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A Time Dependent Approach to Evaluate Capacity Value of Wind and Solar PV Generation

Mehdi Mosadeghy, *Student Member, IEEE*, Ruifeng Yan, *Member, IEEE* and Tapan Kumar Saha, Senior *Member, IEEE*

***Abstract*— Contribution of renewable energies in power systems is increasing due to continuous growth of wind and solar generators. Because of intermittency and uncertainty of these resources, conventional reliability evaluation methods are not applicable and different techniques have been developed to model these generators. However, most of these methods are time-consuming or may not be able to keep time dependency and correlations between renewable resources and load. Therefore, this paper intends to improve the existing methods and proposes a fast and simple approach. In this approach, wind power, PV generation and electricity demand are being modelled as time dependent clusters, which not only can capture their time dependent attributes, but also is able to keep the correlations between these data sets. To illustrate the effectiveness of this framework, the proposed methodology has been applied on two different case studies: IEEE RTS system and South Australia power network. The developed technique is validated by comparing results with sequential Monte Carlo technique.**

***Index Terms*— Reliability assessment, wind and PV, capacity value, South Australia Power System.**

I. Introduction

PARTICIPATION of renewable technologies, particularly wind and solar generation, to supply electricity demand is increasing in many countries. Although these clean energies bring many benefits and opportunities, fluctuation and unpredictability of these resources pose challenges to power systems. Reliability assessment of electricity networks in the presence of these green technologies is one of these challenges. As the nature of these power supplies is different from conventional generators, different techniques are required to evaluate their reliability contribution in power systems.

Several probabilistic and analytical methods have been developed to evaluate the reliability of power systems with wind generators and to model wind power in reliability assessment [1]–[7]. Similar to wind energy, considerable work has been done to model photovoltaic (PV) generators in reliability evaluation [8], [9]. However, a few works have been conducted to investigate the reliability benefits of combined wind and solar PV generators in composite systems [10]. Negative load [1], [2] multistate generator [3]–[6] and probabilistic distribution [7] are some of the proposed models. Negative load models require chronological techniques like sequential Monte Carlo [11] for reliability assessment. These techniques are effective in modelling wind and keeping correlation between wind and demand. However, extensive evaluation time is the main drawback of this method, especially in the composite system studies where the transmission system insufficiency should be considered in the reliability evaluation as well. Unlike sequential methods, multistate and probabilistic models [3]–[7] are fast and time efficient but may not be able to capture the chronological nature and the correlation between wind power, solar energy and demand data. Although some studies presented techniques to keep the relevance between wind farms and load [12]–[14] or even wind, PV and load data [10], these methods will face difficulties in modelling and may become complicated when the number of wind farms or solar generators increases. For instance, in [14] wind farms and load data are being modelled as three dimensional clusters to keep the correlations between them. However, this method is effective for systems with small number of wind farms and by increasing them the size of the matrix will grow and calculation will become complicated. Furthermore, non-iterative techniques in [15], [16] are faster than chronological techniques but they have some drawbacks as well. For instance, [15] cannot capture the correlation between the renewable generation and load, which can cause errors in estimating the reliability benefits of wind and PV. Although [16] is capable of keeping the correlations, as this method uses available capacity probability table, it will become complicated as the number of renewable generators increases. Moreover, this approach is applicable in generation level studies and hasn't addressed the reliability assessment of renewable energy considering transmission system outages and constraints. In addition, in these methods huge amount of historical data is required to create probabilistic models.

Therefore, this proposed time dependent clustering approach will be a complement to the previous studies and addresses their deficiencies. The developed framework can be applied to model both wind and PV systems. This method models renewable generation systems and demand data as time dependent clusters to keep correlation and time dependency of data sets. Also, as this technique does not require huge amount of historical data, it is efficient in case of computational time. In addition, this method will not lose its simplicity even in networks with plenty of wind farms and PV systems. Furthermore, the proposed technique can be easily employed not only in generation adequacy assessment, but also in composite system studies, where the transmission system constrains and outages should be taken into consideration.

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To examine the effectiveness of this approach two power systems have been selected and reliability assessment has been conducted in both Hierarchical Level I (HLI) and Hierarchical Level II (HLII). IEEE Reliability Test System (RTS) has been used as the first case study. Two wind farms with different generation profiles and several aggregated PV systems have been added to this testing network and their reliability contribution under several scenarios have been investigated. South Australia (SA) has been selected as the second case study in order to implement the established approach in a real network. The ratio between installed capacity of wind and solar power to average demand in this system is around 80%, which is the highest in Australia [17].

Fuzzy C-mean clustering algorithm [18] has been utilized to create a time dependant model for wind power, solar generation, exchanged electricity and load data in these two case studies. Then time dependent cluster models are applied with state sampling Monte Carlo [19] to calculate the reliability indices of these power systems with and without renewable generators. Then by means of these indices, capacity value of wind and PV has been investigated. Finally, results have been compared with sequential Monte Carlo technique to validate the accuracy of the developed approach.

II. METHODOLOGY

The proposed framework in this paper aims to capture time dependency and correlations between load, wind and solar data sets, while keeping the reliability assessment simple and fast. For this reason, time dependent clustering technique has been developed. Several years data points are clustered into hourly base groups. Then, by means of random numbers, value of wind power, load and solar generation for each hour is determined. Afterward, reliability indices of the system are obtained, and load carrying capability of renewable generators is calculated based on these indices. In this study, the fuzzy c-mean clustering method has been applied to classify data sets, the random number sampling technique is utilized for selecting the proper value from time dependent clusters and state sampling Monte Carlo is used to calculate reliability indices. These methods are briefly described in the following subsections.

