Non-scheduled generation and load in central dispatch rule change request

Australian Energy Market Commission

5 September 2016

Building a better working world

Notice

Ernst & Young ("EY") was engaged on the instructions of the Australian Energy Market Commission ("AEMC") to provide an analysis of the impact of non-scheduled generation and load on dispatch demand inaccuracy (the "Services") in relation to the non-scheduled generation and load in central dispatch rule change request in accordance with our Panel Contract with AEMC dated 8 April 2016 and our Engagement Letter dated 8 June 2016 ("Agreement")

The results of EY's work, including the assumptions and qualifications made in preparing the report, are set out in EY's report dated 5 September 2016 ("Report"). The Report should be read in its entirety including the cover letter, the applicable scope of the work and any limitations. A reference to the Report includes any part of the Report. No further work has been undertaken by EY since the date of the Report to update it.

EY has prepared the Report for the benefit of the AEMC and has considered only the interests of the AEMC. EY has not been engaged to act, and has not acted, as advisor to any other party. Accordingly, EY makes no representations as to the appropriateness, accuracy or completeness of the Report for any other party's purposes.

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5 September 2016

Non-scheduled generation and load in central dispatch rule change request

Dear Veronika,

In accordance with our Panel Contract with AEMC dated 8 April 2016 and our Engagement Letter dated 8 June 2016 ("Agreement"), Ernst & Young ("we" or "EY") has been engaged by the Australian Energy Market Commission ("you", "AEMC" or the "Client") to provide an analysis of the impact of non-scheduled generation and load on dispatch demand inaccuracy (the "Report").

The enclosed Report sets out the outcomes of our work.

Purpose of our Report and restrictions on its use

The results of our work, including the assumptions and qualifications made in preparing the Report, are set out in the enclosed Report. You should read the Report in its entirety. A reference to the Report includes any part of the Report. We understand that this Report will be used by the AEMC for the purpose of informing the AEMC's assessment of the rule change requests relating to the scheduling of large loads and non-scheduled generators (the "Purpose"). Please refer to a copy of the Agreement for the restrictions relating to the use of our Report.

This Report and its contents may not be quoted, referred to or shown to any other parties except as provided in the Agreement. We accept no responsibility or liability to any person other than to AEMC or to such party to whom we have agreed in writing to accept a duty of care in respect of this Report, and accordingly if such other persons choose to rely upon any of the contents of this Report they do so at their own risk. Third parties seeking a copy of this Report will require permission from EY, and will be required to sign an access letter in the format agreed to between EY and AEMC.

Nature and scope of our work

The scope and nature of our work, including the basis and limitations, are detailed in our Agreement and in this Report.

Our work commenced on 25 May 2016 and was completed on 5 September 2016. Therefore, our Report does not take account of events or circumstances arising after 5 September 2016 and we have no responsibility to update the Report for such events or circumstances.

Limitations

This investigation has been completed based on load and non-scheduled generation data provided by the AEMC. The limitations that arise from this data are discussed in detail in this Report. In summary, the key limitation relates to the unavailability of 5-minute data for all large loads and most non-scheduled generators analysed.

This letter should be read in conjunction with our detailed Report, which is attached.

Thank you for the opportunity to work on this project for you. Should you wish to discuss any aspect of this Report, please do not hesitate to contact Ian Rose on 07 3227 1415 or Michael Fenech on 07 3243 3753.

Yours sincerely

Ian Rose
Executive Director

Michael Fenech
Partner

Executive summary

This Report outlines the analysis conducted by EY to support the AEMC's review into the scheduling of large loads and non-scheduled generators. EY has undertaken a detailed quantitative review of market data recorded in AEMO market systems and provided to EY for the purpose of this assessment to determine the extent to which the current treatment of large loads and non-intermittent, non-scheduled generators results in inaccuracies in the regional forecast of demand for dispatch and pre-dispatch.

A focus of our analysis has been to determine the extent to which dispatch demand forecast inaccuracies are the result of price responsive behaviour. Price responsive behaviour has the potential to result in demand inaccuracies due to the ability for large loads and non-scheduled generation to change their consumption/generation during a dispatch interval without regard for the central dispatch process. Forcing these units to participate in the central dispatch process in some way, would likely reduce the impact of price responsive behaviours on demand forecast inaccuracies.

This Report presents analysis that quantifies the frequency at which the behaviour of large loads and non-scheduled generators contributes to demand forecast inaccuracy. It also contains a qualitative discussion of the potential impacts of the rule change.

The key results of our analysis are as follows:

- There is a correlation between wholesale market prices and dispatch demand inaccuracy. In particular, high wholesale prices in Queensland and South Australia result in an increased likelihood of large overestimates in dispatch demand. Similarly, price volatility at the dispatch interval (DI) level within the previous trading interval (TI) is at times well aligned with underestimates in dispatch demand. However, the majority of DIs with large dispatch demand error have no observable relationship with price responsive behaviour.

- In the majority of DIs with large dispatch demand error, there is no observable contribution from any of the facilities analysed. This could be due to limitations in our analysis due to data availability, or show that other factors such as natural variability in residential and commercial demand are more significant.

- For some facility types, changes in facility consumption/generation are aligned with regional dispatch demand error. This indicates that some facility types are contributing to large errors in the forecast of demand at the regional level. The correlation observed for highly variable facility types such as steel and paper mills is less conclusive. However the contribution from the very large loads such as smelters and Townsville Zinc are highly correlated with DIs of large dispatch demand inaccuracy.

- In South Australia, Angaston's price responsive behaviour was found to have contributed to many of the large dispatch demand inaccuracies. Angaston has since been reclassified as a scheduled generator.

- For the facility types that do contribute to regional error, a significant proportion of the contribution is due to behaviour that is linked to price response.

- Pre-dispatch demand forecast accuracy reduces as the forecast horizon increases. Specifically, pre-dispatch forecasts 30 minutes before the start of a dispatch interval are significantly less accurate than dispatch demand forecasts. The extent to which price responsive behaviour contributes to pre-dispatch error is not as material as the contribution to dispatch demand error. A similar set of facilities are found to contribute to pre-dispatch demand error as was found to contribute to dispatch demand error.

The outcomes above suggest that there is potentially a material issue with the current treatment of large loads and non-scheduled generators. However, the unavailability of 5-minute data for many of the facilities, particularly the large loads, means it is impossible to accurately quantify the proportion of demand inaccuracy that can be attributed to these facilities. Furthermore, the complexity of price responsive behaviour also makes it challenging to conclusively determine whether dispatch demand error is caused by, correlated with, or unrelated to dispatch and pre-dispatch price outcomes.

Moreover, our analysis suggests that some facilities that frequently contribute to dispatch demand error are highly variable in their operation at all times. It is a matter for further consideration whether a rule change to schedule these facilities would result in improved dispatch accuracy. In contrast, the scheduling of facilities such as smelters and Townsville Zinc, whose contribution to regional error appears more closely related to price signals, is more likely to improve dispatch accuracy.

The Report summarises our methodology and outlines important results from our analysis. A more comprehensive set of data analysis was provided to the AEMC in an accompanying Excel workbook.

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1. Introduction

The AEMC is currently considering two rule change requests related to the treatment of large, non-scheduled market loads and non-scheduled generators in the central dispatch process. Under the current rules, these participants are permitted to consume and generate energy without regard to instructions from the Australian Energy Market Operator (AEMO). This may lead to inaccuracies in demand and pre-dispatch demand forecasts which may have implications for efficient, safe and reliable operation of the National Electricity Market (NEM).

AEMO forecast dispatch demand and the first interval of five-minute pre-dispatch (5MPD) demand using a neural network model that uses recent observations of changes in scheduled demand as inputs. There is limited documentation of AEMO's neural network modelling. Key documents are:

- *Five minute electricity demand forecasting: neural network model documentation*, 11 September 2014
- *5-minute pre-dispatch demand forecasting using historical demand change profile business specification*, 1 July 2010.

Wind and solar generation forecasts by the Australian Wind Energy Forecasting System (AWEFS) and the Australian Solar Energy Forecasting System (ASEFS) respectively may also be incorporated but the documentation is unclear. The neural network model does not separately forecast components of load (e.g. large industrial loads), or non-scheduled generators. Consequently, the neural network model could lack the capability to accurately forecast these load and generation components, particularly for unexpected changes such as a response by these non-scheduled facilities to a price spike event.

EY has been engaged to determine the materiality of these issues. In particular, EY has undertaken quantitative analysis to determine the proportion of large demand inaccuracies that can be attributed to large loads and non-wind, non-intermittent non-scheduled generators. EY has also classified the nature of price response in the NEM, and the extent to which price responsiveness contributes to demand forecast inaccuracies.

EY has not been engaged to determine the impact of these inaccuracies on market dispatch outcomes such as wholesale market prices. Our analysis has not considered in a quantitative manner the impact of the changes to the market rules proposed in the rule change requests. If large loads and some non-scheduled generators were to become scheduled as proposed by the rules changes, they would be required to accurately forecast their consumption/generation in order to bid in dispatch. Given the data available, it is not possible to determine their ability to do so.

This Report details the results of our analysis. The Report is structured as follows:

- Section 2 describes the input data that has been provided.
- Section 3 outlines the set of methodologies that have been applied to undertake our quantitative analysis.
- Section 4 presents an analysis of the trends observed in regional error data.
- Section 5 details our analysis of the level of price responsiveness evident in regional errors.
- Section 6 summarises our analysis of individual facility and facility aggregations.
- Section 7 highlights our key observations relating to the contribution of facility types to regional error.
- Section 8 provides a summary of our analysis of pre-dispatch demand error.
- Appendix A contains a list of definitions of key terminology used throughout this document. Each term is also explained in the main body of the Report when it is first used.

2. Input data

We have used a set of large loads >30 MW and non-intermittent small non-scheduled generators > 5 MW supplied by AEMO for the period 31 January 2011 to 4 May 2016. This section describes these data sets and several relevant notes and observations. Overall, we had 5-minute data for nine non-scheduled generators and 30-minute data for 51 non-scheduled generators and 22 large loads.

2.1 5-minute data

All the 5-minute data supplied by AEMO was for non-scheduled generators. There are several issues with the 5-minute data:

- For some DIs, data is 'LAST_TARGET' rather than a 'SCADA' read. According to the explanatory note provided by AEMO,

  If Last Target, the SCADA was not received by AEMO systems, or suspect or bad data and hence we assume the DUID was compliant with the last target issued, and this is used in the dispatch run of the next interval.

  On this basis we understand LAST_TARGET to refer to each generators own SCADA system, as distinct from a target set by AEMO during dispatch.

  This indicates that change in generation after dispatch is not captured in these instances. This change in operation is exactly what we are trying to observe and associate with price response where possible. Furthermore, successive data points flagged as LAST_TARGET could result in accumulating divergence between actual behaviour and the 5-minute data. The data stream will eventually re-synchronise with reality when the next SCADA reading is received, but this means there may be an apparent large change in generation in a single DI, when in reality that change occurred several DIs prior, or over a number of DIs.

  The LAST_TARGET data flag applied to 83% of DIs for ANGAS1 and ANGAS2 and to 10 DIs for CALL_A_4. For ANGAS1 and ANGAS2, we observed their behaviour fits with that of a price responsive peaking generator if we assume the data stream is re-synchronising at the end of each DI. That is, for DIs flagged as LAST_TARGET take the value recorded from the next DI. For example, for a 6:05 DI labelled as LAST_TARGET we assume that the value supplied for the 6:10 DI is equivalent to a SCADA reading at around 6:05.

- Error in SCADA data can be up to ±4%.

- In addition, AEMO notes that some data points have been determined to be suspect and manually replaced "by either the control room, state estimator, or remotely at the site". No analysis of the frequency of these data flags has been performed.

- Several other facilities have all blanks or zero generation (Table 1). These have been excluded from our analysis. We do not know if the zeroes recorded for these facilities are true values, or if the data is actually missing. Portland and Point Henry smelters certainly consumed electricity during the study period – however whether these particular SCADA metering points represent the entire facility is unclear.

Table 1: Non-scheduled generators in AEMO dataset with zero or no generation

DUID	Region	Description	Comment on data
APD01	VIC	Portland	0 MWh recorded in 99.9% of DIs. Remaining DIs have no data recorded.
APD02	VIC	Portland	0 MWh recorded in 100% of DIs
BURRIN	NSW	Burrinjuck hydro	0 MWh recorded in 58.0% of DIs Remaining DIs have no data recorded.
PTH01	VIC	Point Henry 1	0 MWh recorded in 100% of DIs
PTH02	VIC	Point Henry 2	0 MWh recorded in 100% of DIs
PTH03	VIC	Point Henry 3	0 MWh recorded in 100% of DIs
SNOWYGJP	VIC	Jindabyne pump at Guthega (also a load)	0 MWh recorded in 99.9% of DIs Remaining DIs have no data recorded.
STANV1	SA	Pt Stanvac PS diesel compression	No data
STANV2	SA	Pt Stanvac PS diesel compression	No data

- We also excluded all Tasmanian generators from the analysis. There were seven Tasmanian generators with 5-minute data: BBDISEL1, CATAGUN1, GEORGTN1, GEORGTN2, MEADOWB2, PORTLAT1, QUERIVE1 (all diesel generators installed during the Basslink outage from 20/12/2015 to 10/06/2016).
- We also excluded REDBANK1 from our analysis due to its infrequent and small operation. It was registered at non-scheduled between 02/01/2015 and 13/10/2015. In this period is generated 117.8 MWh and operated at a maximum of 2 MW.
- In the 5-minute data for RPCG we observed a string of values of 221.9449 MW between 11/06/2011 18:15 and 12/06/2011 06:55. The nameplate capacity of RPCG in the registration data supplied by AEMO is 30 MW and the corresponding 30-minute for this period was 0 MW. Therefore, we assumed these were erroneous values and treated them as missing data.
- LONSDALE became scheduled on 12/01/2016. The data set provided has 5-minute data available from 04/01/2016, presumably associated with a change in meter prior to becoming scheduled. As there were only a few days of 5-minute data from the period when LONSDALE was non-scheduled, we only used the 30-minute data in our analysis.
- ANGAS1 and ANGAS2 were scheduled until 01/01/2012. They recently returned to scheduled status after our analysis period. In the intervening period of time, these units were non-scheduled but had a special status where they are included in the operational demand definition owing to their status as 'significant non-scheduled non-wind/non-solar generation which have impact on the NEM'[1]. We originally excluded Angaston from our analysis because of this special status. However, at a late stage we were informed by AEMO that this status does not apply to scheduled demand used for dispatch and 5MPD. We have maintained a separate analysis of these facilities to determine their impact on dispatch demand accuracy in the study period. In this analysis, we have aggregated ANGAS1 and ANGAS2 into a single station ANGASTON.
- Where both 5- and 30-minute data was available, we observed discrepancies between the calculated 30-minute average and the recorded 30-minute dispatch. We use the 5-minute data and have not done any further analysis of the 30-minute data in these instances.
- We note that GERMCRK, RPCG and GB01 occasionally consume rather generate. For GERMCRK and GB01 consumption is very small relative to generation in line with small auxiliary load. In contrast, RPCG consumed almost as much energy as it generates. As a bagasse cogen, it presumably exports energy when it has excess and draws energy from the grid when it has a shortfall but needs to run the sugar mill.

[1] AEMO, May 2016, *Demand terms in EMMS data model*, Available at: https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Security-and-reliability/Dispatch-information. Accessed 1 September 2016.

Overall, there were nine non-scheduled generators with 5-minute data included in our analysis (see Table 5). Each has been included in our analysis for the period during which it was registered as non-scheduled.

2.2 30-minute data

AEMO supplied 30-minute data for loads and small non-scheduled generators. There are several points to note regarding the 30-minute data:

- We were supplied data at the NMI level and aggregated all data to the facility level for our analysis. Some NMIs had multiple channels. As instructed by AEMO, we aggregated all channels with the prefix ‘N’. Some DUIDs had multiple NMIs which were aggregated together.

- Most facilities have data which is both positive (consumption) and negative (generation). In most instances, this doesn’t appear problematic. For example, APPIN waste coal mine gas has data in the range -51.58MW to 0.62 MW[2]. For non-scheduled generators, the small positive values are possible when drawing power within the station in intervals of no generation. Negative values for loads are more difficult to understand but have not been investigated further.

- For some facilities the range appears inexplicably large on either side of zero. Specifically, loads with large negative values and non-scheduled generators with large positive values. Facilities that are particularly unusual in this regard are listed in Table 2.

Table 2: Non-scheduled generators and loads with unusually large data ranges (negative is generation, positive is consumption)[3]

Facility	Region	Description	Minimum MW	Maximum MW
Lake Cowal Mine	NSW	Load: Lake Cowal Mine	-5.53	64.49
Maryvale Paper Mill	VIC	Load: Maryvale Paper Mill	-6.81	59.12
Port Kembla Steel Mill	NSW	Load: Port Kembla Steel Mill	-4.64	91.19
Portland Aluminium Smelter	VIC	Load: Portland Aluminium Smelter	-62.39	513.28
Whyalla Steelworks	SA	Load: Whyalla Steelworks	-4.26	39.91
BOLIVAR1	SA	Bolivar waste water treatment plant	-4.78	5.59
BWTR1	NSW	Broadwater bagasse cogen	-54.05	7.82
CONDONG1	NSW	Condong bagasse cogen	-27.48	5.26
GLBWNHYD	NSW	Glenbawn hydro	-4.79	5.21
LONGFORD	VIC	Longford OCGT	-16.67	2.21
MORANBAH	QLD	Moranbah Generation Project waste coal mine gas	-9.08	4.51
RACOMIL1	QLD	Racecourse Mill bagasse cogen	-33.60	8.08
WDLNGNO1	NSW	Woodlawn bioreactor	-6.27	1.71

- There are also some facilities registered as non-scheduled generators that are actually loads (Table 3). These are mostly small auxiliary loads. The exception is SNOWYGJP the Jindabyne pump at Guthega.

Table 3: Facilities registered as non-scheduled generators that are loads

DUID	Region	Description	Max absolute MW	Total energy over study period (GWh)
SNOWYGJP	VIC	Jindabyne pump at Guthega	70.29	393.27
NPSNL1	SA	Playford Northern PS Load 1	23.23	53.53
MPNL1	NSW	Mt Piper PS Load	19.10	1.48

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[2] Negative is generation, positive is consumption.

[3] Values in red are unusual and denote loads that are generating, or generators that are consuming energy.

DUID	Region	Description	Max absolute MW	Total energy over study period (GWh)
WWNL1	NSW	Wallerawang Load	16.35	171.41
CALLNL1	QLD	Callide PS Load	14.50	146.41
TORNL1	SA	Torrens Island PS Load	13.14	126.20
CALLNL4	QLD	Callide A PS Unit 4 Load	13.05	217.85
SWANNL2	QLD	Swanbank Load	10.63	45.05
NPSNL2	SA	Leigh Creek Northern PS Load 2	3.04	48.78
DRYCNL	SA	Dry Creek Load	1.24	4.76
TUMT3NL1	NSW	Lower Tumut T2 Auxiliary	1.09	5.38
MURAYNL2	VIC	Murray Power Station M2 Auxiliary	1.02	13.99
TUMT3NL2	NSW	Lower Tumut T4 Auxiliary	0.97	3.76
GUTHNL1	NSW	Guthega Auxiliary Supply	0.95	2.43
MURAYNL1	VIC	Murray Power Station M1 Auxiliary	0.84	5.74
MURAYNL3	VIC	Geehi Tee off Auxiliary	0.23	0.39
MINTNL1	SA	Mintaro Load	0.16	1.17
TUMT3NL3	NSW	Lower Tumut Pipeline Auxiliary	0.14	1.52
SNUGNL1	SA	Snuggery Power Station Load	0.06	0.29

- Tasmanian generators and wind and solar generators are also excluded from analysis.
- Where there was both 5- and 30-minute data available, we only used the 5 minute data (GERMCRK, JOUNAMA1, MBAHNTH, RPCG, SNOWYGJP, ANGAS1 and ANGAS2), with the exception of LONSDALE.

Overall, after all exclusions, there were 22 loads with 30-minute data, 32 non-scheduled generators with 30-minute data, 19 non-scheduled loads registered as non-scheduled generators (see Table 5 for the list of facilities, alongside the nine generators with 5-minute data). Each facility has been included in our analysis for the period during which it was registered as non-scheduled.

2.3 Omissions from data set

There are some obvious load omissions to this data set such as the now closed Point Henry and Kurri Kurri aluminium smelters.

In addition, there are quite a few facilities registered as non-scheduled, non-intermittent generators with maximum capacity greater than 5 MW in AEMO's registration summary database for which we did not receive data from AEMO. These facilities are listed in Table 4. We understand there is no data available for these facilities. Some are likely disused DUIDs e.g. the Murray 1, Murray 2, Tumut 1, Tumut 2 and Tumut 3 units have been scheduled units with different DUIDs throughout the study period. We also note that all auxiliary loads registered as non-scheduled generators are registered with a maximum capacity of 30 MW. This is also the case for the auxiliary loads listed in Table 3 for which we have data and does not appear to be reflective of the maximum consumption observed at these facilities.

