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Kernel Density Estimation Based Time-Dependent Approach for Analyzing the Impact of Increasing Renewables on Generation System Adequacy

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ABSTRACT Integration of non-conventional renewables such as wind and solar to the power system may affect the system reliability, especially when the proportion of renewable power in the system is large. Therefore, with a significant level of renewable penetration, the intermittency and both diurnal and seasonal variations of renewable power generation should be deliberately modeled in order to accurately quantify the power system reliability. This paper presents a novel method based on Kernel Density Estimation (KDE) for modeling intermittency and both diurnal and seasonal variations of wind and solar power generation using historical renewable power generation data. The proposed KDE based renewable power models are used with non-sequential Monte Carlo simulation to evaluate the generation system adequacy. Several case studies are conducted on IEEE reliability test system to analyze the impact of increasing renewables on the generation system adequacy. The results show that the generation system adequacy tends to decay exponentially when the renewable integration is increased. It is shown that the reliability values obtained using the proposed approach are very close to those provided by the time-consuming sequential simulations. Importance of modeling seasonal variations of wind and solar is also investigated.

INDEX TERMS Kernel density estimation, Monte Carlo simulation, generation system adequacy, reliability assessment, renewable power, wind and solar.

I. INTRODUCTION

Integration of renewable power, especially wind and solar PV is showing a rapid growth in modern power systems [1]. Considerable variations of fossil fuel prices, technological advancements, price reduction in solar panels and environmental concerns have accelerated the renewable power utilization. Moreover, many governments have implemented policies to integrate more renewable power generation to electricity grids [1].

The intermittent nature and both diurnal and seasonal variations of renewable energy sources such as wind and solar often lead to vary the amount of renewable power injection to the power grid. Hence, with an increased proportion of renewable power in the grid, the power system reliability varies drastically throughout the year. Therefore, the intermittency and both diurnal and seasonal variations of renewable power generation should be considered in the reliability evaluation of modern wind and solar integrated power systems.

Power system reliability can be divided into two separate categories i.e. system adequacy and security [2]. System adequacy studies investigate the power system's ability to satisfy consumer demand using existing facilities of the system whereas security is a measure of the ability of the system to respond to dynamic and transient disturbances arising in the system. Adequacy studies are performed in three Hierarchical

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Levels (HLs) which are defined based on the power system's functional zones i.e. generation, transmission, and distribution [2]. These three HLs are;

- HL I – Generation system adequacy evaluation.
- HL II – Composite system adequacy evaluation which considers the adequacy of both generation and transmission systems.
- HL III – Adequacy evaluation of generation, transmission and distribution systems.

The focus of this study is on HL I assessment of a wind and solar integrated power system.

The probabilistic techniques which have been proposed for generating system adequacy evaluation can be categorized as analytical techniques and Monte Carlo Simulations (MCSs). Analytical methods use mathematical modeling of the power system and provide direct analytical solutions. Various analytical approaches for generation adequacy assessments with renewable integration can be found in the literature [3]–[7]. Analytical methods such as Markov chain-based Capacity Outage Probability Table (COPT) [3]–[6] and universal generating functions [7] cannot model diurnal and seasonal variations of the renewable power generation. Moreover, when the renewable power penetration is high, the above methods become more complex and a significant amount of computational power will be required.

MCS is a popular probabilistic method of estimating system reliability indices. There are two main types of Monte Carlo methods i.e. Sequential Monte Carlo Simulation (SMCS) and Non-Sequential Monte Carlo Simulation (NSMCS). SMCS generates chronological system states to obtain state residence series for each component in a system. Then, the series of all the components are combined to get the series of system status to evaluate the system reliability indices [8]. In [9]–[12], SMCS is used for the adequacy evaluation of generating systems. Chronological wind power simulation models are combined with SMCS to evaluate the adequacy of wind integrated generating systems in [11], [12]. Historical wind speed or wind power generation data are used to implement Auto-Regressive Moving Average (ARMA) time-series models for simulating chronological wind speed or wind power generation for a specific time period for e.g. one year [11]–[13]. However, the ARMA model integrated SMCS requires a significant amount of simulation time [11]. Moreover, ARMA models presented in [11], [12] lack seasonality modeling. The seasonal ARMA models require a huge amount of simulation time because the seasonal trend repeats once in every 8760 hours. Auto-Regressive Integrated Moving Average (ARIMA) based model proposed in [14] represents seasonal variations, but diurnal variations are neglected in this model.

In NSMCS, the reliability indices such as Loss of Load Probability (LOLP), Loss of Load Expectation (LOLE) and Loss of Energy Expectation (LOEE) are repetitively computed through stochastically sampling the states of the power system until the selected indices are converged with an acceptable Coefficient of Variation (COV) [8]. In [15], wind power, photovoltaic (PV) generation, and electricity demand are modeled as time-dependent clusters for NSMCS. Renewable power and load data are clustered according to the earth's seasons (spring, summer, etc.) and it is not effective and efficient, for an example, even though there are four seasons, wind power generation may show only two distinctive wind seasons (high and low) throughout the year. In [15], renewable power models represent diurnal correlations, but seasonal correlations are not modeled in the NSMCS algorithm. Moreover, renewable power output is split into a fixed number of steps (8 power levels) using the Fuzzy C-means clustering method. It does not represent the actual renewable power generation because intermediate power values between the steps are not considered. In [6], [16] wind power generation is modeled analytically using multi-state models. Probabilistic distributions such as Weibull, Burr, lognormal and gamma are used to model wind speed in [17]. These methods do not represent the diurnal and seasonal wind power variations. Thus, the correlation between renewable power generation and the load is neglected. In [18], a linear regression function is utilized to describe the relationship between correlated random variables such as the renewable generation and the load. However, the strength of the relationship is important, and it depends on the region's load profile and renewable power generation patterns. In [19], a solar radiation simulation method is proposed for generating data at each hour based on the probability of occurrence of solar radiation at n previous hours. Even though the accuracy of the diurnal distribution of solar radiation is tested, the seasonal distribution is not validated. The power generation of barrage-type tidal power plants is modeled in [20]. The failure rates of the composed components and the effect of tidal height variation on the components' failure rate are considered in the tidal generation model that is used for evaluating the adequacy of power generation systems. Variance reduction methods such as importance sampling [21]–[24] and Latin Hypercube sampling [18] can be used to reduce the convergence time of MCSs.

