CALCULATION OF MINIMUM RESERVE LEVELS FOR THE AUSTRALIAN NATIONAL ELECTRICITY MARKET

Richard Bean
ROAM Consulting Pty Ltd
PO Box 731, Fortitude Valley Qld 4006
Australia
richard.bean@roamconsulting.com.au

Ben Vanderwaal
ROAM Consulting Pty Ltd
PO Box 731, Fortitude Valley Qld 4006
Australia
ben.vanderwaal@roamconsulting.com.au

Abstract - The Australian Energy Market Commission (AEMC) Reliability Panel specifies a "Reliability Standard for Generation and Bulk Supply" for the Australian National Electricity Market (NEM). This specifies the maximum permissible unserved energy (USE) in all regions of the market in any financial year. The Australian Energy Market Operator (AEMO) is tasked with ensuring this standard is met by the periodic calculation and operationalisation of Minimum Reserve Levels (MRLs) in market systems. The most recent MRLs were determined in work by ROAM Consulting and AEMO using an extensive process of NEM system simulation, taking into account factors such as generator outage rates, demand diversity between the regions, the effects of system constraints, and interconnector behaviour. During the process, approximations of USE using non-sequential simulation and estimation of the distribution of available capacity in each region enabled the development of explanations of changes in the MRLs due to changes in any of these factors. As simulation is a computationally expensive process, the amount of unserved energy arising from load input data with various peak demand levels had to be extrapolated from simulated results. Issues of reserve sharing between adjacent regions and sensitivities to outage rates and demand diversity were examined. The MRLs calculated during the study are used in current market operation.

Keywords: reliability, unserved energy, probability distributions

1 INTRODUCTION

The Minimum Reserve Levels (MRL) project is undertaken periodically by the Australian Energy Market Operator (AEMO) in order to provide a measurement which can be used in the operation of the Australian National Electricity Market (NEM) to meet a specified reliability standard. This reliability standard is defined by the Reliability Panel of the Australian Energy Market Commission (AEMC) [1] as: "unserved energy cannot exceed 0.002% of the annual energy consumption for the associated region or regions per financial year."

The most recent project was undertaken to develop MRLs for the 2010-11 and 2011-12 financial years. The work was undertaken by ROAM Consulting with shadow studies being performed by AEMO. The MRLs are a measure of how much generation should be installed in each region of the NEM to meet the reliability standard.

This paper explains the methodology used to calculate MRLs for these years.

2 METHODOLOGY

Currently, the NEM consists of five regions, each states of Australia - Queensland, New South Wales, Victoria, South Australia and Tasmania. The high voltage electricity system of each adjacent region is linked by one or more interconnectors, some of which are high voltage DC and some of which are AC. See Figure 1.

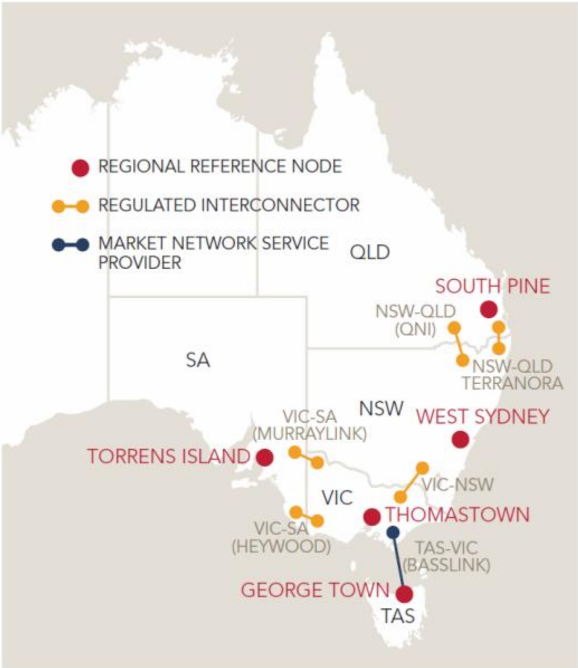

Figure 1: NEM Diagram from AEMO's "An Introduction to Australia's National Electricity Market"

Each region contains a mix of hydro, wind, coal, and gas generation, with coal predominant in Queensland, New South Wales, and Victoria in capacity and energy production terms. Some demand side management is also available in the NEM and modeled in the MRL studies. As this is a reliability study, the main concern is for capacity and its availability. Energy limitations leading to capacity restrictions are also accounted for.

