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**NOVEL MODELING METHODS AND
EVALUATION FRAMEWORKS FOR ASSESSING
AND IMPROVING THE RELIABILITY OF
RENEWABLE-RICH POWER SYSTEMS**

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Doctor of Philosophy in Electrical Engineering

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Thesis submitted in partial fulfillment of the requirements for the degree
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DECLARATION

I declare that this is my own work and this Thesis does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. I retain the right to use this content in whole or part in future works (such as articles or books).

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The supervisors should certify the Thesis with the following declaration.

The above candidate has carried out research for the Doctor of Philosophy in Electrical Engineering Thesis under our supervision. We confirm that the declaration made above by the student is true and correct.

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Signature of the Supervisor:

Date: 07/04/2025

DEDICATION

To my wonderful teachers!

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ABSTRACT

The share of non-conventional renewable energy, such as wind and solar, is gradually increasing in many power systems. However, integrating wind and solar power on a large scale would considerably affect the reliability of power systems due to the stochastic nature of renewables. Conventional reliability evaluation methods cannot efficiently and accurately quantify power system reliability when there is a significant amount of renewable power in the system. Therefore, novel reliability evaluation techniques are required to assess the reliability of modern renewable-rich power systems. This work implements novel modeling methodologies and evaluation frameworks to quantify the reliability of renewable-rich power systems accurately. Different algorithms and techniques are developed to evaluate the reliability of generation, composite generation and transmission, and distribution subsystems because the nature of the problem and its complexity are different in each of the three subsystems. Firstly, a novel method based on Kernel Density Estimation (KDE) is proposed to model 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 (NSMCS) to evaluate the generation system adequacy of the Institute of Electrical and Electronics Engineers (IEEE) Reliability Test System (RTS). The diurnal and seasonal variations of renewables and the correlation between the load and renewable generation are modeled in the proposed renewable power models. Secondly, the applicability of conventional MCS for composite system adequacy evaluation is investigated. It is found that a more computationally efficient reliability evaluation methodology is needed to evaluate the adequacy of composite systems. Hence, a novel population-based intelligent search method called Evolutionary Swarm Algorithm (ESA) incorporated with DC optimal power flow analysis is proposed to evaluate the adequacy of renewable-rich composite power systems. The main objective of the ESA is to find out the most probable system failure events that significantly affect the adequacy of composite systems. The identified system failure events can be directly used to estimate the system adequacy indices. The random search guiding mechanism of the ESA is based on the underlying philosophies of genetic algorithms and binary particle swarm optimization. The computational efficiency of the proposed ESA is significantly higher than that of traditional simulation methods. Thirdly, the proposed ESA is used to evaluate the reliability of solar-integrated power distribution systems. AC optimal power flow analysis is used to assess the system failure events while considering the feeder voltage levels. The annual reliability indices of renewable-rich distribution systems can be estimated using this method, which is not addressed in the prevailing literature. Apart from evaluating the power system reliability, the impact of increasing wind and solar integration on the reliability of power systems is investigated at all hierarchical levels. Further, the proposed reliability evaluation frameworks are used to identify possible methods to improve the reliability of power systems. The outcomes of this research allow precise planning and operation of modern power systems in a time-efficient manner.

Keywords: Evolutionary Swarm Algorithm, Population-based Search Methods, Power System Adequacy, Renewable Power Modelling

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LIST OF ABBREVIATIONS

Abbreviation	Description
ACO	Ant Colony Optimization
AENS	Average Energy Not Supplied
AI	Artificial Intelligence
AISs	Artificial Immune Systems
ANN	Artificial Neural Network
ARIMA	Auto-Regressive Integrated Moving Average
ARMA	Auto Regressive Moving Average
BESSs	Battery Energy Storage Systems
BPSO	Binary Particle Swarm Optimization
CAIDI	Customer Average Interruption Duration Index
CAIFI	Customer Average Interruption Frequency Index
COPT	Capacity Outage Probability Table
COV	Coefficient of Variation
DGs	Distributed Generators
EDLC	Expected Duration of Load Curtailments
EENS	Expected Energy Not Supplied
EFLC	Expected Frequency of Load Curtailments
ELCC	Effective Load Carrying Capability
ESA	Evolutionary Swarm Algorithm
FLD	Fisher Linear Discriminant
FOR	Forced Outage Rate
GAs	Genetic Algorithms
GES	Grid Energy Storage
GSAE	Generation System Adequacy Evaluation
HLs	Hierarchical Levels
ICDFs	Inverse Cumulative Density Functions
IEEE	Institute of Electrical and Electronics Engineers
KDE	Kernel Density Estimation
KNN	K Nearest Neighbor
LOEE	Loss of Energy Expectation
LOLE	Loss of Load Expectation
LOLF	Loss of Load Frequency
LOLP	Loss of Load Probability

Abbreviation	Description
LPs	Load Points
MCS	Monte Carlo Simulation
ML	Machine Learning
MRTS	Modified RTS
MTTF	Mean Time to Failure
MTTR	Mean Time to Repair
NSMCS	Non-Sequential Monte Carlo Simulation
OPF	Optimal Power Flow
PDF	Probability Density Function
PHSs	Pumped Hydro Storages
PIS	Population-based Intelligent Search
PLC	Probability of Load Curtailments
PV	Photovoltaic
RBTS	Roy Billinton Test System
RTS	Reliability Test System
RWS	Roulette Wheel Selection
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
SMCS	Sequential Monte Carlo Simulation
SVM	Support Vector Machine
WTGs	Wind Turbine Generators

CHAPTER 1

INTRODUCTION

The integration of renewables into the electricity grid has shown significant growth. Variations in fossil fuel prices, impacts of global warming, a price reduction of solar PV modules, and technological advancements have accelerated renewable integration into the power grid [2, 3]. Many governments encourage renewable power generation and consumption through various mandates and subsidies [4].

Wind and solar can be identified as two major renewable energy sources that can supply bulk power to the electricity grid [2]. The historical and future cumulative solar PV and wind power capacity additions published in [3] are shown in Figure 1.1. The renewable capacity additions by 2024, 2026 and 2028 are predicted considering the 2023 main case presented in [3]. The renewable capacity addition by 2030 is predicted considering "Net Zero Emissions by 2050" Scenario. Renewable power capacity additions tend to increase during this decade, with solar PV and wind accounting for a record 96% [3].

Wind and solar power generation are intermittent, and both diurnal and seasonal variations cause significant power supply variations, especially when a large proportion of renewable power is in the grid. Hence, wind and solar PV generation vigorously affect power system reliability.

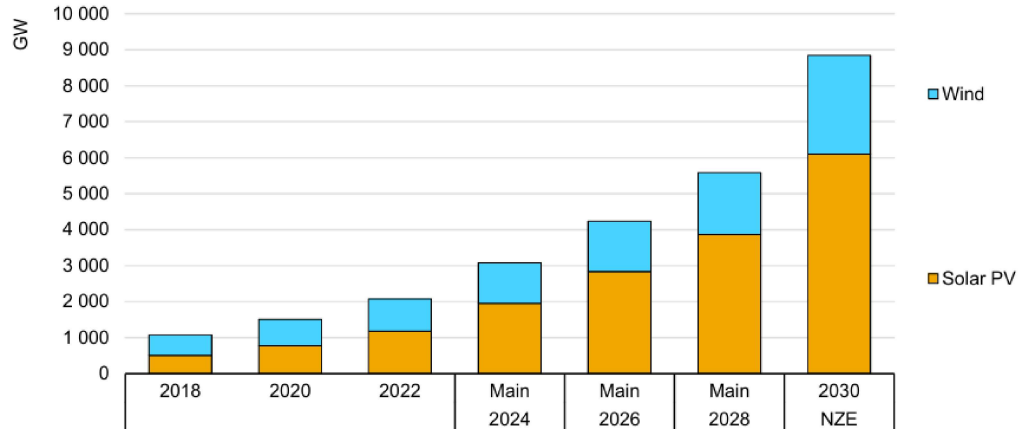


Fig. 1.1: Historical and future cumulative solar PV and wind power capacity additions

Power system reliability can be divided into two categories, i.e., system adequacy and security [5]. System adequacy studies investigate the power system's ability to satisfy consumer demand using existing system facilities. In contrast, security is a measure of the system's ability to respond to dynamic and transient disturbances arising in the system. Evaluation of the reliability of an extensive power system is computationally intractable. Considering the functional zones of a power system, i.e., generation,

transmission, and distribution, three Hierarchical Levels (HLs) are defined for power system reliability assessments. This is illustrated in Figure 1.2. HL1 studies consider generation system reliability evaluation in which the reliability indices are estimated considering the available generation and load demand [6]. Composite generation and transmission system reliability evaluation is carried out in HL2. The available generation capacity, transmission capacity and load demand are considered when estimating reliability indices in HL2 studies [7]. By definition, HL3 studies should consider generation, transmission and distribution subsystems and the load demand. However, the complexity of the model makes the study computationally intractable. Hence, HL3 studies are generally done for the distribution system only [8].

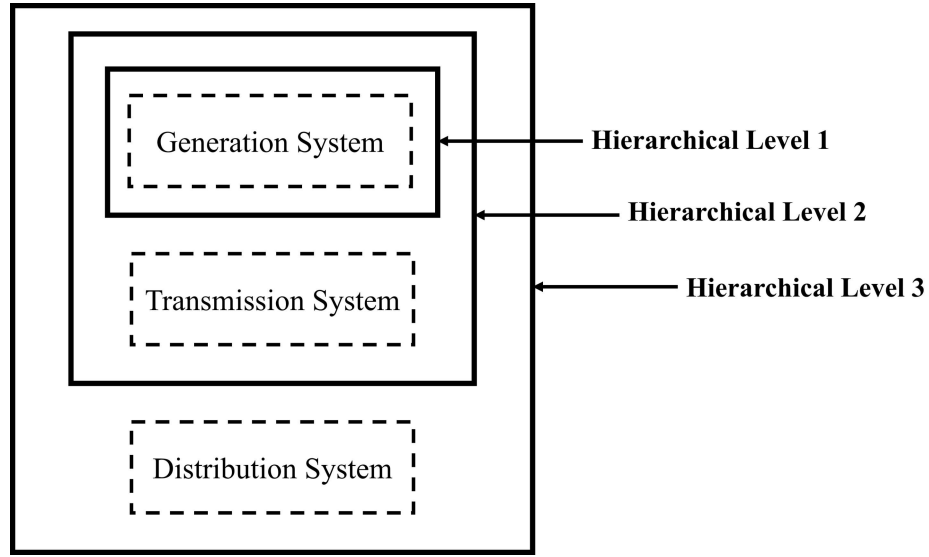


Fig. 1.2: Hierarchical levels of power system adequacy evaluation

Power system adequacy evaluation at each HL is used in generation, transmission, and distribution system planning while considering economic and other constraints. This study focuses on the adequacy assessment of a renewable power-rich power system considering all 3 HLs.

Renewable power modeling is a crucial phase in the adequacy evaluation of modern renewable-rich power systems. The intermittency and both diurnal and seasonal variations of renewable power generation should be accurately modeled into the adequacy evaluation algorithm. The prevailing probabilistic simulation methods and population-based intelligent search methods, such as MCS and genetic algorithms, can be used to evaluate the adequacy of renewable-rich power systems. However, these methods should be custom-tailored according to the requirements of each HL. The computational efficiency and accuracy of the adequacy evaluation algorithms and relevant models should be further increased for precise and convenient power system planning. The functions and procedures that require high computational power (e.g., optimal

power flow analysis) can be simplified or avoided using artificial intelligence techniques. Moreover, compatible renewable power models should be implemented into the adequacy evaluation frameworks considering the complexity of the power system and respective HL. The primary objective of this work is to develop computationally efficient novel adequacy evaluation algorithms.

Generation system adequacy can be evaluated using analytical, MCS, or population-based methods [9]. In the above methods, generators and the system load are modeled considering their probabilistic behavior. The number of system events increases exponentially with the increase of system components. Therefore, the number of events considered in the composite system adequacy evaluation is significantly larger than that considered in the generation system adequacy evaluation. Thus, Artificial Intelligence-based machine learning or optimization techniques are required in the composite system reliability evaluation for faster sampling and evaluation of the selected system events. Further, the distribution system adequacy evaluation requires time-consuming AC optimal power flow solutions [10]. Hence, it can be seen that the problem complexity at each HL varies significantly, and different approaches and methodologies are required to evaluate the adequacy of generation, composite, and distribution sub-systems.

This study proposes a novel framework based on MCS for evaluating the adequacy of renewable-rich power generation systems. Then, a novel population-based intelligent search method is proposed for evaluating the adequacy of power systems at all 3 HLs. Further, recommendations are given for reliability improvements at all three HLs of power system adequacy evaluation with increasing wind and solar integration.

1.1 Problem Statement

Renewable power integration into the power grid has shown significant growth nowadays. Technological advancements and various environmental policies encourage renewable power generation and consumption. In addition, many countries have implemented straight policies to integrate more and more renewable power into the electricity grid [4].

However, power system reliability may be reduced due to the rapid integration of intermittent renewable power such as wind and solar [11]. The increase in renewable energy generation has compelled system operators to modify their methods of ensuring operational reliability, including the procurement of reserves and their sources [12]. Electric Reliability Council of Texas anticipates reserve margins exceeding 30 percent between 2023 and 2026 [13]. Moreover, existing renewable power generation models used for reliability evaluation will not be accurate and efficient, especially when there is a large amount of renewable power in the system. The intermittency and diurnal and seasonal variations of renewable power generation should be deliberately modeled

to accurately evaluate the power system reliability. Especially solar ramp-rate limiting strategies should be implemented to alleviate the impact of PV power ramping on voltage fluctuations [14]. The sampling mechanisms of traditional MCS methods are not efficient for composite system and distribution system event evaluation due to the application of optimal power flow analysis [10]. Moreover, when a power system is expanded to satisfy consumer demand, the number of system events will be exponentially increased. Thus, system event sampling and evaluation may take significant time, especially when using conventional power system adequacy evaluation methods such as analytical and simulation methods. Power systems with a large proportion of renewables may take significant computational power to evaluate the reliability indices because renewables tend to increase the system event space [9]. Further, distribution system reliability significantly varies due to distributed solar generators. When the distribution system is stressed, the integration of distributed renewable generators will improve the distribution system's adequacy. Novel methods are required to quantify the aforementioned adequacy improvements considering the time-consuming AC optimal power flow analysis [10]. Moreover, renewable power generation models that are compatible with different adequacy evaluation methods should be carefully developed, considering the complexity of each HL.

This work proposes novel renewable power generation models representing intermittency and both diurnal and seasonal variations, which can be used to evaluate generation system adequacy. Proposed renewable power models are compatible with non-sequential MCS, which can be conveniently used for generation system adequacy evaluation. A novel reliability evaluation algorithm based on artificial intelligence optimization techniques is proposed to quantify composite system adequacy, as MCS requires significantly high computation time for HL2 adequacy evaluations. Further, the proposed adequacy evaluation algorithm is used for HL1 and HL3 adequacy evaluations with compatible renewable power models. Then, the impact of increasing renewables on the adequacy of generation, composite, and distribution systems is analyzed. The contribution of wind and solar generation to the power system adequacy is analyzed by evaluating the capacity credit of the respective renewable generation. The application of energy storage, such as pump storage plants and battery banks, to improve the power system adequacy is also investigated.

1.2 Thesis Contributions

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

Integration of non-conventional renewables such as wind and solar into the power system may affect the system's reliability, especially when the proportion of renewable

power in the system is large [11]. Therefore, with a significant level of renewable penetration, the intermittency and diurnal and seasonal variations of renewable power generation should be deliberately modeled to quantify the power system's reliability accurately. A novel method based on Kernel Density Estimation [15] is proposed to model intermittency and diurnal and seasonal variations of wind and solar power generation using historical renewable power generation data. KDE is used to find the probability densities of renewable power generation at different hours of the day and different seasons throughout the year. KDE is widely used in applications where the probability density function of a variable is unknown or poorly defined [16]. The proposed KDE-based renewable power models are used with non-sequential MCS to evaluate the generation system adequacy. Several case studies are conducted on the IEEE reliability test system [17] to analyze the impact of increasing renewables on the generation system adequacy. The results show that the generation system adequacy tends to decay exponentially with increased renewable integration. It is shown that the reliability values obtained using the proposed approach are very close to those provided by the time-consuming sequential simulations. The importance of modeling seasonal variations of wind and solar is also investigated.

1.2.2 Novel Evolutionary Swarm Algorithm for Evaluating the Adequacy of Generation, Composite and Distribution Systems

The generation and transmission capacities of many power systems worldwide are significantly increasing due to the escalating global electricity demand [18]. Therefore, the adequacy evaluation of composite power systems has become a computationally challenging and time-consuming task. Recently, population-based intelligent search methods such as Genetic Algorithms (GAs) and Binary Particle Swarm Optimization (BPSO) have been successfully employed to evaluate the adequacy of power generation systems [6]. In this study, I propose a novel Evolutionary Swarm Algorithm (ESA) for the adequacy evaluation of composite generation and transmission systems. The random search guiding mechanism of the ESA is based on the underlying philosophies of GAs and BPSO. The main objective of the ESA is to find out the most probable system failure events that significantly affect the adequacy of composite systems. The identified system failure events can be directly used to estimate the system adequacy indices. The proposed ESA-based framework is used to evaluate the adequacy of the IEEE RTS. The estimated annualized and annual adequacy indices such as Probability of Load Curtailments (PLC), Expected Duration of Load Curtailments (EDLC), Expected Energy Not Supplied (EENS), and Expected Frequency of Load Curtailments (EFLC) are compared with those obtained using Sequential Monte Carlo Simulation (SMCS), GA and BPSO. The results show that the accuracy, computational efficiency, convergence characteristics, and precision of the ESA out-

perform those of GA and BPSO. Moreover, compared to SMCS, the ESA can estimate the adequacy indices more efficiently and in a shorter time.

1.2.3 Adaptation of AC-Optimal Power Flow Analysis in Distribution System Adequacy Evaluation

The adequacy of power distribution systems is significantly affected by the rapid integration of renewable power generation, especially solar PV [19]. The impact of these renewable generators on the distribution system adequacy should be quantified in order to ensure an economical and reliable operation. However, an accurate estimation of distribution system reliability requires an AC Optimal Power Flow (OPF) analysis, which is a time-consuming optimization process when combined with the MCS. In this work, the ESA, combined with AC-OPF analysis, is used to evaluate the adequacy of power distribution systems. The ESA is used to search for the most probable system failure events to estimate the system adequacy indices by reducing the application of AC-OPF. The proposed ESA-based method is demonstrated to evaluate the adequacy of the modified Roy Bilinton Test System Bus 2 distribution system. The estimated adequacy indices are compared with those obtained using SMCS. The results show that the ESA can estimate the adequacy indices more efficiently and without compromising accuracy compared to SMCS. Further, the impact of integrating solar PV on the adequacy of power distribution systems is evaluated. Finally, the authors have proposed a way to improve the adequacy of distribution systems, maintaining feeder voltage levels that are intact with the regulations.

1.3 Thesis Overview

The overview of this thesis can be summarized as follows.

- Chapter 02: Presents Literature review. The prevailing power system adequacy evaluation methods of all three HLs are discussed. Limitations and possible improvements to the existing studies are discussed. Lastly, reliability test systems utilized in the study and respective load, conventional generation, and renewable generation data are presented.
- Chapter 03: Presents two preliminary works conducted using the prevailing reliability evaluation methods, especially MCS. Methods of energy storage modeling and capacity credit evaluation of renewables are investigated.
- Chapter 04: Presents Kernel Density Estimation Based Time-Dependent Approach for modeling renewables and load. The KDE models are incorporated with NSMCS to evaluate generation system adequacy.

- Chapter 05: Presents a novel evolutionary swarm algorithm for evaluating the adequacy of power systems.
- Chapter 06: Presents an adequacy evaluation framework to evaluate the adequacy of power distribution systems. AC optimal power flow is used to assess the system events.
- Chapter 07: Concludes the thesis.

CHAPTER 2

LITERATURE REVIEW

2.1 Power System Adequacy Evaluation

Power system reliability evaluation is an active research field in which domain knowledge is updated frequently. This chapter presents the literature review, which is organized as follows: Firstly, the generation system adequacy evaluation methods are presented. Further, prevailing renewable power generation models are analyzed, and their contributions and limitations are identified. Composite generation and transmission reliability evaluation methods are then explored, and the drawbacks of the existing methods are identified. Finally, distribution system reliability evaluation methods are reviewed. Further, at the end of each section, the limitations of previous research are identified, and the proposed solutions are presented.

The following reliability indices are commonly used to quantify the adequacy of generation systems and composite systems.

- **Loss of Load Probability (LOLP)** : LOLP is a measure of the probability that the system demand exceeds the generating capacity during a given period. The LOLP can be calculated by dividing the total number of failure events by the total number of system events.
- **Loss of Load Expectation (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. LOLE in hours per year can be calculated by multiplying LOLP by 8760.
- **Loss of Energy Expectation (LOEE)** : LOEE is the expected unsupplied energy due to generating inadequacy. Event-wise, unsupplied energy can be calculated in each failure event, and then by accumulating each unsupplied energy value, the overall LOEE can be obtained.
- **Loss of Load Frequency (LOLF)** : LOLF is the number of loss of load occurrences per year.

The following reliability indices are commonly used to quantify the adequacy of the distribution system.

- **System Average Interruption Duration Index (SAIDI)** : SAIDI is a system index of the average duration of interruption in the power supply indicated in minutes per customer.

- System Average Interruption Frequency Index (SAIFI) : SAIFI is a system index of the average frequency of interruptions in power supply.
- Customer Average Interruption Duration Index (CAIDI) : Once an outage occurs, the average time to restore service is found from the CAIDI.
- Customer Average Interruption Frequency Index (CAIFI) : CAIFI measures the average number of interruptions per customer affected per year.
- Average Energy Not Supplied (AENS) : AENS is the annual average energy lost in the system per customer.

2.1.1 Generation System Adequacy Evaluation

Generation System Adequacy Evaluation (GSAE) does not consider transmission constraints. Thus, the available system capacity and the system load are the main subsystems considered in GSAE. Several analytical and MCS methods are used in the GSAE.

Analytical methods use mathematical modeling of the power system and provide direct analytical solutions. Some of the commonly used analytical methods in GSAE are the state-space method using the Markov process, the network reduction method, the conditional probability method, and the cut set or tie set method [9]. The behavior of the power system can be obtained from the random behavior of each component of the system. Therefore, using the state transition diagram of each component in the system, the system state transition diagram can be obtained [9]. Figure 2.1 illustrates the state transition diagram of a two-state component. Usually, generators are modeled as two-state components, and the system load is modeled as multi-state. The system state transition diagram illustrates all possible events that the system can acquire. In addition, it shows the transition rates between events. When the system events are known, each event can be classified as a success or failure event. For example, if the total generation is less than the system demand, that event is marked as a failure event; otherwise, the event is marked as a success event. The system's probability of failure can be obtained by summing the probabilities of all failure events. If event probabilities are known, frequency indices can be obtained [9]. However, this method becomes more complex, especially when the system (i.e., the event space) is large.

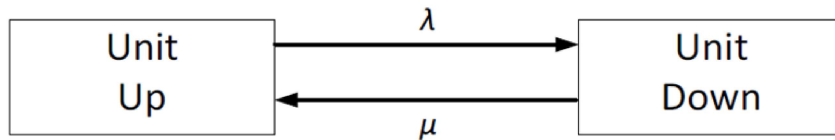


Fig. 2.1: State transition diagram of a two-state component

The network reduction method can be used for GSAE, where the interactions among system components can be easily captured by a block diagram called reliability block diagram [9]. A reliability block diagram illustrates the occurrence of system failures due to failures of the component. A component can be described as either working or failing. If a component failure causes the system to fail, then that component is connected in series in the reliability block diagram. If the failure of a set of components causes the system to fail, those components are connected in parallel in the reliability block diagram [9].

