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Next-generation electric vehicle forecasting: long-term sales projections in the Australian context

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Abstract: The market share of Electric Vehicle (EV) sales in Australia has experienced significant growth in recent years, and future growth appears to be assured with the introduction of the New Vehicle Efficiency Standard (NVES) in 2025, which imposes an efficiency standard on manufacturers for new vehicles sold through to 2029. While the national standard for new vehicles beyond 2029 is currently unknown, state and national commitments to net zero by 2050 and EV sales targets imply a further acceleration of low-emission vehicle sales. This paper outlines a method for predicting future battery electric vehicle (BEV) sales that incorporates state and national transport policies through to 2050. The methodology utilises a consumer technology adoption curve based on a logistic growth model, which is widely used to describe technology diffusion, allowing for the integration of NVES alongside state-level EV sales targets and market saturation assumptions over time. Before the development of this method, a common approach was to calibrate a consumer technology adoption curve, which predicts sales share as a function of the payback period. This method often requires adjustments to model outcomes to force alignment with policy constraints, resulting in discontinuities in the sales trajectory. This paper presents results comparing the modelling of sales as a function of time and policy constraints versus payback. Results show that the proposed method produces smooth, policy-responsive sales forecasts compared to the payback period-based approach. Importantly, the proposed method produces sales forecasts aligned with policy-driven targets, without the manual adjustments or result rewriting often required by the payback period-based method. Additionally, scenario analysis based on the Australian Energy Market Operator (AEMO)'s planning framework is presented, where under the Accelerated Transition scenario, characterised by strong climate action and rapid technology uptake, postcode-level BEV sales shares rise rapidly, with some postcodes exceeding 40% as early as 2025 and nearly all approaching 100% by 2050.

Keywords: *Consumer technology adoption curve, electric vehicles, sales forecasting*

1. INTRODUCTION

The global electric vehicle (EV) market is rapidly growing, with over 20% of new car sales being EVs (IEA 2025). Australia is following this trend, with nearly one in ten new cars sold as EVs by the end of 2024. This growth will accelerate further due to strong policies like the national New Vehicle Efficiency Standard (NVES), which encourages car manufacturers to sell more EVs by making them more accessible for consumers, with state targets aiming for 50% EV sales by 2030. These measures will drive faster than historical EV adoption. Reliable long-term EV sales forecasts are essential to ensure grid stability, guide charging infrastructure investments, support renewable energy integration, inform policies, and align with Australia's decarbonisation goals. Robust forecasting will help manage grid impacts and maximise EVs' potential as flexible, grid-supportive resources.

In the literature, EV sales forecasting has been explored using a variety of methods, such as trend analysis, Grey system theory, machine learning, and diffusion models. Trend analysis methods project future adoption by extrapolating past data, often through regression techniques using extrapolatory variables, for example, fuel savings and tax incentives (Duan et al. 2014). Grey system theory provides tools for forecasting under data-sparse conditions and improves accuracy (Zhang et al. 2016; Goh et al. 2022; Li et al. 2022). Machine learning methods, like neural networks, are increasingly used to capture complex, non-linear relationships in time-series data, incorporating multiple influencing variables such as subsidies and vehicle cost (Liu et al. 2022; Hu et al. 2018). Among these, diffusion models remain particularly prominent in modelling new technology uptake like EVs. The Bass diffusion model, widely used for early-stage forecasting, has been applied in urban contexts (Guo et al. 2019; Zheng et al. 2020) and adapted to demographic clusters (Lee et al. 2019). The logistic growth models, which assume symmetric growth, have been employed to predict EV penetration over time (Botero et al. 2015; Rietmann et al. 2020). Extensions such as the double-species logistic model account for the competition between EVs and internal combustion engine (ICE) vehicles (Fu et al. 2021). While these models are mathematically elegant and useful for long-term forecasting, a key limitation is their assumption of symmetric S-shaped growth, which may not align with real-world dynamics where policy shifts and consumer behaviour can cause rapid surges or slow adoption phases. Moreover, many models fall short of incorporating top-down policy interventions or externally imposed sales targets, which are increasingly relevant in regulatory environments like Australia's NVES.

EV sales forecasting can be done in two ways: (1) a policy-driven approach, where future sales are set to align with predefined policy goals or targets; and (2) a data-driven approach, where forecasts are based on historical trends and model dynamics, enabling the model to project future sales without prescriptive constraints. Much of the literature emphasises the latter, including the ones discussed above. However, in an evolving regulatory landscape like Australia, data-driven approaches may not capture the impact of emerging policies, planned interventions, or shifts in market incentives, but policy-driven forecasting can offer a more responsive and targeted framework for anticipating EV sales. Consequently, we are motivated to develop a policy-driven approach examining how future EV sales can be shaped to achieve specific policy objectives.

