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A noniterative method to estimate load carrying capability of generating units in a renewable energy rich power grid

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Abstract

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Keywords

noniterative, method, estimate, load, carrying, capability, power, generating, grid, units, renewable, energy, rich

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A Non-Iterative Method to Estimate Load Carrying Capability of Generating Units in a Renewable Energy Rich Power Grid

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***Abstract*—It is important to estimate the contribution of the renewable generation units in the evaluation of system generation adequacy for power generation planning taking into account the demand and renewable generation correlation and uncertainty. The effective load carrying capability (ELCC) is usually used for this purpose. In this paper, a non-iterative analytical method is proposed for estimating the peak load carrying capability (PLCC) and ELCC of conventional and renewable generation units. The proposed method is verified using the IEEE RTS and an electricity network in New South Wales, Australia, and the results are compared with other estimation methods. The results show that the correlation between demand and renewable generation influences the ELCC of a renewable generation unit– the higher the correlation, the higher the ELCC and vice versa. The main contribution of this paper is the development of an analytical non-iterative and computationally efficient technique, which accounts for the correlation between demand and available renewable generation.**

***Index Terms*—Approximation method, demand-generation correlation, joint probability distribution, power generation planning, renewable generation system.**

NOMENCLATURE

A. List of Acronyms:

ACPT	Available Capacity Probability Table
ELCC	Effective Load Carrying Capability
FOR	Forced Outage Rate
GRMPT	Generation Reserve Margin Probability Table
LOLE	Loss of Load Expectation
LOLP	Loss of Load Probability
NSW	New South Wales
PLCC	Peak Load Carrying Capability
RTS	Reliability Test System

B. List of Variables:

A_j	Availability of generation unit j with capacity G_j
AGC_i	Available Generation Capacity for i^{th} state
C	Random variable for generation capacity
C_A	Available generating capacity
FOR_j	FOR of generation unit j with capacity G_j
G_j	Available generating capacity of unit j
$G_{R,j}$	Available renewable generation level
L_j	Load level of j^{th} state
M	Number of conventional generation in outage
$P\{.\}$	Probability of the quantity within parenthesis
N	Total number of conventional generation units in the system
N_D	Total numbers of the possible states of the random variable D
N_{GR}	Total numbers of the possible states of the random variable G_R
R_C	Random variable of generation reserve margin
$R_{C,k}$	Generation reserve margin of k^{th} state
$R_{C+R,k}$	Generation reserve margin of k^{th} state with renewable generation unit
T	Number of hours
$n_{d,g}$	number of occurrence of the simultaneous event ($D=d$, $G_R=g$)
$n_{i,j}$	Number of occurrence of the event ($D=d_i$,, $G_R=g_j$)

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I. INTRODUCTION

THE power output from the renewable generation systems and the load demand are uncertain variables due to their inherently fluctuating nature. With growing penetration of renewable generation in the electricity generation system, the generation adequacy estimation methodology needs to be modified to include the variability and uncertainty associated with the renewable generation and load demand and the correlation between the two.

A number of indices to estimate the capacity contribution of the intermittent generation systems, such as effective load carrying capability (ELCC), demand time matching (DTIM), equivalent conventional power (ECP), and equivalent firm power (EFP) has been proposed in the literature [1-4].

Different entities including system operators, power utilities and academics have reached a consensus to use the ELCC index as the capacity value for intermittent renewable generation systems. The ELCC index is an indicator of the contribution of an additional generator (or a group of generators) in the generation adequacy to meet the peak load demand of the system [1-13]. Authors of [9] define ELCC as the amount of increase in the peak demand that can be added to a system while maintaining a specific risk level such as the loss of load expectation (LOLE) after an additional generator (or a group of generators) is added.

The ELCC index has been used for power generation planning of (i) concentrating solar power plants in Southwest United States [1], (ii) tidal wave [7], (iii) solar photovoltaic power plants [2, 4], and (iv) wind generation systems [3, 9, 11, 13, 14].

A graphical method is proposed in [10] to estimate the ELCC of an additional generating unit into the generation system. This is further modified in [11] to include the addition of wind generation unit using multi-state representation of the availability of the wind turbine outputs. The graphical method to estimate LOLE using an exponential function can lead to significant errors [15] as discussed in Section II.

The Z-statistic method, proposed in [12], is a non-iterative method for ELCC estimation, which presumes that the probability distribution of the generation surplus during the peak demand period is a Gaussian distribution. The ELCC of the system is estimated using the changes in the generation surplus probability distribution during peak demand periods of the system due to the additional generation unit. It keeps the Z-statistic value constant which is equivalent to maintaining a constant loss of load probability (LOLP) and therefore can be considered as an approximate method for ELCC calculation during the peak demand period. The main advantage of this method is a significant reduction in computation time compared to the more onerous iterative method using chronological demand and renewable energy system data. However the correlation between the demand and renewable generation has not been taken into account in this method. Further, the Z-statistic method assumes that the addition of a wind plant does not change the probability distribution shape of the generation surplus. Hence it is especially accurate for the addition of small wind generation unit and less accurate for the addition of large unit on a power system.

In [13], a Genetic-Algorithm-based LOLE estimation method is proposed for a power system with wind generation plant using the chronological data of demand and wind generation. An iterative method for estimating the ELCCs of the wind generation units is used in [13, 14] using the data of demand and wind generations for several years. The iterative method along with the time series data can account for both the seasonal and diurnal variation of wind generation, and the correlation between demand and wind generation. However, the iterative method is computationally intensive due to the large time series data set requiring several iterations and is not suitable for generation planning involving optimization of a large system lasting for several years.

In this paper, instead of using chronological data and the commonly used iterative method to account for seasonal and diurnal variation and the correlation between demand and available renewable generations, a non-iterative analytical technique using joint probability distribution of the demand and the renewable generations is proposed to estimate the LOLE and peak load carrying capability (PLCC) of the system, and ELCC of the renewable generation plant. The ELCC of the renewable generation plant is estimated from the PLCC values of the system before and after adding the renewable generation plant in the generation system. Since the proposed method of ELCC estimation for the renewable generation plant is non-iterative, it is less computationally intensive and can provide greater insight into the influencing attributes associated with the ELCC of the renewable generation plant as compared to the iterative method.

II. Motivation for the Research Work

A. Errors in the Graphical Methods for ELCC Estimation

In the non-iterative probabilistic graphical methods [10, 11], the LOLE of the system is approximated by the exponential function of the system peak demand using curve fitting technique. For a small system from reference [15], this approximation using curve fitting will produce large error, particularly for higher peak demand as shown in Fig. 1. For a large system, such as the IEEE reliability test system (RTS) [16], the error reduces as shown in Fig. 2. Despite the closeness of the fitted curve to the actual curve, a large relative error in the estimation of LOLE can be introduced as shown in the zoomed portion inside Fig. 2.

