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| Reserve Level Declaration Guidelines - DRAFT |
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| 1.0 | 16 January 2018 | First issue for *National Electricity Amendment (Declaration of lack of reserve conditions) Rule 2017* |
| 2.0 | 30 November 2018 | Changes to the definition of RXS, the inputs used to determine the prevailing conditions, and the confidence levels used to determine the FUM. |

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# Introduction

## Purpose and scope

These are the *reserve level declaration guidelines* made under clause 4.8.4A of the National Electricity Rules (**Guidelines**).

These Guidelines have effect only for the purpose of declaring lack of reserve (**LOR**)conditions under clause 4.8.4 of the National Electricity Rules (**NER**). They describe the considerations and methodology *AEMO* applies in deciding to declare an LORcondition, and the levels of LOR conditions that may be declared.

An LOR declaration alerts *Registered* *Participants* to a probability of *capacity reserves* being insufficient to avoid *load shedding* (other than *interruptible load*) given reasonably foreseeable conditions and events.

The NER and the National Electricity Law prevail over these Guidelines to the extent of any inconsistency.

## Definitions and interpretation

### Glossary

Terms defined in the NER or the National Electricity Law have the same meanings in these Guidelines unless otherwise specified in this clause. Those terms are intended to be identified in these Guidelines by italicising them, but failure to italicise a defined term does not affect its meaning.

The words, phrases and abbreviations in the table below have the meanings set out opposite them when used in these Guidelines.

|  |  |
| --- | --- |
| Term | Definition |
| AEMO | Australian Energy Market Operator Limited |
| Aggregate capacity of energy limited plant | Total aggregate contribution to supply from scheduled generating units in the region for which a daily energy limit has been specified in ST and PD PASA bids. The value is determined by the PASA process and considers: forecast market availability specified by Generators; forecast daily energy limit as specified by Generators; optimisation of energy limited capacity through the PASA algorithm; and network limitations as specified through network constraint equations. |
| Aggregate capacity of non-energy limited plant | Total aggregate contribution to supply from scheduled and semi-scheduled generating units in the region for which no daily energy limit has been specified in ST and PD PASA bids. The value is determined by the PASA process and considers: forecast market availability specified by Generators; network limitations as specified through network constraint equations; and forecasts for output of semi-scheduled generating units. |
| Aggregate output of semi-scheduled generating units | The forecast output of semi-scheduled generating units in the region. The value is determined by the PASA process and considers: unconstrained intermittent generation forecast determined by AWEFS and ASEFS; and network limitations as specified through network constraint equations. |
| AWEFS | Australian Wind Energy Forecasting System |
| ASEFS | Australian Solar Energy Forecasting System |
| BBN | Bayesian Belief Network |
| FUM | Forecast uncertainty measure |
| Interconnector support | The maximum supply to the region available from adjacent regions after the supply demand balance is satisfied in adjacent regions. The value is determined by the PASA process and considers: network limitations as specified through network constraint equations; and supply demand balance in adjacent regions as determined by the PASA algorithm. |
| LCR | Largest credible risk – see clause 4 |
| LCR2 | Two largest credible risks – see clause 4 |
| LOR | Lack of reserve (may be followed by a number corresponding with a reserve level defined in these Guidelines) |
| LOR assessment horizon | The period of time described in clause 2(a) |
| LOR Load Shedding | The reduction or *disconnection* of *load* (other than *interruptible load*). |
| LOR1 threshold | The level of *capacity reserves* below which AEMO may declare an LOR1 condition – see clause 2(d) |
| LOR2 threshold | The level of *capacity reserves* below which AEMO may declare an LOR2 condition – see clause 2(c). |
| MW | Megawatts |
| MWh | Megawatt hours |
| NER | National Electricity Rules |
| Operational Demand | A quantity (in MW) determined by AEMO representing the instantaneous demand of *load* (other than *scheduled load*) to be supplied by *sent out generation* of *scheduled generating units*, *semi-scheduled generating units*, and significant *non-scheduled generating units*. For further information about demand definitions see “AEMO Operational Demand Definition – Summary Document” on AEMO website |
| RXS | Regional excess supply |
| RXS error | The expected difference between forecast RXS and actual RXS (see clause 3.2) |
| Scheduled demand | The expected value of regional electricity demand (excluding scheduled loads) which will need to be met by supply from scheduled and semi-scheduled generating units in the region or from other regions. The value is determined by AEMO forecasting systems and considers: customer load; output of major non-scheduled generating units; and output of embedded generating units including rooftop solar generation. |
| STPASA | *Short-term PASA* |