South Australia's capacity consists of some coal fired power plants with the other capacity made up of gas (conventional steam turbines, combined and open cycle gas turbines (OCGTs)) and wind.

In the 2010-11 and 2011-12 financial years, and for the near future, the capacity of Tasmanian generation is sufficient to meet Tasmanian demand, because the Tasmanian hydro capacity exceeds 2,200 MW, with backup from gas-fired peakers and a 600MW HVDC interconnector from the mainland, compared with a projected maximum demand of 1,971 MW for the study. Thus, reliability is not a current concern for Tasmania, and a minimum reserve level for Tasmania is not calculated in the study. However, Tasmania can contribute to mainland reliability.

2.1 Simulation of NEM

Simulations were carried out using 2-4-C, a proprietary simulation software package developed by ROAM Consulting since the beginning of the NEM in 1998. The 2-4-C studies were benchmarked by AEMO using an alternative software package called PROPHET. Each package performs Monte Carlo time sequential simulation of the NEM. The data sets applied in the models were made as close to equivalent as possible. The modelling took into account the following factors.

2.2 Ramp rates

Ramp rates measure the ability of generators to respond to changes in the supply demand balance. The fastest responding generators in the NEM are the hydro electric power stations and demand side management (120 – 200 MW / min). After these, open cycle gas turbines are the next fastest generators to respond (9 – 100 MW / min). A full table of ramp rates can be found in [2].

2.3 Outage rates

One of the main factors to take into account while calculating the MRLs is the outage rates of generators in each region. Table 1 shows a list of generator outage rates. Snowy Hydro is a scheme containing generators in both the NSW and VIC regions.

The AEMO Forced Outage Data Working Group (FODWG) collates and updates forced outage statistics on a yearly basis. In order to preserve generator confidentiality, the statistics are aggregated by generator type and region. The inputs to 2-4-C are five variables: full forced outage rate (FFOR), partial forced outage rate (PFOR), number of full outages per year (NFULL), number of partial outages per year (NPART), and derating percentage. The inputs to Prophet are in the form of a 3x3 input matrix which records transition times between the various states of available, partially available, and unavailable. The behaviour of each was carefully benchmarked to ensure equivalence. To model the real world behaviour of the system, the outage rates need to correspond to the Equivalent Demand Forced Outage Rate (EFORd) as defined, for instance, in the NERC Generating Availability Data System (GADS) guidelines [4].

Outage rates for the SA and NSW OCGTs are high by global standards, for example compared to the NERC GADS data.

2.4 Constraint equations

Each year, AEMO updates and revises a set of transmission constraint equations which are used for the system modelling. The equation terms are quantities such as demands in a particular region, line flows, and generator dispatch.

These equations are based on real time constraint equations used in dispatch and provide thermal and stability limits to ensure system security is maintained in the event of any one network element failing.

	FFOR (%)	**PFOR (%)**	**Derate (%)**	**NFULL**	**NPART**
NSW Base	1.96	6.16	18.84	5.37	43.91
NSW Peak	49.68	0.00	0.00	222.49	0.00
QLD Base	4.65	11.32	20.03	6.97	58.36
QLD Hydro	2.61	0.17	29.04	13.67	1.20
QLD Peak	7.14	1.31	48.10	83.51	15.34
SA Base	1.71	4.03	18.44	4.56	27.96
SA Interm ediate	1.99	3.07	14.89	5.83	2.23
SA Peak	24.52	37.73	16.15	125.67	42.09
Snowy Hydro	4.47	0.00	0.00	20.12	0.00
VIC Base	3.01	15.22	9.22	17.17	207.62
VIC Hydro	3.85	0.00	92.62	55.45	0.12
VIC Peak	8.56	3.47	24.30	161.69	9.92

Table 1: Aggregate Generator Forced Outage Rates

The constraint equations are referred to as system normal constraints and protect against single credible contingencies, providing so-called n-1 security.