A. Fuzzy C-Means (FCM)

Clustering is the process of dividing data sets into classes so that elements in the same class have similar values. Similarity index depends on the nature of the data and the clustering purpose. Fuzzy C-means (FCM) is one of the most widely used clustering methods [20]. The FCM algorithm tries to classify a finite collection of M elements into C clusters. This algorithm aims to minimize the distance between elements and centre of clusters which can be formulated as follow [21]:

$$J(U,V) = \sum_{m=1}^{M} \sum_{c=1}^{C} (\mu_c(i))^m \left\| X_i - V_c \right\|^2, \quad 1 \le m < \infty \tag{1}$$

Where U is a fuzzy partition matrix of μ_c, and μ_c is the membership value of data vector (X_i) in the c_{th} cluster with centre of V_c. V is clusters centre matrix and m denotes the index of fuzziness. The membership values should meet the constraints of (2).

$$\sum_{c=1}^{C} \mu_c(i) = 1, \quad \forall\, i \in 1,\ldots,M \tag{2}$$

FCM is an iterative algorithm, and the cluster centres vector for kth iteration is obtained using (3).

$$V_c = \frac{\sum_{m=1}^{M} \left(\mu_c(i)^{(k)}\right)^m X_i}{\sum_{m=1}^{M} \left(\mu_c(i)^{(k)}\right)^m} \tag{3}$$

Then in each iteration, μ_c for all input elements is updated by means of (4).

$$\mu_c(i)^{(k)} = \frac{1}{\sum_{j=1}^{C} \left[\frac{\left\| X_i - V_c \right\|}{\left\| X_i - V_j \right\|} \right]^{\frac{2}{m-1}}} \tag{4}$$

The iterative process will finish when the convergence tolerance is small enough.

$$\left\| \mu_c(i)^{(k)} - \mu_c(i)^{(k-1)} \right\| < \varepsilon \tag{5}$$

Appropriate number of clusters should be selected to obtain an accurate clustered model. Elbow technique is a popular method to find the proper number of clusters [22]. Fig. 1 displays the objective function of FCM to create hourly cluster model for solar generation with different number of clusters.

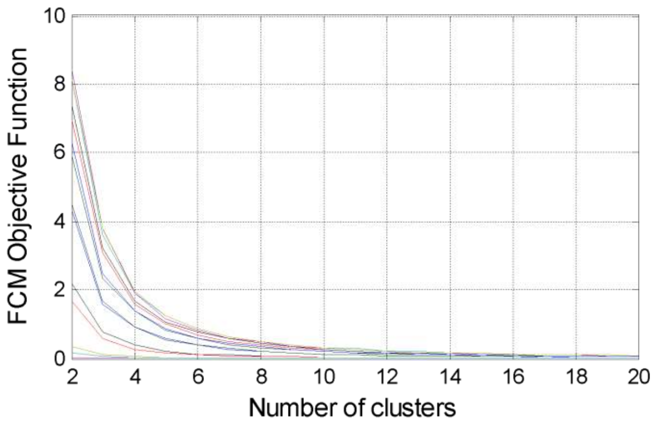

Fig. 1. Number of clusters analysis

It can be observed that for all of these hourly data sets the objective function value can be reduced by selecting higher numbers of clusters. However, this reduction is not significant after selecting eight or more clusters. Hourly 8-step model of per-unit PV generation is demonstrated in Fig. 2. It shows that solar generation can have 8 different states for each hour, while these values are zero before sunrise and after sunset.

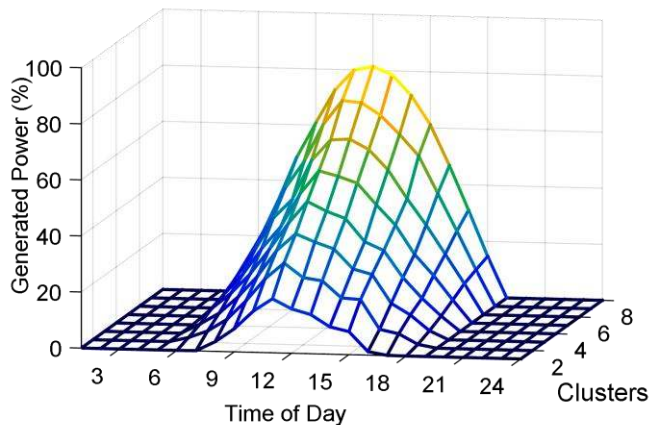

Fig. 2. Time dependent clustered model of PV generation

Each hourly state has a probability of occurrence P_j and these probabilities meet (6).

$$\sum_{j=1}^{n} P_j = 1 \tag{6}$$

When time dependent cluster model is created, to determine the hourly value of wind, PV and load in reliability assessment, sampling technique [19] is employed.

B. Sampling Technique

The probabilities of all clusters P_j are put consecutively in the interval [0, 1]. Then by generating a uniformly distributed random number in same interval, a cluster centre will be selected for each sample according to the value of this random number [19]. Fig. 3 shows this process which should be repeated for each hour data cluster to determine the value of data for that hour in each sample simulation.

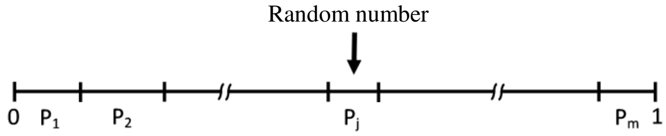

Fig. 3. Explanation of how to sample clustered data

This process should be implemented on all wind power, solar generation and load data sets. Fig 4 illustrates solar PV generation for a sample day created by this technique. Output value of each hour has been determined from time dependent clusters using the sampling technique mentioned above.

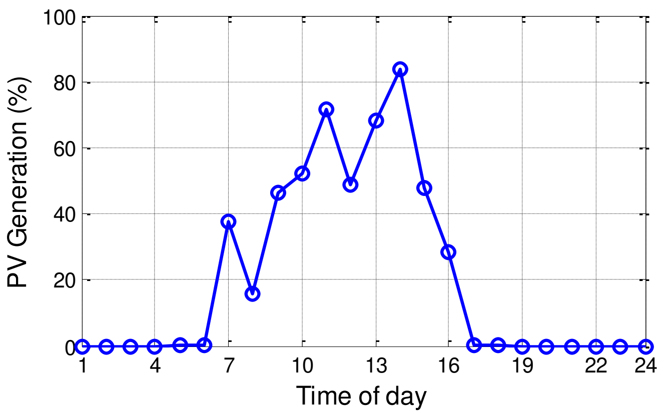

Fig. 4. Hourly PV generation for a sample day obtained from the proposed time dependent clustering technique.

