Forecasting Australia's Electricity Sector Emissions (2025–2035): A Time-Series Modelling Approach

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December 2025

Monash Statistical Analytics Club

Contents

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Acknowledgement

The authors would like to thank Ms.Anika Jain for her help and contribution as Research Program Director at Monash Student Analytics Club throughout this project as well as the executives behind said organisation. The views expressed in this paper are solely those of the authors and any remaining errors or omissions are their own.

Abstract

This study examines historical trends and future trajectories of Australia's electricity-sector emissions using official Australian Government energy and emissions statistics. Long-run national emissions, total electricity generation and state-level renewable energy transitions are analyzed through detailed exploratory data analysis. Emissions are forecast to 2035 using a dynamic regression model with ARIMA errors under two scenarios: Business-As-Usual (BAU) and an accelerated renewable transition. Results show that while emissions have declined in recent years due to structural changes in the electricity generation mix, substantial future reductions depend on continued and intensified renewable energy deployment.

Introduction

Australia's electricity sector has historically been a major contributor to national greenhouse gas emissions due to heavy reliance on coal-fired generation. Over the past three decades, however, the sector has undergone significant transformation driven by policy reform, technological progress and increasing investment in renewable energy. Understanding how electricity-sector emissions have evolved historically and how they may change in the future, is critical for energy system planning and climate policy design. This paper integrates long-run national trends, state-level energy transitions and time-series forecasting to evaluate Australia's electricity-sector emissions trajectory to 2035.

Australia's electricity sector sits at the centre of the country's decarbonisation challenge, accounting for a substantial share of national greenhouse gas emissions while also underpinning economic activity and household welfare. As Australia commits to net-zero targets and accelerates renewable deployment, policymakers and system planners face growing uncertainty about how quickly emissions can decline under different transition pathways. Understanding the dynamic relationship between electricity generation, fuel composition and emissions is therefore critical for evaluating whether current trajectories are sufficient or whether stronger intervention is required.

The findings of this study are relevant for energy policymakers, regulatory agencies and system planners seeking to assess the emissions implications of alternative transition pathways, as well as researchers interested in modelling emissions dynamics in sectors undergoing rapid structural change.

Existing research has extensively examined electricity-sector emissions using structural energy system models, scenario analysis and decomposition techniques to assess the role of fuel switching and renewable adoption. Many studies focus on long-run equilibrium pathways or technology-specific transitions, often relying on detailed engineering or optimisation frameworks. While these approaches provide valuable insights, they typically abstract from observed time-series dynamics and short- to medium-run persistence in emissions.

Fewer studies explicitly model electricity-sector emissions as a dynamic process driven by the evolving generation mix, incorporating both structural change and temporal dependence. In particular, there is limited empirical work applying time-series methods to evaluate how historical emissions responses translate into future trajectories under alternative transition scenarios. This paper addresses this gap by combining exploratory data analysis with a dynamic regression framework to quantify the emissions implications of renewable and non-renewable generation in Australia and to generate policy-relevant forecasts to 2035.

Previous Studies

A substantial literature has modelled decarbonisation pathways and emissions outcomes for the electricity sector using integrated scenario and policy-focused frameworks. For example, Acil Allen Consulting's sector modelling reports examine generation mix outcomes under carbon pricing scenarios in Australia, highlighting how technological substitution affects long-term emissions trajectories.(https://www.climatechangeauthority.gov.au/sites/default/files/Electricty%20sector%20emissions.pdf?) Similarly, broader energy-system studies such as those by Jacobs Australia and national agencies explore emissions reduction policies under different assumptions.

Empirical studies have also investigated the relationship between changes in electricity generation mix and emissions outcomes. Recent work by Zhang et al. (2025) analyses the time-varying carbon intensity of grid electricity as renewable penetration increases, (https://www.nature.com/articles/s41598-025-26528-6?)while studies such as Biswas et al. (2025) link the adoption of solar power to CO_2 emission reductions.(https://pmc.ncbi.nlm.nih.gov/articles/PMC12309663/?) Econometric analyses have further explored renewable energy's short- and long-run impacts on emissions dynamics.

Despite this rich literature, there is limited empirical work that explicitly models the dynamic time-series behaviour of electricity-sector emissions in the Australian context, incorporating both structural shifts in generation mix and short-run persistence. This gap constrains our ability to understand how historical emissions responses translate into future trajectories under evolving policy and technology conditions, a gap this paper aims to address.

Data and Descriptive Scope

The analysis draws on national electricity-sector emissions (https://greenhouseaccounts.climatechange.gov.au/) and electricity generation data (https://www.energy.gov.au/publications/australian-energy-statistics-table-o-electricity-generation-fuel-type-2022-23-and-2023), complemented by state-level electricity generation and emissions information. Examining both national aggregates and state-level dynamics allows long-run trends to be interpreted alongside regional heterogeneity in energy mix, renewable adoption and emissions outcomes. For each year between 1999 and 2023, the following variables are observed:

- Total non-renewable electricity generation (GWh), aggregating coal, gas and other fossil sources
- Total renewable electricity generation (GWh), including hydro, wind, solar and bioenergy
- Total electricity-sector emissions (Mt CO_2-e)
- Year

Exploratory Data Analysis

The exploratory data analysis (EDA) establishes the empirical foundation for the modelling approach by examining long-run emissions patterns, electricity generation dynamics and variation in renewable energy adoption across Australian states.

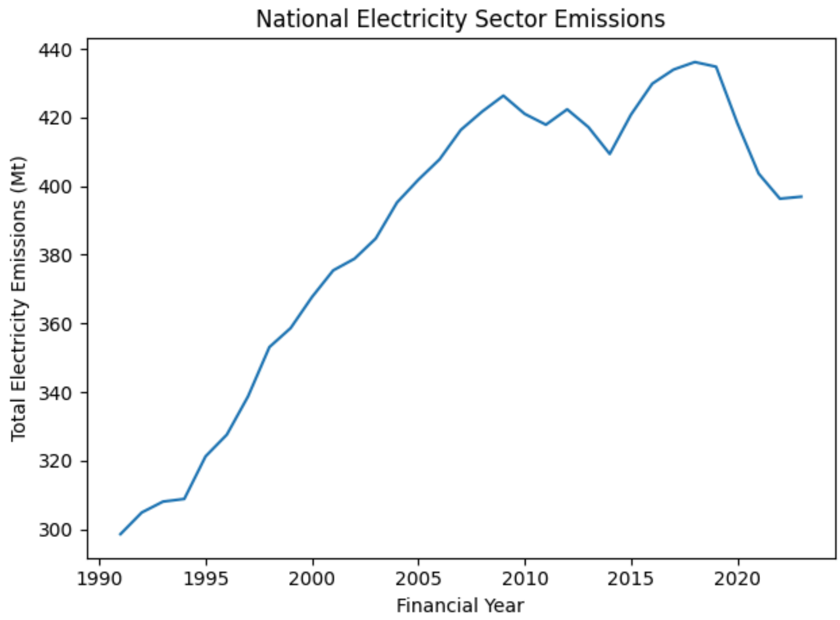

Figure 1. National Electricity Sector Emissions (1991–2023)

Figure 1 shows the evolution of national electricity-sector emissions over time. Emissions increased steadily throughout the 1990s and 2000s, reflecting rising electricity demand and fossil-fuel-based generation. This was followed by a period of sustained decline from around 2010 onwards, coinciding with increased renewable penetration and structural change in the electricity mix.