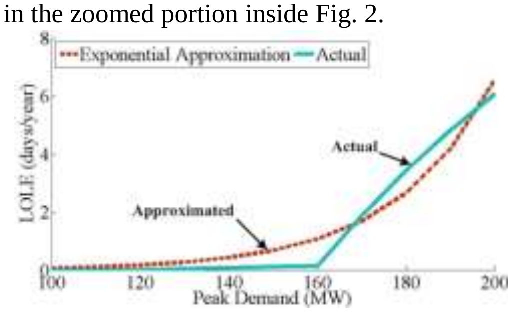

Fig. 1. LOLE vs peak demand curve for a system presented in [15].

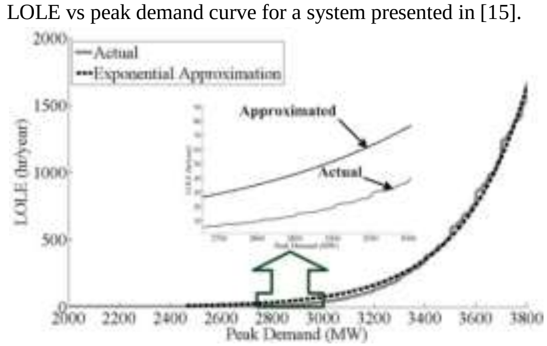

Fig. 2. LOLE vs peak demand curve for a IEEE RTS.

This is particularly acute when the system has a small value of LOLE as the effect of erroneous approximation gets further amplified in such case. The error in LOLE will lead to error in the estimation in ELCC. An improved methodology needs to be developed to reduce this error.

B. Errors in Assuming that the Wind and Load Demand is not Correlated

The multi-state non-iterative method [11] does not incorporate the correlation between demand and the renewable generation, which can lead to errors in the estimation of ELCC.

Fig. 3 shows the total wind generation from all the wind farms in the state of California, USA during a heat wave from 17-26 July, 2006, when excessive usage of air conditioning equipment resulted into the peak demand in the state [17]. In

Fig. 3, the red dots indicate the wind generation level during that period.

Fig. 3 shows that there is a clear negative correlation between peak demand and the wind energy generation. On July 17, the wind energy generation at peak load was 4% of the wind generator nameplate. This suggests that the ELCC of the wind generator for peak load in this case should be very low and other types of generation will be needed to guarantee the reliability of supply for the system in peak hours [17].

This correlation is, however, a complex function of both location and weather. Fig. 4 shows a similar graph to Fig. 3 for the wind generation in summer season (1-10 December, 2010) for the state of New South Wales (NSW), Australia. Fig. 4 shows that there are days when the peak load is correlated with significant wind generator output.

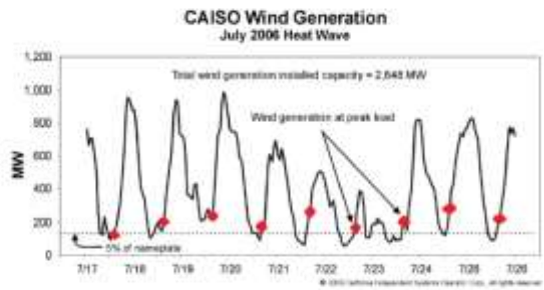

Fig. 3. California heat wave in July 2006 [17].

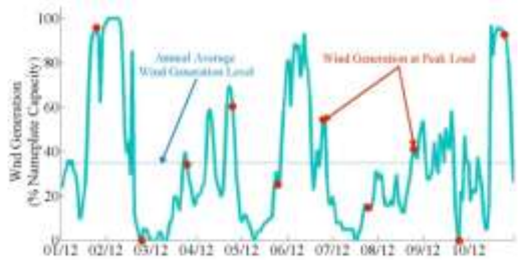

Fig. 4. NSW summer wind generation and peak demand coincidences.

Figs. 3 - 4 show that there is a correlation between demand and renewable generation and it needs to be considered in the estimation of ELCC to avoid significant calculation errors. Errors that can arise in the estimation of ELCC by ignoring the correlation between the renewable generation and the load are demonstrated in Section IV-D.

Therefore, it is important to develop a method that can include the correlation between the renewable generation and the load demand, while avoiding the use of the exponential curve fitting. Moreover, shorter computation time needs to be ensured compared to the iterative method which relies on the chronological data of load and renewable generation.

In the following sections, a non-iterative method to estimate LOLE for a system using the availability capacity probability table (ACPT) is proposed only for conventional i.e. non-renewable generating units. The proposed method is validated using the IEEE RTS and the results are compared with the traditional iterative method. The addition of renewable generating units to the above system, with peak demand-renewable generation correlation, will then be considered using the joint-probability distribution between demand and renewable generation.

III. Proposed Non-Iterative ELCC Estimation Technique for Conventional Generating Units

A. Available Capacity Probability Table

For a generation system composed of N conventional units with M failed units, the available generating capacity, AGC_i and its corresponding state probability, $P\{AGC_i\}$ for state i can be determined by (1) and (2), from which the ACPT can be obtained:

$$AGC_i = \sum_{j=M+1}^{N} G_j \tag{1}$$

$$P\{AGC_i\} = \prod_{j=M+1}^{N} A_j * \prod_{j=1}^{M} FOR_j \tag{2}$$

where A_j, FOR_j and G_j are the availability, forced outage rate (FOR) and the available generating capacity of unit j respectively.

Consider a sample system consisting of three 25 MW generating units, with a forced outage rate of 0.02 for each unit. Table I shows the ACPT for the sample system.