In addition to the above MCS models, population-based methods can be used for evaluating the generating system adequacy [25]. Population-based Intelligent Search (PIS) is used to discover a set of probable failure states, which significantly contribute to the generation system adequacy. PIS is based on the guided stochastic search methods which are inspired by biological or social systems. Genetic algorithms [26], [27], particle swarm optimization [28], [29], ant colony optimization and artificial immune systems are some population-based intelligent search methods.

Previously proposed chronological and non-chronological renewable power generation models lack either diurnal, seasonal or both variations [6], [7], [11], [12], [15]–[18], [22], [24]. In the adequacy evaluation of wind and solar integrated power generation systems, SMCS struggles with the modeling of seasonal variations due to the computational cost of the ARIMA method [6], [11], [12]. On the other hand, the NSMCS method proposed in [15] lacks modeling of seasonal variations of renewable power generation. Both diurnal and seasonal variations of wind power generation are not modeled in the NSMCS proposed in [16], [17]. Analytical renewable power models proposed in [7], [18], [22], [24] also lack diurnal and seasonal variations. Therefore, to accurately evaluate the impact of increasing renewables on the generation system adequacy, novel renewable power models that represent the intermittency and both diurnal and seasonal variations are needed. Moreover, the impact of integrating a large proportion of renewable power on the adequacy of generation systems is not yet analyzed in the literature, while considering the intermittency, diurnal and seasonal variations of renewable power [6], [7], [11], [12], [15]–[18], [22], [24]. Further, studies are required to emphasize the importance of modeling seasonal variations of renewable power generation in reliability evaluations. The computational cost of renewable power generation models is also important because in the real-world power systems the reliability evaluation algorithms may suffer due to the "curse of dimensionality."

There are three main contributions of this paper. Firstly, a novel approach for modeling renewable power generation is proposed using Kernel Density Estimation (KDE) to model both seasonal and diurnal variations of renewable power generation incorporating its intermittent nature. KDE is used to find the probability densities of renewable power generation in different hours of the day and different seasons throughout the year. Apart from modeling both diurnal and seasonal variations and intermittency, the proposed KDE based clustering approach has several advantages. In these proposed models, the number of seasons of each renewable power is decided according to the monthly average renewable power generation throughout the year (For e.g. for wind, three seasons may be identified as high, medium and low wind seasons). Thus, the flexibility of the proposed model is high because the appropriate number of seasons can be selected according to climate patterns of the region. The system load is also modeled as time-dependent clusters and the KDE is used to identify the probability densities of the system load in different hours of the day and different seasons throughout the year. The proposed KDE based renewable power models and the system load model allow NSMCS to model the correlation between renewable power generation and the chronologically varying system load. A novel generating system adequacy evaluation framework based on NSMCS is then developed using the proposed renewable power and load models. SMCS with pre simulated renewable power data is used to validate the proposed generating system adequacy evaluation framework.

Secondly, the proposed framework is used to analyze the impact of increasing renewables on generation system adequacy. The system adequacy variation with different levels of renewable integration is rationalized considering different characteristics of renewable power and the system load. Thirdly, the importance of modeling seasonal variations of renewable power generation is further studied by conducting several case studies.

This paper is organized as follows. Section II describes the proposed methodology for modeling intermittency and both diurnal and seasonal variations of renewable power generation. In Section III, a framework based on NSMCS is proposed for evaluating the generating system adequacy using the developed renewable power models. In Section IV, the impact of increasing renewables on generating system reliability is evaluated under several case studies. In Section V, the proposed framework is validated and the importance of modeling seasonal renewable power variations is discussed. Conclusions are given in Section VI.

II. MODELING OF RENEWABLE POWER

This section explains the methodology of modeling renewable power generation. Subsection A provides a brief description on historical renewable generation data used for modeling renewable power generation. Then, the procedure of modeling wind and solar power generation using KDE is presented in subsection B.

A. HISTORICAL WIND AND SOLAR POWER DATA SETS

The simulated wind and solar power generation data of Belgium are obtained from [30], [31]. The data sets include renewable power generation data with a resolution of 1 hour. Independent system operators also use hourly based production of wind power in their reliability and planning studies [32]. Smaller resolution of renewable power data which is less than 1 hour would require large computational time as well as more data collection. In [30], [31], authors have used NASA's MERRA-2 global meteorological reanalyzes as well as the Meteosat-based CMSAF SARAH satellite data set to produce hourly PV and wind simulations across Europe. The results of the simulation algorithm are validated using real PV and wind generation data in the European region. The total solar and wind power generation of Belgium in year 2014, 2015 and 2016 is used to implement renewable power generation models. The renewable power data are normalized using the respective total wind or solar installed capacities. Hence, several penetration levels of wind or solar power can be added to the power generating system by multiplying the normalized power values by respective installed capacity values (For e.g. the annual wind power output of a 100MW wind plant can be obtained by multiplying the normalized annual wind power data by 100).