Table 4: Registered non-scheduled, non-intermittent generators with no data supplied

DUID	Region	Description	Maximum capacity
BDONGHYD	NSW	Burrendong hydro	14 MW from 1/7/2012 19 MW from 7/12/2012
BERWICK	VIC	Berwick landfill gas	7 MW from 1/7/2012
COLNSNL1	QLD	Collinsville auxiliary load	30 MW from 1/7/2011 to 1/1/2013
EASTCRK2	NSW	Eastern Creek landfill gas	10 MW from 1/7/2012
ERNL1	NSW	Eraring auxiliary load	30 MW from 2/3/2011
GLADNL1	QLD	Gladstone auxiliary load	30 MW
GLENNCRK	NSW	Glennies Creek waste coal mine gas	13 MW
GUTH-1	NSW	Guthega	30 MW from 1/1/2011 to 22/11/2011

DUID	Region	Description	Maximum capacity
GUTH-2	NSW	Guthega	30 MW from 1/1/2011 to 22/11/2011
HWPNL1	VIC	Hazelwood auxiliary load	30 MW
KEEPIT	NSW	Keepit hydro	8 MW
LIDDNL1	NSW	Liddell auxiliary load	30 MW
LYNL1	VIC	Loy Yang auxiliary load	30 MW
MMNL1	NSW	Munmorah auxiliary load	30 MW from 1/1/2011 to 29/5/2014
MORNL1	VIC	Morwell auxiliary load	30 MW from 1/1/2011 to 11/3/2016
MURR1-1	VIC	Murray 1	95 MW from 6/1/2011
MURR1-10	VIC	Murray 1	95 MW from 6/1/2011
MURR1-2	VIC	Murray 1	95 MW from 6/1/2011
MURR1-3	VIC	Murray 1	95 MW from 6/1/2011
MURR1-4	VIC	Murray 1	95 MW from 6/1/2011
MURR1-5	VIC	Murray 1	95 MW from 6/1/2011
MURR1-6	VIC	Murray 1	95 MW from 6/1/2011
MURR1-7	VIC	Murray 1	95 MW from 6/1/2011
MURR1-8	VIC	Murray 1	95 MW from 6/1/2011
MURR1-9	VIC	Murray 1	95 MW from 6/1/2011
MURR2-1	VIC	Murray 2	138 MW from 6/1/2011
MURR2-2	VIC	Murray 2	138 MW from 6/1/2011
MURR2-3	VIC	Murray 2	138 MW from 6/1/2011
MURR2-4	VIC	Murray 2	202 MW from 6/1/2011
SNUG2	SA	Snuggery diesel	21 MW
SNUG3	SA	Snuggery diesel	21 MW
STANNL1	QLD	Stanwell auxiliary load	30 MW
STANV1	SA	Port Stanvac A	32 MW from 1/7/2011 to 12/1/2016
STANV2	SA	Port Stanvac B	32 MW from 1/7/2011 to 12/1/2016
TARNL1	QLD	Tarong auxiliary load	30 MW
TUMUT1-1	NSW	Tumut 1	82 MW from 6/1/2011
TUMUT1-2	NSW	Tumut 1	82 MW from 6/1/2011
TUMUT1-3	NSW	Tumut 1	82 MW from 6/1/2011
TUMUT1-4	NSW	Tumut 1	82 MW from 6/1/2011
TUMUT2-1	NSW	Tumut 2	72 MW from 6/1/2011
TUMUT2-2	NSW	Tumut 2	72 MW from 6/1/2011
TUMUT2-3	NSW	Tumut 2	72 MW from 6/1/2011
TUMUT2-4	NSW	Tumut 2	72 MW from 6/1/2011
TUMUT3-1	NSW	Tumut 3	300 MW from 6/1/2011
TUMUT3-2	NSW	Tumut 3	300 MW from 6/1/2011
TUMUT3-3	NSW	Tumut 3	300 MW from 6/1/2011
TUMUT3-4	NSW	Tumut 3	300 MW from 6/1/2011
TUMUT3-5	NSW	Tumut 3	250 MW from 6/1/2011
TUMUT3-6	NSW	Tumut 3	300 MW from 6/1/2011
VICMILL1	QLD	Victoria mill	24 MW from 9/8/2011
VICSMLT	VIC	Pt Henry aluminium smelter load	300 MW from 1/7/2012 to 11/5/2015
VICSMLT2	VIC	Pt Henry aluminium smelter load	300 MW from 1/7/2012
VPNL1	NSW	Vales Point auxiliary load	30 MW
YWNL1	VIC	Yallourn auxiliary load	30 MW

Additional non-scheduled units that appear in AEMO's generation information page archives[4] are intermittent and excluded from our analysis. This included PIONEER (a bagasse facility) and CLOVER (a run-of-river hydro facility) who produced a reasonable amount of energy in the study period, but are classified as intermittent by AEMO and therefore excluded from the rule change request and our analysis.

[4] AEMO, Generation Information Page, Available at: https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/Generation-information.

2.4 Facility categories

Part of our analysis has involved grouping facilities into categories with similar operational patterns. Where relevant we have aggregated facilities by these categories for the purpose of identifying the contribution of the facility type to regional error. The categories are listed in Table 5.

Table 5: List of facilities included in analysis with facility categories

Facility	Region	Category	Data Type	Description
Albury paper Mill	NSW	Load: mill	30-minute	Albury paper Mill
Port Kembla Steel Mill	NSW	Load: mill	30-minute	Port Kembla Steel Mill
Sydney Steel Mill	NSW	Load: mill	30-minute	Sydney Steel Mill
Waratah Steel	NSW	Load: mill	30-minute	Waratah Steel
Cadia Mine	NSW	Load: mine	30-minute	Cadia Mine
Lake Cowal Mine	NSW	Load: mine	30-minute	Lake Cowal Mine
Orica Botany Chlor Alkali	NSW	Load: other	30-minute	Orica Botany Chlor Alkali
Tomago Aluminium Smelter	NSW	Load: smelter	30-minute	Tomago Aluminium Smelter
GUTHNL1	NSW	NS gen: auxiliary	30-minute	Guthega Auxiliary Supply
MPNL1	NSW	NS gen: auxiliary	30-minute	Mt Piper PS auxiliary load
TUMT3NL1	NSW	NS gen: auxiliary	30-minute	Lower Tumut T2 Auxiliary
TUMT3NL2	NSW	NS gen: auxiliary	30-minute	Lower Tumut T4 Auxiliary
TUMT3NL3	NSW	NS gen: auxiliary	30-minute	Lower Tumut Pipeline Auxiliary
WWNL1	NSW	NS gen: auxiliary	30-minute	Wallerawang auxiliary load
BWTR1	NSW	NS gen: bagasse	30-minute	Broadwater bagasse cogen
CONDONG1	NSW	NS gen: bagasse	30-minute	Condong bagasse cogen
APPIN	NSW	NS gen: coal gas	30-minute	Appin waste coal mine gas spark
TAHMOOR1	NSW	NS gen: coal gas	30-minute	Tahmoor CCGT waste coal mine gas
TERALBA	NSW	NS gen: coal gas	30-minute	Teralba waste coal mine gas spark
TOWER	NSW	NS gen: coal gas	30-minute	Tower waste coal mine gas
BROWNMT	NSW	NS gen: hydro	30-minute	Brown Mountain hydro
BURRIN	NSW	NS gen: hydro	30-minute	Burrinjuck hydro
COPTNHYD	NSW	NS gen: hydro	30-minute	Copeton hydro
GLBWNHYD	NSW	NS gen: hydro	30-minute	Glenbawn hydro
JOUNAMA1	NSW	NS gen: hydro	5-minute	Jounama hydro
PINDARI	NSW	NS gen: hydro	30-minute	Pindari hydro
WYANGALA	NSW	NS gen: hydro	30-minute	Wyangala A hydro
LUCASHGT	NSW	NS gen: landfill gas	30-minute	Lucas Heights I landfill gas spark
WDLNGN01	NSW	NS gen: medium utilisation	30-minute	Woodlawn bioreactor
WILGAPK	NSW	NS gen: medium utilisation	30-minute	Wilga Park Power Station A GT spark
WILGB01	NSW	NS gen: medium utilisation	30-minute	Wilga Park Power Station B GT spark
ERGT01	NSW	NS gen: peaking	5-minute	Eraring 330 BS UN (GT) diesel compression
GB01	NSW	NS gen: peaking	5-minute	Broken Hill GT
HEZ	NSW	NS gen: peaking	30-minute	Hunter Economic Zone diesel peaking compression
Blackwater Mine	QLD	Load: mine	30-minute	Blackwater Mine
Curragh Mine	QLD	Load: mine	30-minute	Curragh Mine
Dawson Mine	QLD	Load: mine	30-minute	Dawson Mine
Peak Downs Mine	QLD	Load: mine	30-minute	Peak Downs Mine
Queensland Alumina	QLD	Load: other	30-minute	Queensland Alumina
Townsville Zinc	QLD	Load: other	30-minute	Townsville Zinc
Yarwun Alumina	QLD	Load: other	30-minute	Yarwun Alumina
Boyne Island Aluminium Smelter	QLD	Load: smelter	30-minute	Boyne Island Aluminium Smelter
CALLNL1	QLD	NS gen: auxiliary	30-minute	Callide PS auxiliary load
CALLNL4	QLD	NS gen: auxiliary	30-minute	Callide A PS Unit 4 auxiliary load

Facility	Region	Category	Data Type	Description
SWANNL2	QLD	NS gen: auxiliary	30-minute	Swanbank auxiliary load
ICSM	QLD	NS gen: bagasse	30-minute	ISIS Central Sugar Mill cogeneration
INVICTA	QLD	NS gen: bagasse	5-minute	Invicta Mill bagasse cogen
RACOMIL1	QLD	NS gen: bagasse	30-minute	Racecourse Mill bagasse cogen
RPCG	QLD	NS gen: bagasse	5-minute	Rocky Point bagasse cogen
DAANDINE	QLD	NS gen: coal gas	30-minute	Daandine coal seam gas compression
GERMCRK	QLD	NS gen: coal gas	5-minute	German Creek waste coal mine gas spark
MBAHNTH	QLD	NS gen: coal gas	5-minute	Moranbah North waste coal mine gas spark
MORANBAH	QLD	NS gen: coal gas	30-minute	Moranbah Generation Project waste coal mine gas compression
OAKYCREK	QLD	NS gen: coal gas	30-minute	Oaky Creek PS waste coal mine gas
KAREEYA5	QLD	NS gen: hydro	30-minute	Kareeya 5 hydro
CALL_A_4	QLD	NS gen: medium utilisation	5-minute	Callide A oxyfuel project
Whyalla Steelworks	SA	Load: mill	30-minute	Whyalla Steelworks
Olympic Dam	SA	Load: mine	30-minute	Olympic Dam mine
DRYCNL	SA	NS gen: auxiliary	30-minute	Dry Creek auxiliary load
MINTNL1	SA	NS gen: auxiliary	30-minute	Mintaro auxiliary load
NPSNL1	SA	NS gen: auxiliary	30-minute	Load: Playford Northern PS Load 1
NPSNL2	SA	NS gen: auxiliary	30-minute	Leigh Creek Northern PS Load 2
SNUGNL1	SA	NS gen: auxiliary	30-minute	Snuggery Power Station auxiliary load
TORNL1	SA	NS gen: auxiliary	30-minute	Torrens Island PS auxiliary load
BOLIVAR1	SA	NS gen: other	30-minute	Bolivar waste water treatment plant
ANGASTON (aggregate of ANGAS1 and ANGAS2)	SA	NS gen: peaking	5-minute	Angaston
LONSDALE	SA	NS gen: peaking	30-minute	Lonsdale diesel peaking
Laverton Steel Mill	VIC	Load: mill	30-minute	Laverton Steel Mill
Maryvale Paper Mill	VIC	Load: mill	30-minute	Maryvale Paper Mill
Geelong Refinery	VIC	Load: other	30-minute	Geelong Refinery
Portland Aluminium Smelter	VIC	Load: smelter	30-minute	Portland Aluminium Smelter
MURAYNL1	VIC	NS gen: auxiliary	30-minute	Murray Power Station M1 Auxiliary
MURAYNL2	VIC	NS gen: auxiliary	30-minute	Murray Power Station M2 Auxiliary
MURAYNL3	VIC	NS gen: auxiliary	30-minute	Geehi Tee off Auxiliary
YWNGAHYD	VIC	NS gen: hydro	30-minute	Yarrawonga hydro
BROADMDW	VIC	NS gen: landfill gas	30-minute	Broadmeadows landfill gas spark
CLAYTON	VIC	NS gen: landfill gas	30-minute	Clayton landfill gas spark
HALAMRD1	VIC	NS gen: landfill gas	30-minute	Hallam Road landfill gas spark
WOLLERT1	VIC	NS gen: landfill gas	30-minute	Wollert landfill gas spark
LONGFORD	VIC	NS gen: medium utilisation	30-minute	Longford OCGT
SNOWYGJP	VIC	NS gen: other	30-minute	Jindabyne pump at Guthega
TGNSS1	VIC	NS gen: other	30-minute	Traralgon Network Support Station gas spark

3. Methodology

This section details the methodology that has been applied to undertake this analysis. This focuses on the methodology for determining regional dispatch and pre-dispatch demand error, and for estimating the contribution of a facility to regional error.

3.1 Calculation of dispatch demand error

The TOTALDEMAND value used in NEM dispatch represents the forecast of demand made just before the start of each DI. In simplistic terms, TOTALDEMAND is based on the input conditions at the start of the DI and a forecast of the change during the DI. The forecast change is the result of the neural network model. This field is called DEMANDFORECAST.

We have calculated an “ex-post” measure of TOTALDEMAND for each DI using the initial conditions in the following DI. Our approach has been informed by input provided by AEMO. The key inputs are:

- Sum of initial MW of generation
- Net metered MW flow into region
- Sum of initial MW of scheduled loads[5]
- Total allocated interconnector losses.

The “dispatch demand error” in each DI is calculated as the difference between the TOTALDEMAND used in dispatch and the outcome of the above calculation. Dispatch demand error is calculated in each NEM region independently and is also referred to in this Report and accompanying results workbook as “regional error”.

In simplistic terms, dispatch demand error compares the forecast used in dispatch, TOTALDEMAND, with the set of inputs used in forecasting demand for the following DI. Any change that occurs after the calculation of TOTALDEMAND will affect the metered initial conditions used to determine dispatch demand in the following DI.

Due to limitations associated with having 30-minute facility data for most facilities we have generally applied a classification approach. This includes classifying whether the magnitude of regional demand error is material. We have used two error thresholds in each region to determine “large” and “small” errors. Any error below the small threshold is classified as “minor”. We have chosen the thresholds for large and small errors in each region that result in approximately 1,000 DIs of large error (whether positive or negative) and approximately 10,000 DIs of small error over the study period. The thresholds are provided in Table 6.

Table 6: Regional dispatch demand error thresholds

Region	Small error (MW)	Large error (MW)
Queensland	115	160
New South Wales	115	165
Victoria	100	150
South Australia	43	75

[5] Currently this is just the Wivenhoe pumps (DUIDs: PUMP1 and PUMP2), Shoalhaven pumps (DUID SHPUMP) and Tumut 3 pumps (DUID: SNOWYP, as distinct from the Snowy Jindabyne pump at Guthega SNOWYGJP). The Tumut 3 pumps are actually registered as non-scheduled but are dispatched as if they were scheduled loads with respect to their dispatch bids, targets and consumption.

3.2 Pre-dispatch demand error

Our analysis also includes a consideration of the impact of large loads and non-scheduled generation on the accuracy of pre-dispatch demand. For this analysis we have focused on the 5-minute pre-dispatch demand (and market) forecast which considers the next hour of DIs. We use a 30 minute time window, i.e. we determine the difference between actual demand and the forecast of demand in that DI in the pre-dispatch forecast from 30 minutes before the start of the DI.

3.3 Calculation of facility error

The key issue that affects the impact of the rule change request is the impact of deviations in the consumption/generation of large loads/non-scheduled generators from what is inherently forecast by the neural network model.

EY has not been provided access to the inputs required to reproduce the outcomes of the neural network model. It is therefore not possible to determine the contribution of any single facility to demand as forecast by the neural network model. Given this limitation, we have used a technique which uses linear regression to "forecast" the next TI/DI demand (depending on data availability) for each facility. The facility error is then determined as the difference between the forecast produced by the linear regression and actual consumption/generation. The assumption here is that these deviations would not have been forecast by the neural network model, and would therefore contribute to regional error.

3.3.1 Facilities with 30-minute data

As seen in Section 2.2, the majority of facility data we have been provided is on a 30-minute basis. With only 30-minute data available, it is impossible to estimate facility error on a 5-minute basis by applying any consistent methodology. Thirty-minute data smears the magnitude and timing of facility error. Due to this limitation of the 30-minute data, we have applied a classification approach rather than a quantification methodology.

We use a linear regression technique as a surrogate for determining "typical operation". The linear regression residual outputs are the departures from typical operation. Each facility's half-hourly consumption/generation dataset is converted into a delta dataset by determining for each TI, the difference relative to the previous TI. The deltas across the entire dataset are then used as an input in a linear regression model. The formulation of the regression is as follows:

$$\begin{aligned}\text{Facility delta } (TI_n) = \; & \text{constant} + \beta_1 \text{*Facility delta } (TI_{n-1}) + \beta_2 \text{*Facility delta } (TI_{n-48}) + \\ & \beta_3 \text{*Facility delta } (TI_{n-96}) + \beta_4 \text{*Facility delta } (TI_{n-144}) + \\ & \beta_5 \text{*Facility delta } (TI_{n-192}) + \beta_6 \text{*Facility delta } (TI_{n-240}) + \\ & \beta_7 \text{*Facility delta } (TI_{n-288}) + \beta_8 \text{*Facility delta } (TI_{n-336})\end{aligned}$$

This regression therefore uses the last half-hourly delta and the half-hourly deltas for the same time of day from the previous seven days to forecast facility delta. The residuals from this model represent the differences between the actual deltas and the forecast deltas – "facility errors".

As with regional demand, facility errors are categorised according to thresholds. The thresholds have been determined individually for each facility based on analysis of the size of the facility, the level of variability, etc. Facility errors are defined as being either positive (overestimates of consumption or underestimates of production), negative (underestimates of consumption or overestimates of production) or minor (below threshold).

Facility errors are compared to regional error which is calculated for each DI. For each facility with only 30-minute data, we set the facility error in each DI of a TI to be equal to the facility error for the 30-minute period. This means that for facilities with 30-minute data, every time facility error exceeds threshold, all six DIs are flagged. This potentially diminishes any apparent relationship between facility error and price spikes or demand error. For example, consider a price spike and large dispatch demand error in a single DI in a TI caused solely by a large facility changing its operation in that DI. If we only have 30-minute data for that facility, the remaining five DIs in the TI will also be flagged as having large facility error, blurring the relationship between facility error, dispatch demand error and price.

Examples of output from 30-minute regression

These examples illustrate the relationship between the typical operating behaviour of facilities and the output of the linear regression model.

The Tomago Aluminium Smelter has a generally stable load. There is no evidence of any time-of-day trend. An example month of Tomago load is shown in Figure 1. Table 7 shows Tomago's coefficients in the linear regression output. The only coefficient that is relatively large is for the delta from the TI directly before. This is in agreement with the empirical observation that significant reductions in load are often spread over two TIs.[6] The low coefficients for all other input deltas show that there is no real pattern on a longer timescale. Rather, in most periods the forecast delta will be close to zero. Therefore any change in load will generally result in an error of a similar magnitude.

Figure 1: Example month – Tomago Aluminium Smelter

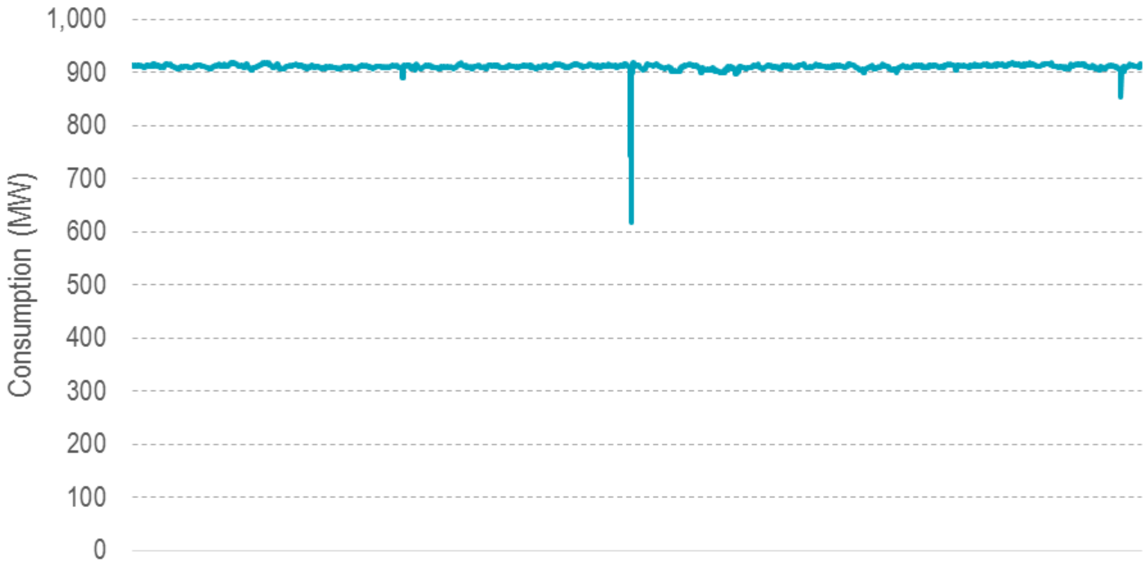


Table 7: Tomago Aluminium Smelter linear regression coefficients

Term	Coefficient
Intercept	-0.001
Delta from 1 TI before	0.134
Delta from 48 TIs before	0.003
Delta from 96 TIs before	0.018
Delta from 144 TIs before	0.002
Delta from 192 TIs before	-0.001
Delta from 240 TIs before	-0.002
Delta from 288 TIs before	0.005
Delta from 336 TIs before	0.003

A very different result is observed for a facility such as the Laverton Steel Mill. Like many of the steel mills, this facility is highly variable. Many of the variable facilities have no clear pattern based on time-of-day, seasonality, etc. Figure 2 shows a typical month of consumption. A typical day is shown in Figure 3.

[6] Although the changes are spread over two TIs, this is likely a result of a limitation of 30-minute data. A reduction in load within a short period of time within a TI can appear as successive smaller reductions over two TIs.

