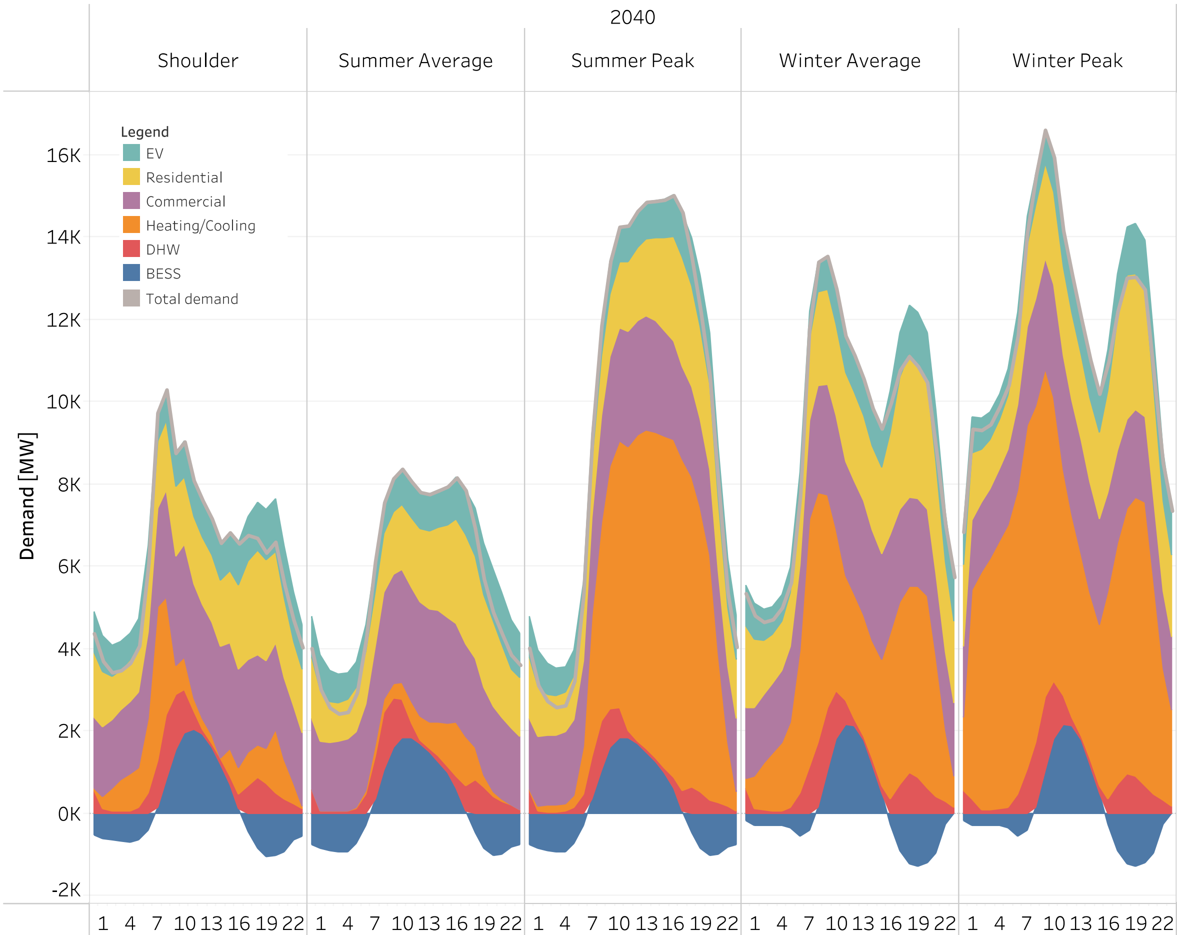

Figure 32 Aggregated profiles 2040

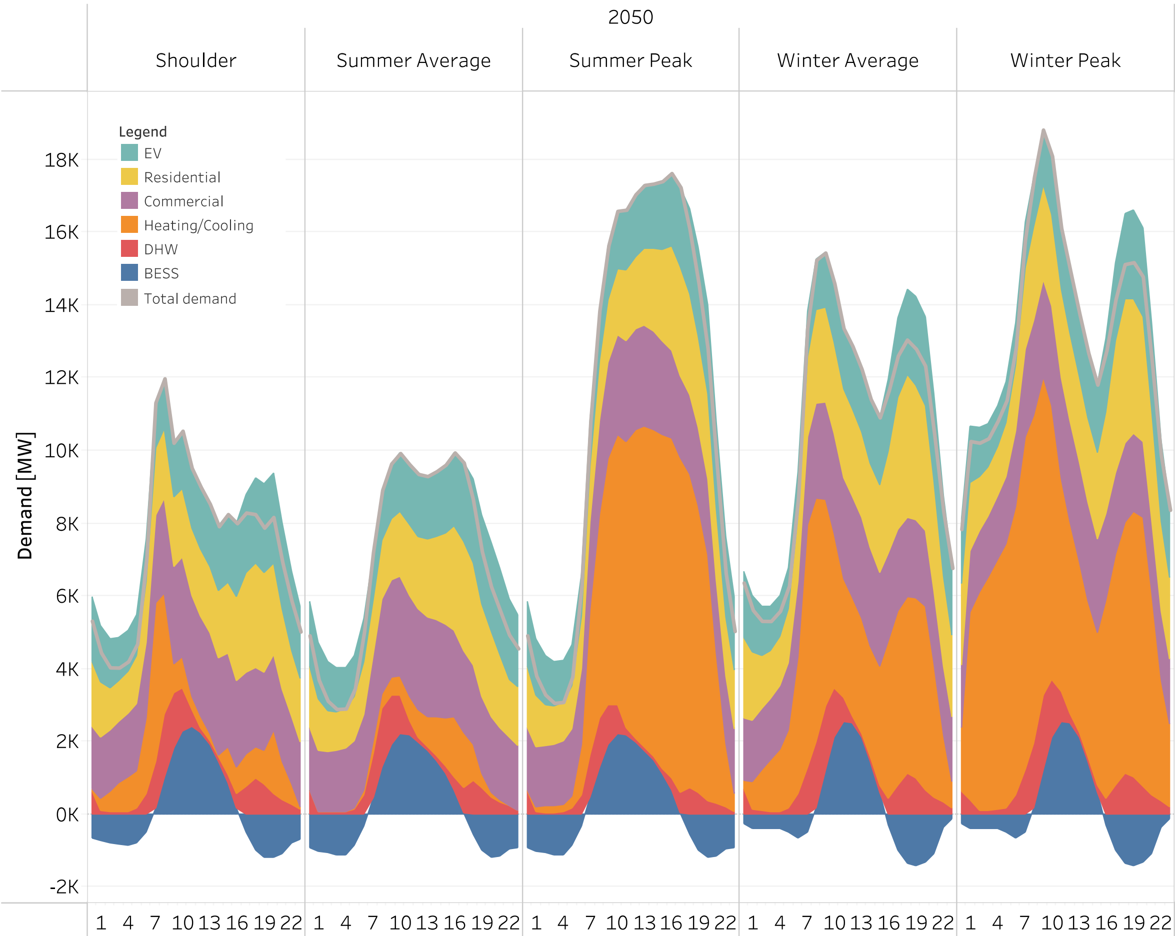

Figure 33 Aggregated profiles 2050

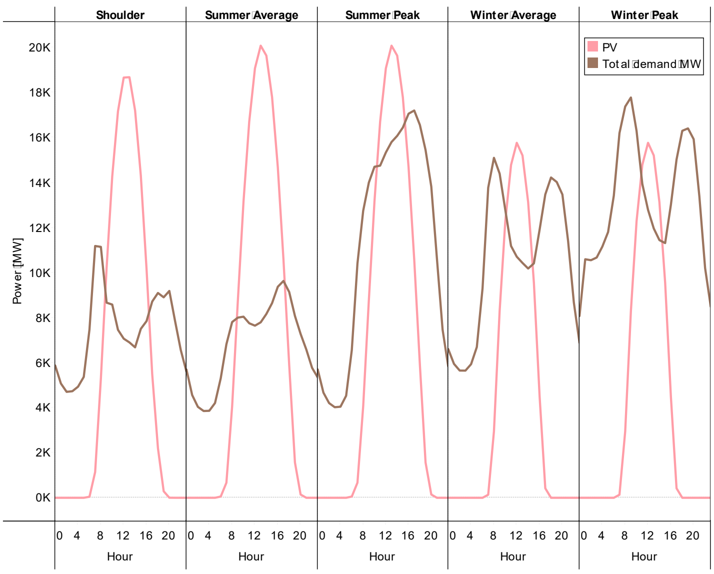

Figure 34 Aggregated profile and distributed PV generation

4 Technology Modelling

The diverse storage technologies within distribution networks, each with unique characteristics, services, and operational behaviours, require accurate representation. Therefore, it is essential to develop distinct models for each technology. This section details the modelling approach for each storage type, beginning with household batteries, which function as conventional storage; EVs, which offer time-varying storage; DHW, which operates as a shiftable load; and heating/cooling demands, which enable demand response through load reduction.

4.1 Household batteries

The household batteries model is given by a conventional BESS representation. The energy balance is defined by equation (1), where E_t is the state of charge, p_t^{ch} is the charging power, p_t^{dch} is the discharging power, and η is the efficiency. Charging and discharging power limits are defined by (2), which depends on the maximum power output of the battery ($\bar{P}^{max}$). The maximum energy constraint is shown in (3), limited by the maximum energy capacity ($\bar{E}^{max}$).

$$E_t = \eta p_t^{ch} - \frac{p_t^{dch}}{\eta} + E_{t-1} \tag{1}$$

$$p_t^{ch}/p_t^{dch} \leq \bar{P}^{max} \tag{2}$$

$$E_t \leq \bar{E}^{max} \tag{3}$$

4.2 Electric vehicles

The EV is modelled as a battery with time varying characteristic, meaning that its maximum charging and discharging power, as well as its minimum and maximum energy levels, are dynamic parameters dependent on the number of EVs connected to the system. The energy balance of the battery is defined in (4). The maximum charging power is constrained by the available chargers ($\bar{P}_t^{max}$) and the demand from connected EVs (P_t), as shown in (5), while the maximum discharging power is similarly limited by the chargers, as defined in (6). The energy limits for EVs are given in (7), where minimum energy ($\underline{E}_t^{min}$) and the maximum energy ($\bar{E}_t^{max}$) vary over time.

To ensure that charging and discharging align with actual EV demand, the model balances energy consumption over a defined period, T^{rec}, which represents the average time EVs remain connected to the system. This constraint, defined in (8), guarantees that the total energy supplied matches the EVs' demand over time.

These dynamic constraints enable flexible EV charging, allowing demand to be shifted between arrival and departure times while also supporting vehicle-to-grid (V2G) interactions.

$$E_t = \eta p_t^{ch} - \frac{p_t^{dch}}{\eta} + E_{t-1} \tag{4}$$

$$p_t^{ch} \leq \bar{P}_t^{max} - P_t \tag{5}$$

$$p_t^{dch} \leq \bar{P}_t^{max} \tag{6}$$

$$\underline{E}_t^{min} \leq E_t \leq \bar{E}_t^{max} \tag{7}$$

$$E_t = E_{tf} \quad for\ t \in T^{rec} \tag{8}$$

4.3 Domestic hot water

The DHW model operates as a load-shifting mechanism, leveraging hot water tanks to enable flexible energy use. Equation (9) defines the shift-up and shift-down energy states, where $e_t^{shup/shdn}$ represents the state of shifting (up and down), and $\gamma_t^{shup/shdn}$ denotes the amount of energy shifted at time t. Equation (10) establishes the shifting balance, incorporating an efficiency factor η.

The shifting capabilities are constrained by equations (11) and (12). Equation (11) limits the maximum shift down, ensuring it does not exceed the actual demand P_t, while equation (12) constrains the maximum shift up to the heat pump's maximum power consumption ($\bar{P}^{max}$).

By combining equations (9) and (10), equation (13) is derived, providing a direct comparison between the DHW shifting model and the battery energy balance equation (4). Both formulations exhibit similar structural components, including charging terms multiplied by efficiency, discharging terms divided by efficiency, and a time-dependent variable related to the previous time step.

$$e_t^{shup/shdn} = e_{t-1}^{shup/shdn} + \gamma_t^{shup/shdn} \tag{9}$$

$$\eta e_t^{shup} = e_t^{shdn} \qquad for\, t \in T^{rec} \tag{10}$$

$$\gamma_t^{shdn} \leq P_t \tag{11}$$

$$\gamma_t^{shup} \leq \bar{P}^{max} \tag{12}$$

$$e_t^{shdn} - e_t^{shup} = \eta \gamma_t^{shup} - \frac{\gamma_t^{shdn}}{\eta} + \eta e_{t-1}^{shup} - \frac{e_{t-1}^{shdn}}{\eta} \tag{13}$$

4.4 Heating and cooling

Heating and cooling demands can provide demand response through load reduction. The maximum load reduction (Γ_t^{shdn}) is constrained by the maximum demand at time t, as shown in equation (14). Additionally, the energy reduction is constrained to a maximum of 50% of the peak demand within each T^{rec} time interval (15). This implies the potential to switch off all coordinated devices for a period of up to half an hour.

$$\Gamma_t^{shdn} \leq P_t \tag{14}$$

$$\sum_{t\, \in T^{rec}} \Gamma_t^{shdn} \leq \frac{\max_{t\, \in\, T^{rec}} P_t}{2} \tag{15}$$

4.5 Technology coordination

To coordinate the different technologies, specific operational constraints must be integrated into the system model. Table 2 details the equations utilized for different coordination strategies. In the absence of coordination, none of the constraints outlined in this chapter are applied, and the storage technologies are modelled as fixed loads. Conversely, when individual technologies are coordinated, the relevant constraints introduced are utilised. Thus, coordinating only BESS activates constraints (1) - (3); for EV coordination, equations (4) - (8), are included; DHW coordination requires equations (9) - (13); heating and cooling loads (BFRS) are coordinated with equations (14) - (15). When the full coordination of all technologies is enabled, the complete set of constraints, equations (1) - (15), is utilised.

Table 2 Equations included in technology coordination

Coordinated technology	Equations included
BESS	(1) - (3)
EVs	(4) - (8)
DHW	(9) - (13)
Heating and cooling (BFRS)	(14) - (15)
All technologies	(1) - (15)

5 Case study

This report includes three case studies. The first, a single-bus model, explores the full potential of coordinated CER without considering network constraints. To understand the impact of incorporating a network, two additional studies are conducted. The first of these is a subtransmission network model, which analyses three networks with distinct characteristics. Finally, one of these subtransmission networks is modelled considering market prices. All these models incorporate the input data developed within this work package and the constraints detailed in Chapter 4 to account for the coordination of BESS, EVs, DHW, and heating/cooling demands.