C. Reliability Assessment

By determining all required values for each hour, the reliability index of system for that moment is being calculated and the overall system index can be obtained by taking the average value of these indices. To calculate the reliability indices, the unserved energy or loss of load of the system should be calculated. For this reason, state sampling Monte Carlo has been utilized. This technique estimates the generation capacity of the system and the status of transmission lines based on their forced outage rate and repair time. Then, the amount of unserved energy, as a system reliability index, is calculated for each hour of the day according to the system's available generation, transmission capacity and the values of load, wind and PV production obtained from the time dependent clustering model.

As all data sets are being clustered on an hourly basis and reliability assessment is conducted for each hour separately, the time dependency attributes and the correlations between all these data sets are automatically taken into account. The unserved energy of the system with and without renewable generators should be calculated using the proposed approach and by comparing these indices the added value of clean generation is evaluated.

The proposed framework is briefly described in the following:

Step1) All wind farms, PV panels and load data sets are being reshaped in 24 hourly groups.

Step2) Proper numbers of cluster for all these hourly data sets are specified and elements in each hourly group are clustered using the Fuzzy C-mean technique.

Step3) The probabilities of all clusters are put successively in the interval of [0, 1]. Then by means of uniformly distributed random numbers, the value of wind power, PV output and electricity demand for each hour will be determined.

Step4) Reliability of the system is evaluated using these time dependent cluster models and the state sampling Monte Carlo technique on an hourly basis. The overall system reliability index is obtained by taking the average value of these hourly indices.

Step5) Capacity values of wind and PV are evaluated by investigating the impact of these renewable generators on the system reliability index.

This approach has been implemented on two different case studies and to clarify it, all the steps of this process are explained in details in the following section.

III. Case Studies

The developed framework has been implemented in two power systems in order to validate and show its efficiency. The first network is IEEE-RTS [23], and the second one is South Australia, which has a high level of wind and solar penetration. Reliability contribution of wind farms has been investigated at two different adequacy assessment levels: generation level (HLI) and composite system level (HLII). Several sensitivity analyses for different wind regimes and renewable penetration levels are performed to test the effectiveness of this methodology.

A. IEEE Reliability Test System

The IEEE-RTS system is modified by adding wind and solar PV generators. This system has 2850MW peak load and its generation capacity is 3405MW. The details of this system can be found in [23].

1) Simulation Data

Two wind farms with different wind regimes have been added to this system. Wind generation data for these two sites are measured from the real South Australia wind farms from 2012 till 2014 output with hourly resolutions [24]. Wind power data for W1 is from the Mount Millar wind farm and data from Clement Gap has been utilized for W2. Fig. 5 (a) and (b) shows the average percentage value of generated power in these two wind farms.

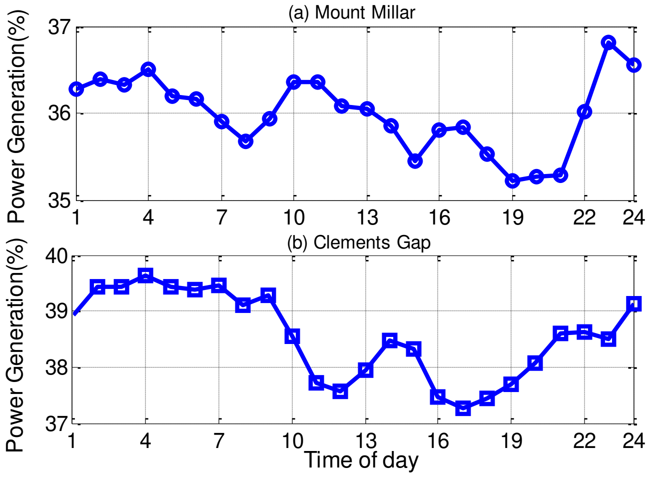

Fig. 5. Average generated wind power for W1 and W2

The time dependent cluster model of the W2 wind farm output is presented in Fig. 6. It shows that the generated power of this wind farm at each hour has ten different clusters (the appropriate number of clusters is obtained from the method explained in Section II- Part A). These clusters vary between 0 to more than 90 percent of the rated capacity. However, similar to load and PV data, the probabilities of clusters are time dependent and different for each hour. For instance, at 11:00am the probability of a low wind level for W2 (1% percent of the rated capacity) is around 32%, while the chance of a similar level of wind at 12:00am is around 12%.

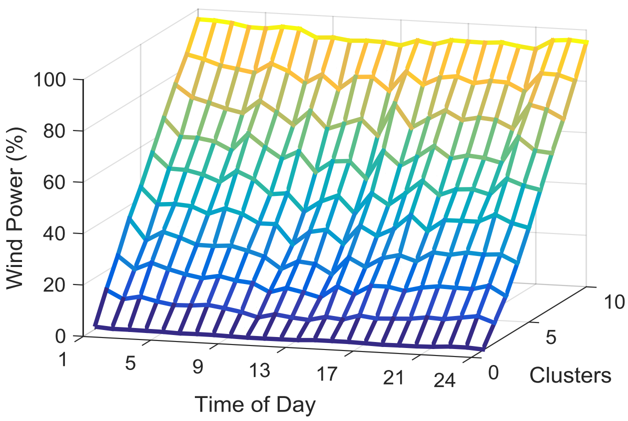

Fig. 6. Time dependent clustered model of W2 power production

Several solar generators with generation profile of PV systems in South Australia have been added to IEEE-RTS. Fig. 7 depicts solar power generation pattern in SA from 2012 to 2014. These PV data sets have hourly resolution and are aggregated values of measured data. It shows that the maximum PV generation is around 85% of the rated PV power (500MW), which happens during summer time. In order to conduct a sensitivity analysis, PV systems with this profile and different installed capacity levels have been added to the RTS system.