TABLE I
AVAILABLE CAPACITY PROBABILITY TABLE

Units Out #	Capacity Out	Capacity In (C_A)	Probability $P[C=C_A]$	Cumulative Probability $P[C \leq C_A]$
None	0 MW	75 MW	(0.98×0.98×0.98)=0.9412	1
1, or 2, or 3	25 MW	50 MW	3×(0.02×0.98×0.98)=0.0576	0.0588
1,2 or 1,3 or 2,3	50 MW	25 MW	3×(0.02×0.02×0.98)=0.0012	0.0012
1,2,3	75 MW	0 MW	(0.02×0.02×0.02)=0.0000	0.0000

B. LOLE Estimation

The generation reserve margin, $R_{C,k}$ of the system for the load level, L_j due to the available generation capacity level, AGC_i can be defined as the excess available generation capacity after serving the demand, L_j as shown in (3). It is assumed that the outage of the conventional generating units is purely random and independent of the demand levels as used in [15]. Therefore, the individual probability of the generation reserve margin level, $P\{R_{C,k}\}$ will be equal to the product of the probability of system demand level, $P\{L_j\}$ and the probability of available system generation level, $P\{ AGC_i\}$ as given in (4).

$$R_{C,k} = AGC_i - L_j \tag{3}$$

$$P\{R_{C,k}\} = P_i\{AGC_i\} \times P\{L_j\} \tag{4}$$

Consider the system whose ACPT is given in Table I. The system has a simplified load duration curve where a peak load of 70MW is present for 40% of the time (3500h) and the off peak load of 40MW is present for the rest of the year as shown in Fig. 5. For the system, the generation reserve margin, $R_{C,k}$, and the associated probability are given in Table II. In Table II, Column 5 shows the generation reserve margin while the associated probability of the generation reserve margin level is given in column 6.

The LOLE is the amount of time when the available generated power is less than the total demand of the system during the period of study [15].

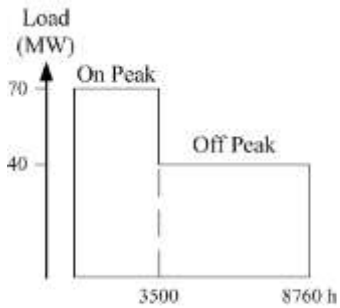

Fig. 5. Simplified load duration curve.

Therefore, a loss of load will take place if the generation reserve margin is negative, and the LOLE of the system with N_{Rcg} number of the negative generation reserve levels can be estimated using (5).

$$LOLE = \sum_{k=1}^{N_{Rcg}} P\{R_{C,k} < 0\} \times T \tag{5}$$

where, T is the number of hours considered for LOLE estimation.

The LOLE of the system with generation reserve margin shown in Table II can be calculated as:

LOLE = (0.0231+0.0005+0.0007+0.0000+0.0000)*8760
= 212.868 h/yr (with a probability of 0.0243).

TABLE II
GENERATION RESERVE MARGIN, $R_{C,G,K}$ AND ASSOCIATED PROBABILITIES FOR THE EXAMPLE SYSTEM

Cap. In AGC_i (MW)	Probability $P[G_{C,i}]$	Demand L_j (MW)	Probability $P[L_j]$	Generation reserve margin, $R_{C,k}$ (MW)	Probability $P[R_{C,k}]$
75	0.9412	70	0.3995	5	0.3760
75	0.9412	40	0.6005	35	0.5652
50	0.0576	70	0.3995	-20	0.0231
50	0.0576	40	0.6005	10	0.0346
25	0.0012	70	0.3995	-45	0.0005
25	0.0012	40	0.6005	-15	0.0007
0	0.0000	70	0.3995	-70	0.0000
0	0.0000	40	0.6005	-40	0.0000

Table III shows the sorted generation reserve margins and their probability referred to as the generation reserve margin probability table (GRMPT) from the most negative to the most positive reserve margin.

TABLE III
GENERATION RESERVE MARGIN PROBABILITY TABLE (GRMPT) OF THE EXAMPLE SYSTEM

Generation reserve margin, $R_{C,k}$	Probability $P[R_C=R_{C,k}]$	Cumulative Probability $P[R_C \le R_{C,k}]$	$P[R_C \le R_{C,k}] \times T$
-70 MW	0.0000	0.0000	0.0000
-45 MW	0.0005	0.0005	4.38
-40 MW	0.0000	0.0005	4.38
-20 MW	0.0231	0.0236	202.356
-15 MW	0.0007	0.0243	212.868
5 MW	0.3760	0.4003	3506.628
10 MW	0.0346	0.4349	3809.724
35 MW	0.5652	1.0000	8760

In table III, the third column of the GRMPT is the cumulative probability of the generation reserve margin levels and the fourth column shows the cumulative probability values multiplied by T, from which the LOLE can be estimated. The LOLE is the value that corresponds to the least negative value of the generation reserve margin levels in column one, which is -15MW. Hence, the value of LOLE in this case is 0.0243 pu or 212.868 h/yr.

C. *Proposed Non-Iterative ELCC Estimation*

Traditionally, for estimating the ELCC of a conventional generating unit, the iterative method is used to estimate the PLCCs of the generation system before and after the addition of a new generating unit into the system. The PLCC of a system is defined as the peak demand of the system that can be supplied by the committed generating units while maintaining a specific level of LOLE.

In the iterative method for estimating PLCC, the demand of a system is adjusted iteratively by either increasing or decreasing certain amount of load demand until the LOLE of the system has reached to a specified level. Subsequently, the increased or decreased demand is added or subtracted, respectively, from the actual peak demand of the system to estimate the PLCC of the system.

In this paper, a non-iterative method is proposed to estimate the PLCC of a generation system. Consider the same sample system whose GRMPT is given in Table III with an assumption that the requisite LOLE level is 0.01 pu or 87.6 h/yr. Since the original LOLE of the system is 0.0243 pu or 212.868 h/yr, 20 MW demand should be deducted from the system (i.e. -20 MW generation reserve margin corresponds to the probability of 0.0236 in the GRMPT and reducing it further will lead to the probability of 0.005 which is below the required LOLE of 0.01 as shown by the window in Table III). The system peak demand that is to be supplied by the committed generating units while ensuring an LOLE of 0.01 pu or 87.6 h/yr is (70 - 20) = 50 MW. Hence, the PLCC of the system before the addition of a new unit is 50 MW. Table IV shows the GRMPT of the system after adding an additional 30 MW of conventional generating unit having forced outage rate (FOR) of 0.02.

The LOLE of the system with the generation reserve margin shown in Table IV is 0.000952 pu or 8.367 h/yr. If the specific LOLE level required is 0.01 pu or 87.6 h/yr, then 10 MW demand should be added to the system (resulting into the LOLE that will be higher than 0.0085 pu and less than 0.032 pu). The PLCC to have an LOLE of 0.01 pu or 87.6 h/yr after the addition of a new generating unit is (70+10) = 80 MW. The ELCC of the new unit in the system with LOLE of 0.01 pu or 87.6 h/yr can be estimated as the difference between PLCCs of the system before and after the addition of the new unit in the system and is found to be (80 - 50) = 30 MW.