In the analytical GSAE methods, wind power generation modeling is typically done using multi-state Markov models [1, 20–24]. The wind power output of a wind generator is mainly determined by the respective wind speed. Figure 2.2 shows the power output curve of a typical wind turbine.

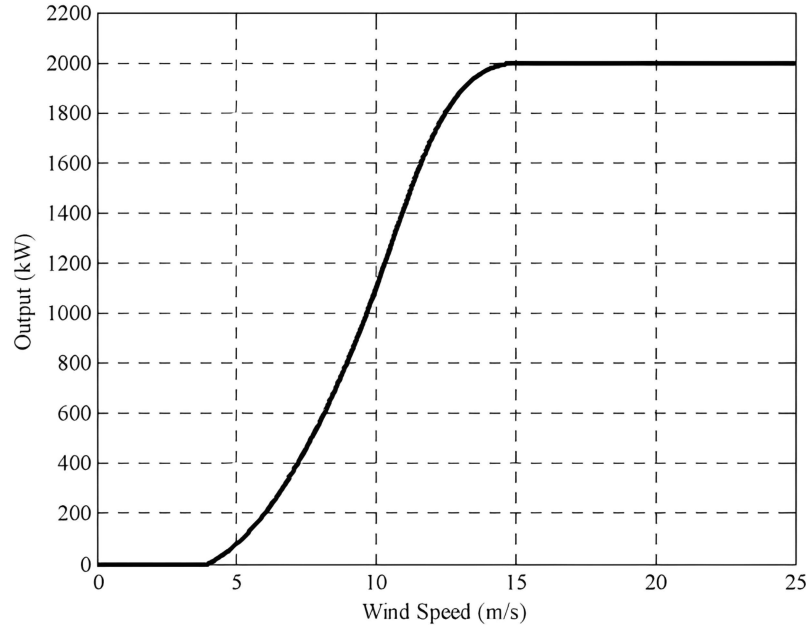


Fig. 2.2: The power output of a typical wind turbine

The hourly wind speed can be obtained from a historical data set, or it can be simulated using an Auto Regressive Moving Average (ARMA) model. Then, the Capacity Outage Probability Table (COPT) of a WTG unit can be created by applying the hourly wind speed to the power curve as described below [22].

- Define the output states for a wind turbine generator unit as segments of the rated power.
- Determine the total number of times that the wind speed results in power output falling within one of the output states.

- Divide the total number of occurrences for each output state by the total number of data points to estimate the probability of each state.

Figure 2.3 illustrates a multi-state wind power generation model, and the respective COPT of the wind generator is shown in Table 2.1.

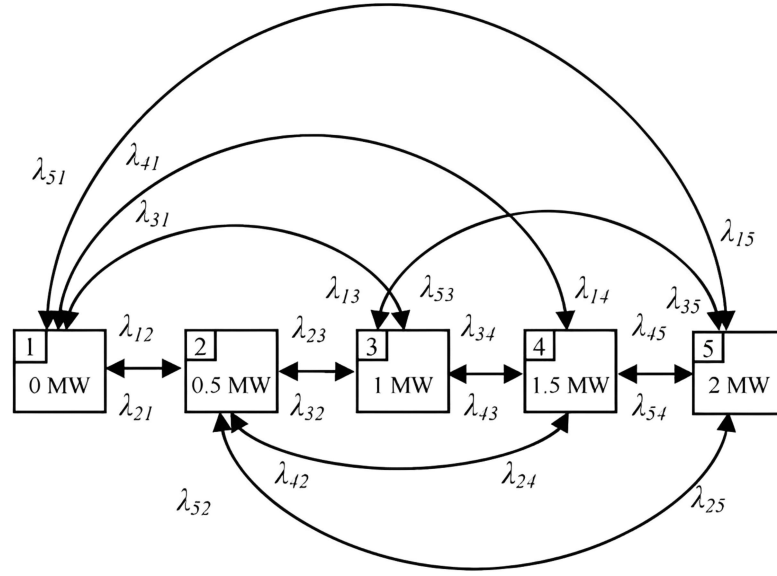


Fig. 2.3: A multi-state wind power generation model [1]

TABLE 2.1: COPT OF THE WIND GENERATOR MODEL ILLUSTRATED IN FIGURE 2.3

Capacity (MW)	Probability	Up Transition Rate (occ/hr)	Down Transition Rate (occ/hr)	Frequency (occ/hr)
0	0.47	0.066	0	0.031
0.5	0.058	0.2677	0.3051	0.0332
1	0.0463	0.3202	0.3473	0.0339
1.5	0.0491	0.3767	0.3326	0.0348
2	0.3766	0	0.0961	0.0362

However, when the generation system has a large number of wind turbines, the complexity of the system state transition model will be increased. Therefore, the reliability evaluation time will be increased. Moreover, both diurnal and seasonal variations of wind power generation cannot be modeled in the multi-state models.

The above-mentioned wind power generation models can also be used with the NSMCS method [1, 21, 24]. MCS is a popular probabilistic method of assessing system reliability indices. There are two major types of Monte Carlo methods, i.e., Sequential Monte Carlo Simulation and Non-Sequential Monte Carlo Simulation. SMCS

generates chronological system events 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 [25]. In [16, 26–30], SMCS is used for the adequacy evaluation of generating systems.

In SMCS, the up and down times of the conventional generators are determined by their mean time to failure and mean time to repair values. The load is modeled using a chronological load curve. Chronological wind power simulation models are combined with SMCS to evaluate the adequacy of wind-integrated generating systems in [16, 28, 29]. Historical wind speed or wind power generation data are used to implement ARMA time-series models for simulating chronological wind speed or wind power generation for a specific time period, e.g., one-year [16, 28–30]. However, the ARMA model integrated SMCS requires a significant amount of simulation time [28]. Moreover, ARMA models presented in [16, 28, 29] lack seasonality modeling. The seasonal ARMA models require huge simulation time because the seasonal trend repeats once every 8760 hours (i.e., 8760-time units). Auto-Regressive Integrated Moving Average (ARIMA) -based model proposed in [30] represents seasonal variations, but diurnal variations are neglected.

In NSMCS, the reliability indices are iteratively computed through stochastic sampling of the power system events until the selected indices are converged within an acceptable variance coefficient [25]. The conventional generators are modeled using two or three-state Markov models. The system load is modeled using either a multi-state Markov model, the annual load curve, or the load duration curve. Figure 2.4 shows the flow chart of a conventional generation modeling algorithm in NSMCS, and Figure 2.5 shows the flow chart of an NSMCS algorithm that can be used for GSAE of a power system with conventional generators.

In [31], wind power, Photovoltaic (PV) generation, and electricity demand are modeled as time-dependent clusters in NSMCS. Renewable power and load data are clustered according to the earth's seasons (spring, summer, etc.). It is not effective and efficient because, for example, wind power generation may show only two distinctive wind seasons (high and low) throughout the year. In addition, these renewable power models in [31] represent diurnal correlations only and do not represent seasonal correlations of renewable power in the NSMCS algorithm. Moreover, the Fuzzy C-means clustering method splits renewable power output into a fixed number of steps (8 power levels). It does not represent the actual renewable power generation because intermediate power values between the steps are not considered.

Variance reduction methods such as Latin Hypercube sampling [32] and importance sampling [33–36] and can be used to reduce the convergence time of MCSs. Population-based methods can be used for evaluating the generating system adequacy [6]. Population-based Intelligent Search (PIS) is used to find a set of probable failure events that significantly contribute to the system adequacy indices. PIS is based

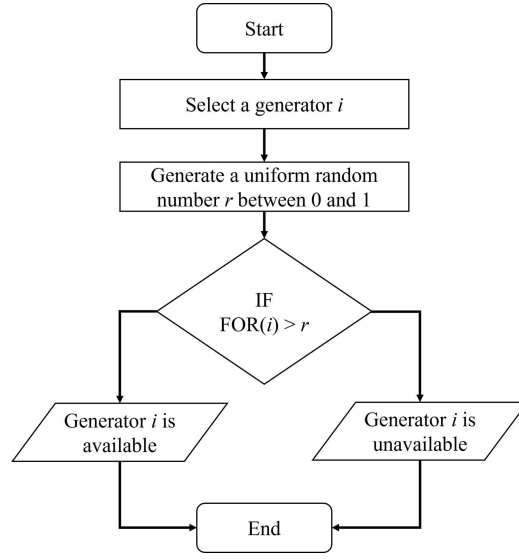


Fig. 2.4: Flowchart of a conventional power generation model

on the guided stochastic search inspired by biological or social systems. Genetic algorithms [37, 38], particle swarm optimization [39, 40], ant colony optimization, and artificial immune systems are some population-based intelligent search methods. A novel optimization technique called the disparity evolution genetic algorithm is proposed for assessing the adequacy of power generation systems in [41]. However, there are several limitations to PIS methods. Revisiting previously considered events should be avoided by saving the visited failure events in a data structure. When there is a large number of failure events, memory management issues may arise. In addition, the stopping criteria are somewhat less mathematically strictly defined as compared with MCS, and in some sense, they are more subjective and thus may demand considerable tuning effort for each specific task.

2.1.1.1 Capacity Credit Evaluation of Renewables

Capacity value can be defined as the amount of additional load that can be served due to the addition of a generator while maintaining the existing level of reliability [42]. When the wind and solar penetration is high, the capacity value of each renewable generator is important for power system planning.

In estimating capacity values of generation units, the power system reliability is assessed using indices such as LOLP and LOLE [31]. LOLP is the probability that the system demand exceeds the generating capacity during a given period. LOLE is the expected number of days (or hours) in a specified period in which the daily peak load exceeds the available generating capacity [43].

Several studies have been conducted in the literature on estimating the capacity

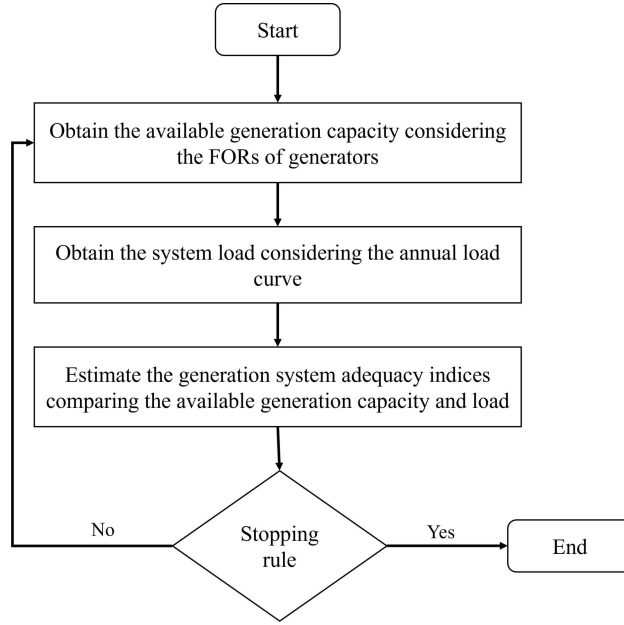


Fig. 2.5: Flowchart of an NSMCS algorithm for GSAE of a power system with conventional generators

value of wind and solar generation. In [44], authors have proposed a chronological approach based on the computation of the capacity factor of wind energy conversion systems over a relevant period, such as peak or off-peak hours. Detailed surveys of different methods of assessing renewable power generation capacity credit can be found in [44–46]. In [47], the capacity credit of a solar PV facility integrated into the Mauritian power system is explored. The capacity credit of a 15 MW solar PV farm is evaluated using an analytical method based on the COPT. In [43], particle swarm optimization is used to obtain capacity credit by finding an optimal combination of traditional generators that could maintain system reliability after integrating solar PV. In [48], authors have followed a probabilistic approach to find the capacity value of wind power generation. In this study, simulations are used to compute complex distribution functions such as residual demand distribution and the power distribution of the resource. A methodology for quantitative evaluation of the capacity credit of solar power plants is proposed in [49]. An analytical method to calculate the capacity credit of PV systems is proposed in [50] by considering both the effect of the input uncertainty and the system components' availability. The intermittency of the input source and the availability of the system components are modeled separately and then convolved to construct a single COPT. A capacity credit calculation method for wind and solar PV bundled power is proposed in [51]. Several case studies evaluating the capacity credit of renewable power in different regions are presented in [52–54]. In addition, detailed reviews of capacity credit evaluation of solar power can be found in [55, 56].

2.1.1.2 Energy Storage Modeling

Grid Energy Storage (GES) has become an essential requirement of modern power systems, especially when there is a significant level of renewable penetration. The total power generation of renewable rich power systems tends to fluctuate frequently due to the intermittent nature and both diurnal and seasonal variations of renewables such as wind and solar. Hence, GESs such as Pumped Hydro Storages (PHSs) or Battery Energy Storage Systems (BESSs) can help to maintain the electricity supply and demand balance without curtailing the system load. In addition, greenhouse gas emissions can be reduced by replacing peak thermal generators with GESs, which indirectly maintains stable electricity prices. Thermal power generators can be operated more efficiently at constant production levels with a GES. Moreover, integrating GESs into the load centers of the power system reduces expensive transmission capacity upgrades. PHSs account for 97% of total energy storages worldwide due to comparatively low operational and maintenance costs [57]. Moreover, PHSs have high dispatchability and are the most cost-effective form of mass-energy storage. There is a significant number of potentially feasible PHS sites located in many countries [57]. Hence, PHSs will be ubiquitous in future power systems. In [57], authors have modeled a 100% renewable power system for Australia, consisting of wind, solar PV, biomass, hydro, and PHSs.

However, PHSs require significant capital expenditure. In the initial feasibility studies, the costs and benefits of the PHS should be accurately evaluated. Therefore, it is important to analyze the reliability improvements that can be obtained by a PHS to identify its contributions and limitations. Several studies can be found in the literature in which the impact of GESs on power system reliability is investigated.

In [58], authors have investigated the adequacy of power-generating systems incorporating wind, solar PV, and BESSs. Generating system adequacy indices are obtained for different levels of renewable penetration and different GES capacities. In [59], the contribution of nightly rechargeable GESs to generation capacity adequacy is explored. Authors have proposed an optimal strategy for single storage in minimizing energy not supplied and compared the contributions of single and multiple energy storages. Moreover, in [59], the benefits of real-time and predetermined storage dispatching are analyzed. In [60, 61], the adequacy of generation systems with Wind Turbine Generators (WTGs) and GESs is evaluated. The adequacy of generation systems is analyzed for different WTG and GES capacities. The capacity credit of combined WTGs and BESSs is derived using reliability curves in [61]. The impact of combined WTGs and GESs on composite systems adequacy is explored in [62, 63]. The adequacy evaluation of a remote microgrid consisting of diesel generators, WTGs, solar PVs, and energy storages is conducted in [64]. Similarly, reliability evaluation of a generating system that consists of WTGs, diesel generators, and energy storage is conducted in

[65]. Authors have analyzed annual fuel savings, and the number of annual average diesel generator starts w.r.t energy storage capacity. In [66], the reliability of a power generation system consisting of conventional generators, solar PV, and a BESS is evaluated. An integrated solar PV and BESS reliability is assessed in [67]. The addition of the BESS significantly improves the system's reliability. The impact of the utilization of energy storage in the renewable integrated local distribution systems on the bulk power system reliability is assessed in [68].

2.1.2 Composite System Adequacy Evaluation

The global electricity demand is expected to grow by 2.4% per year up to 2040 [18]. Therefore, composite power systems must gradually grow in both size and supply capability to satisfy the continuously increasing consumer demand. Hence, the adequacy assessment of future power systems will become a more complicated and time-consuming task due to the increased number of system components such as generators, transformers, and transmission lines.

Analytical and simulation-based probabilistic methods are widely used in power system adequacy evaluation in order to model the stochastic nature of power system components and estimate more realistic adequacy indices. The outage probability of each power system component can be used to determine the status of the component, i.e., unit up or unit down. Then, the system event space can be generated by convolving the status of each power system component. The system events associated with zero load curtailment are success events, whereas those with load curtailment are failure events. The derived system event space can be analyzed to quantify the system adequacy using different adequacy indices such as PLC, EDLC, EENS, and EFLC.

However, the event space of a composite generation and transmission system is significantly large due to the combined number of generation and transmission components. For e.g., if a power system has x number of components, then the event space size will be 2^x . Therefore, the larger the power system, the higher the complexity of the system adequacy evaluation. On the other hand, composite system events are evaluated by the OPF analysis. This optimization problem requires a significant amount of computational time, especially when there is a large number of system events. Thus, more effective and efficient methods are needed to assess the system's adequacy more accurately and conveniently.

Monte Carlo Simulation (MCS) is widely used for evaluating the adequacy of composite power systems due to the increased computational performance and storage of modern computers [25]. In Sequential Monte Carlo Simulation (SMCS), the system events are simulated and analyzed chronologically [7, 25, 69–72]. On the other hand, in Non-Sequential Monte Carlo Simulation (NSMCS), the system events are randomly sampled from the system event space [25, 73–76]. Despite the popularity, MCS meth-

ods require a significant amount of computational time especially when the system is large and highly reliable [69]. The OPF analysis is the main time-consuming task of composite system adequacy evaluation. Several methods are proposed in the literature to reduce the application of OPF analysis in the adequacy evaluation of composite systems [6, 40, 71–87].

One such method is reducing the large event space using state pruning techniques. Then, the adequacy evaluation is carried out in a much smaller event space. This will reduce the convergence time of the adequacy evaluation algorithm. The state-space partitioning method proposed in [77] combines the advantages of the state enumeration method and the MCS. In [78], authors have proposed a method of computing the reliability indices of a composite system by performing MCS selectively on those regions of the event space where the loss of load events is more likely to occur. These regions are isolated by performing state-space decomposition to remove coherent, acceptable subspaces. However, with a large proportion of renewable power in the system, the effectiveness of the state pruning method will be reduced.

The computational cost of optimal power flow analysis can be reduced using several methods [88, 89]. In [88], a sufficient and necessary condition for a line flow constraint to be redundant is established in the form of a linear programming problem based on the concept of a steady-state security region. Then, two redundancy elimination methods are proposed, i.e., a conservative one based on a heuristic and a radical one based on an analytical condition. In [89], a neural network-based approach is used for the problem of real power transfer capability calculations.

The convergence time of MCS methods can be reduced by incorporating variance reduction techniques such as importance sampling [71, 73, 74, 76, 90, 91] and Latin Hypercube sampling [72, 75]. Variance reduction methods increase the precision of the estimates of the reliability indices while reducing the number of events that need to be evaluated until the convergence is reached.

In [79, 80], MCS is conducted in parallel and distributed processing environments instead of a single processor-based environment. However, the total computational cost remains the same because the number of total system events evaluated has not changed.

Artificial Intelligence (AI) based learning and optimization techniques are recently employed for the adequacy evaluation of power systems. The Machine Learning (ML) classification methods such as K Nearest Neighbor (KNN) [81], Artificial Neural Network (ANN) [82, 92], Support Vector Machine (SVM) [83] and Fisher Linear Discriminant (FLD) [84] can be used to classify the system events either as success or failure. The available or unavailable bus generation, generation reserve capacity, and unavailable transmission capacity are used as the input variables to the classification models. These methods can be incorporated into the MCS, and only the events that are classified as system failures are evaluated instead of applying the OPF analysis

to all the sampled events. This significantly reduces the computational cost of MCS [81–84]. However, training the aforementioned ML models is a time-consuming task. Therefore, with the training stage, actual reliability evaluation times should be larger than the values stated in [81–84].

PIS methods such as GAs, Ant Colony Optimization (ACO), Artificial Immune Systems (AISs), and Binary Particle Swarm Optimization (BPSO) are AI-based optimization methods that are inspired by biological or social systems. These PIS methods can be used to find either a set of probable failure or success events from the system event space. In [6, 40, 85–87, 93–95], the ability of the population-based guided random search is used to identify the most probable system success or failure events (e.g., *the events with probability* $> 1e^{-10}$) instead of attempting to find a single optimal solution. In [85], GAs, ACO, AISs, and BPSO are used for pruning the system event space. Firstly, the PIS methods are used to search for the most probable system success events. Then, the MCS is applied to the pruned system event space until the simulation converges. After that, the previously found system success events are reintroduced in the adequacy indices calculation. In [86], a differential evolution algorithm is used to prune the system event space. Then, the pseudo-sequential Monte Carlo simulation is used to obtain the system reliability indices. In [87], a combination of MCS, state-space classification, and BPSO is used to estimate the adequacy of composite systems. However, in the aforementioned hybrid PIS-MCS methods, the MCS phase tends to reduce the overall sampling efficiency of the algorithm [86]. On the other hand, in [6, 40, 93, 94], PIS methods such as GAs, BPSO, ACO, and AISs are used to find out the most probable system failure events. The adequacy indices can be directly derived from the recorded system failure events.

Even though these methods are well established, significant changes to the search mechanism may improve their overall computational efficiency. Moreover, PIS methods do not need to be trained as ML methods [6, 40].

2.1.3 Distribution System Adequacy Evaluation

The Integration of renewable power sources into power distribution systems has become a continuously increasing trend [18]. Solar power integration into power distribution systems has increased incrementally over the last decade [2]. Integrating solar power generation causes harmonic injections into the system and system voltage deviations [96]. Hence, distributed solar generation affects the stability and adequacy of power distribution systems.

The integration of variable power sources, such as solar power, increases the complexity of distribution system adequacy evaluation because of the intraday variation of solar generation. Moreover, AC-OPF analysis should be incorporated into the adequacy evaluation framework to consider the system voltage variations due to the solar

generators. In power system adequacy evaluation, AC-OPF is a time-consuming non-linear optimization problem.

In distribution system adequacy evaluation, the system's ability to cater to consumer demand using the existing network is quantified. This is done by estimating the distribution system reliability indices such as EENS, SAIDI, and SAIFI. In the literature, several analytical, simulation, and machine learning methods are proposed for estimating the aforementioned reliability indices.

In [97], various methods of renewable modeling and distribution system reliability evaluation are reviewed. Most of the analytical and simulation methods ignore the system voltage variations, and hence, the power flow analysis is not conducted. Nonetheless, it is important to conduct a power flow analysis to obtain the contribution of Distributed Generators (DGs) to the adequacy of power distribution systems. Analytical methods are proposed in [8, 98, 99] for evaluating the adequacy of power distribution systems without considering renewable power integration. In [100], an analytical reliability evaluation approach is proposed considering dispatchable and non-dispatchable renewable DG units. In [101], an analytical method is proposed for evaluating the distribution system adequacy considering the AC-OPF analysis. The main objective of the optimization is the minimization of SAIDI. The annual load variation is not considered, and the reliability is evaluated for three load levels. Further, the annual renewable power variation is not modeled. This significantly reduces the computational time, but the realistic reliability of the distribution system cannot be obtained.

MCS is used to evaluate the reliability of power distribution systems in [102–110]. In [108], a combination of analytical techniques and MCS is proposed to evaluate the reliability indices in meshed networks. The problem is formulated as an optimization problem and solved by the gradient projection method to minimize interruption costs. Wind and solar DGs are integrated into the test systems in [103, 104] that are evaluated using MCS. In [103], an algorithm to correctly determine the amount of capacity that may be transferred to other feeders is presented, considering the presence of DGs. However, the chronological load variation is not considered. On the other hand, the annual load variation is considered in [104], which uses the combination of cut sets and MCS for reliability evaluation. In [111], an MCS algorithm is proposed considering solar integration without considering the Power flow analysis. In [112], a systematic approach is proposed to assess distribution system reliability considering intentional islanding. However, renewables are not integrated into the test system. In [107], the reliability of distribution systems with photovoltaic generation is derived using a power flow simulator and a parallel MCS approach. However, the power flow analysis is not optimized to minimize the reliability indices such as SAIDI or EENS.