Figure 2: Example month – Laverton Steel Mill

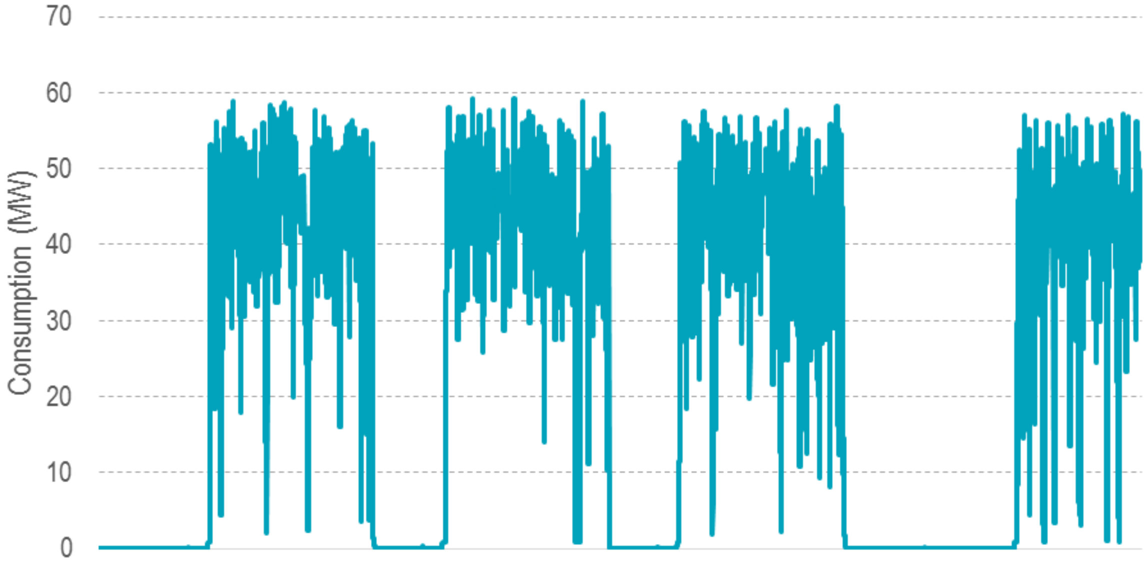
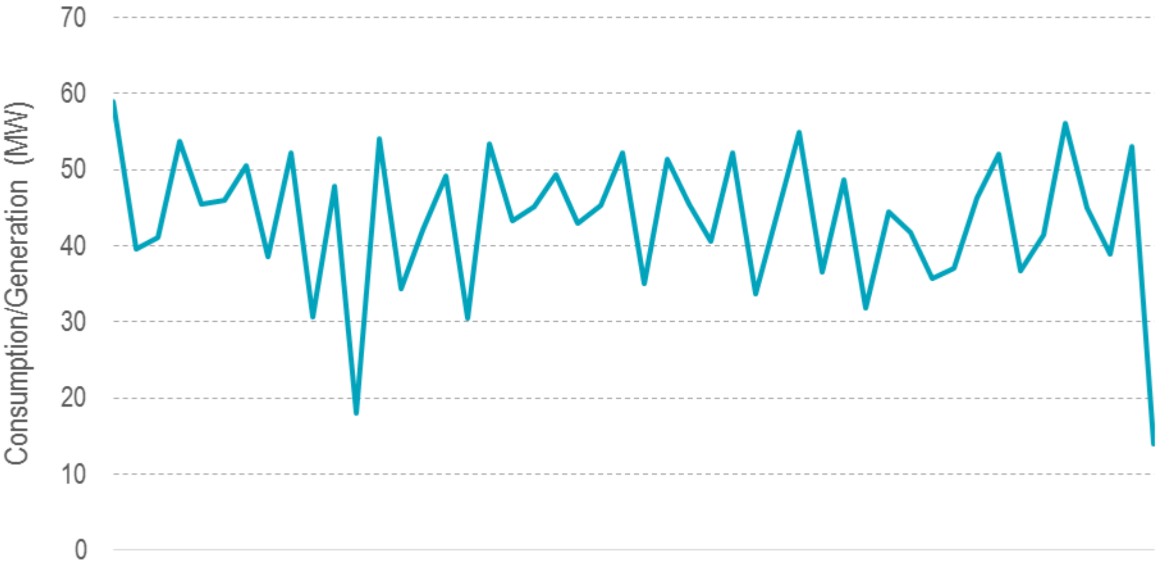


Figure 3: Example day – Laverton Steel Mill



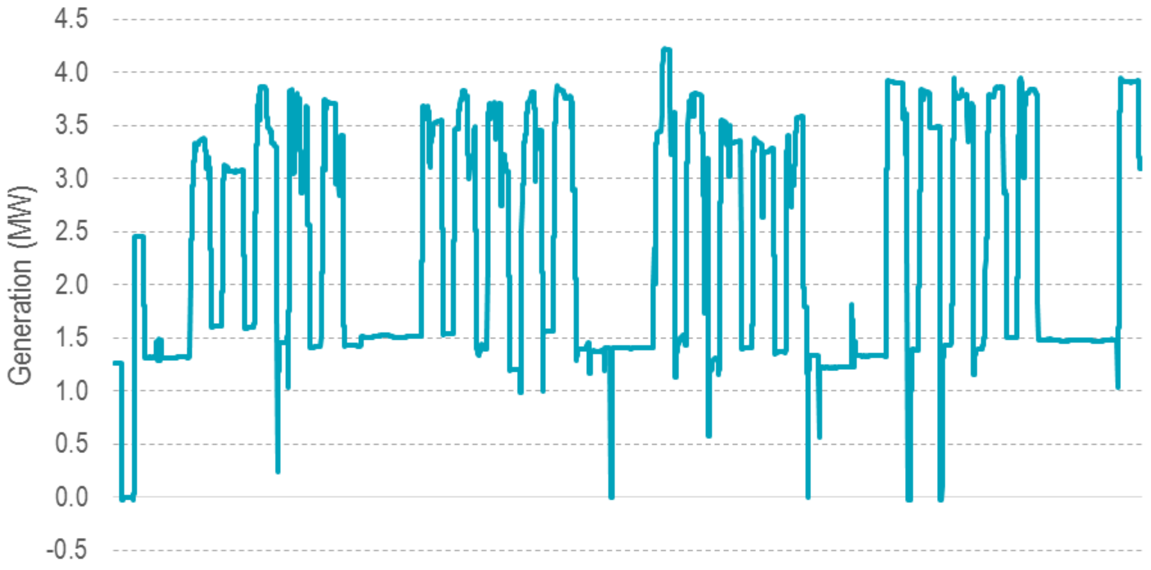
The coefficients from the linear regression are provided in Table 8. The coefficient for the most recent TI delta is both large and negative, meaning that changes in consumption will generally result in a forecast that expects the change to reverse in the next TI. The coefficients for all of the corresponding TIs from the seven days before are very low, an outcome that supports the analysis that the facility has no clear time-of-day pattern, as shown in Figure 3.

Table 8: Laverton Steel Mill linear regression coefficients

Term	Coefficient
Intercept	0.001
Delta from 1 TI before	-0.572
Delta from 48 TIs before	0.002
Delta from 96 TIs before	-0.005
Delta from 144 TIs before	-0.001
Delta from 192 TIs before	0.000
Delta from 240 TIs before	-0.003
Delta from 288 TIs before	-0.002
Delta from 336 TIs before	0.011

Some of the facilities have a clearly observable time-of-day pattern. For example, the BROADMDW facility (a landfill gas generator in Victoria) has a consumption pattern with both a time-of-day and a day-of-the-week pattern. A typical month for the facility is shown in Figure 4.

Figure 4: Example month – BROADMDW



The linear regression coefficients for BROADMDW are provided in Table 9. The TI delta from exactly one week earlier has the highest coefficient reflecting the fact that operation on any given day is most similar to the same day a week ago. Other deltas included in the regression also have a positive coefficient reflecting a time-of-day pattern.

Table 9: BROADMDW linear regression coefficients

Term	Coefficient
Intercept	0.000
Delta from 1 TI before	0.154
Delta from 48 TIs before	0.214
Delta from 96 TIs before	0.027
Delta from 144 TIs before	0.048
Delta from 192 TIs before	0.046
Delta from 240 TIs before	-0.002
Delta from 288 TIs before	0.151
Delta from 336 TIs before	0.308

Illustration of difficulty in relating 30-minute facility data to regional error

The neural network model determines the expected increase or decrease in demand in each DI. These changes in demand are wholly informed by the relationship between changes in demand (deltas) in the previous five DIs and the six DIs one week earlier. This example demonstrates where the neural network model can result in a large error due to a change in the operation of a large facility, and how this change is challenging to accurately quantify given the unavailability of 5-minute data.

A clear example of a potential issue with the neural network model approach is where a high price or a “price spike” occurs. When a price spike occurs, there is an incentive to reduce consumption/increase generation. This can lead to a reduction in demand during the DI of the price spike. Given the current market rules, once a facility is notified of a high price in a DI, loads and non-scheduled generation is entitled to decrease load/increase generation during that interval to reduce cost/increase revenue. Such an entitlement is not granted to scheduled generators and loads. These facilities are required to meet their target generation as determined by the National Electricity Market Dispatch Engine (NEMDE).

Table 10 shows an example of a high price resulting in dispatch demand error in Queensland. In the 5th DI of the first TI (DI ending 18:55), the RRP increases to the Market Price Cap. For this DI, the DEMANDFORECAST value shows the neural network model predicting a slight increase of 19 MW in demand (not shown in table). TOTALDEMAND is slightly higher in this DI, compared to the previous DI. However we calculate that the actual demand at the end of the DI was overestimated by 454 MW. This indicates that demand decreases rapidly during this DI, potentially due to a reduction in consumption at a major industrial load and/or an increase in production from non-scheduled generation in Queensland.

In the following DI (ending 19:00), demand is again forecast to remain relatively constant (not shown in table). The wholesale price has dropped to $33.64/MWh. However, due to the nature of 30-minute settlement, the TI price is assured of being very high given the price spike in the previous DI. This still provides a driver for price response from loads and generators. Our analysis suggests that demand continued to decline in this DI; the TOTALDEMAND value overestimated demand by 142 MW.

The table also shows the half-hourly energy consumption for Boyne Island Aluminum Smelter. This indicates it decreased half-hourly consumption by 64 MW for the TI ending 19:00, relative to TI ending 18:30. This likely contributed to the drop in TOTALDEMAND evident at 19:00 in the 5-minute regional data and the significant overestimate of demand evident at 18:55 and 19:00. However, there is no conclusive evidence that this is so in the 30-minute Boyne Island data. This example demonstrates the difficulty of using 30-minute production or consumption data to inform an analysis of demand forecast inaccuracies, which by necessity are at the DI level.

Table 10: Example of price response in regional demand

DI ending	Price ($/MWh)	Max TI price ($/MWh)	Settlement price ($/MWh)	TOTAL DEMAND (MW)	Dispatch demand error (MW)	Sum of abs demand error (MW)	Boyne Island (half-hourly, MW)	Change in Boyne Island (MW)
28/03/2016 18:30		51.00	45.59	7190	30	318	963	-1
28/03/2016 18:35	51.46			7172	-50			
28/03/2016 18:40	299.91			7235	-49			
28/03/2016 18:45	70.70			7278	35			
28/03/2016 18:50	60.69			7249	-19			
28/03/2016 18:55	13800			7289	454			
28/03/2016 19:00	33.64	13800	2386.07	6852	142	749	899	-64
28/03/2016 19:05	36.00			6744	-233			
28/03/2016 19:10	36.04			6967	-63			
28/03/2016 19:15	36.55			7007	-68			
28/03/2016 19:20	36.00			7039	55			
28/03/2016 19:25	34.79			6972	-55			
28/03/2016 19:30	34.46	36.55	35.64	6986	148	621	925	26
28/03/2016 19:35	34.28			6836	-107			
28/03/2016 19:40	35.03			6948	33			
28/03/2016 19:45	31.48			6893	-65			
28/03/2016 19:50	34.71			6965	-109			
28/03/2016 19:55	34.98			7037	3			
28/03/2016 20:00	31.76	35.03	33.71	6995	79	396	962	37

Consider Table 11 which shows two possible alternatives for Boyne Island's reduction in consumption of 64 MW in the TI ending 19:00. Both yield the same (observed) half-hourly consumption. Option A is well aligned with the price response observed in the regional data. The same is not true of Option B. In this simplified example, we assume any deviation from the previous DI consumption at Boyne Island contributes to dispatch demand error. Not only does Option B not align well with regional demand response, the total dispatch demand error is less than half that calculated for Option A.

Clearly of the two options considered here, Option A is more likely, given the supporting evidence in the demand data. However, there is no clear methodology that converts the half-hourly consumption pattern into a 5-minute pattern that allows an estimate of dispatch demand error in each DI.

Table 11: Alternative 5-minute behaviours that match 30-minute data for Boyne Island near a price spike

		Option A 5-minute movement		Option B 5-minute movement	
DI ending	Observed Boyne Island 30-minute consumption (MW)	Boyne Island consumption (MW)	Possible contribution to dispatch demand error (MW)	Boyne Island consumption (MW)	Possible contribution to dispatch demand error (MW)
28/03/2016 18:30	963	963		963	
28/03/2016 18:35		963	0	932	31
28/03/2016 18:40		963	0	918.8	13.2
28/03/2016 18:45		963	0	905.6	13.2
28/03/2016 18:50		963	0	892.4	13.2
28/03/2016 18:55		796	167	879.2	13.2
28/03/2016 19:00	899	746	50	866	13.2
Total dispatch demand error (MW)			217		97

Table 10 also provides an example of another form of price responsive behaviour that can result in regional demand errors. The DI ending 19:05 is the first DI of the next TI following the price spike. The impact of the earlier price spike is therefore not a relevant driver of load and generator behaviour from this point onwards. As with the previous DIs, the neural network model has not forecast any substantial increase or decrease in demand. Our analysis shows that demand is underestimated by 233 MW in the first DI (ending 19:05), and by 63 MW and 68 MW in the following two DIs. Boyne Island's half-hourly production also increases in this TI. This indicates that facilities such as Boyne Island reverting back towards their typical level of operation after a high price TI may be causing subsequent demand underestimates. As with the original demand overestimate, it is not possible to accurately compare the magnitude of the regional demand errors with a specific facility if only 30-minute data is available.

3.3.2 Facilities with 5-minute data

Where 5-minute data is available, a number of the issues with 30-minute data no longer apply. However, we are still required to determine departures from typical operation using linear regression as surrogate for the neural network model. As with the 30-minute analysis, we conduct linear regression using a dataset of deltas, although in this case the deltas are calculated for each DI. The input deltas applied in the regression are the same as those used for inputs in the neural network model – the previous four DI deltas, and the five deltas leading up to the corresponding DI from one week earlier. This is shown in the formulation below.

$$\begin{aligned}\text{Facility delta } (DI_n) = \;& \text{constant} + \beta_1 \text{*Facility delta } (DI_{n-1}) + \beta_2 \text{*Facility delta } (DI_{n-2}) + \\ & \beta_3 \text{*Facility delta } (DI_{n-3}) + \beta_4 \text{*Facility delta } (DI_{n-4}) + \\ & \beta_5 \text{*Facility delta } (DI_{n-2016}) + \beta_6 \text{*Facility delta } (DI_{n-2017}) + \\ & \beta_7 \text{*Facility delta } (DI_{n-2018}) + \beta_8 \text{*Facility delta } (DI_{n-2019}) + \\ & \beta_9 \text{* Facility delta } (DI_{n-2020})\end{aligned}$$

The residuals from the linear regressions are used to calculate facility error. For facilities with 5-minute data, facility errors are calculated for each DI individually, rather than using a singly half-hourly error in each DI.

4. Trends in regional dispatch demand error

This section describes high-level trends in dispatch demand error in each region: the distribution of error, time-of-day patterns and patterns within a trading interval.

4.1 Distribution of regional dispatch demand error

In each region, the distribution of dispatch demand error is heavily centered around zero. The vast majority of the observed errors are within 100 MW, as shown in Figure 5. However, in all regions there is a large tail in both directions, indicating that at times demand increases or decreases significantly in a DI, in a way that is not forecast by the neural network model. This is illustrated in Figure 6 which shows the same distribution as Figure 5 with the y-axis capped at 500 DIs so that the tails of the distribution are visible.

Figure 5: Distribution of dispatch demand error in each region (all data)

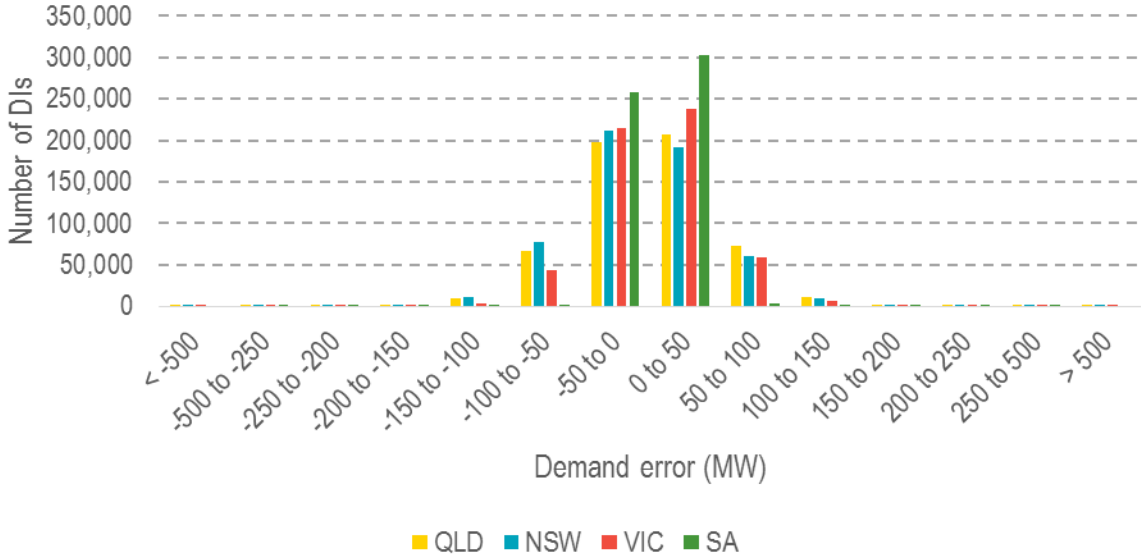
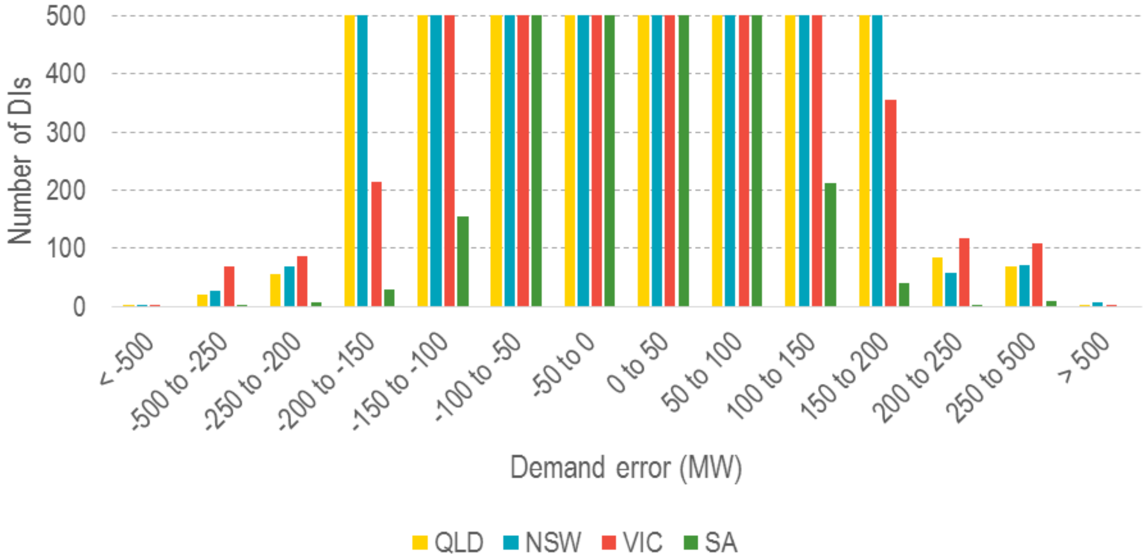


Figure 6: Distribution of dispatch demand error in each region (y-axis capped at 500 to show distribution tails)

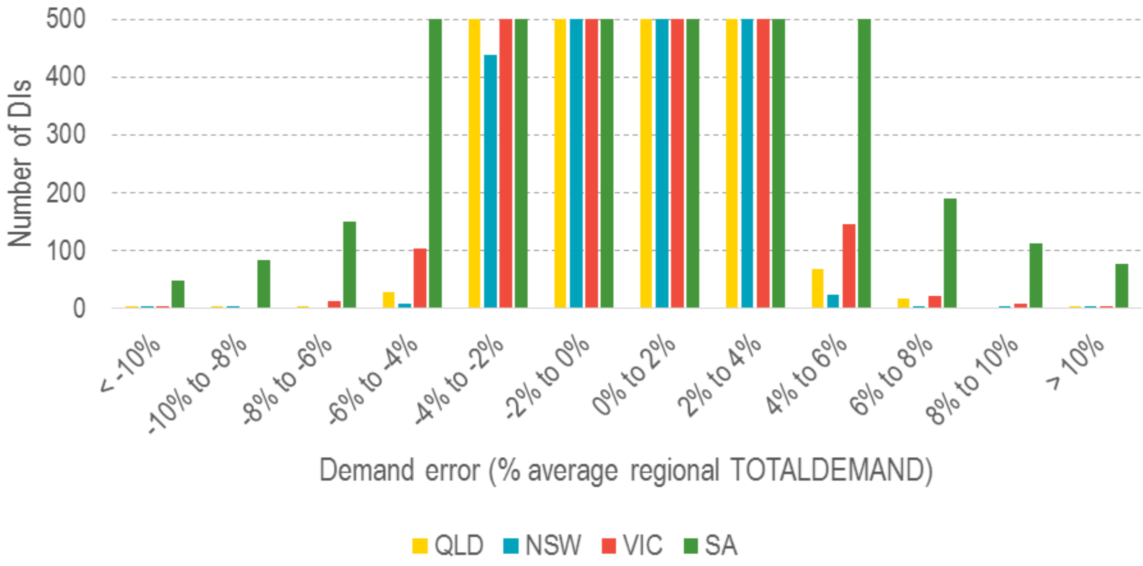


Our analysis focuses on these tails. It aims to determine to the extent possible whether these large inaccuracies are due to the changes in consumption by large loads and/or generation by small non-scheduled generators. As described in Section 3.1, we apply regional error thresholds to classify each DI as having “large”, “small” or “minor” error. The thresholds are set such that approximately 1,000 DIs fall in the large error category (whether positive or negative) and approximately 10,000 DIs fall in the small error category. Error in only a subset of these is related to price response of large loads and non-scheduled generators and hence could be expected to decrease under the proposed rule changes. Frequently, large errors cannot be associated with a price trigger. Dispatch demand error in these DIs may instead be associated with random outages or other unforeseen events and hence would not be improved under the proposed rule changes.

In absolute terms, dispatch demand error has the longest tails in Queensland, New South Wales and Victoria. South Australia has fewer DIs with large dispatch demand error, but demand is significantly lower in South Australia. Figure 7 shows a similar distribution after normalisation to average regional TOTALDEMAND (y-axis has been capped at 500 DIs so that the tails of the distribution are visible). It shows that New South Wales has fewer DIs where dispatch demand error is >4% of average TOTALDEMAND while South Australian demand error exceed 4% of average TOTALDEMAND much more frequently than the other regions.