5.1 Single bus model

This case study investigates how the CER coordination affects peak demand reduction and energy import/export in Victoria. A single-bus system, encompassing Victoria's entire aggregate demand and excluding network constraints, is utilised to fully understand the maximum potential of each technology. The study examines six cases, each characterised by different CER coordination strategies.

The base case establishes system behaviour in the absence of CER coordination, serving as a reference point. Four subsequent cases evaluate the individual impact of each technology: BESS, BFRS (load reduction of heating/cooling demand within a 12-hour period), DHW (energy shifting with a 12-hour recovery period), and EVs (storage with time varying characteristic). The final case, referred to as "All Technologies", assesses the impact of coordinating all the technologies together.

Figure 35 illustrates the total demand as the sum of the base load and the shiftable, reduced, and charging/discharging components resulting from CER coordination in 2040 and 2050, across different representative days: shoulder, summer average, winter average, summer peak, and winter peak. In the figure, each case is represented by a different colour: the base case in orange, BESS coordination in red, BFRS coordination in light teal, DHW coordination in green, EVs coordination in yellow, and the coordinated deployment of all technologies in blue.

The results for both 2040 and 2050 across the analysed typical days demonstrate the effectiveness of technology coordination in peak demand reduction. The BESS case stands out by not only lowering peak demand but also significantly flattening the load profile. This is particularly evident during the summer average day, where in 2040, BESS coordination achieves complete demand flattening from 7:00 to 20:00, and in 2050, it still manages this from 9:00 to 13:00 and again from 16:00 to 20:00. On peak demand days, BESS coordination also proves effective, with clear peak reductions observed during both summer and winter peaks in both years.

The impact of BFRS on peak demand is evident during peak hours, where the model actively reduces load to flatten the demand curve. DHW exhibits a similar behaviour, particularly in winter, where it makes its greatest contribution by reducing peak demand through shifting load from morning peak hours to earlier periods. Besides, on summer average days, DHW also contributes to a slight reduction in peak demand by shifting consumption from the morning peak to earlier hours and from the evening peak to periods of solar generation.

EVs help flatten peak demand during summer and winter peak days in both 2040 and 2050. On summer average day in 2040, EV charging and discharging reduce and flatten demand between 10 AM and 1 PM, and again from 3 PM to 7 PM. The consistent peak demand observed throughout these hours is a result of demand shifting enabled by the coordinated charging and discharging of EVs. Finally, coordinating all technologies simultaneously enables a greater reduction in peak demand by leveraging their combined capabilities and synchronising their actions.

Figure 36 illustrates the hourly energy import and export patterns for 2040 and 2050 across representative day types and coordinated CER strategies. The implementation of CER coordination leads to a marginal increase in exports during solar hours while causing a minor increase in imports during evening and early morning periods. It is important to note that curtailment is avoided in all these scenarios, as any potential excess generation is directed to the grid.

Figure 37 further complement these results by presenting the daily energy imports and exports under different coordinated CER strategies for 2040 and 2050. Imports and exports remain relatively similar across the base, BFRS, EV, and DHW cases. However, the inclusion of BESS coordination leads to a notable increase in exports in both the BESS and all technologies cases. This improvement is driven by the strategic charging and discharging enabled by BESS coordination, which facilitates greater renewable energy generation by charging during periods of surplus PV generation, thereby enlarging the network export envelope.

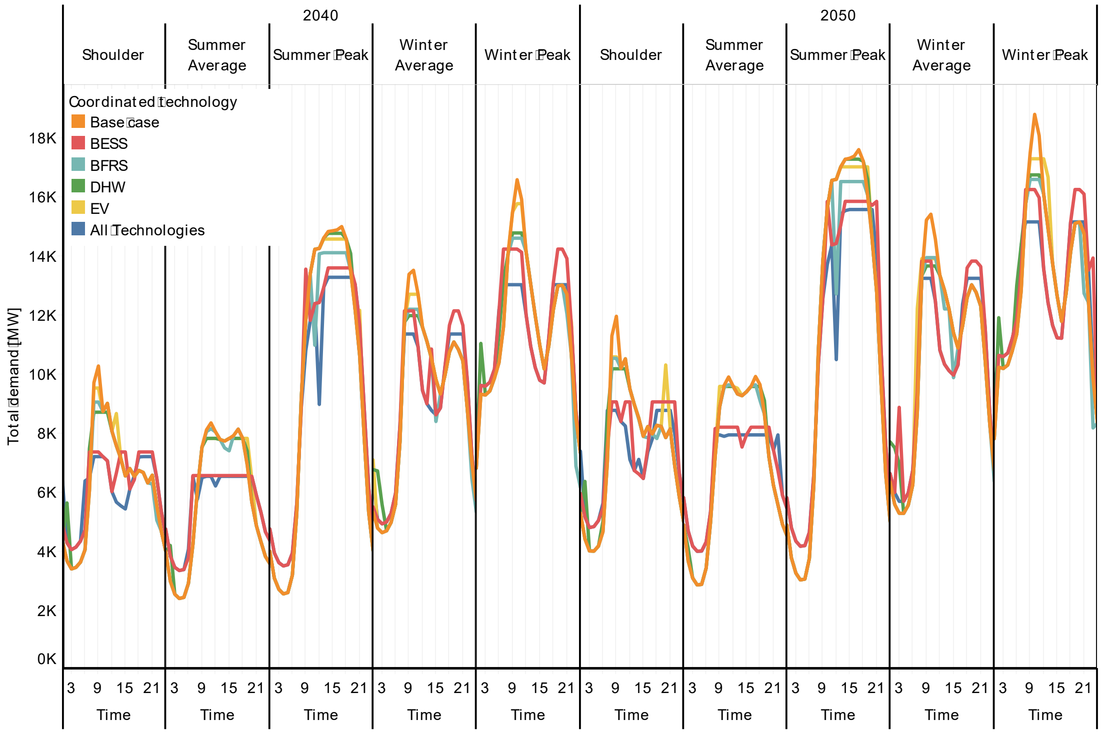

Figure 35 Hourly demand profiles for representative days in 2040 and 2050 for coordination of different CER technologies

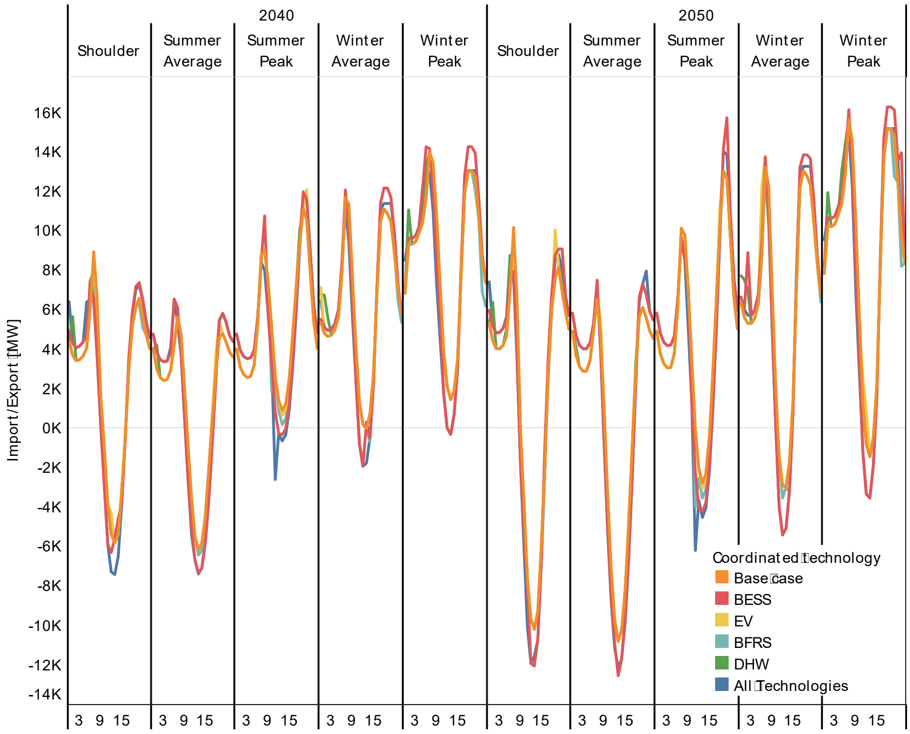

Figure 36 Hourly import and export for representative days in 2040 and 2050 for coordination of different CER technologies

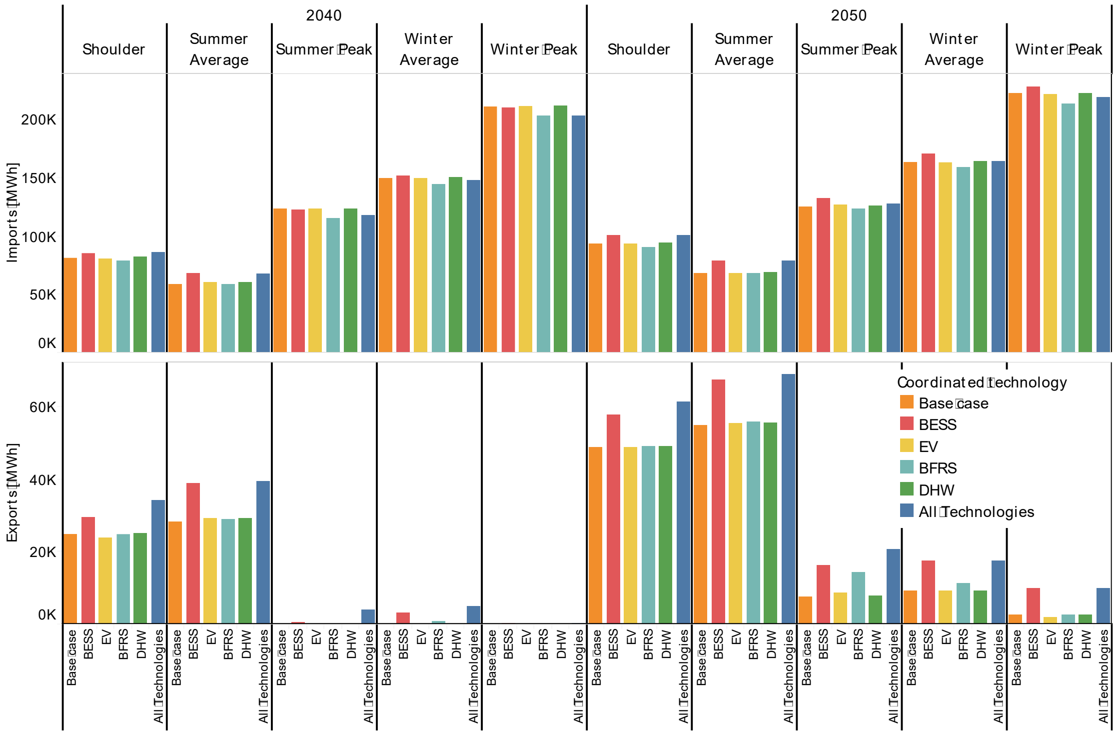

Figure 37 Total Import and exports for representative days in 2040 and 2050 for coordination of different CER technologies

5.2 Subtransmission network model

This study aims to assess how varying levels of CER coordination impacts network operations and show benefits beyond those observed in a simplified single-bus model. To support this analysis, this work package utilises network models developed in [14], with a specific focus on the 66 kV subtransmission networks detailed in [15]. This study employs three 66 kV subtransmission network models owned by AusNet [16]: Cranbourne Terminal Station (CBTS), Glenrowan Terminal Station and Mount Beauty Terminal Station (GNTS-MBTS), and East Rowville Terminal Station (ERTS), depicted figures 38, 39 and 40, respectively.