In [113, 114], distribution system reliability indices are estimated using ANNs, and the ANNs are fine-tuned using AI optimization methods such as GA [113] and PSO [114].

Renewable power generation modeling criteria in power system reliability studies vary with the relevant HL. More accurate and complex renewable power modeling methods can be applied to HL I studies in which the generation system adequacy is evaluated [29]. This is due to the straightforward evaluation of generation system events [29]. Less complex and computationally efficient renewable power models should be used in HL II studies that evaluate composite system reliability. The DC OPF analysis that is used in HL II studies requires a significant amount of computational power [82]. On the other hand, distribution system adequacy evaluation, i.e., HL III studies, requires AC OPF analysis when a large number of renewables are integrated. When renewables are integrated into the power distribution systems, feeder voltage levels should be considered while evaluating the system's reliability. Hence, DC-OPF [115] analysis cannot be used in this context as used in composite power system adequacy evaluation [6, 40, 71–87]. The computational cost of AC OPF analysis is significantly greater than that of DC OPF analysis due to the nonlinear constraints. Thus, more simple and computationally efficient renewable power models should be utilized in HL III studies. In this work, historical solar power generation data is used to model the daily solar power generation while preserving the intraday relationship between renewable power generation and the load.

In this work, AC-OPF analysis [115] is utilized to evaluate the distribution system events. The computational cost of AC-OPF is significantly higher than that of DC-OPF due to the nonlinearity of the optimization problem, increased number of system variables, and relevant constraints such as node voltage, power angle, reactive power generation, and reactive power curtailment. Therefore, using analytical methods or MCS with AC-OPF is computationally unfeasible. Especially in MCS, both system success events and failure events are evaluated to estimate the system adequacy indices using statistical inference, and this considerably extends the duration of computation. When considering the time-varying nature of solar generation and the load, analytical methods become too complex to incorporate the AC-OPF analysis. It has been noted that PIS methods such as GAs and PSO algorithms are not utilized for estimating the reliability of power distribution systems even though the aforementioned algorithms have shown their applicability and performance in both generation and composite system reliability evaluation [6, 40].

2.2 Summary of the Literature Review

2.2.1 Generation System Adequacy Evaluation

Prevailing studies show that the computational cost of Generation system adequacy evaluation is not as significant as that of composite adequacy evaluation due to the lack of application of optimal power flow analysis [6, 9]. However, renewable power

modeling affects the computational efficiency of the adequacy evaluation algorithm. The following limitations in generation system adequacy studies are identified in the existing literature.

- The reliability improvement a grid energy storage can obtain is not quantified.
- Previously proposed chronological and non-chronological renewable power generation models lack either diurnal, seasonal, or both variations [16, 28–31].
- 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 generation.

This work addresses the limitations mentioned above. A pumped hydro model integrated SMCS is proposed for generation system adequacy evaluation. Variation in generation system reliability is observed for different PHS capacities and storage levels. Then, the benefits of integrating GES into power-generating systems are analyzed considering the diurnal and seasonal variations of renewable generation. Generating system adequacy indices are calculated using SMCS, allowing chronological simulation of renewable generation and PHSs. Moreover, the reliability improvement performance of PHSs is compared with that of conventional thermal generators.

Then, a novel approach for modeling renewable power generation is proposed using KDE to model both seasonal and diurnal variations of renewable power generation, incorporating its intermittent nature. KDE determines the probability densities of renewable power generation at different hours of the day and 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 the climate patterns of the region. The system load is also modeled as time-dependent clusters. The KDE is used to identify the probability densities of the system load at different hours of the day and 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.

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

2.2.2 Composite System Adequacy Evaluation

The literature shows that AI machine learning and optimization methods can significantly reduce the computational cost of composite system adequacy evaluation methods [6, 40, 81–83, 85–87, 92–95]. Hence, this work places more emphasis on identifying the limitations of AI machine learning and optimization-based adequacy evaluation algorithms.

- AI classification algorithms that are used to evaluate the system events should be trained, and a significant amount of time and computational effort will be required to obtain the training data. Moreover, the classification models should be re-trained when the system components, such as system load and generators, are changed. This limits the applicability of the algorithm in power system adequacy evaluation [81–83, 92].
- When considering system event sampling, there are several limitations native to the application of two widely used PIS methods (i.e., GAs and BPSO) in power system adequacy evaluation, leading to a low sampling efficiency. The failure system events are not randomly distributed in the event space, i.e., most of the system failure events may have common component failures (e.g., in most of the system failure events, the largest generator of the system may be at the downstate). When a new population is being generated, the offspring generation should have these fit qualities of the parents. In GAs, the crossover operator does not maintain this genealogical link between parent and offspring generations. On the other hand, the ability to search in new areas of the system event space is limited in BPSO due to the velocity limitations of the particles [6, 40, 85–87, 94, 95].

This study extends the work presented in the literature in which PIS methods are directly used for generation system adequacy evaluation without incorporating the MCS. This work investigates the applicability of PIS without MCS to evaluate the adequacy of composite power systems where transmission and generation are considered together. A novel PIS guiding mechanism called the ESA is proposed for this application by combining the useful features of GAs and BPSO while eliminating their limitations. The proposed PIS guiding mechanism consists of two population guiding operators: selection and dynamic mutation. The selection operator is inherited

from the GAs, and the dynamic mutation operator is derived by using the features of swarm intelligence. The dynamic mutation operator helps to deliberately search failure events in the system event space using the most probable failure events that are already found. Instead of randomly searching system failure events, the ESA attempts to search the most probable system failure events that significantly affect the system adequacy indices. This is done by eliminating the least probable system events, as in GAs ("survival of the fittest"), and following the most probable failure events, as in BPSO ("following the leader"). The adequacy studies are conducted on the IEEE RTS using the proposed ESA. The ESA-based composite system adequacy evaluation framework is validated using the reference values obtained from the literature. Then, the computational efficiency, sampling efficiency, and precision of the proposed ESA are compared with those of GAs and BPSO. Moreover, the correlation between computational time and different sampling mechanisms (MCS and PIS) is conceptually and numerically compared.

2.2.3 Distribution System Adequacy Evaluation

This thesis addresses three main limitations in existing distribution system reliability evaluation studies. Firstly, a significant portion of the distribution system reliability evaluation methods does not estimate the annual adequacy indices, which is essential to get a comprehensive idea of the system's reliability [98, 101, 103, 104, 116]. In the aforementioned methods, the system load is modeled as a fixed load, e.g., average load or peak load, when estimating the adequacy indices. Secondly, many studies do not conduct the OPF analysis to identify the system load curtailments and hence, voltage violations are neglected [99, 100, 102, 107, 111–114, 116]. Due to this limitation, further analysis of renewable integrated distribution system adequacy is not viable. Hence, the reliability improvement of distribution systems with renewable DGs has not been studied in great depth. Thirdly, the literature reveals the improved performance of PIS methods in generation and composite system adequacy evaluations, but they are not yet applied to distribution system reliability evaluations. This work builds upon the proposed work on composite system reliability evaluation and extends it to distribution system reliability evaluation with a focus on addressing the above-mentioned limitations. The main contributions of this section can be stated as follows.

1. The chronological variation of renewable (solar) power generation and system load is considered in this work. Hence, annual reliability indices can be estimated.
2. This paper utilizes the AC-OPF to identify the load curtailment at each load point of the system. Thus, node voltage levels will be taken into account. This allows further investigations on distribution system adequacy. As a result, this work

investigates the effectiveness of using transformer tap changing methodology for enhancing distribution system adequacy.

3. This work applies a novel PIS method called ESA to capture the distribution system failure events and evaluate the system's reliability more efficiently.

2.3 Reliability Evaluation Test Systems and Relevant Data

2.3.1 Reliability Evaluation Test Systems

In this study, different reliability test systems are used to evaluate the adequacy of generation, composite, and distribution systems. The IEEE reliability test system and Roy Billinton Test system are widely used systems in the literature. They provide a common test system that could be used to compare the results obtained by different methods. In addition, the Sri Lankan generation system is used in different case studies. Wind and solar power generation data from Belgium and Sri Lanka are used to modify the aforementioned test systems.

2.3.1.1 IEEE Reliability Test System

IEEE RTS was developed by the Subcommittee on the Application of Probability Methods in the IEEE Power Engineering Society [17]. IEEE RTS consists of both generation and transmission systems.

IEEE RTS consists of 32 generation units with capacities ranging from 12MW to 400MW. This system has a total power output of 3405MW, and the peak load of the system is 2850MW. The annual hourly chronological load curve shows diurnal and seasonal variations of the system demand as illustrated in Figure 2.6. The transmission subsystem consists of 24 bus locations connected by 38 lines and transformers. Figure 2.7 shows the IEEE composite generation and transmission RTS. Further, Tables 2.2 and 2.3 tabulate the generation unit capacities and load distribution among the buses. The forced outage rates of generators, transmission lines, and transformers can be found in [17].

2.3.1.2 Roy Billinton Test System

The Roy Billinton Test System (RBTS) [117] consists of 11 generators, nine transmission lines, and six buses. The peak load of the system is 185 MW, and the total generation capacity is 240 MW. The normalized annual load curve is the same as that given in IEEE RTS. Figure 2.8 illustrates the RBTS.

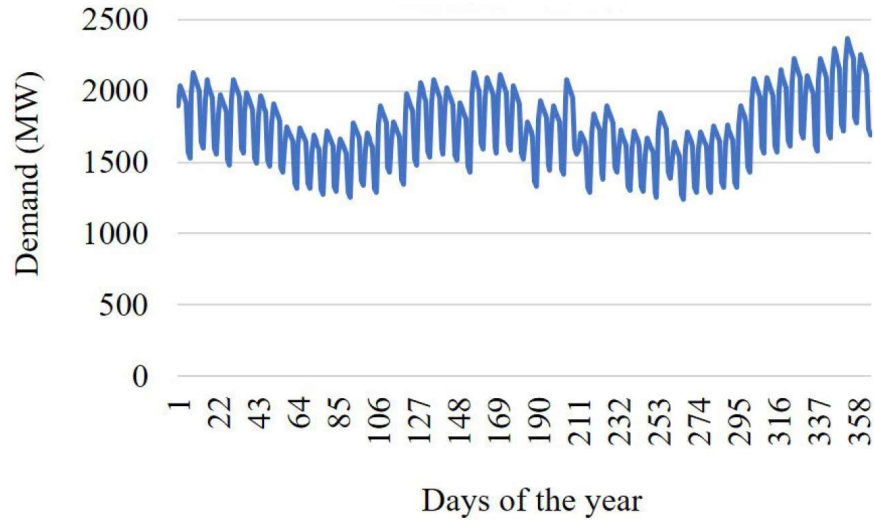


Fig. 2.6: IEEE RTS Load Curve

TABLE 2.2: IEEE RTS GENERATING UNIT LOCATIONS WITH RESPECTIVE CAPACITY (MW)

Bus	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6
1	20	20	76	76	-	-
2	20	20	76	76	-	-
7	100	100	100	-	-	-
13	197	197	197	-	-	-
15	12	12	12	12	12	155
16	155	-	-	-	-	-
18	400	-	-	-	-	-
21	400	-	-	-	-	-
22	50	50	50	50	50	50
23	155	155	350	-	-	-

2.3.1.3 Sri Lankan Power Generation System

Sri Lanka is an island nation in which the power system is isolated from the rest of the world. The power generation system capacity is 4305.66 MW [118]. Table 2.4 shows the generation capacity share.

The peak load of the system is 2502.2 MW. Figure 2.9 shows the daily load curve.

2.3.1.4 Roy Billinton Test System Bus-2 Distribution System

The RBTS consists of 5 load bus bars, i.e. BUS2-BUS6. Two distribution systems are designed for Bus-2 and Bus-4 for study purposes [119]. In this work, the RBTS bus-2 network is used for HL3 adequacy studies. The RBTS Bus-2 distribution system is shown in Figure 6.5. The tie lines are closed to obtain the maximum reliability benefits

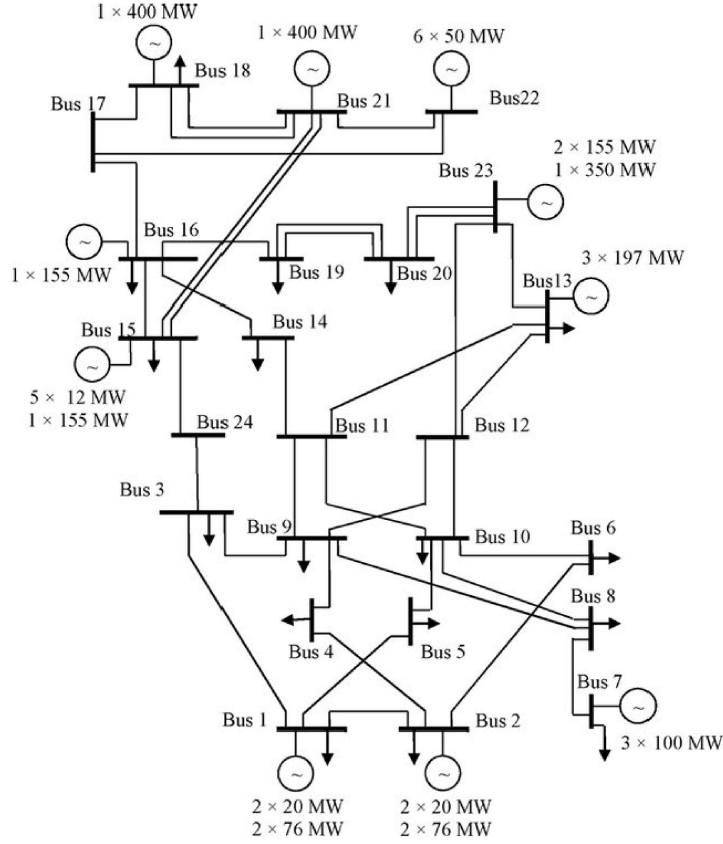


Fig. 2.7: Composite Power System of the IEEE Reliability Test System

of solar power integration. The RBTS Bus-2 average load and maximum peak load are 12.291 MW and 20 MW, respectively. Each feeder and transformer is associated with respective forced outage rates [119]. The feeders and the details of respective load points are tabulated in Tables 2.5 and 2.6.

The forced outage rates of feeders and transformers can be found in [119]. The annual load curve of IEEE RTS can be used for this test system as well.

2.3.2 Renewable Power Generation Data

In this work, renewable power generation data are obtained for Belgium and Sri Lanka.

The simulated wind and solar power generation data of Belgium are obtained from [120, 121]. The data sets include renewable power generation data with a resolution of 1 hour. Smaller resolution of renewable power data, which is less than 1 hour, would require large computational time as well as more data collection. In [120, 121], authors have used NASA's MERRA-2 global meteorological reanalyzes as well as the Meteosat-based CMSAF SARA satellite data set to produce hourly PV and wind simulations across Europe. The results of the simulation algorithm are validated using

TABLE 2.3: IEEE RTS GENERATING UNIT LOCATIONS WITH RESPECTIVE CAPACITY (MW)

Bus	MW	MVar
1	108	22
2	97	20
3	180	37
4	74	15
5	71	14
6	136	28
7	125	25
8	171	35
9	175	36
10	195	40
13	265	54
14	194	39
15	317	64
16	100	20
18	333	68
19	181	37
20	128	26
TOTAL	2850	580

TABLE 2.4: GENERATION SYSTEM CAPACITY SHARE

Generation	Capacity (MW)
Thermal	1973.7
Major Hydro	1464.7
Mini Hydro	413.95
Wind	231.95
Solar (Ground)	51.36
Solar (Roof)	170

real PV and wind generation data in the European region. The total solar and wind power generation of Belgium in the years 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). The simulated Sri Lankan renewable data is obtained in a similar manner.

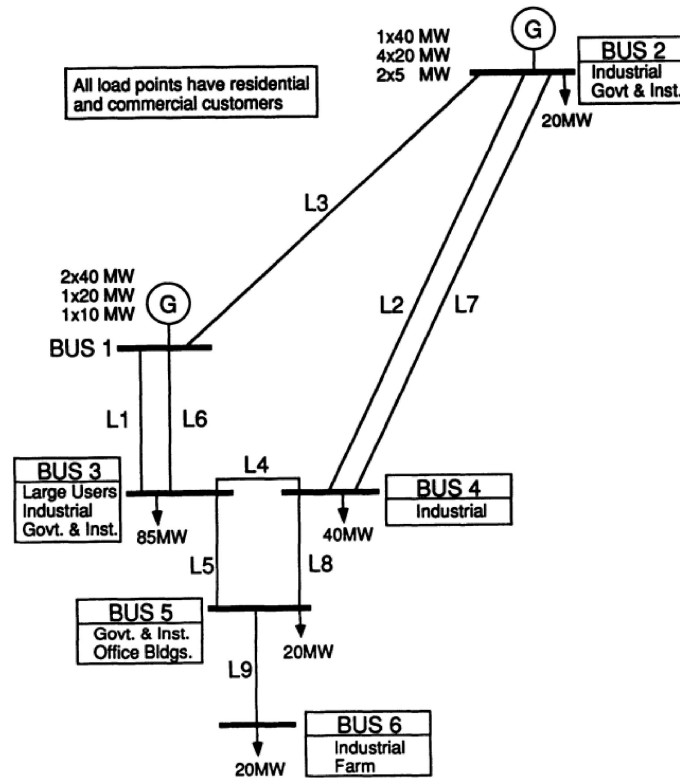


Fig. 2.8: Composite Power System of the Roy Billinton Test System

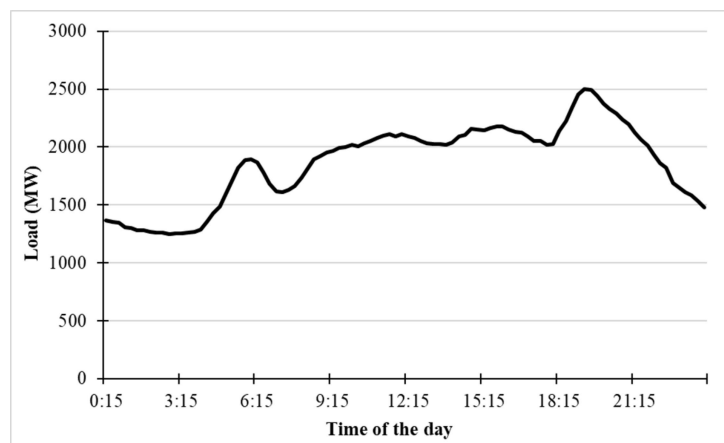


Fig. 2.9: Daily Load curve of the Sri Lankan Power System

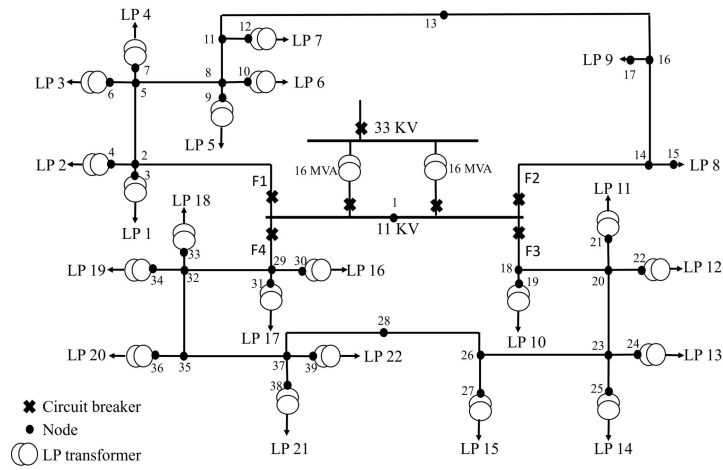


Fig. 2.10: RBTS Bus-2

TABLE 2.5: RBTS BUS-2 LOAD DATA

Feeder number	Load points	Average load (MW)	Peak load (MW)	No. of customers
F1	1-7	3.645	5.934	652
F2	8-9	2.15	3.5	2
F3	10-15	3.106	5.057	632
F4	16-22	3.39	5.509	622
	TOTAL	12.291	20	1908

TABLE 2.6: RBTS BUS-2 CUSTOMER DATA

No. of load points	Load points	Customer type	Average load (MW)	Peak load (MW)	No. of customers
5	1-3, 10, 11	residential	0.535	0.8668	210
4	12, 17-19	residential	0.45	0.7291	200
1	8	small user	1	1.6279	1
1	9	small user	1.15	1.8721	1
6	4, 5, 13, 14, 20, 21	govt/inst	0.566	0.9167	1
5	6, 7, 15, 16, 22	commercial	0.454	0.75	10

CHAPTER 3

PRELIMINARY STUDIES

This chapter describes several preliminary studies carried out to identify the prevailing limitations of the MCS and renewable power modeling methods. Hence, widely used non-sequential and sequential Monte Carlo simulation algorithms are implemented to find out the possible improvements that can be incorporated into the adequacy evaluation frameworks.

3.1 Application of Non-Sequential Monte Carlo Simulation for Evaluating the Adequacy of Generation Systems with Renewables

In this study, an NSMCS algorithm is developed, and as a case study, the capacity credit of renewable generators is evaluated. Two methods are used to quantify the capacity credit of a renewable generator. The first method is the Effective Load Carrying Capability (ELCC) method, in which the capacity credit of a renewable generator is quantified using the ELCC. The second method is called the equivalent capacity method, in which the equivalent capacity values are calculated to quantify the capacity credit of a renewable generator [122]. These methods are briefly described in section 3.1.1. Section 3.1.2 explains the LOLE calculation procedure using NSMCS.

3.1.1 Capacity Credit Quantification Methodologies

In the ELCC method, adding a new generator is benchmarked against an ideal, perfectly reliable unit with 100% availability [45]. The basic steps of obtaining ELCC for a renewable generating unit are stated below [122].

- Step 1: Determine the annual risk, i.e., LOLE of the system without integrating the renewable unit.
- Step 2: Calculate LOLE for a range of loads by varying the annual peak load and each daily peak as a percentage of the annual peak. Draw the variation of LOLE with the annual peak load.
- Step 3: Add the renewable unit into the system and calculate LOLE for a range of loads by varying the annual peak load and each daily peak as a percentage of the annual peak. Plot the variation of LOLE with the annual peak load on the same graph used in Step 2.
- Step 4: The megawatt distance between the two curves drawn in steps 2 and 3 at the LOLE value determined in step 1 is the capacity credit, i.e., the amount of load

growth that the system can accept without changing the reliability level. Thus, ELCC equals this megawatt distance.

The equivalent capacity method considers a realistic generator unit with a stochastic operational nature instead of using an ideal, perfectly reliable unit used in the ELCC method. Therefore, this method can provide more realistic capacity credit values than the ELCC method [45]. The procedure of finding the equivalent capacity is given below [45].

- Step 1: Determine the annual risk of the system, i.e., LOLE, without integrating the renewable unit.
- Step 2: Remove the benchmark unit, i.e., thermal or hydro unit, from the generation system and re-calculate LOLE.
- Step 3: Then, add a small unit of renewable generation (e.g., a unit of 5 MW) to the system and calculate LOLE.
- Step 4: If the LOLE is less than the LOLE value obtained in step 1, add another small unit of renewable generation to the system and re-calculate LOLE.
- Step 5: Repeat step 4 until the LOLE of the system exceeds the LOLE value obtained in step 1.
- Step 6: The total renewable addition that gives the closest LOLE value to the LOLE value obtained in step 1 is the equivalent capacity value w.r.t the benchmark unit.