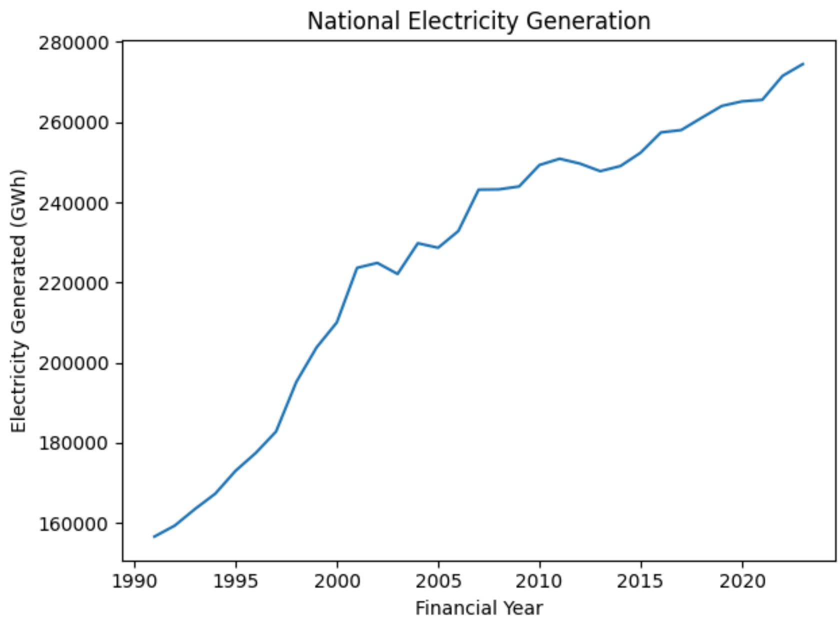

Figure 2. National Electricity Generation (1991–2023)

As shown in Figure 2, total electricity generation increased over most of the sample period. Importantly, generation continued to grow even as emissions declined in later years, indicating a decoupling between electricity demand and emissions intensity.

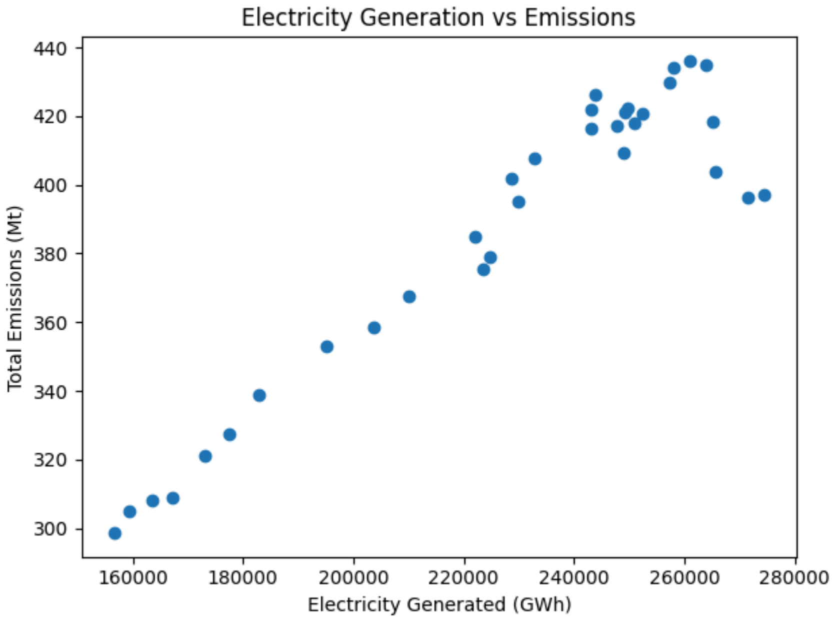

Figure 3. Electricity Generation versus Emissions

Figure 3 illustrates the relationship between total electricity generation and emissions. While a positive association exists, the dispersion of observations suggests that emissions outcomes depend not only on the scale of electricity generation but also on the underlying fuel composition.

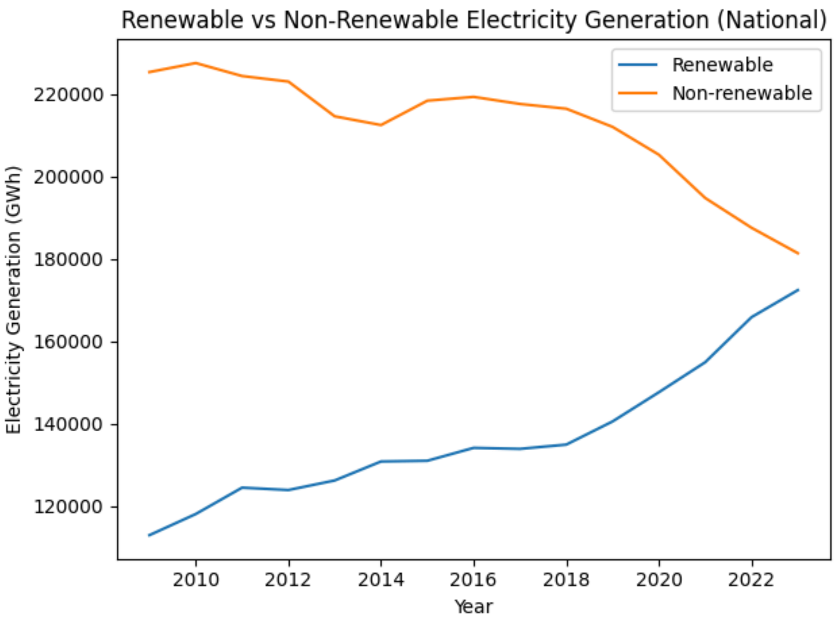

Figure 4. Renewable versus Non-Renewable Electricity Generation (National)

Figure 4 contrasts nationally aggregated renewable and non-renewable electricity generation over time. Renewable generation exhibits a strong and persistent upward trend, while non-renewable generation peaks in the late 2000s and declines thereafter, highlighting the structural transition underlying observed reductions in electricity-sector emissions.