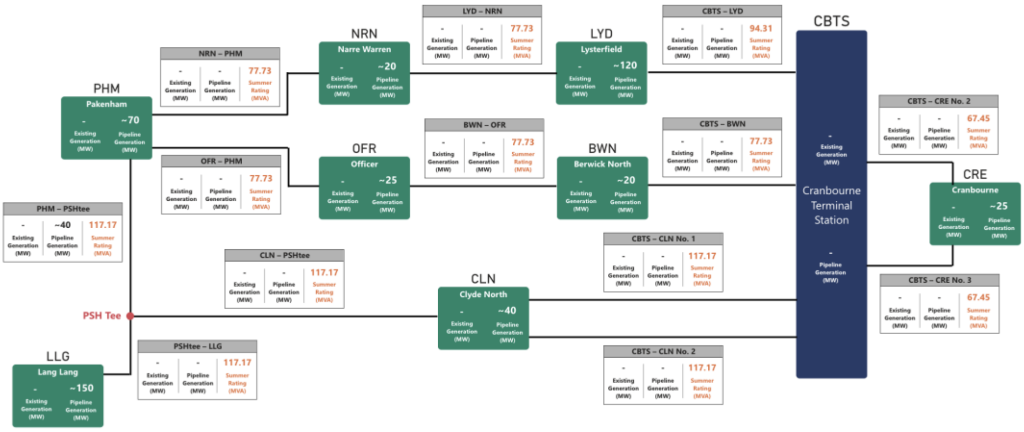

Figure 38 Cranbourne Terminal Station

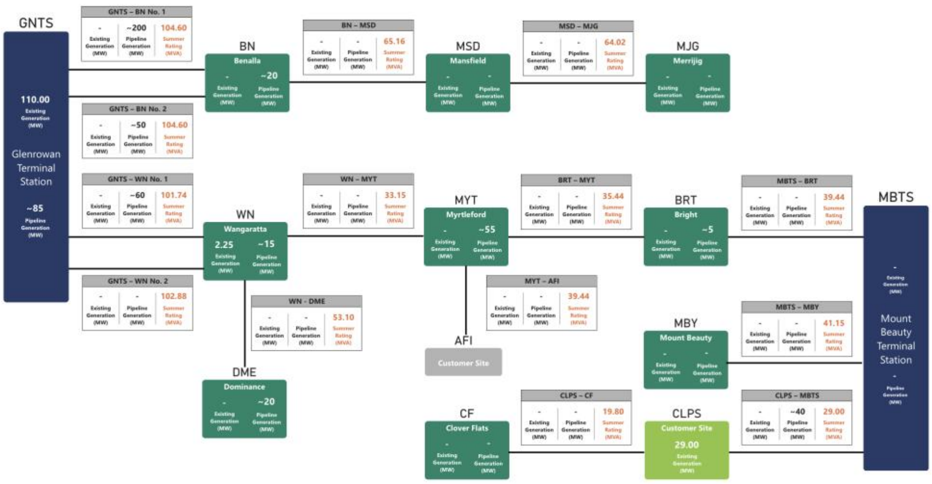

Figure 39 Glenrowan Terminal Station and Mount Beauty Terminal Station

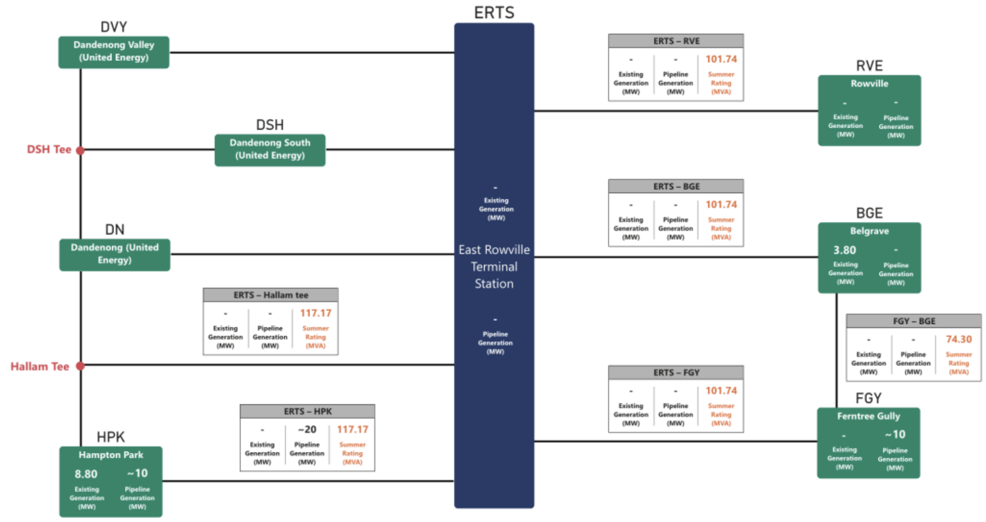

Figure 40 East Rowville Terminal Station

Table 3 characterises each of the selected subtransmission networks by their rooftop PV capacity and peak demand. Table 4 presents the composition of the zone substations associated with each network, which are made up of various combinations of MV-LV typical feeders (urban, suburban, short rural, and long rural) [14]. Additional characteristics of these networks are provided in Table 5, with further details available in Appendix 8.3. These networks were selected to represent a range of demand profiles: CBTS represents a balanced mix of urban and rural loads, GNTS-MBTS[1] corresponds to a primarily rural load profile, and ERTS reflects a predominantly urban demand. The increased granularity achieved through modelling subtransmission loops provides an instance to study the impact of network constraints. However, it is important to note that these subtransmission models do not incorporate constraints arising from a higher granularity within the MV or LV networks.

Table 3 Rooftop PV capacity and peak demand, base year 2024

	Rooftop PV		Peak Demand	
ST Network	Capacity [MW]	Ratio to Victoria [%]	Peak [MW]	Ratio to Victoria [%]
CBTS	345	7.00%	471	4.00%
GNTS-MBTS	61	1.00%	119	1.00%
ERTS	169	4.00%	475	4.00%

[1] GNTS-MBTS network includes 370 MW / 425 MWh of installed BESS capacity within the subtransmission network.

Table 4 Zone substation composition for subtransmission networks

ST Network	Code	Name	Postcodes	Clients	Urban	Suburban	Short Rural	Long Rural
CBTS	CRE	Cranbourne	3977	23,325	4	0	2	0
	LYD	Lysterfield	3156	7,524	2	0	2	0
	BWN	Berwick North	3806	9,009	3	0	1	0
	NRN	Narre Warren	3804, 3805	6,338	4	0	1	0
	OFR	Officer	3809	22,521	2	0	1	1
	CLN	Clyde North	3978	35,625	4	0	4	0
	PHM	Pakenham	3810	16,112	4	0	4	0
	LLG	Lang Lang	3984	7,083	4	0	2	0
GNTS-MBTS	WN	Wangaratta	3677	18,171	2	0	1	4
	BRT	Bright	3741	4,448	0	0	3	0
	MYT	Myrtleford	3737	6,107	0	0	3	1
	MJG	Merrijig	3723	1,368	0	0	1	0
	MSD	Mansfield	3722	6,826	0	0	0	3
	CF	Clover Flat	3315	725	0	0	2	0
	MBY	Mt Beauty	3699	2,150	0	0	4	0
	BN	Benalla	3672	12,462	1	0	1	3
ERTS	DVY	Dandenong Valley - UE	4284, 3805	3,805	11	0	1	0
	DSH	Dandenong South - UE	1707, 3175	3,175	10	0	0	0
	BGE	Belgrave	12145, 3160	3,160	1	0	5	0
	DN	Dandenong - UE	20264, 3175	3,175	14	0	0	0
	FGY	Ferntree Gully	19678, 3156	3,156	8	0	2	0
	HPK	Hampton Park	27495, 3976	3,976	6	0	2	0
	RVE	Rowville	4240, 3178	3,178	1	0	2	0
	UWY	Upwey	1079, 3158	3,158	0	0	1	0

Table 5 MV-LV networks overview

Network Type	Number of Customers	Number of Buses	Number of Transformers	Network Length [km]	Maximum demand [MVA]
Urban	3181	6020	48	20	10.55
Suburban	5514	10902	71	33	13
Short Rural	724	2202	187	93	8.42
Long Rural	3942	9153	877	207	9

5.2.1 CBTS

Figure 41 and Figure 42 illustrate the line loading of the CBTS network at 11 AM for 2050 winter peak demand for cases with no CER coordination, 50% and 100% CER coordination. Without coordination, two lines exceed 150% loading, one exceeds 120%, and three surpass their rate capacity. With 100% technology coordination, line loading decreases, eliminating lines above 150% loading; however, the previously overloaded lines now operate above 120%. Notably, one additional line exceeds 100% loading in this coordinated scenario.

Figures 43 and 44 illustrate the average line overloading across all network lines. Figure 43 shows the hourly average line overloading per year and typical day for 0%, 50%, and 100% CER coordination, indicating peak average overloads of up to

40% in 2050 during a summer average day. Figure 44 displays the average line overload per typical day for the different CER coordination levels in 2040 and 2050. These results demonstrate that enabling CER coordination can reduce line overloading by 2% to 4%, depending on the typical day and year.

Figure 45 displays the total hourly demand across different typical days in 2040 and 2050. The results highlight that higher levels of CER coordination increase demand during solar hours while reducing demand during non-solar hours, thereby decreasing overall imports. This effect is supported by Figure 46, which shows total imports and exports across the typical days and CER coordination levels in 2040 and 2050. The figure shows that as CER coordination increases, total imports consistently decline across all typical days. A slight reduction in exports is also observed, which is attributed to the increased local consumption during solar hours.

Figure 47 illustrates the percentage of curtailment, demonstrating that network constraints limit the system's capacity to dispatch all surplus PV generation. The figure shows that in 2040, CER coordination has the potential to reduce curtailment by approximately 1% to 2%. In 2050, curtailment levels are generally higher due to greater PV penetration. However, increasing CER coordination may reduce curtailment by up to 2%[2].

An interesting exception occurs on a typical shoulder day in 2050, where the 100% coordination case results in slightly higher curtailment compared to the 50% coordination case (though the curtailment still lower than in the no-coordination case). Figures 43-46 explain this: 100% coordination shifts local demand to solar hours, reducing line congestion throughout the day. While increased PV exports would worsen line overloading, the resulting higher curtailment allows for the lowest import levels due to the shifted demand. This trade-off highlights how CER coordination can optimise system performance beyond minimising curtailment, imports, peak demand or line congestions.

[2] This value may be potentially impacted by the actual PV generation observed at the subtransmission networks once additional constraints from a higher-granularity representation of MV/LV networks are incorporated

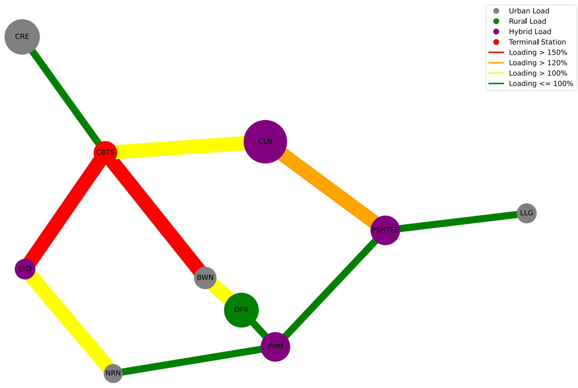

Figure 41 0% CER coordination for 2050 winter peak case at 11 AM

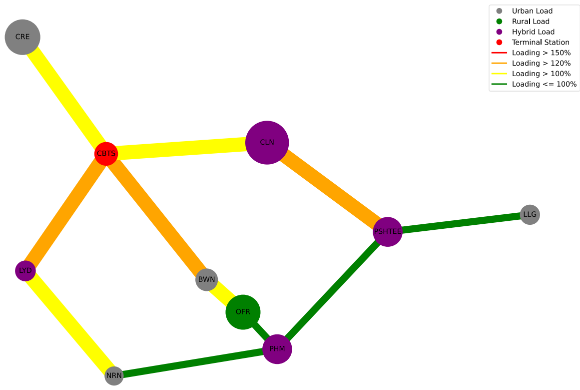

Figure 42 100% CER coordination for 2050 winter peak case at 11 AM

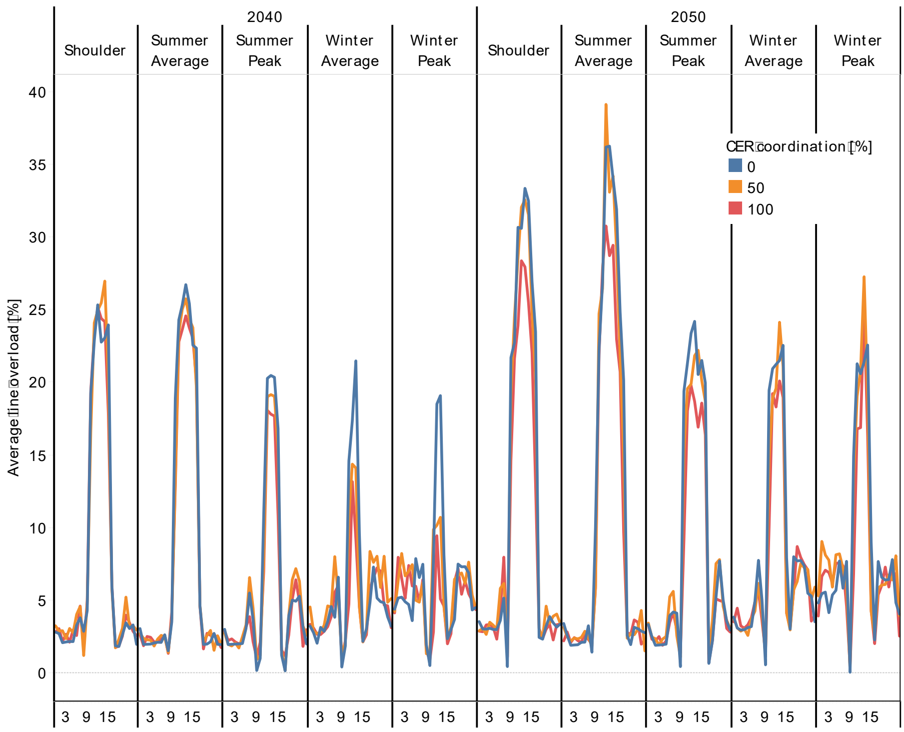

Figure 43 Hourly average line overload for representative days in 2040 and 2050 for different CER coordination levels

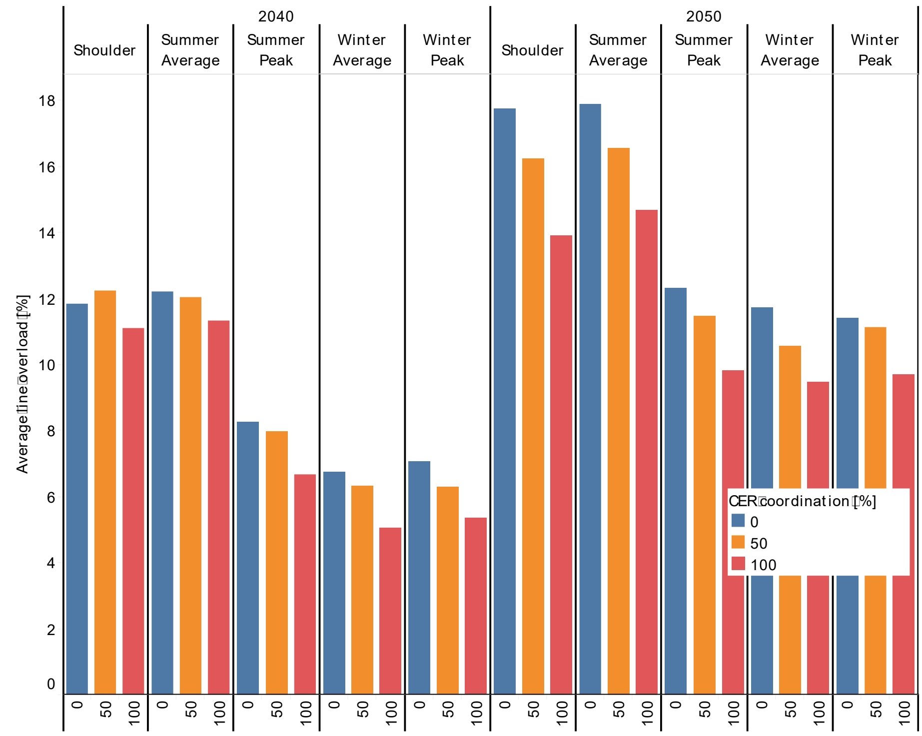

Figure 44 Average line overload for representative days in 2040 and 2050 for different CER coordination levels

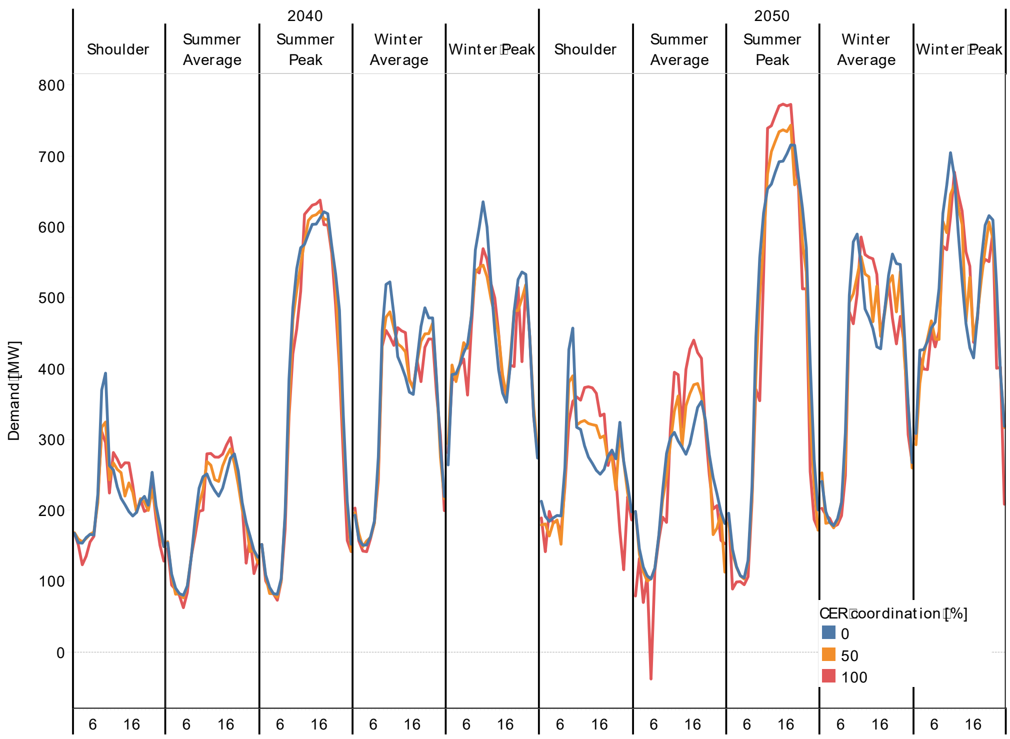

Figure 45 Hourly demand profiles for representative days in 2040 and 2050 for different CER coordination levels