B. MODELING WIND AND SOLAR POWER GENERATION USING KERNEL DENSITY ESTIMATION

The intermittency and both seasonal and diurnal variations of wind and solar power generation should be considered in the process of state sampling i.e. if a load is selected, say from November 13th 9 a.m. hour then both wind and solar power generated in that exact date and time should be selected. If data are available for several years, a random value of renewable power generation can be selected for that exact date and time. However, in many situations, it is difficult to obtain renewable power generation data recorded

Days of the year in chronological order	Power generation in each hour of the day			
	00.00-01.00	01.00-02.00	…	23.00-00.00
Day1	Cluster 11	Cluster 12	Cluster 1j	Cluster 124
Day2				
.				
.				
Day j	Cluster 21	Cluster 22	Cluster 2j	Cluster 224
.				
.				
Day 365				

Season 1 Season 2

FIGURE 1. An example of the clustering approach.

over a significant number of years. Thus, the intermittency of renewables cannot be modeled. A practical solution to this problem is clustering of data sets according to hours of the day and seasons of the year. An example of this approach is illustrated in Fig. 1. The selection of the number of clusters mainly depends on the seasonal changes throughout the year, i.e. if there are two distinctive wind seasons, there will be 48 clusters (24 × 2). Then for each cluster, a Probability Density Function (PDF) of respective renewable power generation is obtained by KDE method. These PDFs can be used to model intermittency and both diurnal and seasonal variations of wind or solar power generation throughout the year. Hence, in NSMCS, a random renewable power generation value can be obtained for a specific hour of the day and season of the year considering the probabilistic nature of renewable generation.

It should be noted that the outage of renewable generators is not considered in this work. Renewable generator outages do not significantly change the overall renewable power output due to the small generating unit capacities of the large number of renewable generators. In these systems, the variation of renewable power generation is more significant than the outage of generating units.

1) KERNEL DENSITY ESTIMATION

The PDF of each renewable power cluster can be determined using either parametric methods such as mixture models or non-parametric methods such as KDE method. In mixture models, the underlying distribution of each cluster is constructed using multiple parametric distributions. Further, there exist numerous levels of renewable power generation due to the large variability of renewables. Hence, the identification of a suitable number of parametric distributions increases the complexity of the generation system adequacy evaluation algorithm. Moreover, the parameters of each distribution are needed to construct the mixture model for each of the clusters in the clustering model shown in Fig. 1.

On the other hand, KDE avoids the problem of the choice of the number of components by using one component (a Kernel) centered on each point of the dataset [33].

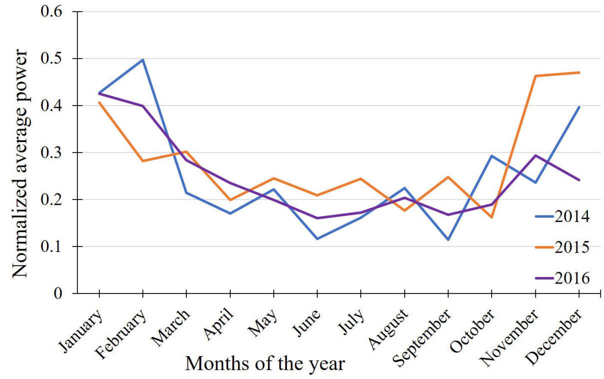

FIGURE 2. Monthly average wind power generation in Belgium.

It provides a smooth PDF for a given set of data points. KDE is widely used in the applications in which the PDF is unknown or poorly defined e.g. forecasting error distributions [34]. The Kernel can be a proper PDF such as normal, Weibull, etc. When determining the PDF of a given random variable, the center of the Kernel is placed right over each data point. According to the type of the chosen Kernel, the influence of each data point is spread about its neighborhood. Finally, the PDF can be obtained by summing the contribution of each data point. Smoothness of the density estimate can be controlled by changing the bandwidth of the selected Kernel.

Given a random sample of observations $x_1, x_2, \ldots, x_n$ with a continuous, uni-variate density f, the Kernel density estimator is,

$$f(x, h) = \frac{1}{nh} \sum_{i=1}^{n} K \frac{(x_i - x_0)}{h} \quad (1)$$

where x_0 is the target point, K is the Kernel and h is the bandwidth.

2) SEASONALITY DETECTION USING K-MEANS CLUSTERING METHOD

Instead of manual determination of seasonal durations of renewable power generation, a K-means clustering algorithm can be used to cluster the months into different seasons. In K-means clustering, n observations can be partitioned into K clusters. The observations are clustered based on feature similarity. The centroids of the K clusters and labels (cluster names) for the observations are the results of a K means clustering algorithm [35].

The seasonal variations of wind and solar power generation are illustrated in Figs. 2 and 3 respectively. Wind power generation data of 36 months in 2014, 2015 and 2016 can be categorized into 2 clusters i.e. 2 seasons and solar power data can be categorized into 3 clusters. Silhouette analysis [36] is used to identify the appropriate number of seasonal clusters of wind and solar power generation throughout the year. The silhouette plot illustrates a measure of distance between each point in one cluster to points in the adjacent clusters. Silhouette score lies in the range of [−1, +1]. A value of +1 implies that the sample is far away from its adjacent

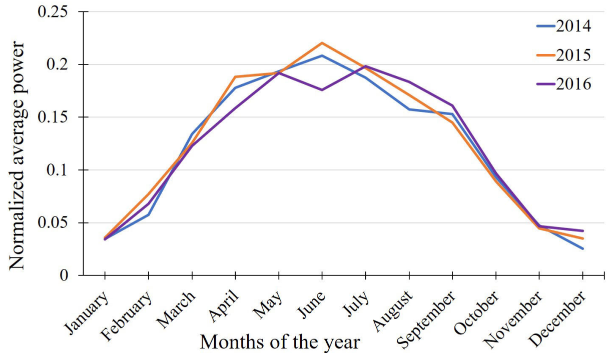

FIGURE 3. Monthly average solar power generation in Belgium.

TABLE 1. Clustering table for three solar seasons.

Month	Year 2014	Year 2015	Year 2016	Selected season
January	Low	Low	Low	Low
February	Low	Low	Low	Low
March	Moderate	Moderate	Moderate	Moderate
April	High	High	High	High
May	High	High	High	High
June	High	High	High	High
July	High	High	High	High
August	High	High	High	High
September	Moderate	Moderate	High	Moderate
October	Moderate	Moderate	Moderate	Moderate
November	Low	Low	Low	Low
December	Low	Low	Low	Low

clusters whereas a value of -1 implies that the sample is far away from its assigned cluster. Hence, the cluster configuration which provides the largest Silhouette score is preferred. Then, the most suitable set of months for each cluster is selected considering the number of votes for the respective cluster. Results of the K-means clustering process conducted for solar power are shown in Table 1.