Although the gap between renewable and non-renewable generation narrows over the sample period, the two series remain distinct rather than convergent. This indicates that, within the historical window, renewable generation has not fully displaced non-renewable output. Instead, the opposing trends point to an ongoing substitution process: incremental increases in renewable generation are associated with the stabilisation and subsequent decline of non-renewable generation, rather than an expansion of total electricity supply.

Quantitatively, renewable generation increases by several hundred gigawatt-hours across the sample, while non-renewable generation reaches a peak in the late 2000s before declining modestly. Despite this decline, non-renewable sources remain the dominant contributor to electricity generation through the final observed year.

Importantly, the growth of renewables coincides with a clear change in the behaviour of non-renewable generation. Following the rapid expansion of renewables from around 2010 onward, non-renewable generation no longer exhibits sustained growth and instead trends downward. The series also displays short-term fluctuations, such as the sharp decline in non-renewable generation around 2014, falling to approximately 210,000 GWh, followed by a recovery to pre-shock levels by 2016. These dynamics indicate that the transition has not followed a smooth or monotonic path.
Overall, the absence of convergence between the two series within the observed period suggests that historical trends alone are insufficient for renewable generation to fully replace non-renewables. Any future intersection of the two trajectories would therefore require sustained or accelerated policy intervention, rather than simple extrapolation of past dynamics.

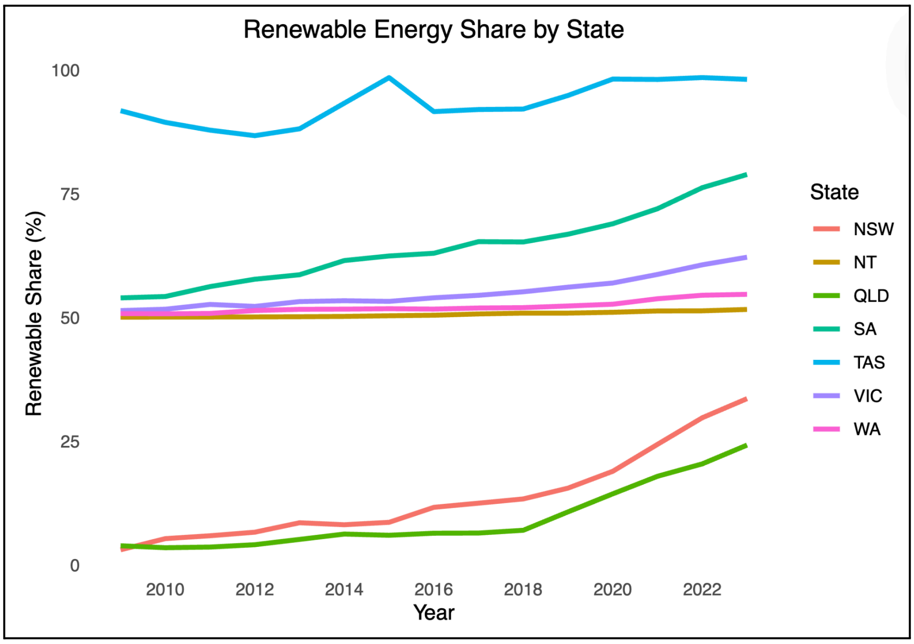

Figure 5. Renewable Share by State

Figure 5 shows renewable electricity share by state over time. The figure highlights substantial heterogeneity in renewable adoption, with some states transitioning rapidly while others exhibit more gradual change.

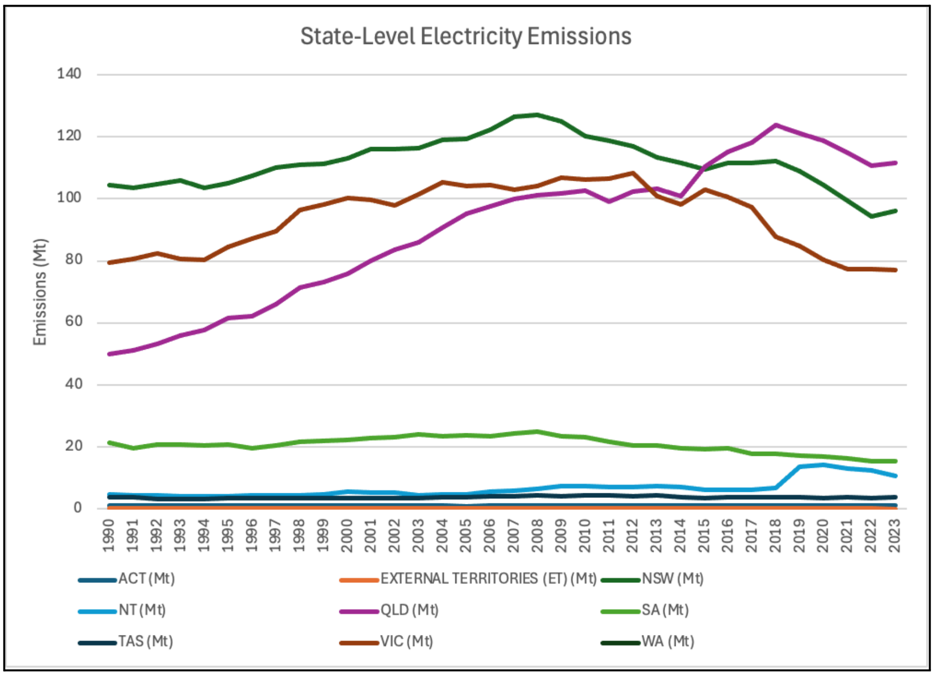

Figure 6. State-Level Electricity Emissions

Figure 6 presents electricity-sector emissions by state. States with higher renewable penetration generally experience earlier and steeper emissions declines, reinforcing the link between energy mix and emissions outcomes.

The exploratory analysis provides the empirical foundation for the modelling strategy adopted in this study. The presence of strong temporal dependence in national emissions motivates the use of a time-series framework, while the observed decoupling between electricity generation and emissions highlights the importance of modelling emissions as a function of the generation mix rather than demand alone. State-level heterogeneity in renewable adoption further demonstrates the feasibility of large structural shifts, informing the design of the forecasting scenarios examined in the subsequent section.

Modelling Approach

Our modelling dataset consists of annual observations from 1999 to 2023, giving a total of 25 observations. The dependent variable is total electricity-sector greenhouse gas emissions, measured in million tonnes of CO_2-equivalent. The explanatory variables are two aggregate energy-mix measures: total non-renewable electricity generation and total renewable electricity generation, both measured in gigawatt-hours.