### Interpretation

The following principles of interpretation apply to these Guidelines unless otherwise expressly indicated:

* + - 1. These Guidelines are subject to the principles of interpretation set out in Schedule 2 of the National Electricity Law.
      2. References to time are references to Australian Eastern Standard Time.
      3. The following mathematical notations used in formulae and equations have these meanings:
         1. MAX ( ) means the maximum (or highest) of two or more values within the brackets,
         2. '{ }', '( )' and '[ ]' indicates that all calculations between a pair of brackets are to be performed separately from expressions outside the brackets. Different forms of brackets are used only for ease of matching the opening bracket with the corresponding closing bracket.

## Related documents

|  |  |
| --- | --- |
| Title | Location |
| Reliability Standard Implementation Guidelines | www.aemo.com.au |
| Short Term PASA Process Description | www.aemo.com.au |
| Intervention, Direction and Clause 4.8.9 Instructions SO\_OP3707 | www.aemo.com.au |
| Procedure for the Dispatch and Activation of Reserve Contracts SO\_OP3717 | www.aemo.com.au |
| AEMO Operational Demand Definition – Summary Document | www.aemo.com.au |

# Assessment and publication

* 1. AEMO assesses the probability of a shortfall in available *capacity reserves* leading to LOR Load Sheddingin each *region* on a continuous basis, from the current time to the end of the period covered by the most recently *published short term PASA*. This is the **LOR assessment horizon**.
  2. AEMO *publishes*, for each 30 minute period commencing on the hour and half-hour within the LOR assessment horizon, and for each *region*:
     1. the expected *capacity reserves* (in MW);
     2. the LOR2 threshold (in MW) – see paragraph (c); and
     3. the LOR1 threshold (in MW) – see paragraph (d).
  3. The LOR2 threshold within the LOR assessment horizon is MAX (LCR, FUM).
  4. The LOR1 threshold within the LOR assessment horizon is MAX (LCR2, FUM).

Figure 1 Schematic representation of LOR Formulation in circumstances of extreme FUM values

# forecast UNCERTAINTY MEASURE

See also Appendix A for more detail.

## Forecast regional excess supply (RXS)

### Mainland regions

For the New South Wales, Queensland, South Australia and Victoria *regions* RXS is defined below.

* 1. The following forecasts and measurements in each *region* for the LOR assessment horizon will be assessed in determining the value of RXS:
     1. *Aggregate capacity of scheduled generation in the region* (C), calculated as:
        1. *Aggregate capacity of non-energy limited plant*, plus
        2. *Aggregate capacity of energy limited plant,* less
        3. *Aggregate output of semi-scheduled generating units*;
     2. *Interconnector support* (IS);
     3. *Aggregate output of semi-scheduled generating units* (SS); and
     4. *Scheduled demand* (D).
  2. Forecast RXS for any time in the LOR assessment horizon is determined by the formula RXS = C + IS + SS - D.

### Tasmania

For the Tasmania *region* RXS is defined below.

* 1. The following forecasts and measurements in each *region* for the LOR assessment horizon will be assessed in determining the value of RXS:
     1. *available capacity* of *scheduled generating units* (A);
     2. *unconstrained intermittent generation forecast* (B); and
     3. Scheduled Demand (C).
  2. Forecast RXS for any time in the LOR assessment horizon is determined by the formula RXS = A + B – C.