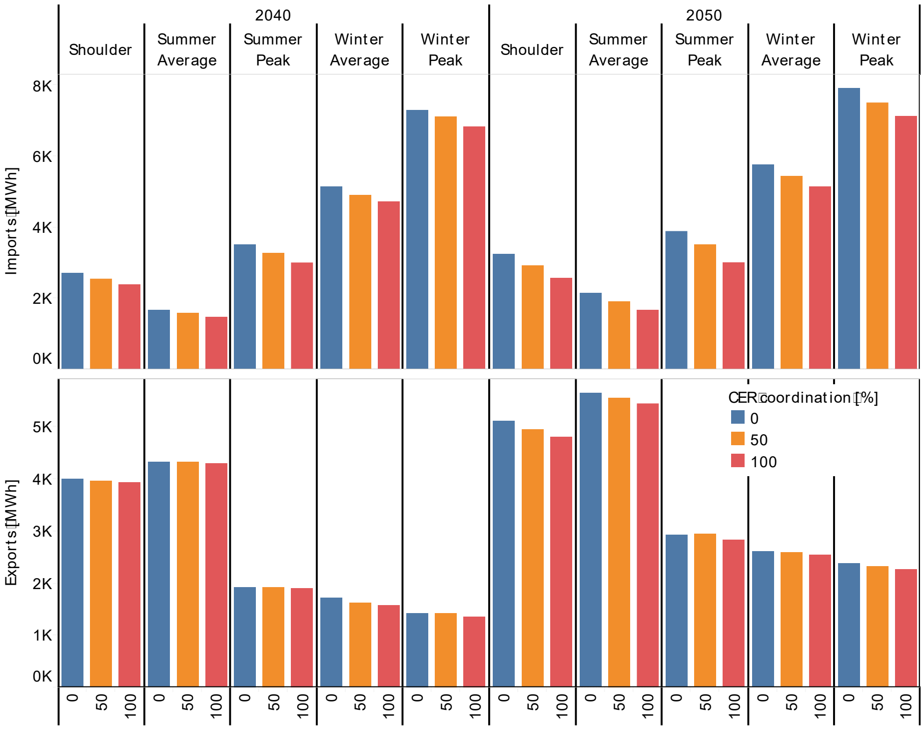

Figure 46 Total Import and exports for representative days in 2040 and 2050 for different CER coordination levels

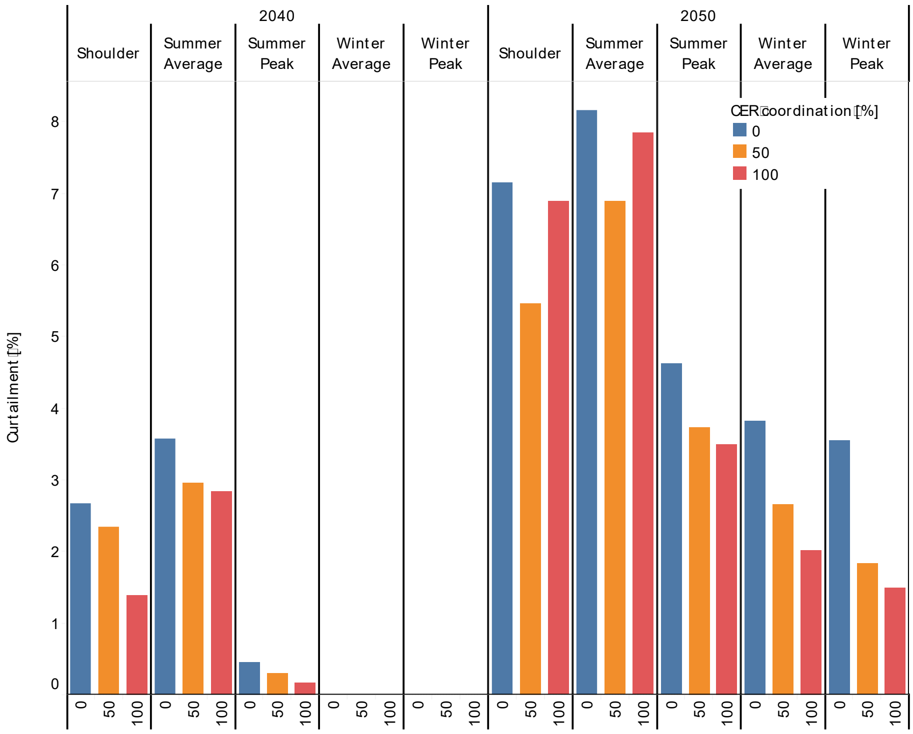

Figure 47 Average curtailment for representative days in 2040 and 2050 for different CER coordination levels

5.2.2 GNTS-MBTS

Figure 48 and Figure 49 illustrate the line loading of the GNTS-MBTS network at 7 PM for 2040 summer peak demand for cases with no CER coordination, 50% and 100% CER coordination[3]. Without coordination, three lines near one terminal station exceed their rate capacity by less than 20%. With 100% technology coordination, three lines still exceed their capacity by under 20%, but the location shifts, having all the lines located around only one terminal station.

Figures 50 and 51 illustrate the average line overload across all network lines. Figure 50 shows the hourly average line overloading per year and typical day for 0%, 50%, and 100% CER coordination, indicating peak average overloads of up to 7% in 2050 during summer peak days. Figure 51 displays the average line overload per typical day for the different CER coordination levels in 2040 and 2050. In general, these results show a decrease in the percentage of overloaded lines. However, given the initially small percentage of overloaded lines, minor adjustments in line flow may lead to an increase percentage of overloaded lines, indicating no clear trend of consistent reduction. To understand these results, it's important to note the absence of curtailment at the subtransmission level[4], meaning all surplus PV generation is exported. Furthermore, CER coordination impacts imports and exports.

Figure 52 displays the total hourly demand across different typical days in 2040 and 2050, highlighting that higher CER coordination decreases peak demand while slightly increasing off-peak demand. Figure 53 shows total imports and exports across typical days and CER coordination levels in both years, revealing a consistent rise in total exports with increasing CER coordination. Additionally, a decrease in imports can also be seen, which mostly driven by BESS and EVs.

[3] The different coordination cases account for the controllability of the BESS installed within the subtransmission loop.

[4] Some curtailment may still occur due to constraints in the MV or LV networks.

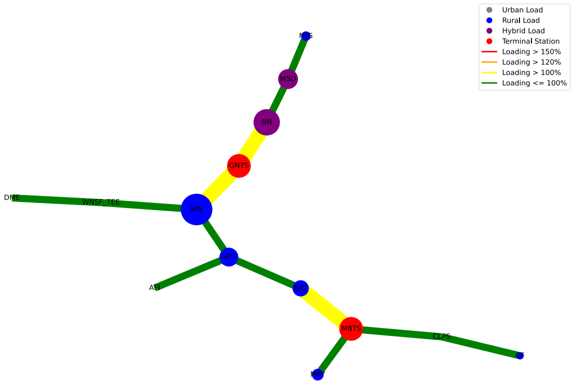

Figure 48 0% CER coordination for 2040 summer peak case at 7 PM

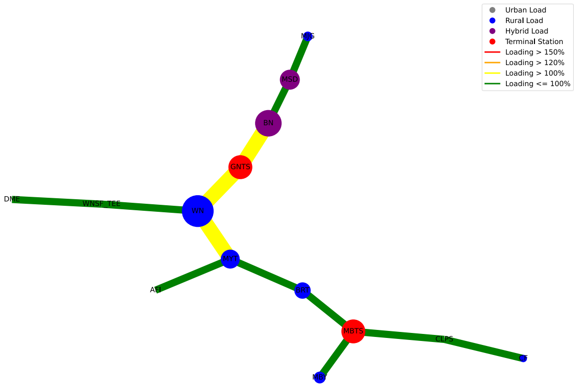

Figure 49 100% CER coordination for 2040 summer peak case at 7 PM

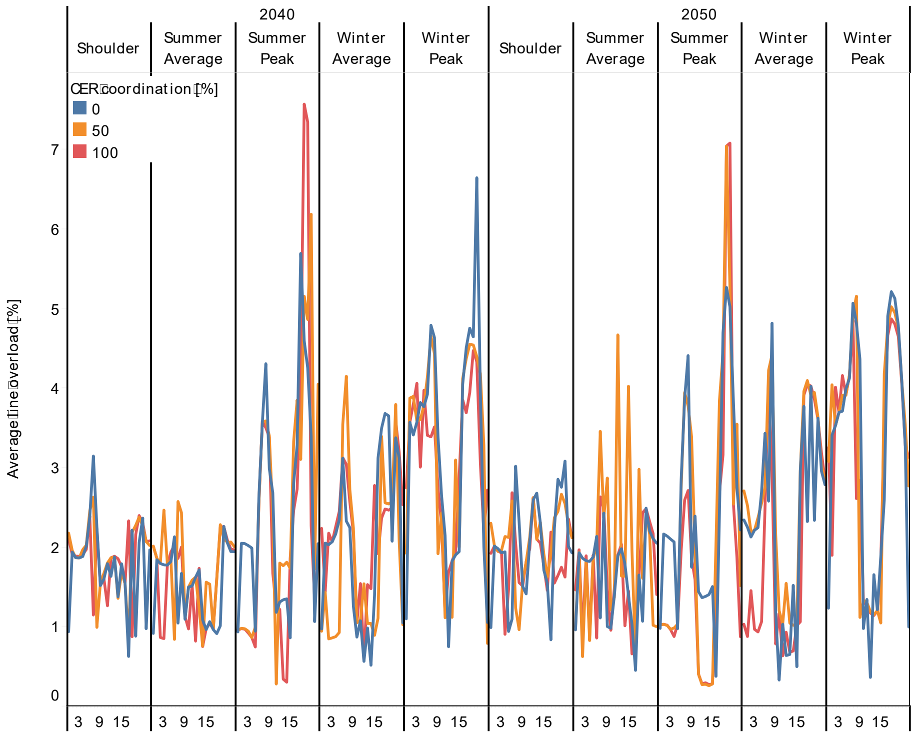

Figure 50 Hourly average line overload for representative days in 2040 and 2050 for different CER coordination levels

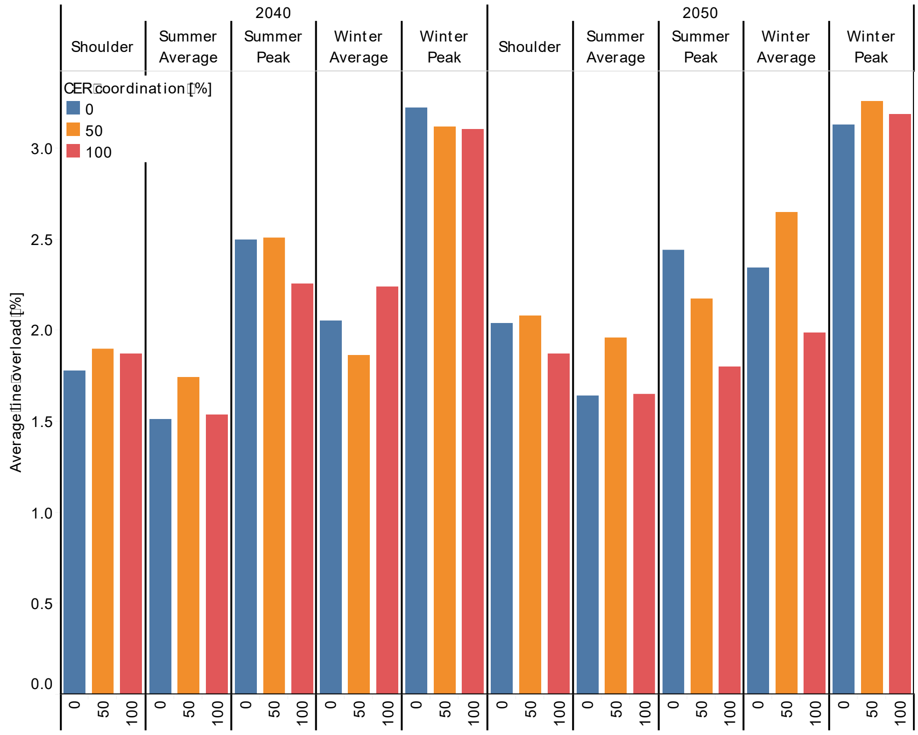

Figure 51 Average line overload for representative days in 2040 and 2050 for different CER coordination levels

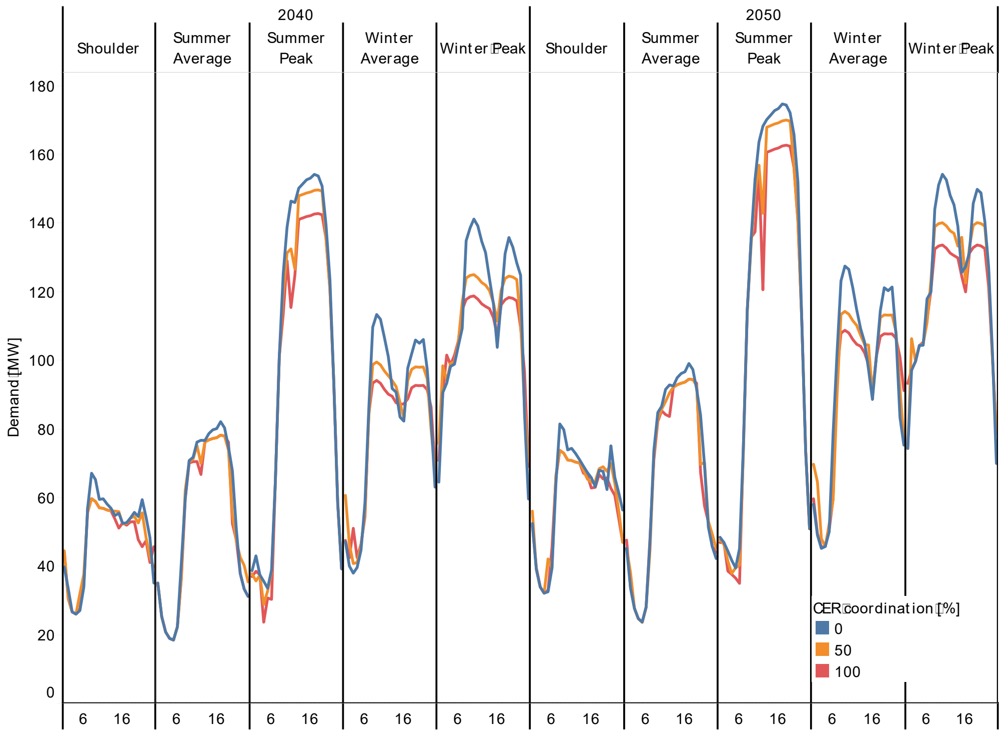

Figure 52 Hourly demand profiles for representative days in 2040 and 2050 for different CER coordination levels