2.5 Interconnectors

Interconnectors have associated inter-regional loss factors (IRLFs) which are modelled within 2-4-C. These factors model losses on the interconnectors using a piecewise linear approximation to the losses in the dispatch engine (NEMDE or "National Electricity Market Dispatch Engine"), which is based on a linear program. For further detail on these equations, see [3].

2.6 Bidding

Bids are developed for each of the approximately 200 generators in the NEM by examining the generation and associated regional pool price of each generator over the most recent twelve month period. Each generator has a set of ten price / capacity pairs which indicate how much capacity a generator will offer at a given price. The prices are chosen from the most recent bids, and then the capacity values are filled in using a least-squares approach which minimises the difference between actual generation and simulated generation over the year. This is performed for the peak times (7am-10pm), and off-peak times, and on weekdays / weekends.

For a particular generator and set of time periods, the objective function is:

$$Minimize: \sum_{all\ periods\ p} (actualgen(p) - simulatedgen(p))^2$$

Simulatedgen(p) is the cumulative sum of the capacity bands which are offered at a price less than or equal to the price in period p. The constraint is that the sum of all the capacity bands must be the capacity of the generator. Other more sophisticated constraints ensure that OCGTs cannot place capacity in low price bid bands, and to ensure that coal and CCGT plants have a minimum "self-dispatch level".

For this study, price outcomes are not important; the bids are a second-order effect and the intention is to make sure that constraint outcomes are somewhat realistic with plants bidding in the merit order that would usually occur in the market. The random outages introduced in Monte Carlo iterations reflect the diversity in the merit order which occurs in practice.

Usually OCGTs are the last generators to come online because their short run marginal cost (SRMC) is the highest of any plant.

2.7 Hydro dispatch

The hydro and other energy limited plant dispatch was managed in the simulation using an SDDP (stochastic dual dynamic programming) type approach first proposed by Pereira and Pinto [5].

2.8 Wind generation

Wind was not considered in the simulation, but methods such as ELCC (effective load carrying capability) of Garver [6] or the peak periods method discussed by Milligan and Porter [7] can be used to estimate the capacity value of wind where necessary.

2.9 Non-sequential simulation

Sensitivities to demand and forced outage rates were modelled, and it was sometimes necessary to explain how the minimum reserve levels had changed from the previous study completed in 2006. In this case, non-sequential simulation using the R software package proved useful, by approximating the reliability contribution of interconnectors in a given region by a 100% reliable generator.

Unserved energy estimates are derived by convolving the supply and demand curves. That is, the following three steps (from [8]) are followed.

1. Create a discrete generation probability distribution

2. Create a discrete load probability distribution

3. Perform a convolution between the two distributions

This approach does not capture the impact of demand diversity between regions but can be performed much more quickly than the full 2-4-C simulation. This proved to be a useful tool for explaining how much of the change in MRLs was due to demand diversity, how much was due to forced outage rate changes, and how much was due to constraint behaviour and other changes.

As explained by Mazumdar and Gaver [9], the distribution of the proportion of plant unavailable in a given region can be approximated closely by a beta distribution. For the Queensland region, this proportion of plant, with a superimposed beta distribution, is shown in Figure 2. Then, as a cruder and faster approximation, the capacity available for a particular region can be calculated as a random variate using estimated parameters, instead of summing the capacities of generators within the region.

