Reliability Analysis of Power Systems Incorporating Renewable Energy Sources

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Abstract: *This paper reviews some of the analytical methods developed in our laboratory for reliability evaluation of large-scale power systems including renewable energy sources like photovoltaic units and wind farms. The methods presented here successfully reflect the correlations existing between the hourly load and the fluctuating energy outputs of unconventional generating units. The basic analysis proceeds by grouping the various conventional and unconventional generating units into several subsystems, and building a generation system model for each subsystem. Three different approaches, each an improvement over its predecessor, are presented for computing reliability indices like Loss of Load Expectation (LOLE) and Expected Unserved Energy (EUE). In the first approach, all the generation system models are combined hourly by means of an efficient algorithm for calculating the relevant reliability indices. The second approach uses a clustering algorithm for identifying a set of system states, such that the reliability indices are calculated for each state and then aggregated to yield overall values. The third approach introduces the concept of mean capacity outage tables for efficiently calculating EUE, thereby eliminating the need for hourly computations of system negative margin tables. Finally, results obtained from case studies performed on sample systems using the proposed approaches are presented.*

Keywords: Renewable energy sources, loss of load expectation, expected unserved energy, clustering, mean capacity outage tables.

1. Introduction

The escalation in prices of energy derived from fossil fuels like coal, oil and gas over the last few decades has led to an increased interest in developing newer and cleaner ways of energy generation. A substantial increase in global population and rising concerns about environmental pollution has given a further impetus to the ongoing research efforts. Though the concept of electrical power generation from alternative energy sources like the sun and wind is well established today, continuous research is being done for improving the current technologies. The total installed capacity of wind generation in the world has increased by about 8.5 times over the last decade alone [1]. A study of the energy mix in the European Union nations also reveals that the percent contribution to the power pool as derived from alternative energy sources like wind and biomass has steadily increased over the last decade [1]. The 2009 long term reliability assessment report published by the North American Electric Reliability Corporation (NERC) projects an additional 260000 MW of new renewable "nameplate" capacity to be coming into effect in US over the next ten years (2009-2018). It further estimates that roughly 96% of this total will be wind and solar, with the wind power alone accounting for about 18% of the total resource mix by 2018 [1]. These figures underscore the growing contribution of renewable energy sources in mainstream power generation. Renewables are thus expected to be major players in the coming years with significant levels of grid penetration.

Though renewable energy generation is cheaper and cleaner as compared to conventional methods, the power outputs of these unconventional units are intermittent by nature due to variations in their basic energy source. As a result, these units have a different impact on overall system reliability from that of conventional units. For planning purposes, it is thus important to develop models of such time-dependent energy sources and incorporate them into traditional reliability studies. For this to be done successfully, the following factors have to be taken into consideration: scheduled outage, failure and repair characteristics of both conventional and unconventional units, the fluctuating nature of energy output from the unconventional units, and the correlation between this intermittent energy supply and the hourly load demand.

Two basic approaches, a multistate unit approach [2] and the load adjustment approach [3], were originally proposed for performing reliability analysis of power systems including renewable energy sources. Both those approaches had some deficiencies as they either failed to incorporate the failure and repair characteristics of unconventional units (e.g. solar or wind) into the study or ignored the correlation between the load and the fluctuating energy outputs of these units.

The Singh and Gonzalez approach was therefore proposed in [4] for accurately modeling the impact of renewable energy sources on the overall system reliability. In this approach, the entire power system is divided into several subsystems containing the conventional and unconventional generating units. A generation system model is then built for each subsystem. Using an efficient algorithm, the models corresponding to the unconventional subsystems are modified hourly in order to reflect the fluctuating nature of energy produced by such units. All the generation system models are then combined hourly in order to calculate the Loss of Load Expectation (LOLE) and Expected Unserved Energy (EUE) indices for the given hour. To further improve the computational efficiency for calculating the different reliability indices, an alternative clustering approach was proposed in [6]. In this approach, the correlation between the hourly load and the intermittent energy outputs of the unconventional subsystems is modeled by defining a set of states or clusters. Each state is identified by a given value of load and the corresponding mean values of the outputs of the different unconventional subsystems. Reliability analysis is performed by combining the conventional subsystem with the unconventional subsystems belonging to each cluster, and the outputs are then aggregated to yield overall indices. The indices calculated using this approach, however, are not as accurate as those obtained in [4] owing to the inherent approximations associated with clustering. A third method was therefore proposed in [7] for accurate determination of the reliability indices (especially EUE) with minimal computational effort. In this new approach, the hourly computation of a system negative margin table for calculating EUE is replaced by the hourly application of a mean capacity outage table, thereby saving considerable CPU time. The remainder of this paper has been structured in the following fashion.