3) WIND POWER GENERATION MODEL

As discussed in Section II *B*2), wind power generation data is divided into two seasons. Then, using K-means clustering, months belong to each season are identified. Months of November, December, January, February, and March are in high wind season and the rest of the months are in low wind season.

For each season, 24 clusters are created according to the hour of the day. Then, KDE is used to derive the PDFs of each cluster. The "normal" distribution given by (2) is used as the Kernel function. The "normal" distribution provides more accurate results than "box", "triangle" and "epanechnikov" Kernels. Moreover, it provides a smooth probability density curve. Hence, all the cluster PDFs are obtained by utilizing the "normal" Kernel. The most suitable value for the bandwidth is automatically selected by the algorithm as 0.04. Fig. 4 illustrates the PDFs of wind power generation from 00.00 a.m. to 01.00 a.m. in the high wind and low wind seasons, respectively.

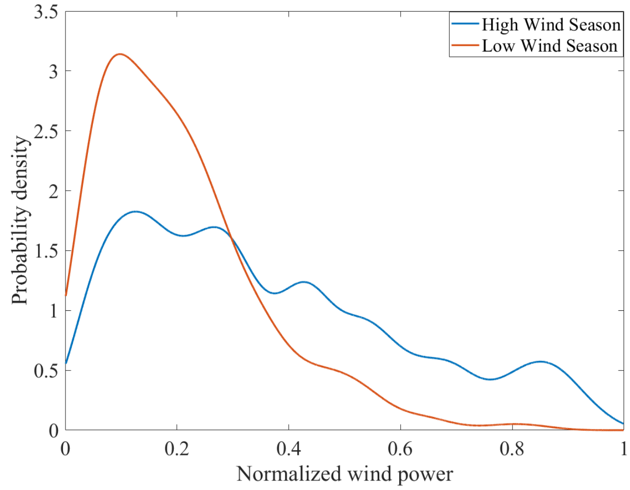

FIGURE 4. Probability density of wind power from 00.00 a.m. to 01.00 a.m. in different wind seasons.

$$P(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2} \tag{2}$$

where μ and σ are the mean and the variance of the distribution P.

4) SOLAR POWER GENERATION MODEL

In solar power modeling, seasons with high and low irradiance levels should be identified. Three distinctive seasons are identified by the Silhouette analysis. Then, the K-means clustering algorithm is used to obtain the respective months.

- High irradiance season- April, May, June, July and August.
- Medium irradiance season- March, September and October.
- Low irradiance season- January, February, November and December.

With having three seasons, 72 clusters are created. Then, PDFs for each cluster are obtained using the KDE and this procedure is similar to the procedure used to find PDFs of wind clusters in Section II *B*3). Fig. 5 illustrates the PDFs of solar power generation from 12.00 p.m. to 01.00 p.m. in the three seasons. It can be clearly observed that the PDFs significantly differ from each other representing the probability density of solar power generation in each season.

III. RELIABILITY EVALUATION USING THE PROPOSED KDE BASED RENEWABLE POWER MODELS

The proposed renewable power generation models are used with the IEEE Reliability Test System (RTS)-79 in order to evaluate the impact of increasing renewables on generation system adequacy. A brief description of IEEE RTS-79 is given in subsection A. The reliability indices used for quantifying the generation system adequacy are explained in subsection B. Subsection C describes the methods of modeling conventional generation, load and renewable generation in

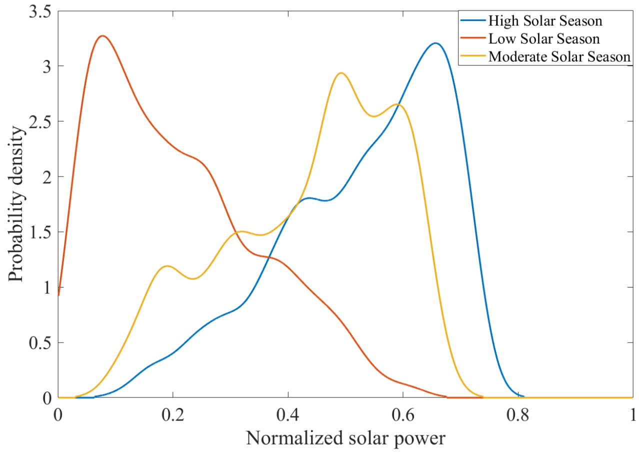

FIGURE 5. **Probability density of solar power from 12.00 p.m. to 01.00 p.m. in different solar seasons.**

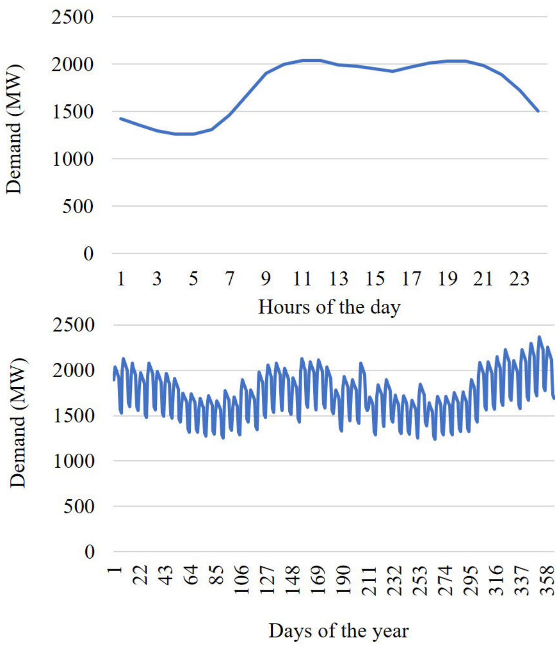

FIGURE 6. **Diurnal and seasonal variations of the system load.**

the NSMCS algorithm. The proposed framework for calculating the generating system reliability indices is presented in subsection D.