The RXS definition for Tasmania excludes components which are affected as an unintended consequence of a *network constraint* that requires Tasmania to export. When this condition occurs, it results in excessive errors in the *interconnector support* and *aggregate capacity of non-energy limited plant components*, which would cause erroneous RXS values if the RXS definition for Tasmania were to include these components.

## Determining RXS error distribution

* 1. RXS Error = Forecast RXS – Actual RXS for a particular forecast and a point in time.
  2. AEMO collects, stores and updates historical statistical data on RXS error, in different *power system*, ambient weather and other relevant conditions.
  3. At the time of assessment, AEMO applies the historical data and the conditions expected for the relevant period in the LOR assessment horizon, as illustrated in Appendix A, to determine a distribution of error (RXS error) across all forecasts within the first 72 hours of the LOR assessment horizon. The input states that will be taken into account in developing the distribution will be:
     1. forecast lead time;
     2. forecast *regional reference node* temperatures;
     3. forecast solar irradiance at the *regional reference node;*
     4. current demand forecast error for forecast lead times below 24 hours;
     5. forecast of *aggregate output of semi-scheduled generating units*; and
     6. current supply mix by fuel type (coal, gas or hydro).

## Forecast uncertainty measure (FUM) calculation

* 1. The FUM for a *region*, point in time and set of expected conditions, is the number of MWs representing the quantity of RXS for which AEMO determines a specified confidence level of the RXS error not exceeding that number of MWs.
  2. Confidence levels are determined in accordance with clause 3.4 and are set out in Appendix B.
  3. FUM will be determined using the RXS error for the first 72 hours of the LOR assessment horizon. For the remainder of the assessment horizon a static value will be used for FUM as set out in clause 3.6.

## Confidence levels for determining FUM

* 1. The confidence level used in determining FUM is to be set at a level that AEMO reasonably expects to achieve an appropriate balance between:
     1. reducing the chance of a situation where LOR Load Shedding arises due to lack of action by AEMO as a result of reserve forecasting error; and
     2. increasing the likelihood of unnecessary declarations due to an overly conservative confidence level.
  2. The confidence levels will also be selected to:
     1. decrease monotonically, where appropriate, with increasing forecasting horizon; and
     2. be consistent across *regions* for the same forecasting horizon where this can be done whilst still reasonably satisfying the other selection criteria.
  3. To achieve this balance, different confidence levels may be required for each *region* and for each forecast timeframe within the LOR assessment horizon.
  4. The current confidence levels are specified in Appendix B.
  5. AEMO must review the confidence levels at least annually to determine whether or not they are still achieving the appropriate balance indicated in paragraph (a).
  6. AEMO must publish the results of its review and, if AEMO concluded that no change should be made to the current confidence levels, must include reasons for that conclusion.

**Note:** If AEMOproposes to change the confidence levels, it is required to consult on an amendment to these Guidelines in accordance with NER clause 4.8.4A(e).

## Reasonability Limits for FUM Values

* 1. Before the FUM value is used to calculate LOR levels (refer to clause 5), the calculated FUM value will be subject to a reasonability check, intended to prevent an unrealistic LOR level being determined due to mal-operation of AEMO systems.
  2. For this purpose AEMO will set upper/lower and delta raise/lower reasonability limits, which may vary between *regions* and forecasting timeframes, and will be revised as AEMO considers necessary.
  3. The upper/lower reasonability limits provide a cap or floor on the FUM value used to calculate LOR levels. The delta raise/lower reasonability limits implement a rate-of-change cap to limit the difference in FUM values for the same *trading interval* from consecutive runs.

## FUM Values for forecasting horizons beyond 72 hours

The BBN model extends to a forecasting horizon of 72 hours. For the remainder of the assessment horizon, FUM values will be set to zero.