We deliberately restrict the model to these two explanatory variables because elefctricity-sector emissions are mechanically generated by electricity production technologies. Other potential variables such as GDP, population or electricity demand affect emissions primarily through their influence on generation levels, and including them directly would introduce multicollinearity and obscure interpretation.

Electricity-sector emissions exhibit strong temporal dependence: shocks in one year tend to persist into subsequent years due to infrastructure lock-in, slow plant turnover and gradual policy implementation. Preliminary diagnostics on the raw emissions series show significant autocorrelation and non-stationarity, indicating that standard regression models with independent errors would be inappropriate.This motivates time-series modelling rather than cross-sectional or static regression approaches.

Although the raw emissions series is non-stationary, stationarity is restored once emissions are modelled as a function of the generation mix. KPSS tests on the innovation residuals fail to reject stationarity, and residual plots show no remaining trend. As a result, differencing is unnecessary, and we set d = 0.

Residual autocorrelation diagnostics indicate a significant first-order autocorrelation, with no evidence of higher-order dependence. Including a single AR term removes all remaining autocorrelation, as confirmed by residual ACF plots and Ljung-Box tests

Adding moving-average terms does not materially improve model diagnostics or forecast performance. MA components increase parameter complexity without reducing residual autocorrelation or improving information criteria.

Model selection was conducted by comparing several candidate error structures, including ARIMA(0,0,0), ARIMA(1,0,0), and higher-order AR and ARMA specifications. The ARIMA(1,0,0) model achieved the lowest AIC among these candidates while also producing well-behaved residuals. More complex specifications did not reduce AIC sufficiently to justify the additional parameters.

To model the relationship between Australia's electricity-sector emissions and the energy-generation mix, we estimated a dynamic regression model with ARIMA errors using the fpp3 framework. The dependent variable is annual electricity-sector emissions, while the explanatory variables are non-renewable and renewable electricity generation (measured in GWh).

The fitted model produced the following estimates:

AR(1) coefficient = 0.678

β_1 (Non-renewable) = 0.0013

β_2 (Renewable) = −0.0014

Intercept = 340.2

AICc = 229.4

<u>Coefficient Interpretation</u>

Higher non-renewable electricity generation is associated with increased emissions. A one-unit increase in non-renewable output leads to an estimated increase of 0.0013 units of emissions, holding renewable generation constant. In contrast, renewable electricity generation has a negative coefficient (−0.0014), indicating that greater renewable supply reduces emissions when non-renewable generation is held fixed.

The AR(1) term of 0.678 indicates substantial persistence in emissions over time, with approximately 68% of the previous year's shock carrying forward. This justifies the use of ARIMA errors rather than ordinary least squares regression.

Stationarity and Model Validity

Stationarity was first assessed on the raw emissions series using the KPSS test, which rejected stationarity ($p = 0.0128 < 0.05$). However, in dynamic regression models, the key requirement is stationarity of the residuals, not the response variable itself.

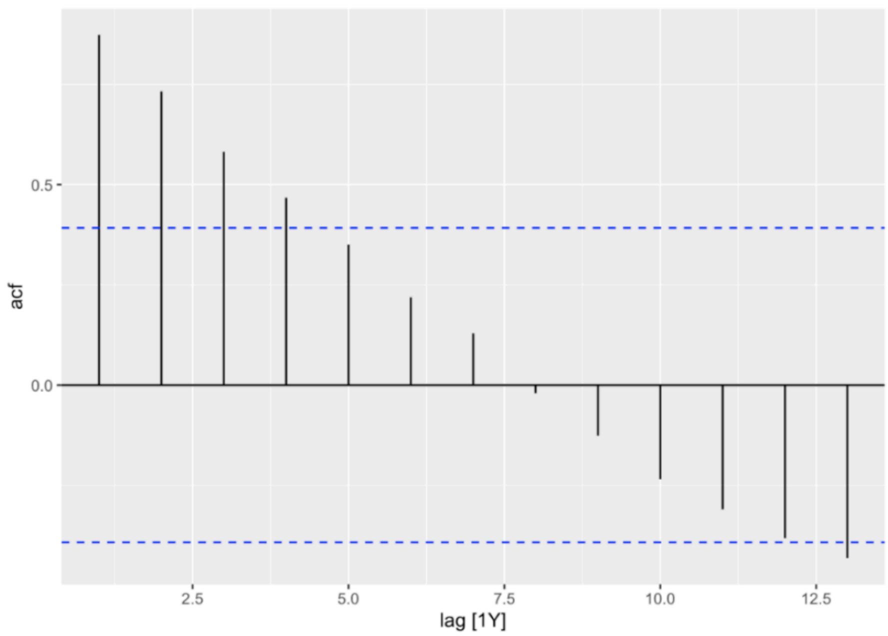

Figure 7. ACF Of Raw Emissions

Autocorrelation of the raw emissions series (Figure 7) shows strong, slowly decaying positive autocorrelation, with the first several lags well outside the 95% bounds. This pattern is consistent with a highly persistent, non-stationary process and confirms the KPSS test result that the undifferenced emission series is not stationary. The gradual decay in autocorrelation suggests an autoregressive structure, motivating the use of a dynamic regression with ARIMA errors rather than a simple independent-errors regression.

After fitting the model, KPSS tests applied to the innovations yielded a p-value of 0.10 (> 0.05), indicating that the residuals are stationary. This confirms that the explanatory variables successfully capture the non-stationary trend in emissions, making differencing unnecessary (d = 0) and validating the ARIMA(1,0,0) error structure.

Residual Diagnostics

The time plot of innovation residuals (Figure 8) shows fluctuations around zero with no visible trend or long-run drift. There are no systematic patterns, no persistent runs of positive or negative errors and no evidence of structural breaks, indicating that the model has effectively removed the non-stationary behaviour present in the raw emissions series.

The autocorrelation function (ACF) shows that all autocorrelation bars fall within the significance bounds, with no statistically significant autocorrelation at any lag. This confirms that the AR(1) component adequately captures temporal dependence, consistent with the KPSS test results.

The histogram of residuals displays a roughly symmetric distribution centred near zero. Although not perfectly normal, it does not exhibit heavy skewness, multimodality or extreme outliers. Overall, these diagnostics indicate that the model assumptions are reasonable and that the model is suitable for forecasting and scenario analysis.