3.1.2 LOLE Calculation

As there is a significant proportion of renewable energy in power systems, it is required to model renewable power generation accurately. Therefore, simulation methods such as MCS are used to obtain reliability indices instead of using analytical adequacy evaluation methods. In this work, authors have used NSMCS because it does not require complex, time-consuming chronological renewable power simulations [31]. Instead of modeling renewable power generation chronologically, historical data can be used to model solar and wind generation in NSMCS [31]. IEEE Reliability Test System 1979 (RTS-79) [17] is used to perform several case studies.

In NSMCS, the stochastic nature of conventional generators can be modeled using their respective FOR values. Load and renewable power generation can be modeled using time clusters as described in [31]. Historical renewable power generation data and load data are clustered into 24 clusters. Then, random load and renewable power values are selected during the event sampling process of NSMCS, considering their

time dependency. Figure 3.1 illustrates the flow chart of NSMCS, and Figure 3.2 illustrates the clustering method.

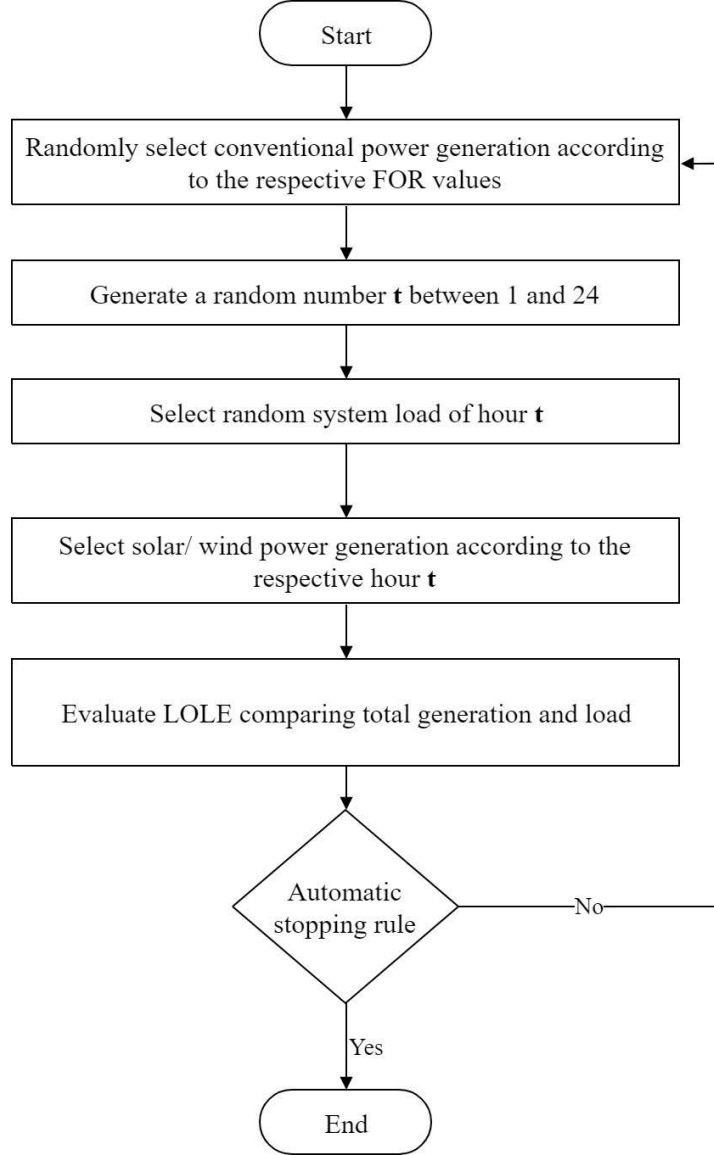


Fig. 3.1: The flow chart of NSMCS

If the coefficient of variation of LOLE is less than 0.01, it is assumed that the NSMCS is converged, and the simulation process is stopped.

3.1.3 Case Studies

In this section, the developed frameworks for quantifying capacity values of wind and solar generation are utilized to conduct several case studies. The case studies are conducted on IEEE RTS. The LOLP and LOLE values of the system are 0.0011 and 9.3927

Days of the year	Power generation in each hour of the day			
	00.00-01.00	01.00-02.00	...	23.00-00.00
Day 1	Cluster 1	Cluster 2	Cluster j	Cluster 24
Day 2				
.				
.				
Day i				
.				
.				
.				
Day 365				

Fig. 3.2: Time-dependent clustering of load and renewable power generation

hours per annum (i.e., 0.39 days per year), respectively [123]. The typical reliability target (LOLE) for a power system is often considered as 0.1 days per year [122]. Therefore, the annual peak load is adjusted to make the LOLE equal to 0.1 days per year. The adjusted annual peak load of 2652 MW is used in case study 1. However, the original annual peak load, i.e., 2850 MW, is used in the rest of the case studies.

Four case studies are conducted to evaluate ELCC and equivalent capacity values under different conditions. ELCC calculations for wind and solar generation in Sri Lanka and Belgium are done in case study 1. Two different wind and solar penetration levels, i.e., 10% and 20% are considered for Sri Lankan renewable data to identify the impact of renewable power penetration levels on the ELCC. The results of case study 1 can be used to compare the capacity credit values of two countries with different climate conditions. In case study 2, Sri Lankan wind and solar ELCC values are obtained for a different system reliability level, i.e., 0.39 days per year. Results of case studies 1 and 2 can be used to identify the impact of system reliability level on the ELCC. Case study 3 is conducted to identify variations of Sri Lankan wind and solar ELCC values with seasons of the year. In case study 4, equivalent capacity values of Sri Lankan wind and solar generation are obtained to quantify the capacity credit values more realistically.

3.1.3.1 Case Study 1: ELCC Calculations for Wind and Solar Generation

The ELCC values of wind and solar PV generation in Sri Lanka are calculated using the ELCC method described in section 3.1.1. Reliability curves w.r.t two penetration levels of solar PV and wind power are illustrated in Figures 3.3 and 3.4, respectively. Figure 3.3 shows that the ELCC values of solar PV for penetration levels of 10% and 20% are 73MW and 113MW. As can be seen in Figure 3.4, the ELCC values of wind

for penetration levels of 10% and 20% are 121MW and 190MW, respectively. The obtained wind and solar PV capacity values are shown in Table 3.1.

Capacity values of wind and solar PV in Brussels, Belgium, are obtained for the wind penetration level of 20% and for the solar penetration level of 20%. Reliability curves of both solar PV and wind are shown in Figure 3.5. According to Figure 3.5, ELCC values of Belgian wind and solar PV are 176MW and 110MW, respectively. The obtained wind and solar PV capacity values for Belgium are also given in Table 3.1.

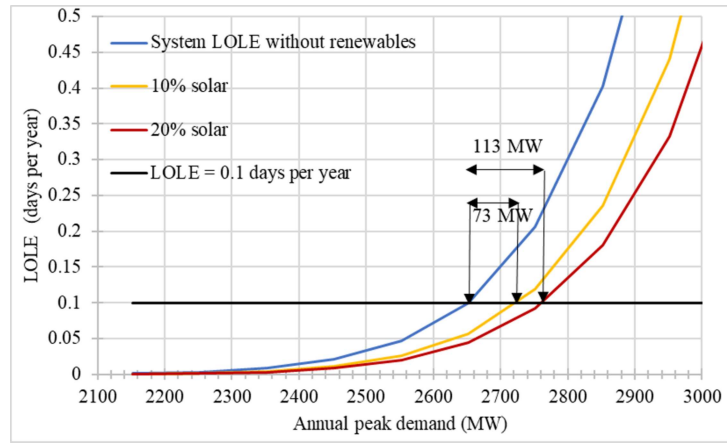


Fig. 3.3: Reliability curves of the system with solar PV in Hambantota for different penetration levels

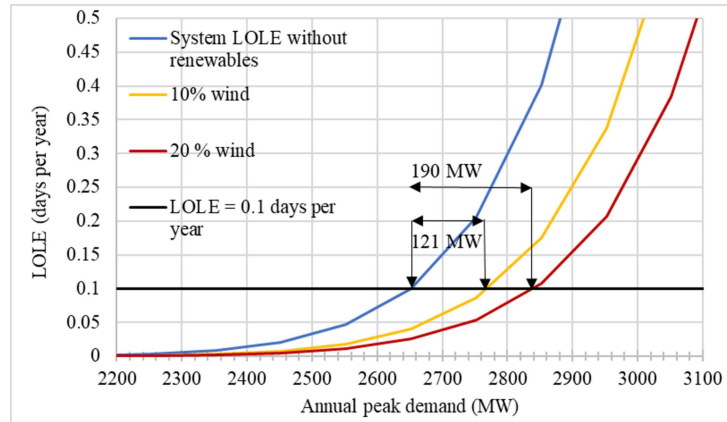


Fig. 3.4: Reliability curves of the system with the wind in Mannar for different penetration levels

The ELCC values of 10% and 20% wind generation in Sri Lanka are 121 MW and 190 MW, respectively. When considering 20% wind penetration, the total wind installed capacity is 851.25 MW. If an 851.25 MW wind plant is installed in Mannar,

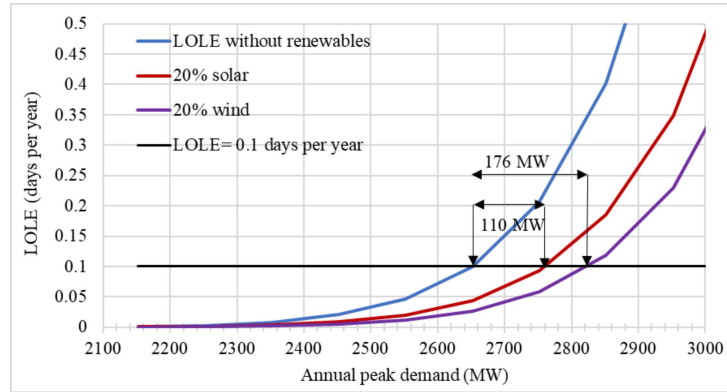


Fig. 3.5: Reliability curves of the system with solar PV and wind in Brussels

TABLE 3.1: CAPACITY VALUES OF RENEWABLE GENERATION FOR DIFFERENT PENETRATION LEVELS

Renewable generation	Penetration level and capacity	Capacity value and percentage
Solar PV - Hambantota	10 % (378.33 MW)	73 MW (19.3 %)
	20 % (851.25 MW)	113 MW (13.27 %)
Solar PV - Brussels	20 % (851.25 MW)	110 MW (12.92 %)
Wind - Mannar	10 % (378.33 MW)	121 MW (31.98 %)
	20 % (851.25 MW)	190 MW (22.32 %)
Wind - Brussels	20 % (851.25 MW)	176 MW (20.68 %)

the annual peak load can be increased from 2652 MW to 2842 MW by keeping the reliability level fixed at 0.1 days per year.

ELCC of solar PV for a penetration level of 10% is 73 MW. As a percentage, 19.3% of installed solar PV behaves like a 100% reliable generator. Moreover, with an increased penetration of 20%, the ELCC increases up to 113 MW, which is only 13.27% of the installed capacity.

The ELCC of wind generation is higher than solar PV because of its high plant factor. When wind penetration is increased from 10% to 20%, the capacity value drops by 9.66%. Similarly, the ELCC of solar drops by 6% when the solar penetration level is increased from 10% to 20%. Therefore, the study shows that a maximum capacity value exists for wind and solar PV, which cannot be increased further by raising the renewable penetration level. Moreover, the generation system reliability will not be increased further when renewable power penetration is increased after a particular level. After reaching the maximum capacity value, the contribution of renewable generation expansion to the generation system reliability will be zero.

Reaching the maximum capacity value of renewable power generation will not be economically viable because when the renewable penetration level is increased, the increment in the capacity value rapidly decreases. The most appropriate method

to decide the desired level of renewable penetration would be a proper cost-benefit analysis.

Capacity values of conventional generators are increased when more conventional generators are connected to the system [122]. Thus, conventional generator additions tend to accelerate the system reliability growth, whereas renewable intermittent power additions tend to decelerate the system reliability growth.

The results of case studies 1 and 2 show that even though the two countries are in different regions with different climate conditions, the capacity values of wind and solar PV do not show significant differences. The differences for 20% penetration of solar PV and wind are 0.35% and 1.64%, respectively.

3.1.3.2 Case study 2: ELCC Calculation of Wind and Solar PV for a Different Reliability Level

Sri Lankan wind and solar generation data are used to obtain ELCC values for the IEEE RTS with its actual peak load of 2850 MW. The LOLE of the system is 0.1 days per year before the renewables are added. Figure 3.6 illustrates the reliability curves obtained for a wind penetration level of 20% and for a solar penetration level of 20%. The obtained ELCC values for wind and solar are 205 MW and 130 MW, respectively. The ELCC values of wind and solar PV obtained from this case study for the reliability level of 0.1 days per year are tabulated in Table 3.2 together with the same obtained in case study 1 for the reliability level of 0.39 days per year.

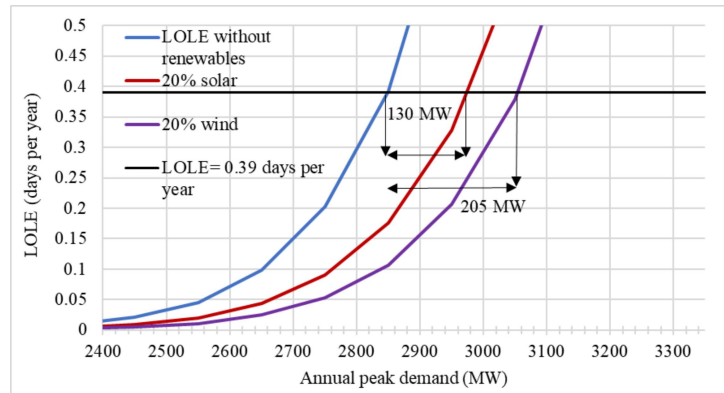


Fig. 3.6: Reliability curves of the system with solar PV and wind in Sri Lanka

According to the results of case studies 1 and 2, the ELCC values slightly increase when the system reliability is derogated, i.e., the risk level is increased. Moreover, the results show that even if the risk level is increased by almost four times, the capacity values of solar PV and wind are increased only by 2% and 3.4%, respectively. The reliability curves tend to stay parallel after reaching the risk level of 0.1 days per year.

TABLE 3.2: CAPACITY VALUES OF RENEWABLE GENERATION FOR DIFFERENT RISK LEVELS

Renewable generation	Capacity value for LOLE= 0.1 days/year	Capacity value for LOLE= 0.39 days/year
Solar PV- Hambantota (20 % penetration)	113 MW (13.27 %)	130 MW (15.27 %)
Wind- Mannar (20% penetration)	190 MW (20.68 %)	205 MW (24.08 %)

3.1.3.3 Case Study 3: Variation of ELCC with Seasons of the Year

ELCC values of wind and solar PV may change throughout the year due to seasonal variations in wind speed and solar irradiance. Figure 3.7 illustrates the normalized monthly average wind and solar PV power generation in Sri Lanka. Solar power generation does not show a significant variation throughout the year. However, the difference between the wind power generations in high and low wind seasons is more than 300%. May to September can be considered as the high wind season, and the rest of the months belong to the low wind season.

For both high and low wind seasons, reliability curves are obtained for a renewable penetration level of 20% and a risk level of 0.39 days per year, as shown in Figure 3.8. Using Figure 3.8, capacity values calculated for high and low wind seasons are 410MW and 102MW, respectively.

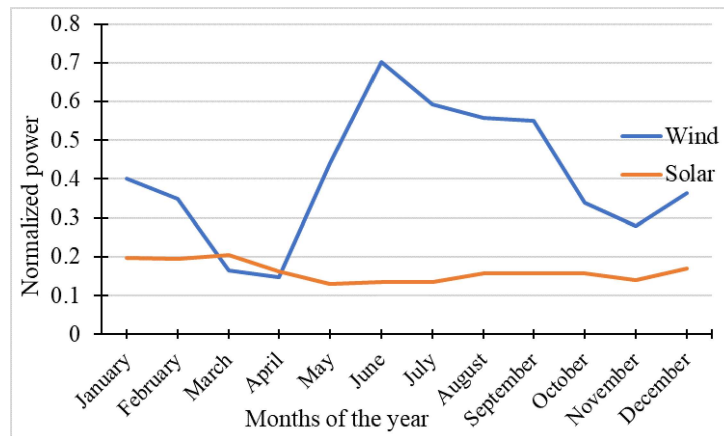


Fig. 3.7: Normalized monthly average renewable power generation in Sri Lanka

In the high wind season, the capacity value of wind power generation is 410 MW, which is 48.16% of the installed capacity (851.25 MW). In the low wind season, the capacity value is 102 MW, which is 12% of the installed capacity. Therefore, due to seasonal variations of wind power, the reliability of the power system changes significantly throughout the year. In the low-wind season, conventional generators will be

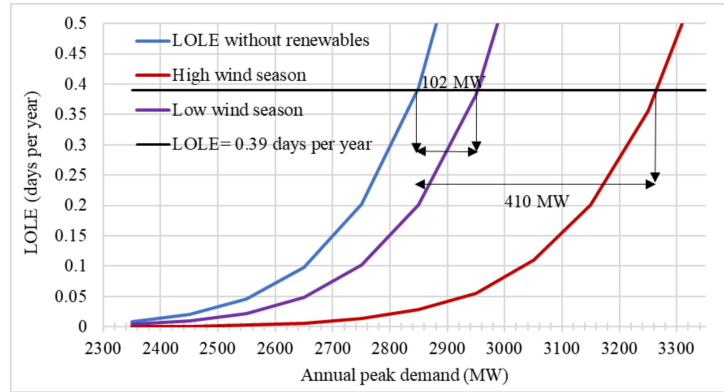


Fig. 3.8: Reliability curves of high and low wind seasons in Sri Lanka

required to maintain the reliability of the power system.

The correlation between renewable generation and annual load plays a crucial role. When the coefficient of correlation between the load and renewable power is close to a positive one, the capacity credit of the renewable generator becomes maximum. On the other hand, a negative correlation coefficient indicates a low contribution of renewables to the reliability of the system.

3.1.3.4 Case Study 4: Evaluation of Equivalent Capacities of Renewable Generators

In this study, the equivalent capacity value is calculated using the equivalent capacity method described in Section 3.1.1. A 50 MW conventional unit with a FOR of 0.01 is considered for benchmarking. Sri Lankan data are used in the NSMCS to determine the LOLE of the system when the annual peak load is 2850 MW. The LOLE obtained is 0.39 days per year.

After removing the benchmark unit, the system LOLE is 0.56 days per year. Then, wind generation is added in 5 MW increments. The closest value of LOLE to 0.39 days per year is obtained when the wind addition equals 145 MW. Therefore, the equivalent wind capacity obtained against the reference unit is 145 MW. A similar procedure is also applied to solar photovoltaic generation. The equivalent capacity of solar photovoltaics compared to the benchmark unit is found to be 230 MW.

It can be observed that 34.5% of wind power contributes to the system reliability as a conventional generator. On the other hand, 21.7% of solar power is equivalent to a 50 MW conventional unit. The equivalent capacity values can be used to identify the required renewable generation capacity in the event of failure of a conventional generator. Further, the benefits and costs of renewable power penetration can be shown using the concept of equivalent capacity. The equivalent wind and solar capacities of a 350 MW coal generator are obtained for the analysis. The FOR of the coal generator is

0.08. Assuming base load operation, the 350 MW generator's annual energy production is 2820.72 GWh. It was found that the 350 MW conventional generation cannot be replaced by even a 10 GW solar farm while maintaining the same system reliability, i.e., LOLE = 0.39 days per year. On the other hand, the equivalent capacity of wind generation is found to be 3.4 GW.

The total energy generated by wind and solar energy can be estimated approximately by considering the energy yields of the Sri Lankan wind and solar generation. The average solar and wind energy yields in Sri Lanka for 2021 and 2022 are 1510.77 MWh/MW and 2715.08 MWh/MW [124]. Consequently, the annual energy generation of a 3.4 GW wind farm is 9231.3 GWh.

It should be noted that the annual energy demand of the test system is 15297.07 GWh. Thus, conventional generators with a capacity of 3055 MW only generate 6065.77 GWh, which shows heavy under-utilization of generators. Furthermore, system stability constraints are not considered in this case. The cost of energy and operational carbon emissions of coal and wind generators are tabulated in Table 3.3. It can be seen that when conventional generators are replaced with renewables, significantly large renewable capacity is required to maintain the same reliability level. It can be seen that a 3.4 GW wind farm generates a significant amount of energy compared to a 350 MW coal plant. However, renewable generation during off-peak hours cannot be harnessed due to reduced load demand. The availability of a generator matters more to the system's reliability than the annual energy output.

Integrating energy storage can achieve a "sweet point" where the benefits and costs of renewables are well balanced, especially when there is a large proportion of renewables in the system. An energy storage can absorb renewable generation at off-peak times and release the power at peak times, reducing the use of costly gas and diesel generators. Generally, system planners suggest generator additions according to the load forecasts, keeping a defined reliability level. For e.g., according to the Australian Energy Market Commission, the maximum expected unserved energy in a region should be 0.002 % of the total energy demand in that region for a given financial year [125]. Therefore, different strategies should be followed to increase the renewable proportion in the grid. Interconnecting power systems and adding energy storage can optimize renewable energy utilization, which benefits both consumers and the utility.

TABLE 3.3: LEVELIZED COST OF ENERGY AND OPERATIONAL CARBON EMISSIONS OF COAL AND WIND GENERATORS

Generation	Levelized cost (USD/MWh) [126]	Energy generation (GWh)	Carbon emission (Gigatons) [118]
Coal 350 MW	91	2820.7	2.5
Wind 3400 MW	49	9231.3	0

Carbon emissions and the levelized cost of wind generators are significantly lower

than those of coal generators. Even though the system reliability remains the same, the stability of the system may be affected by the large proportion of wind generation [11]. Hence, system reliability and stability studies are crucial when integrating renewables into power systems.

3.2 Application of Sequential Monte Carlo Simulation for Evaluating the Adequacy of Generation Systems with Renewables

In this section, the SMCS algorithm is developed, and several case studies are performed considering a PHS. The IEEE RTS is utilized to analyze the impact of PHSs on the adequacy of the generation system. In this application, the RTS is modified by integrating Belgian wind and solar generation and a PHS.

The IEEE RTS load curve shows seasonal load variation throughout the year, as shown in Figure 2.6. The system load is comparatively higher in the summer and winter seasons than in spring and fall. Similarly, Belgium's wind and solar power generation show significant seasonal variations as illustrated in Figure 3.9. As shown in Figures 2.6 and 3.9, the load is positively correlated with wind generation in winter and solar generation in summer. Moreover, wind and solar generation show a negative correlation with the load in summer and winter, respectively. However, when the system has equal wind and solar capacities, the seasonal renewable generation variations tend to be minimized, as shown in Figure 3.9.

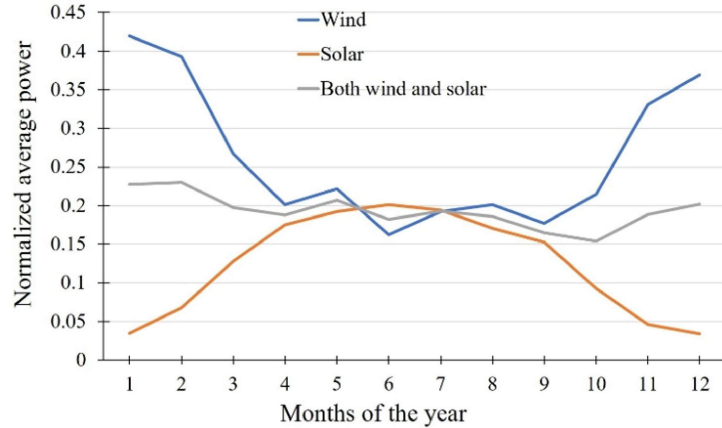


Fig. 3.9: Normalized monthly average renewable power generation

The diurnal variations of system load, solar, and wind power generations are illustrated in Figure 3.10. Wind power generation is approximately constant throughout the day. However, solar power generation shows a significant correlation with the system load in the daytime. Moreover, the night load peak is not correlated with wind or solar power generation. Hence, a PHS can be used to improve system reliability, especially at nighttime.