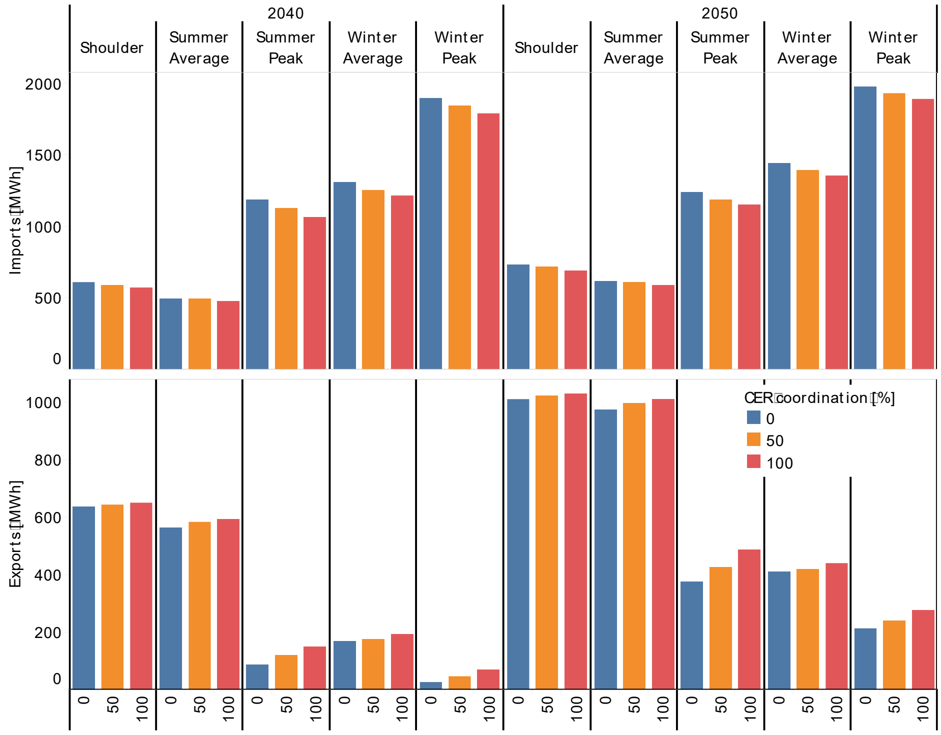

Figure 53 Total Import and exports for representative days in 2040 and 2050 for different CER coordination levels

5.2.3 ERTS

Figure 54 and Figure 55 illustrate the line loading of the ERTS network at 1 PM for 2050 summer average demand for cases with no CER coordination, 50% and 100% CER coordination. Without coordination, one lines exceed 150% loading, one exceeds 120%, and two surpass their rate capacity. With 100% technology coordination, line loading decreases, eliminating the line above 150% loading; however, this line now operates above 120%.

Figures 56 and 57 illustrate the average line overloading across all network lines. Figure 56 shows the hourly average line overloading per year and typical day for 0%, 50%, and 100% CER coordination, indicating peak average overloads of up to 40% in 2050 during a summer average day. Figure 57 displays the average line overload per typical day for the different CER coordination levels in 2040 and 2050. These results demonstrate that enabling CER coordination can reduce line overloading up to 5% during days with high PV generation, such as summer average and shoulder days.

Figure 58 displays the total hourly demand across different typical days in 2040 and 2050. The results highlight that higher levels of CER coordination increase demand during solar hours for days with high PV availability, such as shoulder and summer average days. Notably, there is no curtailment arising from subtransmission constraints in this case. Furthermore, greater CER coordination levels lead to a higher reduction in peak demand, especially for winter and summer peak days in both years.

Figure 59 shows total imports and exports across the typical days and CER coordination levels in 2040 and 2050. The figure shows that as CER coordination increases, total imports consistently decreases across all typical days. A slight reduction in exports is also observed, which is attributed to the increased local consumption during solar hours.

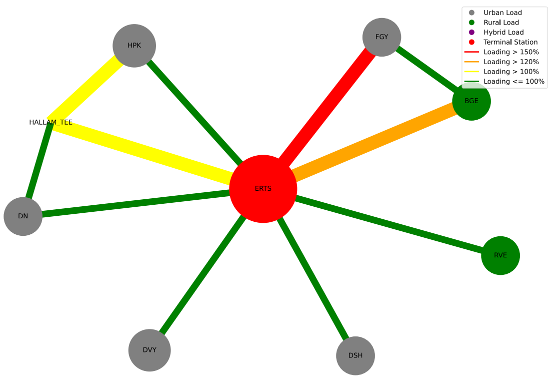

Figure 54 0% CER coordination for 2050 summer average case at 1 PM

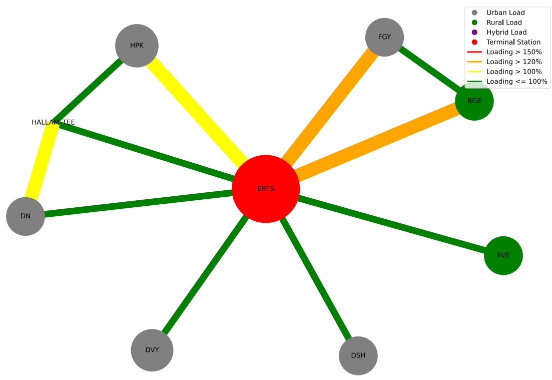

Figure 55 100% CER coordination for 2050 summer average case at 1 PM

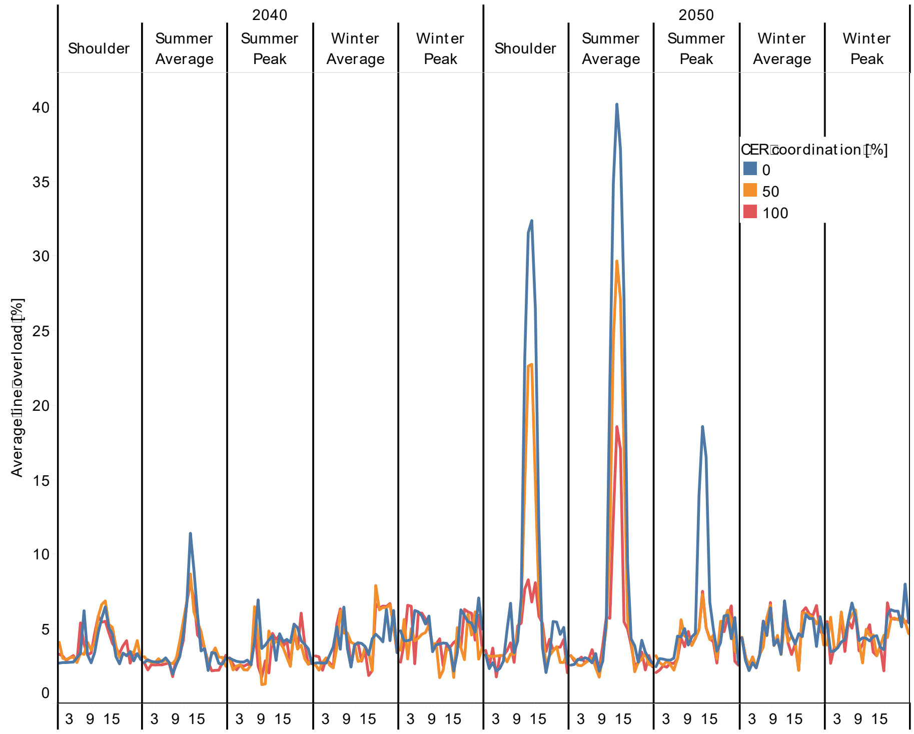

Figure 56 Hourly average line overload for representative days in 2040 and 2050 for different CER coordination levels

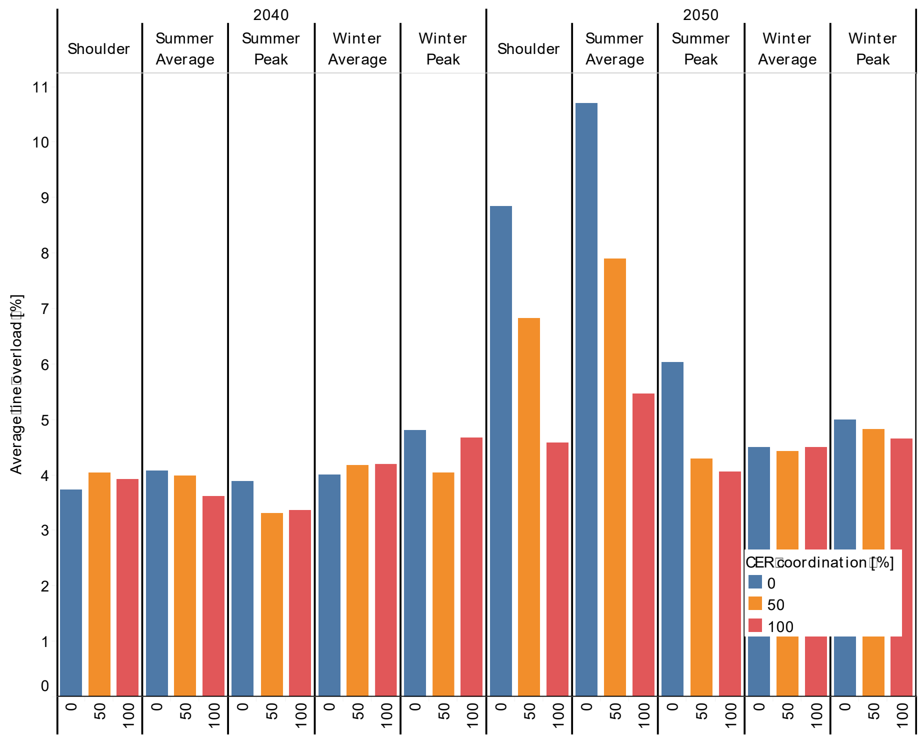

Figure 57 Average line overload for representative days in 2040 and 2050 for different CER coordination levels

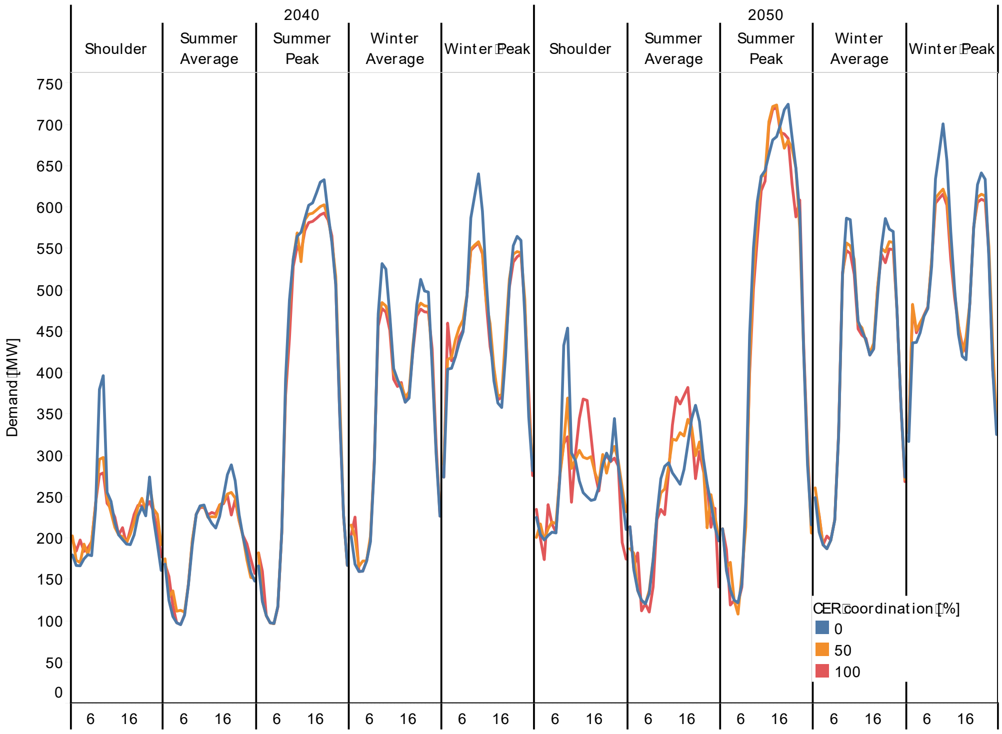

Figure 58 Hourly demand profiles for representative days in 2040 and 2050 for different CER coordination levels

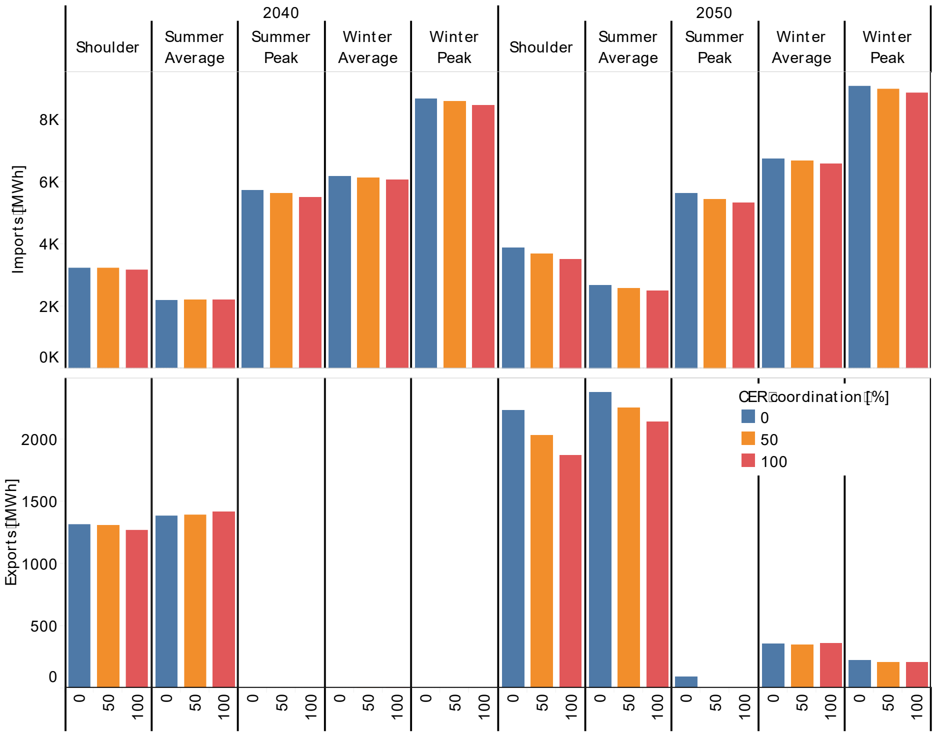

Figure 59 Total Import and exports for representative days in 2040 and 2050 for different CER coordination levels

5.3 Market price sensitivity

This case study seeks to understand the impact of market prices on CER coordination. The GNTS-MBTS network, characterised by low line overloading (up to 7%) and demand, has been chosen as an illustrative example. The average hourly seasonal market prices used for this study are based on Victoria market price in 2023[5], obtained from [17] are shown in Figure 60. These price signals are incorporated into the optimisation model through an additional term that reflects the time-varying exposure of an aggregator or retailer, operating at the subtransmission level, would face when interacting with the wholesale electricity market.