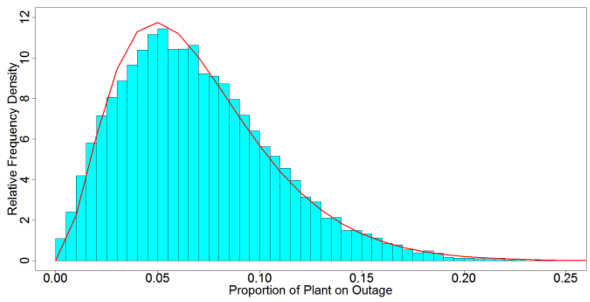

Figure 2: Queensland capacity on outage, with superimposed beta distribution

Examination of the unserved energy results showed that expected unserved energy results could be closely approximated by distributions such as the Weibull or gamma distributions, as noted previously by authors such as Patton and Stasinos [10] with reference to statistics such as loss-of-load probability (LOLP). This was verified using maximum-likelihood fitting in R.

Actual data from the NEM Short-Term Projected Assessment of System Adequacy (STPASA) shows that in many cases, the capacity of generators in a region could be approximated well over time by a Weibull distribution. With a large number of small generators each of the same size, the Central Limit Theorem implies that the capacity distribution approaches the normal distribution.

2.10 Demand forecasting

Each year, the transmission network service providers (TNSPs, for example Powerlink for Queensland, Transgrid for New South Wales) provide energy and peak demand forecasts to AEMO for the following ten years. The forecasts are provided on a probability of exceedence (POE) basis; for example the 10% POE demand is the demand expected to be exceeded in 10% of years. Queensland, New South Wales, and Tasmania forecasts were available for 5%, 10%, 50%, and 90% POE peak demands. Forecasts for Victoria and South Australia were available for many more values in the spectrum. This is due to the operators in these regions being recently affected by extreme weather conditions in 2008 and 2009, leading to the refinement of demand forecasting (see Hyndman and Fan [11]).

Demands are "grown" by taking an historic half-hourly load trace reference year such that the peak demand and energy of the input year are adjusted to be the same as the peak demand and energy forecast of the target year. In addition to meeting these targets, the gradient of the top demand periods (considered as demand over time, with demand sorted in decreasing order; the top 0.5% was considered in the study) must match the gradient of the input data, as this factor is crucial to accurately estimate unserved energy.

The MRLs are expressed as a capacity requirement (MW) over the forecast 10% POE demand, rather than a percentage reserved margin over the 50% POE as more commonly used internationally. Reserve margin refers to the proportion of available capacity in a system at peak compared to the demand of the whole system.

Unserved energy is also "pain-shared" across the interconnectors where interconnector capacity is available after the simulation by adjusting the unserved energy outcome so that it is weighted by the demand occurring in adjacent regions in these periods.

2.11 Extrapolating unserved energy

Peak demands are sometimes only known for 5%, 10%, 50%, and 90% POE levels, and simulations are performed with load traces for each region corresponding to these demands. However, it is necessary to estimate expected unserved energy by taking into account the whole spectrum of demand POE possibilities. Hence, the unserved energy must be interpolated and extrapolated using existing information about the demand and unserved energy at these points. Previously, a method developed by NEMMCO, the predecessor to AEMO, was used to extrapolate USE (unserved energy) at decile POE points as peak demands were available on a decile POE basis, and before that, a method using Gaussian quadrature following Miller and Rice [12] was used.

Calculating the expectation value of a function requires one to multiply all possible values of the function (in this case, USE outcomes for different annual peak demands) by their probability of occurring (in this case, the probability of each peak demand).

$$< U > = \int P(p) \times U(p) dp \qquad (1)$$

where

$< U >$ = expected USE

$P(p)$ = probability (density) of peak demand p occurring

$U(p)$ = unserved energy (USE) observed for a given peak demand p in that year

p = peak megawatt demand in that year

For a particular peak demand value, the forecast load trace for a year with that peak demand value is generated by scaling a reference year's actual load (up or down) to ensure that the highest demand period in the reference trace maps to the highest demand period in the output trace, while preserving the general shape of the reference trace and ensuring that the total energy is the same in all forecast traces.