Any unit with a reliability value less than 100% should have a capacity value less than its installed capacity. The mismatch between the result and that from practical experience is due to the simplistic nature of the example. In the example system, the load duration curve contains only two load levels and the generation system consists of three generation units each with a force outage rate of 0.02. As a result, the difference between two consecutive generation reserve margin values is large in the GRMPT and the generation reserve margin levels jump from 5 MW and 10 MW as shown in Table IV. This results in the capacity value of a 30 MW generation unit equal to 30 MW. However, for a practical system with many generation units and a load duration curve with many demand levels, the difference between two consecutive generation reserve margin levels will be very small and the appropriate number can be found from GRMPT. A validation of this for the IEEE RTS system is given in Section III-E.

TABLE IV
GRMPT OF THE EXAMPLE SYSTEM WITH 30 MW GENERATION UNIT

Generation reserve margin, $R_{C,k}$ (MW)	Probability $P[R_C=R_{C,k}]$	Cumulative Probability $P[R_C\le R_{C,k}]$	$P[R_C\le R_{C,k}]\times T$
-70	0	0	0
-45	9.60E-06	9.60E-06	0.084096
-40	0	9.60E-06	0.084096
-20	0.0004608	0.0004704	4.120704
-15	0.0004848	0.0009552	8.367552
-10	0	0.0009552	8.367552
5	0.0075296	0.0084848	74.326848
10	0.0232704	0.0317552	278.175552
15	0.0007056	0.0324608	284.356608
35	0.3802448	0.4127056	3615.301056
40	0.0338688	0.4465744	3911.991744
65	0.5534256	1	8760

In order to justify the validity of the proposed method for the small systems, the load duration curve of the example system presented in Section III-B is modified. The load of the system increases by 1 MW step from the minimum load level of 40 MW to the peak load of 70 MW as shown in Fig. 6. The probability of each load level is assumed to be equal. The cumulative probability of the GRMPTs for the system with and without the 30 MW additional generation unit is presented in Fig. 7. The PLCC of the system without the 30 MW generation unit is found to be 54 MW corresponding to the LOLE level of 0.01 pu. The PLCC of the system with 30 MW generation plant is estimated 81 MW maintaining the system LOLE level of 0.01 pu. Hence the ELCC of the 30 MW generation unit is found to be 27 MW using the proposed method.

D. Computational Procedures

The sequential computational procedures associated with the proposed non-iterative method of estimating the ELCC of an additional conventional generation unit are presented as follows.

a) Construct the ACPT with the aid of relevant information related to the conventional generation units of the system without additional generation unit, such as installed capacity, FOR, and availability rate using (1) and (2).
b) Construct the GRMPT using the data from ACPT and probability distribution of demand using (3) and (4).
c) Estimate the PLCC of the system without additional generation unit using the GRMPT and the specific LOLE for the system.
d) Obtain the availability model and FOR of the additional conventional generation unit.
e) Construct the new ACPT with the aid of the previously constructed ACPT and the availability model of the additional generation unit using (1) and (2).
f) Construct the new GRMPT using the data from the new ACPT and the probability distribution of demand using (3) and (4).
g) Estimate the new PLCC level of the system with the additional generation unit using the new GRMPT and the specific LOLE for the system.
h) Estimate the ELCC of the additional generation unit from the PLCC values of the system with and without the additional generation unit.

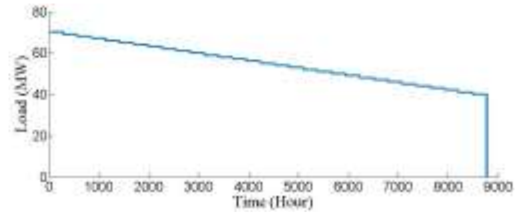

Fig. 6. Load Duration Curve.

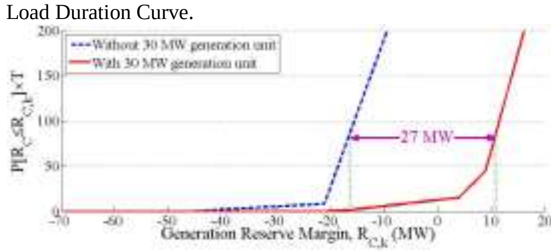

Fig. 7. Generation Reserve Margin.

E. Validation using IEEE RTS

The IEEE RTS [16] is used to validate the proposed non-iterative method for estimating the ELCC of additional generating units. The generation and demand data of IEEE RTS can be found in [16]. One of the 100MW generating units is considered as an additional unit. The ELCC of the additional 100 MW generating unit is estimated using the proposed method and compared with the value estimated using the iterative method [6]. In this analysis, the number of load levels considered in the system load duration curve is 100. The system risk level for ELCC estimation of the additional 100 MW generating unit is considered to be an LOLE of 9.3452 hrs/yr which is the actual chosen LOLE for the IEEE RTS. The comparative results are presented in Table V.

TABLE V
ELCC OF 100 MW UNIT IN IEEE RTS

	Proposed Method	**Iterative Method [3]**	**% Error**
$PLCC_{-100MW}$	2754.3 MW	2753.1 MW	0.04
PLCC	2850 MW	2850 MW	0
$ELCC_{100MW}$	95.7 MW	96.9 MW	1.24

The PLCC of the IEEE RTS is found to be 2754.3 MW and

2850 MW using the proposed method without and with the additional 100 MW generation unit, respectively. Hence, the ELCC of the 100 MW generating unit is found to be 95.7 MW and 96.9 MW using the proposed method and the iterative method, respectively, which corresponds to the relative error less than 1.5% highlighting the acceptable level of accuracy for the proposed estimation method. This error is mainly due to the quantization of the demand carried out during the probability distribution estimation.

IV. Proposed Non-Iterative ELCC Estimation of a Non-Conventional Generating Unit Using Joint Probability Distribution

The load demand and available renewable generation profile usually contain both seasonal and diurnal variation. Usually, there is a correlation between the peak demand and the available renewable generation within the same time interval as demonstrated in Section II-*B*.

The non-iterative method proposed in the previous section can be used to estimate the value of ELCC of an additional renewable generating unit if the generation availability of renewable generating unit is independent of the load demand. However, to take into account the correlation between peak demand and renewable generation due to seasonal and diurnal variation, a large dataset of historical values involving complex computation is required.

A. Joint Probability Distribution

To reduce the computational efforts, the joint probability distribution between demand and renewable generation is firstly obtained in this paper from the chronological data of the available renewable generation during the different levels of demand. Once it is obtained, it can be used in the proposed non-iterative method described in Section III-*C*, to estimate the ELCC of the renewable generating unit in terms of the difference between the PLCC of the system before and after the addition of the renewable generating unit.