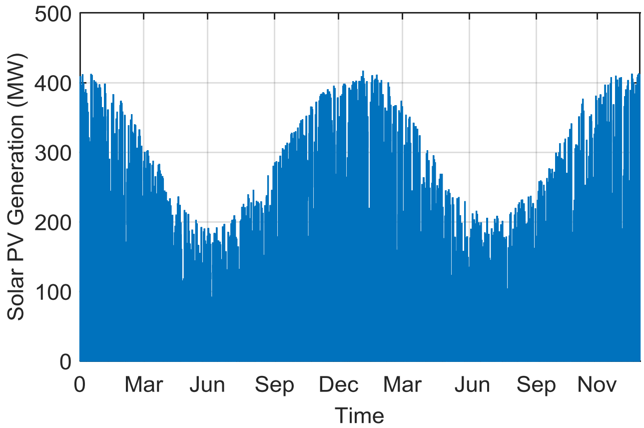

Fig. 7. Solar PV generation pattern in South Australia in 2012-2014

After implementing the developed method on solar, wind power and load data, their time dependent clustered models are created. Then by applying the sampling technique and implementing these models in the state sampling Monte Carlo, the hourly and total reliability indices of the RTS system at the HLI and HLII levels are calculated.

2) Generation System Adequacy Study

In generation adequacy or hierarchical level I, different reliability indices have been implemented to calculate the reliability benefit of renewable energies. Loss of load expectation (LOLE) [1]–[3], severity index (SI) [25] and at-risk and healthy state possibilities [26] are some of these indices. In this study Loss of Energy Expectation (LOEE) is adapted, because this index not only incorporates the effect of inadequacies but also includes their probability [19]. To calculate LOEE, firstly, Demand Not Supplied (DNS) should be computed by means of (7).

$$DNS_{s,t} = \max\left\{0, D_t - \sum_{j=1}^{g} G_{js}\right\} \tag{7}$$

Where g is the total number of generators and G_j represents the available capacity of the j_{th} generator in the s_{th} iteration. D_t denotes the total demand for each hourly cluster t and can be calculated using (8).

$$D_t = L_t + P_{\exp} - P_{imp} - P_{PVt} - P_{Wt} \tag{8}$$

Where L_t is system load and $P_{\exp}$ and P_{imp} represent hourly exported and imported power to the system, respectively. P_{PV_t} and P_{W_t} are total solar PV and wind power generation at that moment. After calculating DNS, the annualized LOEE of each hourly cluster and for N iterations is calculated using (9).

$$LOEE_t = \frac{\sum_{s=1}^{N} DNS_{s,t} \times 8760}{N} \tag{9}$$

Fig. 8 depicts the LOEE index of IEEE-RTS for each hourly cluster after 10,000 iterations. As this graph shows

LOEE value is different for each hourly cluster and is expected to be higher during the peak period. The overall LOEE of this system is 1,132MWh/yr, which is the average value of these 24 clusters.

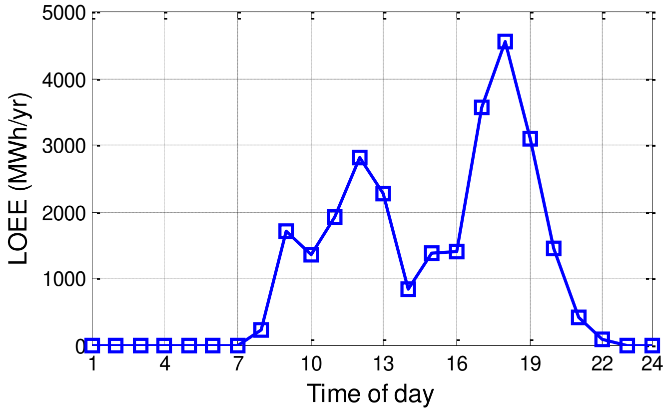

Fig. 8. RTS loss of energy expectation value for hourly clusters

3) Composite System Study

Reliability assessment in the hierarchical level II includes generation and transmission system adequacy. Therefore, reliability assessment results in this level can show the impact of transmission lines outages and insufficiencies on the capacity value of renewable generators. In this level, the amount of unserved energy can be calculated by running load flow for each system state and recording unserved load in each iteration. In this work, MATPOWER [27] has been used to run load flow and record the total curtailed load due to any element outage(s). Then this value has been utilized in (10) to calculate hourly value of Expected Energy Not Supplied (EENS), which is an important index to represent the amount of unserved energy and is similar to LOEE in HLI.

$$EENS_t = \sum_{l \in S} C_l p_l \times 8760 \quad (10)$$

Where p_l is the probability and C_l denotes the amount of curtailed load in system state *l*. Overall EENS of the system is the mean value of these hourly indices.

By comparing the reliability indices of the system with and without renewable generators, the capacity value of these resources can be computed.

4) Capacity Value of Renewable Energies

Capacity value or effective load carrying capability (ELCC) is the amount of extra load that can be met by renewable generators while the reliability level of a system remains unchanged [2]. The standard framework to calculate the capacity value of wind energy is explained in [1]. Fig. 9 can be used to briefly describe this ELCC evaluation process.

The red dashed line is the LOEE of the original RTS system without any wind or PV generators and 2,850MW peak demand. The blue line is LOEE index for this system in the presence of the W1 wind farm with 500MW installed capacity and for different levels of peak load. It shows that in the presence of W1, around 144MW extra load can be added to the system peak load while the reliability level of RTS system is maintained at the original level (1132 MWh/yr).

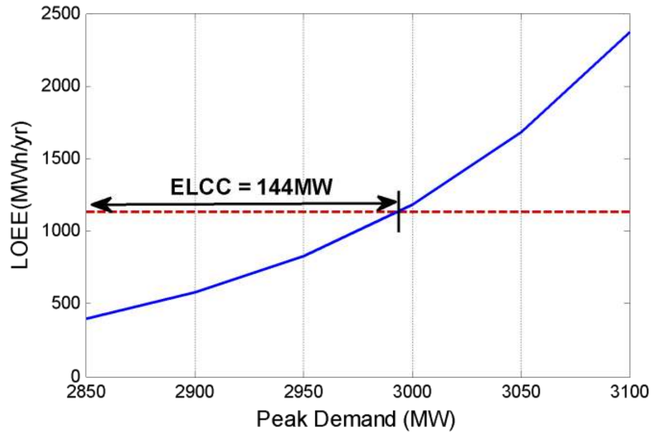

Fig. 9. Capacity value of W1 wind farm

5) Results of HLI assessment

In order to investigate the impact of wind regime and penetration levels of wind, the developed method has been applied for different wind profiles and various levels of wind farms. Also reliability contribution of PV systems has been estimated using the time dependent technique to validate its effectiveness to model solar energy. In addition, reliability assessment of RTS with significant amount of wind and PV has been conducted to evaluate the precision and simplicity of the proposed approach in modelling high levels of renewables. Results of this clustering technique and sequential Monte Carlo are given in Table I. It should be mentioned that all of the clustered models of wind and PV are generated by using two years historical hourly data sets.