Figure 61 illustrates the line loading of the GNTS-MBTS network at 11 AM during the 2050 summer peak demand with 100% CER coordination by including market prices. With full technology coordination, two lines near the terminal stations exceed 120% loading. Additionally, two lines between the terminal stations exceed 100% loading.

Figures 62 and 63 illustrate the average line overloading across all network lines. Figure 62 shows the hourly average line overloading per year and typical day for 0%, 50%, and 100% CER coordination. In the figure are observed peak average line overloads of up to 30%. These overloads appear as spikes occurring multiple times per day and they become more pronounced as CER coordination levels rise. Additionally, Figure 63 displays the average line overload per typical day for the different CER coordination levels in 2040 and 2050. This figure shows that enabling CER coordination increases the average overloading to up to 3%.

A comprehensive understanding of these results requires an examination of both the demand profile and the coordinated CER patterns[6]. Figure 64 illustrates total demand, revealing the presence of two to three distinct positive and negative peaks during the typical days. Figure 65 provides further insight by illustrating the charging and discharging patterns of all the BESS connected to the network across the different

[5] It is important to note that these prices may not represent market conditions in 2040 or 2050. However, they are still useful for analysing how market-driven CER coordination can impact network operation.

[6] The demand profile and the coordinated CER patterns may be also impacted by additional constraints obtained from a higher-granularity representation of MV/LV networks.

typical days for 2040 and 2050, and for 0%, 50% and 100% CER coordination levels. The figure shows that BESS operation aligns with peaks observed in the total demand and with the peaks observed in the overloading lines. Thus, these peaks are aligned with market prices to charge during low-price periods and discharge during high-price periods, maximising energy arbitrage to leverage the price differentials shown in Figure 60. Thus, higher levels of CER coordination results in higher line overloading.

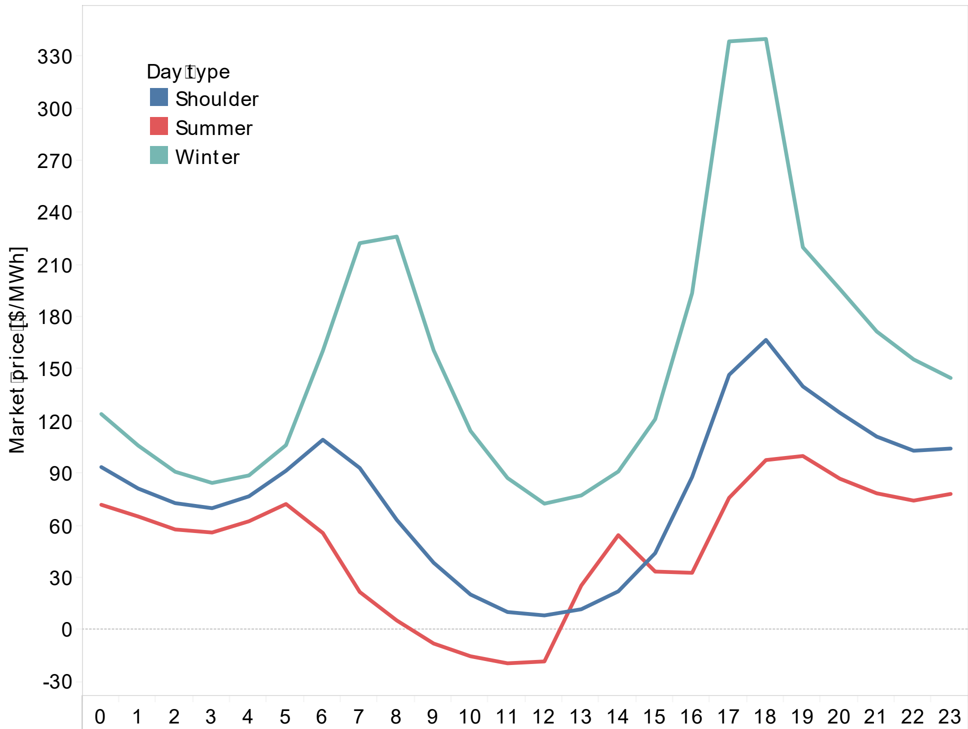

Figure 60 Average market prices per hour and season in Victoria 2023

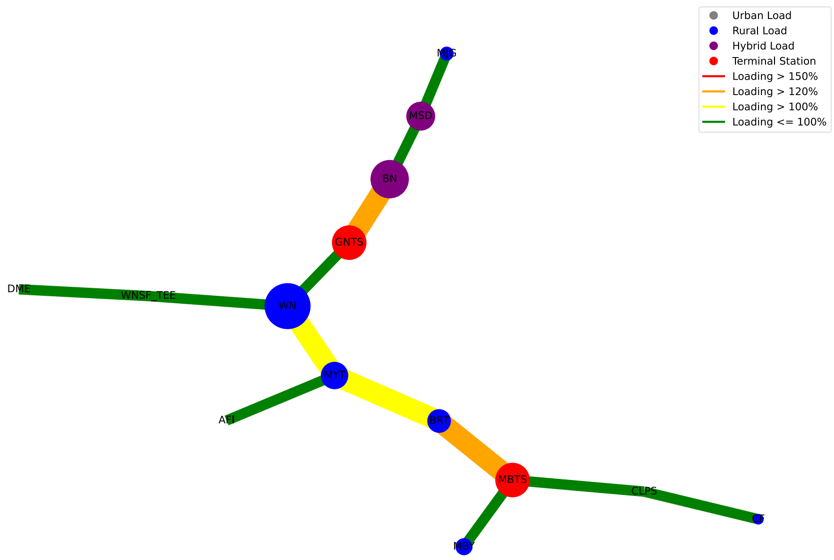

Figure 61 GNTS-MBTS network 100% CER coordination for 2050 summer peak case at 11 AM

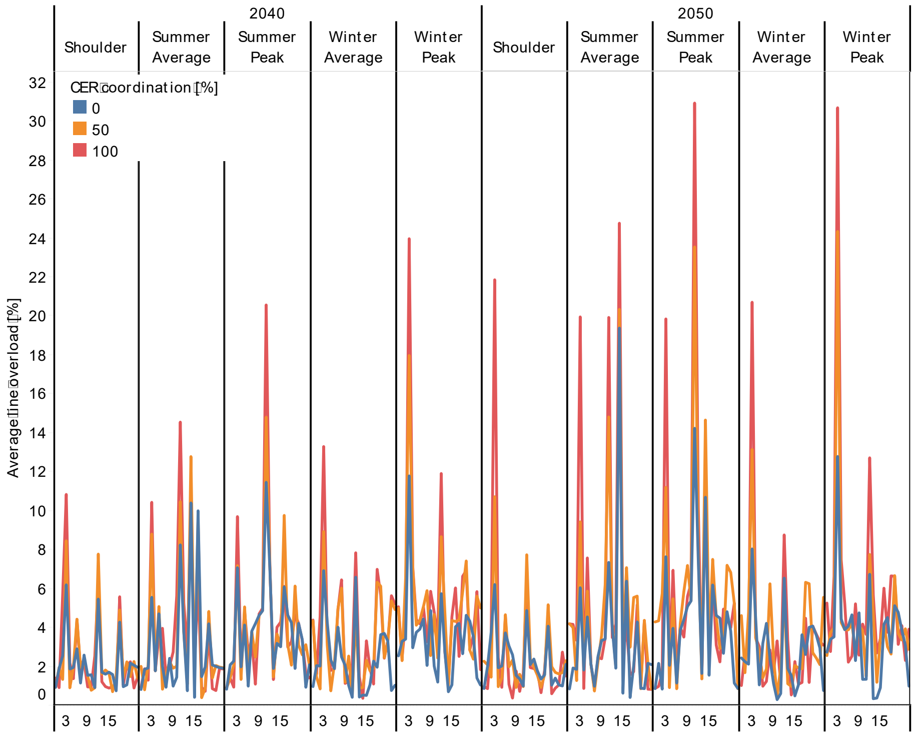

Figure 62 Hourly average line overload for representative days in 2040 and 2050 for different CER coordination levels

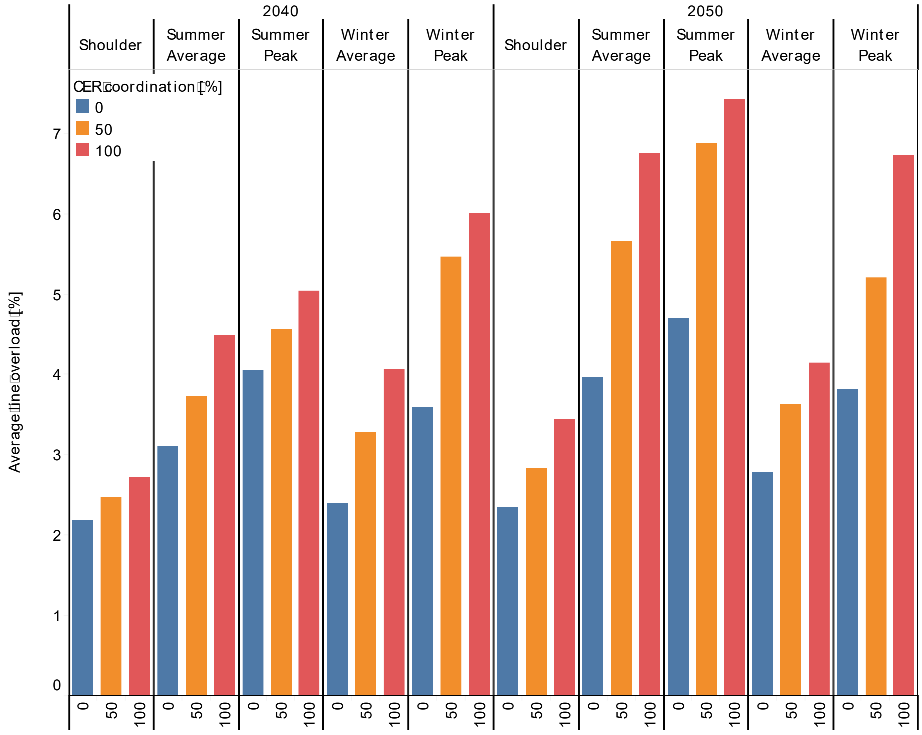

Figure 63 Average line overload for representative days in 2040 and 2050 for different CER coordination levels

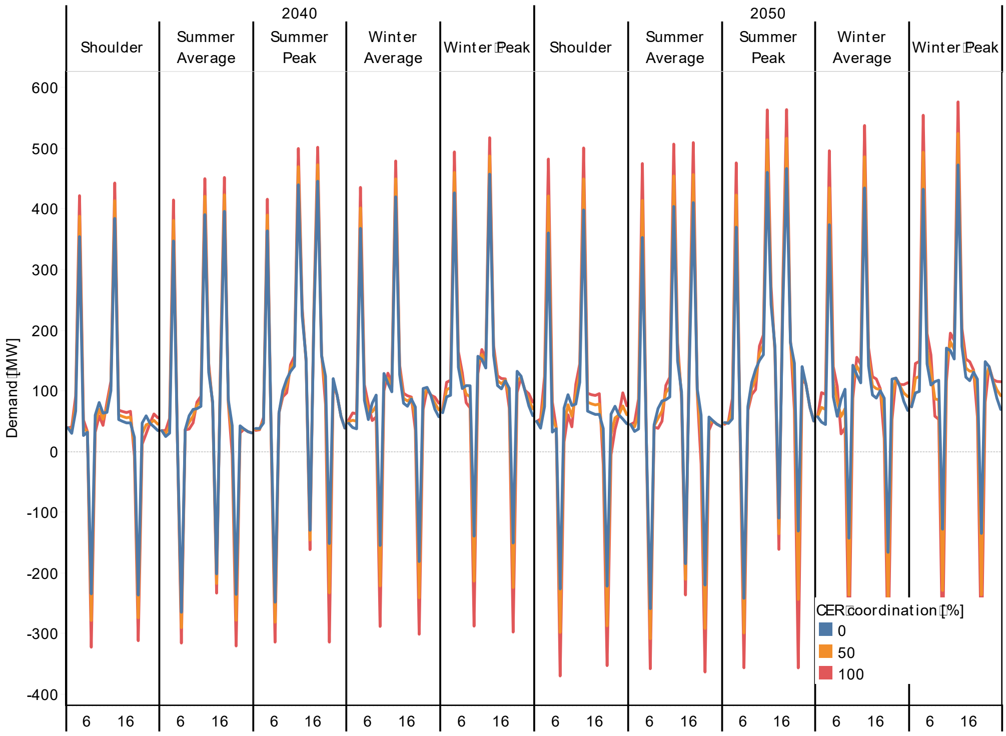

Figure 64 Hourly demand profiles for representative days in 2040 and 2050 for different CER coordination levels