In practice, in unserved energy studies, we are most concerned with the highest demand points. At these highest demand points, the scaling of the input trace effectively multiplies the demand value of the input trace by a constant factor.

For example, consider the plot in Figure 3. The three lines are the top demands for the year sorted into descending order, with demand decreasing from left to right. The demand traces have been produced from a 2008-09 reference year in SA with a peak demand of 3338 MW.

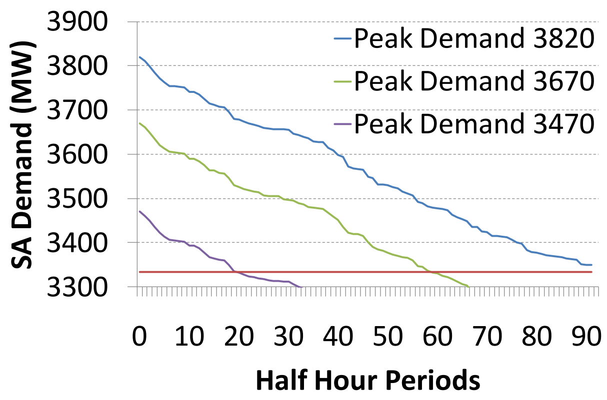

Figure 3: South Australia demand in descending order

In each of the three cases, a straight line provides a very good fit (with R-squared value greater than 0.99) to the demand plotted against the half hour (half hours beginning at 0 and increasing). We assume that effective available capacity (for the purposes of USE estimation) remains constant over these periods. In the above case, this has been determined to be approximately 3333 MW, which is the horizontal line in the diagram[1]. This is considered to be the long run average availability of stations for a large number of Monte Carlo simulations, taking into account outages. For a particular Monte Carlo iteration, the availability would vary from this average availability.

[1] Note that this "average availability" will be determined through a fitting procedure in actual applications, and might be more appropriately considered an "effective availability". This allows for more complex effects to be absorbed into this relatively simple model.

The resulting USE for each demand trace can be measured as the area of the triangle bounded by the y-axis, the red line and the line corresponding to the demand (blue, green or purple). That is, the resulting USE is the total energy required beyond what can be produced from available capacity.

The assumption of a straight line being a good approximation to peak demand periods against time was also tested for actual summer peak demands for the last ten summers in the National Electricity Market for each region and found to be true.

Hence, we proceed on the assumption that in a typical year (although summer is most relevant in terms of USE in an Australian context) that if demand in a reference year can be approximated by:

$$y = a - bx \tag{2}$$

where y is demand and x is the half hour index starting at 0, then, recalling that scaling the input trace effectively multiplies the input values by a constant, a reference year with peak demand p derived from this year has demand which can be approximated by:

$$y = p - \frac{bp}{a}x \tag{3}$$

Then the estimated USE is the area of the triangle, where u corresponds to effective availability:

$$\text{Estimated USE} = \tag{4}$$

$$\frac{base \times height}{2} = \frac{p-u}{bp/a} \times (p-u) \times \frac{1}{2}$$

Substituting $c = a/(2b)$ we obtain:

$$\text{Estimated USE} = \frac{c}{p}(p-u)^2 \tag{5}$$

This is a two-parameter function and hence we can estimate c and u if, for example, we have simulated USE and MW values at 10% and 50%, or 5% and 10% POE demand values. For levels between known POE values, linear interpolation is used, and for extrapolation at the higher POE values this function is used.