This paper presents a method for predicting annual battery electric vehicle (BEV) sales shares across the states within the Australia's National Electricity Market (NEM): New South Wales (NSW), Victoria (VIC), South Australia (SA), Queensland (QLD), Tasmania (TAS), and the Australian Capital Territory (ACT), from 2025 to 2050. Covering both short- and long-range BEV models, the forecasts break down sales shares by vehicle type, including passenger cars (small, medium, large), light commercial vehicles (small, medium, large), motorcycles, trucks (rigid and articulated), and buses. The forecasts are centred on three key points: current sales share, 2030 targets aligned with the NVES, and the eventual market saturation point where BEV sales dominate all vehicle sales within each vehicle type. The paper's key contribution is a policy-driven approach based on a non-symmetric logistic consumer technology adoption model that enables long-term BEV sales forecasting aligned with the NVES, state-level targets and Australia's net-zero emission targets, capturing varying growth rates at different adoption stages. The approach is complemented by a highly granular analysis that disaggregates projections to the postcode level and refines them by vehicle type, offering detailed insights into BEV sales patterns.

The rest of the paper is organised as follows. Section 2 presents a previous method based on the payback period and the proposed method. Section 3 outlines results and Section 4 concludes the paper.

2. METHODOLOGY

Here, Section 2.1 outlines a pre-NVES EV sales forecasting method that serves as a benchmark for comparison with the new approach presented in Section 2.2. EV sales shares are defined as the proportion of EV sales relative to total sales of the same vehicle type, including those of internal combustion engine (ICE) vehicles. The forecasting analysis is based on three scenario narratives aligned with (AEMO 2025): (1) Slower Growth, reflecting current policies with slower economic and technological progress; (2) Step Change, representing a faster pathway supporting a sub-2°C climate goal; and (3) Accelerated Transition, envisioning a rapid shift to net-zero through strong decarbonisation and widespread adoption of electrification and green fuels.

2.1. Previous projection method

This method was developed in the context of state EV sales targets, which existed in only a few states with relatively weak enforcement. State strategies generally involved limited EV charging infrastructure, modest tax reductions, small direct vehicle subsidies (e.g., for up to 20,000 vehicles), and efforts to electrify government fleets. Despite these programs, the relative cost of EVs compared to ICE vehicles is assumed to remain the main driver of consumer adoption. To model this, a logistic consumer technology adoption curve in (1) was developed, representing how EV sales share changes with the payback period. The curve is calibrated by fitting it to two points: the current payback period and EV sales share, and the maximum sales share with the corresponding payback period.

$$S(p) = 1 - \frac{1}{1 + e^{\alpha(p-\beta)}} \tag{1}$$

where S and p represent the EV sales share and the payback period, respectively. Parameters α and β are calculated for each postcode by using (2) and (3) with the two calibration points of the current sales share and current payback period (S_1, p_1) and the final maximum sales share and corresponding payback period (S_2, p_2).

$$\alpha = \frac{ln\left(\frac{S_1}{1-S_1}\right) - ln\left(\frac{S_2}{1-S_2}\right)}{p_2 - p_1} \tag{2}$$

$$\beta = p_1 + \frac{\ln\left(\frac{S_1}{1-S_1}\right)}{\alpha} \tag{3}$$

Payback periods are relatively straightforward to calculate. The payback period formula, in years, is expressed as, $p_{m,s,t} = \left(CapitalCost^{EV}_{m,s,t} - CapitalCost^{ICE}_{m,t}\right)/\left(OperatingCost^{ICE}_{r,m,t} - OperatingCost^{EV}_{r,m,s,t}\right)$, with r being the region, m being the ten vehicle types, and s and t being the scenario and the financial year, respectively. Additionally, $OperatingCost^{EV}_{r,m,s,t} = FuelCost^{EV}_{m,s,t} + MaintenanceCost^{EV}_{m} + RegistrationCost^{EV}_{r,m} + InsuranceCost^{EV}_{r,m,s,t}$ and $OperatingCost^{ICE}_{r,m,t} = FuelCost^{ICE}_{m,t} + MaintenanceCost^{ICE}_{m} + RegistrationCost^{ICE}_{r,m} + InsuranceCost^{ICE}_{r,m,t}$.