The joint probability distribution is one of the established concepts in the technical literature. For example, the joint probability distribution of the wind speed and the wind generator location has been used in [18] to estimate the reliability indices of a generation system. The joint probability between demand and available renewable distributed generation (DG) output has also been used in the optimization problem to estimate the DG hosting capacity of a distribution network [19]. However, it is to be noted that the joint probability distribution of load demand and renewable generation has not been used in the estimation of ELCC till date, which is one of the newly proposed subject matters of this paper.

B. Joint Probability Distribution Considering Dependency

Let us consider two dependent random variables, D and G_R. The probability distribution that defines the probability of the simultaneous occurrence of $D = d$ and $G_R = g$ is referred to as the joint probability distribution [20], and can be estimated using (6):

$$P\{D=d, G_R=g\} = \frac{n_{d,g}}{\sum_{i=1}^{N_D} \sum_{j=1}^{N_{GR}} n_{i,j}} \tag{6}$$

Where, $P\{D=d,\ G_R=g\}$ and $n_{d,g}$ are the joint probability density and number of occurrence of the simultaneous event ($D=d$, $G_R=g$) respectively, and $n_{i,j}$ is the number of occurrence of the event ($D=d_i$,, $G_R=g_j$). N_D and N_{GR} are the total numbers of the possible states of the random variables D and G_R, respectively. If the random variables are not dependent, the joint probability between them would be the product of the individual probability.

The joint probability distribution between the dependent demand and available renewable generation can be evaluated using (6) from the chronological time series data of demand and available renewable generation. The use of joint probability distribution in the ELCC estimation of renewable generation systems can reduce the computational effort when compared with the time-series based estimation methods. One important drawback of using joint probability distribution in ELCC estimation is that the accuracy of the results depends on the number of coincidental demand-generation levels used to evaluate the joint probability distribution. It is difficult to define the optimal number of the demand-generation levels in the joint probability distribution evaluation. However, similar difficulties can be found in the iterative method of ELCC estimation in terms of the selection of the optimal step value.

The red-dotted line in Fig. 8 shows that the available renewable generation is 0 MW during peak demand and 100% of the nameplate capacity (say 30MW) during off-peak period. In other words, the FOR of the wind generating unit is 0.4. The sample case for the state of California, USA, shown in Fig. 3, where there is a negative correlation between demand and the renewable generation output is simulated to test the concept. The first three columns of Table VI show the joint probability distribution between the demand and available renewable generation calculated using (6).

TABLE VI
JOINT PROBABILITY DISTRIBUTION BETWEEN DEMAND AND AVAILABLE WIND GENERATION (NEGATIVE AND POSITIVE CORRELATION)

Negative Correlation			Positive Correlation		
Demand	Wind Generation	Probability	Demand	Wind Generation	Probability (Considering Dependency)
70 MW	30 MW	0	70 MW	30 MW	0.114
70 MW	0 MW	0.4	70 MW	20 MW	0.285
40 MW	30 MW	0.6	70 MW	10 MW	0
40 MW	0 MW	0	40 MW	30 MW	0.172
			40 MW	20 MW	0
			40 MW	10 MW	0.429

The joint probability distribution between demand and available renewable generation in the last three columns of Table VI is estimated considering the case where the available renewable generation during the peak demand is 30 MW for 1000 hours and 20 MW for 2500 hours and the available renewable generation during the off-peak demand time is 30 MW for 1500 hours and 10 MW for 3760 hours shown as blue-dotted line in Fig. 8. This case is derived from the state of NSW, Australia as shown in Fig. 4, where there is a positive correlation between demand and the renewable generation output.

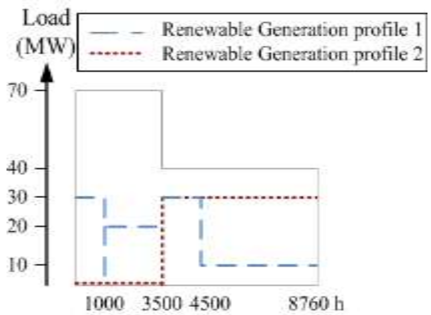

Fig. 8: Coincidental load duration and generation curve

C. The Non-Iterative PLCC and ELCC Estimation Using Joint Probability Distribution

The generation reserve margin level and the associated probability distribution after the addition of the renewable generation unit can be estimated using (7) and (8), respectively.

$$R_{C+R,k} = AGC_i + G_{R,j} - L_j \tag{7}$$

$$P\{R_{C+R,k}\} = P_i\{AGC_i\} \times P\{L = L_j, G_R = G_{R,j}\} \tag{8}$$

Where, $R_{C+R,k}$ is the k^{th} generation reserve margin due to i^{th} available conventional generation level and j^{th} demand and renewable generation level of the system. $G_{R,j}$ is the available renewable generation level occurring simultaneously with demand level of L_j. $P\{L=L_j,G_R=G_{R,j}\}$ is the joint probability distribution between demand level of L_j and renewable generation level of $G_{R,j}$.

For the red-dotted line in Fig. 8, the generation reserve margin levels and associated probability of the system with ACPT shown in Table I, and joint probability distribution between demand and available renewable generation with negative correlation shown in Table VI are calculated and presented in Table VII.

Table VIII shows the sorted generation reserve margins and their probabilities, referred as the GRMPT, from the most negative to the most positive reserve margin.

TABLE VII
GENERATION RESERVE MARGIN TAKING INTO ACCOUNT THE JOINT PROBABILITY DISTRIBUTION

Cap In (MW)	Probability $P(G_{C,i})$	Demand L_j (MW)	Wind Generation $G_{R,j}$ (MW)	Probability $P(L_j, G_{R,j})$	Generation Reserve Margin, $R_{C,k}$	Probability $P(R_{C,k})$
75	0.9412	70	30	0	35	0
75	0.9412	70	0	0.4	5	0.37648
75	0.9412	40	30	0.6	65	0.56472
75	0.9412	40	0	0	35	0
50	0.0576	70	30	0	10	0
50	0.0576	70	0	0.4	-20	0.02304
50	0.0576	40	30	0.6	40	0.03456
50	0.0576	40	0	0	10	0
25	0.0012	70	30	0	-15	0
25	0.0012	70	0	0.4	-45	0.00048
25	0.0012	40	30	0.6	15	0.00072
25	0.0012	40	0	0	-15	0
0	0	70	30	0	-40	0
0	0	70	0	0.4	-70	0
0	0	40	30	0.6	-10	0
0	0	40	0	0	-40	0

From Table VIII, it can be seen that the LOLE of the system has been improved from 0.0243 pu (or 212.868 h/yr) as given in Table III to 0.02352 pu (or 206.035 h/yr) with the integration of the renewable generation unit. The PLCC after integrating the renewable generation unit for an LOLE of 0.01 pu (or 87.6 h/yr) is (70-15) = 55 MW. From Section III-*C*, the PLCC before integrating the renewable generating plant is 50MW and therefore, the ELCC of the additional renewable generating unit for an LOLE of 0.01 pu (or 87.6 h/yr) is (55-50) = 5 MW. This suggests that the additional renewable generation unit, which has a negative correlation between its output and peak demand will result in little benefit to the system.