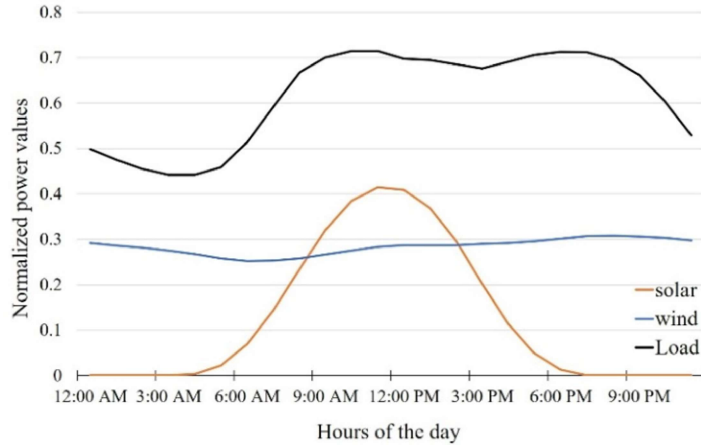


Fig. 3.10: Normalized diurnal renewable power generation and load demand

The diurnal and seasonal correlations between renewable power generation and the system load affect the generation system reliability. The correlation coefficients of diurnal and seasonal renewable power generation and the load are 0.631 and 0.085. Therefore, a moderately strong relationship exists between diurnal renewable generation and load. However, the seasonal correlation is negligible. The reliability improvements obtained by a PHS significantly depend on the diurnal and seasonal correlation between load and renewable generation. If a negative correlation coefficient exists, there will be a considerable reliability improvement because a PHS can be used to neutralize the negative correlation between load and renewable generation. The PHS can store energy when the system load is low and renewable generation is high. Then, the stored energy can be harnessed when the system load is high and renewable generation is low.

Section 3.2.1 describes the chronological modeling procedure of conventional and renewable generators. PHS modeling method is explained in section 3.2.2. SMCS steps are explained in section 3.2.3.

3.2.1 Modeling of Conventional and Renewable Generators

In SMCS, a chronological system event series is derived to obtain system reliability indices. The stochastic nature of conventional generators can be modeled using two-state Markov models as explained in section 2.1.1. The Mean Time to Failure (MTTF) and the Mean Time to Repair (MTTR) values of the generator can be obtained using Equations 3.1 and 3.2 where λ is the failure rate and μ is the repair rate. Then, the up and downtimes of the generator unit can be calculated using 3.3 and 3.4 where $U1$ and $U2$ are random numbers between 1 and 0. The annual outage curve of the generating unit can be obtained using the derived unit up and downtimes.

$$MTTF = \frac{1}{\lambda} \quad (3.1)$$

$$MTTR = \frac{1}{\mu} \quad (3.2)$$

$$Unit\ up\ time = -MTTF \times \ln(U1) \quad (3.3)$$

$$Unit\ down\ time = -MTTR \times \ln(U2) \quad (3.4)$$

The chronological total conventional power generation of the system can be obtained by aggregating the outage curves of each of the conventional generators.

Wind power generation can be modeled using multi-state models [22] or ARMA methods [58]. However, multi-state Markovian models cannot represent the diurnal and seasonal variations of wind power generation. Furthermore, ARMA methods require a significant amount of computational time for seasonality modeling. Hence, in this study, authors have used pre-simulated wind power generation data of Belgium for 15 years [120]. Similarly, simulated solar power generation data of Belgium is obtained from [121]. Renewable generator outages do not significantly change the overall simulated power output due to the small generating unit capacities. Unit capacities and a large number of turbines make the probability of significant capacity outage small. In these systems, the variation of wind capacity is more significant than the outage of turbines.

3.2.2 Modeling of Pumped Hydro Storage

A two-state Markov chain can be used to model the PHS operation. Then, using 3.1, 3.2, 3.3 and 3.4, the PHS operation can be chronologically modeled. However, unlike conventional generators, PHS energy output is limited. Therefore, the energy reservoir limits should be chronologically updated throughout the simulation. In this study, MTTF and MTTR values of 50 MW hydro generators in IEEE RTS are used to model the PHS. The cycle efficiency of the PHS is considered to be 70%. The operation of the PHS is described below.

- Step 1: Initialize PHS parameters, *Generation and pumping capacity* = PC ,
Energy storage capacity = ES , *Existing energy storage capacity* = $EP\%$
and *PHS cycle efficiency* η .
- Step 2: If *total system generation* $\leq$ *load*, Calculate the surplus power using 3.5.
Else, move on to step 3.

$$Surplus\ power = Total\ generation - Load \quad (3.5)$$

Step 3: If Surplus power > PC, then

$$Pumping\ power = PC \times \eta \quad (3.6)$$

Else,

$$Pumping\ power = Surplus\ power \times \eta \quad (3.7)$$

3.6 and 3.7 are subject to the constraint $EP \leq 100\%$.

Update EP.

$$EP = EP + ((Pumping\ power \times 1h))/ES \quad (3.8)$$

Step 4: Calculate the power curtailment using 3.9

$$Curtailement = Load - Total\ generation \quad (3.9)$$

If Curtailed power > PC, then

$$Generating\ power = PC \quad (3.10)$$

Else,

$$Generating\ power = Curtailed\ power \quad (3.11)$$

3.10 and 3.11 are subjected to the constraint $EP \geq 0\%$. Update EP.

$$EP = EP - ((Generating\ power \times 1h))/ES \quad (3.12)$$

3.2.3 Evaluating Generation System Adequacy Using Sequential Monte Carlo Simulation

Sequentially modeled total power generation, pumped storage, and load demand curves are convolved to obtain the generating system reliability indices. The basic steps of calculating system loss of load indices using SMCS are stated below.

Step 1: Initialize the total number of events $N=0$, the total number of failure events $F=0$, and Energy curtailment $E=0$.

Step 2: Sequentially model annual conventional power generation of each generator using 3.1, 3.2, 3.3 and 3.4.

Step 3: Calculate the total conventional generation at each hour of the year by convolving the power generating curves of each generator.

$$Power_{(Conventional,h)} = \sum_{i=1}^n P_{(i,h)} \quad (3.13)$$

Where $h = 1, 2, 3, \dots, 8736$, i.e., hours of the year, n is the total number of conventional generators in the system, and $P_{(i,h)}$ is the power generation of i^{th} generator at h^{th} hour.

Step 4: Calculate the total conventional and renewable power generation.

$$Power_{(Generation,h)} = Power_{(Conventional,h)} + Power_{(Solar,h)} + Power_{(wind,h)} \quad (3.14)$$

Step 5: Charge or discharge the PHS according to the steps stated in section 3.2.2 for each hour of the year.

Step 6: Calculate the total power generation of the system.

$$Power_{(Total,h)} = Power_{(Generation,h)} \pm Power_{(PHS,h)} \quad (3.15)$$

Where $+Power_{(PHS,h)}$ is the PHS discharging state ($Power_{(generation,h)} < Load_h$) and $-Power_{(PHS,h)}$ is the PHS charging state ($Power_{(generation,h)} > Load_h$) For each hour of the year, determine whether the system event is a failure or not.

Step 7: if ($Power_{(total,h)} < Load_h$) then, failure event

$$H = H + 1 \quad (3.16)$$

$$E = E + (Load_h - Power_{(total,h)}) \quad (3.17)$$

$$N = N + 1 \quad (3.18)$$

else, success event

$$N = N + 1 \quad (3.19)$$

Step 8: Calculate the loss of load indices.

$$LOLP = \frac{H}{N} \quad (3.20)$$

$$LOLE = LOLP \times 8760 \quad (3.21)$$

$$LOEE = \frac{E \times 8760}{N} \quad (3.22)$$

Repeat steps 2-8 until the stopping rule is reached. The COV of LOLE expressed in 3.23 is used as the stopping criteria of the SMCS where $E(LOLE)$ is the expected value of LOLE [25]. For convenience, COV is calculated in 20000-hour intervals for 20000 observations. The simulation is continued for a maximum of $1e10$ time steps until COV reaches $1e-2$.

$$COV = \frac{\sqrt{var(E[f])}}{E[f]} \quad (3.23)$$

Figure 3.11 shows an example time series representation of total generation and load. In Figure 3.11, it can be observed that PHS provides power to the system at 4th, 5th, 6th and 7th hour. However, at the 8th and 9th hour, the system load is curtailed due to the low reservoir level of the PHS.

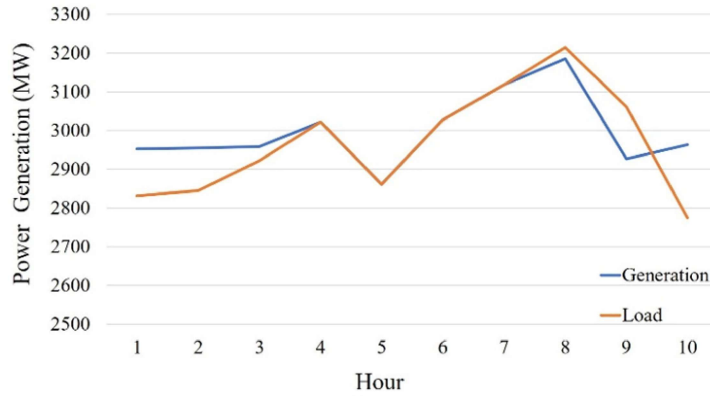


Fig. 3.11: An example time series representation of power generation and load

3.2.4 Case Studies

This section explains several case studies conducted on the MRTS and their respective results. In case study 1, the loss of load indices, i.e., LOLP, LOLE, and LOEE of the MRTS, are obtained without a PHS. Then, a PHS is integrated into the MRTS, and case study 2 is conducted to observe the variations of the system LOLE with different PHS capacities and storage levels. The diurnal and seasonal system failure trends of the PHS-integrated MRTS are obtained in case study 3. In case study 4, the capacity credit of a 300 MW PHS with a 1000 MWh storage level is evaluated to identify the contribution of a PHS to the generation system reliability.

3.2.4.1 Case Study 1: Reliability Indices of MRTS Without a PHS

In this case study, the adequacy indices of MRTS are calculated for 10% wind and 10% solar penetration. Accordingly, 425.7 MW of solar capacity and 425.7 MW of wind

capacity are integrated with the RTS. Moreover, the peak load of the MRTS is increased such that the reserve margin of the RTS is kept constant, i.e., 19.47%. Table 3.4 shows the generation system reliability indices with respective generation and peak demand values. The LOLP, LOLE, and LOEE of the MRTS are 0.0168, 146.73 hours per year, and 26708 MWh, respectively. Figure 3.12 illustrates the diurnal and seasonal variations of system failure events. It shows that most of the system failures occur in the seasons of winter and summer.

TABLE 3.4: LOSS OF LOAD INDICES OF MRTS WITHOUT A PHS

Generation capacity	4256.3 MW
Peak load	3562.5 MW
LOLP	0.0168
LOLE	146.73 hours/ year
LOEE	26708 MWh

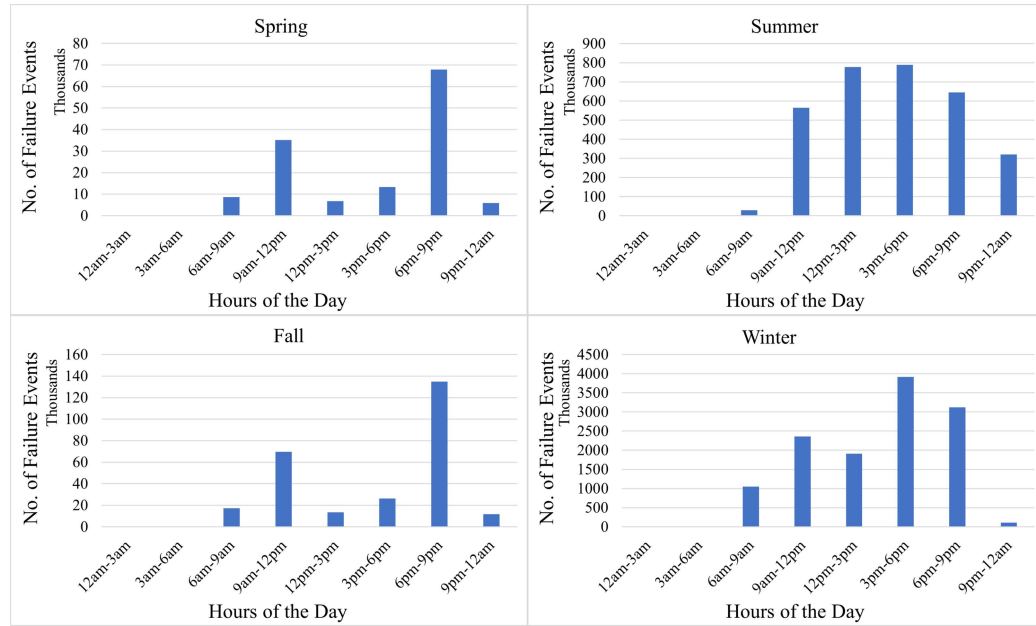


Fig. 3.12: Diurnal and seasonal variation of system failures without PHS

The results of case study 1 show that generation system failures mostly occur in the winter season between 6 p.m. to 9 p.m. This may be due to the large domestic heating load, which is essential in the winter. In the summer, the number of failures is high compared to that of spring and fall but significantly less than that of the winter. Air conditioning loads could be the reason for these high-generation system failures in the summer. The number of generation system failures is comparatively very small in the seasons of spring and fall.

3.2.4.2 Case Study 2: Impact of PHS Capacity and Reservoir Level on The Adequacy of Generation System

The reliability improvement that can be obtained by a PHS mainly depends on the PHS power capacity and the storage capacity. Therefore, the variation of LOLE of the MRTS is investigated for different PHS capacities and storage levels. The PHS reservoir level is varied with an increment of 200MWh, and the PHS capacity is varied with an increment of 100MW to observe the variation of system LOLE with the reservoir level and the PHS capacity. Figure 3.13 illustrates the variation of system LOLE w.r.t both storage capacity and storage level.

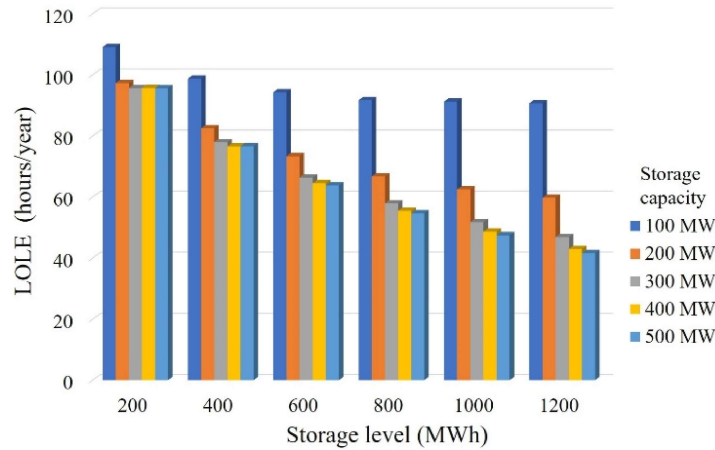


Fig. 3.13: The variation of LOLE w.r.t different PHS capacities and storage levels

The results of case study 2 illustrate the variation of generating system LOLE with PHS capacity and storage. The generation system LOLE tends to get reduced when the capacity and storage of the PHS are increased. This is due to the increase in system generation and the respective storage levels. However, when the PHS capacity is higher than 200 MW, the LOLE variation within the same storage level is not significant. The reliability improvement gradually decreases with the storage level and capacity. The reliability levels that are shown in Figure 3.13 can be used to identify the suitable PHS capacity and the suitable storage level for a given generating system. Nonetheless, financial limitations should be considered when deciding the PHS capabilities.

3.2.4.3 Case Study 3: Diurnal and Seasonal Reliability Improvements Obtained by a PHS

In this case study, a PHS is integrated into the MRTS to identify the corresponding reliability improvements. The PHS capacity and storage level are selected as 300 MW and 1000MWh, respectively. Table 3.5 shows the LOLP, LOLE, and LOEE values of the system with respective generation and peak demand values. The LOLP, LOLE,

and LOEE of the system are found to be 0.00592, 51.85 hours per year, and 15657 MWh, respectively. The exact hour of the day and season of the year of each of the system failure events is recorded during the SMCS. The diurnal and seasonal trends of generation system failure are illustrated in Figure 3.14

TABLE 3.5: LOSS OF LOAD INDICES OF MRTS WITH A PHS

Generation capacity	4256.3 MW
PHS capacity	300 MW
PHS storage	1000 MWh
Peak load	3562.5 MW
LOLP	0.00592
LOLE	51.85 hours/ year
LOEE	15657 MWh

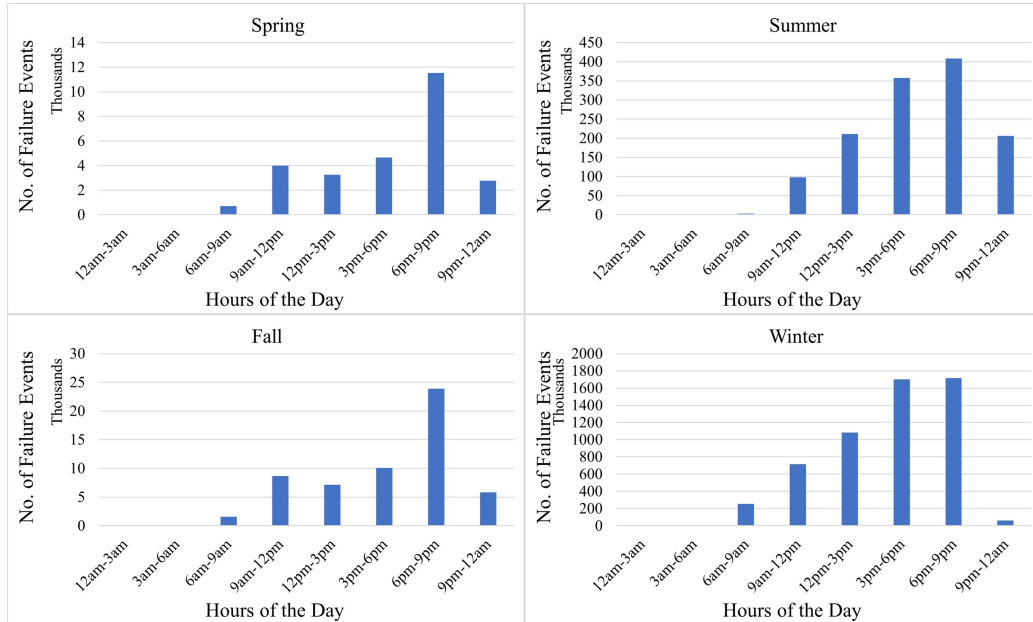


Fig. 3.14: Diurnal and seasonal variation of system failures with a PHS

The results of case study 3 show the diurnal and seasonal variations of system failure events when a PHS is integrated into the MRTS. It can be seen that a significant improvement in generating system reliability can be obtained by integrating a PHS. The overall reliability improvement is 64.7% in terms of LOLE/LOLP reduction. Furthermore, the LOEE reduction of MRTS with PHS is 41.4%. When considering the diurnal reliability improvements, daytime and nighttime generation system failures are found to be reduced by 42.8% and 44.8%, respectively. Furthermore, generation system failures in spring, fall, summer, and winter are found to be reduced by 80.4%, 79.1%, 58.9%, and 55.6%, respectively.

The diurnal reliability improvements are almost the same in the daytime and nighttime. This can be rationalized by observing the diurnal renewable generation and load curves illustrated in Figure 3.10. The load curve shows two peaks in the daytime and nighttime. Moreover, the system load is significantly high in the daytime, i.e., 6 a.m. to 6 p.m. When considering the daytime, solar power injection to the grid is at its maximum. In addition, intraday wind generation is almost constant. Hence, solar generation helps to satisfy the comparatively high daytime system demand.

On the other hand, solar generation is zero, and the system load is significantly low in the nighttime. Hence, the absence of solar energy in the nighttime would not significantly affect system reliability. Due to these factors, daytime and nighttime reliability improvements tend to be the same. However, if there is any excess solar energy in the daytime, PHS can be charged, and in the night peak, PHS can be discharged if necessary. This may be the reason for the slight increase in the nighttime system reliability.

However, seasonal reliability improvements significantly vary in different seasons. The reliability improvements of soft climate seasons, such as spring and fall, are significantly higher than that of extreme climate seasons, such as summer and winter. As can be seen in Figure 3.9, the system load demand is comparatively high in both the summer and winter seasons. Hence, in the summer and winter, both the PHS capacity and the storage level may not be sufficient to provide power in system failure events.

3.2.4.4 Case Study 4: Equivalent Capacity of The PHS

The equivalent capacity of a 300 MW PHS with a storage level of 1000 MWh is evaluated using the procedure described in section 3.1.1. It can be used to identify the actual contribution of the PHS towards generation system reliability.

According to the results of case study 4, 72% of PHS capacity can contribute to the generation system adequacy as a conventional generating unit. Thus, this PHS is equivalent to a 216 MW conventional generating unit. However, the equivalent capacity of the PHS depends on the amount of renewable power generation, the diurnal and seasonal correlations between renewable generation and load, the system's annual load curve, and the available conventional generation capacity.

3.3 Conclusion

In this chapter, NSMCS and MCS algorithms are developed to estimate the reliability indices of a modified IEEE RTS.

Several case studies have been conducted using NSMCS to estimate the capacity credit of solar PV and wind power generation in Sri Lanka. The impact of climate conditions, system reliability level seasonal wind speed, and solar irradiance variations on

capacity credit values are analyzed in detail. It is found that wind power generation varies significantly in high wind and low wind seasons. Thus, it was found that the system reliability level significantly varies throughout the year when the renewable penetration level is high. These impacts should be taken into account when a large proportion of renewable generation is added to the system. Even though the system reliability level can be maintained by integrating a large amount of wind or solar power generators into the grid, it may not be economically viable. It is found that 230 MW of solar capacity installment is required to replace a 50 MW conventional generator. This requires large capital expenditure and heavy transmission line upgrades. On the other hand, the transmission lines will be under-utilized at night due to the unavailability of solar power. Moreover, in Sri Lanka, the electricity demand reaches its maximum in the evening hours, and the solar power is zero at that time, i.e., between 7 p.m. and 8 p.m. Therefore, power system planners cannot replace large conventional generators with wind or solar generators without integrating energy storage, such as large battery bank systems or pumped storage plants. If energy storage is used to store the additional energy generated in off-peak time, the amount of wind or solar capacity required to replace the conventional generator will be reduced. Moreover, transmission line upgrades can be minimized by using energy storage together with renewable power generators. By integrating energy storage and renewable power generators, it may be possible to develop more economically and technically viable generation plans.

MCS is used to conduct several case studies to investigate generating system reliability improvements that can be obtained by integrating a PHS into the system. The MRTS and a PHS operation are sequentially simulated to calculate the system loss of load indices. It is found that the number of diurnal and seasonal system failure events can be drastically reduced by integrating a PHS. The larger the PHS capacity and the storage level, the higher the system reliability level. The equivalent capacity of a PHS is calculated in terms of a conventional generation unit, and the capacity credit percentage is found to be 72%. Even though a conventional 216 MW generator seems more economical than a PHS, a proper cost-benefit analysis is required to identify the most suitable option. However, a PHS would be more appropriate for a renewable rich power system because it can reduce the effects of the “Duck curve.” The duck curve is a graph that illustrates daily conventional power production [127]. It shows the timing imbalance between peak demand and renewable power generation. Renewable power, especially solar, is unavailable at the night peak demand time, and a large conventional generation capacity will be required to satisfy the night peak demand. Hence, cost-effective energy storage, such as a PHS, can be used to flatten the duck curve.