# credible contingency sizes

* 1. AEMO determines the size of the two largest relevant *credible contingency events* that could affect the available *supply* of electricity for each *region* from time to time*.* These will generally be determined automatically, consistent with a list of relevant *credible contingency events* to be published by AEMO on its website alongside these Guidelines.
  2. AEMO then determines the reduction in *capacity reserves* expected to result in that *region* from the occurrence of:
     1. the single largest of those relevant *credible contingency events* (LCR) (in MW); and
     2. both of the two largest *credible contingency events*, assuming they occurconsecutively with sufficient time to return the *power system* to a *secure operating state* prior to the second event (LCR2) (in MW).
  3. The temporary reclassification of a *non-credible contingency event* may affect the size of the largest or second largest *credible contingency event* in a *region* at any time. In accordance with the NER and AEMO’s normal procedures, AEMO issues a market notice when reclassification occurs.
  4. If other unusual temporary operating conditions result in situations that require manual specification of LCR and LCR2 levels, AEMO will inform *Market Participants* by issuing a market notice.
  5. On infrequent occasions the list of relevant *credible contingency events* may need to be revised if new classes of events need to be added or existing classes revised. If this occurs, AEMO will update the published list as soon as reasonably practicable.

# Description of Reserve Levels

## General

* 1. AEMO will declare LOR conditions when it determines there is a non-remote probability of LOR Load Shedding due to a shortfall of available *capacity reserves* at a given time in the LOR assessment horizon, by reference to the criteria described in this clause for levels LOR3, LOR2 and LOR1. This is shown in Figure 1.
  2. In some cases where published forecast *capacity reserves* are below these LOR levels, AEMO may decide not to declare an LOR condition. Examples of such circumstances include:
     1. clearly incorrect PASA results due to software issues or incorrect performance of *network constraint* equations; or
     2. situations where the shortfall is clearly transient and will be resolved through normal *dispatch* processes without presenting an ongoing threat to reliability of *supply*,

and in those circumstances AEMO will issue a market notice to explain why it has not declared an LOR condition.

## LOR3

LOR3 will be declared for a *region(s)*:

* 1. when LOR Load Sheddingis occurring as a result of a shortfall of available *capacity reserves* (**actual LOR3**); or
  2. for a period within the LOR assessment horizon when the forecast of available *capacity reserves* in the *short term PASA* or *pre-dispatch* *schedule* is at or below zero (**forecast LOR3**).

## LOR2

LOR2 will be declared for a *region(s)*:

* 1. when the occurrence of the largest relevant *credible contingency event* would result in LORLoad Sheddingas a result of a shortfall of available *capacity reserves* (**actual LOR2**); or
  2. for a period within the LOR assessment horizon when the forecast of available *capacity reserves* in the *short term PASA* or *pre-dispatch schedule* is less than LCR (**forecast LOR2**); or
  3. for a period within the LOR assessment horizon when the forecast of available *capacity reserves* in the *short term PASA* or *pre-dispatch schedule* is less than FUM for the relevant period and *region* (**forecast LOR2**).

## LOR1

LOR 1 will be declared for a *region(s)*:

* 1. when the consecutive occurrence of both the largest and the second largest relevant *credible contingency events* (as described in clause 4(b)(b)(ii)) would result in LORLoad Sheddingoccurring as a result of a shortfall of available *capacity reserves* (**actual LOR1**); or
  2. for a period within the LOR assessment horizon when the forecast of available *capacity reserves* in the *short term PASA* or *pre-dispatch schedule* is less than LCR2 (**forecast LOR1**); or
  3. for a period within the LOR assessment horizon when the forecast of available *capacity reserves* in the *short term PASA* or *pre-dispatch schedule* is less than FUM for the relevant period and *region* (**forecast LOR1**).

1. Forecast Uncertainty Error Methodology

This Appendix describes how the historical forecasting data is analysed under different prevailing conditions in order to estimate the combined forecasting error.