These outcomes do not appear to be correlated with the average consumption by large loads or the consumption relative to average demand shown in Section 6.1.1. There is however evidence of a relationship between the total capacity of non-scheduled generation in a region and the spread of relative regional dispatch error shown below. In particular, South Australia has the highest proportion of non-scheduled generation capacity relative to regional demand, and has the largest variance in regional dispatch error. South Australia has a number of non-scheduled peaking generators. They operate infrequently, and therefore their average production as a proportion of regional demand is low, as shown in Section 6.2.1. However, they tend to move quickly and in a correlated manner.

Figure 7: Distribution of dispatch demand error relative to demand in all regions (y-axis capped at 500 to show distribution tails)



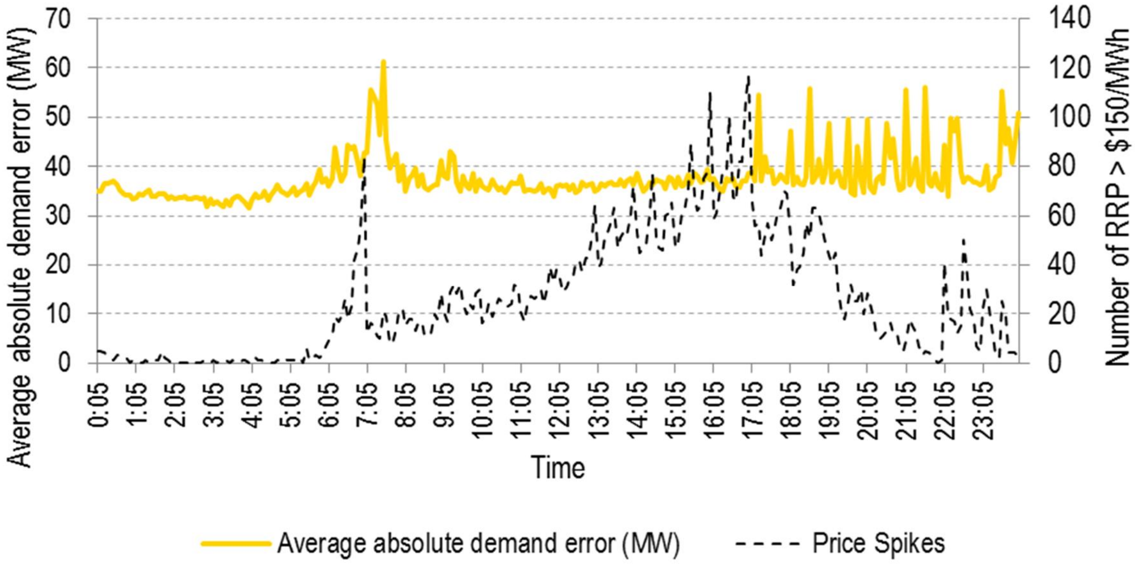
4.2 Trends in dispatch demand error

We have analysed each region to determine whether there are any trends in dispatch demand forecast errors. This analysis illustrates when errors tend to occur, and whether errors in the positive or negative direction are more closely related to different times of the day, the number DI in the TI, etc.

We use the term "overestimate" where the dispatch demand is greater than our calculation of the resulting regional demand at the end of the DI, i.e. where the dispatch demand error is positive. Overestimates would occur where loads reduce consumption during a DI. An "underestimate" is therefore where dispatch demand is less than the resulting regional demand.

Figure 8 shows the average absolute error by time-of-day in Queensland. The frequency of DI prices that exceed $150/MWh[7] is also provided. Dispatch demand error tends to be higher in the morning and in the late afternoon and evening. This generally fits with the occurrence of price volatility, however the relationship does not appear to be particularly strong or clear. The errors in the evening in particular show a level of variability that is not evident at other times of the day.

Figure 8: Average absolute error by time-of-day in Queensland



A consideration of the relationship between dispatch demand error and the number DI in the TI indicates that the variability in dispatch demand error in the evening may be related to the cycle of the trading interval. Figure 9 shows that absolute dispatch demand error is higher in the first DI of the TI. Further analysis shows that this discrepancy is due to an increase in the magnitude of dispatch demand underestimates in the first DI of the TI as shown in Figure 10 (yellow line). This trend provides some indication that demand forecast errors are related to price responsive behaviour from large loads and possibly non-scheduled generation.

Consider an example where demand response occurs during a TI as high prices are observed. At the end of the TI, assuming that prices are not expected to remain high, there is no need for large loads to continue to curtail production. During the first DI, the loads increase their energy consumption back towards their original level. This results in a dispatch demand underestimate in the first DI, as the neural network model was likely not forecasting a reversion in its forecast.

Further evidence of this return to normal operation after a price response is given in Figure 10 which shows similar data to Figure 9, but only for DIs where the price in the previous TI exceeded $150/MWh and hasn't so far in the current TI (blue line). These are the price conditions under which we would expect a return to normal operation and therefore an underestimate in regional demand in the first few DIs of the TI. The pattern of demand error within a TI in this subset of DIs (Figure 10, blue line) is stronger than for all DIs (Figure 10, yellow line).

[7] We apply a $150/MWh threshold for a price spike. This threshold was chosen so that we had a sample of several hundred 'price spike' DIs in each region in each study year, including NSW and Victoria where prices rarely exceeded $300/MWh in the study period (50-60 times annually in NSW and 60-80 times annually in Victoria).

Figure 9: Average absolute dispatch demand error over dispatch intervals in a trading intervals in Queensland (all DIs)

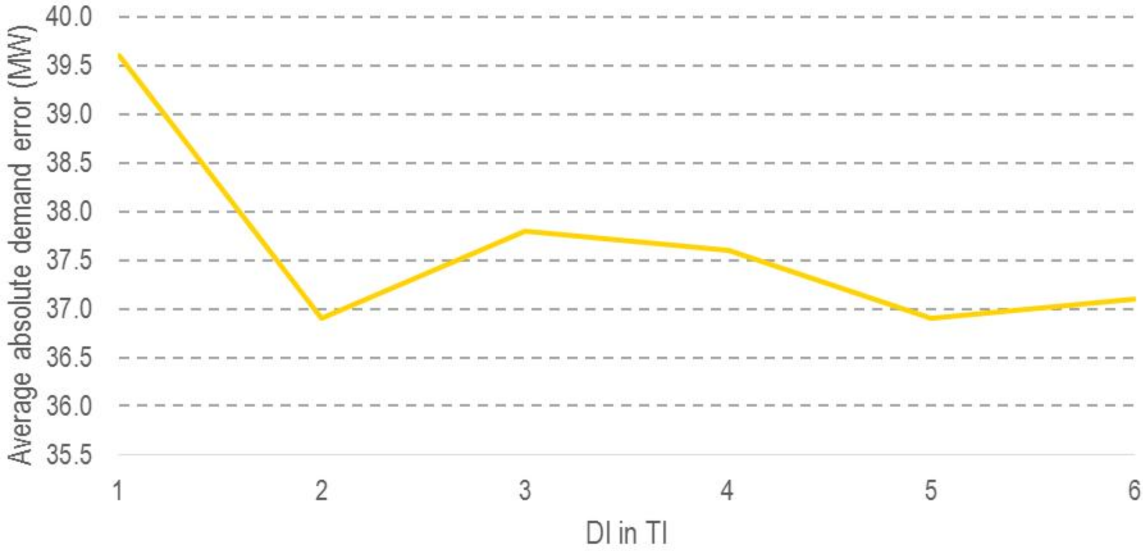
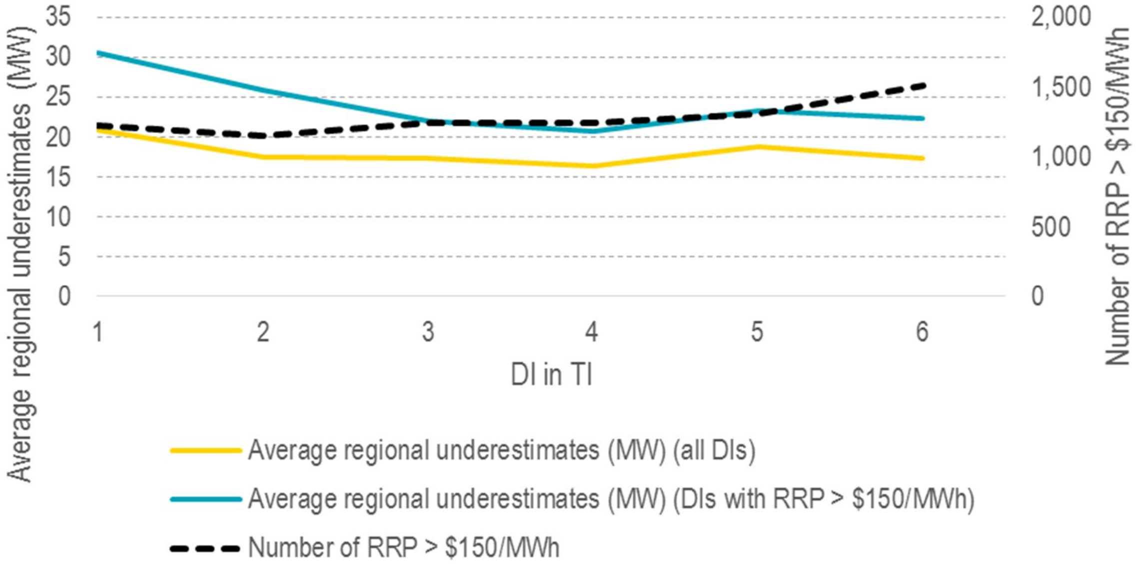


Figure 10: Average absolute dispatch demand error over dispatch intervals in a trading interval in Queensland (DIs where RRP > $150/MWh in the previous TI but not so far in the current TI)



5. Evidence of price responsiveness in regional error

Price responsive behaviour from large loads and non-scheduled generation could contribute to regional dispatch demand inaccuracies. They are currently entitled to respond to price signals without regard for dispatch orders. Hence, the inaccuracies caused by this price responsive behaviour could be improved by requiring these facilities to bid in the central dispatch process. Decreasing consumption or increasing generation in response to high prices would not require facilities to be able to accurately forecast their consumption/generation. Consequently, improvement in demand inaccuracy through bidding in response to price could presumably be achieved more easily than improvement through managing general variability which is not related to wholesale market prices.

Our analysis indicates that price responsiveness does result in large dispatch demand errors, particularly in Queensland and South Australia. The most observable form of price response is that large demand overestimates are more likely to occur during DIs where the price is high. There is only limited evidence that a more delayed response to price volatility (e.g. in the DIs following a price spike) is significant.

The reversion towards typical operating patterns that follows an initial price response is also found to be correlated with large regional demand underestimates. Again, this is more likely in Queensland and South Australia.

The impact of high pre-dispatch price forecasts has a relatively weak influence on dispatch demand accuracy, above what is observed due to price volatility that actually occurs.

Although a range of price responsive behaviours have been identified that reduce dispatch demand accuracy, the majority of large dispatch demand errors are not found to be related to any observable form of price response.

Section 5.2 provides an exhaustive analysis of the price responsiveness of demand to wholesale prices in the current DI. Section 5.3 onwards highlights a number of other forms of price responsive behaviour and their effect on regional dispatch demand error. These later sections provide analysis of a single region that exhibits behaviours of interest.

5.1 Price responsiveness

We have undertaken quantitative analysis to consider the extent to which wholesale price outcomes affect the regional error. A strong relationship suggests there may be a significant amount of price responsive non-scheduled capacity. If regional demand inaccuracies are the result of price responsive behaviour by non-scheduled facilities, it is possible that the rule changes would improve dispatch demand forecast accuracy.

This section considers a range of possible price responsive behaviours that could result in regional errors. A key outcome is the extent to which material errors in the demand forecast can be attributed to this range of price responsive behaviours.

5.2 Response to high prices in the current DI

When a price spikes in a DI, loads and non-scheduled generators are able to reduce consumption/increase generation during the DI. If this occurs, the forecast of dispatch demand could be overestimated. To respond to a price spike in this time period, a facility would need to be able to act very rapidly, as the time window is short.

Our analysis considers for each region, the number of DIs in each category of error in which the RRP exceeds or does not $150/MWh[8]. Using this frequency, we consider the likelihood that regional dispatch demand error will exceed the error thresholds given a high RRP; this provides an indication of the likelihood regional error will be large if the price spikes.

We also consider the percentage of the DIs in each error category that occur during high price DIs. This represents an estimate of the percentage of large regional dispatch demand errors that may be linked to this form of price response.

5.2.1 Queensland

Table 12 provides an analysis of the evidence of the contribution to regional error of a response to wholesale prices in the current DI. The hypothesis that high prices may cause loads to reduce consumption and/or non-scheduled generators to increase production is supported by evidence of a higher proportion of small and large overestimates of dispatch demand when the price is above the threshold; the likelihood of a material demand overestimate increases significantly during high price DIs (Table 12, 3.9%/1.4% for small/large overestimates when price > threshold c.f. 0.8%/0.1% when price is <= threshold). In contrast, the likelihood of material demand underestimates decreases (Table 12, 0.1%/0.5% for large/small underestimates when price > threshold c.f. 0.1%/0.8% when price is < threshold).

However, Table 12 also shows that majority of material demand overestimates occur during DIs where the RRP is below the threshold (93.8% of small overestimates and 82.1% of large overestimates). This is not to say that price response is an immaterial factor in material demand overestimates. Consider that 17.9% of DIs of large overestimates have DI prices above $150/MWh; for comparison, the likelihood of price exceeding this threshold in any DI over this period is 1.3%.

Therefore there is evidence that high DI prices may be causing or contributing to large regional demand overestimates. The analysis also shows that material demand overestimates more frequently occur in DIs without high DI prices.

[8] We apply a $150/MWh threshold for a price spike. This threshold was chosen so that we had a sample of several hundred ‘price spike’ DIs in each region in each study year, including NSW and Victoria where prices rarely exceeded $300/MWh in the study period (50-60 times annually in NSW and 60-80 times annually in Victoria).

Table 12: Regional error – evidence of response to current DI RRP - Queensland

	Large under	Small under	Minor	Small over	Large over
Where current DI RRP <= Threshold	479	4316	548145	4546	487
Where current DI RRP > Threshold	6	36	7186	301	106
Probability of Error | Price <= Threshold	0.1%	0.8%	98.2%	0.8%	0.1%
Probability of Error | Price > Threshold	0.1%	0.5%	94.1%	3.9%	1.4%
Probability that Price <= Threshold | Error	98.8%	99.2%	98.7%	93.8%	82.1%
Probability that Price > Threshold | Error	1.2%	0.8%	1.3%	6.2%	17.9%
Number of DIs where current DI RRP >= Threshold (% of all DIs)	7635	1.3%			

5.2.2 New South Wales

In comparison to Queensland, New South Wales wholesale prices have been lower, and less volatile, than Queensland between 2011 and 2016. The analysis of the impact of prices in the current DI on regional error is shown in Table 13.

These results show that the increased probability of a material demand overestimate given that the RRP is above $150/MWh is not as significant as was observed in Queensland (Table 13, 2.3%/0.4% for small/large overestimates when price > threshold c.f. 0.9%/0.1% when price is <= threshold). This metric is normalised to the number of DIs above threshold so takes into account the reduction in the occurrence of volatility, and therefore suggests that the level of price responsiveness in New South Wales is lower. It could be that this is in part indirectly due to lower levels of volatility, as this provides less incentive for large loads and non-scheduled generation to invest in infrastructure and/or processes that allow them to provide this price response.

Due to the lower level of volatility and the weaker price responsiveness, the proportion of DIs with material demand overestimates where the price is above $150/MWh is quite low; 1.1% for small overestimates and 2.1% for large overestimates. This is still more frequently than price exceeds this threshold in any DI (0.4%), but the increase in likelihood is not as large as in Queensland.

Table 13: Regional error – evidence of response to current DI RRP – New South Wales

	Large under	Small under	Minor	Small over	Large over
Where current DI RRP <= Threshold	404	5561	551937	4854	474
Where current DI RRP > Threshold	3	25	2285	55	10
Probability of Error | Price <= Threshold	0.1%	1.0%	98.0%	0.9%	0.1%
Probability of Error | Price > Threshold	0.1%	1.1%	96.1%	2.3%	0.4%
Probability that Price <= Threshold | Error	99.3%	99.6%	99.6%	98.9%	97.9%
Probability that Price > Threshold | Error	0.7%	0.4%	0.4%	1.1%	2.1%
Number of DIs where current DI RRP >= Threshold (% of all DIs)	2378	0.4%			

5.2.3 Victoria

The results provided in Table 14 show that Victoria is very similar to New South Wales, both with regards to the level of price volatility and also the level of price responsiveness.

Table 14: Regional error – evidence of response to current DI RRP – Victoria

	Large under	Small under	Minor	Small over	Large over
Where current DI RRP <= Threshold	366	3378	552872	6248	572
Where current DI RRP > Threshold	6	27	2072	54	13
Probability of Error | Price <= Threshold	0.1%	0.6%	98.1%	1.1%	0.1%
Probability of Error | Price > Threshold	0.3%	1.2%	95.4%	2.5%	0.6%
Probability that Price <= Threshold | Error	98.4%	99.2%	99.6%	99.1%	97.8%
Probability that Price > Threshold | Error	1.6%	0.8%	0.4%	0.9%	2.2%
Number of DIs where current DI RRP >= Threshold (% of all DIs)	2172	0.4%			

5.2.4 South Australia

South Australia has exhibits a similar level of price volatility to Queensland over this time period. The results provided in Table 15 indicate that South Australian demand is highly price responsive. If prices are high, the probability of regional demand being overestimated is much higher than if prices are low (Table 15, 5.6%/4.2% for small/large overestimates when price > threshold c.f. 1.1%/0.05% when price is <= threshold).

47.6% of the DIs which have a large overestimate of regional demand occurred where the price exceeded $150/MWh; in comparison, only 1.2% of all DIs over this period had a price which exceeded this threshold.

Of all mainland regions, the results indicate that South Australia had the most price responsive demand during the study period. Our analysis suggests that wholesale market prices were a dominant factor in large overestimates of regional demand.

Table 15: Regional error – evidence of response to current DI RRP – South Australia

	Large under	Small under	Minor	Small over	Large over
Where current DI RRP <= Threshold	379	3023	549230	6031	306
Where current DI RRP > Threshold	37	83	5866	375	278
Probability of Error | Price <= Threshold	0.1%	0.5%	98.3%	1.1%	0.05%
Probability of Error | Price > Threshold	0.6%	1.3%	88.4%	5.6%	4.2%
Probability that Price <= Threshold | Error	91.1%	97.3%	98.9%	94.1%	52.4%
Probability that Price > Threshold | Error	8.9%	2.7%	1.1%	5.9%	47.6%
Number of DIs where current DI RRP >= Threshold (% of all DIs)	6639	1.2%			

5.2.5 Impact of wholesale price on magnitude of error

The sections above showed the increased likelihood of large regional demand overestimates associated with high pool prices. Table 16 shows the effect of pool prices on the average magnitude of regional error. For all regions, the average magnitude of dispatch demand overestimates increases when price is > threshold, particularly in Queensland and South Australia. In contrast the magnitude of dispatch demand underestimates remains relatively constant.

The average error, which is generally close to zero, is a positive number in all regions. This follows from the above discussions, as high prices increase dispatch demand overestimates (positive errors) and are relatively immaterial for the size of dispatch demand underestimates (negative errors).

Although the results support the theoretical assumption that high prices cause price responsive behaviour which leads to regional dispatch demand error, the average size of this error during price spikes is not particularly high in any region. Even in South Australia, the average dispatch demand overestimate during high price DIs of 26 MW is less than 2% of average demand. Errors of this size are unlikely to been influential in the setting of market prices in dispatch, although at times dispatch price can be very sensitive to small deviations in supply and demand.

Table 16: Average magnitude of contribution to regional error due to response to current DI RRP

Region		Average magnitude of demand underestimates (MW)	Average magnitude of overestimates (MW)	Average regional demand error (MW)
QLD	Where current DI RRP <= Threshold	-37.5	38.2	1.4
	Where current DI RRP > Threshold	-36.6	53.5	19.5
NSW	Where current DI RRP <= Threshold	-38.5	36.9	-3.1
	Where current DI RRP > Threshold	-40.3	46.1	5.6
VIC	Where current DI RRP <= Threshold	-29.7	32.5	3.5
	Where current DI RRP > Threshold	-36.6	41.2	4.2
SA	Where current DI RRP <= Threshold	-12.5	13.9	1.8
	Where current DI RRP > Threshold	-15.3	26.0	10.9

5.3 Response to high prices in previous DIs in the TI

Price responsiveness to wholesale prices in the current DI relies on either of two models of behaviour:

- The ability of facilities to respond immediately to high prices (or potentially to have forecast the high prices) that allows them to reduce consumption during the 5-minute period.
- Multiple periods of high price that allow slower responding units to have reduced consumption or increased production in periods flagged as above the threshold.

Due to the nature of 5 minute dispatch pricing and 30 minute settlement, price responsive behaviour could also be exhibited by demand reductions after a price spike. For example, if a price spike occurs in the 2nd DI, loads have an incentive to reduce consumption in the 2nd, 3rd, 4th, 5th and 6th DIs, as any reduction during the trading interval will reduce load costs (and non-scheduled generators have an incentive to increase production). To determine whether this form of price response is evident, we have applied an alternative measure of price volatility: whether the maximum price so far this TI (including the current DI) exceeds $150/MWh. The DIs where the current RRP exceeds $150/MWh (Section 5.2) is therefore a subset of the DIs that meet this alternative price condition.

Comparing this measure against the current DI condition shows the number of additional DIs where material overestimates of demand are correlated with this form of delayed price response. Table 17 shows the number of DIs in each category of regional error for DIs where the maximum price so far in the TI has/has not exceeded $150/MWh, for South Australia. The percentage of the DIs of large regional overestimates where this price condition is met has increased to 52.2%; this is relative to 47.6% when considering only the current DI RRP (Table 15).

Table 17: Regional error – evidence of response to max TI RRP – South Australia

	Large under	Small under	Minor	Small over	Large over
Where max RRP in TI so far <= Threshold	324	2903	545722	5876	279
Where max RRP in TI so far > Threshold	92	203	9374	530	305
Probability of Error | Price <= Threshold	0.1%	0.5%	98.3%	1.1%	0.05%
Probability of Error | Price > Threshold	0.9%	1.9%	89.2%	5.0%	2.9%
Probability that Price <= Threshold | Error	77.9%	93.5%	98.3%	91.7%	47.8%
Probability that Price > Threshold | Error	22.1%	6.5%	1.7%	8.3%	52.2%
Number of DIs where max RRP in TI so far >= Threshold (% of all DIs)	10504	1.9%			

To determine whether this increase is significant, it is necessary to compare it against the additional number of DIs that meet the expanded price condition. Table 18 shows only the DIs that meet the expanded price condition, but did not meet the current DI condition; this comprises DIs where current DI RRP does not exceed $150/MWh and where an earlier DI price in the TI exceeded $150/MWh.