A. IEEE RTS-79

IEEE RTS-79 [37] consists of 32 generation units, with unit capacities ranging from 12 MW to 400 MW. This system has a total power output of 3405 MW, and the peak load of the system is 2850 MW. The annual hourly chronological load curve shows diurnal and seasonal variations of the system demand as illustrated in Fig. 6. The generation system is modified by adding renewable generation. This Modified RTS (MRTS) is used to evaluate generation system adequacy under several case studies in Section IV. Moreover, the proposed generation system adequacy evaluation methodology is validated and the importance of modeling seasonal renewable variations is explored using the MRTS in Section V.

B. RELIABILITY INDICES

1) LOLP

LOLP is a measure of the probability that the system demand exceeds the generating capacity during a given period [8]. In NSMCS, LOLP can be calculated by dividing the total number of failure states by the total number of system states.

2) LOLE

LOLE is the expected number of days (or hours) in a specified period in which the daily peak load exceeds the available generating capacity [8]. LOLE in hours per year can be calculated by multiplying LOLP by 8760.

3) LOEE

LOEE is the expected unsupplied energy due to generating inadequacy [8]. State-wise unsupplied energy can be calculated in each failure state and then by accumulating each unsupplied energy value, the overall LOEE can be obtained.

C. MODELING OF CONVENTIONAL GENERATION, RENEWABLE GENERATION AND LOAD IN NSMCS

Conventional generators are modeled using 2-state Markov models. Forced Outage Rate (FOR) of each generator is used to determine the availability of the generator. Thus, the stochastic operating nature of generators is considered in the simulation.

The derived PDFs of renewable power generation models can be transformed into Inverse Cumulative Density Functions (ICDFs). Two uniform random numbers ranging from 1-24 (hour of the day) and 1-365 (day of the year) are used to select the respective wind and solar clusters i.e. ICDFs. If a uniform random number between 0 and 1 is used as the input to an ICDF of the selected cluster, the output will be a renewable power generation value which is generated according to the historical power generation of the same cluster.

The load is modeled in the same manner as the renewable power models. The annual load curve which consists of hourly chronological demand values is used to implement the time dependent load clusters. The annual demand curve can be divided to three distinctive seasons i.e. summer, winter and spring/fall as described in [37]. The "normal" Kernel is used to form the respective PDFs of the load clusters using KDE. The most suitable bandwidth value is selected as 5 which is obtained by the trial and error method. Then, the finalized load model is obtained by converting all the PDFs to their respective ICDFs. In NSMCS sampling, the same uniform random numbers which are generated to obtain wind and solar clusters are used to select the corresponding load cluster. This approach is needed to accommodate the correlation between load, wind generation and solar generation in NSMCS.

D. PROPOSED KDE BASED NSMCS FRAMEWORK FOR CALCULATING RELIABILITY INDICES

In NSMCS, states of the power system are generated randomly and analyzed to check whether the available generation can satisfy consumer demand or not. The Monte Carlo Simulation is a fluctuating convergence process. The longer the simulation period, the larger is the number of samples and higher is the accuracy of the estimated system adequacy indices. Hence, the simulation should be stopped when the estimated reliability indices achieve a specified degree of confidence. The purpose of a stopping rule is to provide a compromise between the accuracy needed and the computation cost.

The COV is often used as the convergence criterion in Monte Carlo simulation [8].The smaller the prespecified tolerance of COV the higher the accuracy of adequacy estimations as it leads to tighter upper and lower bounds to the estimated value for a given level of confidence [38]. Hence, the tolerance value of COV should be selected considering the accuracy needed and the computational cost. In this work, the tolerance value of COV is selected by conducting several simulation trials. The tolerance value which provides acceptable estimations in a computationally efficient manner is selected. Therefore, it is assumed that the NSMCS is converged if the Coefficient of Variation (COV) of LOLE is less than a defined margin ε. This is illustrated in (3).

$$COV = \frac{\sqrt{var(E[f])}}{E[f]} \tag{3}$$

where $E[f]$ is the estimator of the expected value of the LOLE. The COV of LOLE margin ε is selected as 10^{-5}. The maximum number of sampling states is limited to 10^8. In order to make the NSMCS more efficient, the convergence is assessed in blocks of 10000 samples.

The proposed framework for calculating the generating system adequacy indices is briefly described below. Further, the adequacy evaluation methodology is illustrated in Fig. 7.

Step 1: Initialize H (Number of failure states) = 0, N (Total number of states) = 0, E (Energy not supplied) = 0.

Step 2: For $i = 1, 2, 3, \ldots,$ n where n is the total number of conventional generators in the generating system, repeat the following step; i.e. step 3 to find out the availability of conventional generators.

Step 3: Generate a uniform random number U_1 between 0 and 1.
If U1 < FOR of i$^{\text{th}}$ generator (G_i), then the unit is not available ($C_i = 0$) otherwise the unit is available with full capacity (C_i = Capacity of G_i).

Step 4: Calculate the total available conventional generating capacity C_c using (4),

$$C_c = \sum_{i=1}^{n} C_i \tag{4}$$

Step 5: Generate a uniform random number U_2 between 1 and 365.

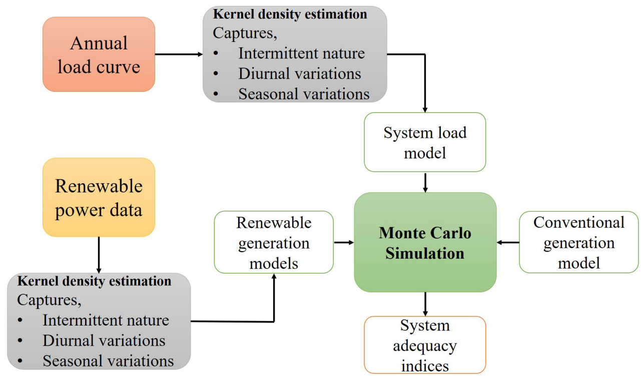

FIGURE 7. An overview of the proposed generation system adequacy evaluation framework.