Section 2 gives an overview of the LOLE and EUE reliability indices used in generation adequacy studies. Sections 3 to 5 give a detailed description of the Singh and Gonzalez approach, the clustering approach and the mean capacity outage table approach respectively. While Section 6 presents the various case studies performed using the proposed approaches, Section 7 discusses the important results. Finally, Section 8 summarizes the conclusions.

2. System Reliability Indices

Reliability indices commonly used for generation capacity adequacy evaluation are the Loss of Load Expectation (LOLE) and Expected Unserved Energy (EUE). This section gives a brief description of these indices along with relevant equations for their computation.

2.1 Loss of Load Expectation (LOLE)

LOLE, or more commonly HLOLE (Hourly Loss of Load Expectation) is the expected number of hours during the period of observation of the system load cycle when insufficient generating capacity is available to serve the load [8]. The system load is described as a chronological sequence of ‘N_t’ discrete load values ‘L_i’ for successive time steps k = 1, 2, 3… N_t. Each time step has equal duration $\Delta T = (T/N_t)$ hours, where ‘T’ represents the total duration of the period of observation of the system load cycle [7]. For a given time step ‘k’, the probability of the system margin (capacity - load) being less than or equal to ‘M’ MW can be computed as:

$$P_k(M) = \hat{P}_j(C \leq C_j) \tag{1}$$

In equation (1), ‘j’ is the smallest integer representing a particular discrete capacity state such that the expression $(C_j - L_k) \leq M$ is satisfied, ‘C_j’ is the generation capacity associated with state ‘j’, ‘L_k’ is the system load level during time step ‘k’, and ‘$\hat{P}_j(C \leq C_j)$’ is the cumulative probability that the generation capacity ‘C’ is less than or equal to ‘C_j’. Note that the various generation capacity states (C_j’s) are arranged in descending order, i.e., C_{j+1} is less than C_j. The Loss of Load Expectation for the time step ‘k’ can then be calculated using equation (2) as:

$$LOLE_k = P_k(0)*(\Delta T) \tag{2}$$

The LOLE for the entire duration of the period of study is then obtained as:

$$LOLE = \sum_{k=1}^{N_t} LOLE_k \tag{3}$$

2.2 Expected Unserved Energy (EUE)

The EUE index measures the expected amount of energy which will fail to be supplied during the period of observation of the system load cycle due to generating capacity differences and/or shortages of basic energy supplies [8]. A general expression for the computation of the Expected Unserved Energy is [7]:

$$EUE = (\Delta T) * \sum_{k=1}^{N_t} U_k \tag{4}$$

In equation (4), the term ‘U_k’ represents the expected unserved load during the time step ‘k’, and is calculated using the following equation [7]:

$$U_k = (\Delta M)*[\sum_{M=0}^{-G_k} P(M) - 0.5*\{P(0) + P(-G_k)\}] \tag{5}$$

For practical cases, a system negative margin table is built for each time step ‘k’, and ‘P(M)’ is then computed at discrete negative margins M = 0, -ΔM, -2ΔM,…, $-G_k$. Here, ‘$-G_k$’ represents the smallest possible negative margin during time step ‘k’, and ‘ΔM’ is a fixed positive increment value. An example demonstrating how to construct a system negative margin table for a given time step ‘k’, and then calculate ‘U_k’, is given in [7].

3. Approach I: Singh & Gonzalez Method

In this approach [4], the entire power system is divided into several subsystems. While one of these corresponds to all the conventional units combined, the others correspond to the different types of unconventional units. For simplicity sake, all the approaches mentioned in this paper are explained using a sample system consisting of a conventional and two unconventional subsystems. The unconventional subsystems consist of units being operated on solar and wind energy respectively. General expressions for calculating the LOLE and EUE indices for a system consisting of ‘n’ number of unconventional subsystems can, however, be found in [7].