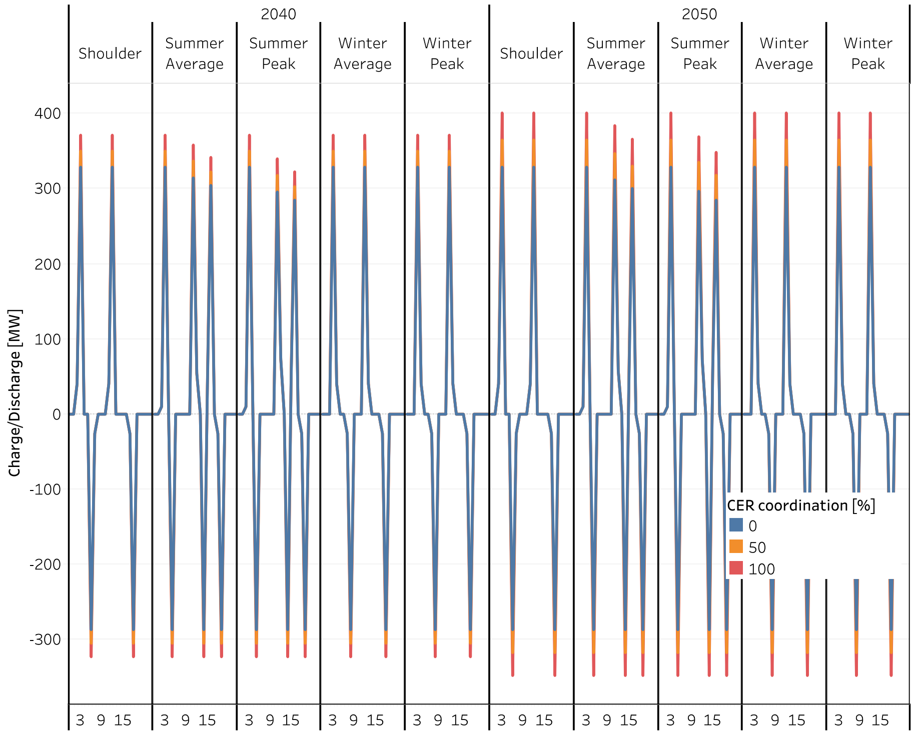

Figure 65 Hourly charging/discharging of BESS for presentative days in 2040 and 2050 for different CER coordination levels

6 Conclusions

This report presents a comprehensive techno-economic analysis for evaluating the impact of coordinated Consumer Energy Resources (CERs), including Household batteries referred to as Battery Energy Storage Systems (BESS), Electric Vehicles (EVs), Domestic Hot Water (DHW) systems, and Building Fabric Related Storage (BFRS) from heating and cooling demand. This study employs a bottom-up approach to create high-granularity energy demand and storage profiles on Victoria, considering diverse factors such as network type (urban, suburban, rural), location (Ballarat, Melbourne, Shepparton, Traralgon), and seasonal variations.

Each CER technology presents distinct operational and storage characteristics. EV charging behaviour depends heavily on battery size, charger type, driving patterns, and the user's location on the network (rural users, for example, typically require more frequent charging due to longer travel distances). The thermal loads such as BFRS and DHW can reduce and shift their demand respectively and they are impacted by insulation, size, and external conditions (weather and occupancy).

To explore the potential of the different technologies and the impact of different penetration of coordination levels of CER, this report presents three case studies. The first study uses a single-bus model to represent aggregate demand in Victoria and demonstrates the potential of coordinating each CER technology individually and as a full coordination of all the technologies. The results show that CER coordination can help to reduce peak demand, increase solar self-consumption, and flatten the overall demand profile.

The second case study investigates the impact of network constraints within three subtransmission networks. CER coordination generally leads to reductions in peak demand, energy imports, PV curtailment, and line overloading. The effectiveness of CER coordination in mitigating congestion varied across the networks, illustrating the importance of considering local grid characteristics in operational strategies.

The third case study examined the integration of market price signals into CER coordination within a rural subtransmission network. The findings highlight that while CERs responding to market prices maximised energy arbitrage opportunities, this behaviour at times worsened line congestion. This trade-off points to the need for more refined strategies that simultaneously consider economic drivers and technical constraints.

This work highlights the importance of incorporating networks into the assessment of CER coordination value, as it reveals hidden limitations not apparent in less granular models, showing the potential of CER coordination as a cost-effective alternative to traditional infrastructure upgrades. Besides, the presented approach could be further expanded to include Medium Voltage (MV) and Low Voltage (LV) networks, which could shed lights on the challenges in MV-LV networks with high CER penetration, offering insights into operational bottlenecks and demonstrating the broader potential of CER coordination at different levels.

In addition to the average and peak day shown in this report, the presented model could be extended to incorporate contingency events, which could result in even greater benefits from CER coordination. This is particularly relevant for storage technologies such as BESS and EVs with Vehicle-to-Grid (V2G) capabilities, which have a high potential to provide valuable services during these events[7].

Overall, this report highlights the potential of coordinated CER to enhance subtransmission system flexibility by reducing peak demand, increasing alignment between demand solar generation, and alleviating network overloading. By leveraging the synergies between diverse storage technologies, coordinated CER operation offers a powerful tool for shaping energy demand in Victoria, as demonstrated in this work, and potentially elsewhere, providing a pathway to reduce reliance on grid imports, shift consumption to periods of high PV generation, ultimately mitigating network overloading and minimising PV curtailment. Unlocking this potential will require balancing economic incentives with technical constraints, potentially necessitating new policies to enable the full integration of coordinated CERs.

[7] The overall impact of these technologies is strongly influenced by consumer preferences; adoption and coordination of larger battery in both household BESS and EVs could substantially impact the potential benefits delivered for these technologies.

7 References

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8 Appendix

8.1 PV profiles

Figure 66 shows the average EV profile per season based on real data available in [2]. It is easy to see how the summer, has the highest demand, followed by shoulder and finally, winter profile is the lowest one. The size of PV systems is assumed to increase progressively, reaching approximately 9 kW per household by 2050, as projected in [2].

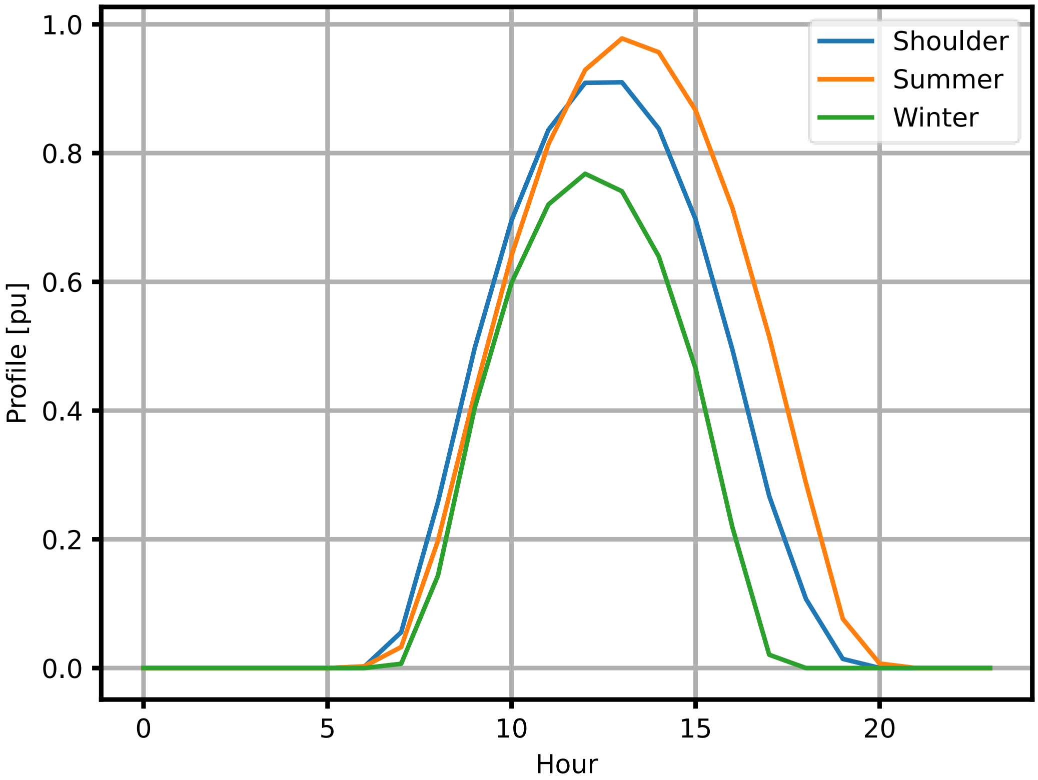

Figure 66 PV profile per season in Victoria

8.2 EV profiles

8.2.1 Real EV profiles

Real-world charging data was collected from 594 household EV users over a full year. Due to data issues with two users, 592 datasets were utilised. Following data cleaning, the normalised charging patterns were clustered into distinct groups[8].

[8] For simplicity, four clusters were selected. However, the number could be increased to improve the pattern identification among household EV users.

EV charging behaviour reveals four distinct user groups, each with unique charging patterns. Figure 67 illustrates the *evening users*, comprising 28% of the sample, who predominantly charge between 6 PM and 6 AM. Figure 68 highlights the *night users*, representing 13% of the sample, focusing their charging between 10 PM and 6 AM. *Morning users*, comprising 16% of the sample, are shown in Figure 69 and primarily charge from 12 AM to 12 PM. Finally, Figure 70 showcases the largest group, *whole day users*, which are 43% of the sample and exhibits intermittent charging throughout the entire 24-hour period. The average charging behaviour of these user types is summarised in Figure 71.

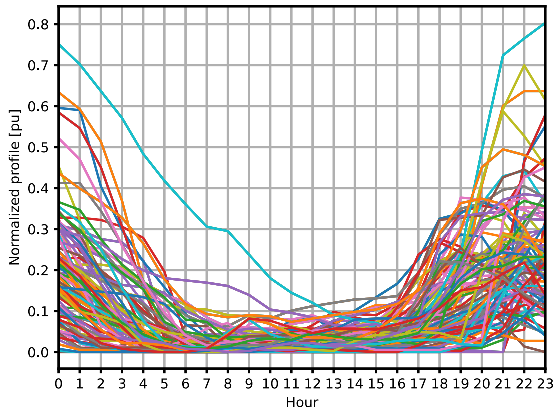

Figure 67 Evening profiles existing users (represent 28% of existing users)

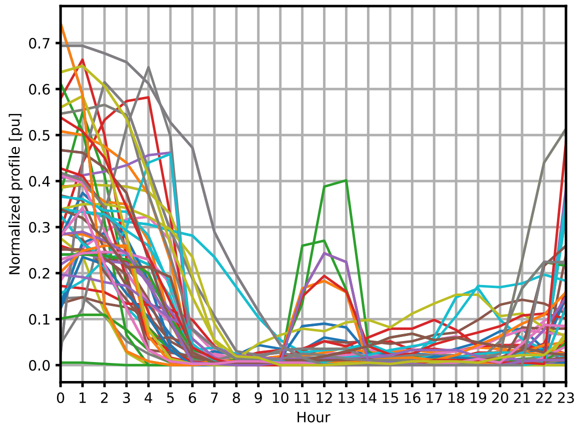

Figure 68 Night profiles existing users (represent 13% of existing users)

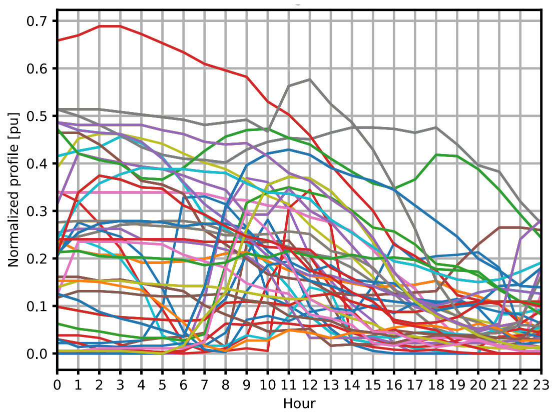

Figure 69 Morning profiles existing users (represent 16% of existing users)

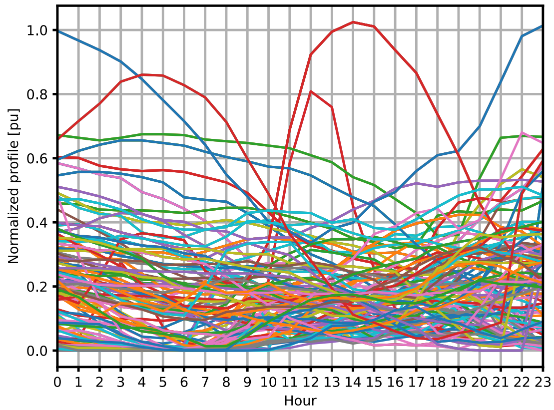

Figure 70 Whole day profiles existing users (represent 43% of existing users)

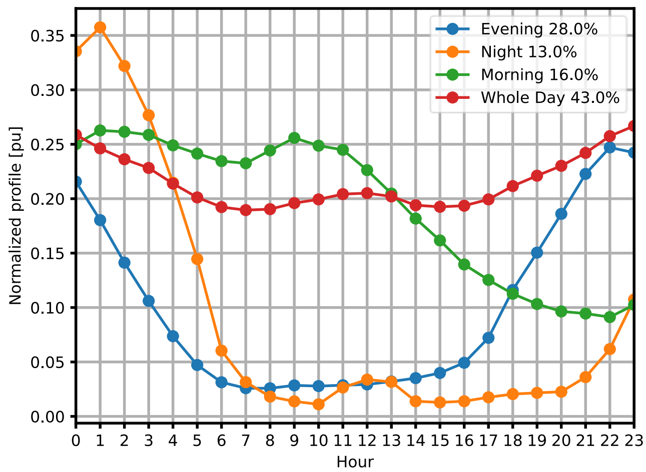

Figure 71 Average behaviour for different low-voltage users

8.2.2 AEMO profiles

AEMO has identified six user profiles based on users charging behaviours:

1. Unscheduled: Charging driven by user lifestyle choices rather than cost reduction, typically occurring at residences with flat tariffs.
2. TOU Grid Solar: Charging incentivised by time-of-use (TOU) tariffs, promoting the utilisation of low-cost solar energy from the grid, even for customers without their own solar installations.
3. Off-Peak and Solar: Traditional TOU tariffs without daytime incentives (except for home solar use), focused on charging during off-peak hours (primarily overnight).
4. TOU Dynamic: Dynamically priced TOU tariffs reflecting solar energy availability, used for charging only, excluding vehicle-to-home (V2H) and V2G clients.
5. Public: Charging facilitated by dedicated public infrastructure using DC fast chargers (Level 3 or higher).
6. V2G/V2H: Charging integrated with V2H or V2G capabilities, dynamically controlled by the system.

Figure 72 illustrates various EV charging profiles expected by AEMO [3]. In this figure, V2G and V2H charging are assumed to follow the same profile as unscheduled charging, with the key difference being their ability to discharge power back to the grid or home. Additionally, the TOU dynamic profile does not have a predefined profile, as its charge and discharge patterns are optimised during operation.

Figure 73 shows the projected popularity of these charging profiles. As seen in the figure, certain charging behaviours are expected to decline over time. In the long run, unscheduled charging and public charging profiles are anticipated to become the predominant charging methods.

