Temperature Forecast Analysis for Winter 2019

March 2020

A report exploring the forecast accuracy of AEMO's operational weather service providers in the National Electricity Market from 1 May 2019 to 30 September 2019

Important notice

PURPOSE

This report has been prepared to give the weather providers used by AEMO for operational forecasting an insight into their comparative temperature forecast performance across the 2019 winter period.

DISCLAIMER

AEMO has made every reasonable effort to ensure the quality of the information in this publication but cannot guarantee it is accurate, complete or appropriate for your circumstances. This document or the information in it may be subsequently updated or amended. This document does not constitute legal or business advice, and should not be relied on as a substitute for obtaining detailed advice about the National Electricity Law, the National Electricity Rules, or any other applicable laws, procedures or policies.

Accordingly, to the maximum extent permitted by law, AEMO and its officers, employees and consultants involved in the preparation of this document:

- make no representation or warranty, express or implied, as to the currency, accuracy, reliability or completeness of the information in this document; and
- are not liable (whether by reason of negligence or otherwise) for any statements or representations in this document, or any omissions from it, or for any use or reliance on the information in it.

GLOSSARY

Term	Definition
electrical demand (operational demand)	The sum of scheduled, semi-scheduled, and non-scheduled generation connected to the National Electricity Market.
forecast error	Forecast value – actual value. Forecast error is used in reference to either temperature (°C) or demand (MW) in this paper.
mean absolute error (MAE)	The calculated average of the absolute (unsigned) forecast error. Mean absolute error is only used in reference to temperature forecast error (°C) in this paper.
peak demand	The time period or quantity of power that corresponds to the highest amount of electrical power delivered over a defined period (day, season or year)
rolling forecast horizon	A forecast that is always created X hours ahead of the actual observation. For example, for a 4-hour-ahead rolling forecast horizon, the observation at 12:00 pm was forecast at 8:00 am, and the observation at 4:00 pm was forecast at 12:00 pm.

Executive summary

This report examines the temperature forecast accuracy of AEMO's three operational weather service providers in the National Electricity Market (NEM) from 1 May to 30 September 2019. It follows the *Temperature Forecast Analysis for Summer 2018-19*, and highlights differences between summer and winter forecasting performance.

The weather stations analysed in this report are Archerfield (Queensland), Bankstown (New South Wales), Hobart Airport (Tasmania), Kent Town (South Australia), Melbourne Airport (Victoria), Melbourne Olympic Park (Victoria), and Penrith (New South Wales). These weather stations represent the largest electricity load centres in each region of the National Electricity Market.

The key findings from the analysis were:

- In Melbourne, while the summer forecast analysis showed relatively low temperature forecast accuracy, weather service providers were able to forecast winter temperatures with significantly improved accuracy.
- The finding for Brisbane was the opposite, with Archerfield winter temperatures forecast poorly in comparison to summer temperatures.
- Penrith was also forecast with lower accuracy in winter than in summer, and was generally forecast with the least accuracy of any of the considered weather stations.
- Two of AEMO's three weather service providers showed tendencies to consistently over- or under-forecast winter temperatures at certain weather stations. Though generally of a small magnitude, these tendencies were not observed in summer temperature forecasts.
- Winter temperatures were consistently forecast with most accuracy during the period from late morning to late evening. This was not shown to be the case in the summer analysis.
- A case study analysis of forecasting performance in New South Wales on 29 August 2019 showcased how weather service providers forecast days with sudden temperature changes. When the timing of change is uncertain, temperature 'point forecasts' often indicate more gradual temperature changes than are likely to occur. This was shown for both increases and decreases in temperature. This analysis supports the findings for 25 January 2019 in the summer analysis paper.
- The same case study for New South Wales on 29 August 2019 highlights how rainfall can simultaneously induce temperature, rooftop photovoltaic (PV), and model error in the demand forecast.

This analysis will be used by AEMO to aid operational decision-making and will be shared with weather providers to draw attention to potential areas of improvement.

Contents

Figures

1. Introduction

This report examines the temperature forecast accuracy of AEMO's operational weather service providers in the National Electricity Market (NEM) from 1 May 2019 to 30 September 2019. It is an extension of the *Temperature Forecast Analysis for Summer 2018-19* paper that AEMO published in August 2019[1].

This report aims to contrast winter and summer performance across weather providers and weather stations. Like the summer analysis, this is primarily intended as a resource for weather service providers so they can benchmark their forecast performance against other providers. It also includes a case study to highlight how temperature forecasts are linked to the operational challenges AEMO faces in winter demand forecasting.

2. Winter forecast performance

This section contains a selection of insights into temperature forecasting performance for winter 2019 in the NEM. It highlights cases where the winter forecast performance differs from summer performance. Full results are included in appendices A1 and A2.

The results below and in A1 are displayed as error density plots, which can be interpreted as follows:

- The x-axis shows forecast error. Positive values indicate over-forecasting (the forecast temperature exceeds the actual temperature), and negative values indicate under-forecasting (the forecast temperature is less than the actual temperature).
- The y-axis shows error density. This reflects the relative likelihood of a particular forecast error.
- In general, the height of the error density peak captures the level of forecast precision, and the positioning of the peak with respect to a forecast error of zero captures the level of forecast bias. The higher the peak, the greater the precision and the smaller the expected deviation from the average level of error. The further the peak is from zero error, the greater the bias, and the larger the tendency for over- or under-forecasting on average.

Appendix A2 contains intraday mean absolute error (MAE) profiles for every site by provider.

2.1 Insights by weather station

Melbourne temperature forecasts were more accurate in winter than in summer

Figure 1 and Figure 2 compare forecast error for Melbourne Airport in summer to winter. They show the forecast error spread for all one-hour intervals during summer 2018-19 and winter 2019 at Melbourne Airport at 4-, 24-, and 72-hour ahead time horizons.

Across all time horizons and providers, Melbourne Airport's temperatures were forecast more accurately in winter than in summer. Similar results were observed at Melbourne Olympic Park, as shown in Appendix A1.2.

[1] At https://www.aemo.com.au/-/media/Files/Electricity/NEM/Planning_and_Forecasting/Load-Forecasting/Temperature-Forecast-Analysis-Summer-2018-19.pdf.

Figure 1 Melbourne Airport, all winter of 2019, 4-, 24-, and 72-hour ahead time horizons

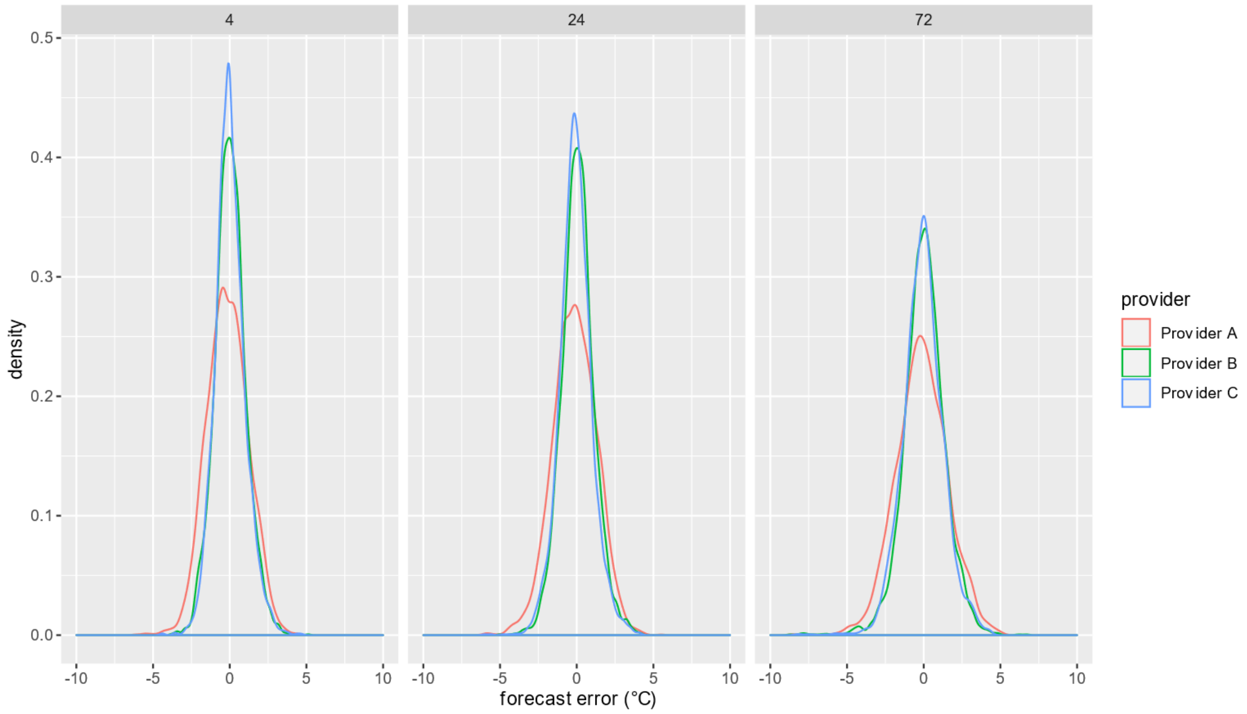
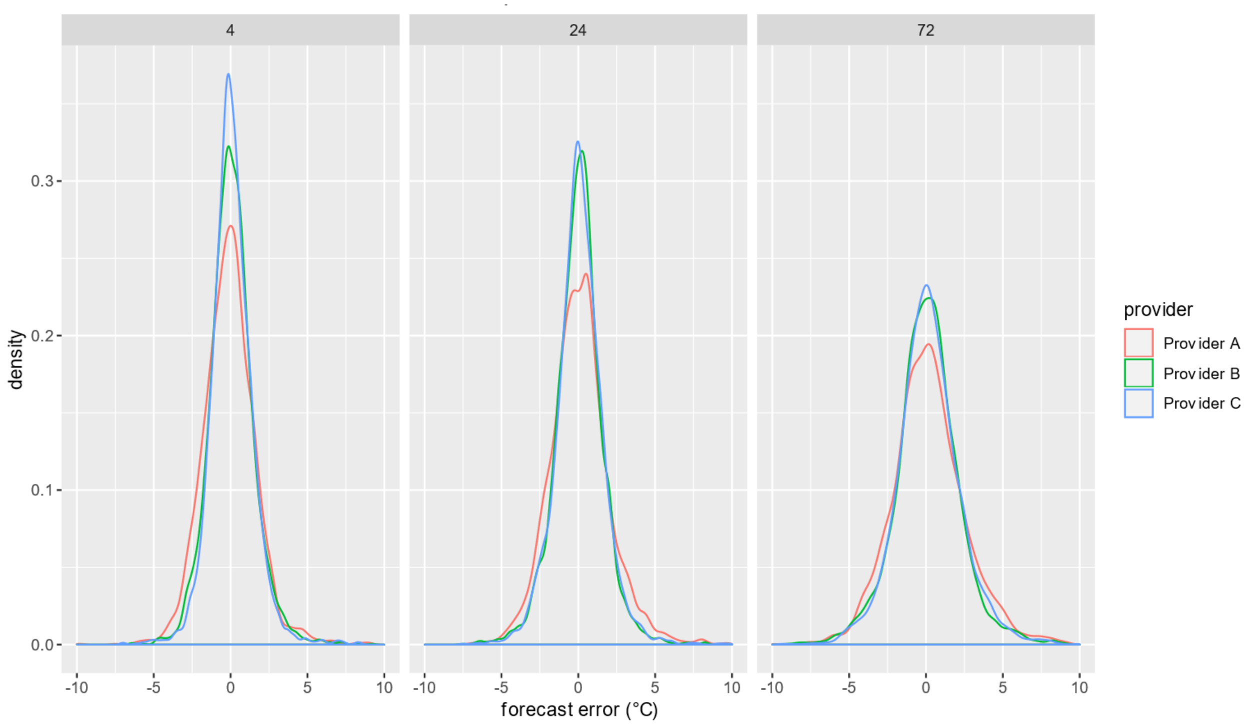


Figure 2 Melbourne Airport, all summer of 2019, 4-, 24-, and 72-hour ahead time horizons



Brisbane temperature forecasts are not as accurate in winter as they are in summer

Figure 3 and Figure 4 shows the forecast error spread for all one-hour intervals during summer 2018-19 and winter 2019 at Archerfield Airport at 4-, 24-, and 72-hour ahead time horizons.

The results for Brisbane were the inverse of Melbourne. Archerfield's temperatures were forecast with greater precision in summer than in winter across all time horizons and weather providers.