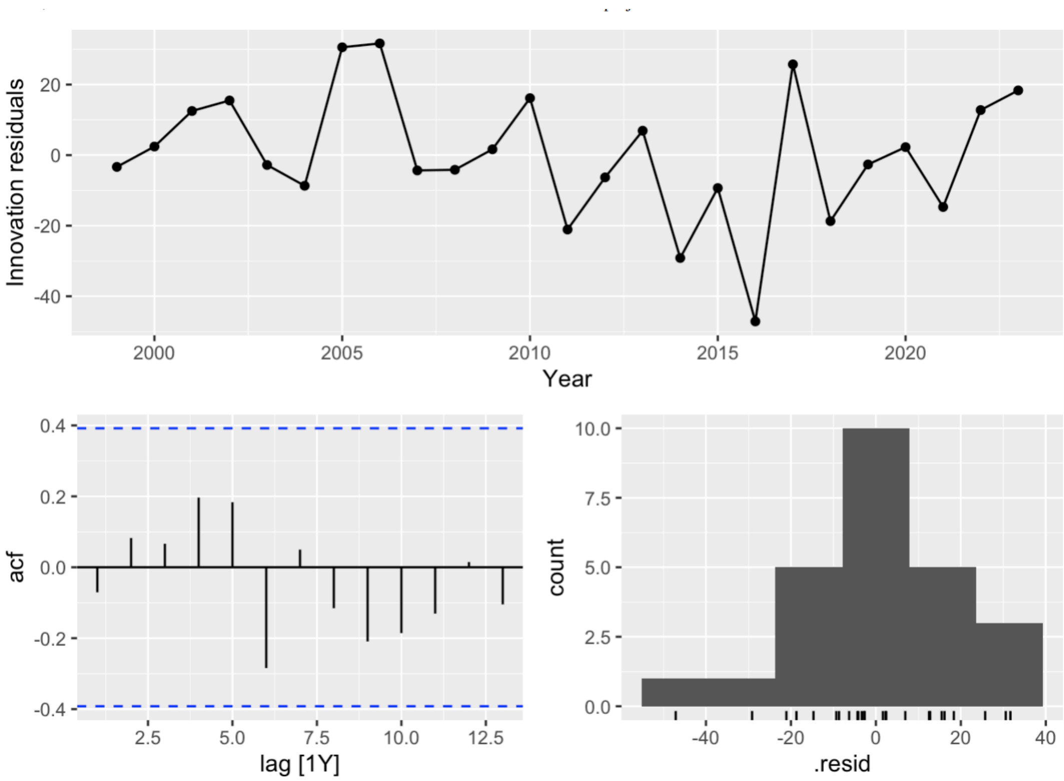

Figure 8. Residual Plots

Train-Test Evaluation

To evaluate out-of-sample performance, a train-test split was conducted using annual data from 1999 to 2023. The training set covers 1999–2018, while the test set includes 2019–2023, providing five years of unseen data to assess forecast performance.

During the training period, the fitted model produced ARIMA(0,0,0) errors, indicating that the relationship between emissions and the energy mix was fully explained by the regressors, with no remaining autocorrelation in the residuals. Estimated coefficients for the training period were:

- Non-renewable coefficient: +0.002
- Renewable coefficient: −0.0034
- Intercept: 237.9

These estimates are consistent with theoretical expectations: increasing non-renewable generation raises emissions, while increasing renewable generation reduces emissions.

Using data up to 2018, out-of-sample forecasts for 2019–2023 were generated using observed values of renewable and non-renewable electricity generation as regressors. The forecast plot, Figure 9, compares actual emissions (black line) with model forecasts and 80% and 95% prediction intervals.

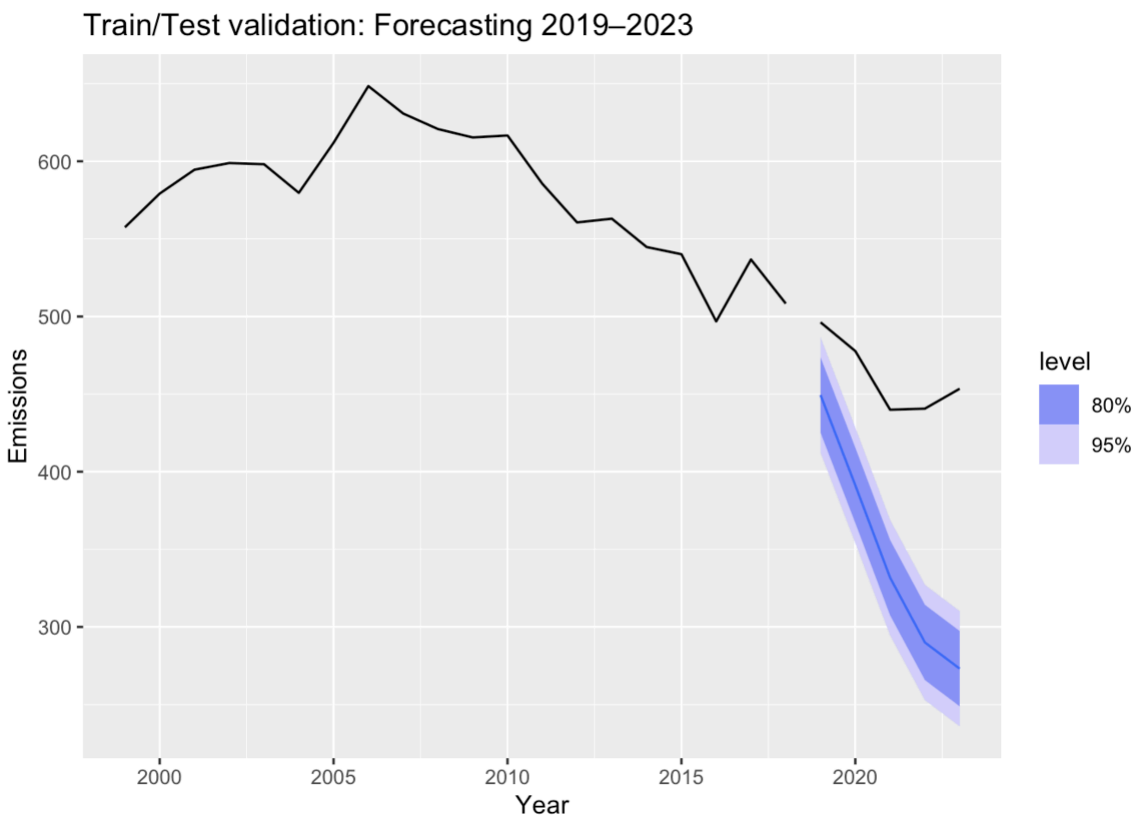

Figure 9. Train-Test Validation

Forecast Performance

The forecasted trajectory exhibits a continuing downward trend, consistent with observed decarbonisation since approximately 2013. Prediction intervals widen appropriately as the forecast horizon increases, reflecting rising uncertainty. While the model captures the overall direction of decarbonisation, observed emissions in 2022–2023 exceed the upper bounds of the 80–95% prediction intervals, suggesting a systematic underforecast and narrower-than-ideal uncertainty estimates.