* 1. Sources of error

As described in clause 3.1, RXS error is determined using forecasts and measurements for:

* a*ggregate capacity of scheduled generation in the region*, calculated as:
  + *aggregate capacity of non-energy limited plant,* plus
  + *aggregate capacity of energy limited plant,* less
  + *aggregate output of semi-scheduled generating units.*
* *interconnector support*
* *aggregate output of semi-scheduled generating units*
* *scheduled demand*

In the case of the Tasmanian region, RXS error is determined using forecasts and measurements for:

* *available capacity* of *scheduled generating units*;
* *unconstrained intermittent generation* *forecast*; and
* *scheduled demand*.
  + 1. Aggregate capacity of non-energy limited plant

This value is the total aggregate contribution to supply determined by the *PASA* process from *scheduled generating units* and *semi-scheduled generating units* for which no daily *energy limit* has been specified in *short term PASA* and *pre-dispatch PASA* bids. The calculation of this value considers the forecast available capacity as specified by *Generators*, the network limitations as specified by AEMO through *network constraint* equations, and AEMO-produced *unconstrained intermittent generation forecasts* for *semi-scheduled generating units*. Each of these components is a potential significant source of forecasting error.

* + 1. Aggregate capacity of energy limited plant

This value is the total aggregate contribution to supply determined by the *PASA* process from *scheduled generating units* for which a daily *energy limit* has been specified in *short term PASA* and *pre-dispatch PASA* bids. The calculation of this value considers the forecast available capacity as specified by *Generators*, the forecast daily *energy limit* as specified by *Generators*, the optimisation of energy limited capacity through the *PASA* algorithm, and the network limitations as specified by AEMO through *network constraint* equations. Each of these components is a potential significant source of forecasting error.

* + 1. Aggregate output of semi-scheduled generating units

This value is the total aggregate forecast output of *semi-scheduled generating units* in the *region* determined by the *PASA* process. The calculation of this value considers the AEMO-produced *unconstrained intermittent generation forecasts* for *semi-scheduled generating units*, and the network limitations as specified by AEMO through *network constraint* equations. Each of these components is a potential significant source of forecasting error.

* + 1. Interconnector support

This value is the maximum supply to the *region* available from adjacent *regions* after the demand to be met from supply is satisfied in the adjacent *region* as determined by the *PASA* process. The calculation of this value considers the network limitations as specified by AEMO through *network constraint* equations, and the supply demand balance in adjacent *regions* as determined by the *PASA* algorithm. Each of these components is a potential significant source of forecasting error.

* + 1. Available capacity of scheduled generating units

Every *Scheduled Generator* is required to submit an estimate of *available capacity* of each *scheduled generating unit* for every *trading interval* for the next 8 days. This provides AEMO with an estimate of how much *generation* is available for *dispatch* and may be updated at any time up to the point of *dispatch*. This variation is a significant source of forecasting error.

* + 1. Unconstrained Intermittent Generation Forecast

AEMO produces a *generation* forecast for every *semi-scheduled* *generating unit* and large *intermittent non-scheduled generating units* through its AWEFS and ASEFS forecasting systems. These forecasts are a potential significant source of forecasting error.

In some situations these *generating units* may be subject to *constraints.* This is a rare situation, and in *trading intervals* where this occurred, the relevant *generating units* were simply removed from the RXS calculation.

* + 1. Scheduled Demand

AEMO currently produces Scheduled Demand forecasts at a *regional* level. The demand forecast considers customer *load*, the output of major *non-scheduled generating units* and the output of *embedded generating units* including rooftop solar generation. Each of these components is a potential significant source of forecasting error.