The preliminary studies revealed below aspects relevant to the adequacy evaluation of power systems.

- Conventional simulation methods can still be used for HL1 adequacy studies as

state evaluation does not need OPF analysis. **However, more efficient adequacy evaluation techniques might be needed for HL2 and HL3 studies as they require OPF analysis, which is computationally challenging.**

- More accurate and complex renewable power modeling techniques can be incorporated into HL1 adequacy studies due to the simplicity of the event evaluation procedure. **This allows precise modeling of diurnal and seasonal variations and the correlation between the load and renewable power generation.**
- Capacity credit of a renewable generator is vital in power system planning as it directly affects the reliability of the power system.
- PHSs can be used to accommodate more renewable energy sources while improving the reliability of the system and reducing carbon emissions.

CHAPTER 4

KERNEL DENSITY ESTIMATION BASED TIME-DEPENDENT APPROACH FOR MODELLING RENEWABLE POWER GENERATION IN GENERATION SYSTEM ADEQUACY EVALUATION

The intermittent nature and both diurnal and seasonal variations of renewable energy sources such as wind and solar often lead to varying amounts of renewable power injection into the power grid. Hence, with an increased proportion of renewable power in the grid, the power system reliability varies drastically throughout the year [128]. 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.

In this chapter, a novel renewable power modeling method based on Kernel Density Estimation is proposed for evaluating the adequacy of renewable-integrated power generation systems.

4.1 Kernel Density Estimation based Generation System Adequacy Evaluation Framework

4.1.1 Modeling Wind and Solar Power Generation Using Kernel Density Estimation

The simulated wind and solar power generation data of Belgium [120, 121] are used in this study. The data sets include renewable power generation data with a resolution of 1 hour.

The intermittency and both seasonal and diurnal variations of wind and solar power generation should be considered in the process of event 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, obtaining renewable power generation data recorded over a significant number of years is difficult. Thus, the intermittency of renewables cannot be modeled. A practical solution to this problem is clustering data sets according to hours of the day and seasons of the year. An example of this approach is illustrated in Figure 4.2. 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 Probabil-

ity Density Function (PDF) of respective renewable power generation is obtained by the 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. Thus, this chapter focuses on the adequacy evaluation of power generation systems using NSMCS, as shown in Figure 4.1.

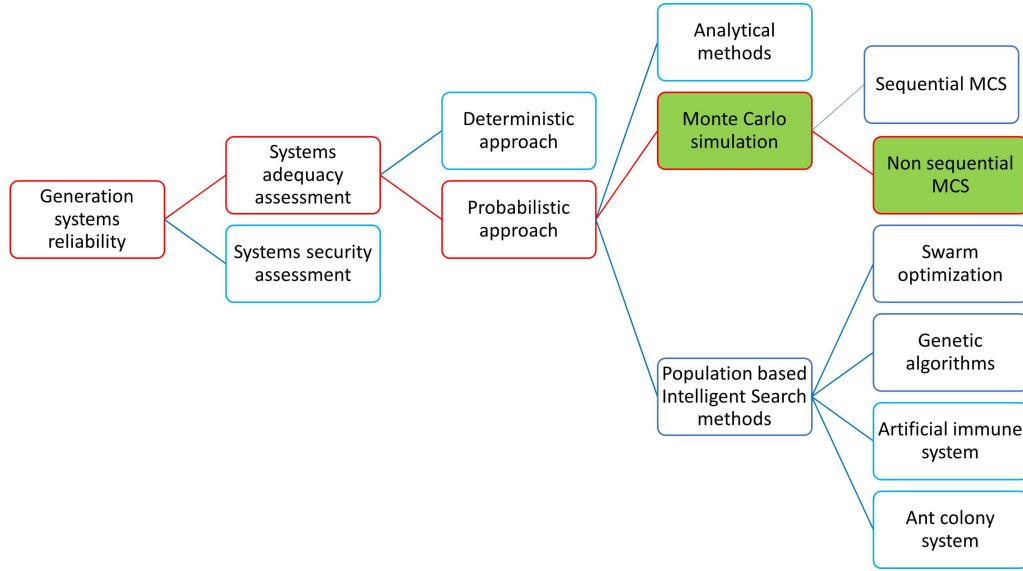


Fig. 4.1: The selection of adequacy evaluation method

KDE-based renewable power models have several specific advantages. They can be implemented for any power plant worldwide using historical power generation data. Knowing the renewable power generation patterns and probabilities is unnecessary, as KDE is a non-parametric method. Unlike Markov models, KDE-based PDFs represent numerous renewable power levels and can be easily integrated into NSMCS. The computational burden of modeling renewable power generation using KDE is significantly less than ARIMA models [30].

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 a large number of renewable generators. In these systems, the variation of renewable power generation is more significant than the outage of generating units.

4.1.1.1 Kernel Density Estimation

The PDF of each renewable power cluster can be determined using parametric methods, such as mixture models, or non-parametric methods, such as the KDE method. In

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

Fig. 4.2: An example of the clustering approach

mixture models, the underlying distribution of each cluster is constructed using multiple parametric distributions. Further, numerous levels of renewable power generation exist due to the large variability of renewables. Hence, identifying 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 cluster in the clustering model shown in Figure 4.2.

On the other hand, KDE avoids the problem of choosing the number of components by using one component (a Kernel) centered on each point of the data set [15]. It provides a smooth PDF for a given set of data points. KDE is widely used in applications in which the PDF is unknown or poorly defined, e.g., forecasting error distributions [129]. 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. The smoothness of the density estimate can be controlled by changing the bandwidth of the selected Kernel.

Given a random sample of observations $X_1, X_2, \dots, X_n$ with a continuous, univariate density f , the Kernel density estimator is,

$$f(x, h) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x - X_i}{h}\right) = \frac{1}{n} \sum_{i=1}^n K_h(x - X_i) \quad (4.1)$$

$$K_h(u) = h^{-1}K(h^{-1}u) \quad (4.2)$$

where X_i is the target point, K is the unscaled Kernel, K_h is the scaled Kernel and h is the bandwidth.

4.1.1.2 Seasonality detection using K-means clustering method

Instead of manually determining the 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 [130].

The seasonal variations of wind and solar power generation are illustrated in Figures 4.3 and 4.4, respectively. Wind power generation data from 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 [131] 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 the distance between each point in one cluster and points in the adjacent clusters. Silhouette's score lies in the range of $[-1, +1]$. A value of $+1$ implies that the sample is far away from its adjacent 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 4.1.

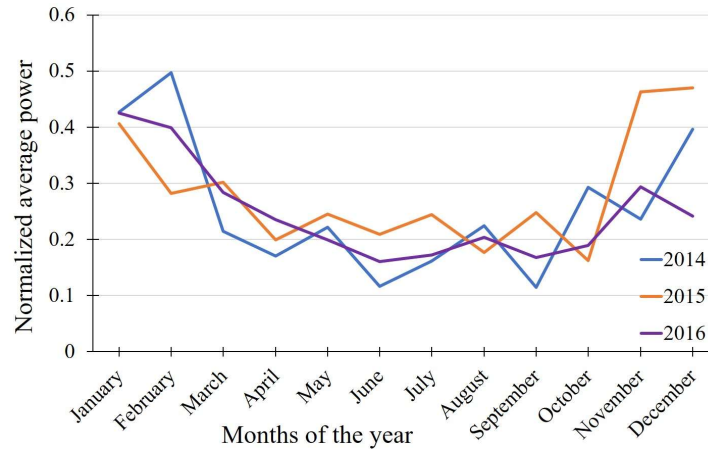


Fig. 4.3: Monthly average wind power generation in Belgium

4.1.1.3 Wind power generation model

Wind power generation data is divided into two seasons. Then, using K-means clustering, months belonging 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

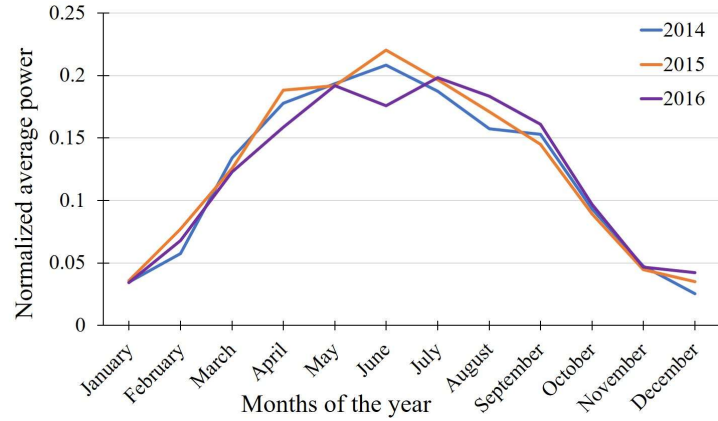


Fig. 4.4: Monthly average solar power generation in Belgium

TABLE 4.1: 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

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 Equation 4.3 is used as the Kernel function where μ and σ are the mean and the variance of the distribution P . 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 using the "normal" Kernel. The most suitable value for the bandwidth is automatically selected by the "Ks-density" algorithm as 0.04. Numerous trial and error tests have confirmed the selected value for the bandwidth. Figure 4.5 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.

$$P(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2} \quad (4.3)$$

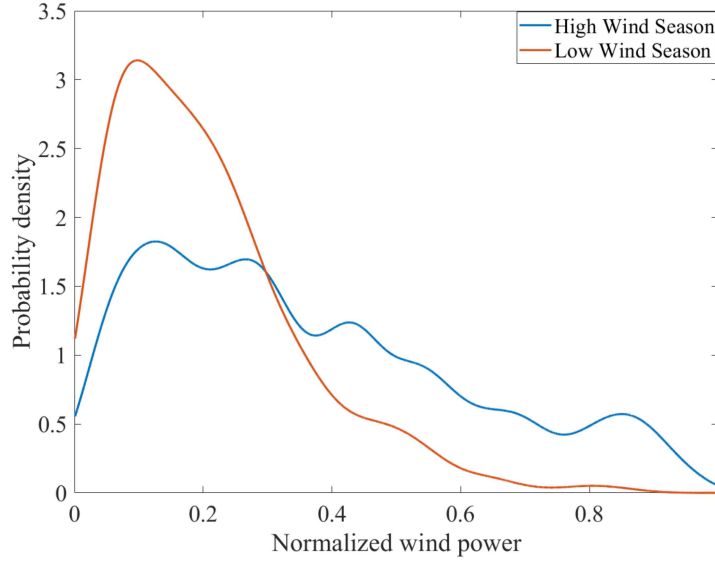


Fig. 4.5: Probability density of wind power from 00.00 a.m. to 01.00 a.m. in different wind seasons

4.1.1.4 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 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. Figure 4.6 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.

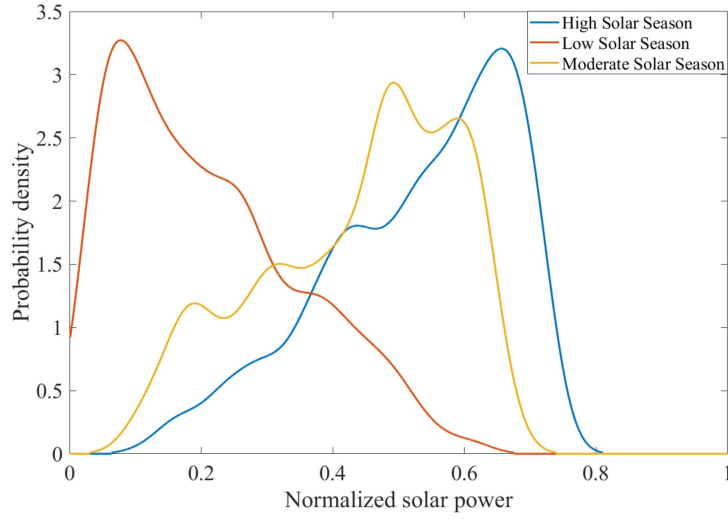


Fig. 4.6: Probability density of solar power from 12.00 p.m. to 01.00 p.m. in different solar seasons

4.1.2 Reliability Evaluation Using the Proposed KDE-Based Renewable Power Models

The IEEE RTS is used in this study. The generation system is modified by adding renewable generation. This Modified RTS (MRTS) is used to evaluate generation system adequacy under several case studies.

4.1.2.1 Modeling of Conventional Generation, Renewable Generation and Load in NSMCS

Conventional generators are modeled using 2-state Markov models. The 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 into three distinct seasons, i.e., summer, winter, and spring/fall, as described in [17]. 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 that 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.

4.1.2.2 Proposed KDE-based NSMCS Framework for Calculating Reliability Indices

In NSMCS, events 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 the number of samples and the higher 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 [25]. 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 [132]. 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 Equation 3.23.

Where $E[f]$ is the estimator of the expected value of the LOLE. The COV of LOLE margin ε is selected as 10^{-2} . The maximum number of sampling events 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 Figure 4.7.

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

Step 2: For $i = 1, 2, 3, \dots, n$ 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

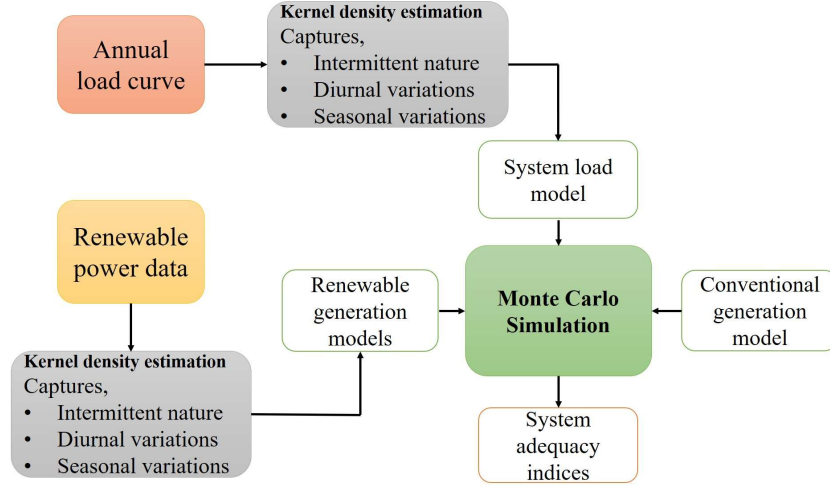


Fig. 4.7: An overview of the proposed generation system adequacy evaluation framework

availability of conventional generators.

Step 3: Generate a uniform random number U_1 between 0 and 1.

If $U_1 < \text{FOR of } i^{\text{th}} \text{ generator } (G_i)$, then the unit is not available ($C_i = 0$) otherwise the unit is available with full capacity ($C_i = \text{Capacity of } G_i$).

Step 4: Calculate the total available conventional generating capacity C_c using Equation 4.4,

$$C_c = \sum_{i=1}^n C_i \quad (4.4)$$

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

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 Equation 4.5,

$$C = C_c + C_w + C_s \quad (4.5)$$

Step 13: If $C < L$ then $H = H + 1$ (Failure event),

$$E = E + (L - C), N = N + 1, \text{ else } N = N + 1$$

Step 14: Calculate,

$$LOLP = H/N \quad (4.6)$$

$$LOLE = LOLP \times 8760 \quad (4.7)$$

$$LOEE = (E \times 8760)/N \quad (4.8)$$

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

4.2 Case Studies

The proposed KDE-based NSMCS framework is used to perform three case studies. In case studies 1 and 2, LOLP, LOLE, 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 [5].

$$\text{Reserve margin} = \frac{\text{Max_gen_cap} - \text{Max_demand}}{\text{Max_demand}} \quad (4.9)$$

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% [123]. All 3 case studies are performed by maintaining the reserve margin at its original value (19.47%).

The results of case studies 1, 2, and 3 are tabulated in Tables 4.2, 4.3, and 4.4, respectively. Figure 4.8 shows the variation of LOLE values with different renewable penetration levels considered in case studies 1, 2, and 3. As shown in Figure 4.8, LOLE increases almost linearly up to 10% of wind or solar in the system. Then, it exponentially increases when the proportion of wind or solar energy 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 seen in Figure 4.8. 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's reliability, especially when the proportion of renewable power in the system is large.

Secondly, solar power is unavailable at night, and when a large proportion of solar power is present in the system, solar power injection to the power grid during the day significantly varies from that of the nighttime.

TABLE 4.2: 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 4.3: 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

The adequacy of a wind and solar integrated power system may be 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 Figures 4.3 and 4.4 and [133], 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 Figure 4.8.

TABLE 4.4: 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

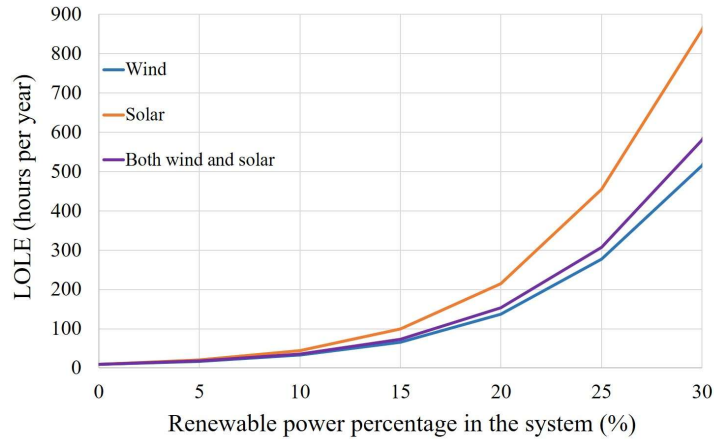


Fig. 4.8: Variation of LOLE values with different proportions of renewable power in the system

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.

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, rela-

tively 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 compared to case study 2. As can be seen in Figure 4.8, 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 [31]. 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 Figure 4.9.

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, the 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.

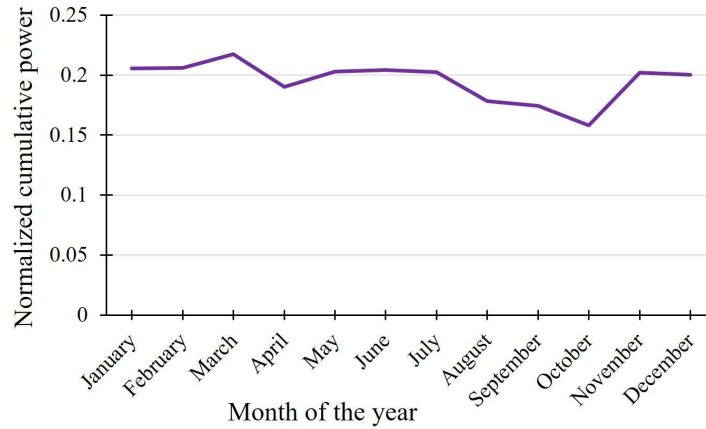


Fig. 4.9: Normalized monthly average wind and solar power generation

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, the capacity credit of wind and solar generation should be considered when deciding the capacity of conventional generation for a given peak load.

4.3 Model Validation and the Importance of Modeling Seasonal Renewable Power Variations

This section provides brief descriptions of model validation and the importance of modeling seasonal variations of renewable power. Subsection 4.3.1 describes the validation procedure of the proposed KDE-based NSMCS framework. In subsection 4.3.2, the importance of modeling seasonal renewable power variations is analyzed using the results of a crude NSMCS, which considers only diurnal variations of renewable power generation.

4.3.1 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 [123] 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 [120, 121] are used for SMCS. SMCS using hourly renewable and load data with tight COV should provide good reference values for validation.

The second, third, and fourth columns of Tables 4.5, 4.6 and 4.7 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.

TABLE 4.5: 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

The sequential Monte Carlo simulation provides 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

TABLE 4.6: 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 4.7: 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

in this work. Given that both NSMCS and SMCS are probabilistic simulation methods, a certain degree of estimation error in the LOLE of the proposed framework w.r.t SMCS is acceptable. This shows that the proposed KDE-based NSMCS framework can be used to evaluate the reliability indices of power systems accurately.

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 [1, 28, 29]. In this work, the 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) are 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 renewable data for only one year. Thus, the proposed models can be practically used for the reliability evaluation of real systems together with an NSMCS model instead of using sequential renewable power simulations such as the

ARIMA method that cannot model seasonal variations.

4.3.2 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 [31]. 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 4.5, 4.6 and 4.7. 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 cases ranges approximately from 3.5% to 5%. In the 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 only has solar power. This may happen mainly due to two reasons. Firstly, the seasonal variation of solar power generation is relatively large compared to the wind, as shown in Figures 4.3 and 4.4. Wind generation doubles the output in the high wind season, and solar generation quadruples the output in the high solar season. Secondly, seasonal solar power generation shows a negative correlation with the system load. 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 discussed previously.

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

4.4 Conclusion

This chapter proposes a novel method based on KDE to model the intermittency and diurnal and seasonal variations of renewable power generation. Then, the proposed renewable power models are integrated into an 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 variation of renewable power generation should be taken into account in the 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 significantly large number of simulation years required.

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 are 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 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 storage, 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.

CHAPTER 5

COMPOSITE SYSTEM ADEQUACY EVALUATION

The global electricity demand is expected to grow by 2.4% per year up to 2040 [18]. Therefore, power systems must gradually grow in both size and supply capability to satisfy the continuously increasing consumer demand. Hence, the adequacy assessment of future power systems will become a more complicated and time-consuming task due to the increased number of system components such as generators, transformers, and transmission lines.

Analytical and simulation-based probabilistic methods are widely used in the evaluation of power system systems to model the stochastic nature of power system components and estimate more realistic adequacy indices [9]. The outage probability of each power system component can be used to determine the status of the component, i.e., unit up or unit down. Then, the system event space can be generated by convolving the status of each power system component. The system events associated with zero load curtailment are success events, whereas those with load curtailment are failure events. The derived system event space can be analyzed to quantify the system adequacy using different adequacy indices such as PLC, EDLC, EENS, and EFLC [25]

However, the event space of a composite generation and transmission system is significantly large due to the combined number of generation and transmission components. For e.g., if a power system has x number of components, then the event space size will be 2^x . Therefore, the larger the power system, the higher the complexity of the system adequacy evaluation. On the other hand, composite system events are evaluated by the OPF analysis, and this optimization problem requires a significant amount of computational time, especially when there is a large number of system events. Thus, more effective and efficient methods are needed to assess the system's adequacy more accurately and conveniently.

5.1 Composite System Adequacy Evaluation Procedure

Three basic steps are needed to estimate the adequacy indices in power system adequacy evaluation. Firstly, system events are sampled from the system event space. Then, each sampled event is evaluated to determine whether it is a success or failure. Finally, the adequacy indices are derived from the sampled system events[6].

5.1.1 System Event Sampling

The system success and failure events are scattered over the system event space. In PIS methods, the most probable system failure events are enumerated from the system

event space as they significantly affect the system adequacy [6, 40].

A system event is a combination of the states of the system's individual components, such as generators and transmission lines. In PIS, each system event is represented as an array in which the component status is assigned to the respective cells of the array. The system event configuration is illustrated in Figure 5.1. Similar components are grouped, and each cell represents the availability of the corresponding generator or transmission line, i.e., 0 or 1.

The step-down transformers, e.g., 220 kV to 132 kV, can also be represented as transmission lines.