The $CapitalCost$ of ICE vehicles varies by vehicle type and time, while the $CapitalCost$ for EVs also depends on the scenario and is net of any subsidies. Annual $FuelCost$s for ICE vehicles are calculated by multiplying petroleum prices, average fuel efficiency, and yearly kilometres travelled, with assumptions varying by vehicle type and time. For EVs, the same formula applies but accounts for scenario-specific electricity prices. Additionally, each postcode is assigned an average maximum market share per scenario, which is then adjusted by about ±25% based on local demographic factors such as education, commuting habits, housing type, and income. This incorporation of non-financial factors helps improve the accuracy of adoption forecasts, as supported by Higgins et al. (2014).

Once the adoption curve is calibrated with relevant factors, the rate of EV adoption evolves over time by changing inputs such as technology costs and prices between scenarios, which affect the payback period and shift the position on the curve. Although there is no fixed relationship between time and maximum market share, the declining payback period indirectly changes market share over time. These calculations are performed at the postcode level. This approach effectively captures a broad range of technical, economic, spatial and demographic factors influencing EV sales. However, it has limitations: based on global EV cost trends, the payback period often falls to zero within five to ten years, causing sales shares to saturate early in the 25-30 forecast horizon. Additionally, integrating external influences like state sales targets or policy changes (e.g., the NVES scheme) requires manual adjustments, which can create discontinuities in the projected sales share trajectory.

2.2. Proposed projection method

2.2.1 Method overview

With the NVES starting in 2025, alongside existing state sales policies, policy intervention will be stronger and sooner than previously expected. A payback period-based adoption curve is not an efficient projection method because, within a few years, the existence of the NVES policy means the projected sales share must be manually rewritten to meet the sales targets implied by the policy. This new policy reality requires a consumer technology adoption curve that is based on time, rather than the payback period. A time-based consumer technology adoption curve can incorporate the time-based polices of both NVES and state targets directly into the logistic function.

For each postcode in Australia, the proposed curve is calibrated using three key points: the current EV sales share in the financial year 2024–25; the sales share in 2029–30, which marks the final NVES target financial year which also aligns with most state sales targets; and the final sales share once EVs have reached their maximum share in global vehicle manufacturing (e.g., by 2050). This approach applies only to BEVs, while other technologies, such as plug-in hybrid EVs (PHEVs), are modelled using separate curves suited to their expected adoption paths.

2.2.2 Three-point generation for the logistic function

Starting point

The 2024–25 postcode BEV sales share is calculated by downscaling state sales shares to the postcode level using each postcode's share of the state BEV fleet. This approach is necessary because postcode-level sales are unavailable, though fleet data are. State sales data are from (FCAI 2025) and fleet data from (AAA 2025).

Third point (market saturation point)

The final Australian sales share when BEVs achieve their maximum share is assumed to be 91% to 97% for light vehicles and 28% to 92% for heavy vehicles, depending on the scenario and further vehicle sub-categories. This high saturation range for light BEVs relies on the assumption that the world will coordinate to achieve a strong policy ambition of reducing greenhouse gas emissions, and this will support Australia in achieving its domestic goal of net zero emissions by 2050. It also assumes that fuel cell vehicles and PHEVs will ultimately play a small role in light vehicles long term. The residual also allows for some ICE vehicles to remain for specialised technical or cultural reasons. Some of the remaining ICE vehicles might also be able to use biofuels or low-emission synthetic fuels to reduce emissions, although with a significantly higher fuel cost. The much wider saturation range for heavy vehicles is because fuel cells still have some potential to play a significant role in long-haul trucking.

The final sales share timing is set as a scenario assumption. Eliminating most ICE vehicles from the fleet by 2050 is challenging. Given the slow turnover of the fleet (just over 5% per year), it would require the BEV sales share to reach the saturation level within a few years to achieve the same fleet share by 2050. More realistically, the scenarios assume the BEV sales share reaches saturation between 2040 and 2050, depending on the scenario.

Mid-point

Calibrating the 2029-30 sales share is more challenging than setting the 2024-25 share or the saturation point. The properties that the 2029-30 calibration must meet are:

- Meets both the national NVES and state sales targets whilst considering differences between postcodes.
- Considers the uncertainty between the level of electrification needed to meet the NVES target versus other means, such as more efficient ICE vehicles
- Recognises other differences between states, such as driving distances and preferences for vehicle sizes.
- Accounts for differing electrification rates across vehicle sizes and types

The NVES target can be met by different combinations of EVs and more efficient ICE vehicles, including hybrid EVs. Also, the NVES does not need to be met in a single year, but rather shortfalls in some years can be offset by over-achievement in other years. Consequently, many combinations of EV sales paths can be consistent with meeting the target. Three national sales paths were selected that form a plausible range of feasible paths, and these are assigned to the three scenarios.