3 DEVELOPMENT OF MRLS

With all the input data required for the simulation, the methodology applied was then to remove or add plant from each region, simulating the system with 5%, 10%, 50% and 90% POE demands, until the expected unserved energy in each region was 0.002% of the energy in that year or less. Plant removed was generally of the baseload type in order to try to ensure that the outage rate of removed plant was close to the average outage rate in the region. In South Australia, intermediate plant was removed due to the higher number of OCGTs in this region. Also, removed plant was chosen so as to affect constraint outcomes as little as possible.

Another approach which could be used is to scale plant capacities, which for a given amount of capacity would tend to decrease USE compared to removing discrete plants. For larger systems where removing or adding plant manually is arduous, this approach may be required.

In each study, 100 iterations of Monte Carlo simulation were used. This proved to be sufficiently many for the 5% POE demand simulation to converge to a reasonable degree, but more iterations would improve convergence for higher POE demand studies. Time constraints prevented the use of more iterations in this study.

3.1 Results

The minimum reserve levels obtained are shown in Table 2. Stoll [13] noted that a typical reserve margin is approximately 15% - 25% above the expected (50% POE) peak demand. Across the mainland NEM, taking into account the effect of expected interconnector support, and assuming 95% coincidence in the NEM peak demand, the 2010-11 result is 18.79% above the 50% POE demand. NSW and SA vary considerably from this NEM reserve margin. This is because NSW is advantaged by two large interconnections, while SA is a smaller region on the extremities of the NEM.

3.2 Reserve sharing

There are four sets of interconnectors between the five regions: Queensland to NSW (QNI and Directlink), NSW to Victoria, Victoria to SA (Murraylink and Heywood), and Victoria to Tasmania (Basslink). At times of USE in Victoria, Basslink is already transferring as much capacity northward into Victoria as possible, so it is not relevant for this study.

We investigated the possibility of transferring capacity between adjacent regions for the other three sets of interconnectors. That is, capacity was removed from one region and then added to the adjacent region so that unserved energy remained below 0.002% in every region. It was found that this was most effective across the Victoria to South Australia interconnectors due to the very low diversity of demand between the two states. The implementation of this reserve sharing in market systems is a work in progress.

	QLD	NSW	VIC	SA	NEM
10% POE Peak Demand (MW)	10368	15250	10651	3478	39747
50% POE Peak Demand (MW)	9852	14290	9884	3238	35401
Minimum Reserve Level (MW)	829	-1218	-601	19	-971
Expected IC support (MW)	170	1324	1203	578	3275
Reserve Plant Margin (%)	15.38	7.46	13.85	25.85	18.79

Table 2: Minimum Reserve Levels for mainland regions in 2010-11

3.3 Sensitivity studies

We examined different reference years for the demand and adjusted the forced outage rates of generators by a constant proportion in order to see the effect on the MRLs. After this examination, the initial reference year of 2005-06 was retained in order to avoid extreme weather events in the input data which might affect the output trace.

3.4 Implementation of MRLs

The MRLs are used as inputs to two processes: MTPASA, the Medium Term Projected Assessment of System Adequacy, and the Supply Demand Calculator.

The objective of MTPASA is to determine if the capacity of the system is sufficient to avoid unserved energy over a two-year period. The MRLs are applied as a buffer to the 10% POE forecast peak demand for the forecast period, which ensures that enough installed generation is present to meet the Reliability Standard.

The Supply Demand calculator is a spreadsheet tool used to determine when a Low Reserve Condition (LRC) point occurs in the future. The LRC point indicates when the reliability standard will not be met.

4 CONCLUSION

The MRL determination process resulted in a set of numbers which are used daily in medium term assessments of system adequacy in the Australian National Electricity Market. This kind of assessment helps the market operator decide when intervention may be required and in the longer term may help guide investor decisions on where to develop generation.

Collating the data required for the simulations, verifying and calibrating the models, performing the simulations, and writing the reports took approximately ten months. The methods described here can help speed up the process of examining how the MRLs have changed over time and help explain how changes to the input parameters would affect the result, without the need for time-consuming resimulation. This paper also describes a novel method for extrapolation of unserved energy at high levels of demand.