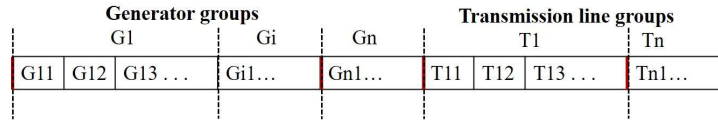


Fig. 5.1: The representation of a system event

Various power system adequacy evaluation methods use different sampling mechanisms for system event selection. In this study, the main emphasis is given to the sampling mechanisms of widely used PIS methods, i.e., GAs and BPSO. The most probable system failure events are found in the aforementioned methods by iteratively applying evolutionary or swarm intelligence-based operations on a set of randomly selected system events.

5.1.1.1 Genetic Algorithms

In GAs, genetic operators such as selection, crossover, and mutation are applied to the existing population, i.e., a set of system events to generate a new population with a large number of system failure events [134]. Firstly, individuals, i.e., system events with comparatively high fitness values, are selected from the existing population to form a new population. Roulette Wheel Selection (RWS) is a widely used selection method in GAs. In RWS, the probability of selecting an individual is proportional to its fitness value. The higher the fitness, the larger the probability of selection. Individuals with high fitness values may be selected more than once, and the worst will die off eventually. Secondly, the selected individuals are considered as parents, and the crossover operation is applied to each pair of selected individuals. This is illustrated in Figure 5.2. The crossover operation is applied according to the crossover probability, which is defined according to the nature of the application. The crossover position is selected randomly. Finally, the child chromosomes are subjected to the mutation operator to introduce random changes in the chromosomes. The genes, i.e., bits in each chromosome, are changed according to the defined mutation probability. This prevents the GA from being trapped in a local area of the system event space.

However, several limitations are native to the application of GAs in power system adequacy evaluation. The failure system events are not randomly distributed in the event space, i.e., most of the system failure events may have common component failures (For e.g., in most of the system failure events, the largest generator of the system will be at the downstate). When a new population is being generated, the offspring generation should have these fit qualities of the parents. In GAs, the crossover operator does not maintain these genealogical links between parent and offspring generations. Furthermore, the crossover operator does not provide a significant advantage over mutation because it is a form of mutation itself.

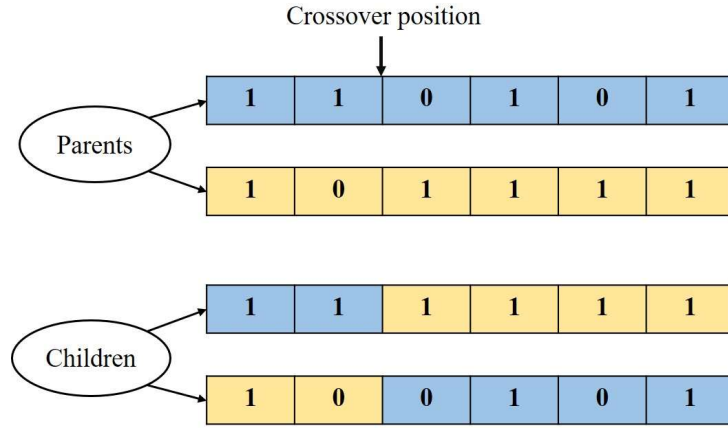


Fig. 5.2: The crossover operation

5.1.1.2 Binary Particle Swarm Optimization

Particle swarm optimization is a form of swarm intelligence in which the optimization problem is solved by a swarm of particles roaming in a multi-dimensional search space [135]. The swarm particles have two main features, i.e., position and velocity. The particles record the best positions (p_best) that they have visited, and then, the best position of the whole swarm is identified (g_best). The velocity provides an idea of the solution distance w.r.t the current particle position. For each particle, the velocity is calculated using p_best and g_best , and then, the next particle positions are computed according to respective velocities. In BPSO, each swarm particle is represented by a binary number. Hence, the system event representation illustrated in Figure 5.1 can also be employed in the BPSO for composite system adequacy evaluation. Thus, a swarm particle represents a system event. The system component events, i.e., individual binary digits, are changed according to their respective velocities to form the next population of swarm particles. The velocity of each individual component is calculated using Equation 5.1 [136]. V_i^K is the velocity of i^{th} component at K^{th} generation. c_1 and c_2 are learning factors known as cognitive acceleration constant and social accel-

eration constant, respectively. r_1^K and r_2^K are uniformly distributed random numbers between 0 and 1 that are generated for the K^{th} generation. $p_best_i^K$ is the status of the i^{th} component (i^{th} bit) of the most probable system failure event that the swarm particle has encountered up to the K^{th} generation. $g_best_i^K$ is the status of the i^{th} component (i^{th} bit) of the most probable system failure event that any of the swarm particles has encountered up to the K^{th} generation. x_i^K is the status of the i^{th} component (i^{th} bit) at K^{th} generation.

$$V_i^{(K+1)} = (V_i^K) + c_1 r_1^{(K+1)} (p_best_i^K - x_i^K) + c_2 r_2^{(K+1)} (g_best_i^K - x_i^K) \quad (5.1)$$

Similarly, the component velocities are calculated for the other particles present in the population. The velocity of an individual component provides an idea of the probability of the component's availability. The Sigmoid limiting transformation function explained by Equation 5.2 is used to transform the velocity of component i (V_i) to a probability of availability. Then, the new status of the component i (x_i^{K+1}) can be derived using Equation 5.3 where r is a uniform random number between 0 and 1 [136]. Moreover, the velocities should be limited by an upper bound V_{max} and a lower bound V_{min} to avoid the ultimate probability of the availability of a bit in a particle being zero or one.

$$S(V_i^{K+1}) = \frac{1}{1 - e^{-V_i^{K+1}}} \quad (5.2)$$

$$x_i^{K+1} = 1 \text{ if } r < S(V_i^{K+1}), \text{ } 0 \text{ else} \quad (5.3)$$

However, the ability to search in new areas of the system event space is limited in BPSO. Generally, the velocity of a bit, i.e., a component in a particle, will be bounded by $[V_{min}, V_{max}]$, and then, the probability of availability of the component $S(V_i)$ will become a fixed value.

5.1.2 Event Evaluation

In event evaluation, each selected system event is analyzed to identify the respective load curtailments associated with the event. The main objective of the optimization is to minimize the cost of load curtailments. AC or DC OPF analysis can be used in this context. However, DC OPF is more computationally effective for composite system reliability evaluation, as the resistance of transmission lines is significantly lower than reactance [25]. A general representation of the DC OPF problem is explained by Equations 5.4 to 5.8 [25].

$$\text{Min } f = \sum_{i=1}^k x_i C_i \quad (5.4)$$

$$\sum_{i=1}^k Pg_i + \sum_{i=1}^k C_i = \sum_{i=1}^k Pl_i \quad (5.5)$$

$$|[A].[P]| \leq [T_{limit}] \quad (5.6)$$

$$0 \leq Pg_x \leq Pcap_x \quad (5.7)$$

$$0 \leq C_i \leq Pl_i \quad (5.8)$$

Where x_i and C_i are the cost of load curtailment and the curtailed load at the i^{th} bus, respectively. k is the total number of buses in the transmission system. Pg_i and Pl_i are the power generation and load requirement at the i^{th} bus, respectively. A is the sensitivity matrix in which the transmission line power flows are expressed, P is the net bus injection vector, and T_{limit} is the transmission line capacity vector. Pg_x is the power generation of x^{th} generator with a maximum capacity of $Pcap_x$. For a selected system event, if $\sum_{i=1}^k C_i > 0$, then the event is classified as a failure event and stored for further analysis.

5.1.3 Estimation of System Adequacy Indices

Several adequacy indices that are employed to quantify the composite system adequacy are described by Equations 5.9 to 5.12 [25].

5.1.3.1 Probability of Load Curtailments (PLC)

$$PLC = \sum_{i=1}^n Event_p_i \quad (5.9)$$

Where $Event_p_i$ is the probability of failure of the system failure event i and n is the total number of system failure events.

5.1.3.2 Expected Duration of Load Curtailments (EDLC) (Hours per year)

$$EDLC = 8760 \times PLC \quad (5.10)$$

5.1.3.3 Expected Energy Not Supplied (EENS) (MWh per year)

$$EENS = \sum_{i=1}^n LC_i \times Event_p_i \quad (5.11)$$

Where LC_i is the load curtailment of the system failure event i .

5.1.3.4 Expected Frequency of Load Curtailments (EFLC) (Occ. per year)

$$EFLC = \sum_{i=1}^n (F_i - f_i) \quad (5.12)$$

where F_i is the frequency of the departing system event i and, f_i is the portion of F_i which corresponds to the subsequent system failure events.

5.2 Proposed Evolutionary Swarm Algorithm

The proposed ESA inherits the useful features of GAs and BPSO while eliminating the limitations. The ESA generates a new population using two main steps, namely selection and dynamic mutation, which are explained in sections 5.2.1 and 5.2.2 respectively. Section 5.2.2 describes the composite system adequacy evaluation procedure.

5.2.1 Selection Operator

The selection operator is inherited by the GAs. It is used to select the most probable system failure events from the present population to form a new population. The RWS is used in this work.

5.2.2 Dynamic Mutation Operator

In the dynamic mutation mechanism, variable mutation probabilities are used to mutate each bit of the particles (i.e., the status of each component in the system events) in the population. Hence, for each particle, a mutation probability array should be maintained. This is somewhat similar to the velocity principle of BPSO. However, the Sigmoid transfer function is not required in the proposed mechanism because the mutation probability of system components is directly derived by the dynamic mutation operator. The dynamic mutation mechanism can be explained by Equation 5.13.

$$P_i^{(K+1)} = Pm + r^{(K+1)} * |p_best_i^K - x_i^K| \quad (5.13)$$

$P_i^{(K+1)}$ is the dynamic mutation probability of the i^{th} component at the $(K + 1)^{th}$ generation. Pm is the permanent mutation constant. Pm is commonly a small con-

stant, e.g., 0.03, that is used to avoid premature convergence. Instead of always following the fittest particles, new search areas are explored due to the introduction of Pm . In composite system reliability evaluation, different Pm values may be used for generators and transmission lines according to their forced outage rates. r is a uniform random number between zero and one, which is used to exploit new solutions around the p_best events while avoiding particles from moving exactly towards them. Similarly, the component mutation probabilities are calculated for the other particles present in the population.

According to the mutation probability, the status of each component of the particle population is updated using Equation 5.14 where r is a uniform random number between zero and one.

$$x_i^{(K+1)} = \neg x_i^K \text{ if } r < P_i^{(K+1)}, \quad x_i^K \text{ else} \quad (5.14)$$

System failure events commonly involve the failure of a specific generator or transmission line. This fact can be used to find system failure events using the failure events that have already been identified. The dynamic mutation operator is designed considering this ideology, which is lacking in the prevailing PIS methods. The dynamic mutation operator described by 5.13 and 5.14 changes the future solution space by considering the best solutions for the previous solution space. Thus, the system failure events can be captured within a small number of iterations compared to other PIS algorithms such as GA and BPSO.

5.2.3 Composite System Adequacy Evaluation Framework

The generation system adequacy evaluation procedure proposed in [6] is extended in this work to evaluate the adequacy of composite systems as follows. Thus, this chapter focuses on the adequacy evaluation of composite systems using AI optimization methods as shown in Figure 5.3. Figure 5.4 illustrates the adequacy evaluation procedure.

- Step 1: Generate a population of particles, i.e., system events randomly where the events of generators and transmission lines are initialized using binary digits.
- Step 2: Calculate the probability of each system event using Equation 5.15 and select the most probable system events e.g., *event probability* $> 1e^{-10}$.

$$P_i = \prod_{j=1}^m P_{comp_j} \quad (5.15)$$

Where m is the total number of individual components and P_{comp_j} is the state probability of j^{th} component. The fitness of the unqualified system events e.g., *event probability* $\leq 1e^{-10}$ is assigned to a small value e.g., $P_i \times 1e^{-5}$.

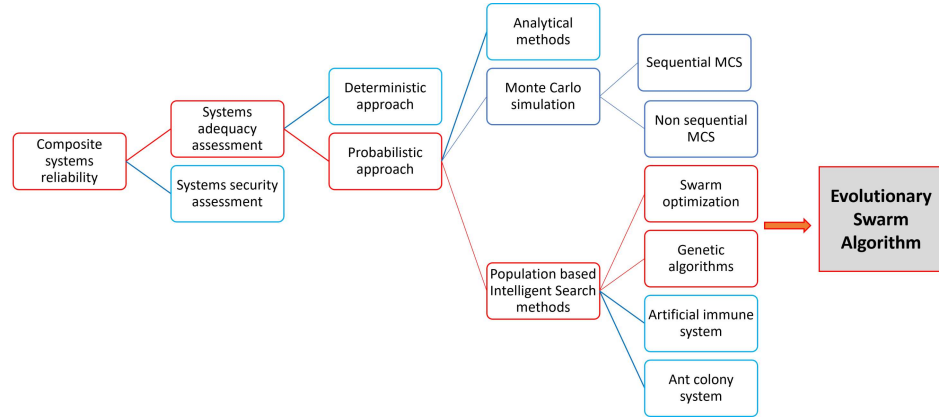


Fig. 5.3: The selection of composite system adequacy evaluation framework

Step 3: Select a most probable system event and evaluate it using DC OPF w.r.t the maximum load demand. Derive the load curtailment LC'_i .

Step 4: If $LC'_i = 0$ (success event), a very small fitness value is assigned to the event and, repeat from step 3. If $LC'_i > 0$ (failure event), go to the next step.

Step 5: Calculate the number of all possible permutations of the evaluated system failure event as follows.

$$Perm_i = \binom{G_1}{n_1} \times \dots \times \binom{G_i}{n_i} \times \dots \times \binom{G_n}{n_n} \quad (5.16)$$

Where G_i is the length of group i and n_i is the number of available components in group i .

Step 6: The fitness of the event is calculated by Equation 5.17.

$$Fit_i = Perm_i \times P_i \quad (5.17)$$

Step 7: Frequency of the event can be calculated by Equation 5.18.

$$F_i = P_i \times \left(\sum_{j=1}^m (1 - b_j) \times \mu_j - \sum_{j=1}^m b_j \times \lambda_j \right) \quad (5.18)$$

Where b_j indicates the component status, i.e. 0 or 1. μ_j and λ_j are the expected repair rate and the expected failure rate of component j , respectively.

Step 8: Save the derived information e.g., *system event*, P_i , $Perm_i$, F_i and LC'_i of the failure event in an array.

- Step 9: Repeat steps 3-8 until the remaining system events, i.e., individuals, are evaluated. Before each evaluation, the selected system event is checked to ensure that it has not been previously evaluated. If it is a previously evaluated event, the fitness of the event is assigned to a very small value. Therefore, it will not appear in the following generations.
- Step 10: Increase the iteration number by one. Check whether any stopping criterion is satisfied. If yes, go to step 13. Else, go to the next step.
- Step 11: PIS guidance mechanism is applied to the current population for generating the next population.
- Step 12: Repeat steps 2-11.
- Step 13: Calculate the annualized composite system adequacy indices described in Equations 5.9 to 5.12 using the derived system event array where $Event_p_i = Perm_i \times P_i$. The EFLC explained in Equation 5.12 is calculated as follows.

$$EFLC = \sum_{i=1}^n Fi \times Perm_i \quad (5.19)$$

- Step 14: Calculate the annual adequacy indices as follows.

- The chronological load curve is transformed to a q number of load levels, for e.g., 15 load levels. Then, sort the load levels in descending order in which the first state has the highest load value, and the q^{th} state has the lowest.
- Calculate the load step probabilities and load transition rates per year (λ) between the load events.
- For each system failure event, DC OPF analysis is applied for different load levels. If $LC_{ix} = 0$ for a certain load cluster x , the event evaluation process is stopped, and it is restarted on the next system failure event.
- While evaluating all the system failure events for different load levels, calculate the composite system adequacy indices using Equations 5.9 to 5.12 where $Event_p_{ix} = Perm_i \times P_i \times Lp_x$. $Event_p_{ix}$ is the probability of the i^{th} event for the x^{th} load step. Lp_x is the probability of the x^{th} load step. The EFLC is calculated as follows [137].

$$\begin{aligned}
EFLC = & \sum_{i=1}^n \sum_{x=1}^q Lp_x \times F_i \times Perm_i + \\
& \sum_{i=1}^n \sum_{x=1}^q \left(\sum_{j=r+1}^q \lambda_{rj} - \sum_{j=1}^{r-1} \lambda_{jr} \right. \\
& \left. \times \frac{Lp_j}{Lp_x} \right) \times P_i \times Perm_i \times Lp_x
\end{aligned} \tag{5.20}$$

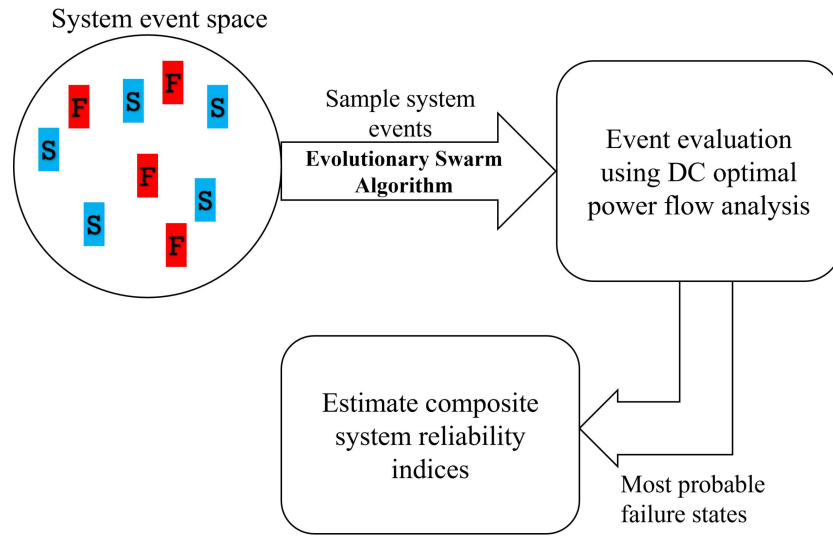


Fig. 5.4: Proposed composite system adequacy evaluation framework

There are several criteria to determine the stopping rule of meta-heuristic algorithms [138]. In this work, the number of population iterations is set to a maximum number, and reaching this maximum number of iterations is used as the stopping rule. The appropriate number of iterations is determined using the trial and error method, considering the required accuracy and the computational cost.

5.3 Composite System Adequacy Evaluation of RBTS and IEEE RTS

In this section, SMCS, GA, BPSO, and the proposed ESA are used to estimate the annualized and annual adequacy indices of the IEEE RTS system. The results of a GA and BPSO are used to elaborate on the accuracy, sampling efficiency, convergence and precision of the proposed ESA.

The SMCS is used to compare the computational efficiency of PIS and Monte Carlo sampling methods. In SMCS, the number of simulation years is fixed to 500 years while maintaining the coefficient of variation of PLC less than $1e^{-2}$. MATLAB is used

to implement the PIS and SMCS methods in a single-core processing environment. The DC OPF analysis is conducted by a linear optimization function called “linprog.” A system with the Intel Core i7-8750H processor and 8 GB RAM is utilized in this work.

In the adequacy evaluation of RBTS, the total number of iterations, i.e., new generations, of GA, BPSO, and ESA is selected as 200. The population size of the algorithms is set at 100. Annualized composite system adequacy indices, number of failure events evaluated, adequacy evaluation time of SMCS, and PIS methods are tabulated in Table 5.1. Annual composite system adequacy indices and the respective evaluation time are shown in Table 5.1.

In the adequacy evaluation of IEEE RTS, the total number of iterations and population size of GA, BPSO, and ESA are assigned as 1500 and 100, respectively. Annualized RTS adequacy indices, the number of failure events evaluated, and the adequacy evaluation time of SMCS and PIS methods are tabulated in Table 5.3. Annual composite system adequacy indices and the respective evaluation time are shown in Table 5.4

5.3.1 Validation of the Proposed ESA

The proposed ESA can be validated using the results of SMCS presented in [7]. Table 5.5 shows the comparison of annualized adequacy indices obtained from the ESA and the reference SMCS [7]. It can be seen that the adequacy indices obtained by the ESA are very close to the reference values presented in [7]. Given that SMCS is a probabilistic simulation method, a certain degree of estimation difference can be accepted.

Moreover, the bias of the estimated EDLC of GA, BPSO, and ESA is 18.49, 38.05 and 11.44. The sample size is 50, and the number of iterations is limited to 1500 for each sample. Further discussion on the bias of estimators can be found in the section 5.5.1

TABLE 5.1: ANNUALIZED ADEQUACY INDICES, NUMBER OF FAILURE EVENTS, AND ADEQUACY EVALUATION TIME OF SMCS AND PIS METHODS FOR RBTS

	SMCS	GA	BPSO	ESA
PLC	0.00983	0.00974	0.00967	0.00975
EDLC (hours/year)	86.01	85.28	84.67	85.44
EENS (MWh/year)	1001.2	1046.8	1040.8	1049.7
EFLC (occ. /year)	3.94	4.13	4.09	4.15
Failure events	-	800	615	765
Time (s)	27666.7	6.96	6.79	6.98

TABLE 5.2: ANNUAL ADEQUACY INDICES AND ADEQUACY EVALUATION TIME OF SMCS AND PIS METHODS FOR RBTS

	SMCS	GA	BPSO	ESA
PLC	0.00122	0.00125	0.00125	0.00128
EDLC (hours/year)	10.71	10.96	10.94	11.17
EENS (MWh/year)	125.9	132.3	129.6	132.4
EFLC (occ. /year)	1.15	1.25	1.25	1.25
Time (s)	26820	41.78	31.39	37.7

TABLE 5.3: ANNUALIZED ADEQUACY INDICES, NUMBER OF FAILURE EVENTS, AND ADEQUACY EVALUATION TIME OF SMCS AND PIS METHODS FOR IEEE RTS

	SMCS	GA	BPSO	ESA
PLC	0.0849	0.0841	0.0813	0.0844
EDLC (hours/year)	743.57	736.5	711.95	739.59
EENS (MWh/year)	129145.9	127301.7	122269.7	128138.2
EFLC (occ. /year)	19.19	19.11	17.47	19.33
Failure events	-	10962	7722	12068
Time (s)	25817.6	267.11	243.08	277.70

5.3.2 The computational efficiency of the ESA

In SMCS, accurate estimations for system adequacy indices can be obtained by employing a tight coefficient of variation for the adequacy estimators as the stopping rule. However, the higher the accuracy of estimators, the larger the computational time. Tables 5.1, 5.2, 5.3 and 5.4 show the computational time associated with each PIS method and SMCS. When comparing the computational times, PIS methods are more computationally efficient than the SMCS. When compared with the SMCS, ESA can estimate the system adequacy indices in a significantly short time period. The main reason is the difference between the sampling mechanism of PIS methods and SMCS. In SMCS, the system events are sampled stochastically, and both success and failure events are used to estimate the system adequacy indices. Hence, the OPF analysis is

TABLE 5.4: ANNUAL ADEQUACY INDICES AND ADEQUACY EVALUATION TIME OF SMCS AND PIS METHODS FOR IEEE RTS

	SMCS	GA	BPSO	ESA
PLC	0.001437	0.001416	0.001258	0.001426
EDLC (hours/year)	12.59	12.41	11.02	12.49
EENS (MWh/year)	1490.0	1285.4	1136.1	1308.7
EFLC (occ. /year)	2.3	2.13	1.88	2.21
Time (s)	26414.2	510.6	448.1	566.7

TABLE 5.5:]

COMPARISON OF ANNUALIZED ADEQUACY INDICES OBTAINED USING
THE ESA AND THE REFERENCE SMCS [7]

	PLC	EDLC	EENS	EFLC
Percentage (%) difference of results of ESA for IEEE RTS	1.63	1.54	2.48	1.48
Percentage (%) difference of results of ESA for RBTS	1.61	1.58	0.87	1.43

conducted on both success and failure system events. This significantly increases the computational time. Moreover, when the system is more reliable, the probability of sampling failure events will be less, and the simulation convergence criterion may not be satisfied even for a large number of samples. On the other hand, PIS methods only focus on the most probable system failure events that significantly affect the system adequacy indices. Hence, the OPF analysis will be conducted on a limited number of events, and this can drastically reduce the computational time.