Figure 3 Archerfield Airport, all winter of 2019, 4-, 24-, and 72-hour ahead time horizons

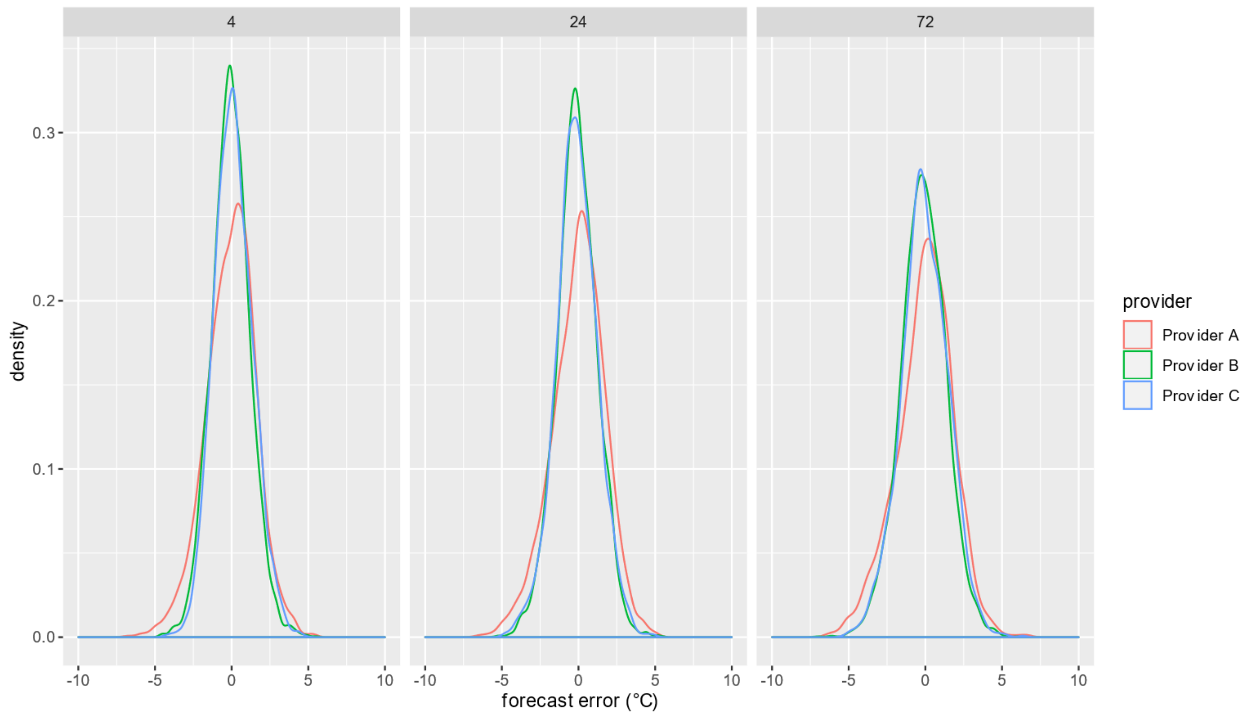
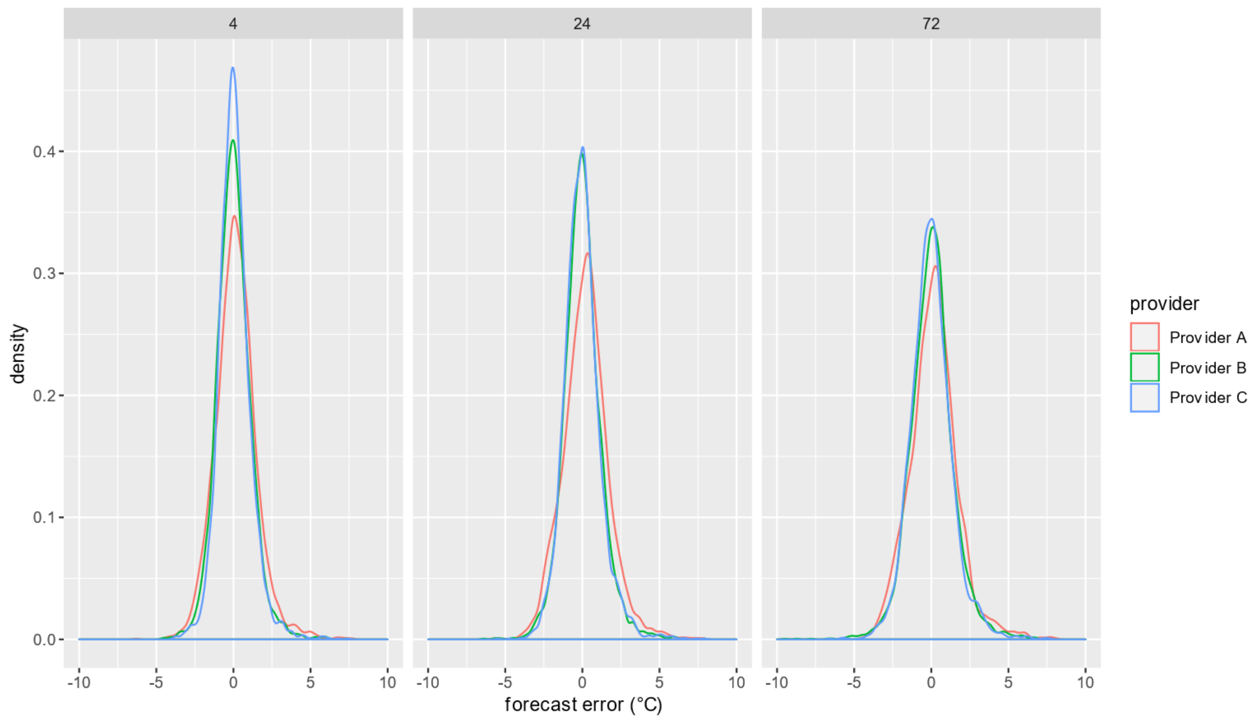


Figure 4 Archerfield Airport, all summer of 2019, 4-, 24-, and 72-hour ahead time horizons



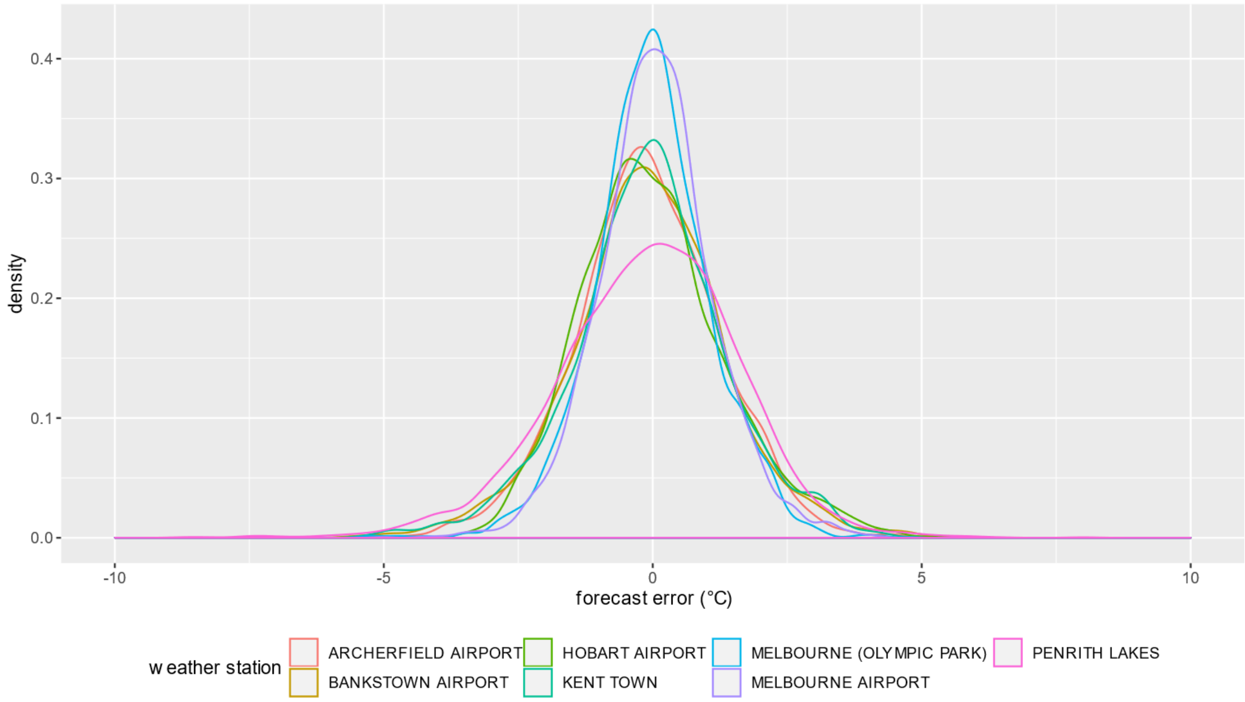
Penrith Lakes is the most difficult weather station to forecast in winter

Figure 5 shows Provider B's forecast performance at each weather station at the 24 hour-ahead time horizon.

It shows that winter temperatures were forecast with similar precision by Provider B in Adelaide (Kent Town), Hobart, Archerfield, and Bankstown. Melbourne winter temperatures were forecast most accurately, and Penrith temperatures were forecast with least accuracy.

Similar results were observed for Provider C. Although Provider A forecast Penrith temperatures with a similar accuracy to other sites, its Penrith forecasts were still less accurate than both other providers. This is shown in Figure 8 and Figure 9, and in Appendix A1.1.

Figure 5 All weather stations, Provider B, all winter of 2019, 24-hour ahead time horizon



Hobart Airport was forecast with similar levels of accuracy in winter and summer

Tasmania is the only NEM region to consume more electricity in winter than summer, making its winter temperature forecasts especially important.

A comparison of Figure 6 with Figure 7 shows Provider C's winter forecast performance was strongest across all time horizons at Hobart Airport, whereas Provider B had the strongest performance at the 72-hour ahead time horizon in summer. Otherwise, the differences between summer and winter are subtle. The performance of Provider A at Hobart is discussed in Section 2.2.

Figure 6 Hobart Airport, all summer of 2019, 4-, 24-, and 72-hour ahead time horizons

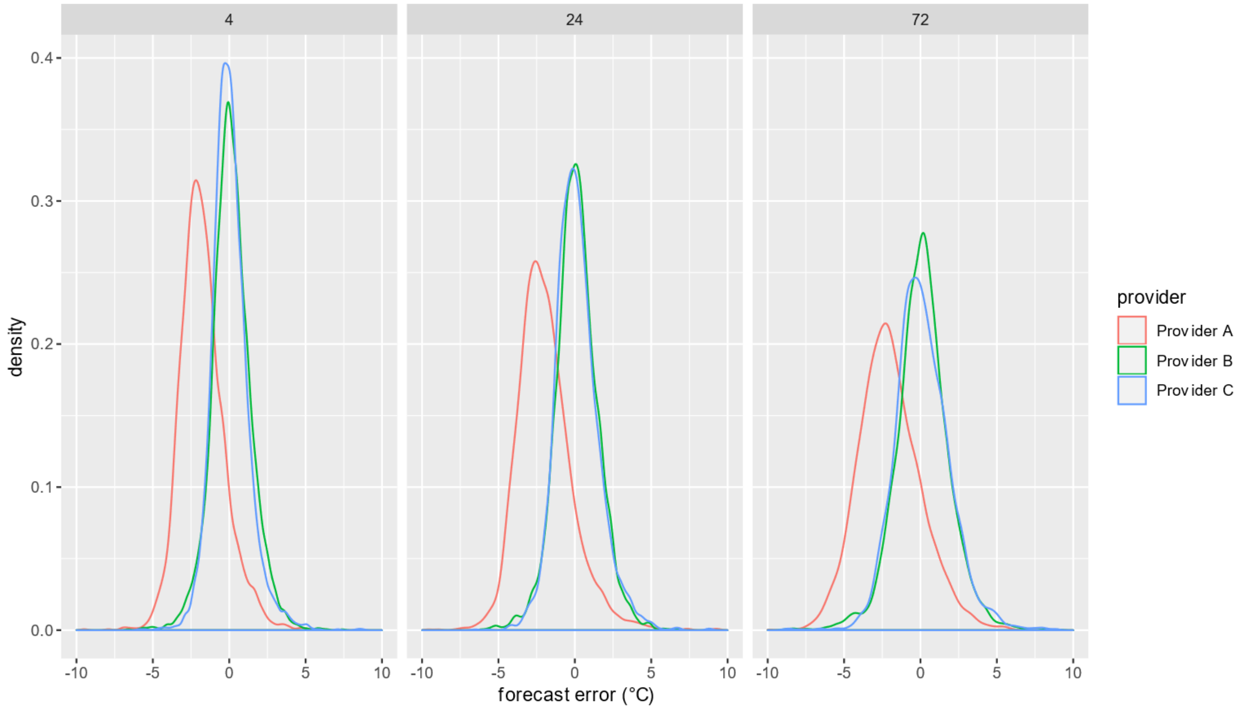
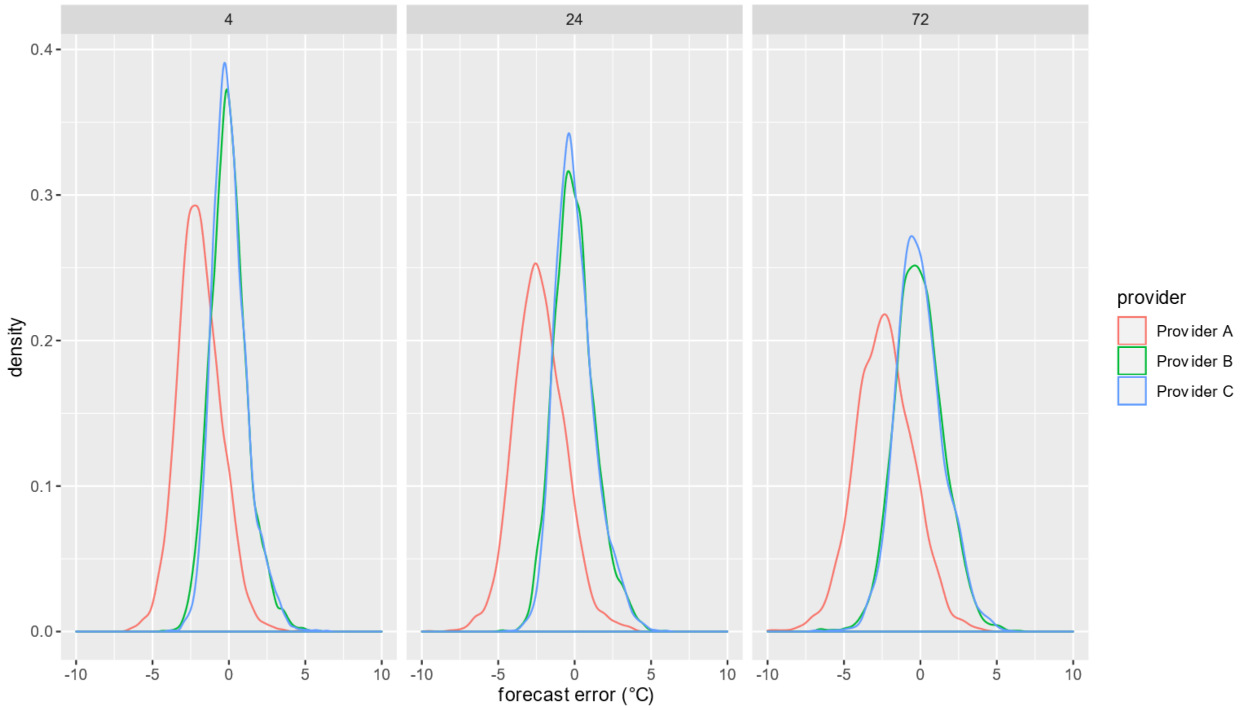