This table shows that for this set of DIs, the probabilities of small and large overestimates of regional demand are 4.0% and 0.7% respectively. These probabilities indicate that the likelihood of material overestimates is much larger than in a DI with no price volatility (price has not exceeded $150/MWh in the TI). The inference is therefore that there is some evidence of delayed response.

However, this delayed response is not as significant as the immediate response to price spikes. Consider that the likelihood of a large dispatch demand overestimate due to a delayed response is 13.9 times more likely than in a DI with no price volatility (Table 18). In comparison, the likelihood of a large overestimate due to an immediate response to price volatility is 76.5 times larger than in a DI with no price volatility (Table 15, 4.2% divided by 0.05%).

There is also an increased likelihood of large dispatch demand underestimates (Table 18, 24.4 times more likely to have a large underestimate due to a delayed response than in a DI with no price volatility). This may be due to the beginnings of a "reversion" towards typical operating in the later DIs of the TI (see Section 5.4)

Table 18: Regional error – evidence of delayed response – South Australia

	Large under	Small under	Minor	Small over	Large over
Additional DIs of price response that occur after RRP > $150 in TI (i.e. where current DI RRP <= $150/MWh)	55	120	3508	155	27
Additional DIs which are covered by this price condition	3865				
Proportion of additional DIs in each regional error category	1.4%	3.1%	90.8%	4.0%	0.7%
Proportion of DIs with no price volatility in each regional error category	0.1%	0.5%	98.3%	1.1%	0.05%
Ratio of likelihoods	24.4	5.9	0.9	3.8	13.9

South Australia shows the strongest evidence of delayed price responsiveness. In Queensland, and New South Wales there is very little evidence of any delayed price response. In Victoria, there is some evidence that there is a delayed response, and that the effect is almost as large as the impact of immediate price response. The complete set of results can be found in the worksheet 'Regional - PR current DI+TI'.

5.4 Response to high prices in previous TI

Another form of price responsive behaviour which could affect dispatch demand error is the return of facilities to their typical operational behaviour after price volatility subsides. In this behaviour, a price spike occurs and a facility responds during that DI and/or TI. When that TI ends, if further price volatility is not expected then there is no incentive for the facility to remain at its lower level of consumption (or for non-scheduled generation to continue to generate). As a result, the facility may increase its consumption back towards the level it was at prior to responding to the initial price response. If this is not forecast by the neural network model, then this could result in underestimates of regional demand. This type of response was briefly described in the Boyne Island Aluminium Smelter example in Section 3.3.1.

To test this form of response, we have applied another price threshold condition. To isolate the reversion that could occur after price volatility, we consider DIs where there was a price spike in the previous TI, but there has not been a price spike in any of the DIs so far this TI. It is likely this price condition is missing periods where a reversion to typical behaviour could be occurring, for example to a price spike that occurred two DIs ago. However, this price condition captures the most obvious form of this reversion subsequent to a price response.

Analysis of the average magnitude of dispatch demand error in each DI of the TI shows larger underestimates of regional demand in the first few DIs of the TI, particularly under this price condition (Figure 10). Table 19 shows additional analysis of this price condition for Queensland. From this table is evident that when this price condition is met, the likelihood of dispatch demand underestimates increases relative to the average of all DIs. 8.7% of DIs where a large dispatch demand underestimate is observed occur when this price condition is met; this is relative to the price condition being met in 1.8% of all DIs.

As with the initial price response, there is an obvious effect of price volatility in the previous TI on material dispatch demand underestimates. But this price response behaviour does not explain the majority, or even a large proportion, of the large dispatch demand underestimates that do occur.

In New South Wales and Victoria, prior volatility explains an immaterial proportion of large dispatch demand underestimates. In South Australia, prior volatility explains 35.6% of large regional underestimates. The complete set of results can be found in the worksheet 'Regional - PR previous TI'.

Table 19: Regional error – evidence of response to previous TI – Queensland

	Large under	Small under	Minor	Small over	Large over
Where max RRP in previous TI <= Threshold OR max RRP so far in TI > Threshold	443	4155	545772	4727	566
Where max RRP in previous TI > Threshold AND max RRP so far in TI <= Threshold	42	197	9559	120	27
Probability of Error | Price <= Threshold	0.1%	0.7%	98.2%	0.9%	0.1%
Probability of Error | Price > Threshold	0.4%	2.0%	96.1%	1.2%	0.3%
Probability that Price <= Threshold | Error	91.3%	95.5%	98.3%	97.5%	95.4%
Probability that Price > Threshold | Error	8.7%	4.5%	1.7%	2.5%	4.6%
No. of DIs where max RRP in previous TI > Threshold AND max RRP so far in TI <= Threshold (% of all DIs)	9945	1.8%			

Magnitude of dispatch demand underestimates in first DI of the TI

Section 4.2 showed that in all regions, the magnitude of regional error was highest in the first DI of the TI, and that the predominant cause was an increase in the size of dispatch demand underestimates. A possible explanation of this pattern is that the reversion to typical behaviour after volatility generally occurs in the first DI; the logic being that at the start of the first DI of the TI, there is no price incentive to reduce consumption or increase non-scheduled production.

Table 20 is the South Australian equivalent to Table 19, and considers only the set of DIs which are the first DI of the TI. The table shows that large dispatch demand underestimates are much more likely in the first DI of the TI than expected by chance (36.3% in comparison to 1/6 = 16.7%). This is true of all regions, particularly Queensland where 44.5% of large regional underestimates occur in the first DI of the TI.

This could be evidence that large dispatch demand underestimates are due to the reversion to typical operational patterns after a TI with high prices is finished. This table shows that for South Australia, 73.5% of large dispatch demand underestimates in the first DI are associated with a price spike in the previous TI. Despite Queensland having a high proportion of large dispatch demand underestimates in the first DI, the evidence linking this to a price response is far weaker, with only 13.4% of large underestimates associated with a price spike in the previous TI. This evidence of a price response to the previous TI is virtually nonexistent in New South Wales and Victoria.

Although the price response we have identified may be a contributing factor in some regions, and possibly a dominant factor in South Australia, there appears to be other effects which are causing dispatch demand underestimates to be larger in the first DI. This could be due to more complex forms of reversion we have not identified (e.g. in later TIs) or due to an inherent behaviour of all loads that is not related to price response (e.g. shifts starting on the hour, on the half-hour, etc.).

Table 20: Regional error – evidence of response to previous TI – 1st DI of TI – South Australia

	Large under	Small under	Minor	Small over	Large over
Where max RRP in previous TI <= Threshold OR max RRP so far in TI > Threshold	40	619	91264	941	132
Where max RRP in previous TI > Threshold AND max RRP so far in TI <= Threshold	111	68	1068	22	3
Proportion of error in category that occurs in 1st DI of TI	36.3%	22.1%	16.6%	15.0%	23.1%
Probability of Error | Price <= Threshold	0.0%	0.1%	16.3%	0.2%	0.0%
Probability of Error | Price > Threshold	1.8%	1.1%	16.9%	0.3%	0.0%
Probability that Price <= Threshold | Error	26.5%	90.1%	98.8%	97.7%	97.8%
Probability that Price > Threshold | Error	73.5%	9.9%	1.2%	2.3%	2.2%
Number of DIs where max RRP in previous TI > Threshold AND max RRP so far in TI <= Threshold (% of all DIs)	1272	1.3%			

5.5 Response to high pre-dispatch price forecasts

Another potential price response that may lead to errors in regional forecasts is where loads reduce consumption and/or non-scheduled generators increase production in the lead-up to an anticipated price spike. To assess the materiality of this response, we have considered the 5-minute pre-dispatch price forecast which is produced by AEMO for the next hour every five minutes. In this analysis we consider pre-dispatch price forecasts over the previous 30 minutes.

The price condition considers whether the maximum of the following forecasts intervals exceeds $150/MWh:

- The pre-dispatch forecast from 30 minutes before, for all DIs from that point to the current DI
- The pre-dispatch forecast from 25 minutes before, for all DIs from that point to the current DI
- The pre-dispatch forecast from 20 minutes before, for all DIs from that point to the current DI
- The pre-dispatch forecast from 50 minutes before, for all DIs from that point to the current DI
- The pre-dispatch forecast from 10 minutes before, for all DIs from that point to the current DI
- The pre-dispatch forecast from 5 minutes before, for all DIs from that point to the current DI
- Dispatch RRP for the current DI

The set of DIs where this price condition is met therefore includes all DIs where the current DI price exceeds $150/MWh (analysed in Section 5.2). We therefore consider whether the additional DIs covered by this expanded pre-dispatch price condition show any significant increase in material demand forecast errors. In particular, we might expect an increase in material overestimates of regional demand.

The price condition defined above has limitations in that it frequently spans TI boundaries, potentially blurring the outcomes. For example, consider a DI ending 16:05. If the pre-dispatch forecast at 15:40 forecasts a price spike at 15:50, the above condition will be TRUE for 16:05. If that price spike did occur, and as 16:05 is the first DI of a new trading interval following a price spike, we might expect an underestimate of demand as consumption by a large load reverts to normal.

Any measure of pre-dispatch price volatility is difficult to work with given the uncertainty over the timing of a participant’s response to these forecasts. There may be effects of pre-dispatch on regional dispatch demand error that are not captured by this analysis.

Table 21 provides an analysis of the additional significance of forecast pre-dispatch price volatility above actual dispatch prices in Victoria. This indicates that a high pre-dispatch price forecast results in a marginal increase in the likelihood of material dispatch demand errors, both under- and overestimates (e.g. 0.4% c.f. 0.1% for large underestimate and large overestimates). The strength of this relationship is relatively weak, particularly compared to a number of the relationships detailed above.

Table 21: Regional error – evidence of pre-dispatch impact – Victoria

	Large under	Small under	Minor	Small over	Large over
Additional DIs of price response that occur when max of pre-dispatch >$150/MWh above current DI spike	7	50	1773	37	7
Additional DIs which are covered by this price condition (i.e. max of PD > $150/MWh, current DI RRP <= $150/MWh)	1874				
Proportion of additional DIs in each regional error category	0.4%	2.7%	94.6%	2.0%	0.4%
Proportion of DIs with no pre-dispatch price volatility in each regional error category	0.1%	0.6%	98.1%	1.1%	0.1%
Ratio of likelihoods	5.9	4.5	1.0	1.8	3.7

Some impact of high pre-dispatch price forecasts on regional demand overestimates is evident in each region, and is strongest in Victoria and South Australia. The complete set of results can be found in the worksheet ‘Regional - PD’. In all regions, the extent of this impact is relatively limited compared to the other forms of price response detailed above.

5.6 The importance of price responsiveness in regional dispatch demand error

Much of our analysis focuses on the impact of price responsive behaviour on regional dispatch demand error. Large loads and non-scheduled generators can cause errors in regional demand due to behaviour that is not related to price response: e.g. facilities rapidly reducing consumption or generation due to electrical outages, facilities operating erratically without regard for wholesale market prices, etc.

The focus on price responsiveness is because errors related to this behaviour would likely be reduced if the proposed rule changes were adopted. Having these facilities as part of the dispatch process, and therefore required to bid, would mean they would not be able reduce consumption during a DI unless instructed by the central dispatch procedure, which would then incorporate this response in the forecast of demand for the DI.

Other forms of regional dispatch demand error due to movement of large loads and non-scheduled generators may not reduce if a rule change is introduced. For example, unexpected shutdowns or reductions in consumption by large loads would still occur, as they do for large generators. This would not be forecast for the DI in which they occur. In the following DI, the initial reading that forms the basis of dispatch would incorporate the reduction, but this is the case now. It is possible that the return to typical operating behaviour, which could lead to dispatch demand underestimates under the current market rules, would be reduced as the load would inform the market of its return towards higher consumption by submitting bids, or similar.

Loads and non-scheduled generators that vary to a large degree, and not according to a clear pattern, may also be unlikely to more accurately forecast their behaviour under a possible rule change. Loads or non-scheduled generators that move up and down to a large degree without any discernable relationship to wholesale market prices are most likely operating based on considerations which are primarily related to its core process, e.g. processing a commodity. It is possible that these facilities would not be capable of providing an accurate forecast of consumption/production in the future, particularly at the 5-minute level, noting we do not currently have data that details how variable many individual facilities are in this time window.

Whether the forecasts that could be produced by the operators of these facilities represent a significant improvement on the forecasts by the neural network model is a key consideration in determining whether the proposed rule changes would have sufficient benefit. Furthermore, this needs to be weighed against the costs that would be borne by these facilities if they were obliged to produce more accurate forecasts and implement the processes required to participate in the NEM. Under the rule changes, facilities that don't have the ability to produce better forecasts or make the investment required to produce better forecasts may simply pay non-conformance costs when they fail to comply with dispatch instructions. These facilities would not help improve dispatch demand accuracy.

5.7 Illustrations of price response and impact on regional dispatch demand error

The following figures show DIs that meet several price triggers, outlined previously. The x-axis represents the increase that was forecast based on the neural network model. The y-axis represents the increase that actually occurred based on our calculations of actual demand. If the neural network model was perfectly accurate, these points would lie along a 45% line.

Points that lie negatively along the y-axis are DIs where no reduction in demand was forecast but demand actually decreased by a large magnitude – this would be an overestimate of demand and is linked with high pool prices causing a price responsive load reduction. It is evident that in Queensland (Figure 11) and South Australia (Figure 14), many of the points in this area of the chart are red – i.e. high priced DIs.

Points that lie positively along the y-axis are DIs where no increase in demand was forecast but demand increased by a large magnitude (i.e. an underestimate of demand). This is particularly evident in South Australia, where many of these points are yellow which indicates there was a high price in the previous TI. This is again an example of a price responsive behaviour, i.e. a reversion back towards typical operating levels.

Figure 11: Forecast vs Actual demand change (Queensland)

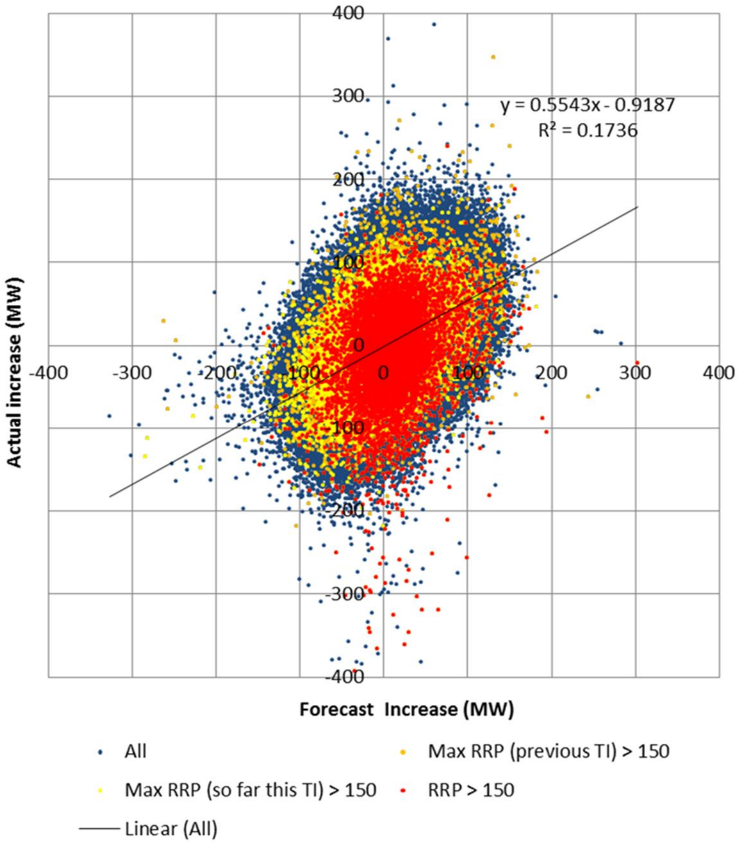


Figure 12: Forecast vs Actual demand change (New South Wales)

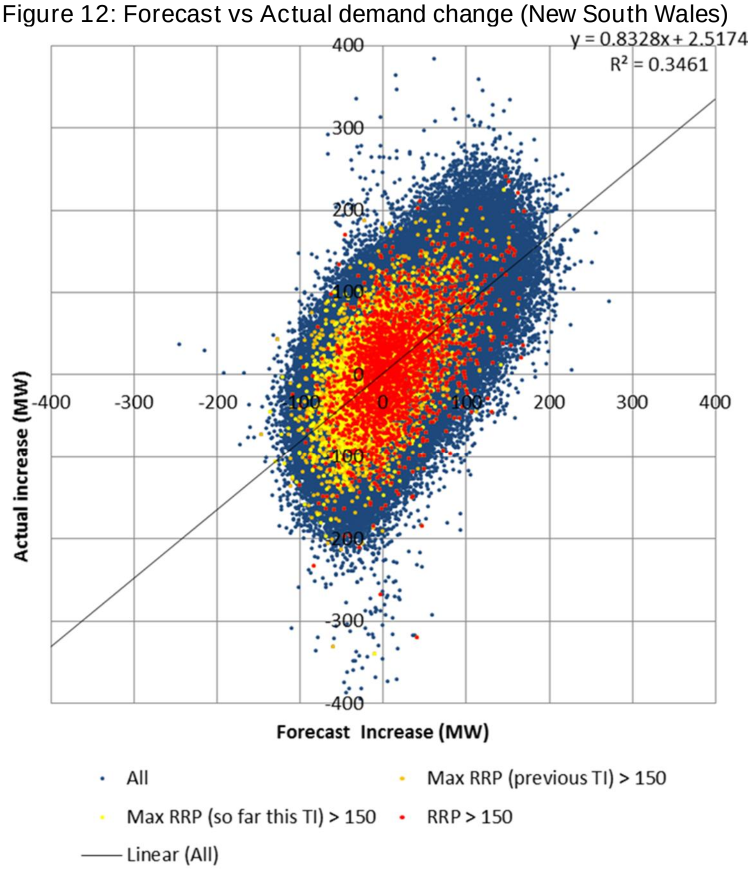


Figure 13: Forecast vs Actual demand change (Victoria)

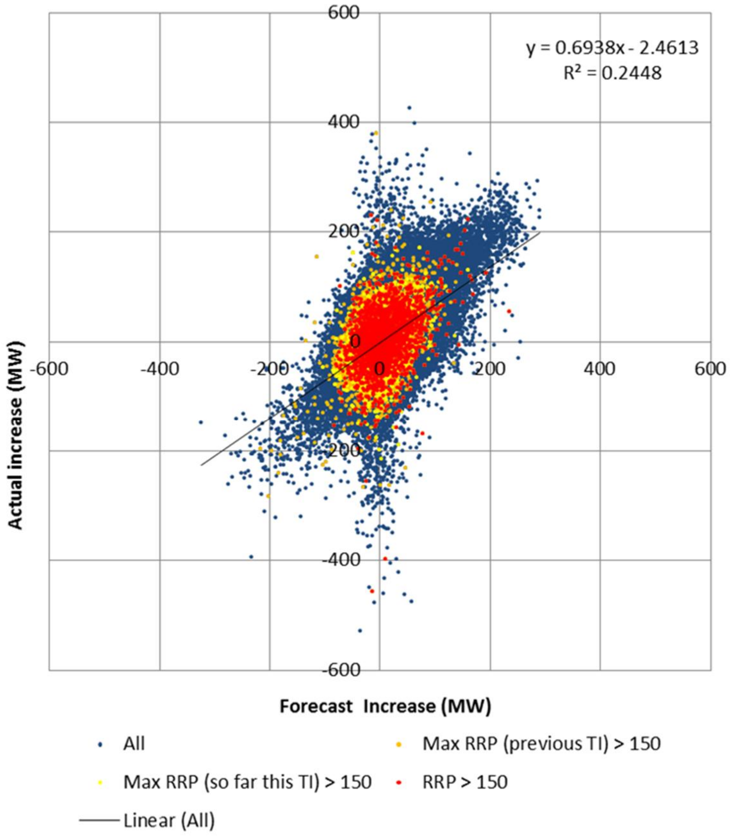
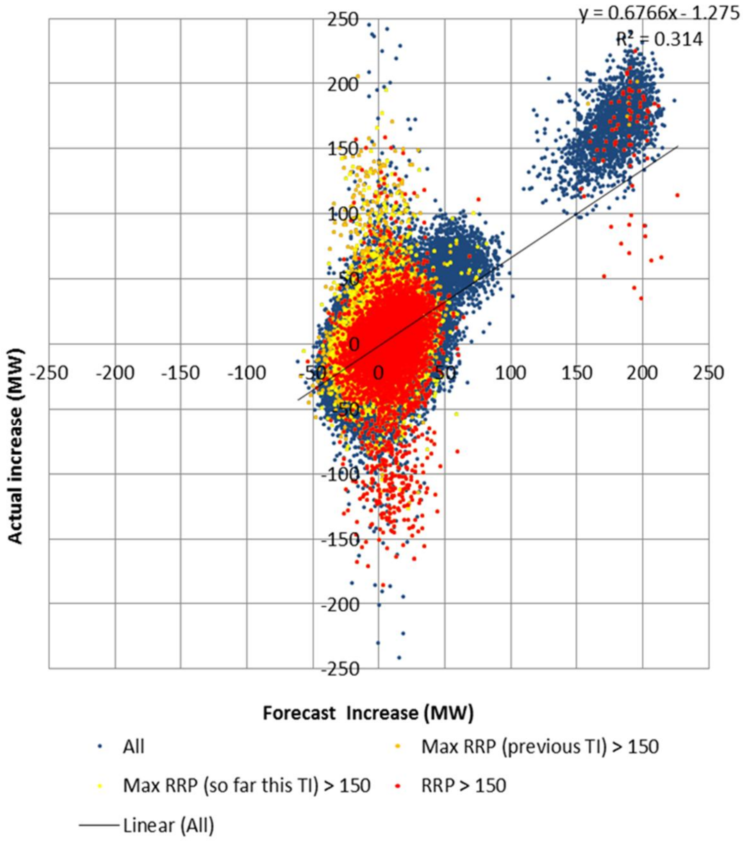


Figure 14: Forecast vs Actual demand change (South Australia)



Further discussion of each of these charts can be found in the worksheet 'Actual v Forecast'.