Step 6: Generate a uniform random number U_3 between 1 and 24.

Step 7: Select the respective ICDFs of wind and solar models for the U_2^{th} day of the year and U_3^{th} hour of the day.

Step 8: Select the corresponding ICDF of the load model for the U_2^{th} day of the year and U_3^{th} hour of the day.

Step 9: Generate a uniform random number U_4 between 0 and 1 and obtain the respective wind power output (C_w) from the ICDF of wind.

Step 10: Generate a uniform random number U_5 between 0 and 1 and obtain the respective solar power output (C_s) from the ICDF of solar.

Step 11: Generate a uniform random number U_6 between 0 and 1 and obtain the respective demand value (L) from the ICDF of load.

Step 12: Calculate the total power generation C using (5),

$$C = C_c + C_w + C_s \tag{5}$$

Step 13: If $C < L$ then $H = H + 1$ (Failure state), $E = E + (L - C)$, $N = N + 1$, else $N = N + 1$

Step 14: Calculate,

$$LOLP = H/N \tag{6}$$
$$LOLE = LOLP \times 8760 \tag{7}$$
$$LOEE = (E \times 8760)/N \tag{8}$$

.

Step 15: Repeat steps 2-14 until the stopping rule is reached.

IV. THE IMPACT OF INCREASING RENEWABLES ON GENERATION SYSTEM RELIABILITY

Several case studies are conducted to evaluate the impact of increasing renewables on generation system reliability. Subsection A provides a brief description of case studies conducted on MRTS. Then, the results are discussed in subsection B.

A. CASE STUDIES

The proposed KDE based NSMCS framework is used to perform three case studies. In case studies 1 and 2, LOLP, LOLE

TABLE 2. LOLP, LOLE and LOEE values for different proportions of wind.

Total Gen. (MW)	Peak load (MW)	Wind capacity %	LOLP	LOLE (hours/year)	LOEE (MWh)
3584.2	3000	5	0.002	17	2252
3783.1	3166.7	10	0.004	32.78	4697
4005	3352.9	15	0.008	65.90	10417
4256.2	3562.5	20	0.016	137.12	24252
4540	3800	25	0.032	277.21	56698
4864.3	4071.4	30	0.059	516.35	125739
5238.5	4384.6	35	0.103	902.87	273609
5675	4750	40	0.159	1390.28	546728

TABLE 3. LOLP, LOLE and LOEE values for different proportions of solar.

Total Gen. (MW)	Peak load (MW)	Solar capacity %	LOLP	LOLE (hours/year)	LOEE (MWh)
3584.2	3000	5	0.002	20.25	2758
3783.3	3166.7	10	0.005	44.56	6779
4005.9	3352.9	15	0.011	99.34	16995
4256.3	3562.5	20	0.024	214.12	42349
4540	3800	25	0.052	456.69	105710
4864.3	4071.4	30	0.099	864.72	245431
5238.5	4384.6	35	0.162	1421.3	508785
5675	4750	40	0.240	2098.76	978586

and LOEE values are calculated for different proportions of wind power and solar power respectively. Then, in case study 3, the same reliability indices are calculated by varying both solar and wind in equal proportions.

The reserve margin of a power system can be defined as follows [2].

$$Reserve\ margin = \frac{Max\_gen\_cap - Max\_demand}{Max\_demand} \tag{9}$$

where Max_gen_cap is the maximum available generating capacity and Max_demand is the maximum annual demand. The reserve margin of the IEEE test system is 19.47% [40]. All 3 case studies are performed by maintaining the reserve margin at its original value (19.47%).

B. RESULTS AND DISCUSSION

The results of case studies 1, 2 and 3 are tabulated in Tables 2, 3 and 4 respectively. Fig. 8 shows the variation of LOLE values with different renewable penetration levels considered in case studies 1, 2 and 3. As can be seen in Fig. 8, LOLE increases almost linearly up to 10% of wind or solar in the system. Then, it exponentially increases when wind or solar energy proportion is further increased. The results of case studies 1 and 2 show that the power system reliability degrades more in solar power integration than in wind power integration. This difference in LOLE of wind and solar drastically increases after the 15% penetration level as can be seen in Fig. 8. This can happen due to two main reasons. Firstly, the variability of solar power is higher than that of wind power and it significantly affects the system reliability especially,

TABLE 4. LOLP, LOLE and LOEE values for different proportions of wind and solar.

Total Gen. (MW)	Peak load (MW)	Wind capacity %	Solar capacity %	LOLP	LOLE (hours/year)	LOEE (MWh)
3584.2	3000	2.5	2.5	0.002	18.05	2420
3783.3	3166.7	5	5	0.004	36.07	5255
4005.8	3352.9	7.5	7.5	0.008	73.22	11716
4256.3	3562.5	10	10	0.018	153.45	27917
4540	3800	12.5	12.5	0.035	308.1	63376
4864.3	4071.4	15	15	0.066	581.45	143545
5238.5	4384.6	17.5	17.5	0.115	1007.94	305743
5675	4750	20	20	0.181	1587.49	607436

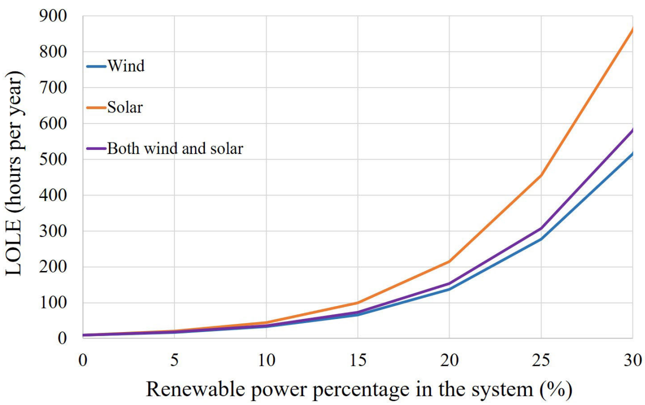

FIGURE 8. Variation of LOLE values with different proportions of renewable power in the system.

when the proportion of renewable power in the system is large. Secondly, solar power is unavailable in the nighttime and when a large proportion of solar power presents in the system, solar power injection to the power grid in the day time significantly varies from that of the nighttime.