* + 1. Preparation of data
  1. For every 30 minute trading interval since July 2011 AEMO calculated forecast RXS for the next 384 trading intervals (8 days ahead).
  2. Each 30 minute forecast was assessed against the actuals for each of the next 144 trading intervals. For example, a forecast run at 01-01-2017 01:00 would have forecasts for each 30 minute interval from 01-01-2017 01:30 to 04-01-2017 01:00 and an RXS error created for each of these.
  3. The known prevailing conditions that were present just prior to the forecast run were included to develop an understanding of how these conditions affect the forecasting error. Those prevailing conditions were:
     1. Current temperature (temperature by *region*);
     2. Forecast temperature (temperature by *region*);
     3. Current demand forecast error;
     4. Forecast solar irradiance;
     5. Forecast output of semi-scheduled generating units;
     6. Current supply mix by fuel type;
     7. *Regional reference price* ($/MWh);
     8. Time of day (daytime / night-time forecast); and
     9. Other inputs as specified in A.2.1.
  4. Not all of the prevailing conditions were found to be significant to the RXS error distribution. The prevailing conditions which were deemed to be insignificant were discarded in order to simplify the calculation and enable the distributions to be built using a greater input sample size.
  5. This data was then used to train a Bayesian Belief Network to produce a RXS error distribution for each of the next 144 *trading intervals*. This is dynamic: the error distributions will update based on the current prevailing conditions when the forecast is produced.
  6. The data used for initial training of the BBN was from the period 1 July 2011 to 1 August 2017. The BBN will be retrained on quarterly basis; at the time of retraining, additional data available since the last retraining will be added to the training data set. Any changes to forecasting systems which result in a change in any of the error distributions (for example, an upgrade to the forecasting system resulting in an improvement to forecasting accuracy) will be reflected in the BBN (and subsequent FUM values) following the next scheduled retraining.
  7. The output of the BBN is a measure of the RXS error in MW for each of the next 144 *trading intervals*. As we are dealing with a forecasting error distribution, the “At Risk” MW (FUM) is associated with a confidence level. For example, a 6 hour ahead forecast that was run at 22:00 for 04:00 (overnight forecast) would have less uncertainty associated with the error than a forecast run at 10:00 for 16:00 (daily peak forecast). The BBN outputs a MW value for each of the forecasts, associated with a fixed confidence level. So for example in the 22:00 forecast run a typical FUM value for 6 hours ahead might be 200MW whereas for the 10:00 forecast run a typical FUM value for 6 hours ahead would be 300MW.
  8. Before the FUM value is used to calculate LOR levels (refer to clause 5), the calculated FUM value will be subject to a reasonability check (refer to clause 3.5).
  9. Bayesian Belief network

References and citations corresponding with the numbers in square brackets in this section are listed in Appendix C.

*Bayesian Belief Networks* (BBNs) [1], are probabilistic models used in artificial intelligence to deal with problems that are associated with uncertainty [2]. They can be used to investigate and present causal relationships between essential elements and output values of a system in a simple and understandable manner. They can be readily extended, modified, and incorporate missing data through the application of Bayes’ theorem [3]. They are useful for calculating the impact of interventions such as examining alternative policies or decisions for optimizing a desired outcome. In addition, at the same time the uncertainties integrated with these causal relationships can be investigated.

BBNs are probabilistic graphical models based on directed acyclic graphs which are made of nodes connected by edges with a direction associated with them, and with no cycles [2]. The nodes in the networks depict a set of random variables, V = V1,...,Vi,...,Vn, and directed arcs connect pairs of nodes, Vi → Vj, representing the dependencies between variables. In each pair of connected nodes, the parent node affect the child node and the direction of the arc between them shows the direction of the effect. The absence of an arc between two nodes denotes that those nodes are independent. The relationship between a child node and all its parents is described by a Conditional Probability Table (CPT). The CPT should be formed as follows:

* 1. each row represents the probability of being within a state, given a combination of values of parent states;
  2. each row must sum to 1; and
  3. a node without parents has one row and it can be described probabilistically by a marginal probability distribution.

Once a problem and its uncertainty is modelled by a BBN, the BBN reasons about the problem through applying a flow of new information, evidence, i.e., a probabilistic inference system. Such an inference system is able to compute the posterior probability distribution for a set of query nodes, given values for some evidence nodes. The types of evidence can be categorized as follows:

* 1. definite evidence, a definite information about that variable X has a specific value x;
  2. negative evidence, information about that variable Y is not in the certain state y1, however, may take any other values; and
  3. likelihood evidence, uncertain source of information.