6. Trends in facility data

Our analysis indicates that a number of the large loads exhibit some form of price responsive behaviour. This is particularly true of loads that are relatively stable. For these facilities, many of the changes in consumption are linked with a price signal in some way.

More variable loads such as mills and some mines show relatively limited evidence of price responsive behaviour. TIs categorised as material errors for these facilities show no strong correlation with the range of price signals we have considered.

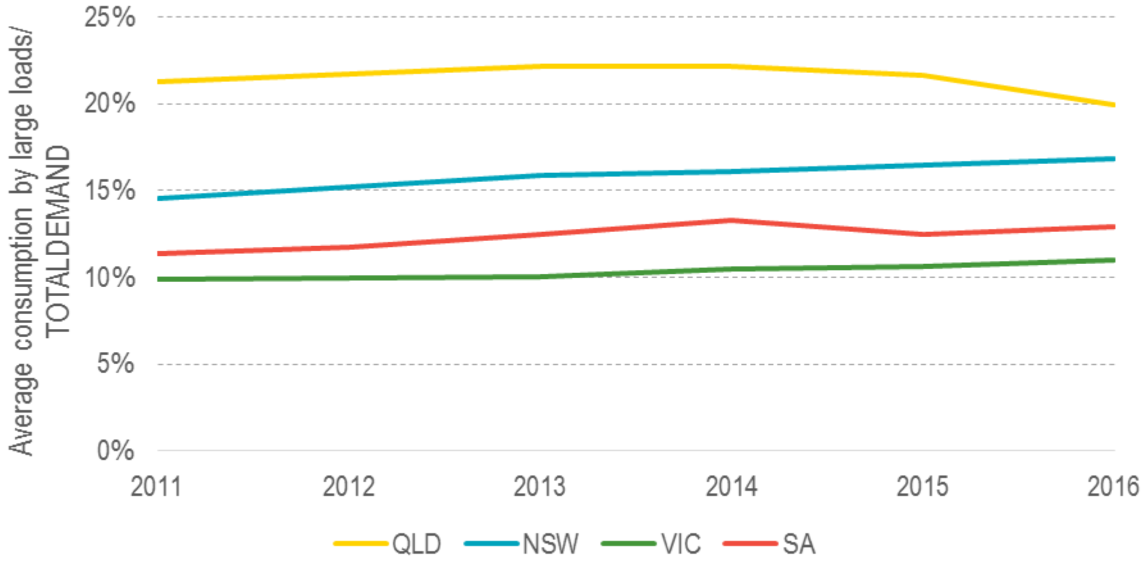
The set of non-scheduled generators analysed are diverse with regards to their production patterns and price responsiveness. Non-scheduled generators that have been identified as having a peaking role are more likely to be price responsive, this includes hydro and gas generators. Generators associated with another process, e.g. cogens, generally show less evidence of price responsive behaviour.

6.1 Large loads

6.1.1 Share of regional demand

The consumption by large loads analysed in this Report as a proportion of demand in each region averaged across each year, is shown in Figure 15. These are only those loads subject to the rule change request and with data provided to us by AEMO. Queensland has the highest proportion; large loads consume between 20% and 22% of total demand in each study year. Victoria has the smallest proportion of large loads at around 10%. The total consumption by large loads relative to demand in each region means that movements of large loads not forecast by the neural network model can potentially have a large impact on regional dispatch demand error.

Figure 15: Consumption by large loads analysed in this Report as a proportion of regional demand



6.1.2 Evidence of price response

The majority of large loads are found to be price responsive to some degree. The worksheet 'Facility – all periods' in the accompanying workbook shows the percentage of DIs with facility overestimates, underestimates, no data, and minor facility error across all DIs compared to DIs where a range of price conditions are met. This section does provide a number of examples of facility analysis rather than an exhaustive review of the price responsiveness of the each facility.

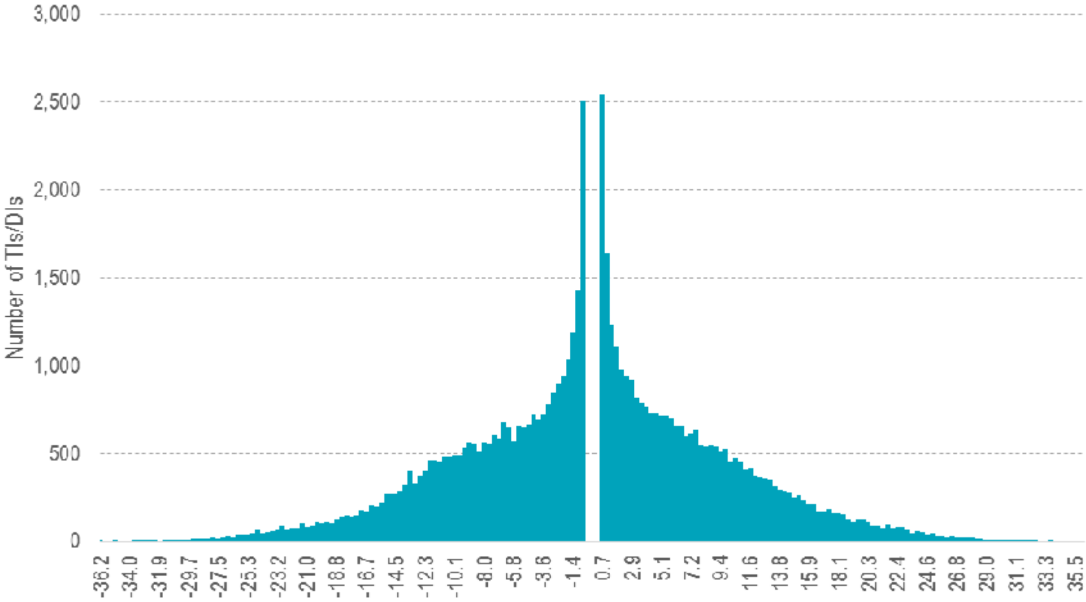
Price responsive facilities are those where the probability of facility overestimates and/or underestimates is higher in DIs where price conditions are met. One of the most obviously price responsive facilities is the Townsville Zinc load in Queensland. This facility is found to be responsive to a range of price triggers, as shown in Table 22. The probability of facility overestimates increases significantly in DIs with high pool prices, high pool prices earlier in the TI, and high pool prices forecast in pre-dispatch. The probability of facility underestimates is much higher in DIs where a price spike occurred in the preceding TI.

Table 22: Evidence of price response – Townsville Zinc

	All DIs	DI RRP > $150/MWh	Max RRP in TI > $150/MWh	Max RRP last TI > $150/MWh, not so far in TI	PD price from last 30 minutes > $150/MWh
% all DIs with negative facility error (underestimates of consumption)	2.2%	3.2%	3.8%	18.4%	7.1%
% all DIs with positive facility error (overestimates of consumption)	2.3%	19.6%	22.3%	9.7%	18.2%
% all DIs with no data	1.0%	2.4%	2.6%	2.6%	2.5%
% all DIs with minor facility error	94.5%	74.8%	71.3%	69.3%	72.2%

Facilities with more variable consumption levels generally show weaker evidence of price responsiveness. Table 23 shows the results for the analysis of the Waratah Steel Mill, a 55 MW load in New South Wales. Compared to the Townsville Zinc results presented above, there is a higher proportion of DIs where the Waratah Steel Mill is classified as having a material over- or underestimate. The higher proportion of material facility errors is due to the variability of the facility's consumption, as shown by the histogram of TI deltas in Figure 16.

Figure 16: Delta histogram for Waratah Steel Mill (with middle removed to make tails visible)



Furthermore, the proportions in each facility error category stay relatively constant across all of the price triggers (Table 23). This indicates that the variability of the facility is not strongly related to wholesale market price outcomes.

Table 23: Evidence of price response – Waratah Steel Mill

	All DIs	DI RRP > $150/MWh	Max RRP in TI > $150/MWh	Max RRP last TI > $150/MWh, not so far in TI	PD price from last 30 minutes > $150/MWh
% all DIs with negative facility error (underestimates of consumption)	4.9%	8.1%	7.6%	5.9%	7.4%
% all DIs with positive facility error (overestimates of consumption)	5.6%	6.2%	5.7%	6.8%	6.2%
% all DIs with no data	1.0%	6.6%	7.0%	8.1%	8.3%
% all DIs with minor facility error	88.4%	79.1%	79.7%	79.2%	78.0%

There are also facilities where consumption patterns are not volatile that are not found to be particularly price responsive. The Olympic Dam load for example shows very little evidence of being price responsive. Facilities may not be price responsive due to:

- limitations at the facility that prevent price response being physically possible or cost effective
- contracting strategies or other arrangements that mean that the facility is not highly exposed to wholesale prices
- a lack of volatility in wholesale prices that reduce the incentive for loads to engage actively in demand management; this may explain the relatively weak evidence of price responsiveness in loads in New South Wales and Victoria.

Table 24 shows that for Olympic Dam, the proportion of DIs in each facility error category is relatively unchanged for the set of price conditions considered.

Table 24: Evidence of price response – Olympic Dam

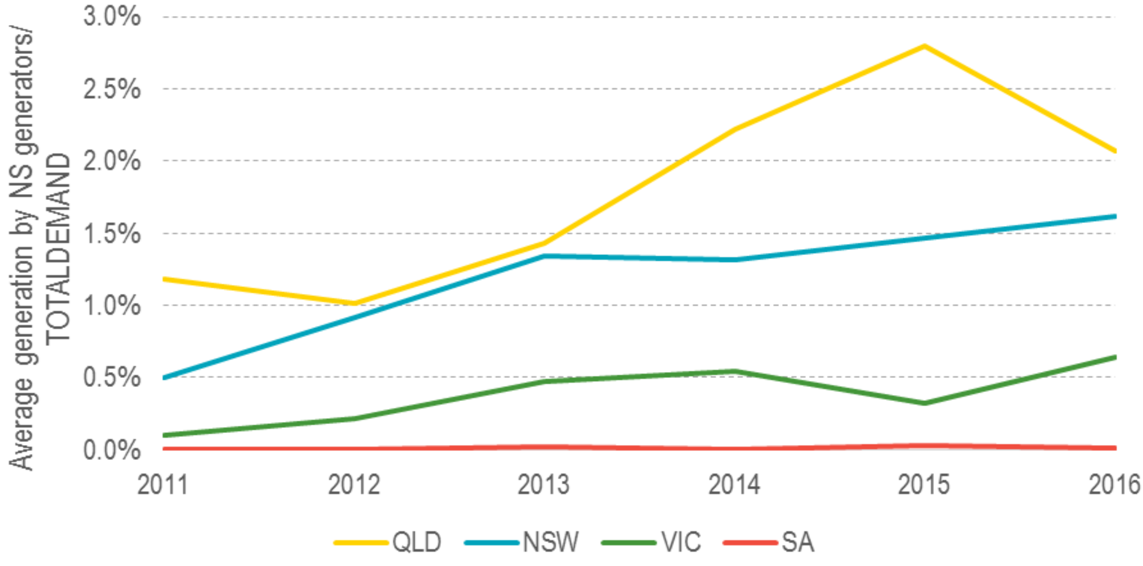
	All DIs	DI RRP > $150/MWh	Max RRP in TI > $150/MWh	Max RRP last TI > $150/MWh, not so far in TI	PD price from last 30 minutes > $150/MWh
% all DIs with negative facility error (underestimates of consumption)	0.2%	0.4%	0.5%	0.0%	0.4%
% all DIs with positive facility error (overestimates of consumption)	0.2%	0.3%	0.4%	0.3%	0.4%
% all DIs with no data	1.0%	2.5%	2.7%	3.5%	2.8%
% all DIs with minor facility error	98.6%	96.7%	96.4%	96.2%	96.4%

6.2 Non-scheduled generators

6.2.1 Share of regional demand

Generation by non-scheduled generators analysed in this Report as a proportion of demand in each region, averaged across each year is shown in Figure 17. These are only those non-scheduled generators subject to the rule change request and with data provided to us by AEMO. It does not include non-scheduled intermittent generators such as wind farms. As for large loads, Queensland again has the highest proportion with non-scheduled generators comprising between 1% and 3% of average power dispatched. The total size of non-scheduled generation compared to large loads suggests that even large, coordinated movements by non-scheduled generators that are not correctly forecast by the neural network model have a much smaller potential to produce significant regional demand error.

Figure 17: Non-scheduled generation analysed in this Report as a proportion of regional demand



6.2.2 Evidence of price response

The non-scheduled generators we have considered exhibit a wide range of operational patterns. Similarly, there is a wide range in the extent of the price responsiveness of facilities. Facilities that are identified as being more likely to provide a peaking role such as hydro and gas generators are generally found to be more likely to be price responsive. An example of a peaking non-scheduled generator is TNGSS1 (Traralgon Network Support Station gas spark) in Victoria; the results in Table 25 demonstrate the high correlation between facility errors and price signals.

Table 25: Evidence of price response – Traralgon Network Support Station gas spark

	All DIs	DI RRP > $150/MWh	Max RRP in TI > $150/MWh	Max RRP last TI > $150/MWh, not so far in TI	PD price from last 30 minutes > $150/MWh
% all DIs with negative facility error (overestimates of production)	2.8%	3.5%	3.7%	23.0%	8.8%
% all DIs with positive facility error (underestimates of production)	2.5%	19.4%	23.0%	16.9%	20.1%
% all DIs with no data	46.5%	33.4%	29.4%	23.2%	28.3%
% all DIs with minor facility error	48.2%	43.6%	43.9%	37.0%	42.8%

The evidence of price responsive behaviour is weaker for facilities that are linked to some other operation, e.g. cogens, bagasse, coal mine gas, etc. It is likely that the generation of these facilities is more dependent on the operation of their core process, rather than the electricity market. An example of a facility that shows no evidence of price responsive behaviour is provided in Table 26.

Table 26: Evidence of price response – German Creek waste coal mine gas spark

	All DIs	DI RRP > $150/MWh	Max RRP in TI > $150/MWh	Max RRP last TI > $150/MWh, not so far in TI	PD price from last 30 minutes > $150/MWh
% all DIs with negative facility error (overestimates of production)	0.2%	0.4%	0.3%	0.3%	0.3%
% all DIs with positive facility error (underestimates of production)	0.2%	0.2%	0.2%	0.4%	0.3%
% all DIs with no data	57.0%	60.4%	59.8%	53.9%	58.9%
% all DIs with minor facility error	42.5%	39.0%	39.7%	45.4%	40.5%

7. Contribution of facility types to regional error

Given data limitations it is difficult to quantify the contribution of any facility or facility type to dispatch demand error. Instead, we identify the frequency with which facility errors are correlated with large regional dispatch demand inaccuracies. This analysis indicates that there are two key facility types that most commonly contribute to regional dispatch demand error.

Highly variable facility types such as some steel mills are regularly correlated with regional dispatch demand errors. However, there are many DIs where consumption by these facilities is identified as being either over- or underestimated. Therefore, the frequency of a contribution to regional error is generally in line with the proportion of all DIs with a facility error, suggesting that this apparent correlation could be random.

Some of the less variable facility types such as aluminium smelters and Townsville Zinc are also observed to contribute regularly to regional error. In contrast with the highly variable facilities, the proportion of the DIs with material regional error where a contribution is observed is substantially higher than in other DIs. This indicates that when these facilities change their consumption, it is more likely that regional dispatch demand error will increase. Due to the size of these facilities, their contribution to regional dispatch demand error can be very large, to the extent that this could influence wholesale market outcomes.

It is evident that the facilities we have analysed, particularly large loads, contribute to dispatch demand inaccuracy. However, in the majority of DIs with large regional dispatch demand inaccuracies, there is no evidence of a contribution from any of the facilities in our dataset. This could be due to limitations in our analysis due to data availability, or show that other factors such as natural variability in residential and commercial demand are more significant.

7.1 Contribution of facility types to regional error – all DIs

This section considers the contribution of the different facility types to regional dispatch demand error in each region. The mapping of facilities to a type is given in Table 5. A facility type "contributes" to regional error where the total of material (not minor) facility error across all the facilities in a given type is in the same direction as regional error.

It is important to note that contribution does not necessarily mean causation, particularly given the issues associated with comparing 5-minute regional error data with the 30-minute facility data. Rather, a contribution is where the direction of a facility type error is correlated with total regional error.

The tables in this section show for each category of regional error, the percentage of those DIs in which the facility type contributed to that error (e.g. Table 27). For example for a large regional overestimate, the number of DIs in which a facility type has a positive error (overestimate of consumption or underestimate of production) and the regional error is a large overestimate divided by the number of DIs where the regional error is a large overestimate.

This percentage is then compared to the likelihood of that facility type having an error in that direction across all DIs (e.g. Table 28). For facilities that are generally very stable, a contribution to regional error indicates that the change in that facility's behaviour is likely to be a strong indicator of regional error. For facilities that are very volatile, and therefore have many DIs of large under- and over-estimate, the percentage contribution of these facilities may be more in line with their typical volatility. Examples of each of these types of behaviour are detailed in the remainder of this section.

7.1.1 Queensland

Table 27 shows the percentage of DIs in each regional error category with a contribution from each facility type. The key facility types that contribute to regional dispatch demand errors are smelters (Boyne Island Aluminium Smelter) and other large loads (predominantly Townsville Zinc). This is particularly evident in large regional overestimates which are commonly characterised by an overestimate of consumption for facilities of these types. The contribution from these facility types to regional underestimates is not as significant.

An important point from this table is that only a relatively low percentage of DIs with a significant regional dispatch demand error are found to have any contribution from large loads and non-scheduled generators. This indicates that even if the rule change requests under consideration result in a vast improvement in the forecasting of large loads and non-scheduled generators, the majority of the large errors in regional demand are likely to continue to occur.

Table 27: Contribution of facilities by type – all DIs – Queensland

	Large regional underestimate	Small regional underestimate	Small regional overestimate	Large regional overestimate
Load: smelter	2.5%	0.7%	0.5%	10.5%
Load: mine	2.5%	2.2%	3.7%	3.9%
Load: other	6.4%	4.5%	7.5%	15.9%
Load: mill				
NS gen: other				
NS gen: bagasse	3.3%	3.5%	3.5%	4.9%
NS gen: coal gas	2.3%	2.2%	3.9%	3.9%
NS gen: peaking				
NS gen: hydro	2.1%	1.4%	3.0%	2.7%
NS gen: auxiliary	0.4%	0.4%	0.6%	0.7%
NS gen: medium utilisation	0.2%	0.1%	0.0%	0.2%
NS gen: landfill gas				

Table 28 shows the increase in the likelihood of facility error moving in the same direction as regional error in each regional error category compared to the probability of facility movement in that direction across all DIs.

For example, for smelters in Queensland (i.e. the Boyne Island Aluminum Smelter) a value of 96.6 means that the probability that the smelter will have a material positive error is 96.6 times higher in DIs where regional error is a large overestimate than in any randomly chosen DI.

Where this ratio is low, and the contribution in the above table is high, this means that either:

► The magnitude of the facilities response is not of a sufficient magnitude to have a significant effect on regional error. This could be for example if the size of the facility type on aggregate is small; this is particularly the case for the non-scheduled generators which can be very small.

► The facility is highly variable, and therefore the percentage of DIs where the error “contributes” is not materially different from the percentage of DIs which are characterised as having that direction of error in any DI. This indicates that when the facility has positive error (overestimate of consumption or underestimate of production), that this does not necessarily increase the likelihood of a material regional overestimate. This is more likely to be true for facilities with variable behaviour that is less closely linked to a price response.

Table 28: Increased likelihood of facility error – all DIs – Queensland

	Large regional underestimate	Small regional underestimate	Small regional overestimate	Large regional overestimate
Load: smelter	25.4	6.8	4.8	96.6
Load: mine	1.5	1.3	1.3	1.4
Load: other	2.6	1.8	2.9	6.2
Load: mill				
NS gen: other				
NS gen: bagasse	1.1	1.1	1.3	1.8
NS gen: coal gas	1.2	1.2	1.8	1.8
NS gen: peaking				
NS gen: hydro	1.8	1.2	2.7	2.4
NS gen: auxiliary	0.5	0.5	0.7	0.9
NS gen: medium utilisation	1.8	0.8	0.0	1.1
NS gen: landfill gas				

Table 29 shows the average size of the facility error by facility type during the DIs that have been categorised as contributing to regional error. This again supports the significance of smelters in particular as when these facilities are contributing, the size of the facility error is significant. With the exception of the smelter and other load categories, the size of any individual facility type’s contribution is relatively small.

Table 29: Average magnitude of facility error when contributing – all DIs – Queensland (MW)

	Large regional underestimate	Small regional underestimate	Small regional overestimate	Large regional overestimate
Load: smelter	-175	-189	144	151
Load: mine	-7	-7	9	8
Load: other	-32	-34	39	43
Load: mill				
NS gen: other				
NS gen: bagasse	-7	-5	4	5
NS gen: coal gas	-7	-5	5	4
NS gen: peaking				
NS gen: hydro	-1	-1	1	1
NS gen: auxiliary	-2	-2	2	2
NS gen: medium utilisation	-5	-7		7
NS gen: landfill gas				

7.1.2 New South Wales

Table 30 shows the percentage of DIs in each regional error category with a contribution from each facility type for New South Wales. There are two facility types that contribute to a significant proportion of material regional errors. For smelters (i.e. the Tomago Aluminum Smelter), a significant proportion of the large regional over- and underestimates occur during DIs where the facility is categorised as having a corresponding overestimate/underestimate. This is not true of small regional errors, suggesting that when the smelter is characterised as having a material error that the regional error is more likely to be very large. The Load: mill category is found to contribute to all categories of regional error. The following section examines this category in more detail.

Table 30: Contribution of facilities by type – all DIs – New South Wales

	Large regional underestimate	Small regional underestimate	Small regional overestimate	Large regional overestimate
Load: smelter	11.1%	0.6%	0.2%	13.8%
Load: mine	1.2%	1.5%	1.6%	1.4%
Load: other	0.0%	0.3%	0.2%	0.2%
Load: mill	14.3%	11.7%	13.2%	14.0%
NS gen: other				
NS gen: bagasse	2.2%	2.5%	2.9%	2.9%
NS gen: coal gas	2.5%	2.1%	2.6%	2.9%
NS gen: peaking	0.5%	0.2%	0.3%	0.0%
NS gen: hydro	4.7%	3.3%	3.1%	4.5%
NS gen: auxiliary	2.5%	4.2%	2.5%	2.5%
NS gen: medium utilisation	3.2%	2.1%	2.4%	4.3%
NS gen: landfill gas	2.2%	2.1%	2.4%	4.3%

A sizable proportion of material errors in regional demand occur in DIs with no observable contribution from any of the facility types under consideration, although the proportion is smaller than in Queensland.