TABLE VIII
GRMPT OF TABLE VII

Generation Reserve Margin, $R_{C+R,k}$	Probability $P[R_{C+R}=R_{C+R,k}]$	Cumulative Probability $P[R_{C+R}\le R_{C+R,k}]$	$P[R_{C+R}\le R_{C+R,k}]\times T$
-70	0	0	0
-45	0.00048	0.00048	4.2048
-40	0	0.00048	4.2048
-20	0.02304	0.02352	206.0352
-15	0	$\boxed{0.02352}$	206.0352
5	0.37648	$\boxed{0.4}$	3504
10	0	0.4	3504
15	0.00072	0.40072	3510.3072
35	0	0.40072	3510.3072
40	0.03456	0.43528	3813.0528
65	0.56472	1	8760

The PLCC after integrating the renewable generating unit with the generation pattern given by the blue-dotted line in Fig. 8 can be similarly estimated, and the PLCC and ELCC of the additional renewable generating unit are found to be 70 MW and 20 MW, respectively.

The results show that the ELCC of the additional renewable generating unit depends on whether there is negative or positive correlation between the load demand and the available renewable generation output.

D. Impact of Demand-Generation Correlation on ELCC

To further investigate the impact of time varying renewable generation and the intermittent period of peak demand on the ELCC value, three cases are simulated for the system whose ACPT is given in Table I and the load demand is given in Fig. 5. In Case 1, the FOR of the additional renewable generation unit is varied from 1 to 0, independent to the demand level. In Case 2, at the beginning, no generation is available from additional renewable generating unit (i.e. FOR of the unit having a value of 1), and then with a small increment of generation available from the additional renewable generation is added, starting from the 8760th hour to the 1st hour causing the FOR to decrease from 1 to 0, as shown in Fig. 9(a). In Case 3, the increment is started from the 1st hour to the 8760th hour resulting in the FOR to decrease from 1 to 0 as shown in Fig. 9(b). Case 2 initially corresponds to the case when the additional renewable generation only available during off-peak hour, and Case 3 initially corresponds to the state when the additional generation is available mainly in the peak hour. The ELCC is estimated for an additional renewable generation rated at 30 MW.

Fig. 10 shows the variation in the values of ELCC as the FOR of the new generation unit is reduced in all the three cases. For Case 1, the ELCC values increase from 5 to 25 MW when the FOR reduces to 0.41 while the ELCC increases to 30 MW when the FOR reduces to 0.025. For Case 2, when the additional new generation unit is incremented starting from the off-peak period, the ELCC value increases from 5 MW to 25MW when the FOR reduces to 0.17 (i.e. 2052 hours of peak demands and 5260 hours of off-peak demand are reduced by the additional unit) and then increases to 30MW when the FOR is 0.01 (i.e. 3412 hours of peak demand and 5260 hours of off-peak demand are reduced by the additional units). However in Case 3, when the new unit starts incrementing during the peak period, the ELCC value increases to 25MW even when the FOR is 0.77 (i.e. 2000 hours of peak demand are reduced by the additional unit), and rises to 30MW when the FOR is 0.6 (i.e. 3416 hours of peak demand are reduced by the additional unit).

Fig. 10 shows that the ELCC value of the additional generation unit could be different depending on the level of correlation between the available generation and the peak demand. For example, when there is no correlation between the generation and the peak load (Case 1), the ELCC of the additional generation unit with FOR of 0.3 is found to be equal to 25 MW. However, when the available generation is correlated with the off-peak demand (Case 2), the ELCC of the additional generation unit with the same FOR and installed capacity is found to be 0 MW. This corresponds to an error of 25 MW in the ELCC value of the generation unit because the demand-generation correlation is ignored. When the available generation is correlated with the peak demand (Case 3), the ELCC value of the additional generation unit with same FOR and installed capacity is found to be 30 MW. The corresponding error in ELCC value due to ignoring the demand-generation correlation is 5 MW. Hence, the correlation between the available generation and the demand is important and should be considered in order to avoid the error in the ELCC estimation of the intermittent generation units such as renewable generation units. Moreover, it is noted that the reduction of peak load due to the additional generation is more important than the reduction of the off-peak load.

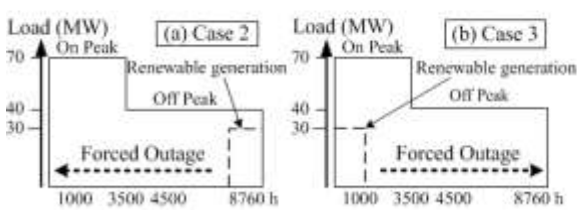

Fig. 9. Load duration curve along with the operation duration curve for a 30 MW renewable generation unit for (a) Case 2, and (b) Case 3.

E. Computational Procedures

The sequential computational procedures associated with the proposed non-iterative method of estimating the ELCC of an additional renewable generation unit, taking into account its correlation with the load demand, are presented as follows.

a) Estimate the joint probability density between the demand and available renewable generation based on the associated co-incidental time series data using (6).
b) Construct the ACPT with the aid of relevant information related to the conventional generation units, such as installed capacity, FOR, and availability rate using (1) and (2).
c) Construct the GRMPT using the data from ACPT and joint probability distribution between demand and available renewable generation using (7) and (8).
d) Estimate the PLCC of the system with and without renewable generation unit using the GRMPT and specific LOLE for the system.
e) Estimate the ELCC of the renewable generation unit from the PLCC values of the system with and without a renewable generation unit.

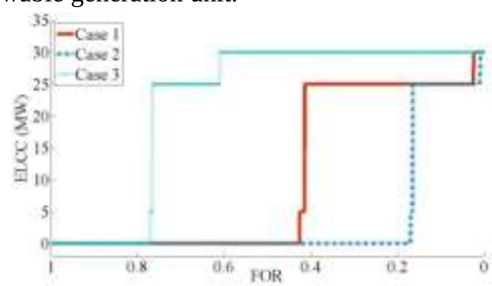

Fig. 10. Impact of FOR of a renewable generation unit on the ELCC.