Figure 7 Hobart Airport, all winter of 2019, 4-, 24-, and 72-hour ahead time horizons



Like Hobart, there were no major forecasting performance differences observed between winter and summer at either Adelaide (Kent Town) or Bankstown.

2.2 Insights by provider

Providers A and C over- or under-forecast winter temperatures on average at certain sites

Figure 8 shows winter performance by station for Provider A, and Figure 9 shows the same for Provider C.

Figure 8 All weather stations, Provider A, all winter of 2019, 24-hour ahead time horizon

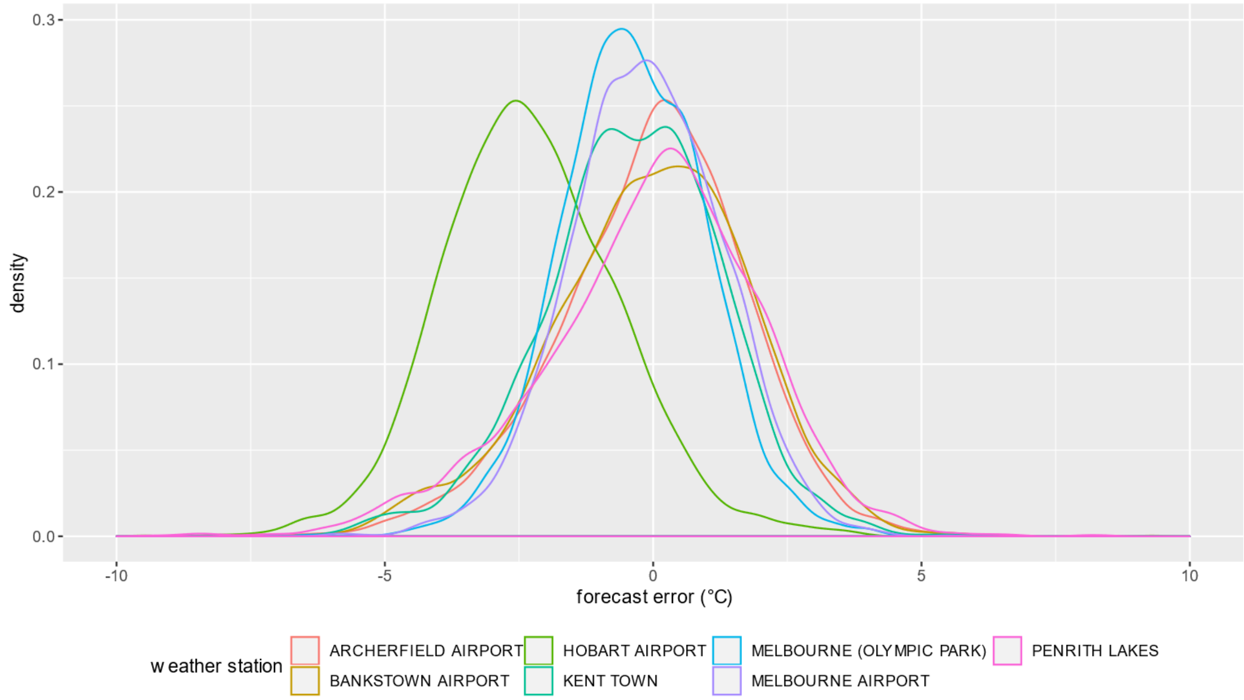
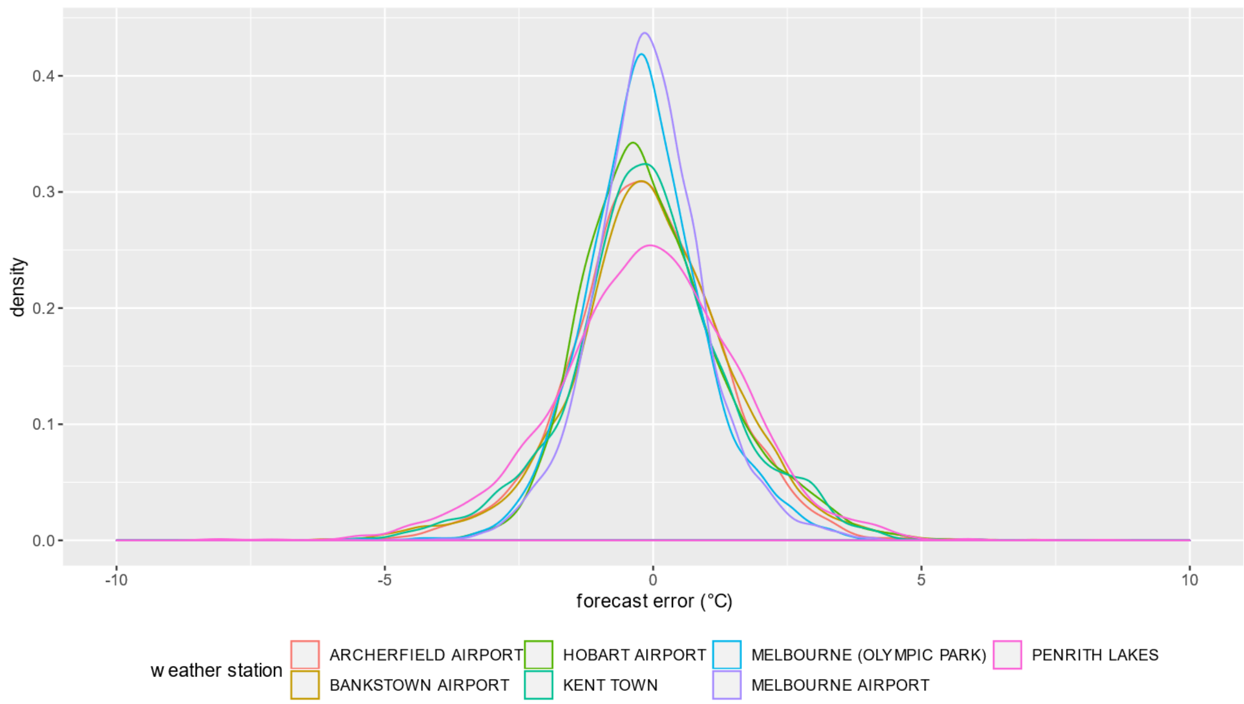


Figure 9 All weather stations, Provider C, all winter of 2019, 24-hour ahead time horizon



Although the magnitude of deviation is small, Provider A noticeably over-forecast at Bankstown and Penrith, under-forecast in Melbourne, and substantially under-forecast (by an average of 2.5°C) in Hobart. Provider C had a general tendency to under-forecast (though by less than 1°C) across all sites with the exception of Penrith.

Provider B was generally unbiased in its temperature forecasts across all sites, as shown in Appendix A1.1.

2.3 Intraday insights

Daytime and evening temperatures are generally forecast with greatest accuracy

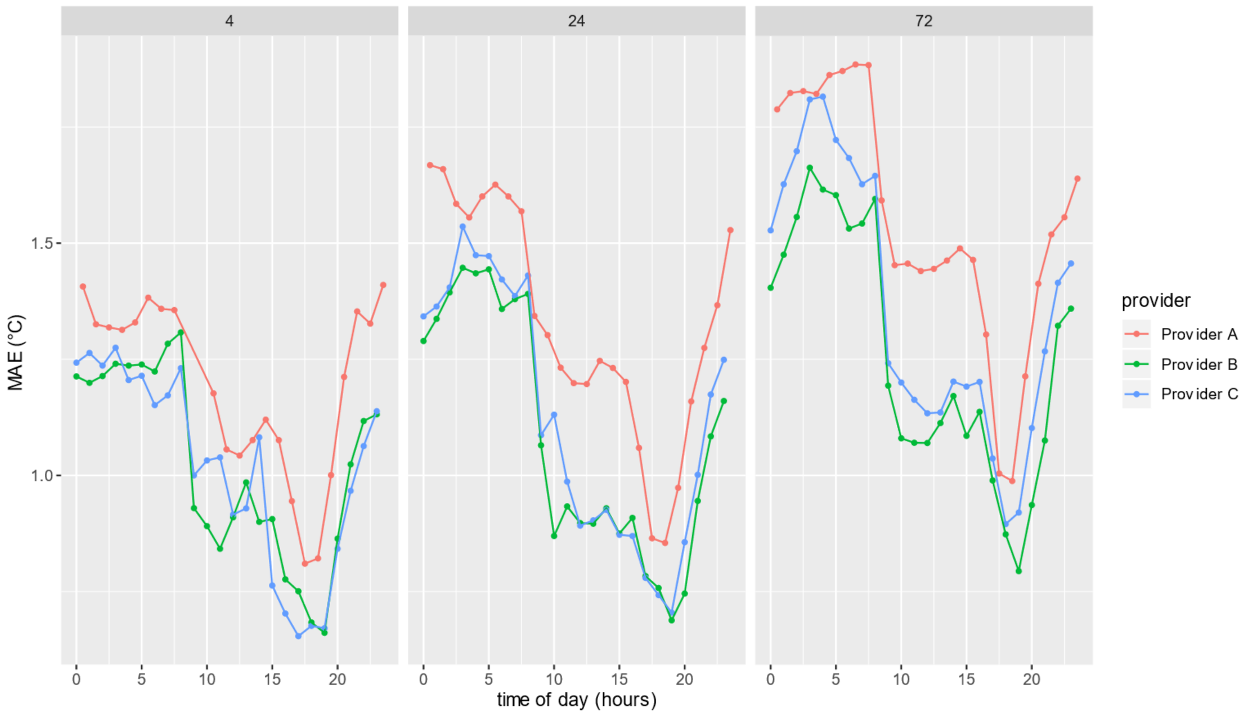
Intraday MAE profiles show that temperature forecast performance between late morning and late evening was superior to forecast performance at other times. This is shown for Adelaide (Kent Town) in Figure 10, but was generally consistent across time horizons, weather stations and providers, as shown in Appendix A2. Such a pattern was not generally observed in the summer analysis.