Table 31 shows the increase in the likelihood of the direction of facility error when the regional error is in each regional error category in comparison to the probability across all DIs.

The very high ratio observed for the smelter in New South Wales is consistent with the ratio observed the smelter in Queensland. The key to this result is that smelters are not very variable, but when they do change consumption by a material quantity, regional error is likely to be large.

In the table above, it was seen that the ‘Load: mill’ facility type contributes to regional error across all regional error categories. However, a number of the loads of this facility type, in particular the Sydney Steel Mill and the Waratah Steel Mill, are very variable as shown in Section 7.3.2. As a result, there are many DIs categorised as having an overestimate or underestimate of consumption for these facilities, and for the ‘Load: mill’ facility type on aggregate. In Table 31 it is evident that the likelihood of a material facility error for the ‘Load: mill’ facility type is not increased when the regional error is large. Therefore, there is a relatively low correlation between errors for the steel mills and the regional dispatch demand error.

Table 31: Increased likelihood of facility error – all DIs – New South Wales

	Large regional underestimate	Small regional underestimate	Small regional overestimate	Large regional overestimate
Load: smelter	77.2	4.1	1.4	104.4
Load: mine	0.9	1.1	1.1	1.0
Load: other	0.0	1.2	0.7	0.6
Load: mill	1.5	1.2	1.1	1.2
NS gen: other				
NS gen: bagasse	1.0	1.1	1.1	1.1
NS gen: coal gas	1.1	0.9	1.1	1.2
NS gen: peaking	2.2	0.7	1.6	0.0
NS gen: hydro	1.5	1.1	1.0	1.4
NS gen: auxiliary	0.7	1.2	1.0	1.0
NS gen: medium utilisation	1.2	0.8	0.9	1.7
NS gen: landfill gas	0.9	0.8	0.9	1.6

Table 32 shows the average size of the facility error during the DIs that have been categorised as contributing to regional error. The size of the impact of errors for the smelter is very large, and supports the high likelihood of large regional errors when the smelter has a material error.

Table 32: Average magnitude of facility error when contributing – all DIs – New South Wales (MW)

	Large regional underestimate	Small regional underestimate	Small regional overestimate	Large regional overestimate
Load: smelter	-196	-166	123	194
Load: mine	-15	-13	13	23
Load: other		-3	3	3
Load: mill	-22	-22	22	21
NS gen: other				
NS gen: bagasse	-5	-8	6	5
NS gen: coal gas	-6	-6	4	3
NS gen: peaking	-2	-12	13	
NS gen: hydro	-2	-2	2	2
NS gen: auxiliary	0	0	0	0
NS gen: medium utilisation	-2	-2	1	1
NS gen: landfill gas	-1	-1	1	1

7.1.3 Victoria

Table 33 shows the percentage of DIs in each regional error category with a contribution from each facility type. The significant contributions by facility type in Victoria are very similar to those found above in New South Wales; the most significant impact from smelters and mills.

There are also relatively significant contributions from some categories of non-scheduled generators, particularly the ‘other’ category and landfill gas.

Table 33: Contribution of facilities by type – all DIs – Victoria

	Large regional underestimate	Small regional underestimate	Small regional overestimate	Large regional overestimate
Load: smelter	21.2%	2.4%	2.0%	38.3%
Load: mine				
Load: other	0.0%	0.0%	0.0%	0.0%
Load: mill	12.1%	14.0%	11.0%	9.7%
NS gen: other	7.3%	8.2%	5.9%	7.0%
NS gen: bagasse				
NS gen: coal gas				
NS gen: peaking				
NS gen: hydro	0.5%	0.5%	0.5%	0.5%
NS gen: auxiliary	2.2%	2.6%	1.0%	0.9%
NS gen: medium utilisation	0.3%	0.5%	0.5%	0.9%
NS gen: landfill gas	4.8%	5.8%	5.0%	7.4%

Table 34 shows the increase in the likelihood of the direction of facility error when the regional error is in each regional error category in comparison to the probability across all DIs.

The results here are consistent with observations in both Queensland and New South Wales, with contributions from facilities other than the smelters being consistent with the general variability of the facility type. The probability of a facility error for the smelter is far more likely in DIs found to have a material regional error. The average sizes of the contributions from each facility type are provided in Table 35.

Table 34: Increased likelihood of facility error – all DIs – Victoria

	Large regional underestimate	Small regional underestimate	Small regional overestimate	Large regional overestimate
Load: smelter	37.5	4.3	4.0	74.9
Load: mine				
Load: other	0.0	0.0	0.0	0.0
Load: mill	1.3	1.5	1.3	1.2
NS gen: other	1.2	1.4	1.1	1.3
NS gen: bagasse				
NS gen: coal gas				
NS gen: peaking				
NS gen: hydro	1.0	1.0	1.0	1.0
NS gen: auxiliary	1.4	1.7	1.0	0.8
NS gen: medium utilisation	0.6	1.1	1.2	2.0
NS gen: landfill gas	1.1	1.4	1.0	1.5

Table 35: Average magnitude of facility error when contributing – all DIs – Victoria (MW)

	Large regional underestimate	Small regional underestimate	Small regional overestimate	Large regional overestimate
Load: smelter	-143	-124	151	174
Load: mine				
Load: other				
Load: mill	-22	-23	22	24
NS gen: other	-12	-12	13	14
NS gen: bagasse				
NS gen: coal gas				
NS gen: peaking				
NS gen: hydro	-3	-3	2	2
NS gen: auxiliary	0	0	0	0
NS gen: medium utilisation	-2	-3	3	3
NS gen: landfill gas	-3	-2	2	2

7.1.4 South Australia

In the analysis presented in this section, we list Angaston as its own category rather than including it in the 'NS gen: peaking' category. A more detailed analysis of Angaston is also provided in Section 7.3.4.

Table 36 shows the percentage of DIs in each regional error category with a contribution from each facility type. The contribution from any of the load facility types in South Australia is much lower than in any other region. However, the contribution from non-scheduled generators is larger than in any other region, particularly the Angaston and other generators designated as having a peaking role.

Table 36: Contribution of facilities by type – all DIs – South Australia

	Large regional underestimate	Small regional underestimate	Small regional overestimate	Large regional overestimate
Load: smelter				
Load: mine	0.5%	0.3%	0.3%	1.0%
Load: other				
Load: mill	1.9%	2.4%	2.8%	4.6%
NS gen: other	3.1%	1.7%	1.5%	3.4%
NS gen: bagasse				
NS gen: coal gas				
NS gen: peaking	24.3%	2.9%	2.1%	27.7%
NS gen: hydro				
NS gen: auxiliary	10.6%	5.0%	5.0%	10.3%
NS gen: medium utilisation				
NS gen: landfill gas				
NS gen: Angaston	47.8%	4.8%	2.5%	47.3%

Table 37 shows the increase in the likelihood of the direction of facility error when the regional error is in each regional error category in comparison to the probability across all DIs. This table shows that an error in the forecast for peaking non-scheduled generators is far more likely in DIs with material errors.

Table 37: Increased likelihood of facility error – all DIs – South Australia

	Large regional underestimate	Small regional underestimate	Small regional overestimate	Large regional overestimate
Load: smelter				
Load: mine	2.8	1.9	1.4	4.3
Load: other				
Load: mill	0.9	1.1	1.2	1.9
NS gen: other	2.1	1.2	1.0	2.3
NS gen: bagasse				
NS gen: coal gas				
NS gen: peaking	48.6	5.8	5.4	70.5
NS gen: hydro				
NS gen: auxiliary	4.1	1.9	1.5	3.0
NS gen: medium utilisation				
NS gen: landfill gas				
NS gen: Angaston	306.1	30.5	14.5	271.7

The tables above indicate that the contribution from peaking non-scheduled generators in South Australia is comparable to smelters in Queensland, New South Wales and Victoria. However, Table 38 shows that the average magnitude of the error from peaking non-scheduled generators in South Australia is not large (4 MW). An error of this size would not on its own lead to a material error at the regional error. One possibility is that the contribution from non-scheduled generation is correlated with some other load or non-scheduled generator which is causing large regional errors. Further investigation revealed that the 'missing' facility was ANGASTON, a large peaking generator that we erroneously believed to be treated as scheduled by the neural network model. Subsequent analysis suggested most DIs with large error in South Australia are associated with movement in the correct direction by ANGASTON (Section 7.3.4). It is also possible that Port Stanvac, a 58 MW non-scheduled peaking generator (recently changed to scheduled) not included in our dataset due to the unavailability of data during the period it was non-scheduled, could have a significant contribution to regional error in South Australia not captured in our analysis.

Table 38: Average magnitude of facility error when contributing – all DIs – South Australia (MW)

	Large regional underestimate	Small regional underestimate	Small regional overestimate	Large regional overestimate
Load: smelter				
Load: mine	-20	-18	23	35
Load: other				
Load: mill	-6	-5	5	5
NS gen: other	-2	-2	1	2
NS gen: bagasse				
NS gen: coal gas				
NS gen: peaking	-4	-4	4	4
NS gen: hydro				
NS gen: auxiliary	-1	-1	1	0
NS gen: medium utilisation				
NS gen: landfill gas				
NS gen: Angaston	-38	-33	27	39

As in all other regions, a large proportion of material regional errors occur in DIs without an observable contribution from any facility type under consideration. However, South Australia differs from the other regions in that the combination of the magnitude and frequency of Angaston's (and to a lesser extent other peaking generators') contribution to regional demand error means that material demand error in South Australia is more attributable to the actions of non-scheduled facilities.

7.2 Contribution to regional error due to price responsiveness

This section highlights some examples of the contribution by facility types to regional error which have been linked with different types of price responsiveness.

Table 39 shows the contribution of facility types to regional errors in each category that occur during DIs where the DI price exceeds $150/MWh. The columns on the right of this table therefore show the percentage of DIs in which a material regional overestimate has occurred during a high price where a facility type on aggregate also has positive error (overestimate of consumption or underestimate of production). The very high values for 'Load: other' indicate that in the majority of DIs we have linked as a price responsive overestimate, 'Load: other' has been contributing to this price response. (This contribution is mostly Townsville Zinc. Its individual contribution is analysed in 7.3.1.) Consumption by the facility type 'Load: smelter' (Boyne Island Aluminium Smelter) is also overestimated frequently in DIs with a price spike and a large regional overestimate of demand.

Table 39: Contribution of facilities by type – current DI price spike – Queensland

	Large regional underestimate	Small regional underestimate	Small regional overestimate	Large regional overestimate
Load: smelter	16.7%	0.0%	0.3%	17.9%
Load: mine	0.0%	0.0%	6.6%	5.7%
Load: other	16.7%	8.3%	42.2%	56.6%
Load: mill				
NS gen: other				
NS gen: bagasse	16.7%	5.6%	3.3%	1.9%
NS gen: coal gas	0.0%	5.6%	9.0%	3.8%
NS gen: peaking				
NS gen: hydro	16.7%	2.8%	4.3%	3.8%
NS gen: auxiliary	0.0%	0.0%	0.7%	0.0%
NS gen: medium utilisation	0.0%	0.0%	0.0%	0.0%
NS gen: landfill gas				

Table 40 shows the contribution of facility types to errors in each category that occur during DIs where the previous TI has a price that exceeded $150/MWh and where the maximum price so far in the TI is less than $150/MWh. We understand this form of price response as being due to a reversion back towards typical operational behaviour.

In Table 40, it is evident that the 'Load: other' facility type is contributing in 14.3% of the DIs where this form of price response is evident in the regional error data. Smaller contributions are evident for the smelter. However, it is also clear that the majority of this price response is not observed in any of the facility types under consideration. This could be due to data limitations that make this reversion very difficult to determine in half-hourly data, where the half-hourly consumption from the preceding trading interval has some form of initial price response.

Table 40: Contribution of facilities by type – previous TI price spike – Queensland

	Large regional underestimate	Small regional underestimate	Small regional overestimate	Large regional overestimate
Load: smelter	4.8%	1.0%	8.3%	7.4%
Load: mine	2.4%	4.6%	8.3%	7.4%
Load: other	14.3%	28.9%	8.3%	7.4%
Load: mill				
NS gen: other				
NS gen: bagasse	0.0%	2.0%	0.0%	0.0%
NS gen: coal gas	0.0%	6.6%	0.0%	0.0%
NS gen: peaking				
NS gen: hydro	0.0%	2.5%	8.3%	7.4%
NS gen: auxiliary	0.0%	1.0%	8.3%	7.4%
NS gen: medium utilisation	0.0%	0.0%	0.8%	0.0%
NS gen: landfill gas				

The complete set of results that detail the contribution of each facility type to regional error categorised as potentially due to price response can be found in the worksheets 'Facility agg. - current DI', 'Facility agg. - previous TI', 'Facility agg. – PD' and 'Facility agg. - magnitude'. In general, the facility types that most contribute to large regional errors linked to price response are smelters across all regions, as well as non-scheduled peaking generation in South Australia.

The worksheet 'Facility agg. - price response' shows the percentage of each facility type's contribution to regional error that is linked to price response. Facility types where a high proportion of the contribution to regional error is linked to price response include Queensland smelters and Load: other, peaking and other non-scheduled generation in South Australia.

7.3 Example of individual facilities

This section outlines evidence of price responsive behaviour for several facilities. Each individual facility can be examined using the drop downs in the worksheets 'Facility – all periods', 'Facility – current DI+TI', 'Facility – previous TI', 'Facility – Pre-dispatch'.

7.3.1 Townsville Zinc

Townsville Zinc is a particularly price responsive Queensland load of up to 136 MW. An example month of consumption data is shown in Figure 18. As already presented in Table 22, the probability of overestimates of consumption by this facility increases significantly in DIs with high pool prices, high pool prices earlier in the TI, and high pool prices forecast in pre-dispatch. The probability of underestimates of consumption by this facility is much higher in DIs where a price spike occurred in the preceding TI.

Figure 18: Example month – Townsville Zinc

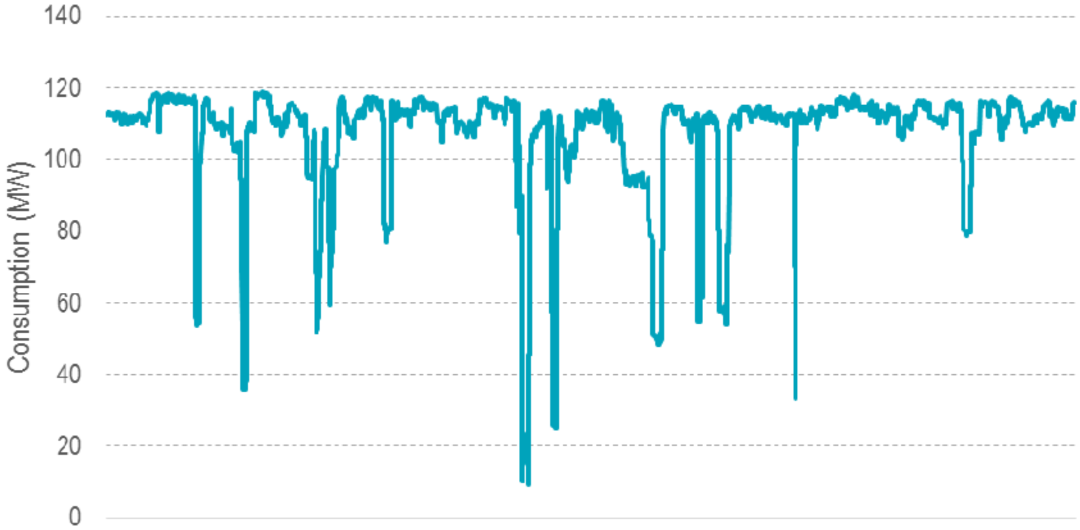


Table 41 shows the percentage of DIs in each regional error category with a contribution by Townsville Zinc. This facility appears to frequently contribute to Queensland dispatch demand error. This is particularly evident in large regional overestimates where 15.3% of DIs with a large regional overestimate have an associated overestimate of Townsville Zinc consumption. However, in the majority of DIs with material regional error, Townsville Zinc does not have material error indicating there are frequently other causes of material regional error in Queensland.

Table 41: Contribution of Townsville Zinc error to Queensland dispatch demand error – all DIs

	Large regional underestimate	Small regional underestimate	Small regional overestimate	Large regional overestimate
% DIs with negative facility error (underestimates of consumption)	6.0% (contributing)	4.2% (contributing)	2.2% (countering)	2.4% (countering)
% DIs with positive facility error (overestimates of consumption)	2.9% (countering)	0.8% (countering)	7.1% (contributing)	15.3% (contributing)
% DIs with no data	0.2%	0.8%	1.3%	1.3%%
% DIs with minor facility error	90.9%	92.8%	89.4%	80.9%
% all DIs with negative facility error (underestimates of consumption)	2.2%			
% all DIs with positive facility error (overestimates of consumption)	2.3%			
Likelihood ratio of having negative error when regional error exceeds threshold	2.7 (contributing)	1.9 (contributing)	1.0 (countering)	1.1 (countering)
Likelihood ratio of having positive error when regional error exceeds threshold	1.3 (countering)	1.0 (countering)	3.1 (contributing)	6.8 (contributing)
Average negative contribution (MW)	-34.1	-35.5	-31.7	-29.8
Average positive contribution (MW)	32.8	35.3	40.7	44.6

When the price in a DI exceeds $150/MWh, the proportion of DIs with material overestimates of regional demand and an associated overestimate of consumption by Townsville Zinc increases to 54.7% for large overestimates of Queensland demand and 41.9% of small overestimates, as shown in Table 42. This suggests decrease in consumption by Townsville Zinc due to high prices is highly correlated with overestimates of Queensland demand. However, the average magnitude of the contribution is smaller than the regional error thresholds suggesting the reduction in consumption by Townsville Zinc alone is not enough to cause material dispatch demand error in Queensland. Changes in behaviour in response to high prices are likely coincident between Townsville Zinc and other loads including Boyne Island Aluminium Smelter (analysed in Section 7.2).

Table 42: Contribution of Townsville Zinc error to Queensland dispatch demand error – current DI price spike

	Large regional underestimate	Small regional underestimate	Small regional overestimate	Large regional overestimate
% DIs with negative facility error (underestimates of consumption)	16.7% (contributing)	8.3% (contributing)	4.0% (countering)	2.8% (countering)
% DIs with positive facility error (overestimates of consumption)	0.0% (countering)	8.3% (countering)	41.9% (contributing)	54.7% (contributing)
% DIs with no data	0.0%	0.0%	3.7%	3.8%
% DIs with minor facility error	83.3%	83.3%	50.5%	38.7%
% DIs with current DI price spike and negative facility error (underestimates of consumption)	3.2%			
% DIs with current DI price spike and positive facility error (overestimates of consumption)	19.6%			
Likelihood ratio of having negative error when regional error exceeds threshold	5.2 (contributing)	2.6 (contributing)	1.2 (countering)	0.9 (countering)
Likelihood ratio of having positive error when regional error exceeds threshold	0.0 (countering)	0.4 (countering)	2.1 (contributing)	2.8 (contributing)

	Large regional underestimate	Small regional underestimate	Small regional overestimate	Large regional overestimate
Average negative contribution (MW)	-22.3	-41.6		
Average positive contribution (MW)			45.3	46.0

There is also evidence that in DIs with material underestimates of regional demand in the TI following price volatility, consumption by Townsville Zinc is underestimated.

7.3.2 Waratah Steel Mill

Waratah Steel Mill is a highly variable load in New South Wales of up to 55 MW. An example month of consumption data is shown in Figure 19. As already presented in Table 23, the probability of overestimates and underestimates of consumption by this facility are relatively constant in all DIs, in DI with high pool prices, high pool prices earlier in the TI, and high pool prices forecast in pre-dispatch. This indicates that the variability of the facility is not strongly related to wholesale market price outcomes.

Figure 19: Example month – Waratah Steel Mill

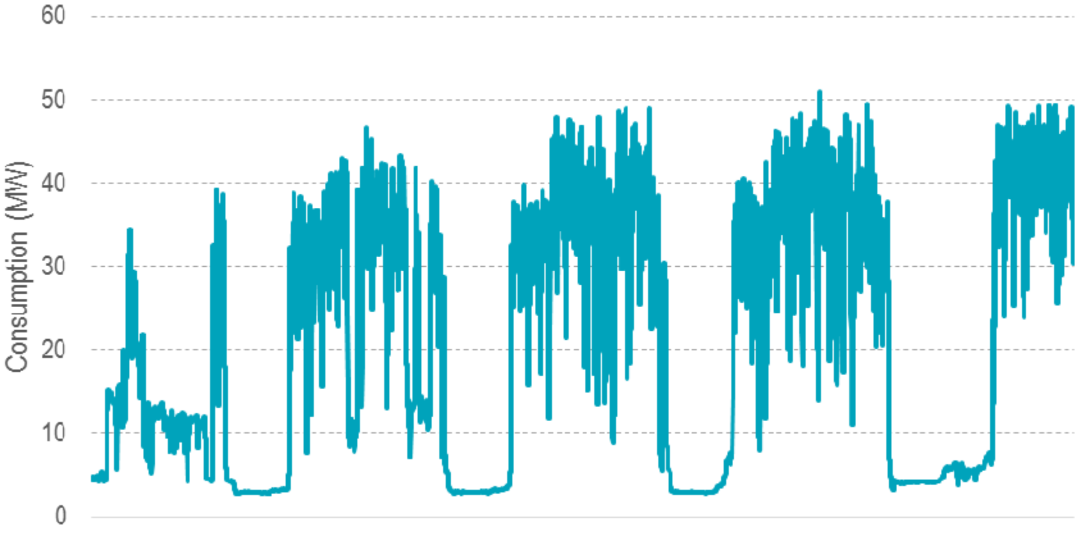


Table 43 shows the percentage of DIs in each regional error category with a contribution by Waratah Steel Mill. The frequency that this facility contributes to dispatch demand error in New South Wales is similar to the frequency at which it counters regional error. These frequencies are also similar to the incidence of facility underestimates and overestimates of consumption across all DIs (not just those with material regional demand under- and overestimates).