There are some issues raised in the study which need closer examination: confidence intervals for the MRLs, the approximation of the top demand periods, and the issue of concurrent high demand in each region.

Sahinoglu et al [14] comment that "error propagation in reliability computations because of outage data uncertainty can be indicated by quoting confidence intervals for the indices". The studies would ideally produce a confidence interval for each MRL.

The process of removing and adding plants from each region was carried out manually. This approach was considered feasible for the Australian NEM network, but using the approach for larger networks or more regions would require either automation of the removing and adding process or simply scaling some plant capacities.

The top demand periods are approximated by a linear function, whereas Diesendorf and Martin [15] found that a shifted Rayleigh distribution is a good probability distribution function for the load of a large grid.

The results of the simulation are quite conservative in that demands in each region are set to have the same POE demand – in effect, it is assumed that in one of every 10 years, each region will experience 10% POE demand simultaneously, which is actually a less likely outcome. Similarly, the USE extrapolation does not take this factor into account. This requires further investigation.

REFERENCES

[1] AEMC Reliability Panel, "NEM Reliability Standard – Generation and Bulk Supply", http://www.aemc.gov.au/Media/docs/NEM%20Reliability%20Standard%20-%20December%202009-bf56806c-1e4e-4c7a-ab73-46e695fb10a2-0.pdf

[2] AEMO, "2010 National Transmission Network Development Plan", http://www.aemo.com.au/planning/ntndp.html

[3] AEMO, "Pre-dispatch process description, Version 3.1", http://www.aemo.com.au/electricityops/0140-0040.pdf

[4] North American Electricity Reliability Corporation. "Appendix F - Performance Indices and Equations - GADS Data Reporting Instructions", January 2010. http://www.nerc.com/files/Appendix_F_Performance_Indexes_and_Equations.pdf

[5] M. V. F. Pereira and L. Pinto, "Multi-stage stochastic optimisation applied to energy planning", Mathematical Programming, Vol. 52 (1991), pp 359-375.

[6] L. L. Garver, "Effective Load Carrying Capability of Generating Units", IEEE Transactions on Power Apparatus and Systems, Vol. 85 (1966), pp 910-919.

[7] M. Milligan and K. Porter, "Determining the Capacity Value of Wind: An Updated Survey of Methods and Implementation", WindPower 2008, Houston, Texas, June 1-4, 2008. http://www.nrel.gov/docs/fy08osti/43433.pdf

[8] W. Li, "Risk Assessment of Power Systems", Wiley, 2005, ISBN 0471707716.

[9] M. Mazumdar and D.P. Gaver, "A comparison of algorithms for computing power generating system reliability indices", IEEE Tranactions on Power Apparatus and Systems, Vol. 103 (1984), pp 92-97.

[10] D. Patton and A. Stasinos. "Practical Methods in the computation of LOLP variances and confidence limits", IEEE Tranactions on Power Apparatus and Systems, Vol. 95 (1976), pp 287-290.

[11] R. J. Hyndman and S. Fan, "Forecasting long-term peak half-hourly electricity demand for South Australia", Report for ESIPC, 13 May 2009. http://www.aemo.com.au/planning/e400-0004.pdf

[12] A.C. Miller and T.R. Rice, "Discrete Approximations of Probability Distributions", Management Science, Vol. 29 (1983), pp 352-362.

[13] H. G. Stoll, "Least-cost electric utility planning", Wiley, 1989, ISBN 0471636142.

[14] M. Sahinoglu, M. T. Longnecker, L. J. Ringer, C. Singh, A. K. Ayoub, "Probability distribution functions for generation reliability indices – analytical approach", IEEE Transactions on Power Apparatus and Systems, v.102 (1983), pp 1486-1493.

[15] M. Diesendorf and B. Martin, Optimal Generation Planning for Electricity Grids Containing Wind Farms, Proceedings of the World Solar Congress, 1983, pp 2323-2329.