Importantly, the period of superior forecast performance encompasses both the evening electricity demand peak and the period leading into the peak. The hours prior to the peak have a significant impact on residential heating loads in winter and cooling loads in summer.

However, in winter more so than summer, demand is also driven by overnight minimum temperatures. Further, AM demand peaks occur more frequently in winter than in summer across the NEM. Thus, the observation that winter temperatures were forecast relatively inaccurately is still of concern to AEMO.

Figure 10 also demonstrates the superior forecast performance of providers B and C in comparison to Provider A. This finding was consistent across all sites and forecast horizons, and is in line with results of the summer analysis.

Figure 10 Intraday hourly MAE profile for each provider at Kent Town, winter 2019



3. Case study: New South Wales, 29 August 2019

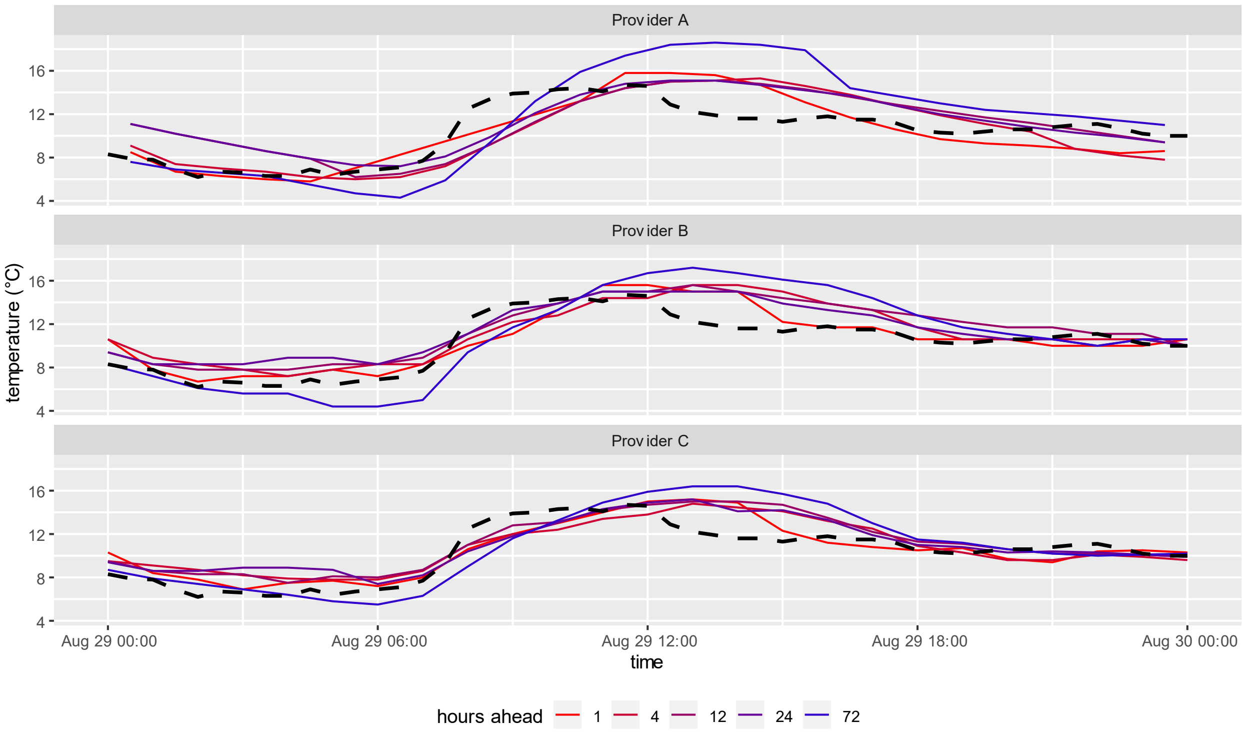
3.1 Temperature forecasting

This section examines an instance of poor temperature forecasting performance, at Penrith Lakes weather station on 29 August 2019.

AEMO's regional forecast models intake temperature forecast feeds from multiple weather stations across a region, and weight these feeds according to their relative value in predicting load. For context, Penrith and Bankstown are typically the most heavily weighted weather stations in the New South Wales region.

New South Wales demand on 29 August 2019 was under-forecast by up to 750 megawatts (MW) compared to projections from 24 hours prior. Across the day, approximately 25% of the region's demand forecast error was attributed to temperature over-forecasting at Penrith. The remainder of the deviation of demand from forecast was predominately a combination of weather forecast error at other stations, deviation of rooftop photovoltaic (PV) generation from estimates, and residual 'model' error.

Figure 11 Penrith forecast temperature profile against observations, all providers, 29 August 2019

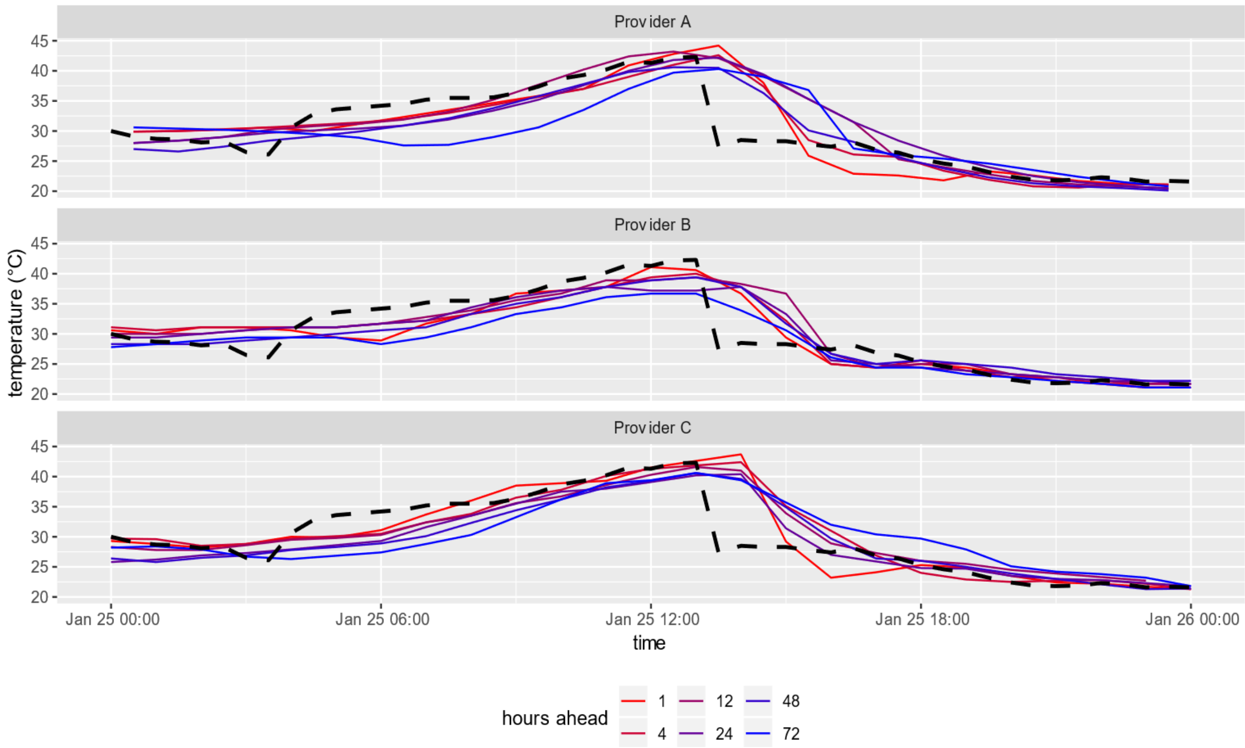


Notable observations from Figure 11 include:

- The 72-hour ahead forecast for all providers was significantly higher than actual temperatures (dashed black line) in the afternoon/evening. It was worst for Provider A and tended to improve for all providers with shorter time horizons. This is consistent with the findings of Section 2.1 and of the summer forecast analysis, which showed improved forecast performance at shorter time horizons.

- The actual temperature profile of the day featured both a sharp increase in temperature at approximately 0730 hrs and a sharp decrease in temperature at approximately 1200 hrs. On average, providers B and C captured the timing of the AM change better than Provider A. All three providers predicted that the PM temperature change would occur several hours later than it actually did at all forecast time horizons. This demonstrates the inherent challenges of forecasting the timing of significant temperature changes.
- For both the AM and PM temperature changes, forecast rates of change of temperature were lower than actual rates of change of temperature. This was true across all three providers and did not clearly improve with a shortening time horizon. This outcome is a symptom of temperature 'point forecasts' whose objective is to minimise forecasting error and avoid large outliers, not to predict the steepness of ramps. In the presence of change timing uncertainty, temperature forecasts avoid large outliers by predicting more gradual changes than what are likely to occur. This concept is supported by Figure 11, and Figure 12 (included in the summer analysis report) demonstrates a similar observation on 25 January 2019. Notably, smooth temperature point forecasts are conducive to low-volatility demand forecasts, which are generally operationally advantageous. This section shows that smooth temperature forecasts may not be as operationally valuable in contexts where the rate of demand ramping is of particular interest.

Figure 12 Melbourne Olympic Park forecast temperature profile against observations, 25 January 2019

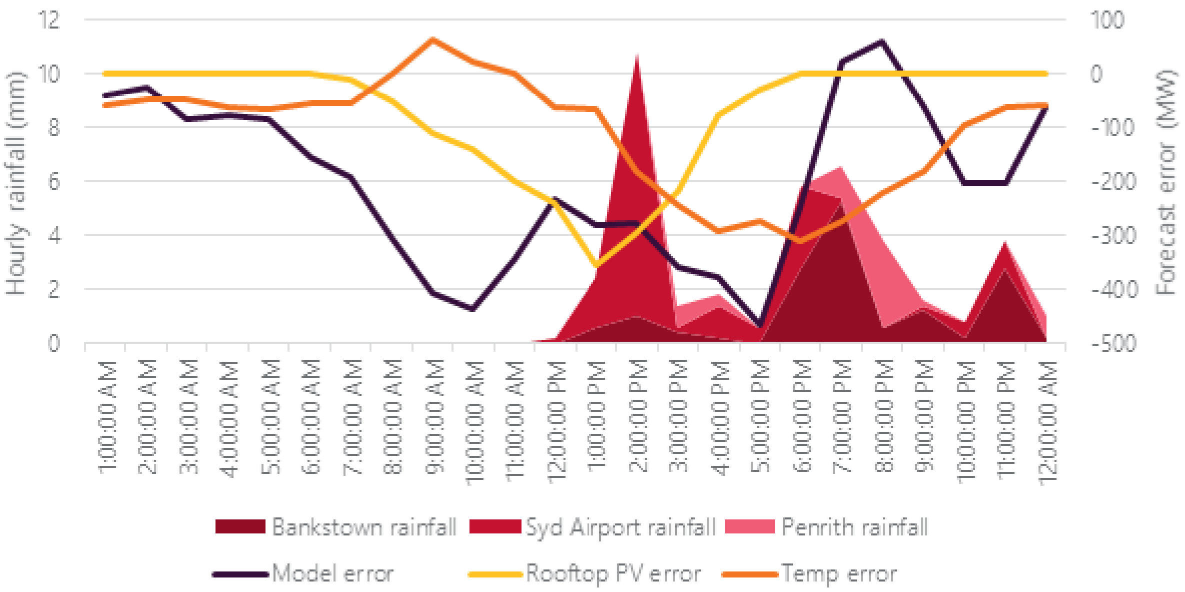


3.2 Demand forecasting

This section uses the same case study day and region (29 August 2019, New South Wales) to highlight some unique challenges of demand forecasting in winter. In particular, it shows how interdependencies between different weather phenomena can lead to forecast errors which impact demand in compounding ways. The following should be noted when interpreting Figure 13:

- Figure 13 is not based on a rolling forecast horizon. Instead it compares actuals to forecasts from 1230 hrs the previous day[2]. This timing is significant to the market and is often used by AEMO to assess forecast performance.
- There are three types of demand forecast error included in the chart:
  - Rooftop PV – the deviation of demand from forecast due to deviation of rooftop PV generation from forecast.
  - Temperature[3] – the deviation of demand from forecast due to deviation of temperature from forecast.
  - Model – the deviation of demand from forecast that cannot be explained by errors in inputs to the demand forecast model.
- Over-forecasting of rooftop PV generation is shown as negative, to reflect that it contributes to under-forecasting of demand. Displayed in this way, the three sources of error shown in the figure cumulate in the same direction.
- Rainfall is not currently included in AEMO's demand forecasts[4]. Rainfall may impact rooftop PV generation and temperature in ways not captured by PV and temperature forecasts. To this extent it can contribute to PV and temperature error in the demand forecast. The behavioural impacts of rainfall on demand (for example, an increased tendency for consumers to stay indoors) are considered model error.