Accuracy metrics further support this conclusion:

- RMSE ≈ 124
- MAE ≈ 115
- MAPE ≈ 25%

These values indicate moderate forecast precision, which is expected for annual data in a period characterised by significant structural change, including COVID-19 disruptions, rapid renewable expansion and coal plant retirements. The positive mean error (ME) suggests a tendency to under-predict emissions in recent years, consistent with the forecast plot.

Given the small sample size and the highly transitional nature of Australia's electricity sector during this period, these results indicate that the model captures the direction and scale of change, even if exact emission levels are modestly underestimated.

Forecast Results

After validating the model, the dynamic regression with ARIMA errors was re-estimated using the full dataset (1999–2023) to generate long-run forecasts to 2035.

Business-As-Usual Scenario

The Business-As-Usual (BAU) scenario assumes that the electricity generation mix remains fixed at 2023 levels, with non-renewable and renewable generation held constant. This represents a "no new policies, no further transition" baseline commonly used as a reference case.

Figure 10: Under BAU assumptions, emissions are projected to decline modestly over time. This decline occurs despite the constant generation mix because the ARIMA component captures an underlying downward trend visible since approximately 2012, reflecting historical efficiency improvements, plant retirements and structural momentum in the sector.

The point forecast slopes gently downward from approximately 450 Mt in 2023 to the high-400s by 2035. Both the 80% and 95% confidence intervals widen over time, reflecting increased uncertainty associated with long-term forecasting, technological change and limited sample size. Because the BAU scenario assumes no further renewable expansion, emissions stabilise rather than fall sharply.

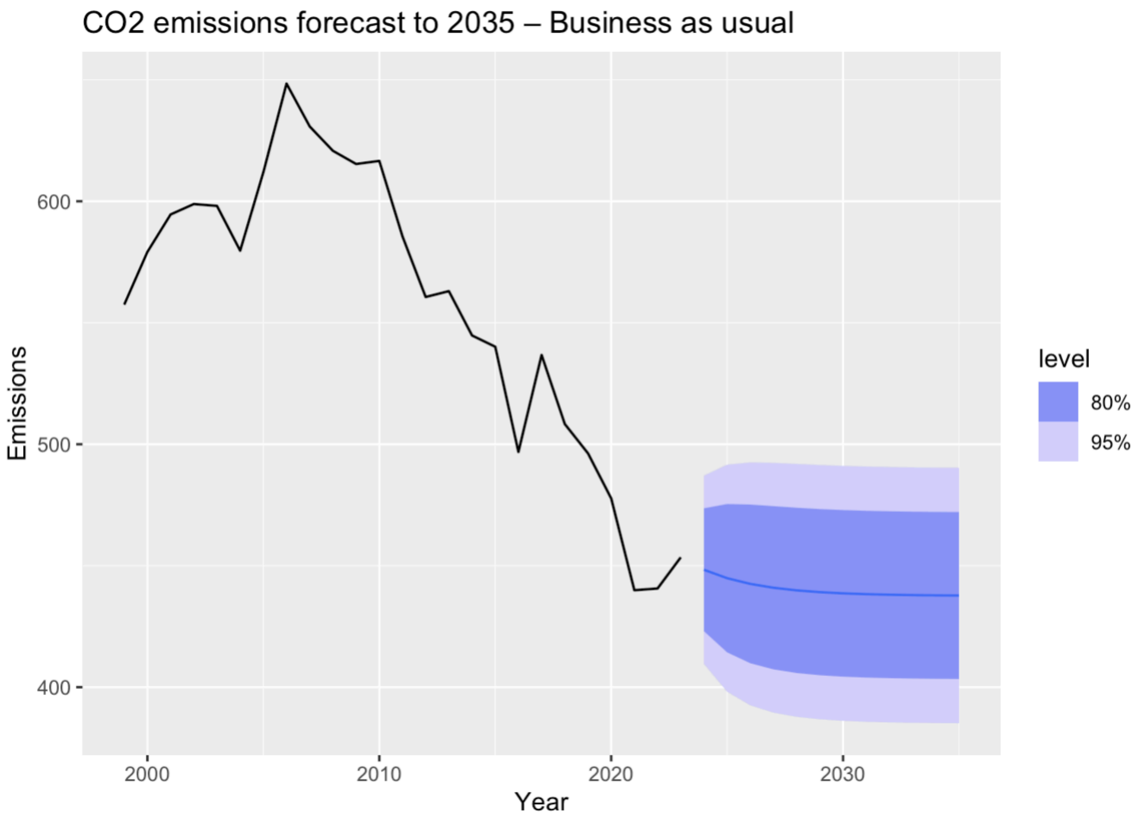

Figure 10. BAU Forecast

Accelerated Renewable Transition Scenario

The policy scenario assumes a gradual 50% reduction in non-renewable electricity generation by 2035, with the displaced generation fully replaced by renewable electricity. Under this scenario, emissions decline sharply, falling from approximately 450 Mt in 2023 to below 250 Mt by 2035 in the central forecast. (Figure 11)

This trajectory is consistent with the estimated model coefficients: reductions in fossil-fuel generation directly lower emissions, while increased renewable generation produces additional reductions. Prediction intervals widen substantially over the forecast horizon, reflecting structural uncertainty inherent in long-range projections. However, the entire uncertainty band lies well below the BAU trajectory, indicating robust evidence of substantial emissions reductions under the policy scenario.

The divergence between BAU and policy projections is small in the early years (2024–2026) but widens significantly by the end of the forecast horizon as reductions in non-renewables compound annually. This widening gap quantifies the long-term benefits of accelerated renewable adoption.