TABLE I.
EXPECTED LOAD CARRYING CAPABILITY OF RENEWABLE ENERGIES FOR IEEE RTS AT GENERATION LEVEL

Capacity Value	Sequential Monte Carlo		Time Dependent Cluster		Error
	MW	%	MW	%	%
Wind Regime 1 – 250MW	84	33.6	90	36.0	2.4
Wind Regime 1 – 500MW	144	28.8	141	28.2	0.6
Wind Regime 1 – 1000MW	230	23.0	211	21.1	1.9
Wind Regime 2 – 250MW	65	26.0	67	26.8	0.8
Wind Regime 2 – 500MW	104	20.8	110	22.0	1.2
Wind Regime 2 – 1000MW	145	14.5	157	15.7	1.2
250MW PV	60	24.0	55	22.0	2.0
500MW PV	98	19.6	91	18.2	1.4
500MW Wind+250MW PV	201	26.8	189	25.2	1.6
1000MW Wind+500MW PV	319	21.3	313	20.8	0.5

This table shows that in both techniques, ELCC of W1 is higher than W2 and by increasing their installed capacity, the percentage value of their load carrying capability will decrease. Table I also illustrates that the differences between the proposed approach and the sequential technique for these wind farms with two different wind regimes are small. In addition, estimated results obtained from the clustering method are acceptable for different levels of wind power. Thus, it can be concluded that the time dependent approach can effectively estimate the ELCC of wind farms regardless of their wind regime and installed capacity. Moreover, simulation results for solar energy indicate that the time dependent clustering technique is also applicable to model

PV systems, and it can precisely estimate the reliability contribution of solar generators with various capacities. Furthermore, it can be seen that this method can also be applied in systems with high levels of PV and wind without losing its simplicity and accuracy.

6) Outcomes of HLII study

In order to evaluate the time dependent technique at HLII level, same approach has been applied in the RTS composite system and results are presented in Table II. The capacity values of these resources have decreased due to transmission system outages and congestions.

TABLE II.
CAPACITY VALUE OF RENEWABLE ENERGIES IN IEEE RTS FOR HLII STUDIES

Capacity Value	Sequential Monte Carlo		Time Dependent Cluster		Error
	MW	%	MW	%	%
Wind Regime 1 – 500MW	121	24.2	113	22.6	1.6
Wind Regime 2 – 500MW	80	16.0	88	17.6	1.6
250MW PV	49	19.6	43	17.2	1.4
500MW Wind + 250MW PV	151	20.1	145	19.3	0.8

Table II shows that the time dependent technique is also suitable to model wind and PV in HLII studies. It can be used to estimate ELCC of wind and solar power, separately and combined, at the composite system level with an acceptable correctness.

From Table I and II it can be observed that results of the proposed method in both reliability evaluation levels have an error of less than 2.5% compare to the sequential Monte Carlo technique. However, this clustering technique is much faster as it just needs to be performed for 24 clusters in each sample year in compare with 8760 hours in the sequential method. This time efficiency is especially noticeable in the composite system assessment, where load flow execution might be required for each simulation run. It should be mentioned that for large systems with hundreds of buses the data requirement for the composite system study is a serious concern, but this is inevitable for all existing reliability methods. However, the proposed methodology requires less historical data compared to the conventional techniques [2]. The same methodology has been applied to an existing power system in Australia to demonstrate the effectiveness of this time dependant clustering technique.

B. *South Australian Power System*

1) System data

South Australia is a southern state in Australia. This system has been selected for this study because SA has a high installed level of wind and solar generation, which can supply around 80% of its average load. Historical hourly load data of the SA system is extracted from [28]. However, this data is not the pure demand and includes the output power of solar PV. Thus, to obtain the pure load data, the installed capacity of PV in each area of SA has been determined [29]. Then by means of SA solar irradiation data [30] and formulas given in [31], hourly output power of PV systems in each area and entire South Australia have been computed. Finally, the total solar production has been added to the given load data for obtaining the pure hourly demand. Average daily load profile of South Australia with and without solar PV generation is depicted in Fig. 10.

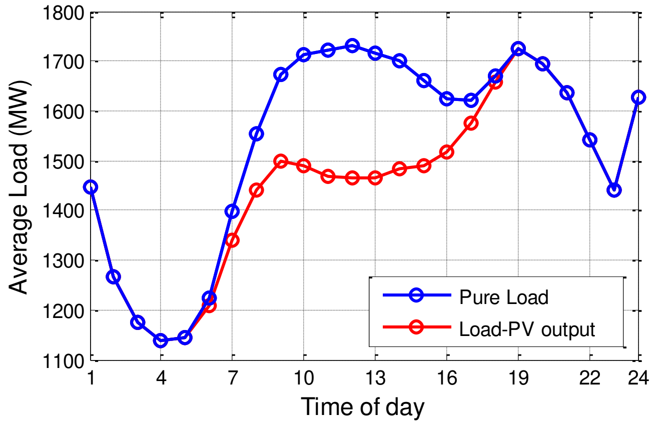

Fig. 10. Average daily load profile of South Australia in 2012-2013 [28]

The generation profile of South Australia is a mixture of thermal and renewable generators. The total installed capacities of thermal and renewable generation in SA are approximately 3,600MW and 1,700MW, respectively [17]. Table III shows number, type and capacity of generators in South Australia.