State sales targets, which are 50% or greater, exceed what is required to meet the national NVES sales target, which tends to be in the range of 40% to 50%. To avoid exceeding the national target, states without their own sales targets (e.g., NSW, TAS) are assumed to achieve lower shares. If these states also have longer driving distances, their contribution is further decreased as EVs are less applicable in long-range driving applications.

Early BEV uptake has been concentrated on medium-sized vehicles. By 2029-30, meeting the NVES target will require broader adoption across small and large vehicles as more models become available, though large vehicles are still expected to have the lowest uptake due to heavy-duty needs. The NVES applies only to light vehicles (passenger and light commercial), with state-level targets for heavy vehicles (trucks and buses), set by assumption, varying from 0.02% to 7.5% across scenarios and vehicle types, reflecting the greater challenges in electrifying these segments. These state- and vehicle-size-specific sales assumptions provide the starting point for each postcode's 2029-30 sales share. However, these cannot always be applied directly because in some cases, the 2024-25 postcode share already exceeds the 2029-30 target, making the logistic curve calibration invalid. For example, in the ACT, where overall EV sales share exceeds 20%, some suburbs have medium passenger EV sales shares above 60%. To resolve this, 2029-30 postcode targets that fall below their 2024-25 historical shares are set above the historical level, while the remaining postcodes in that state have their targets reduced. This ensures postcodes with higher BEV uptake contribute more to meeting the target, within limits (e.g., no more than 85% sales).

Overall, the new method relies on historical EV fleet shares at the postcode level to identify suburbs with strong future sales. In contrast, the previous payback-period method focused more on favourable demographics to shape the adoption curve through the saturation point. However, when EVs are expected to dominate the fleet long-term due to climate change policies, this demographic-based feature becomes less important.

2.2.3 Logistic function-based consumer technology adoption model

The proposed consumer technology adoption model employs a three-parameter logistic function to capture the non-symmetric nature of BEV sales trajectories. Having established the three calibration points (S_1, t_1), (S_2, t_2), and (S_3, t_3) representing the current sales share (2024-25), mid-point target (2029-30), and saturation point, respectively, as in Section 2.2.2, we fit a generalised logistic function, given in Bewley et al. (1988), of the form

$$S(t) = \frac{K}{\{1 + exp[-\bar{\alpha} - \bar{\beta} f(\bar{\mu})]\}} \tag{4}$$

where $f(\bar{\mu}) = [e^{\bar{\mu}t} - 1]/\bar{\mu}$, $K = 1$ represents the carrying capacity (maximum sales share), $\bar{\alpha}$ and $\bar{\beta}$ are shape parameters controlling the curve's steepness and inflection point, and $\bar{\mu}$ is the parameter allowing for non-symmetry. The three unknown parameters ($\bar{\alpha}$, $\bar{\beta}$, $\bar{\mu}$) are determined by solving the non-linear system of equations created using standard curve-fitting methods (here, the Python SciPy "curve_fit()" function). In our algorithm, the SciPy function searches for $\bar{\alpha}$, $\bar{\beta}$, and $\bar{\mu}$ within the bounds [-20, 20], [-10, 10], and [-1, 1], respectively, across all postcodes and scenarios until the percentage normalised root mean square error between the fitted values and the calibration points falls below 5%. The resulting curves naturally accommodate the varying adoption rates across different postcodes and vehicle types while ensuring compliance with both state and national policy targets.

3. RESULTS AND DISCUSSION

This section presents postcode BEV sales shares from the proposed method (Section 3.1) and compares NEM-level projections to the payback period-based method in Section 3.2. All simulations were conducted using Python.