The types of reasoning using BBNs can be categorized in to four categories:

* 1. diagnostic, reasoning from indications to cause;
  2. predictive, reasoning from new knowledge about causes to new beliefs about results;
  3. inter causal, reasoning about the common causes of a predictable result; and
  4. mixed reasoning.

BBNs perform probabilistic updating by incorporating new information and evidence, provide a combination of predictive and diagnostic reasoning by incorporating new information and evidence through Bayes’ theorem.

*Dynamic Bayesian Belief Networks* (DBNs)*:* Most of the events that happen around us in everyday life cannot be depicted based on the fixed point in time, they should be explained through a sequence of observations that lead to the inference of one final event. Time is an important dimension in the field of artificial intelligence and reasoning. However, BBNs variables are time independent, in fact they are not able to model temporal relationships explicitly and they are a static model. In contrast, DBNs [4]–[5] consider how the variables change with time. Thus DBNs relate variables to each other over the sequences of time steps. Through this approach, a user is able to monitor and update the system continuously over the time steps. DBNs consist of a prior network, which comprises the prior probabilities for all of the variables in the network at time step t = 0, and a transition network, which encodes the probabilities for each variables conditioned on other variables for all time steps, t = 1, 2,..., n.

Figure 2 below provides an example of a Short Term (Less than 6 hours) BBN network for the South Australian *region*. The blue nodes are the parent nodes which represent the prevailing conditions that existed just prior to the forecast run and the green nodes represent the child node or forecasting error for each of the next 30 minute *trading intervals*. The black bars represent the probability associated with each of the corresponding bins. For example, below circled in red is the temperature recorded at the Adelaide Airport. It shows that 15.5% of the time the temperature recordings have been between 0 and 12 degrees.

1. Bayesian Belief Network



* + 1. Sensitivity Analysis

Once a BBN network has been trained it is possible to statistically assess the impact that each of the prevailing conditions (input nodes) has on the forecasting errors. Using just the link structure of the net, you can determine which nodes are completely independent of other nodes. However, dependence is a matter of degree and once the net has been trained it can be used to assess how changes in the prevailing conditions change the probabilities or uncertainties in our forecasting error nodes (output nodes). From this analysis it was determined that the most significant prevailing conditions (the conditions that cause the largest change in forecasting uncertainty) are the following:

* 1. Temperature forecast
  2. Solar irradiance forecast
  3. Forecast output of semi-scheduled generating units
  4. Current demand forecast error for forecast lead times below 24 hours.
  5. Current supply mix by fuel type (gas, coal or hydro)

Additional prevailing conditions that were assessed and determined to not cause a significant impact include:

* 1. Price
  2. Current semi-scheduled forecasting error
  3. Current actual RXS
  4. Precipitation, humidity, wind speed forecasts
  5. Temperature forecast differential between different forecast providers
  6. Forecasts of reserve
  7. Forecasts of interconnector support

Therefore the BBN includes the temperature forecast, solar irradiance forecast, forecast output of semi-scheduled generating units, the current demand forecast error and the current supply mix by fuel type as the input data for the BBN models.

* + 1. Selection of Confidence Level

The final step is selecting the MW values associated with the confidence level. Figure 3 below is the forecasting error associated with the 5-hour ahead forecasts. This demonstrates the combined forecasting error from all three forecasting systems 5 hours after the forecast was run. The black bars are the probabilities associated with each of the bin ranges and the bins are in MW. For example 19.8% percent of the time AEMO produces a forecasting error of between 30-100 MW.

1. 5 Hour Ahead Forecasting Error



In order to determine the associated MW value for the confidence level, all the probabilities are accumulated until they exceed the specified confidence interval and the associated MW value in that bin becomes FUM.

1. Confidence Levels

The confidence levels chosen for determination of FUM are as follows

1. Confidence levels for determination of FUM values

|  |  |  |
| --- | --- | --- |
| Region(s) | Forecasting Horizon (Hrs) | Confidence level |
| All | 0.5 to 72 | 95% |

1. References
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