For each subsystem, a generation system model is developed using the unit addition algorithm [5]. To start with, the unconventional units are treated in a conventional manner in the sense that the traditional two and three states unit models [9] are used. Also, full capacities for each state of the unconventional units are used.

The next step is to create vectors containing the hourly power outputs of the unconventional subsystems such that the term ‘$POU_{l,k}$’ represents the power output of the l^{th} unconventional subsystem during the k^{th} hour of the period of study [4]. The vector corresponding to a given unconventional subsystem is then divided by its rated power output in order to obtain the ‘weight vector’ which indicates the fraction of the total rated unconventional power that is being effectively generated at the various hours of study. This can be mathematically expressed as:

$$\boldsymbol{A_l} = (1/PRU_l)*[POU_{l,1}\ POU_{l,2}\ POU_{l,3} \ldots POU_{l,N_t}] \quad (6)$$

In equation (6), the terms '$\mathbf{A_l}$' and 'PRU_l' respectively represent the weight vector and the rated power output corresponding to the l^{th} unconventional subsystem.

To incorporate the effect of fluctuating energy, the generation system models of the unconventional subsystems are modified hourly depending on their energy output levels. This is achieved by multiplying the rated generation capacity vector '**CU**' of a given unconventional subsystem (say 'l') with the term '$A_{l,k}$', where '$A_{l,k}$' represents the fraction of the total rated unconventional power produced by the l^{th} subsystem for the k^{th} hour of study. It should, however, be noted that these hourly modifications do not affect the state probability vectors of the respective generation system models. The models corresponding to all the subsystems are then combined hourly using a discrete state method in order to calculate the LOLE and EUE indices.

3.1 Discrete State Method

We shall explain this method [4] using our sample system consisting of a conventional and two unconventional subsystems. Let us now define the following vectors associated with the three generation system models as:

CC, $\widehat{\mathbf{PC}}$ = Generation capacity and cumulative probability vectors associated with the model corresponding to the conventional subsystem.

$\mathbf{CU_l}$, $\widehat{\mathbf{PU_l}}$ = Generation capacity and cumulative probability vectors associated with the model corresponding to the l^{th} unconventional subsystem, where $l \in [1, 2]$.

Since each of these subsystems is treated as a multistate unit, the combination of their generation system models for the k^{th} hour of study results in distinct states with capacities given by [4]:

$$C_{ijn,k} = CC_i + A_{1,k}*CU_{1,j} + A_{2,k}*CU_{2,n} \quad (7)$$

In equation (7), the subscripts 'i', 'j' and 'n' refer to the different states in the first, second and third subsystem respectively. The state space diagram for this combination can be represented by a cuboid as shown in Fig. 1.

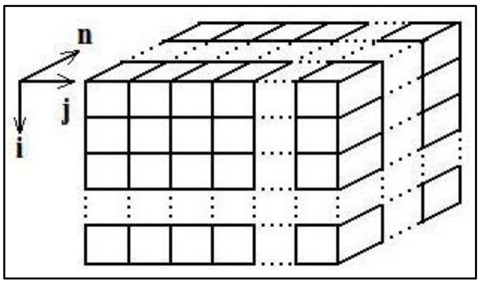

Fig. 1: State space diagram for the combination of three subsystems

The next step is to find the boundary states that define a loss of load, and compute the corresponding probability and expected unserved energy. Looking at Fig. 1, one may observe that for a given value of 'n', there exists a two dimensional state space for different values of 'i' and 'j'. The boundary of capacity deficiency in this state space can then be found by varying 'i' for each value of 'j', until '$C_{ijn,k}$' is found to be less than or equal to the load for the hour in question [4]. The Loss of Load Probability (LOLP) computed along a given i-j state space for the k^{th} hour of study can thus be expressed as:

$$LOLP_{k,n} = \sum_{j=1}^{nu1} \widehat{PC_{th}} * \left(\widehat{PU_{1,j}} - \widehat{PU_{1,j+1}}\right) * \left(\widehat{PU_{2,n}} - \widehat{PU_{2,n+1}}\right) \quad (8)$$