3.1. Projected sales share distributions from the proposed method

Figure 1 shows the postcode-level light BEV sales shares across the NEM states under the three AEMO-aligned scenarios, for 2025, 2030, and 2050. The number of light BEVs is calculated by summing all BEVs in the passenger and light commercial types across small, medium, and large sizes. In 2025, BEV sales shares are generally low and consistent across postcodes in most states. However, the ACT shows noticeably higher median values, and across all states, a few postcodes reach or exceed 40%. By 2030, sales speed up considerably, especially under the Accelerated Transition scenario, with wider interquartile ranges indicating regional differences in sales uptake. By 2050, the distribution approaches saturation, where nearly all postcodes show sales shares close to 100% across all scenarios. The ACT leads in the early sales market, while larger states such as QLD and SA display more postcode-level variability in the mid-term. NSW and TAS differ from the other states in that they have no state EV sales target, whereas the remaining states do, and as a result, VIC, QLD, SA and the ACT take a stronger lead in meeting the nation's NVES target. These patterns highlight the impact of scenario-specific policies and infrastructure readiness on the speed and uniformity of EV adoption

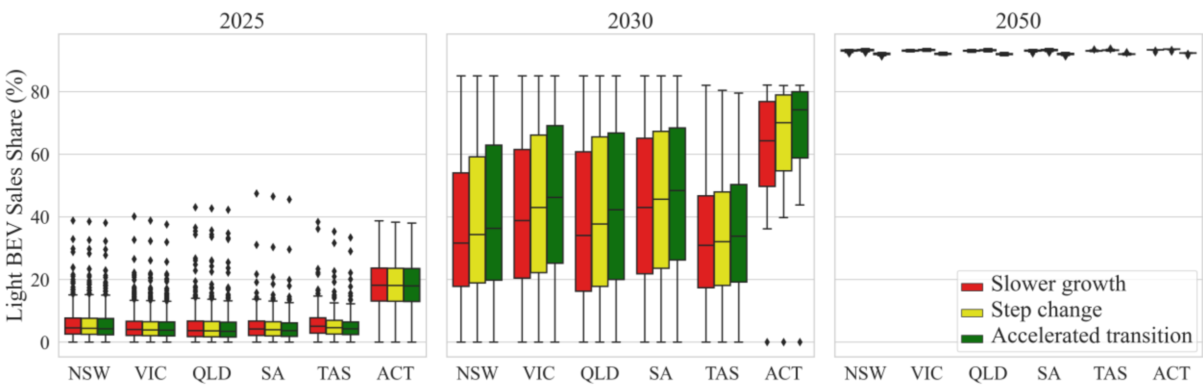

Figure 1 Distribution of postcode-level light BEV sales shares for the National Electricity Market states under three scenarios for three selected years

Figure 2 displays average BEV sales shares by vehicle type across illustrative and randomly selected urban (Bayside, Sydney, Waverley) and non-urban (Cowra, Liverpool Plains, Warren) local government areas (LGAs) in NSW. Due to space constraints, we only present the heatmaps for NSW and the vehicle types with the greatest contrast. However, we observed that all other light vehicle types show similar trends to the light passenger vehicles shown. Additionally, Urban LGAs consistently report higher BEV sales across all vehicle types, especially for passenger and light commercial vehicles, due to greater infrastructure and policy support. Sales progress slowly under the Slower Growth scenario, with faster growth in the Step Change scenario and the most rapid increase in the Accelerated Transition scenario, where saturation is expected by 2050. Non-urban LGAs show similar trends over time but with lower overall sales, notably for heavier vehicles like buses. While only NSW is shown, the observed patterns, driven by urbanisation and scenario ambition, are broadly consistent with those in other states.