Table 43: Contribution of Waratah Steel Mill error to New South Wales dispatch demand error – all DIs

	Large regional underestimate	Small regional underestimate	Small regional overestimate	Large regional overestimate
% DIs with negative facility error (underestimates of consumption)	6.4% (contributing)	5.6% (contributing)	5.7% (countering)	6.0% (countering)
% DIs with positive facility error (overestimates of consumption)	5.7% (countering)	6.1% (countering)	6.5% (contributing)	7.9% (contributing)
% DIs with no data	1.2%	1.2%	0.4%	0.4%
% DIs with minor facility error	86.7%	87.1%	87.4%	85.7%

	Large regional underestimate	Small regional underestimate	Small regional overestimate	Large regional overestimate
% all DIs with negative facility error (underestimates of consumption)	4.9%			
% all DIs with positive facility error (overestimates of consumption)	5.6%			
Likelihood ratio of having negative error when regional error exceeds threshold	1.3 (contributing)	1.1 (contributing)	1.2 (countering)	1.2 (countering)
Likelihood ratio of having positive error when regional error exceeds threshold	1.0 (countering)	1.1 (countering)	1.2 (contributing)	1.4 (contributing)
Average negative contribution (MW)	-16.9	-16.7	-16.8	-17.3
Average positive contribution (MW)	14.6	15.8	16.1	16.5

When the price in a DI exceeds $150/MWh, the proportion of DIs with material overestimates of regional demand and an associated overestimate of consumption by Waratah Steel Mill appears to increase slightly, as shown in Table 42, but small sample sizes make the outcomes difficult to interpret. Overall, this facility does not appear to reduce its consumption due to high prices more frequently than occurs by chance.

Table 44: Contribution of Waratah Steel Mill error to New South Wales dispatch demand error – current DI price spike

	Large regional underestimate	Small regional underestimate	Small regional overestimate	Large regional overestimate
Number of DIs in regional demand error category	3	25	55	10
% DIs with negative facility error (underestimates of consumption)	33.3% (contributing)	12.0% (contributing)	9.1% (countering)	10.0% (countering)
% DIs with positive facility error (overestimates of consumption)	0.0% (countering)	12.0% (countering)	7.3% (contributing)	20.0% (contributing)
% DIs with no data	0.0%	0.0%	9.1%	0.0%
% DIs with minor facility error	66.7%	76.0%	74.5%	70.0%
% DIs with current DI price spike and negative facility error (underestimates of consumption)	8.1%			
% DIs with current DI price spike and positive facility error (overestimates of consumption)	6.2%			
Likelihood ratio of having negative error when regional error exceeds threshold	4.1 (contributing)	1.5 (contributing)	1.1 (countering)	1.2 (countering)
Likelihood ratio of having positive error when regional error exceeds threshold	0.0 (countering)	1.9 (countering)	1.2 (contributing)	3.2 (contributing)
Average negative contribution (MW)	-18.3	-17.1		
Average positive contribution (MW)			12.1	13.5

7.3.3 Lonsdale

Lonsdale is a price responsive peaking generator in South Australia with a registered capacity of 20 MW (although only observed to generate up to 11 MW during the study period). An example month of production data is shown in Figure 20. Lonsdale generated in 14.8% of DIs with pool prices above $150/MWh compared to 0.4% of all DIs. The probability of underestimates in production also increases significantly in DIs with high pool prices earlier in the TI and high pool prices forecast in pre-dispatch. Furthermore, production by Lonsdale is overestimated in 16.0% of DIs with high prices in preceding TI, compared to 0.5% of all DIs.

Figure 20: Example month – Lonsdale

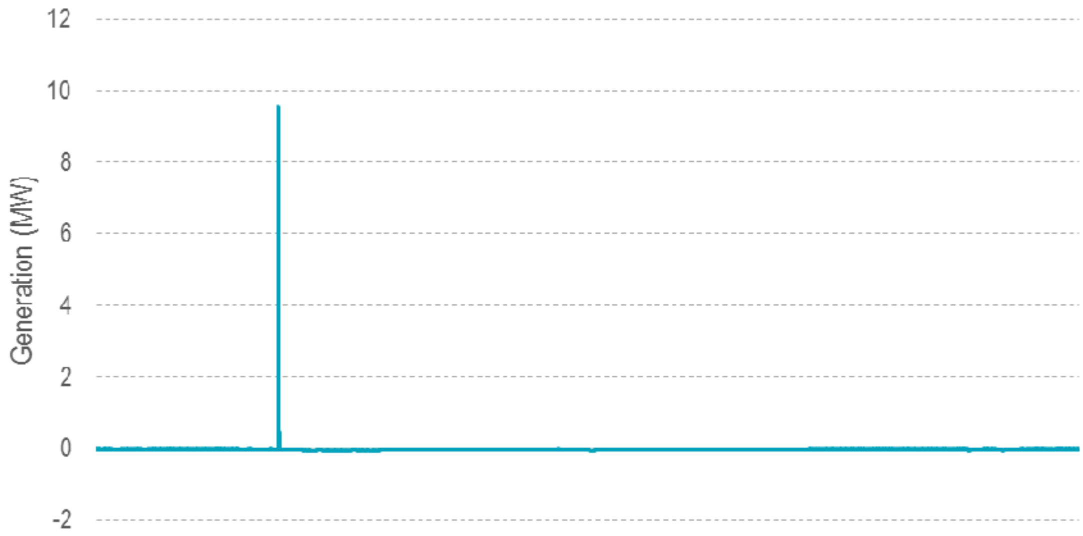


Table 45 shows the percentage of DIs in each regional error category with a contribution by Lonsdale. This facility appears to frequently contribute to South Australian dispatch demand error. This is particularly evident in large regional overestimates where 27.7% of DIs with a large regional overestimate have an associated underestimate of Lonsdale production, compared to only 0.4% of all DIs with an underestimate of Lonsdale production.

Table 45: Contribution of Lonsdale error to South Australian dispatch demand error – all DIs

	Large regional underestimate	Small regional underestimate	Small regional overestimate	Large regional overestimate
% DIs with negative facility error (overestimates of production)	24.3% (contributing)	2.9% (contributing)	1.5% (countering)	5.5% (countering)
% DIs with positive facility error (underestimates of production)	16.1% (countering)	3.2% (countering)	2.1% (contributing)	27.7% (contributing)
% DIs with no data	36.3%	53.3%	57.7%	42.1%
% DIs with minor facility error	23.3%	40.6%	38.8%	24.7%
% all DIs with negative facility error (overestimates of production)	0.5%			
% all DIs with positive facility error (underestimates of production)	0.4%			
Likelihood ratio of having negative error when regional error exceeds threshold	48.6 (contributing)	5.8 (contributing)	2.9 (countering)	11.0 (countering)
Likelihood ratio of having positive error when regional error exceeds threshold	40.9 (countering)	8.0 (countering)	5.4 (contributing)	70.5 (contributing)
Average negative contribution (MW)	-4.0	-3.5	-3.2	-3.2
Average positive contribution (MW)	3.3	3.6	4.5	4.4

When the price in a DI exceeds $150/MWh, the proportion of DIs with material overestimates of regional demand and an associated underestimate of production by Lonsdale increases to 49.3% for large overestimates of regional demand and 23.5% of small overestimates, as shown in Table 46. This suggests increase in production by Lonsdale due to high prices is correlated with overestimates of South Australian demand. However, the average magnitude of the contribution is smaller than the regional error thresholds (43 MW for small errors and 75 MW for large) suggesting the increase in production by Lonsdale alone is not enough to cause material dispatch demand error in South Australia. Changes in behaviour in response to high prices are likely coincident between Lonsdale and other non-scheduled generators and loads, in particular with Angaston, analysed in Section 7.3.4.

Table 46: Contribution of Lonsdale error to South Australian dispatch demand error – current DI price spike

	Large regional underestimate	Small regional underestimate	Small regional overestimate	Large regional overestimate
% DIs with negative facility error (overestimates of production)	37.8% (contributing)	13.3% (contributing)	13.1% (countering)	6.8% (countering)
% DIs with positive facility error (underestimates of production)	29.7% (countering)	25.3% (countering)	23.5% (contributing)	49.3% (contributing)
% DIs with no data	18.9%	49.4%	45.6%	35.3%
% DIs with minor facility error	13.5%	12.0%	17.9%	8.6%
% DIs with current DI price spike and negative facility error (overestimates of production)	7.7%			
% DIs with current DI price spike and positive facility error (underestimates of production)	14.8%			
Likelihood ratio of having negative error when regional error exceeds threshold	4.9 (contributing)	1.7 (contributing)	1.7 (countering)	0.9 (countering)
Likelihood ratio of having positive error when regional error exceeds threshold	2.0 (countering)	1.7 (countering)	1.6 (contributing)	3.3 (contributing)
Average negative contribution (MW)	-2.9	-4.6		
Average positive contribution (MW)			4.3	4.6

7.3.4 Angaston

Angaston is a price responsive peaking generator in South Australia with a registered capacity of 50 MW. An example month of production data is shown in Figure 21. Angaston generated in approximately 7.5% of DIs with pool prices above $150/MWh, compared to 0.2% of all DIs. The probability of underestimates in production also increases significantly in DIs with high pool prices earlier in the TI and high pool prices forecast in pre-dispatch. Furthermore, production by Angaston is overestimated in 6.6% of DIs with high prices in preceding TI, compared to 0.2% of all DIs.

Figure 21: Example month – Angaston

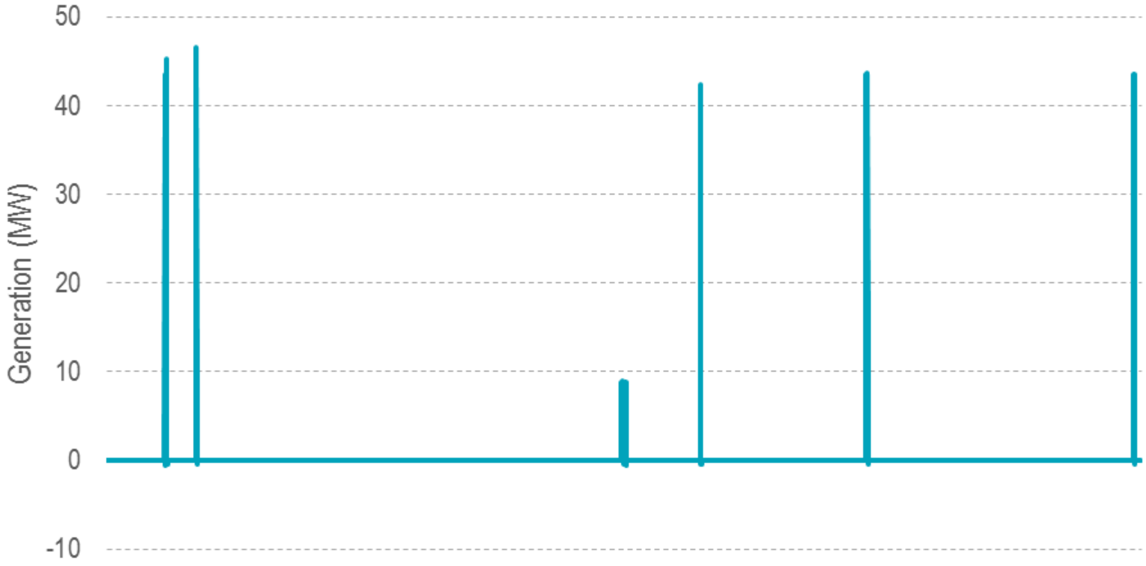


Table 47 shows the percentage of DIs in each regional error category with a contribution by Angaston. This facility appears to frequently contribute to South Australian dispatch demand error. This is particularly evident in large regional overestimates where 47.3% of DIs with a large overestimates of regional demand have an associated underestimate of Angaston production, compared to only 0.2% of all DIs with an underestimate of Angaston production. Similarly, 47.8% of DIs with large underestimates of regional demand have an associated overestimate of Angaston production. Both the frequency at which Angaston contributes to regional demand error and the average magnitude of that contribution is higher than observed for Lonsdale (Section 7.3.3).

Table 47: Contribution of Angaston error to South Australian dispatch demand error – all DIs

	Large regional underestimate	Small regional underestimate	Small regional overestimate	Large regional overestimate
% DIs with negative facility error (overestimates of production)	47.8% (contributing)	4.8% (contributing)	0.1% (countering)	0.0% (countering)
% DIs with positive facility error (underestimates of production)	0.0% (countering)	0.6% (countering)	2.5% (contributing)	47.3% (contributing)
% DIs with no data	14.7%	22.3%	20.5%	14.7%
% DIs with minor facility error	37.5%	72.3%	76.8%	38.0%
% all DIs with negative facility error (overestimates of production)	0.2%			
% all DIs with positive facility error (underestimates of production)	0.2%			
Likelihood ratio of having negative error when regional error exceeds threshold	306.1 (contributing)	30.5 (contributing)	0.9 (countering)	0.0 (countering)
Likelihood ratio of having positive error when regional error exceeds threshold	0.0 (countering)	3.5 (countering)	14.5 (contributing)	271.7 (contributing)
Average negative contribution (MW)	-37.9	-33.1	-6.9	N/A
Average positive contribution (MW)	N/A	8.2	26.6	38.9

When the price in a DI exceeds $150/MWh, the proportion of DIs with material overestimates of regional demand and an associated underestimate of production by Angaston increases to 83.5% for large overestimates of regional demand and 24.0% of small overestimates, as shown in Table 48. This suggests an increase in production by Angaston due to high prices is highly correlated with overestimates of South Australian demand. Unlike Lonsdale, the average magnitude of Angaston's contribution is a significant proportion of the South Australian regional error thresholds (43 MW for small errors and 75 MW for large) suggesting the increase in production by Angaston alone can cause material dispatch demand error in South Australia.

Table 48: Contribution of Angaston error to South Australian dispatch demand error – current DI price spike

	Large regional underestimate	Small regional underestimate	Small regional overestimate	Large regional overestimate
% DIs with negative facility error (overestimates of production)	73.0% (contributing)	24.1% (contributing)	1.6% (countering)	0.0% (countering)
% DIs with positive facility error (underestimates of production)	0.0% (countering)	4.8% (countering)	24.0% (contributing)	83.5% (contributing)
% DIs with no data	8.1%	13.3%	11.7%	6.5%
% DIs with minor facility error	18.9%	57.8%	62.7%	10.1%
% DIs with current DI price spike and negative facility error (overestimates of production)	2.5%			
% DIs with current DI price spike and positive facility error (underestimates of production)	7.5%			
Likelihood ratio of having negative error when regional error exceeds threshold	29.2 (contributing)	9.6 (contributing)	0.6 (countering)	0.0 (countering)
Likelihood ratio of having positive error when regional error exceeds threshold	0.0 (countering)	0.6 (countering)	3.2 (contributing)	11.1 (contributing)
Average negative contribution (MW)	-36.2	-31.2		
Average positive contribution (MW)			31.3	39.6

8. Pre-dispatch error

The accuracy of pre-dispatch demand forecasts is far lower than the accuracy of dispatch demand forecasts. There is evidence that price responsive behaviour is reducing the accuracy of pre-dispatch demand, demonstrated by correlations between high prices and large pre-dispatch demand errors.

There are a range of facility types that are observed to contribute to pre-dispatch demand error. Highly variable facility types have errors that are relatively highly correlated with pre-dispatch demand error. Smelters and Townsville Zinc have lower contributions, but these contributions are a relatively high proportion of the facilities' total variability, indicating that when these facilities change their consumption significantly that there is a higher likelihood of inaccurate pre-dispatch forecasts.

8.1 Contribution of price response to pre-dispatch demand error

Compared to dispatch demand error, there are many DIs where the error in the pre-dispatch forecast from 30 minute before the start of the DI exceeds the regional error thresholds. We therefore focus only on the large over- and underestimates of pre-dispatch demand.

Table 49 compares the proportion of DIs with large pre-dispatch demand overestimates where the price has exceeded $150/MWh in the TI with the proportion of all DIs where this price condition is met. This table shows in all regions other than New South Wales, there is relatively strong evidence that high prices are increasing the likelihood of large pre-dispatch demand overestimates. This indicates that loads reducing their consumption and/or non-scheduled generators increasing production in response to high prices are reducing the accuracy of pre-dispatch forecasts.

Table 49: Evidence of price response in pre-dispatch error – max so far in TI

	QLD	NSW	VIC	SA
Proportion of large PD demand overestimates where Max RRP so far in TI > $150/MWh	6.2%	0.8%	1.6%	9.2%
Proportion of all DIs where Max RRP so far in TI > $150/MWh	2.2%	0.7%	0.7%	1.9%

Similarly, Table 49 shows that in all regions there is a higher likelihood that there was a price spike in the previous TI in DIs with a large underestimate in pre-dispatch demand. This is likely to be in part the result of higher prices in the previous TI causing a price response that reduces load. Pre-dispatch forecasts at this point in time are based on measurements of demand that include the reduced consumption levels. This results in a demand underestimate where there is a reversion back towards typical operating.

Table 50: Evidence of price response in pre-dispatch error – max in previous TI

	QLD	NSW	VIC	SA
Proportion of large PD underestimates where Max RRP in previous in TI > $150/MWh	6.0%	2.1%	3.2%	7.6%
Proportion of all DIs where Max RRP in previous in TI > $150/MWh	3.1%	0.9%	0.9%	2.3%

8.2 Contribution of facility types to pre-dispatch error

Categorising facilities and facility types as contributing to pre-dispatch error has an additional layer of complexity compared to the approach used for dispatch accuracy. Given the 30-minute time window, there is the possibility that errors are caused by a facility response in any of the six DIs between the forecast and the DI of interest. For 30-minute facilities, these six DIs can be across two TIs.

Facility responses are categorised based on whether there is a facility error above the facility error thresholds in any of the last six DIs; for facilities with 30-minute data, this could be a response in either the current or previous TI. The number of DIs flagged as responsive for a facility of facility type can therefore be up to twice as large as the number of DIs flagged as responsive when analysing dispatch demand error.

Table 51 and Table 52 show the percentage of the DIs where pre-dispatch forecast error is large and that also have an error in the same direction for the facility type. As with dispatch demand error, highly variable facilities such as mills have a high contribution due to their high variability. Only the smelters, the Load: other category in Queensland and peaking non-scheduled generation in South Australia have a proportional contribution in DIs of high pre-dispatch demand error that is materially higher than their level of variability across all DIs. These results are shown in the 'Pre-dispatch demand' worksheet of the accompanying workbook.

Table 51: Contribution of facilities by type to pre-dispatch error – Queensland and New South Wales

	Queensland		New South Wales	
	Large under	Large over	Large under	Large over
Load: smelter	5.1%	4.4%	2.6%	3.1%
Load: mine	4.6%	6.6%	3.3%	3.0%
Load: other	12.7%	13.4%	0.5%	0.7%
Load: mill			21.9%	24.9%
NS gen: other				
NS gen: bagasse	7.8%	7.3%	3.8%	4.0%
NS gen: coal gas	6.8%	7.5%	4.9%	4.4%
NS gen: peaking			0.3%	0.4%
NS gen: hydro	2.2%	2.6%	6.1%	7.3%
NS gen: auxiliary	1.3%	1.5%	7.4%	5.6%
NS gen: medium utilisation	0.7%	1.0%	4.5%	5.0%
NS gen: landfill gas			4.6%	5.5%

Table 52: Contribution of facilities by type to pre-dispatch error – Victoria and South Australia

	Victoria		South Australia	
	Large under	Large over	Large under	Large over
Load: smelter	9.4%	8.4%		
Load: mine			0.5%	0.9%
Load: other	0.0%	0.0%		
Load: mill	19.7%	18.0%	3.5%	6.2%
NS gen: other	11.4%	10.2%	3.3%	2.8%
NS gen: bagasse				
NS gen: coal gas				
NS gen: peaking			4.0%	5.2%
NS gen: hydro	1.0%	1.2%		
NS gen: auxiliary	5.2%	2.4%	5.7%	9.6%
NS gen: medium utilisation	1.2%	1.2%		
NS gen: landfill gas	10.0%	11.0%		
NS gen: Angaston	N/A	N/A	5.4%	7.1%

Appendix A Summary of key terminology and abbreviations

Terminology	Definition
Actual demand	Calculated ex-post demand. See Section 3.1.
Dispatch demand error	The difference between TOTALDEMAND and actual demand. Can be positive (an overestimate) or negative (an underestimate).
Facility error	The difference between expected or typical behaviour predicted by the linear regression model and actual behaviour. Can be positive or negative. For loads, positive error (an overestimate) occurs when forecast consumption exceeds actual consumption for a given time period. Non-scheduled generation is treated as a negative load. Therefore, positive error (an underestimate) occurs when forecast production is less than actual production for a given time period.
Negative error	Applied to regional dispatch demand error and facility error. Negative error is one which leads to an underestimate of scheduled demand. - Dispatch demand is less than actual demand i.e. is underestimated. - A load operates more than forecast by the linear regression model i.e. is underestimated. - A non-scheduled generator operates less than forecast by the linear regression model i.e. is overestimated.
Overestimate	Applied to regional dispatch demand error and facility error. An overestimate is when an expected value is greater than actual. Non-scheduled generation is treated a negative load. Specifically: - Dispatch demand is greater than actual demand; this is a positive error. - A load operates less than forecast by the linear regression model; this is positive error. - A non-scheduled generator operates less than forecast by the linear regression model; this is negative error.
Positive error	Applied to regional dispatch demand error and facility error. Positive error is one which leads to an overestimate of scheduled demand. - Dispatch demand is greater than actual demand i.e. is overestimated. - A load operates less than forecast by the linear regression model i.e. is overestimated. - A non-scheduled generator operates more than forecast by the linear regression model i.e. is underestimated.
Price spike	Where the wholesale market price in a DI exceeds $150/MWh. This threshold was chosen so that we had a sample of several hundred ‘price spike’ DIs in each region in each study year, including NSW and Victoria where prices rarely exceeded $300/MWh in the study period (50-60 times annually in NSW and 60-80 times annually in Victoria). We apply a $150/MWh threshold for a price spike.
Regional error	Used interchangeably with “dispatch demand error”.
Regional pre-dispatch error	The difference between pre-dispatch demand forecast 30 minutes before the start of a DI and the actual demand for that DI.
Regional Reference Price (RRP)	The wholesale price of electricity in each region calculated by NEMDE in each dispatch interval
TOTALDEMAND	The demand value used in NEM dispatch; scheduled generators are dispatched to meet this value. TOTALDEMAND represents the forecast of demand made just before the start of each DI.
Underestimate	Applied to regional dispatch demand error and facility error. An underestimate is when an expected value is less than actual. Non-scheduled generation is treated a negative load. Specifically: - Dispatch demand is less than actual demand; this is a negative error. - A load operates more than forecast by the linear regression model; this is negative error. - A non-scheduled generator operates more than forecast by the linear regression model; this is positive error.

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