In equation (8), the term 'th' denotes a threshold and is valid only for given values of 'j' and 'n'. It is numerically equal to the smallest value of 'i' such that the expression $(CC_{th} + A_{1,k}*CU_{1,j} + A_{2,k}*CU_{2,n}) \leq L_k$ is satisfied for the k^{th} hour of study. 'L_k' is the system load level for the k^{th} hour and 'nu1' represents the total number of states in the first unconventional subsystem. It may be noted that equation (8) is basically a generalization of equation (1) with 'M' being set to 0. The LOLP for the given hour in question can then be calculated by summing up equation (8) over all values of 'n'. Thus:

$$LOLP_k = \sum_{n=1}^{nu2} LOLP_{k,n} \quad (9)$$

In equation (9), the term 'nu2' refers to the total number of states in the second unconventional subsystem. The Loss of Load Expectation for the k^{th} hour of study, $LOLE_k$, can be computed using equation (2) by replacing '$P_k(0)$' with '$LOLP_k$' and 'ΔT' with 1 hour. Thus, '$LOLE_k$' is numerically equal to '$LOLP_k$' for our case. Finally, the LOLE for the entire period of study is obtained as:

$$LOLE = \sum_{k=1}^{N_t} LOLE_k \quad (10)$$

The Expected Unserved Energy (EUE) can be computed using equations (4) and (5) by constructing a system negative margin table for each hour of the period of study, and by noting that 'ΔT' for our case is equal to 1 hour.

A detailed algorithm for implementing this proposed approach, as well as relevant equations for calculating the hourly power outputs of solar power plants and wind turbine generators are given in [4].

4. Approach II: Clustering Method

The Singh and Gonzalez approach described in Section 3 yields accurate values of the system reliability indices, but is computationally inefficient owing to the hourly calculations involved. It is particularly unsuitable for calculating EUE, as the hourly construction of a system negative margin table and the subsequent computations of 'U_k' (see equation (5)) drastically increases the CPU time. The clustering approach was therefore proposed in [6] for efficiently calculating the reliability indices with minimum computational effort.

Clustering, or grouping, is done on the basis of similarities or distances between data points. The inputs required are similarity measures or data from which similarities can be computed. The study conducted in [6] was based on the FASTCLUS [10] method of clustering owing to its suitability for use on large data sets. The central idea of the FASTCLUS approach is to choose some initial partitioning of the data units and then alter cluster memberships so as to obtain a better partition. FASTCLUS is designed for performing a disjoint cluster analysis on the basis of Euclidian distances computed from one or more variables. The observations are partitioned into clusters such that every observation belongs to one and only one cluster. A detailed description of the FASTCLUS clustering method can be found in [11]. The relevant algorithm for implementing this method as well as an example demonstrating how to use it for grouping some random observations into two clusters are given in [6].

The first few steps of this approach are similar to those of Approach I, in the sense that the entire system is again divided into several subsystems corresponding to the conventional and the different types of unconventional units. A generation system model is then built for each such subsystem. The next step is to compute the hourly power outputs of the unconventional subsystems and define a set of 'N_t' different vectors as described below:

$$\mathbf{d_k} = [(L_k/L_{peak})\ A_{1,k}\ A_{2,k}\ .\ .\ .\ .\ A_{l,k}],\ k \in [1, 2, \ldots N_t] \qquad (11)$$

All terms used in equation (11) are as described in Sections 2 and 3. 'L_{peak}' refers to the peak load for the entire period of study. Equation (11) basically aims to model the correlation between the hourly load and the fluctuating power outputs of the unconventional subsystems. Using the FASTCLUS method, the set of vectors defined by equation (11) are then grouped into different clusters. Assuming that the c^{th} cluster contains a set of 'v' vectors (as defined by equation (11)), it's 'centroid' is defined as the mean of all these vectors, and is in turn denoted by the vector '$\mathbf{d^c}$'. Thus:

$$\mathbf{d^c} = [L^c\ A_1^c\ A_2^c\ .\ .\ .\ .\ A_l^c],\ c \in [1, 2, \ldots N_c] \qquad (12)$$

In equation (12), while the term 'L^c' refers to the mean value of the load in the c^{th} cluster expressed as a fraction of the peak load, the term 'A_l^c' refers to the mean value of the fraction of the total rated unconventional power which is effectively produced by the l^{th} unconventional subsystem in the c^{th} cluster. 'N_c' refers to the total number of clusters chosen for a given simulation. At the end of the simulation, the FASTCLUS routine thus outputs the following parameters for each cluster: Frequency (the total number of vectors '$\mathbf{d_k}$' belonging to a given cluster), and the Cluster Centroid (the vector '$\mathbf{d^c}$' for that cluster) [6].