The adequacy of a wind and solar integrated power system may get affected by two characteristics of renewable power generation. The first characteristic is the average amount of renewable power generation. Different forms of renewable sources provide different amounts of electrical power output for a fixed capacity installment. As shown in Figs. 2, 3 and [39], the normalized average wind power output is greater and more consistent than the normalized average solar power output. The second characteristic is the diurnal and seasonal correlations between the load and renewable power generation. These attributes of renewable power generation are analyzed to rationalize the LOLE curves shown in Fig. 8.

Out of three case studies, MRTS is more reliable in case study 1. The average renewable power generation in case study 1 is higher than that in case studies 2 and 3. Moreover, the correlation coefficients of diurnal and seasonal variations of wind power generation and the load are found to be 0.39 and 0.17 respectively. Hence, the diurnal and seasonal wind power generation show a weak relationship with the load. However, the reliability of MRTS is improved due to the relatively large and consistent wind power input to the generation system.

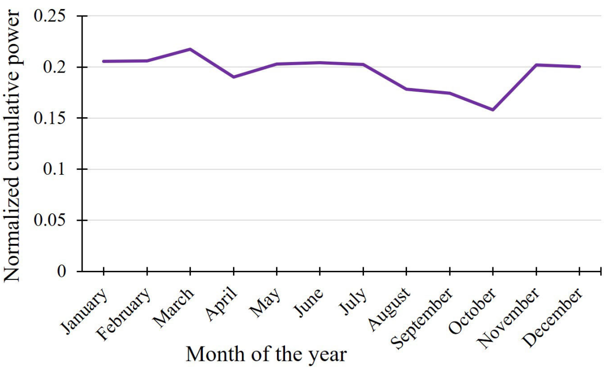

FIGURE 9. Normalized monthly average wind and solar power generation.

In case study 2, MRTS has the lowest system reliability levels. The average renewable power generation in case study 2 is less than that in case studies 1 and 3. The correlation coefficients of diurnal and seasonal variations of solar power generation and the load are 0.58 and −0.26 respectively. This implies that although solar PV contributes to the system reliability diurnally, it reduces the system reliability seasonally due to the negative correlation with the load. Therefore, due to the intermittency, relatively low power output and weak seasonal correlations of solar PV, case study 2 has the highest LOLE values.

According to the results of case study 3, when wind and solar have equal penetration levels, reliability indices have improved significantly than in case study 2. As can be seen in Fig. 8, the system reliability curve of case study 3 lies in between those of case studies 1 and 2. However, the system reliability curve of case study 3 is closer to that of case study 1 because the contribution of wind to the power system reliability is larger than that of solar [15]. The diurnal correlation coefficient of cumulative renewable power generation and the load is 0.63 which shows a moderately strong relationship. Hence, the reliability improvement in case study 3 is entirely due to the comparatively high renewable power output and the moderately strong diurnal correlation between renewable power generation and the load. Moreover, the seasonal correlation coefficient of cumulative renewable generation and the load is found to be 0.09 which reflects a weak relationship. Thus, seasonal renewable power variations are minimized when the system has both wind and solar power in equal capacities. This is illustrated in Fig. 9.

The diurnal and seasonal correlation coefficients of wind and solar generation are −0.24 and −0.43. If there is a strong negative correlation i.e. a correlation coefficient close to −1, integration of both wind and solar will further increase the generating system reliability. Then, when the wind generation is low, solar generation will be high and vice versa, the renewable power supply variation will be minimized.

This study also shows that, a higher reserve margin does not guarantee an acceptable adequacy level when the renewable energy proportion in the grid is large. The system adequacy degrades even though the reserve margin is kept constant at 19.47%. Therefore, capacity credit of wind and solar generation should be considered when deciding the capacity of conventional generation for a given peak load.

TABLE 5. Comparison of LOLE (hours/year) obtained from different methods for wind integration.

Wind capacity %	SMCS	Proposed framework	Error %	Crude NSMCS	Error %
5	16.92	17	0.47	17.52	3.52
10	32.83	32.78	0.15	34.42	4.83
15	66.78	65.9	1.32	70.2	5.13
20	137.88	137.12	0.55	144.94	5.12
25	278.14	277.21	0.33	291.92	4.95
30	526.24	516.35	1.88	551.64	4.83
35	899.44	902.87	0.38	943.18	4.86
40	1363.3	1390.28	1.98	1427.82	4.73

V. MODEL VALIDATION AND THE IMPORTANCE OF MODELING SEASONAL RENEWABLE POWER VARIATIONS

This section provides brief descriptions on model validation and the importance of modeling seasonal variations of renewable power. Subsection A describes the validation procedure of the proposed KDE based NSMCS framework. In subsection B, the importance of modeling seasonal renewable power variations is analyzed using results of a crude NSMCS which considers only diurnal variations of renewable power generation.

A. VALIDATION OF THE PROPOSED FRAMEWORK

Firstly, the NSMCS algorithm used in this study is validated by conducting a reliability evaluation of the generating system without adding renewables. Obtained LOLP, LOLE and LOEE of the system without renewables are 0.0011, 9.3928 hours and 1.179 GWh per annum, respectively. These values are very close to the reference values presented in [40] i.e. 0.001072, 9.39418 hours and 1.176 GWh per annum respectively.

Then, SMCS is used to validate the proposed KDE based NSMCS model. Simulated chronological hourly wind and solar power generation data obtained from [30], [31] are used for SMCS. SMCS using hourly renewable and load data with tight COV should provide good reference values for validation.

Second, third and fourth columns of Tables 5, 6 and 7 show the LOLE values of SMCS and the proposed framework and the percentage error in LOLE of the proposed framework w.r.t SMCS for different penetration levels of wind and solar.