Figure 13 Rainfall at Sydney weather stations and New South Wales 1230 hrs pre-dispatch demand forecast error, 29 August 2019



Two key observations from Figure 13 are:

- From 1200-1700 hrs, there was a simultaneous increase in the magnitude of under-forecasting due to temperature error and model error. Rooftop PV error tends to decrease in magnitude in absolute terms through this period, however, this largely reflects that rooftop PV itself decreases from noon. Rooftop PV error is much larger in the afternoon than in the morning as a proportion of output. It is not uncommon

[2] At 1230 hrs the pre-dispatch (PD) schedule is extended to include an extra trading day in accordance with the Spot Market Operations Timetable, at https://www.aemo.com.au/-/media/Files/Electricity/NEM/Security_and_Reliability/Dispatch/Spot-Market-Operations-Timetable.pdf.

[3] Strictly, 'Temp Error' in Figure 13 refers to apparent temperature error, which also captures the effects of humidity forecast error on demand. Humidity deviation from forecast on 29 August 2019 was negligible.

[4] Rainfall forecasts and the impact of rainfall on demand both carry significant uncertainty which diminishes the value of including rainfall in demand forecasts. Model refinement work to capture the impact of different weather phenomena on demand is ongoing. This section highlights the value of such work.

to observe a correlation between rainfall and forecast errors compounding in this fashion. It is reasoned that the arrival of rain in Sydney at approximately 1200 hrs had a threefold impact:

- Rainfall and thicker cloud cover reduced the output of rooftop PV systems and therefore increased operational demand. This contributed to rooftop PV error.
- Reduced sunlight incident on buildings and reduced temperatures increased heating loads. This contributed to model error and temperature error.
- Appliance use increased with greater numbers of consumers remaining indoors. This contributed to model error.

Notably, the above describes a uniquely winter phenomenon for most NEM load centres. In summer, rainfall has similar effects on rooftop PV output to those described above, but tends to decrease air-conditioning load rather than increase it. With these two factors offsetting each other, the impact of rainfall on summer demand forecasting is generally less severe. This section has shown that, in winter, consideration of temperature error in isolation does not necessarily capture the full extent of weather-driven deviations of demand from its forecast.

The impact of temperature forecast error on demand accumulated through the afternoon. In degree terms, the largest temperature error occurred from 1300-1430 hrs, with the Penrith temperature over-forecast by 2.9°C (Figure 11). However, in megawatt terms, temperature error was of greatest magnitude at 1800 hrs.

This partly reflects higher demand at 1800 hrs, however it also illustrates a lag in the effects of temperature on demand. The evening peak winter heating load reflects not only the temperature at the peak but also the extent to which a space that was cooled during the day needs to be heated up again during the evening. Therefore, if temperature was over-forecast during the daytime, it can be expected that evening heating loads will be under-forecast.

This underscores AEMO's need for temperature forecasts which are accurate, not only in terms of minima and maxima, or in terms of peak demand, but are accurate at all times of day.

4. Conclusion

The results presented in this paper supplement the findings of the summer 2018-19 forecast analysis, and AEMO will use them to aid operational forecasting and decision-making. As was done for the summer paper, this analysis will be shared with weather service providers to draw attention to their potential areas of improvement.

Key findings of this report are:

- Melbourne temperature forecasts were more accurate in winter than in summer.
- Brisbane temperature forecasts were not as accurate in winter as they are in summer.
- Penrith's temperatures were forecast with low accuracy in winter.
- Provider A and Provider C's winter temperature forecasts were consistently over- or under-forecast at certain weather stations.
- Winter temperatures were generally forecast most accurately between late morning and late evening.
- Poor forecasting by weather service providers of the timing, magnitude, and rate of temperature changes is a challenge for AEMO in both summer and winter.
- Certain instances of winter rainfall are linked to significant under-forecasting of demand. This is due to rainfall's simultaneous impact on rooftop PV generation, temperature, and consumer behaviour.

A1. Error density plots

A1.1 Site comparison by provider

Figure 14 All weather stations, Provider A, all winter of 2019, 24-hour ahead time horizon

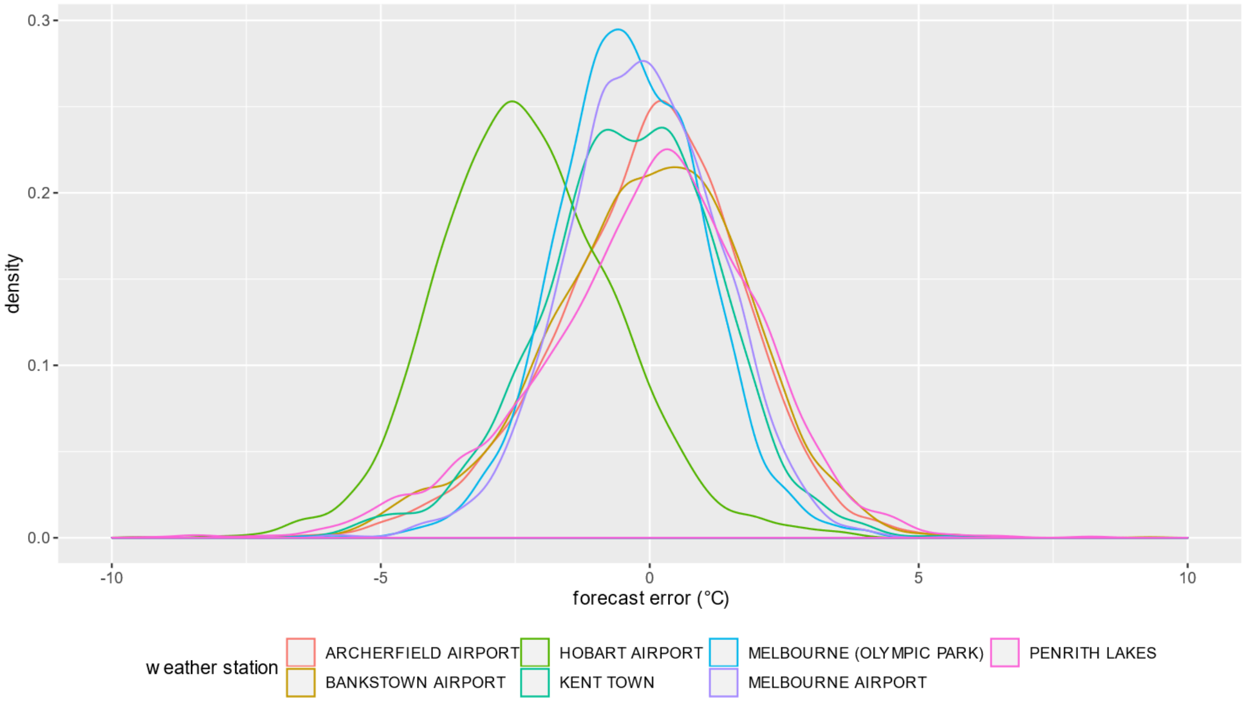


Figure 15 All weather stations, Provider B, all winter of 2019, 24-hour ahead time horizon

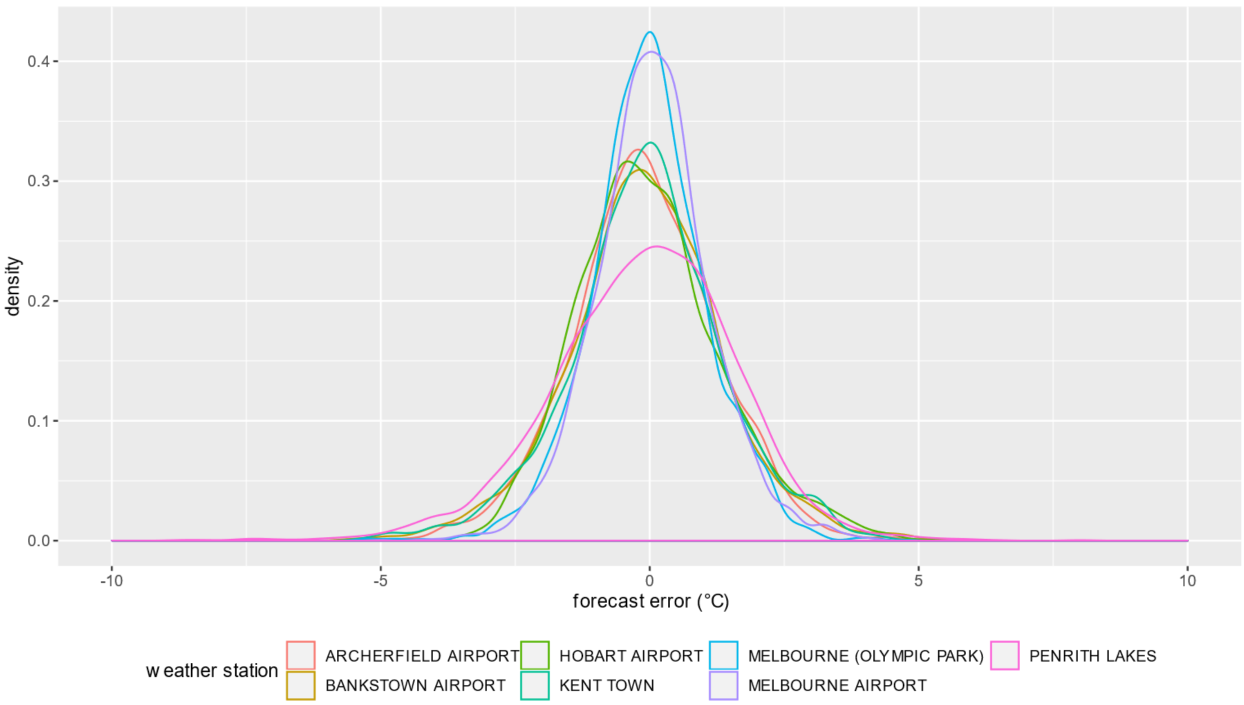
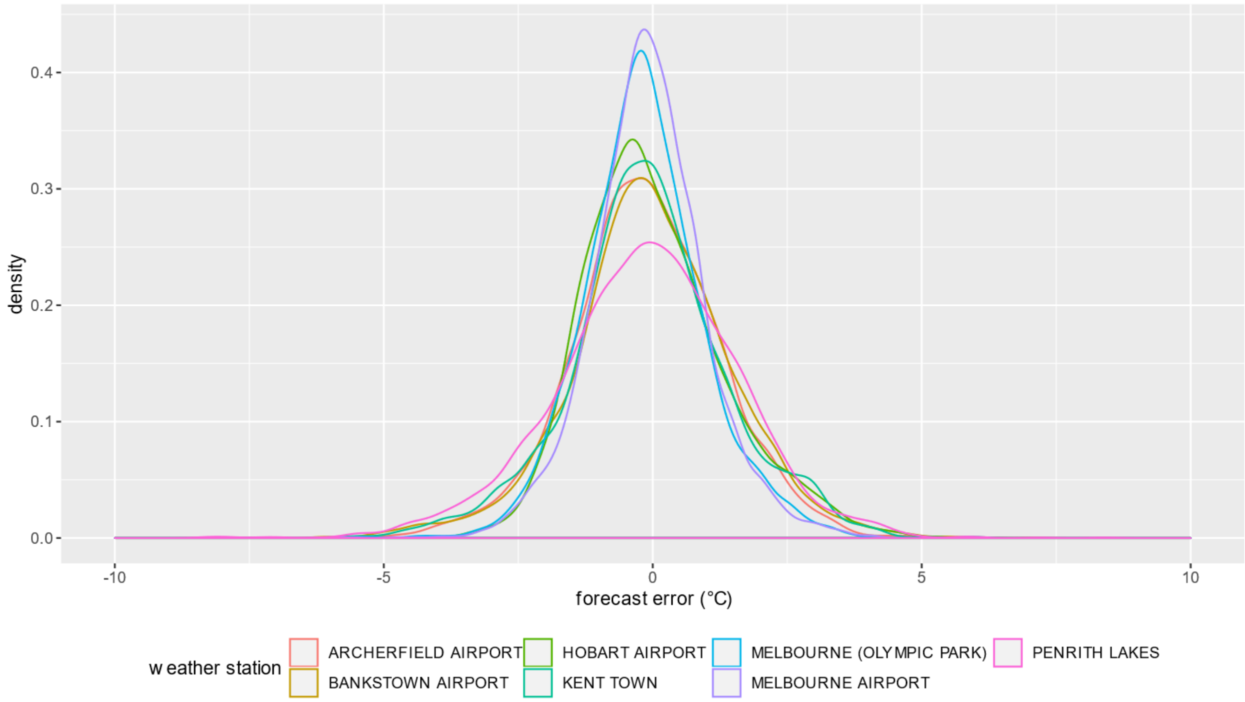


Figure 16 All weather stations, Provider C, all winter of 2019, 24-hour ahead time horizon