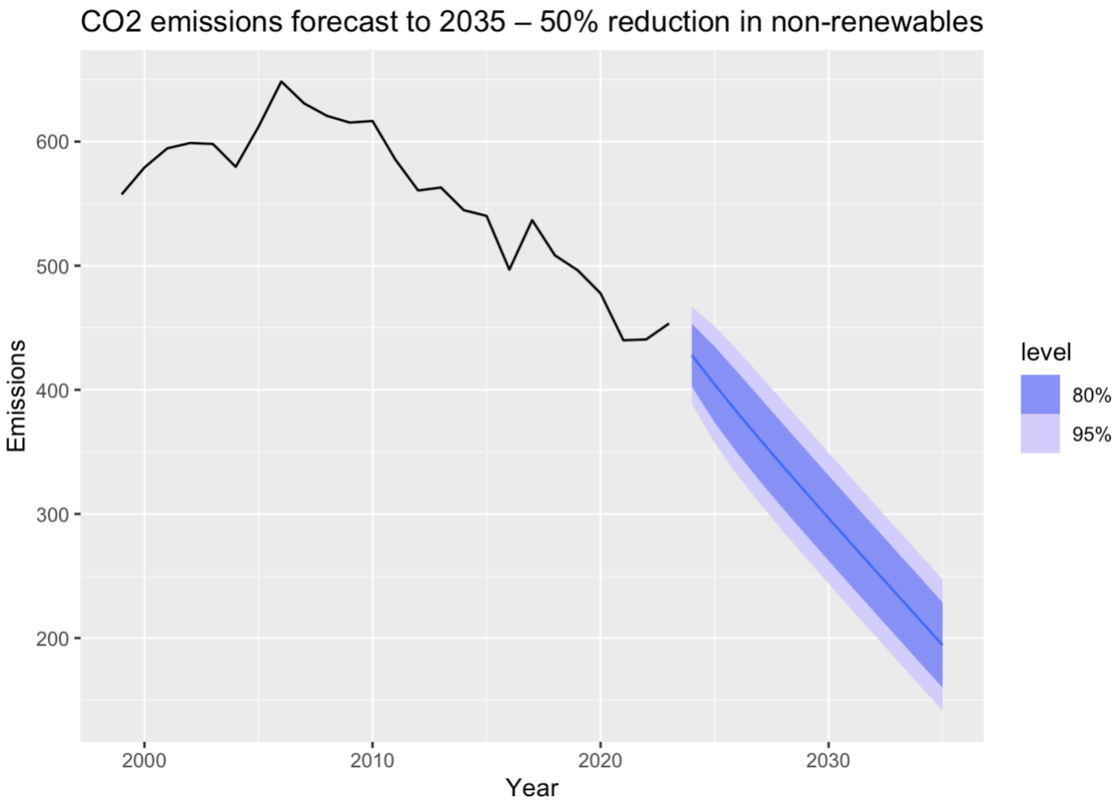

Figure 11. Transition Scenario Forecast

Elastic Net Benchmark

To complement the ARIMA-based dynamic regression, an Elastic Net regression model was estimated using lagged emissions and energy-mix variables as predictors. The model was trained on the 1999–2018 period and evaluated on the 2019-2023 hold-out period, mirroring the train-test split used for the ARIMA model.

Figure 12 compares the model's out-of-sample forecasts (blue line) with observed emissions (black line). The Elastic Net model captures the overall downward movement in emissions over the test period; however, it systematically under-predicts the level of emissions. The predicted series declines almost linearly from approximately 474 Mt in 2019 to 343 Mt in 2023, whereas actual emissions fall more modestly and flatten, even rebounding slightly in 2023. This indicates that while the model correctly identifies the direction of change, it extrapolates a stronger decline than actually occurred.

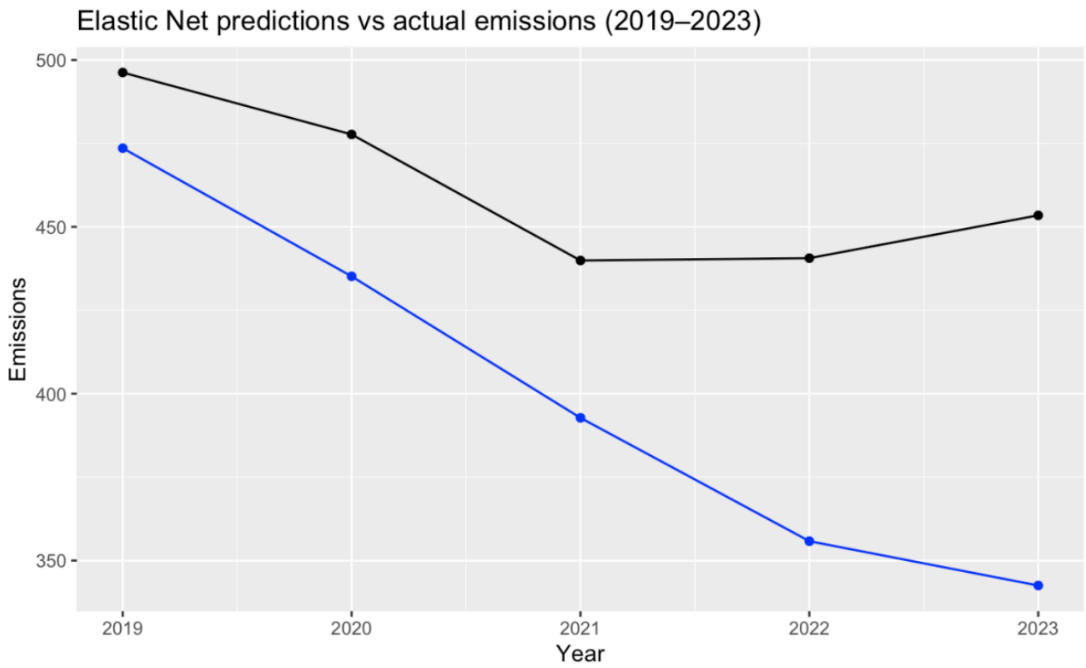

Figure 12. Elastic Net Predictions vs Actual Emissions

The forecast accuracy metrics for the Elastic Net model over the 2019–2023 test period are:

- RMSE ≈ 69.4 Mt
- MAE ≈ 61.6 Mt
- $R^2 \approx 0.75$

These values imply that the model explains approximately 75% of the variation in emissions over the five-year test period, with typical absolute forecast errors on the order of 60-70 Mt. Compared with the dynamic regression model with ARIMA errors which recorded an RMSE of approximately 124 Mt and an MAE of 115 Mt over the same test period, the Elastic Net achieves smaller point-forecast errors.

However, both models exhibit similar qualitative behaviour: they reproduce the broad downward trend in emissions but fail to anticipate the recent stabilisation and slight rebound. Given the very small size of the test sample (five years) and the structural volatility of the electricity sector during this period, differences in error magnitudes should be interpreted with caution.

Importantly, the Elastic Net model confirms the same substantive relationships identified by the ARIMA regression: emissions increase with non-renewable generation and decrease with renewable generation. Like the ARIMA model, it also tends to project continued declines when recent trends have been downward. For this reason, the ARIMA-based dynamic regression is retained as the primary forecasting model for scenario analysis, while the Elastic Net serves as a robust machine-learning benchmark that supports the main conclusions.