To incorporate the effect of fluctuating energy, the generation system models of the unconventional subsystems are modified for each cluster. This is achieved by multiplying the rated generation capacity vectors of the various unconventional subsystems with the corresponding 'A_l^c' terms derived from the respective clusters. The generation system models corresponding to all the subsystems are then combined for each cluster in order to calculate the relevant reliability indices. To illustrate this concept using our sample system (refer to Section 3), let us now rewrite equation (7) with respect to the c^{th} cluster as follows:

$$C_{ijn}^{\ c} = CC_i + A_1^c.CU_{1,j} + A_2^c.CU_{2,n} \qquad (13)$$

Referring to our sample system, the Loss of Load Probability for the c^{th} cluster ($LOLP^c$) can be calculated using equations (8) and (9). One should note that the subscript 'k' denoting a given hour in those two equations will now be replaced by the superscript 'c' denoting a given cluster. Using the concept of conditional probability, the LOLP for the entire system can then be obtained as:

$$LOLP = \sum_{c=1}^{N_c} LOLP^c * P(d^c) \qquad (14)$$

In equation (14), the term '$P(d^c)$' refers to the probability of occurrence of the c^{th} cluster and is obtained by dividing the cluster's frequency by 'N_t'. Finally, the LOLE for the entire period of study is obtained as:

$$LOLE = LOLP*N_t \qquad (15)$$

The expected unserved load for the c^{th} cluster, U^c, can be calculated using equation (5) by constructing a system negative margin table for the given cluster and by noting that the subscript 'k' in the equation will now be replaced by the superscript 'c'. The Expected Unserved Energy for the c^{th} cluster, EUE^c, can then be obtained by multiplying 'U^c' with 'N_t'. Using the concept of conditional probability, the EUE for the entire system is finally obtained as:

$$EUE = \sum_{c=1}^{N_c} EUE^c * P(d^c) \qquad (16)$$

A close look at the approaches I and II reveals that while in the former, the modifications of the generation capacity vectors of the unconventional subsystems and the combination of the generation system models were carried out every hour; these operations are performed on a cluster-by-cluster basis in the latter. Since the number of clusters is typically much smaller than the number of hours under study, the clustering method is much more efficient. It should however be noted that the indices calculated using this approach are not as accurate as those obtained in [4], as the contents of the '$\mathbf{d^c}$' vectors based on which the computations are performed for each cluster are obtained by averaging the corresponding values over a number of hours. This gives rise to some approximations in the calculations. It will be shown in later sections that the accuracy of the indices calculated using this method is a function of the number of clusters chosen for a given simulation. The Cubic Clustering Criterion [12] can however be used for choosing the optimum number of clusters. One should also note that if the number of clusters is equal to the number of hours in the study period, i.e. if 'N_c' is equal to 'N_t', the approaches I and II become identical to each other.

5. Approach III: Introduction of Mean Capacity Outage Tables

As described earlier, the reliability indices calculated using the clustering method are not accurate owing to the inherent approximations involved with clustering. Additionally, since the calculations are performed for each cluster, it is impossible to obtain the hourly contributions to the reliability indices using Approach II. The concept of Mean Capacity Outage Tables was therefore proposed in [7] for efficiently and accurately calculating EUE on an hourly basis. It should be pointed out at this time that this approach is essentially used for simplifying the EUE calculations only. The equations concerning the computation of LOLE are still the same as formulated in Section 3 (refer to equations (8) – (10)).

The first few steps of this approach are again similar to those of Approach I, in the sense that the entire system is divided into several subsystems corresponding to the conventional and the different types of unconventional units. A generation system model is then built for each such subsystem. To incorporate the effect of fluctuating energy, the generation system models of the unconventional subsystems are modified hourly depending on their energy output levels. The models corresponding to all the subsystems are then combined hourly in order to calculate the LOLE and EUE indices.

Referring to our sample system described in Section 3, let us now define the following vectors in addition to those ($\mathbf{CC}$, $\widehat{\mathbf{PC}}$, $\mathbf{CU_l}$, $\widehat{\mathbf{PU_l}}$) already presented in Section 3.1:

XC = Capacity outage vector associated with the generation system model corresponding to the conventional subsystem.

$\mathbf{XU_l}$ = Capacity outage vector associated with the generation system model corresponding to the l^{th} unconventional subsystem, where $l \in [1, 2]$.