V. Case Study

The PLCC and ELCC of different renewable generation systems, such as wind and solar PV generation, currently under consideration for a large scale integration in the electricity network of NSW, Australia are estimated using the proposed methodology. The annual peak demand of the system is 11,810 MW in year 2010. The generation system for the state of NSW is composed of 19 conventional generation units with a total generation capacity of 16,392 MW [21]. Also, the NSW grid has tie-line interconnections with the three adjacent states with a total capacity of 2,378 MW. In this paper, it is assumed that all the generation units are committed to supply load demand during the entire time period of the year. Individual generation units and the associated network interconnection are modeled using a two-state availability model. The data associated with the centrally dispatched generators of the NSW electricity system can be found in [21], from which the ACPT is set up based on the procedure explained in section III-*A*. The load demand data for the years 2008-2011 is collected from the Australian energy market operator (AEMO) website [22].

Seven geographical areas within the state of NSW, known as wind bubbles [23], are identified as the potential sites for the wind generation units as shown in Fig. 11. The solar power generation site is located in Hunter Valley area as shown in Fig. 11. In this paper, the wind and solar generation data are derived from the database of year 2010 of the national transmission network development plan (NTNDP 2010) [21] to estimate the ELCC of the respective wind and solar generation units.

The joint probability distributions of demand-generation for the HUN wind bubble and the demand-generation for the solar plant, as shown on the state map in Fig. 11 are calculated and shown in Fig. 12. The probabilities of the variable wind generation levels during peak demand periods are higher than those of the solar generation levels. The correlation coefficients between the monthly demand and the wind generation of HUN and MUN wind bubbles from 10 years data are presented in Fig. 13, which shows that the monthly demand and the wind generation of HUN and MUN wind bubbles are consistently correlated year to year. Similar consistent correlation coefficients between the monthly demand and the renewable generation are also observed for the other three wind bubbles and the solar power over the 10 years period. Hence, the correlation between the demand and renewable generation should be considered in the ELCC estimation of the renewable based generation plants.

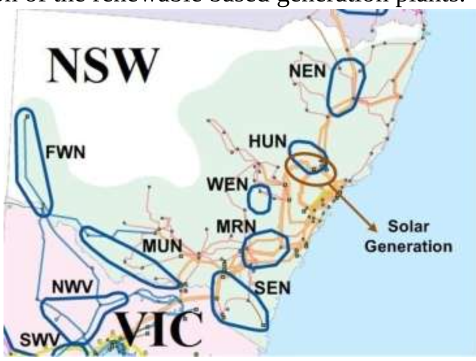

Fig. 11. Wind bubbles and solar generation in NSW, Australia [23].

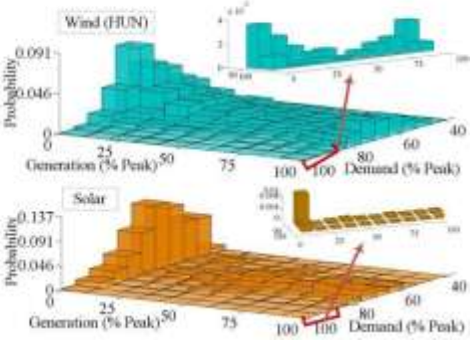

Fig. 12. Joint probability distribution for wind and solar generation during peak load.

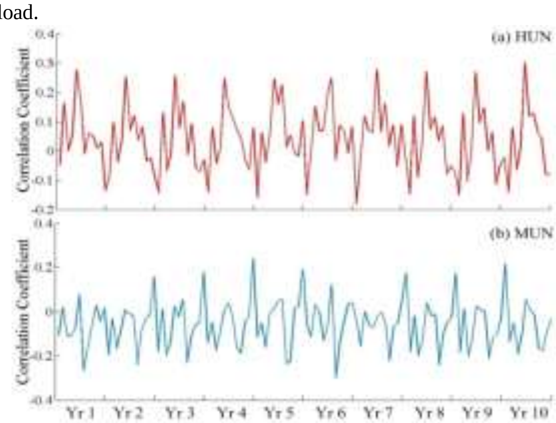

Fig. 13. Correlation coefficients between demand and wind generation of (a) HUN and (b) MUN wind bubble.

A computer program has been developed to implement the proposed non-iterative method of the ELCC estimation using MATLAB. The PLCC of the wind generation units of the five wind bubbles are estimated using the proposed and the iterative method [6]. To show the effect of increasing the number of demand-generation levels in the evaluation of the joint probability distribution of demand and wind generation, 250 and 800 demand-generation levels are used in the simulation studies.

The installed capacity of each type of wind generation unit is assumed to be the same as that of an existing wind farm in the state of NSW, which is 140 MW. The results of the PLCC estimations using the proposed and the iterative method using 250 and 800 demand-generation levels in the evaluation of the joint probability distribution are presented in Fig. 14. The relative errors between the PLCC values estimated using the proposed and the iterative method are shown by the numbers above the respective bars in Fig. 14. For example for the HUN wind bubble, the relative errors between the proposed and the iterative method using 250 and 800 demand-generation levels in the joint probability distribution are 0.1% and 0.04%, respectively.

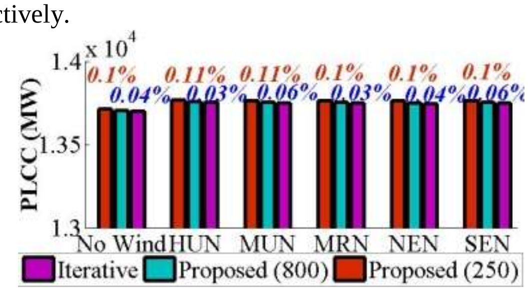

Fig. 14. PLCC of the NSW generation system.

Since, the multi-state graphical method [11] cannot estimate the PLCC of a system, the PLCC results cannot be compared for this method. It is found that the relative errors of the proposed method are within 0.1% of those from the iterative method, which implies that the proposed method can estimate the PLCC of the system with an acceptable accuracy. Fig. 14 shows that the results obtained using the proposed method with 800 levels in the joint probability distribution between demand and wind generation is closer to the results obtained using the iterative method compared to those with 250 levels. This is due to the quantization of the demand and wind generation output value carried out during the joint probability distribution estimation. Joint probability distribution between demand and wind generation with 250 demand-generation levels has higher quantization error than that with 800 demand-generation levels. This confirms that the relative error can be reduced by increasing the number of demand-generation levels used in the joint probability distribution calculation. However, increasing the number of levels in the joint probability distribution will also increase the computation time.