Policy simulation scenario

This policy simulation scenario reflects the Australian Government's Electricity and Energy Sector Plan, which targets 82% renewable electricity generation by 2030, while emissions reductions in other sectors are primarily driven through electrification (e.g., electric vehicles, electric heating, and industrial electrification). Under this policy, the electricity sector becomes the central lever for economy-wide decarbonisation. In this scenario, the non-renewable share of electricity generation is reduced linearly from its last observed level to 18% by 2030 to generate an emissions forecast till 2030. We also assumed total electricity generation to grow at 1% per year to reflect increased demand from electrification in transport, industry and buildings. (https://www.dcceew.gov.au/climate-change/emissions-reduction/net-zero/electricity-and-energy-sector-plan)

The forecast shows a sharp downward trajectory in emissions between now and 2030, with emissions falling from around current levels to approximately 100 Mt CO_2 by 2030 under the central forecast. The 95% interval captures risks such as slower build-out, higher demand growth, or residual fossil generation. Despite uncertainty, all intervals show a clear downward emissions path, indicating robustness of the policy impact.

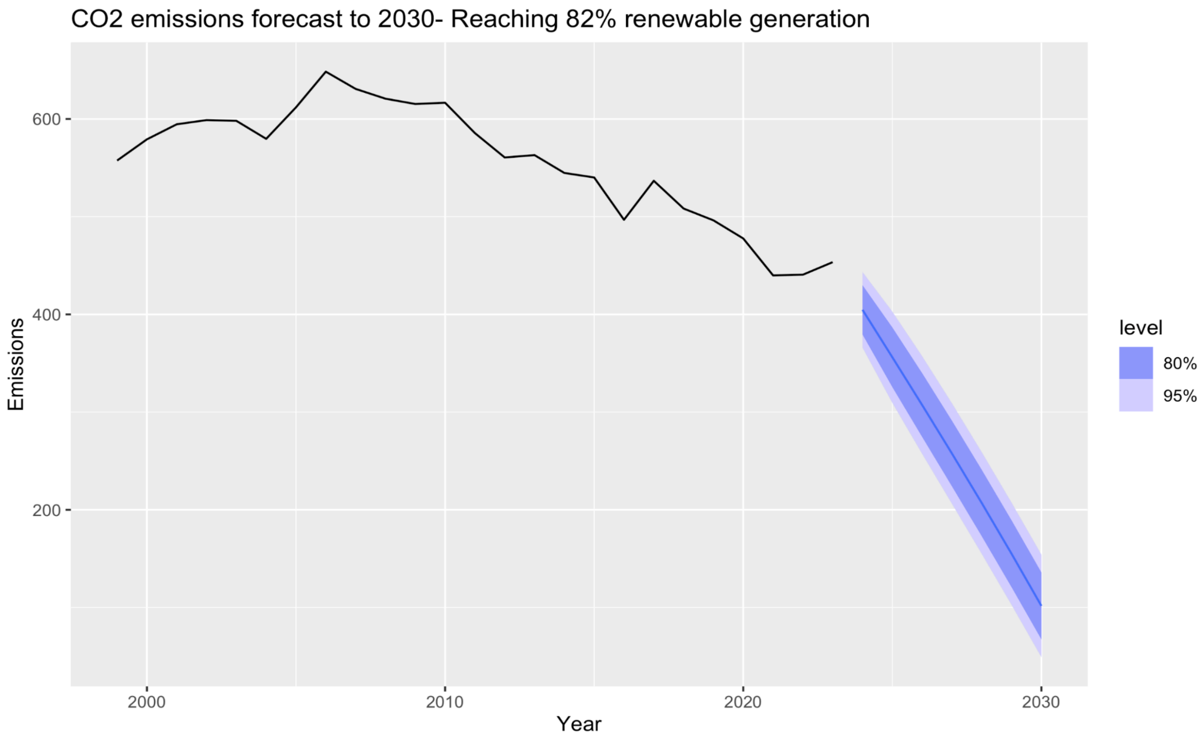

Figure 13: Policy Stimulation forecast

Discussion and Conclusion

This study examines how changes in Australia's electricity generation mix shape electricity-sector emissions and what recent trends imply for emissions trajectories to 2035. By combining exploratory data analysis (EDA), dynamic regression with ARIMA errors and an Elastic Net benchmark, the analysis provides a coherent empirical assessment of past drivers and future pathways for emissions.

The EDA highlights the central role of structural change in the electricity generation mix. While total electricity generation has continued to increase, emissions have declined since the early 2010s, indicating that reductions are not driven by falling demand. Instead, declining non-renewable generation and rising renewable penetration underpin observed emissions reductions. State-level evidence reinforces this conclusion: jurisdictions with higher renewable shares exhibit earlier and steeper emissions declines, demonstrating that large structural shifts in the energy mix are not merely theoretical but already realised in parts of the Australian electricity system.

These patterns directly motivate the modelling framework. In the dynamic regression, emissions are strongly and positively associated with non-renewable generation and negatively associated with renewable generation. Once these variables are included, remaining temporal dependence is modest and well captured by a simple autoregressive structure. Model diagnostics indicate that residuals are stationary and free of autocorrelation, supporting the statistical validity of the specification.

Out-of-sample validation over the 2019-2023 period further supports the credibility of the results. The ARIMA-based dynamic regression captures the overall downward trajectory of emissions, with actual outcomes generally falling within prediction intervals, though the model tends to under-predict recent levels. The Elastic Net benchmark achieves smaller point-forecast errors but exhibits similar qualitative behaviour, projecting a steeper decline than observed and failing to anticipate recent stabilisation. Given the very small test sample and substantial structural volatility in the electricity sector during this period, differences in numerical accuracy should be interpreted cautiously. Importantly, both approaches confirm the same substantive relationships between emissions and the energy mix.

The most policy-relevant insights emerge from the scenario analysis. Under a Business-As-Usual assumption in which the 2023 generation mix is effectively maintained, emissions decline only gradually and stabilise by the mid-2030s. This trajectory reflects the momentum of past improvements but does not deliver deep decarbonisation. In contrast, a policy scenario involving a 50% reduction in non-renewable generation by 2035, with replacement by renewables, produces a much steeper decline in emissions. The divergence between scenarios widens over time, illustrating the cumulative impact of sustained fossil-fuel displacement.

Several limitations should be noted. The analysis relies on a relatively short annual time series and abstracts from factors such as technology-specific emissions, regional constraints, demand-side responses and future policy shocks. The policy scenario is stylised and should be interpreted as indicative rather than predictive.

Overall, the findings underscore a clear conclusion: meaningful long-term reductions in electricity-sector emissions depend on accelerating the transition away from non-renewable generation. While historical trends have delivered progress, relying on inertia alone is unlikely to achieve substantial further reductions. Sustained structural change in the electricity generation mix is central to Australia's decarbonisation pathway over the coming decade.

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