TABLE III.
GENERATING UNIT DATA[29], [32]

Type		Number of Units	Total installed Capacity (MW)
Conventional	Diesel	6	136.5
	Natural Gas	36	2716
	Brown Coal	6	770
Renewable	Wind	15	1202
	PV	(Distributed)	500

South Australia had fifteen wind farms with a total capacity of 1202MW in 2013. Table IV gives the information of these wind farms [17]. Total generated power of these wind farms in 2012 and 2013 is displayed in Fig. 11. It shows that in those specific years, the maximum electricity generated by wind farms in SA was higher than 1,000MW [24].

TABLE IV.
SOUTH AUSTRALIA WIND FARMS [17]

Wind Farm's Name	Capacity (MW)	Capacity Factor
Canunda	46	0.3742
Cathedral Rocks	66	0.4081
Clements Gap	56.7	0.3855
Hallett (Brown Hill)	94.5	0.3975
Hallett Hill	71.4	0.3975
North Brown Hill	132.3	0.4115
Bluff Wind Farm	52.5	0.3835
Lake Bonney Stage 1	80.5	0.3452
Lake Bonney Stage 2	159	0.3364
Lake Bonney Stage 3	39	0.3408
Mount Millar	70	0.3934
Snowtown	98.7	0.4036
Starfish Hill	34.5	0.3786
Waterloo	111	0.3950
Wattle Point	90.75	0.3220

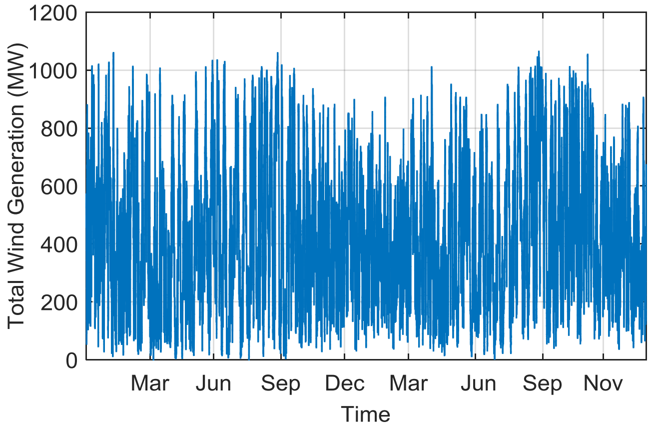

Fig. 11. Total wind generation in South Australia 2012-2014 [24]

South Australia is connected to other states through two high voltage interconnections; Murraylink 220 MW, ±150 kV HVDC Light bipolar interconnector and Heywood 275 kV HVAC with 460 MW capacity [33]. Average value of transferred power through these lines in 2012 and 2013 are illustrated in Fig. 12 [24].

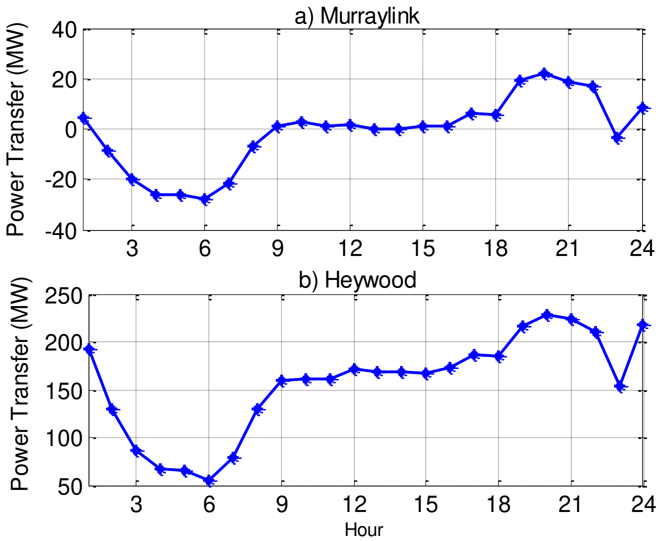

Fig. 12. Mean value of power flow through tie-lines for 2012-2013 [24]

In this figure, when SA is importing power the transferred power is shown as positive and during exportation this value is negative. It can be observed that most of the time, South Australia imports power during evening.

2) Simulation results

In this study all fifteen wind farms output, solar generation and transferred power through interconnectors have been modelled separately as hourly clusters using two years of historical data. In the HLI reliability assessment these clustered values have been subtracted from load clusters and the LOEE of South Australia has been calculated using (7) - (9). Fig. 13 shows the LOEE of this system without wind and PV generation for 2,000 sample years. It can be seen that LOEE of SA system is converging to 80 MWh/yr.

In order to investigate the capacity value of clean energies in SA, LOEE of this system with renewable generators has been calculated again for different extra loading levels.

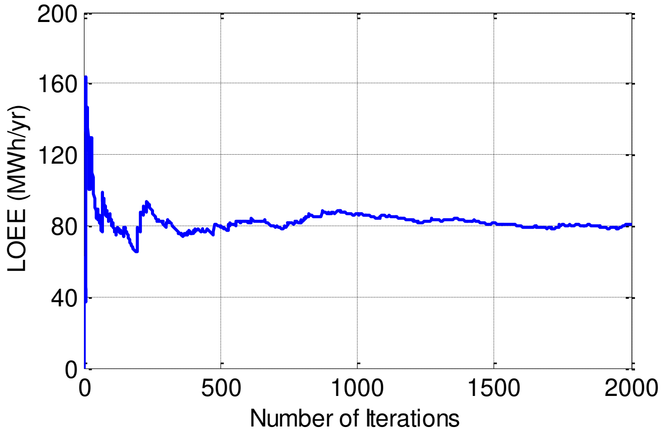

Fig. 13. Loss of energy expectation of SA for 2000 sample years

Fig. 14 demonstrates the process of calculating capacity value of wind farms and PV systems for South Australia at generation level. The red line is the LOEE of this system without renewable resources, which was shown in Fig. 13. Blue line represents LOEE of SA system with 1202MW wind energy, and Green line shows same index for SA with all wind farms and 500MW PV panels.