The ELCC of the additional wind generation units, each rated at 140 MW as indicated earlier, located at the five different wind bubbles in NSW are estimated using the multi-state graphical method, the proposed method, and the iterative method (using 20 states) for each of the wind generation unit. The ELCC estimated using the three different methods are presented in Fig. 15.

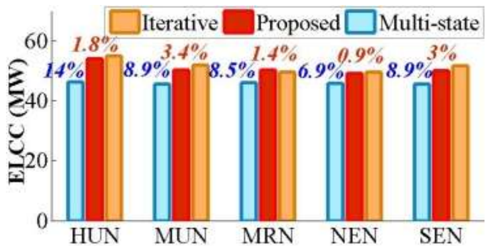

Fig. 15. ELCC and relative errors for the five wind bubbles in NSW.

The relative errors in ELCC estimation for the proposed method and the multi-state graphical method are compared with respect to the iterative method and the associated values are shown above the respective bar graphs in Fig 15. The five wind bubbles have different correlation coefficients with the load demand in NSW which signify the spatial diversity among the wind generations from different wind bubbles located at different geographical locations. Hence, the ELCCs of the different wind bubbles are different from each other. For example, a higher correlation exists between the demand and the wind generation of HUN wind bubble when compared to that with the MUN wind bubble as apparent from Fig. 13. As a result, the ELCC value of the wind generation from HUN wind bubble is higher when compared with that from the wind generation from MUN wind bubble as shown in Fig. 15.

The phenomena can be observed in Fig. 15 for the ELCC estimated using the proposed method and the iterative method. On the other hand, the multi-state graphical method cannot account for the correlation between the renewable generation units and the load demand, and hence produces the same ELCC values for the different wind generation units. As a result, the relative errors in the ELCC estimation using the multi-state graphical method vary between 7 - 14% for different wind generation units, which is quite high compared to the relative errors of 0.8 - 3% obtained using the proposed method.

The efficiency of the proposed non-iterative method for ELCC estimation is compared with the iterative method in terms of computation time. For the iterative method, an accelerated iterative method [24] is used for fast convergence. The computational time to estimate the ELCC of the MUN wind bubble using the proposed non-iterative method (with 250 and 800 demand-generation levels in the evaluation of the joint probability distribution) and the conventional iterative method are presented in Table IX.

TABLE IX
COMPUTATION TIME COMPARISON

	Iterative	Non-iterative (250 levels)	Non-iterative (800 levels)
Computation Time (Sec)	39.8006	5.6497	12.4844

From Table IX, it is observed that the number of demand-generation levels in evaluating joint probability distribution has an impact on the computation time. When the number of demand-generation levels is 250 and 800, the proposed non-iterative method takes 5.6497 sec and 12.4844 sec to estimate the ELCC of the wind generation system in the MUN wind bubble. Though the number of demand-generation levels is increased by 3.20 times, the computation time only increases by 2.56 times. Hence, the computation time does not change dramatically due to the increase in the number of the demand-generation levels in the joint probability distribution evaluation. Further, the proposed non-iterative method with 800 demand-generation levels in the evaluation of the joint probability distribution takes less than one third computation time when compared with the iterative method in the ELCC estimation of the wind generation system in the MUN wind bubble. This result emphasises the computational efficiency of the proposed non-iterative method in the ELCC estimation of renewable generation systems.

The ELCC of the wind generation unit in the HUN wind bubble region and the ELCC of the solar generation unit (shown in Figure 9) for different installed capacities are estimated using the proposed method with and without considering the correlation between the demand and the available renewable generation, and the results are presented in Fig. 16.

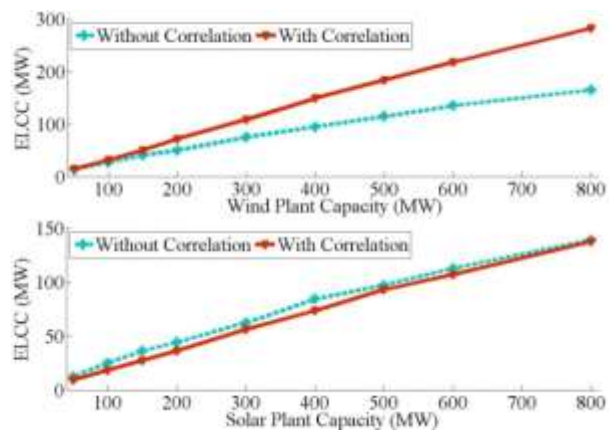

Fig. 16. ELCC of renewable generation plants in NSW.

Fig. 16 shows that the correlation between the load demand and the wind generation has a significant impact on the estimated ELCC values of the additional wind generation unit, particularly when its capacity is higher.

The correlation between the load demand and the solar generation has a small impact on the estimated values of ELCC. The reason for this phenomenon can be explained from the joint probability distribution for wind and solar generation plants during peak load as shown in Fig. 12. Since the marginal probabilities for different levels of wind generation during the period of system peak demand are higher than those of the solar generation, this implies that the availability of wind generation is more than the availability of the solar generation during system peak demand. This results in the ELCC of the wind generation unit to be higher than the ELCC of the solar generation unit of the same installed capacity. As a result, the wind generation unit in HUN wind bubble can contribute more to the generation adequacy of the NSW electricity generation system than the solar generation unit.

VI. Conclusion

In this paper, a non-iterative analytical method is proposed for estimating the ELCC of conventional and renewable generating units. A generation reserve margin probability table is generated using the available capacity probability table for the conventional generation units and the probability density of system demand. A procedure has been presented with examples to estimate the system risk level and the ELCC of the conventional generating unit using the generation reserve margin probability table. One of the main advantages of the proposed non-iterative analytical approach is an efficient estimation of the ELCC. The proposed method is tested on a standard reliability test system and compared with the iterative method. The results are found to be very close. Procedures have also been demonstrated to estimate the system risk level and hence the ELCC of the renewable generation unit. The seasonal and diurnal variation in the renewable generation availability and the correlation between demand and available renewable generation are taken into consideration using the joint probability distribution between demand and available renewable generation. The proposed approach is then applied to estimate the ELCC of potential renewable generation units in a practical system and the results are compared with an iterative and a non-iterative method reported in the literature. The performance of the proposed method is found to be better than the existing non-iterative approach and comparable with the iterative approach. It is to be noted that the proposed method accounts for the correlation between the renewable generation and the load demand while avoiding the use of the exponential curve fitting techniques. Moreover, the proposed method is found to be computationally efficient than the iterative technique. Results demonstrate that the proposed analytical method can be used to accurately estimate the ELCC of future addition of renewable generation units to the existing electricity system.

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