A1.2 Provider comparison by site

Figure 17 Archerfield Airport, all providers, all winter of 2019, 4-, 24-, and 72-hour ahead time horizons

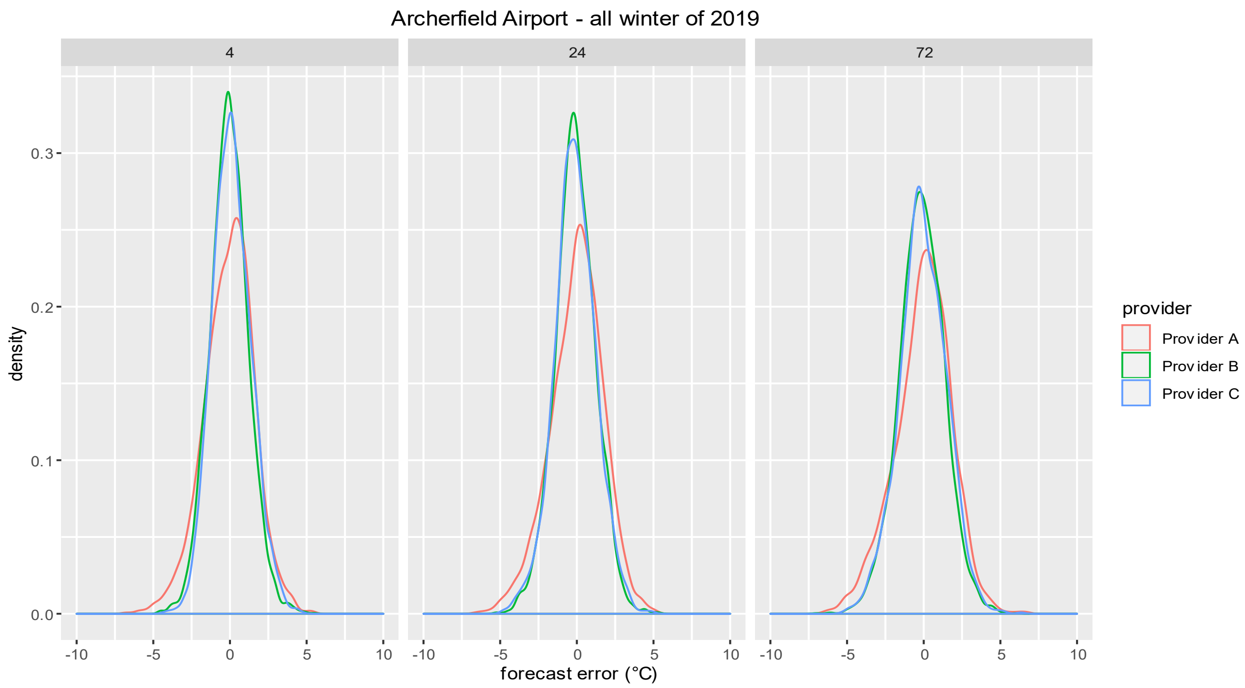


Figure 18 Bankstown Airport, all providers, all winter of 2019, 4-, 24-, and 72-hour ahead time horizons

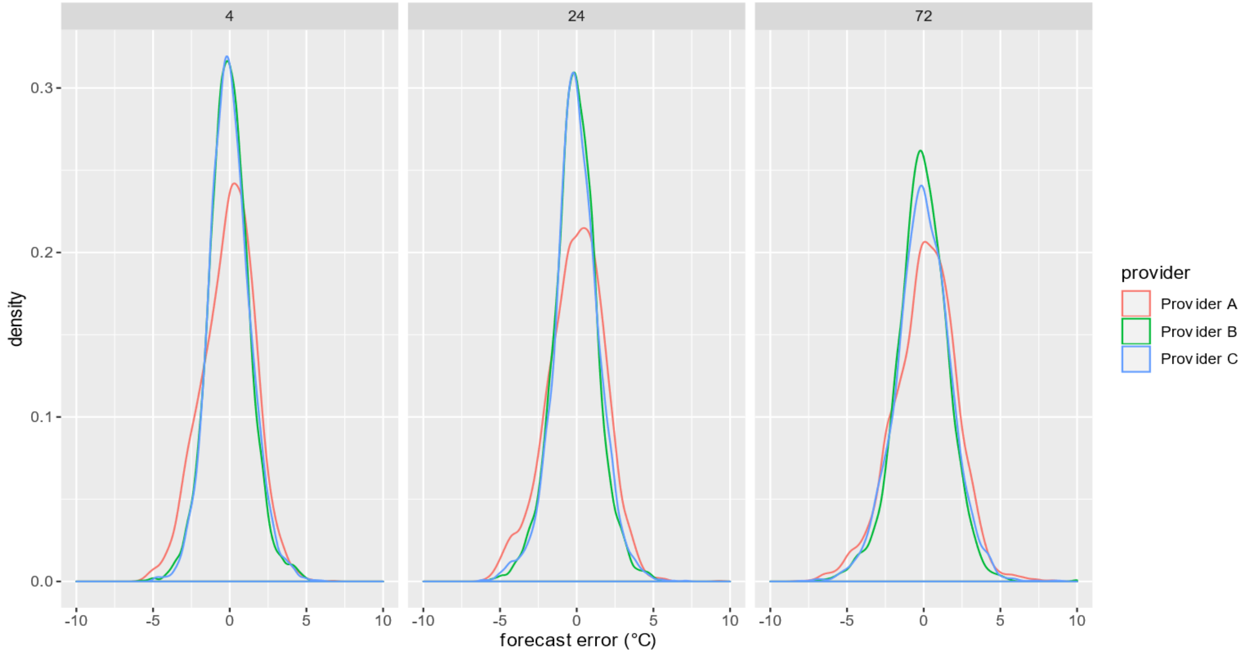


Figure 19 Hobart Airport, all providers, all winter of 2019, 4-, 24-, and 72-hour ahead time horizons

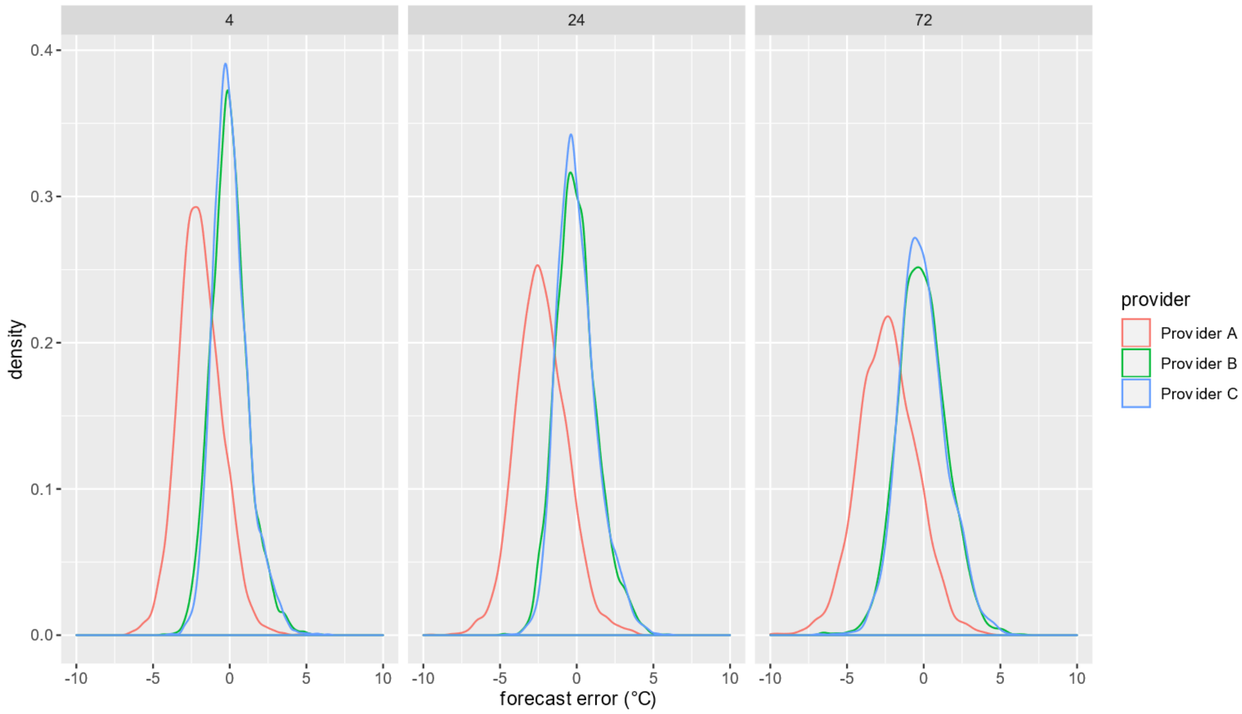


Figure 20 Kent Town, all providers, all winter of 2019, 4-, 24-, and 72-hour ahead time horizons

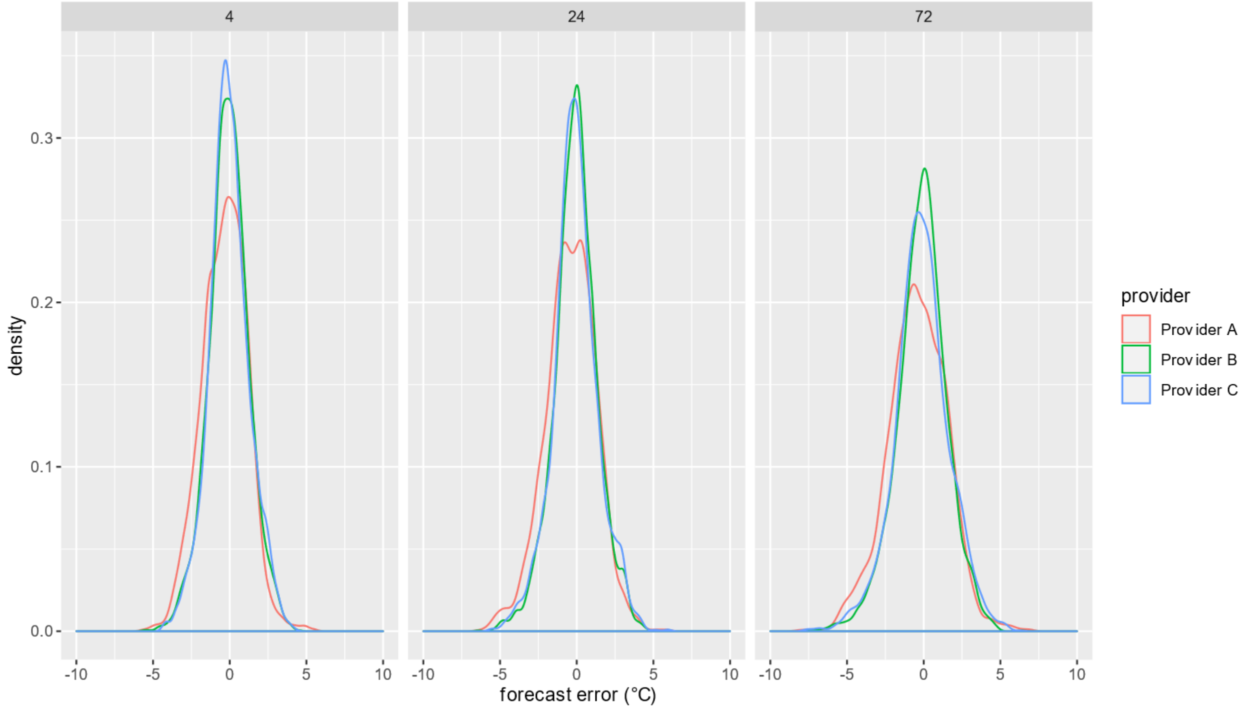


Figure 21 Melbourne (Olympic Park), all providers, all winter of 2019, 4-, 24-, and 72-hour ahead time horizons