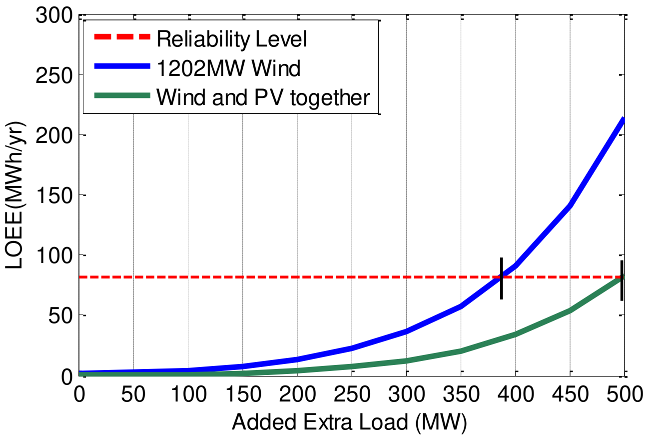

Fig. 14. Reliability benefits of renewable energy generation in SA

It can be seen that the capacity value of wind and PV together in South Australia is around 500MW, which is 115MW higher than the ELCC of wind farms alone.

To investigate the impact of transmission network contingencies on the capacity value of wind and PV, the proposed approach has been conducted on the SA system at the HLII level. At transmission level, this system has around 400 high voltage buses (132kV and 275kV). All adjacent solar generators in SA are aggregated and twenty one PV systems have been created to model solar power in the SA transmission level. While sequential Monte Carlo requires substantial amount of time to execute thousands of hourly load flow analyses for each of 2000 sample, the proposed approach only needs twenty-four load flows to be performed in each sample year. On the other hand, this time dependent clustering technique could easily model 15 wind farms and 21 aggregated PV systems while maintaining their chronological features and their correlation, which may not be applicable in multistate methods. Table V summarizes the ELCC of renewable energies in South Australia for the HLI and HLII levels.

TABLE V.
ELCC OF RENEWABLE ENERGIES IN THE SA SYSTEM

Capacity Value	1202MW Wind		1202MW Wind + 500MW PV	
	MW	%	MW	%
HLI – Sequential Monte Carlo	385	32.0	498	29.3
HLI – Time Dependent Cluster	382	31.8	517	30.4
HLII – Sequential Monte Carlo	306	25.5	406	23.8
HLII –Time Dependent Cluster	312	26.0	420	24.7

This table shows that the reliability contributions of renewable resources at the HLII level have decreased due to transmission system insufficiency and contingencies. The ELCC of wind power has decreased around 70MW and the reduction value for combined wind and PV is 97MW. It can be observed that results obtained from the time dependent clustering technique in both HLI and HLII levels are accurate and close to Sequential Monte Carlo method.

In order to compare the speed of the proposed clustering technique with sequential Monte Carlo method, the computational time and number of simulations to reach the stopping criterion in evaluating the reliability benefits of renewable generators in the composite system level of South Australia are given in **Error! Reference source not found.**. It should be mentioned that the LOEE coefficient of variation tolerance, which is 0.1, is utilized as the convergence criterion and the stopping rule is as follow. After reaching a given number of samples, the variation tolerance is checked to see if it is acceptable. If not, the number of samples is increased.

TABLE VI.
SPEED COMPARISON FOR SOUTH AUSTRALIA HLII STUDIES

Method	Number of Sample Years	Computation time (min)
Sequential Monte Carlo	2,000	2165.6
Time Dependent Cluster	50,000	118.55

From this table, it can be seen that the number of sample years to reach the proper tolerance error in clustering approach is higher than sequential method. For HLII studies of South Australia, in the sequential Monte Carlo method 2,000 sample years were used while in the proposed method this number was 50,000. However, in the sequential Monte Carlo it should be simulated for 8,760 hours per sample year, while in the clustering methodology it just needs 24 simulations per year. Therefore as it is shown, the computational time of the time dependent clustering technique is much lower than the sequential Monte Carlo method.

C. Summary

By comparing the results of IEEE-RTS and the South Australia systems derived in this section, it can be observed that although the load and generation levels of these systems are close, the reliability benefits of renewable generation are different in these networks, and the load carrying capability is smaller in the RTS system. There are several reasons for this; the first one is the difference between their generators and transmission system outage and repair rates, which affects their reliability indices. The other one is their different load profiles and their difference in the correlation levels between renewable generation and load. Since the same wind and solar data have been used for both systems and their demand profiles are not the same, the correlations between load and renewable generation are dissimilar in these systems and the results are different.

IV. SEASONAL CORRELATION

The proposed technique is also capable of capturing seasonal features of renewable resources and load data. In order to illustrate its effectiveness, a seasonal case study has been conducted for the South Australia network. Three different seasons are considered for this state: summer, spring-autumn and winter, and time dependent cluster models for renewable generation systems, electricity demand, and exchanged power are created based on these seasons. Clustered models of SA solar generation and load data in summer and winter are presented in Figs. 15-18.

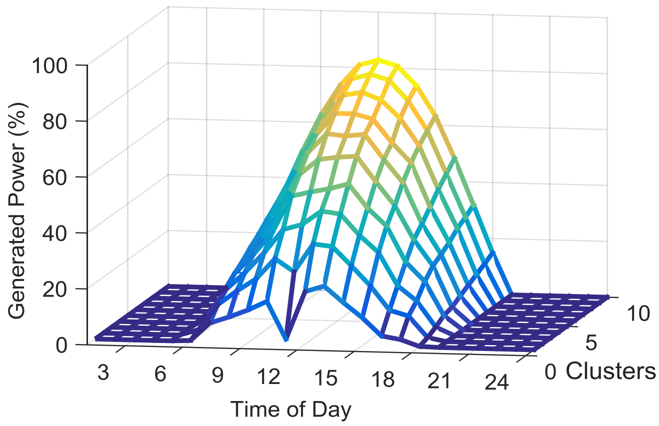

Fig. 15. PV output model for South Australia in summer

From these figures it can be seen that load and solar generation have different profiles during summer and winter. For example, in Fig. 15 the PV system can generate close to 85% of its installed capacity during solar peak time, while as shown in Fig. 16, in winter its output power can go up to around 55%.