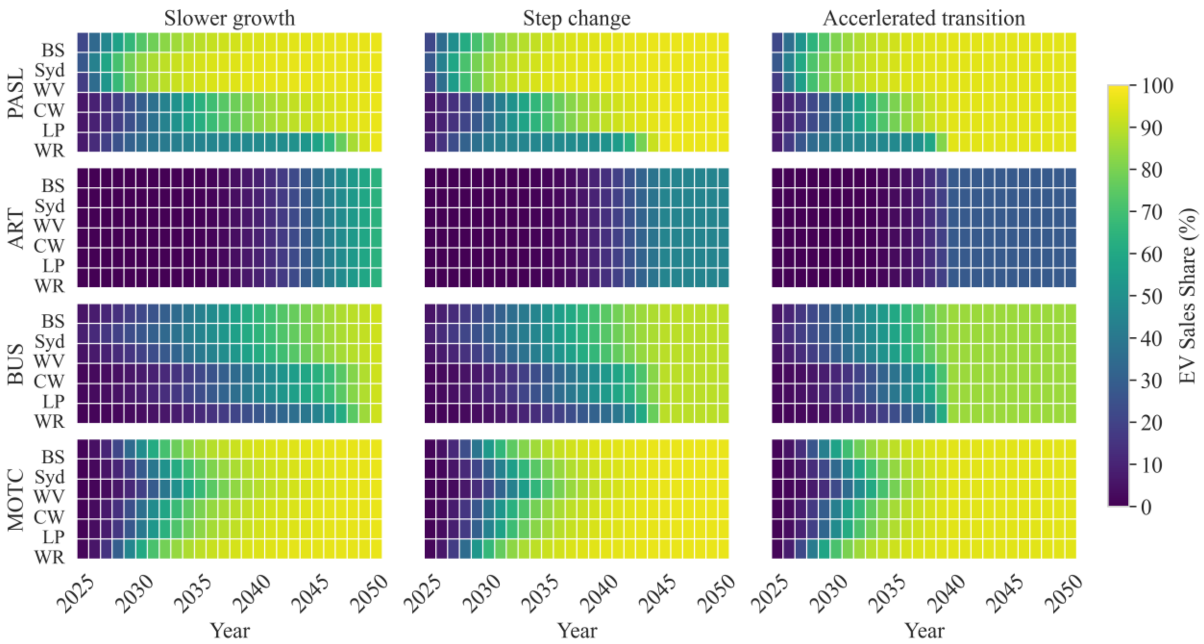

Figure 2 Average BEV sales shares by vehicle type for urban and non-urban local government areas of New South Wales (PASL – Passenger small, ART – Articulated trucks, MOTC – Motorcycles) (urban areas: BS - Bayside, Syd - Sydney, WV – Waverley; non-urban areas: CW - Cowra, LP – Liverpool Plains, WR – Warren)

3.2. Projected sales under the previous and new methods

Figure 3 shows the projected number of BEVs sold each year within the NEM using the previous and new methods. The sales shares are multiplied by a projection of total vehicles sold, which accounts for differences across the scenarios in economic growth, population growth and cost of road transport. Both methods were given the same information and so track fairly well with each other, although the previous method requires manual intervention to achieve some of the time-based targets. The manual interventions amount to writing over the results of the payback-based adoption curve with results that meet the time-based targets that need to be imposed due to policies or scenario design features. Essentially, all of the trajectory post-2030 is not from the payback period-sales function but rather imposed assumptions. These manual interventions result in discontinuities in the trajectory in 2030 and in the mid-2030s to 2040s. In contrast, the new method results in a smooth trajectory throughout the projection period from a single mathematical function.

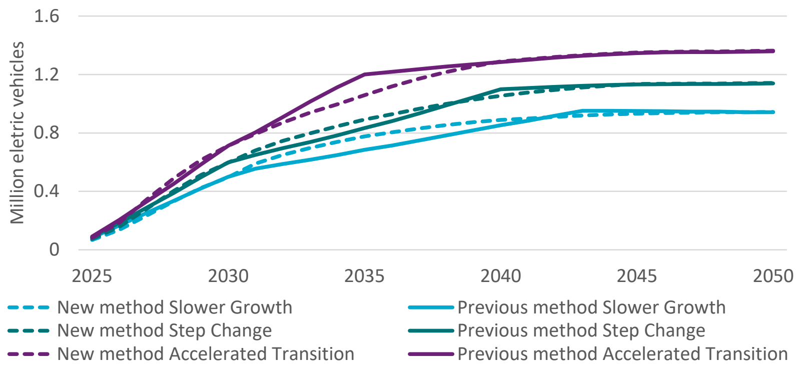

Figure 3 Projected BEV sales in the National Electricity Market using the previous and new methods by scenario

4. CONCLUSION

With the rapid expansion of Australia's EV market, driven by strong policy interventions such as the New Vehicle Efficiency Standard introduced in 2025, this paper presents a long-term battery electric vehicle (BEV) sales forecasting method. The method applies a non-symmetric logistic consumer technology adoption model to project BEV sales at postcode-level resolution across the National Electricity Market states from 2025 to 2050, disaggregated by vehicle types, including motorcycles, passenger vehicles (small, medium, large); light commercial vehicles (small, medium, large), heavy trucks (articulated and rigid), and buses. All projections align with the AEMO's three planning scenarios: Slower Growth, Step Change, and Accelerated Transition. Results demonstrate that the proposed method generates smooth, policy-responsive sales trajectories that meet national and state-level targets, avoiding discontinuities seen in the previous payback-period approach. Moreover, postcode and local government area-level sales results highlight that scenario ambition and urban infrastructure readiness play a critical role in shaping the speed and consistency of BEV uptake across regions.

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