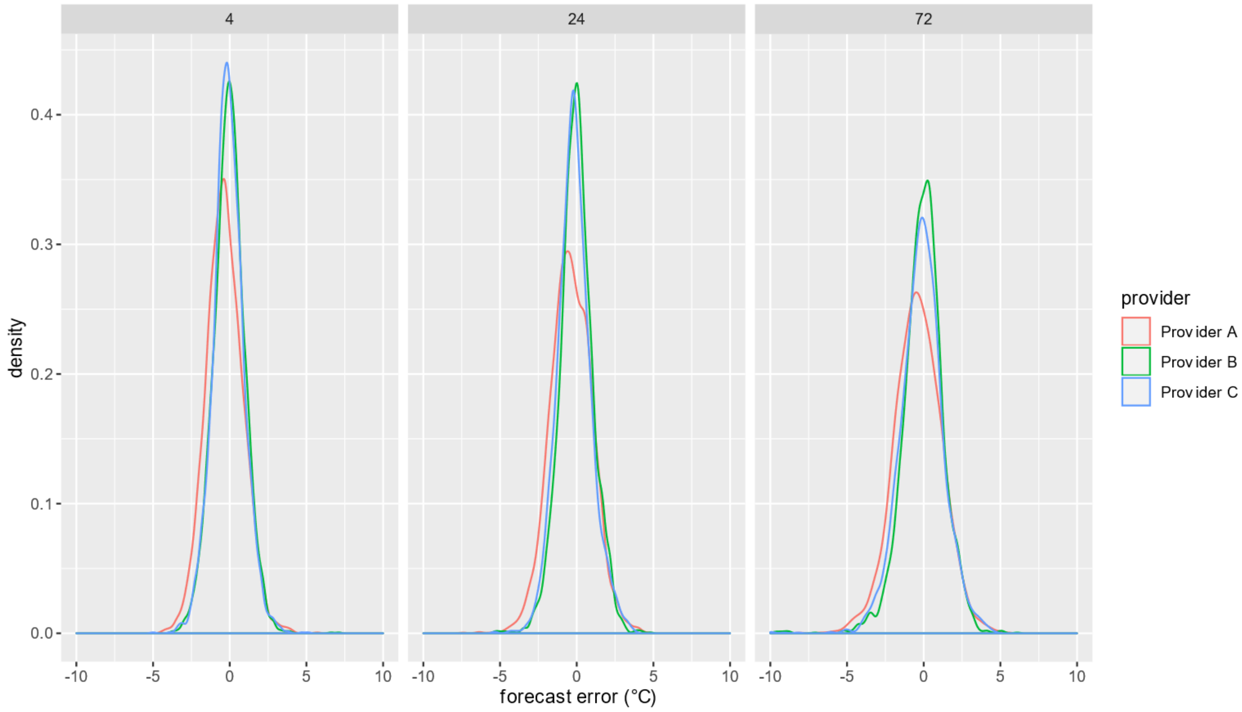


Figure 22 Melbourne Airport, all providers, all winter of 2019, 4-, 24-, and 72-hour ahead time horizons

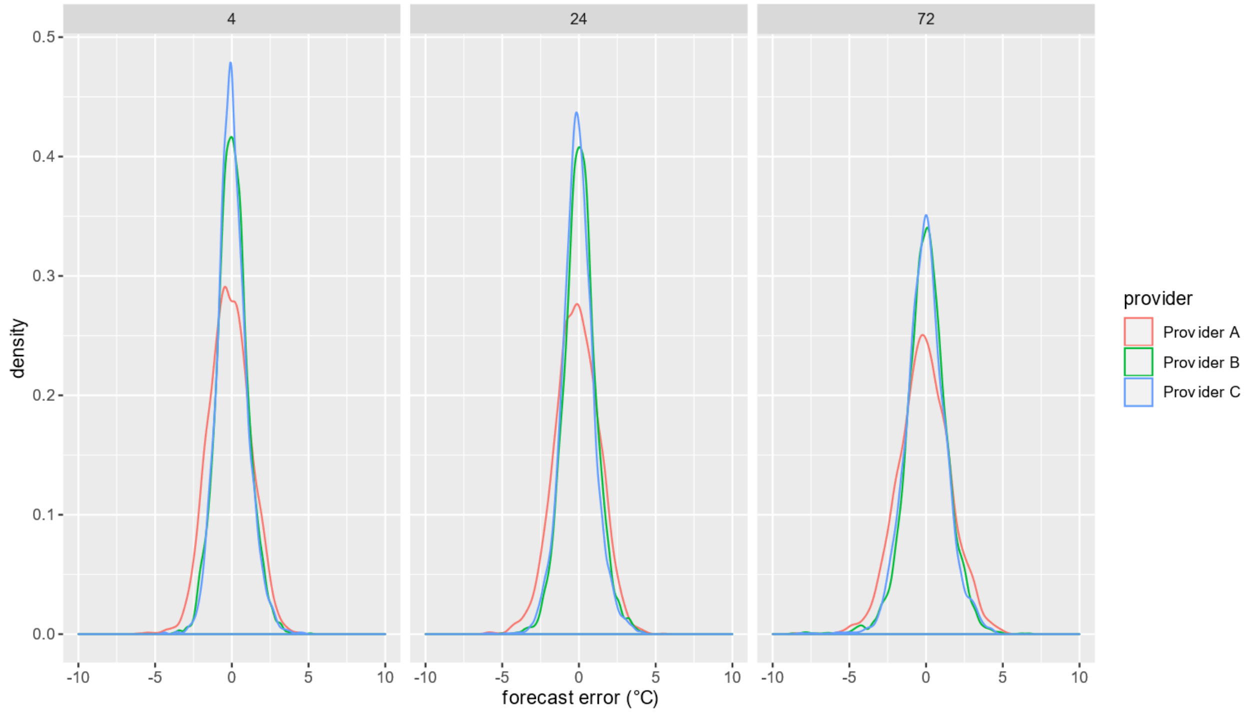
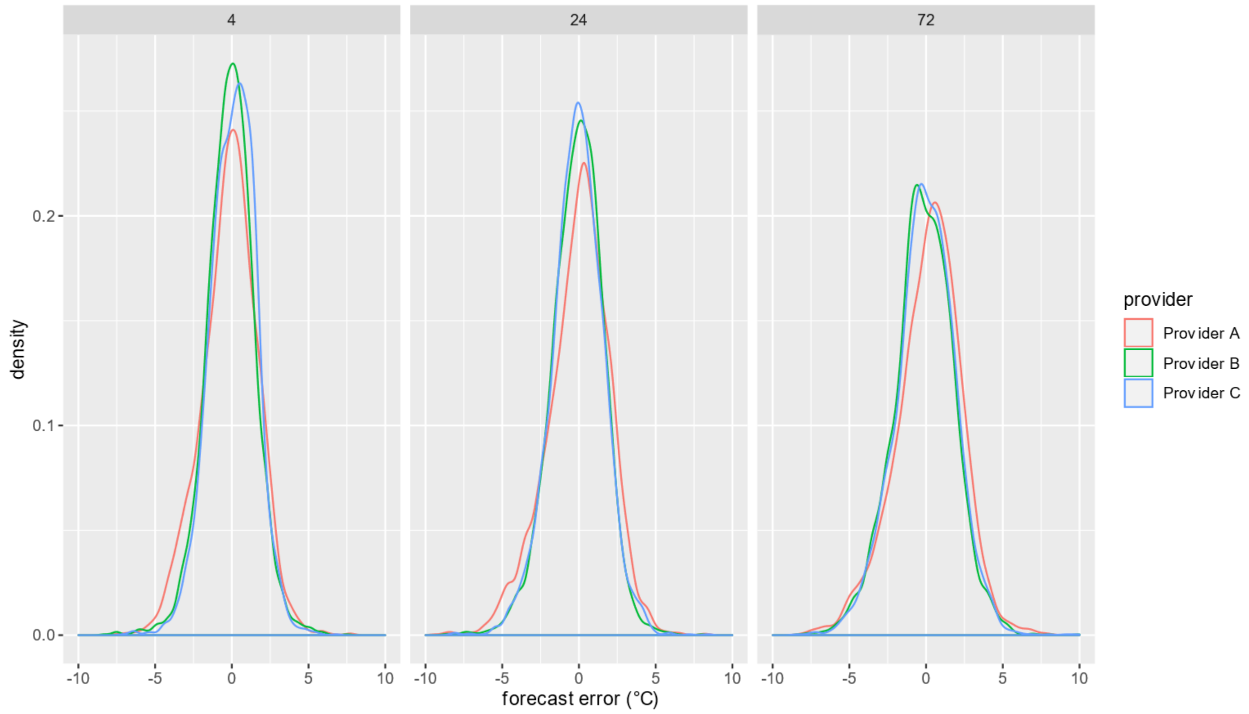


Figure 23 Penrith Lakes, all providers, all winter of 2019, 4-, 24-, and 72-hour ahead time horizons



A2. Intraday Mean Absolute Error profiles

Figure 24 Intraday hourly MAE profile for each provider at Archerfield Airport, winter 2019

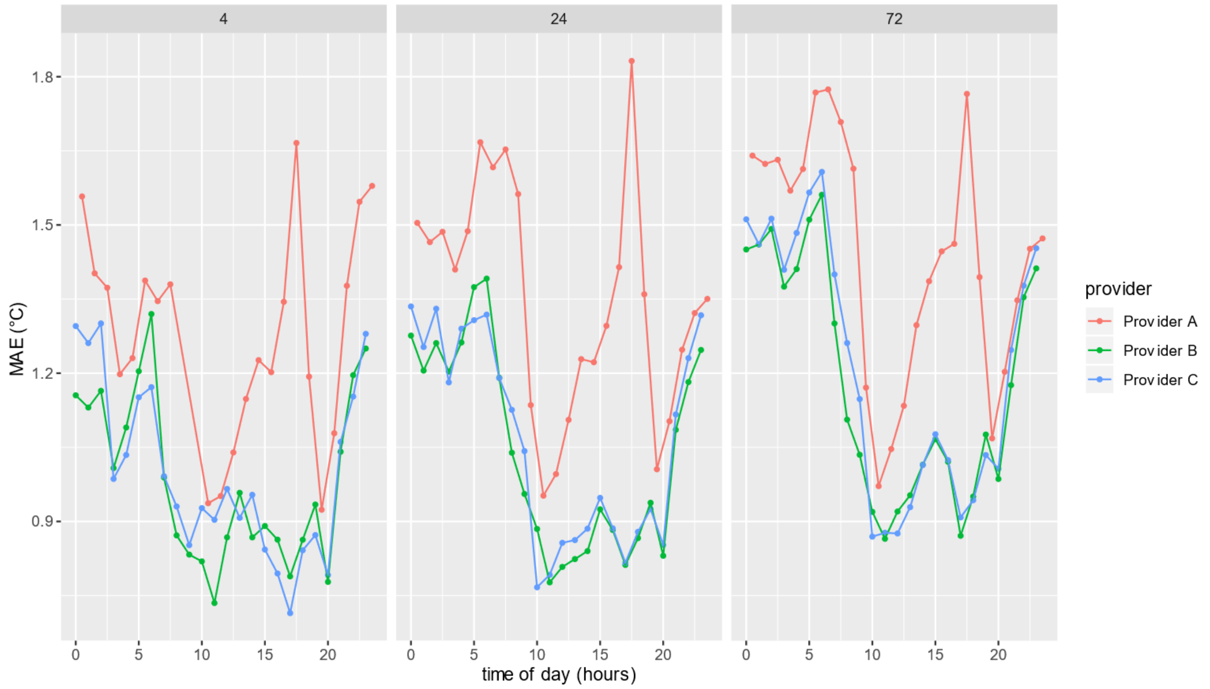


Figure 25 Intraday hourly MAE profile for each provider at Bankstown Airport, winter 2019

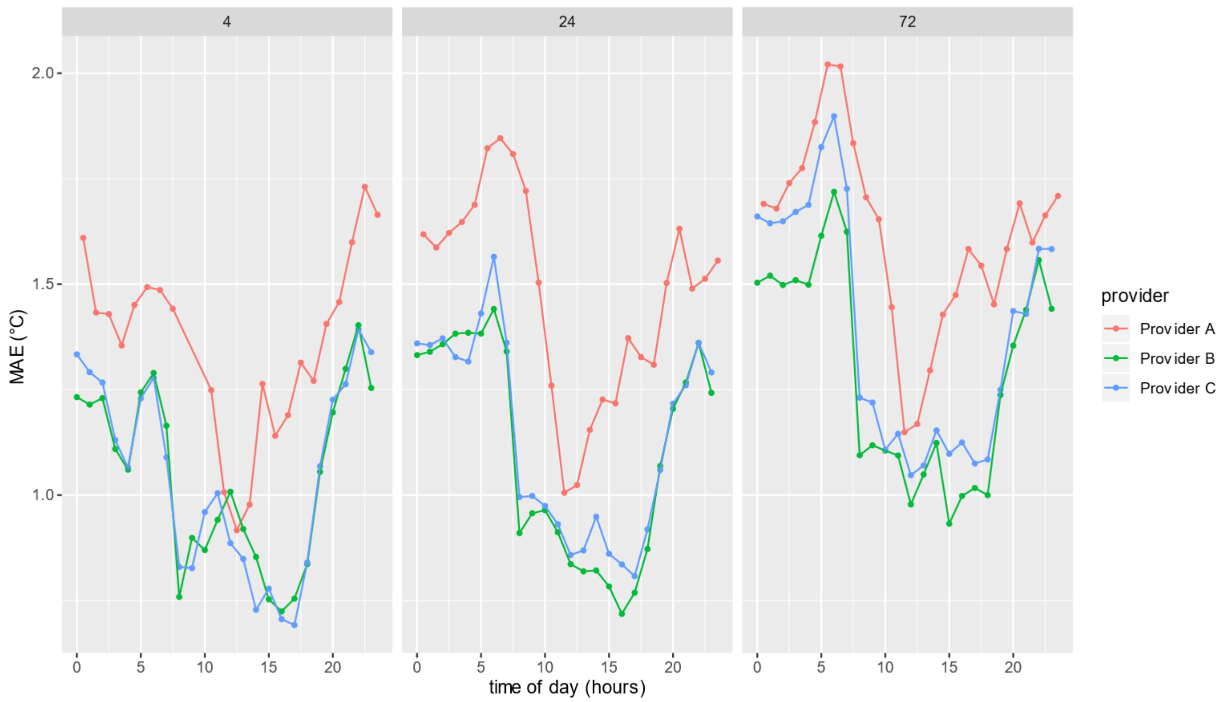


Figure 26 Intraday hourly MAE profile for each provider at Hobart Airport, winter 2019