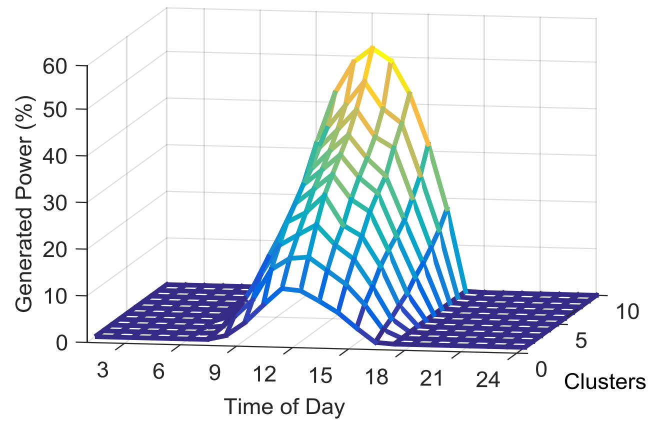

Fig. 16. PV output model for South Australia in winter

In addition, these figures also show that the PV system generates power for a longer period in summer in comparison to winter. Furthermore, the range of hourly cluster values illustrates that the variation of solar energy in South Australia during summer is higher than that in the wintertime. For instance, solar generation during noontime in summer may change from 20% to 85% while in winter during the same period it varies from 15% to 55%.

This clustering technique is not only capable to capture seasonal features of renewable resources but also can model seasonal pattern of electricity load. Figs 17 and 18 represent the SA load model during summer and winter.

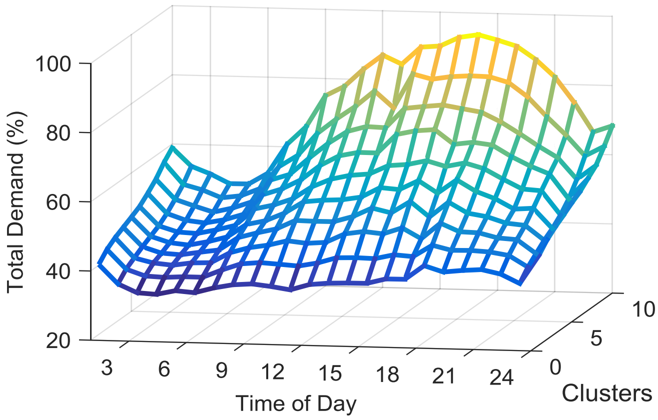

Fig. 17. Load clustered model for South Australia in summer

These figures show that the load patterns are different for hot and cold seasons. During summer peak demand happens in the noontime, whereas, winter load model has two peak periods. First peak is in the early morning and the second one occurs in the late evening. By comparing these two figures, it can also be concluded that the maximum demand during the hot season is generally higher than the winter period in South Australia.

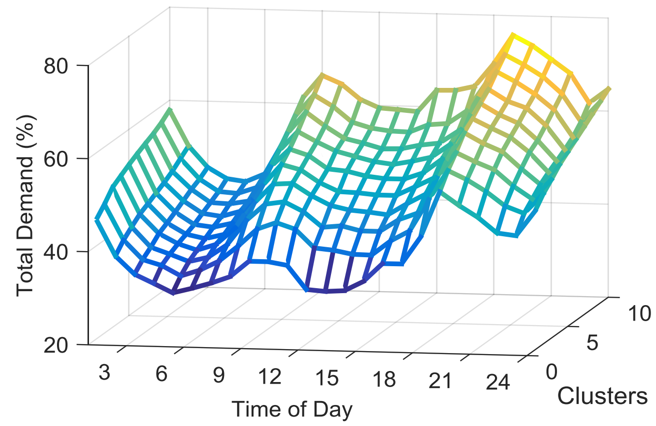

Fig. 18. Load clustered model for South Australia in winter

After making seasonal clustered models for wind, PV, load and exchanged electricity, seasonal LOEE of the system is calculated and load carrying capabilities of wind and solar PV systems are evaluated based on the time dependent clustering methodology proposed in Section II. Results of the seasonal studies for South Australia using both the sequential Monte Carlo and the time dependent clustering methods are summarised in Table VII.

This table shows that the capacity value of wind during winter and summer is similar, while the added value of solar PV during summer is the highest and load carrying capability of renewable resources during spring-autumn is the lowest. It can also be observed that the results of the clustering method are accurate and close to those of the sequential technique, which implies that the proposed approach is able to capture the seasonal features precisely.

TABLE VII.
SEASONAL RELIABILITY BENEFITS OF WIND AND PV GENERATION IN SOUTH AUSTRALIA

ELCC (MW)		Summer	Spring-Autumn	Winter
1202MW Wind	Sequential Monte Carlo	403	338	392
	Time Dependent Cluster	391	333	409
	Error (%)	0.99	0.42	1.4
1202MW Wind + 500MW PV	Sequential Monte Carlo	561	390	415
	Time Dependent Cluster	550	382	429
	Error (%)	0.65	0.71	0.82

V. CONCLUSIONS

In this paper a new approach has been presented to evaluate the reliability contribution of wind and solar generators. This method is not only much faster than the sequential technique but also is able to capture the time dependent characteristics of these clean resources and the correlation between them. In order to demonstrate its effectiveness, this method has been applied on two different case studies; IEEE 24 buses as a standard reliability test system and South Australia network as a realistic power system with high penetration of wind and PV.

Results show that the new approach can estimate the ELCC of wind and PV with an acceptable accuracy. It is also concluded that this method can be utilized for different penetration levels of wind and PV, and will provide precise results regardless of the wind profile and the size of renewable generators. Also, this approach is capable of capturing seasonal behaviour of power system and renewable resources.

Furthermore, it is shown that this method is not only applicable at the generation adequacy assessment level but also can be employed in the composite system studies where the sequential techniques may require a huge amount of time and state sampling and multistate models may not be able to keep the correlation between resources and capture time dependencies. In addition, contrary to multistate models, this time dependent clustering approach can be utilized in systems with several wind farms and solar generators without facing difficulties and losing its simplicity.

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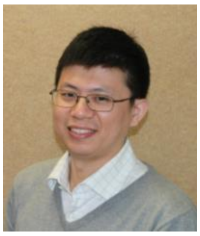

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