We shall now rewrite equation (7) in terms of the system capacity outages as follows:

$$X_{ijn,k} = XC_i + A_{1,k}*XU_{1,j} + A_{2,k}*XU_{2,n} \quad (17)$$

Let us also define the term 'critical capacity outage' for the k^{th} hour of study, X_k, as [7]:

$$X_k = CC_1 + \sum_{l=1}^{2}(A_{l,k} * CU_{l,1}) - L_k \quad (18)$$

All terms used in equation (18) are as described in Section 3. It may be noted that the expression ($CC_1 + \sum_{l=1}^{2}(A_{l,k} * CU_{l,1})$) represents the effective total generation capacity of the system during the k^{th} hour of study. For a given hour, say 'k', a loss of load situation occurs when $X_{ijn,k} > X_k$ for given values of 'i', 'j' and 'n'. The expected unserved load during the k^{th} hour of study, U_k, can now be expressed as follows [7]:

$$U_k = \sum_{X_{ijn,k} > X_k}\left(\left(X_{ijn,k} - X_k\right) * P(X_{ijn,k})\right) \quad (19)$$

In equation (19), the term '$P(X_{ijn,k})$' is used to represent the probability that a system capacity outage occurs exactly equal to '$X_{ijn,k}$' MW. We shall now demonstrate how the hourly computation of the system negative margin table for calculating 'U_k' can be avoided by the application of a mean capacity outage table. The Loss of Load Probability for the k^{th} hour of study, '$LOLP_k$' can be expressed as [7]:

$$LOLP_k = \sum_{X_{ijn,k} > X_k} P(X_{ijn,k}) \quad (20)$$

Let 'H_k' represent the expected (mean) value of all system capacity outages which would cause capacity deficiency during hour 'k' [7]. Thus:

$$H_k = \sum_{X_{ijn,k} > X_k}(X_{ijn,k} * P(X_{ijn,k})) \quad (21)$$

Using equations (20) and (21), we can rewrite equation (19) as [7]:

$$U_k = H_k - X_k*LOLP_k \quad (22)$$

While the term 'X_k' in equation (22) can be calculated using equation (18) for a given hour 'k', '$LOLP_k$' can be computed using equations (8) and (9). Let us now expand equation (21) by using relevant terms from equations (8), (9) and (17).

$$H_k = \sum_{n=1}^{nu2}\sum_{j=1}^{nu1}\sum_{i=th}^{nc}[(XC_i + A_{1,k} * XU_{1,j} + A_{2,k} * XU_{2,n}) * PC_i * PU_{1,j} * PU_{2,n}] \quad (23)$$

It should be noted that the terms 'PC' and 'PU' in equation (23) refer to the respective state probabilities and *not* the cumulative probabilities as was the case in equation (8). 'nc' represents the total number of states in the conventional subsystem. The term 'th' in equation (23) can now be redefined in terms of the system capacity outages as the smallest value of 'i' for which the expression ($XC_i + A_{1,k}*XU_{1,j} + A_{2,k}*XU_{2,n}) > X_k$ is satisfied for given values of 'j' and 'n'. Using the relevant notation for cumulative probability (refer to equation (8)), equation (23) can be rearranged as:

$$H_k = \sum_{n=1}^{nu2}\sum_{j=1}^{nu1}\{PU_{1,j} * PU_{2,n} * [A_{1,k} * XU_{1,j} * \widehat{PC}_{th} + A_{2,k} * XU_{2,n} * \widehat{PC}_{th} + \sum_{i=th}^{nc}(XC_i * PC_i)]\} \quad (24)$$

In order to simplify equation (24), we define [7]:

$$\widehat{HC(q)} = \sum_{i=q}^{nc}(XC_i * PC_i) \quad (25)$$

Substitution of equation (25), with q = th, in equation (24) yields:

$$H_k = \sum_{n=1}^{nu2}\sum_{j=1}^{nu1}\{PU_{1,j} * PU_{2,n} * [A_{1,k} * XU_{1,j} * \widehat{PC}_{th} + A_{2,k} * XU_{2,n} * \widehat{PC}_{th} + \widehat{HC(th)}]\} \quad (26)$$

We refer to the term '$\widehat{\mathbf{HC(q)}}$' for q = 1, 2, 3, … nc, as the Mean Capacity Outage Table of the conventional subsystem. This table is the key concept proposed in [7] for efficiently computing EUE. Once the cumulative probability vector '$\widehat{\mathbf{PC}}$' associated with the generation system model of the conventional subsystem is computed, the construction of the mean capacity outage table '$\widehat{\mathbf{HC(q)}}$' requires little additional computational effort as one can use a simple recurrence relation [13]. The expected unserved load during hour 'k' (U_k), as expressed in equation (22), can therefore be calculated using equations (8), (9), (18) and (26). The EUE for the entire period of study is then finally calculated using equation (4).