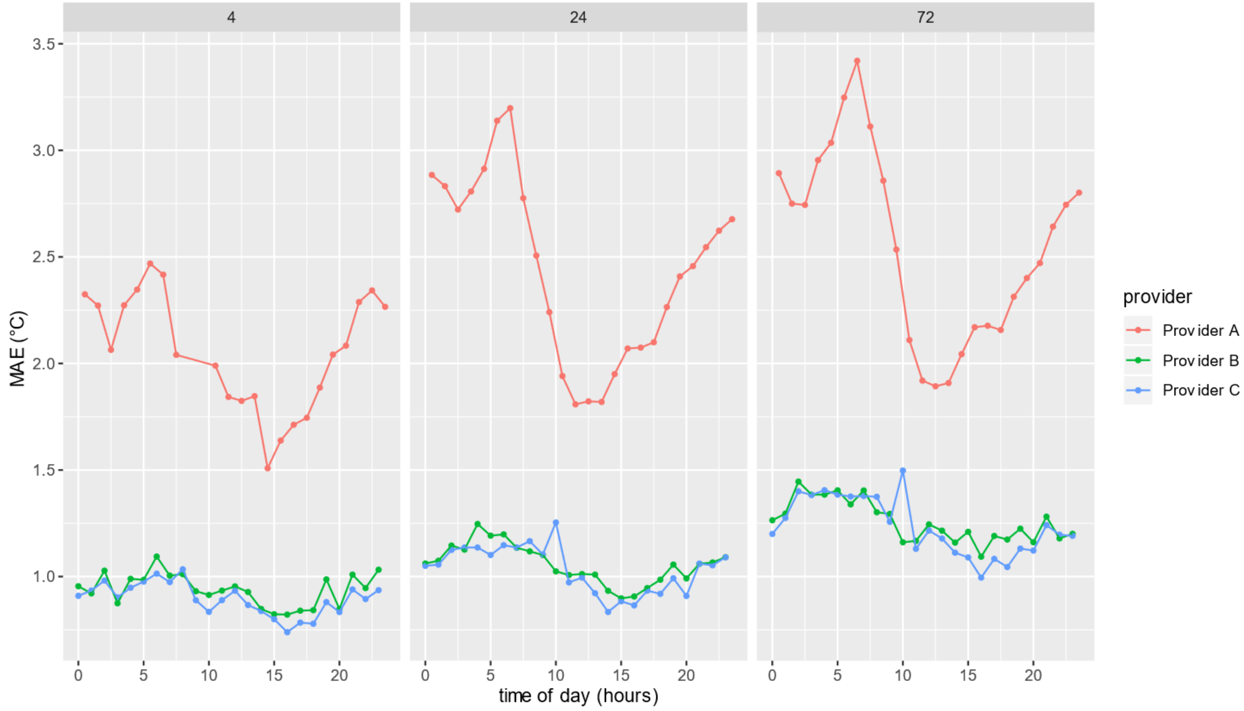


Figure 27 Intraday hourly MAE profile for each provider at Kent Town, winter 2019

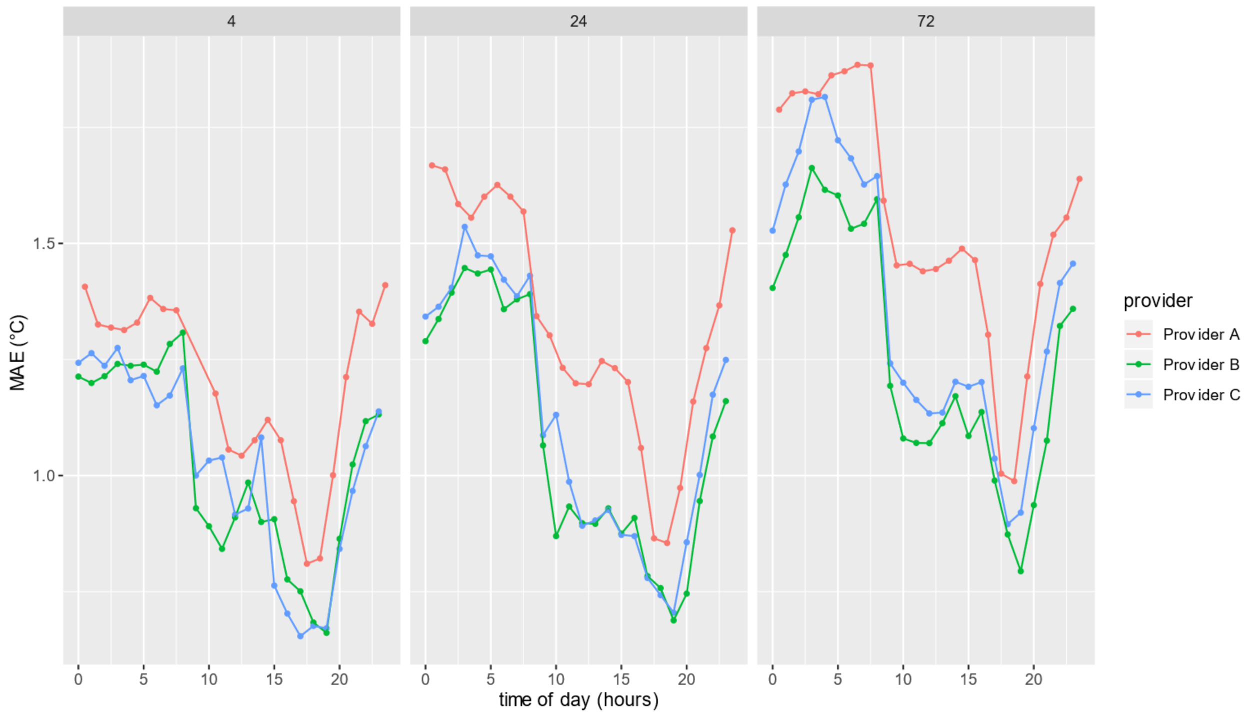


Figure 28 Intraday hourly MAE profile for each provider at Melbourne (Olympic Park), winter 2019

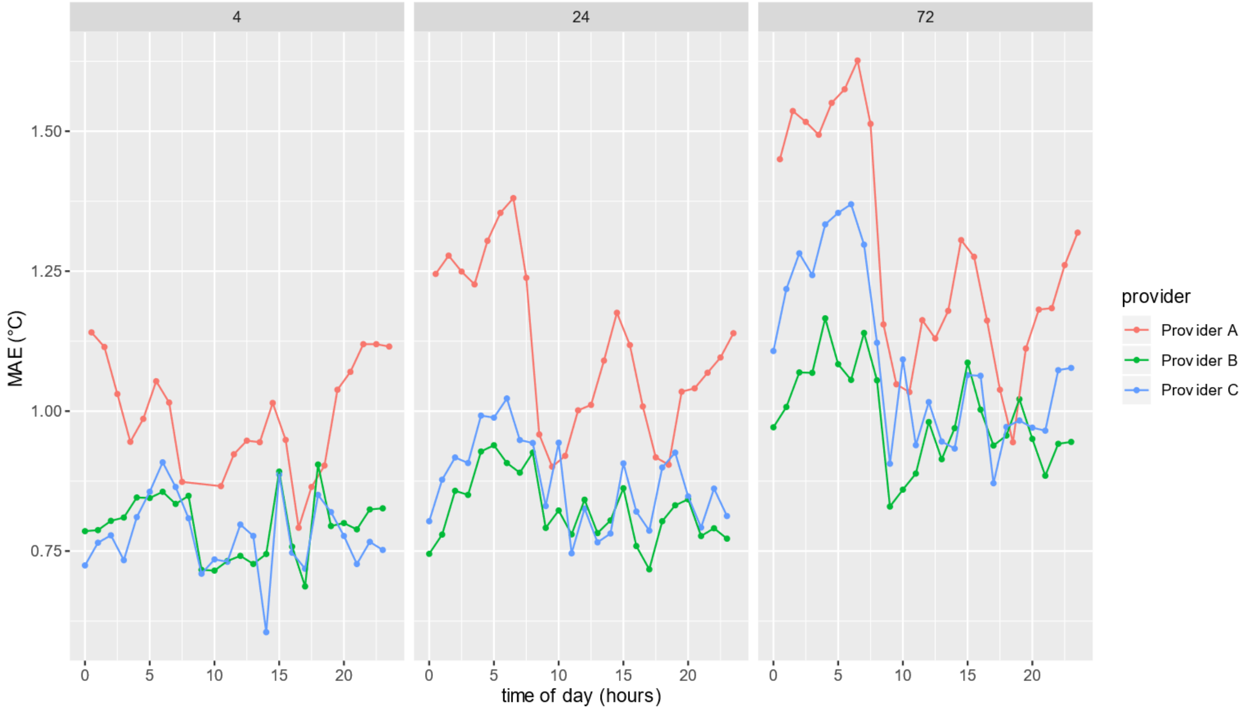


Figure 29 Intraday hourly MAE profile for each provider at Melbourne Airport, winter 2019

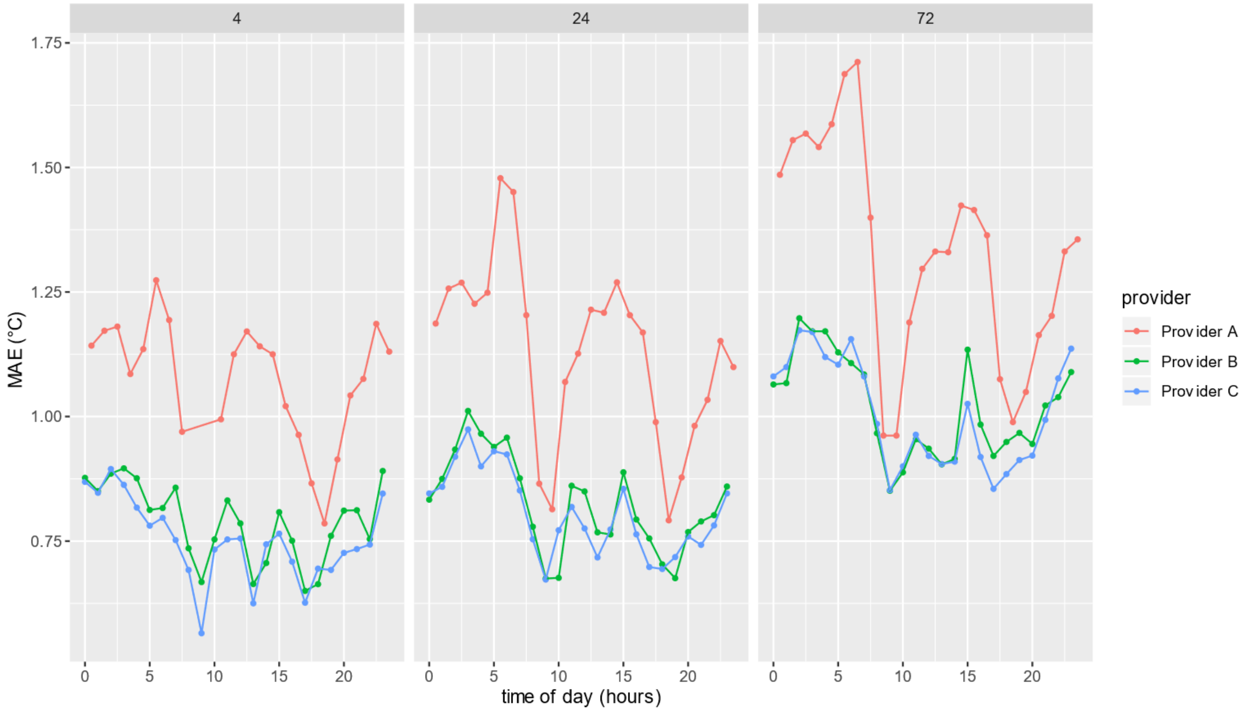


Figure 30 Intraday hourly MAE profile for each provider at Penrith Lakes, winter 2019