Future charging stations located on freeways, parking lots, and at logistics centres will require high-power charging capabilities within short timeframes. These charging stations will likely connect to medium-voltage networks to support their high-power demands [7].

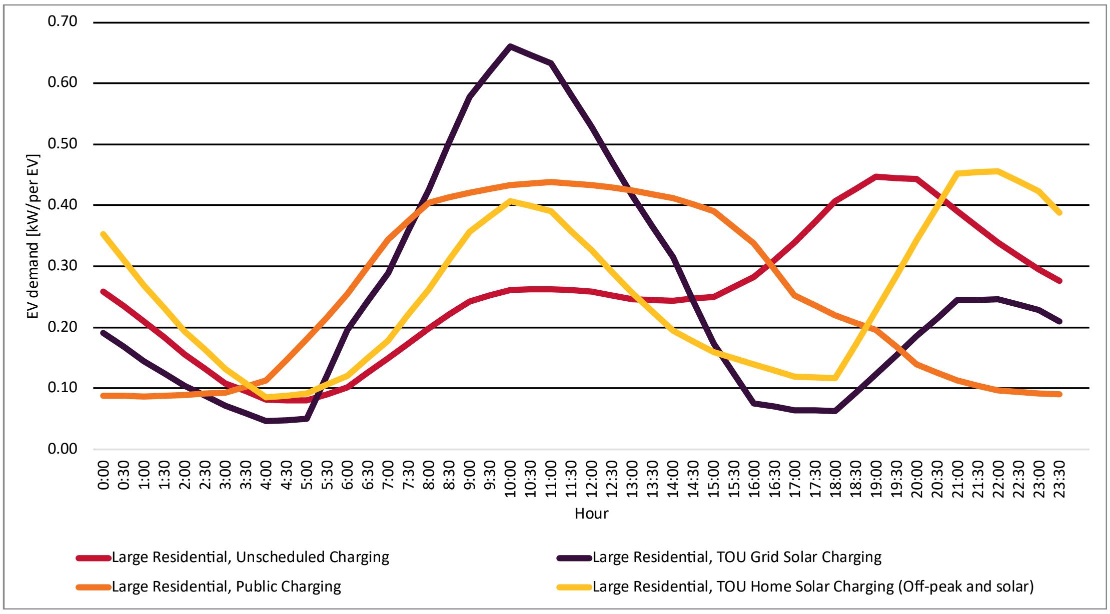

Figure 72 Charging profiles of different EV charging types for large residential vehicles in Victoria based on data from [1]

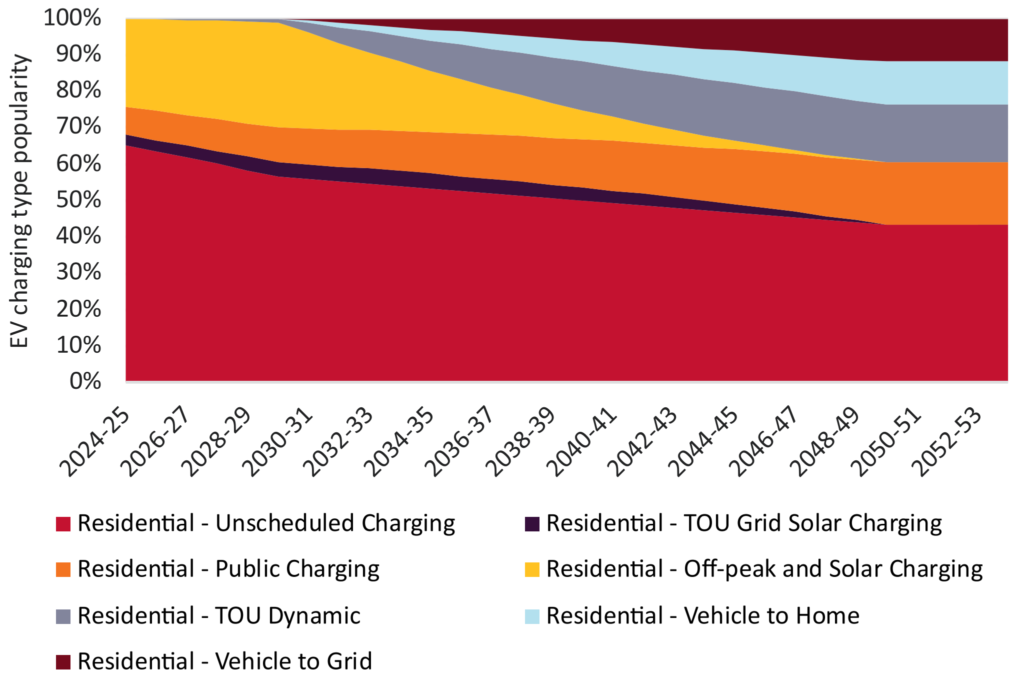

Figure 73 EV charging type popularity in Victoria based on data from [1]

8.2.3 Comparison of EV Charging Profiles

Some similarities emerge between the behaviour based on measurement shown in Figure 71 and the expected profiles by AEMO. The evening hours of the TOU Grid/Home Solar Charging profiles align with the Evening and Night profiles, as both involve charging during night hours. The charging pattern demonstrated by the

Morning users is consistent with the anticipated morning behaviour of the TOU Grid/Home Solar Charging profile, which exhibits a secondary peak around 9 AM. The Whole day users display charging behaviour similar to the Unscheduled Charging Profile. Similar to AEMO's forecast, this group is also the most prevalent in the dataset, indicating a significant portion of users engage in charging throughout the day without a strict schedule, matching with AEMO's description of this user type.

8.3 Low voltage and medium voltage networks

This study included four network types developed in [14]. The composition of these networks showing the location of commercial and residential loads; HV/MV and MV/LV transformers; and the MV, LV and services lines can be seen in the figures 74, 75, 76 and 77 for the urban, suburban, rural long and short rural, respectively.

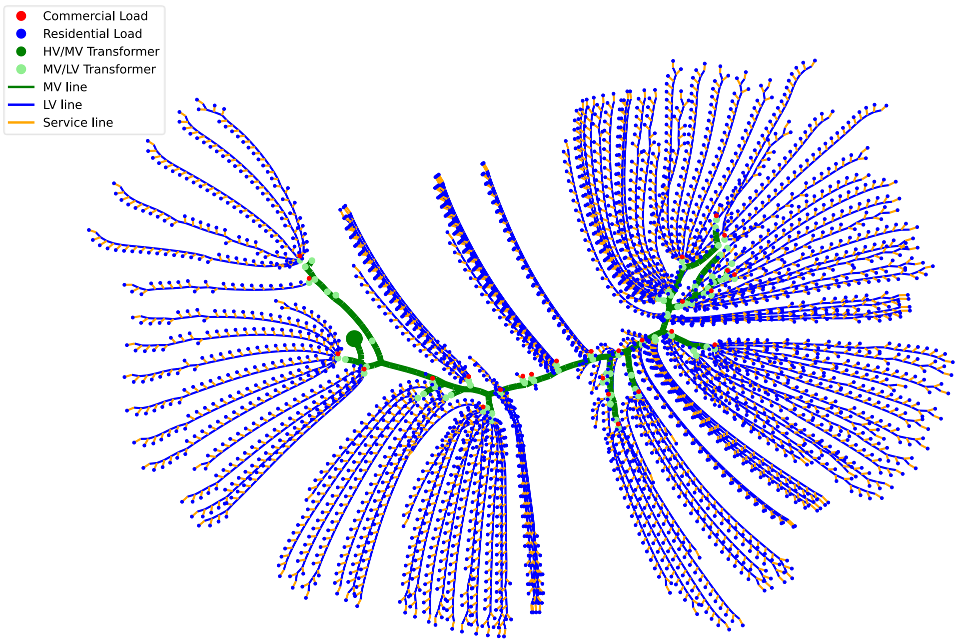

Figure 74 Urban network

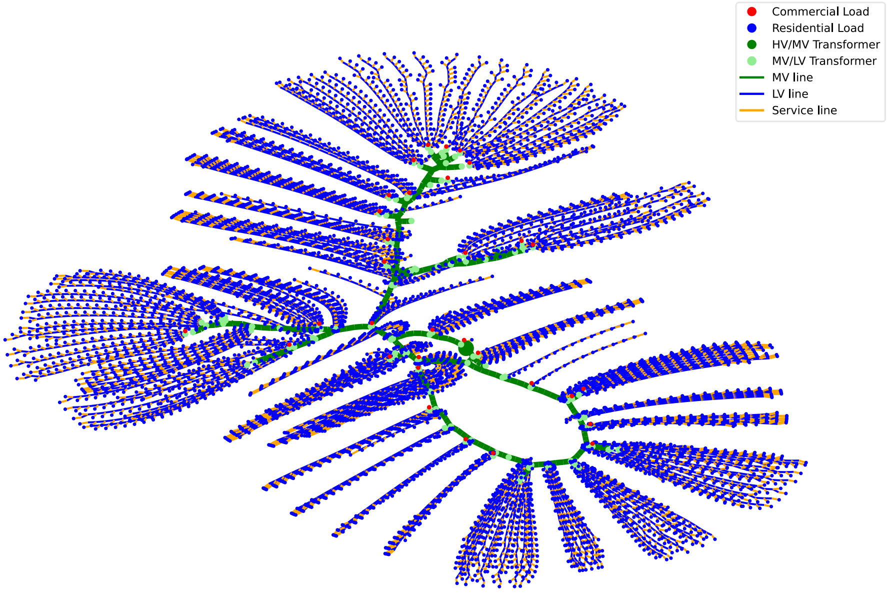

Figure 75 Suburban network

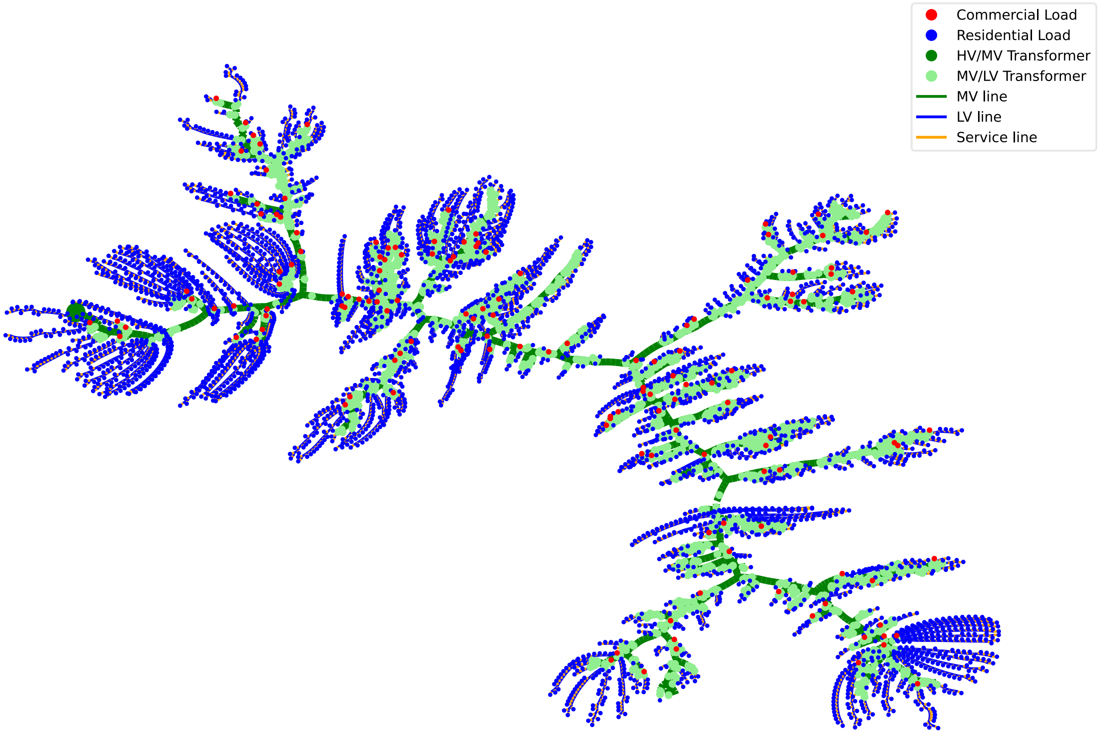

Figure 76 Rural long network

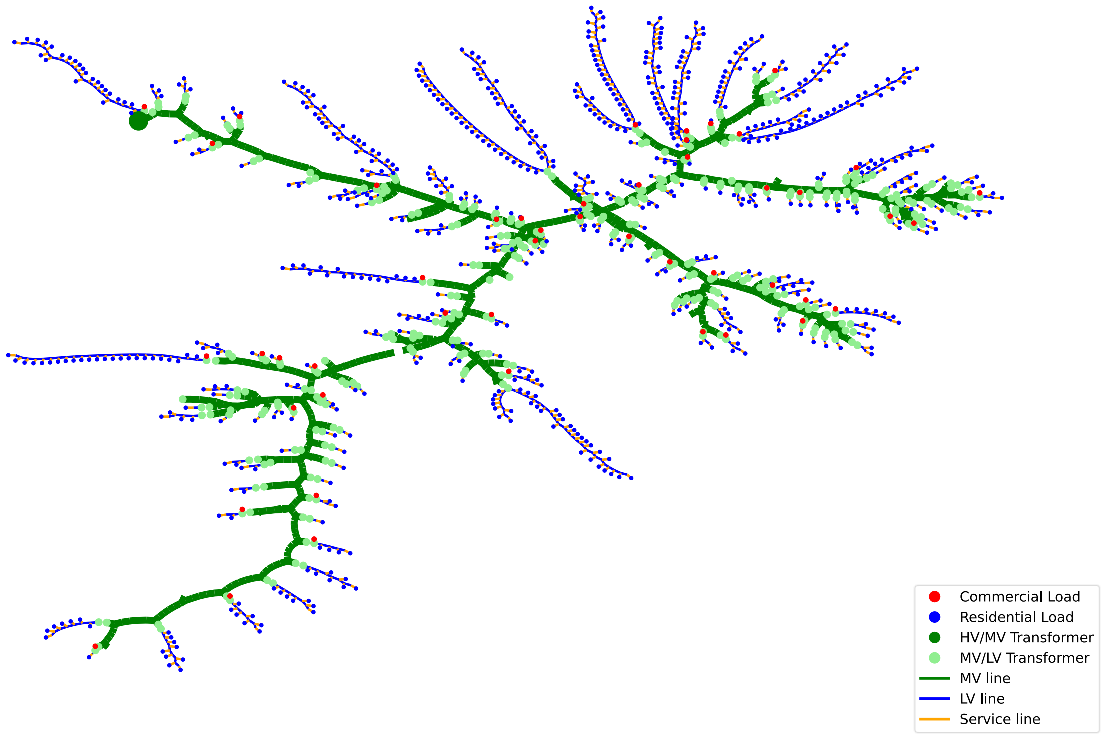

Figure 77 Rural short network