The sequential Monte Carlo simulation provides the system adequacy indices very close to those provided by the proposed algorithm. This shows that the renewable generation and the correlation between renewable generation and the load are modeled in this work. Given that both NSMCS and SMCS are probabilistic simulation methods, a certain degree of estimation error in LOLE of the proposed framework w.r.t SMCS is acceptable. This shows that the proposed KDE based NSMCS framework can be used to accurately evaluate the reliability indices of power systems.

TABLE 6. Comparison of LOLE (hours/year) obtained from different methods for solar integration.

Solar capacity %	SMCS	Proposed framework	Error %	Crude NSMCS	Error %
5	19.88	20.25	1.86	19.09	4
10	43.96	44.56	1.36	40.45	7.99
15	98.56	99.34	0.79	87.25	11.47
20	220.43	214.12	2.86	187.61	14.89
25	461.50	456.69	1.04	388.70	15.77
30	893.48	864.72	3.22	739.23	17.26
35	1463.18	1421.3	2.86	1281.93	12.39
40	2131.56	2098.76	1.54	1955.3	8.27

TABLE 7. Comparison of LOLE (hours/year) obtained from different methods for both wind and solar integration.

Renewable capacity %	SMCS	Proposed framework	Error %	Crude NSMCS	Error %
w 2.5% & s 2.5%	17.97	18.05	0.45	17.95	0.13
w 5% & s 5%	35.94	36.07	0.36	35.51	1.2
w 7.5% & s 7.5%	74.14	73.22	1.24	71.70	3.29
w 10% & s 10%	152.4	153.45	0.69	150.40	1.31
w 12.5% & s 12.5%	307.28	308.10	0.27	301.17	1.99
w 15% & s 15%	584.04	581.45	0.44	568	2.75
w 17.5% & s 17.5%	1010.22	1007.94	0.23	992.81	1.72
w 20% & s 20%	1552.19	1587.49	2.27	1566.61	0.93

Generally, the seasonal renewable power variations are not modeled in practical applications of SMCS because the simulation of renewable power generation with both diurnal and seasonal variations is computationally intractable [6], [11], [12]. In this work, authors have used a pre-simulated renewable power dataset with SMCS to validate the proposed KDE based NSMCS.

Significantly large pre-simulated wind and solar generation data (say, for more than 20 years) is difficult to obtain for places where wind and solar farms are located. Hence, SMCS cannot be implemented using pre-simulated renewable power data for real-world applications. On the other hand, the proposed renewable power models can be implemented using the renewable data of only one year. Thus, the proposed models can be practically used for reliability evaluation of real systems together with an NSMCS model, instead of using sequential renewable power simulations such as ARIMA method that cannot model seasonal variations.

B. IMPORTANCE OF MODELING SEASONAL VARIATIONS IN RENEWABLE POWER GENERATION

To analyze the importance of modeling seasonal variations of renewable power generation, a crude NSMCS model is implemented without considering seasonal variations. The developed crude NSMCS considers diurnal variations of wind and solar power generation as described in [15]. LOLE values obtained from crude NSMCS and the percentage error in LOLE of crude NSMCS w.r.t SMCS for different proportions of wind and solar in the system are shown in fifth and sixth columns of Tables 5, 6 and 7. As can be seen in these tables, the error percentages of crude NSMCS w.r.t SMCS are significantly different when the system has only wind, only solar and both wind and solar.

The percentage error in LOLE of crude NSMCS w.r.t SMCS for wind only case ranges approximately from 3.5% to 5%. In solar only case, the same percentage error ranges approximately from 4% to 17%. Therefore, the percentage error in LOLE of crude NSMCS w.r.t SMCS is relatively high when the system has only solar. This may happen mainly due to two reasons. Firstly, the seasonal variation of solar power generation is relatively large compared to wind as shown in Figs. 2 and 3. Wind generation doubles the output in the high wind season and solar generation quadruples the output in the high solar season. Secondly, the seasonal solar power generation shows a negative correlation with the system load as discussed in Section IV*B*. Hence, crude NSMCS provides relatively small LOLE values without detecting this negative correlation between solar power generation and the system load. When both wind and solar penetrations are equal, the LOLE values of crude NSMCS and SMCS are very close due to the reduction of seasonal effects previously discussed in Section IV*B*.

This analysis shows that it is important to model the seasonal variations of renewables to obtain more accurate reliability indices. Especially, when different regions have different amounts of wind and solar resources, seasonality modeling is essential as it significantly affects system reliability assessments.

VI. CONCLUSION

In this paper, a novel method based on KDE is proposed to model the intermittency and both diurnal and seasonal variations of renewable power generation. Then, the proposed renewable power models are integrated into a NSMCS framework to calculate system reliability indices. Several case studies are conducted using the proposed framework to evaluate the impact of increasing wind and solar generation on the reliability of generating systems. Results show that the reliability decreases when the renewable penetration increases. The proposed KDE based NSMCS framework is validated by comparing its reliability evaluations with those obtained using more time consuming SMCS. It is also shown that the seasonal variations of renewable power generation should be taken into account in reliability evaluation of power systems as it significantly affects the system reliability.

The time needed to implement the proposed clustering-based renewable power and load models is 71 seconds. The simulation time of the proposed model is not compared with that of the utilized SMCS because the renewable modeling phase is not included in the SMCS. Renewable power modeling in SMCS using ARIMA models with diurnal and seasonal variations is computationally intractable due to the required significantly large number of simulation years.

In this study, wind generation and solar generation are modeled using aggregated values of the respective renewable generation. However, if multiple wind or solar plant generation data is available, separate KDE based clustering models can be integrated into the NSMCS. The developed renewable power models can be further utilized to find capacity credit of both wind and solar generation. In addition, KDE-based renewable power models can be used with intelligent search-based methods in order to reduce the computational cost and reliability evaluation time. Energy storages such as pump storage plants or battery storage systems can be used to increase the reliability level of a wind and solar integrated power system. Therefore, an energy storage model can be combined with the proposed framework to find out the impact of integrating energy storage on the reliability of wind and solar integrated power systems.

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