The advantage of using equation (22) over equation (5) for calculating 'U_k' can be realized by observing that the use of the mean capacity outage table essentially eliminates the need for carrying out hourly computations of a system negative margin table, thereby saving considerable simulation time. The relevant algorithm for implementing this proposed approach, as well as an example demonstrating how to use it on a sample system for calculating EUE can be found in [7].

6. System Case Studies

This section presents the results obtained from case studies performed on sample systems using Approaches I, II and III. The following subsections give the relevant details.

6.1 Approach I vs. Approach II

Reduced synthetic system E [5] was used for this case study, which was performed using Approaches I and II for two different load cycle shapes, January and July, representing winter and summer peak respectively. The reliability indices calculated using both the approaches were then compared to each other for analyzing the efficiency and accuracy of the individual methods. The synthetic system E consists of the units shown in Table I.

TABLE I: Power Generation System Used in Case Study

Unit Type	Number of Units	Unit Cap. (MW)	Total Cap. (MW)
Nuclear	2	800	1600
Coal, fossil > 500 MW	1	800	800
Coal, fossil > 500 MW	2	600	1200
Coal, fossil: 250-499 MW	1	400	400
Coal, fossil: 100-249 MW	1	200	200
Gas, fossil > 500 MW	1	800	800
Gas, fossil > 500 MW	2	600	1200
Gas, fossil: 250-499 MW	2	400	800
Gas, fossil: 100-249 MW	11	200	2200
Oil, fossil: 250-499 MW	1	400	400
Oil, fossil: 100-249 MW	1	200	200
Combustion Turbine	10	50	500
System Total Capacity (MW)			10300

The reliability indices were calculated for different degrees of penetration, which is an indication of the percentage of the system generation capacity that is substituted by unconventional generation. Two different types of unconventional units were used for the study, photovoltaic electric power plants (PEPS) and wind turbine generators (WTG). For each degree of penetration, the amount of unconventional generation was equally divided between the two subsystems. All the units contained in each of the two unconventional subsystems were assumed to be identical. Depending on the degree of penetration, the units of the 'Gas, fossil' type of capacity 200 MW each (refer to Table I) were replaced by the corresponding amount of unconventional generation [6]. Hourly load data was obtained from [14], while unit reliability parameters were drawn from [5]. An operating reserve of 15% was also assumed.

The FASTCLUS procedure was used in the part of the study performed using Approach II for obtaining the various clusters. Since the outputs of the PEPS and WTG units are usually a small fraction of the load, per unit values were used for obtaining the clusters [6]. This prevented any set of particular variables from dominating the procedure of clustering. The results obtained from this study are as presented in Tables II – IV [6]. While Tables II and III present the LOLE and EUE indices respectively, Table IV gives a comparison of the CPU time spent while performing the studies using Approaches I and II.

TABLE II: LOLE Results for the Months of January and July

Penetration (%)	LOLE (hrs/month) January		LOLE (hrs/month) July	
	Appr. I	Appr. II	Appr. I	Appr. II
0	21.93	21.64	108.61	107.93
5	20.02	16.51	71.70	74.70
10	30.50	36.73	86.36	82.80
15	55.30	63.19	112.25	112.30

TABLE III: EUE Results for the Months of January and July

Penetration (%)	EUE (GWh) January		EUE (GWh) July	
	Appr. I	Appr. II	Appr. I	Appr. II
0	9.677	9.465	77.633	76.672
5	7.896	5.923	59.517	61.442
10	14.82	13.487	94.164	104.147
15	24.417	22.212	144.557	142.683

TABLE IV: Comparison of CPU Time

Penetration (%)	CPU Time (sec) January		CPU Time (sec) July	
	Appr. I	Appr. II	Appr. I	Appr. II
0	11.63	6.84	11.43	6.68
5	42.26	11.84	44.05	10.42
10	58.40	15.66	58.85	14.29
15	77.93	21.86	79.58	17.96

6.2 Approach II vs. Approach III

The IEEE reliability test system (RTS) [15] was used in this case study for comparing the indices obtained from simulations run using Approaches II and III. The conventional subsystem used for the study comprised of the entire RTS containing 32 binary units with unit capacities ranging from 12 to 400 MW with a total system generation capacity of 3405 MW. Four different cases were considered for performing the simulation runs: a base case with no unconventional capacity and three others with the rated unconventional generation capacity CU = 100, 200 and 400 MW respectively [7]. The unconventional generation was incorporated into the study by considering a subsystem consisting of identical wind turbines, each with an installed capacity of 1 MW, a mean up time of 190 hours and a mean down time of 10 hours.

Typical hourly mean wind velocity data was obtained from [16]. Reliability indices were calculated for a period of one week, with the hourly load values being obtained from [8] using the load cycle for week 51 with a peak load of 2850 MW, a low load of 1368 MW and a weekly energy demand of 359.3 GWh. The results obtained from this study are as presented in Tables V – VI [7]. While Table V presents the LOLE and EUE indices computed using Approach III as well as the CPU time spent in performing the corresponding simulations, Table VI lists the EUE values computed using Approach II as a function of the number of clusters chosen for a given simulation.

TABLE V: Results Obtained Using Approach III

CU (MW)	EUE (MWh)	LOLE (hrs/week)	CPU Time (seconds)
0	278.917	1.951174	12.1
100	207.902	1.487951	30
200	159.402	1.185692	48.2
400	99.085	0.78984	84.2

TABLE VI: EUE Results (MWh) Obtained Using Approach II

CU (MW)	Number of Clusters (N_c)					
	10	15	20	40	60	80
100	155.6	176.8	185.5	198.7	206	207.7
200	117.5	134.5	143.1	153.2	158	159.2
400	73	85.4	90	96.1	98.2	98.9

7. Discussions

7.1 Approach I vs. Approach II

A close look at Tables II and III reveals that the reliability indices computed at low penetrations have lesser values as compared to those calculated at zero penetration. The reason is that the unconventional units, in this case, are more reliable than the conventional units they substitute. As the degree of penetration increases, however, the uncertainty in the energy outputs of the unconventional units produces the overall effect of reducing reliability [6]. It can also be noted that the indices calculated using Approach II are reasonably accurate when compared to those computed using Approach I, provided that an optimum number of clusters is chosen. As described earlier, the optimum number of clusters for a given simulation can be chosen using the Cubic Clustering Criterion, as described in [12]. Finally, one may observe from Table IV that the CPU time spent in performing the simulation runs using Approach II are much lesser than that spent using Approach I. The reduction in simulation time becomes even more significant at higher degrees of penetration.

7.2 Approach II vs. Approach III

It may be noted from Tables V and VI that the values of the reliability indices computed using Approaches II and III decrease with increasing levels of unconventional generation capacity. Regarding the computation of EUE using Approach II, the accuracy of the values obtained depends on the number of clusters chosen, the choice of initial seeds in the clustering algorithm and the correlation between hourly load and the wind energy supply [7]. It may be observed from Table VI that the accuracy of the EUE values increases with an increase in the number of clusters chosen for a given simulation. Thus, for N_c = 15, the EUE values computed using Approach II differs from those calculated using Approach III by 15%, 15.6% and 13.8% for CU = 100, 200 and 400 MW respectively. For a sufficiently large number of clusters ($N_c \geq 60$), however, the error in the EUE values computed using Approach II becomes less than 1%. It should be pointed out at this time that increasing the number of clusters does not always produce more accurate results, because the relationship between load and reliability is non-linear [6]. Note that the EUE values listed in Table VI are systematically lower than those in Table V because the impact of the peak values is reduced in the process of obtaining average values [7].

8. Conclusions

This paper gives a detailed description of the approaches used for performing quantitative reliability analysis of large-scale power systems incorporating renewable energy sources. Three different approaches are presented along with relevant equations and diagrams. The results obtained from simulation runs performed using the individual approaches are then compared for analyzing their efficiency and accuracy. Approach III turns out to be the most efficient, as it is conceptually simple, accurate and the least time consuming.

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