The computational time of PIS methods depends mainly on two factors: the number of new most probable system events (for e.g., *event probability* $> 1e^{-10}$) identified and the complexity of the PIS guide operation. However, in applications of composite system adequacy evaluation, the computational time of the PIS methods significantly varies with the number of most probable system events evaluated. These most probable system events include both success and failure events. In PIS methods, the exploration of the system success events throughout the generation iterations is minimized as they are not needed in the calculation of system adequacy indices. Hence, the computational time of PIS methods significantly varies with the number of failure events evaluated. This can be observed in the Tables 5.1, 5.2, 5.3 and 5.4. Hence, the performance of the PIS methods cannot be compared by using the respective computational times observed for a given number of iterations (e.g., 1500). In fact, the convergence characteristics of the PIS methods showcase the respective computational efficiencies.

The computational efficiency of the proposed ESA can be compared with that of GA and BPSO as follows. The computational times, the number of events, and the number of iterations that are required for reaching different tolerance levels of EDLC (or PLC) can be obtained for ESA, GA, and BPSO as shown in Table 5.6. The maximum number of iterations is limited to 15000. As can be seen in Table 5.6, the BPSO method significantly struggles to get into the defined tolerance levels of EDLC. Especially, the tolerance level of 1.5% cannot be reached even for 15000 iterations. The computational times of the ESA are the lowest for each EDLC tolerance level. The ESA computational time is reduced by 31.24% and 90.24% when compared with GA and BPSO for the EDLC tolerance level of 1.5%. Similarly, for the EDLC tolerance

TABLE 5.6: COMPUTATIONAL TIME, NUMBER OF ITERATIONS, NUMBER OF FAILURE EVENTS OF ESA, GA, AND BPSO FOR DIFFERENCE TOLERANCE LEVELS OF ANNUALIZED EDLC

Algorithm	Observations	Different Tolerance Levels of annualized EDLC [7]		
		1.50% (739.9 h/yr)	2% (736.15 h/yr)	2.50% (732.39 h/yr)
ESA	Time (s)	250.15	157.46	89.88
	# Iterations	1574	783	525
	# Failure events	12070	8915	7080
GA	Time (s)	363.81	203.34	123.92
	# Iterations	2657	1497	905
	# Failure events	14163	11134	8539
BPSO	Time (s)	2563.23	1260.74	762.72
	# Iterations	**15000	8137	5520
	# Failure events	16745	14335	12380

levels of 2% and 2.5%, the average computational time reduction of ESA is 25.02% and 87.86% w.r.t. GA and BPSO.

When comparing the results shown in Table 5.6, several interesting facts can be observed. In all the cases, ESA reaches the defined tolerance levels with the lowest number of system failure events, the lowest number of iterations, and the lowest computational time. Although GA and BPSO have accumulated more system failure events, they were unable to reach EDLC tolerance levels faster than ESA. Hence, having the highest number of system failure events does not guarantee the accuracy of the derived adequacy indices. The sampled set of failure events should include the most probable failure events of the system. If the probabilities of sampled events are low, the estimations become inaccurate. The results show that ESA can sample the most probable system failure events within fewer iterations than GA and BPSO.

5.3.3 The sampling efficiency of the ESA

The sampling efficiency of PIS methods can be compared by observing the number of sampled failure events from a system event space with defined dimensions (e.g., population size and the number of iterations). When considering the adequacy evaluation of IEEE RTS, GA, BPSO, and ESA found 10962, 7722, and 12068 failure events from the search space of 100×1500 , i.e., 150000.

The size of the search space assigned for the adequacy evaluation of RBTS is 40×200 , i.e., 8000. GA, BPSO, and ESA found 800, 615, and 765 failure events from the search space, respectively. In this scenario, GA found more system failure events than ESA. However, the ESA has given the highest adequacy indices. This shows that

ESA has done sampling in a more meaningful manner, i.e., ESA has sampled more probable system failure events than GA.

PLC is a good measure for quantifying the ability of PIS in a more meaningful manner. In PIS-based adequacy evaluation methods, the larger the PLC, the higher the accuracy of the PIS method. As can be seen in Tables 5.3 and 5.4, ESA found the largest number of system failure events and provides the largest PLC value. Thus, the proposed PIS mechanism outperforms GA and BPSO in terms of sampling efficiency.

5.3.4 The convergence performance of the ESA

The evolution of PLC in terms of computational iterations is illustrated in Figure 5.5 for each PIS algorithm. It can be seen that ESA converges significantly faster than GA and BPSO. The GA requires a significant number of iterations to reach convergence. This may have happened due to the elimination of important genealogical links between parent events and child events by the crossover operator. This limitation is addressed in the ESA, which can rapidly reach convergence.

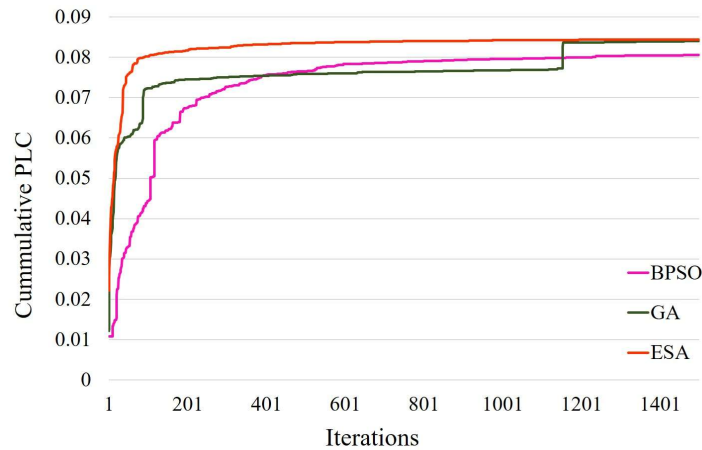


Fig. 5.5: The evolution of PLC in terms of computational iterations

The PIS ability of BPSO is significantly reduced in the adequacy evaluation of IEEE RTS. This happens mainly due to the lack of mutation operator as in GAs. This causes the convergence of particle velocities to the maximum permitted values, i.e. $[V_{min}, V_{max}]$. This will limit the BPSO's ability to search for new search spaces. The swarm intelligence philosophy, i.e., "following the leader," cannot be applied to large event spaces because there may be a significant number of leaders (most probable system failure events) that need to be followed.

The convergence path in traditional optimization problems shows a gradual improvement of solutions in each iteration when approaching the minima or maxima. In other words, the latest solution explored will be better than the previous solution. In this work, PIS algorithms search for system failure events instead of finding an optimal

solution. Therefore, the convergence of the algorithms cannot be theoretically proven, as stated in [139].

5.3.5 The precision of the ESA

When comparing the adequacy indices obtained by the PIS methods, the larger the adequacy indices such as PLC, EDLC, EENS, and EFLC, the higher the accuracy of the estimations. This means that the most probable system failure events are sampled during the PIS process. Tables 5.3 and 5.4 show that the proposed ESA has provided the most accurate system adequacy indices. However, the adequacy indices should be consistent throughout several executions of the algorithm. Therefore, to identify the consistency and precision of the PIS methods, the standard deviation of the annualized EDLC estimator of the IEEE RTS is calculated for the results of 50 executions. The standard deviation of EDLC obtained by GA, BPSO, and ESA are found to be 1.15, 6.38, and 0.22, respectively. The standard deviation of EDLC is the lowest in the ESA. Hence, the precision of the proposed algorithm is significantly greater than that of the GA and BPSO.

5.4 Application of Evolutionary Swarm Algorithm for Analyzing the Impact of Integrating Renewables on the Adequacy of Composite Power Systems

The proposed ESA that was applied to the composite systems lacks renewable power modeling. The chronological renewable power model used for the generation system adequacy evaluation in [6] cannot be utilized in composite systems due to the time-consuming event evaluation process that requires an OPF analysis. Hence, the integration of renewables such as wind and solar to the composite systems requires a novel renewable power modeling method that can be incorporated into the PIS methods. Moreover, the impact of renewable power models on the event evaluation process should be minimized in order to retain the computational efficiency of the PIS algorithm.

In this section, an ESA-based framework is proposed for evaluating the adequacy of wind and solar-integrated composite systems. The wind and solar power generation are modeled using the annual effective renewable power generation data considering the intraday renewable power variations. Then, the proposed renewable power generation models are integrated into the ESA to evaluate the adequacy of renewable integrated power systems. The correlation between the system load and renewable power generation is modeled in the adequacy evaluation framework. Then, case studies are conducted using the IEEE RTS, and the proposed methodology is validated using the results of MCS. Finally, the impact of integrating renewables on the ade-

quacy of composite power systems is analyzed for different wind and solar penetration levels. The equivalent capacities of wind and solar generation are quantified in terms of conventional generating capacity to investigate the contribution of renewables to the composite system adequacy. The adequacy evaluation framework is executed in a parallel processing environment to reduce computational time.

5.4.1 Modeling of Renewable Power Generation.

When considering the adequacy evaluation of wind and solar integrated composite systems, there exist several challenges to overcome. The main time-consuming task of the composite system adequacy evaluation is the OPF analysis. When calculating the system annual adequacy indices, OPF analysis should be repeatedly applied for the recorded system failure events w.r.t the defined number of load clusters. However, if there is no renewable integration, the load clusters can be sorted in descending order in such a way that the first cluster has the highest load value and the final cluster has the lowest. Then, for each system failure event, the OPF analysis can be started from the first load state. If the load curtailment is zero for any load cluster, the rest of the load clusters are omitted, and the next system failure event is considered for evaluation. Thus, most of the time, the OPF analysis is not required for each load cluster. The integration of renewables into the system eliminates this advantage because of the variability of wind and solar. Load values in one load cluster may be correlated with different renewable power outputs. Therefore, the system load model used in section 5.2.3 cannot be used in this work. Both load and renewable power generation data should be clustered according to the intraday and seasonal variations to preserve the correlation between the load and renewable power generation. This increases the computational burden of the algorithm. In this work, the authors have used simulated wind and solar power generation data to model renewable power generation. There are several advantages of using the simulated wind and solar generation data over the meteorological data, such as wind speed or solar irradiance.

1. If wind speed or solar irradiance data is used, separate mathematical models are required to obtain the respective wind and solar power generation outputs. This increases the computational time and the complexity of the adequacy evaluation procedure. Pre-simulated wind and solar power generation data ease this task.
2. The FORs of wind turbines and PV systems are considerably low. Hence, the failure of several renewable generators is highly unlikely, and corresponding system failure events do not significantly affect the adequacy of power systems. Moreover, wind turbines and solar arrays provide only a fraction of total renewable power output. Therefore, the failure of several renewable generators does not significantly change the overall renewable power output. Thus, if the simu-

lated wind or solar power generation data is available for a location, the overall power generation of the wind or solar farm can be directly modeled without considering the FORs of renewable generators.

3. The length of the system event representation will be reduced because wind and solar generators are assumed to be always available. Thus, pre-simulated renewable power data reduces the computational burden of the adequacy evaluation algorithm.

The system load and renewable power generation models should be able to maintain the respective mutual correlation. Hence, the structure of the load and renewable power models should be the same. Solar power generation shows significant diurnal variations. Therefore, the diurnal and seasonal load and renewable power generation should be tightly correlated in the respective models. In this work, a clustering-based load and renewable power generation modeling approach is proposed, considering the aforementioned conditions. The annual load curve and effective wind and solar power generation values are used to implement the respective clustering-based models. The structure of the clustering-based model is illustrated in Figure 5.6.

	Bihourly power generation of the day			
	00.00-02.00	02.00-04.00	...	22.00-00.00
Cluster 1	C1.1	C1.2	C1.j	C1.12
Cluster 2	C2.1	C2.2	C2.j	C2.12
⋮				
Cluster 10	C10.1	C10.2	C10.j	C10.12

Fig. 5.6: The structure for clustering-based load and renewable power models

Three different clustering-based models are implemented to represent the system load, wind generation, and solar generation. When considering the system load model, the intraday load is first clustered bi-hourly to obtain 12 diurnal clusters. Then, each bi-hourly data group is clustered according to the month of the year to generate 144 distinctive load clusters. The center of each cluster is used in the adequacy evaluation, and the respective load probability of n^{th} cluster P_n can be obtained using Equation 5.15.

$$P_n = (\text{cluster size})/730 \times 1/12 \quad (5.21)$$

Similarly, wind and solar generation data are categorized into bi-hourly groups and vertically clustered according to the months of the year. For e.g., if 1st load cluster is selected, then solar cluster 1 and wind cluster 1 are considered in the adequacy evaluation algorithm. Thus, the correlation between the load and renewable power generation is modeled.

5.4.2 Composite System Adequacy Evaluation Framework.

The proposed load and renewable power generation models can be integrated into the adequacy evaluation framework proposed in section 5.2.3 for evaluating the adequacy of wind and solar integrated composite systems. The probability of i^{th} failure event w.r.t n^{th} load cluster i.e. $P_{event_{i\ n}}$ can be calculated using Equation 5.22. The adequacy indices, such as PLC, EDLC, and EENS, can be estimated as follows.

$$P_{event_{i\ n}} = Perm_i \times P_i \times Pl_n \quad (5.22)$$

where $Perm_i$ is the total number of permutations of the i^{th} system event with a probability of P_i , and Pl_n is the probability of load cluster n .

$$PLC = PLC + P_{event_{i\ n}} \quad (5.23)$$

$$EDLC = PLC \times 8760 \quad (5.24)$$

$$EENS = EENS + LC_{i\ n} \times P_{event_{i\ n}} \quad (5.25)$$

where $LC_{i\ n} > 0$ is the load curtailment of $i^{th} event$ w.r.t n^{th} cluster.

The IEEE RTS is modified by integrating solar and wind generation into buses 9 and 10, respectively. Figure 2.7 shows the IEEE RTS. The simulated solar and wind power generation data are obtained from [120, 121] for Hambantota, Sri Lanka, and Mannar, Sri Lanka, respectively.

The annual adequacy indices are estimated in a parallel processing environment. The simulations are executed on a computer with an Intel Core i5-1135G7 processor and 16 GB of RAM, with four workers (cores) employed in parallel.

5.4.3 Results and Discussion

5.4.3.1 The Variation of Composite System Adequacy with Wind and Solar Penetration Levels

For the RTS, annual adequacy indices are estimated considering different wind and solar penetration levels to identify possible reliability improvements. Wind and so-

lar integration levels are increased by 50 MW increment up to 200 MW according to three scenarios: solar only, wind only, and both wind and solar in equal capacities. Moreover, the SMCS is conducted on the same scenarios for the validation of the proposed ESA-based adequacy evaluation framework. The SMCS is iteratively executed for 500 years. The computational times of the ESA and SMCS are 2.6772 hours and 7.361 hours, respectively. Table 5.7 shows the EDLC and EENS estimations obtained by ESA and SMCS for different wind and solar penetration levels. According to the results shown in Table 5.7, the SMCS and ESA provide approximately similar estimations for composite system adequacy indices. Therefore, the ESA can be used to accurately evaluate the adequacy of the composite system.

TABLE 5.7: ANNUAL ADEQUACY INDICES FOR DIFFERENT LEVELS OF WIND AND SOLAR INTEGRATION

Renewable Power (MW)		EDLC (hours/ year)			EENS (MWh/ year)		
		SMCS	ESA	Diff. %	SMCS	ESA	Diff. %
Wind	50	11.14	10.48	5.92	1172.9	1175.6	0.23
	100	10.01	10.45	4.40	1025.4	1072.7	4.61
	150	9.04	8.89	1.66	902.7	911.1	0.93
	200	8.19	8.24	0.61	802.9	819.9	2.12
Solar	50	11.19	11.25	0.54	1167.6	1246.1	6.72
	100	10.9	10.64	2.39	1157.1	1155.3	0.16
	150	10.23	9.84	3.81	1084.8	1082.5	0.21
	200	9.72	9.36	3.70	1025.7	1016.6	0.89
Wind and Solar	50	11.14	11.66	4.67	1356.5	1276.5	5.90
	100	10.86	11.08	2.03	1058.3	1080.6	2.11
	150	9.27	9.20	0.76	961.2	972.8	1.21
	200	8.58	8.72	1.63	878	900	2.51

In this study, the renewables are integrated into the composite system without changing the system load. Therefore, when renewables are integrated, the reliability of the system increases. Due to the intraday variations of solar irradiance, the availability of solar power is lower than that of wind power. Therefore, the system reliability improvement provided by wind farms is higher than that provided by solar farms of the same capacity. When wind and solar have equal capacities, the system reliability improves significantly compared to the solar-only scenario.

The impact of renewables on the adequacy of composite systems depends on the effective renewable power output and the correlation between system load and renewable power. The effective power output of a wind turbine is greater than that of a solar array due to the higher availability of wind. In this study, the diurnal correlation between wind generation and the load is -0.33. Therefore, when intraday wind power is high, the load tends to be low and vice-versa. Thus, wind generation cannot provide

the most optimum reliability improvement that can be achieved by having a higher positive correlation with the load. On the other hand, the diurnal correlation coefficient of solar generation and load is found to be 0.55. Hence, solar generation is moderately correlated with the system load.

The integration of renewables is commonly limited by transmission line constraints. However, in this study, renewable generation is not curtailed due to the transmission line capacity restrictions because the transmission system of the RTS has redundant capacity.

5.4.3.2 Equivalent Capacities of Wind and Solar Generation.

The equivalent capacities of wind and solar generators provide an idea of the contribution of each renewable generation to the adequacy of composite power systems. Thus, the calculation of the equivalent capacity of a renewable generator is a method of quantifying the corresponding capacity credit. The equivalent capacity calculation method is explained in section 3.1.1. In this work, a hydro generator of 50 MW with FOR of 0.01 is selected as the benchmark unit. Equivalent capacities of wind generation and solar generation are found to be 125 MW and 215MW w.r.t the benchmark unit. This implies that, instead of a 50 MW hydro generator, 125 MW of wind generation or 215 MW of solar generation can be added to the IEEE RTS without changing the system reliability.

The estimation of the equivalent capacity of a renewable generator requires numerous executions of the system adequacy evaluation algorithm. The conventional SMCS is not suitable for this task due to the significantly large computational time. Hence, more efficient ESA can be used to address the aforementioned computationally challenging problem.

5.4.4 Reliability Improvements When Renewables are Integrated into 230 kV vs. 138 kV Subsystems.

As shown in Figure 2.7, the 230 kV system of IEEE RTS is more reliable than the 138 kV system due to comparatively high power generation and low system load. Thus, the integration of renewables into these subsystems may provide different adequacy levels. Hence, in this case, wind and solar generators are connected to different busses in both 230 kV and 138 kV subsystems to identify the aforementioned reliability improvement differences.

The transmission network of IEEE RTS is stressed to distinguish the reliability improvements when renewables are connected to different busses. This is done by reducing the transmission line capacity by 50% and by increasing the system load by 10%. Table II shows the EDLC of the modified IEEE RTS for different renewable penetration levels at different busses in 230 kV and 138 kV subsystems. Results in

Table 5.8 show that when the renewable power penetration is increasing, the reliability improvement provided by the renewables varies based on the placement of renewables at different buses. When the renewables are integrated into the 138 kV system, the reliability improvement is higher than that obtained by integrating the same renewable capacity into the 230 kV system. If renewables are integrated into less reliable parts of the system, the overall reliability improvement becomes high. Moreover, when renewable penetration increases, this difference in reliability improvement increases. Therefore, the regional power grid reliability level should be taken into account when integrating renewables into the power grid.

TABLE 5.8: MODIFIED IEEE RTS EDLC AND EENS FOR DIFFERENT RENEWABLE INTEGRATION LEVELS INTO DIFFERENT BUSSES IN 230 KV AND 138 KV SUBSYSTEMS

Renewables: 200 MW solar and 200 MW wind			
Solar- bus 9, Wind-bus 10		Solar- bus 20, Wind-bus 19	
EDLC (hrs/yr)	EENS (MWh)	EDLC (hrs/yr)	EENS (MWh)
48.1	4945	52.5	5023
Renewables: 500 MW solar and 500 MW wind			
Solar- bus 9, Wind-bus 10		Solar- bus 20, Wind-bus 19	
EDLC (hrs/yr)	EENS (MWh)	EDLC (hrs/yr)	EENS (MWh)
21.15	1634	30.9	1995
Renewables: 800 MW solar and 800 MW wind			
Solar- bus 9, Wind-bus 10		Solar- bus 20, Wind-bus 19	
EDLC (hrs/yr)	EENS (MWh)	EDLC (hrs/yr)	EENS (MWh)
13.9	771	25.9	1660

5.5 Additional Application Studies

Even though the ESA is proposed to evaluate the adequacy of composite systems, it can be used to evaluate the adequacy of power generation systems that are less complex than composite systems. Hence, an additional application study has been conducted to evaluate the adequacy of power-generating systems using the proposed ESA.

The simulated wind and solar power data for the years 2015, 2016, and 2017 are used in this study. The hourly chronological wind and solar power data are simulated for the locations of Mannar and Hambantota, Sri Lanka. Renewable generation in the years 2015, 2016, and 2017 can be averaged to estimate the effective wind and solar

generation. These synthetic hourly chronological renewable power generation curves represent diurnal and seasonal wind and solar variations.

The adequacy evaluation is the same as the method explained in section 5.2.3.

5.5.1 Results and Discussion

The proposed ESA-based generation system adequacy evaluation framework is validated using the exact reliability indices and the estimated indices of SMCS. The convergence criterion, i.e., the Coefficient of Variation of PLC of the SMCS, is set as $1e-2$. The maximum number of simulation years is 1 million.

Table 5.9 shows the estimated LOLE, LOEE, and LOLF indices of the RTS without integrating renewables. The adequacy indices are estimated using ESA, GA, BPSO, and SMCS. Furthermore, in Table 5.9, the exact adequacy indices of the RTS are tabulated. The number of iterations of the population in PIS methods is set at 1000.

The estimated adequacy indices of the proposed ESA are compared with those of GA, BPSO, and SMCS in terms of accuracy, precision, bias and computational time. The LOLE of the RTS is estimated 100 times to identify the accuracy and precision of the aforementioned methods. Table 5.10 shows the mean, standard deviation, bias and computational time of LOLE that is estimated using ESA, GA, BPSO, and SMCS.

TABLE 5.9: LOLE, LOEE, AND LOLF OF THE RTS WITHOUT INTEGRATING RENEWABLES

Method	LOLE (hours/year)	LOEE (MWh/year)	LOLF (occ. /year)
ESA	9.376	1171.87	2.015
GA	9.357	1168.15	2.012
BPSO	9.288	1154.61	1.995
SMCS	9.423	1175.07	1.921
Reference [123]	9.394	1176	-

TABLE 5.10: MEAN, STANDARD DEVIATION, BIAS AND COMPUTATION TIME OF LOLE ESTIMATED USING ESA, GA, BPSO, AND SMCS

Parameters	ESA	GA	BPSO	SMCS
Mean	9.378	9.367	9.296	9.407
Standard deviation	0.002088	0.013588	0.021774	0.042044
Bias	0.016397	0.028361	0.098264	-0.012796
Time (s)	4.9	6.46	19.23	271.33

Table 5.9 shows that ESA provides more accurate estimations for system adequacy indices than GA and BPSO. The exact adequacy indices presented in [123] are very close to the indices estimated by the ESA. Thus, the ESA can identify a large portion

of the most probable system failure events. Moreover, when the number of iterations of the ESA is increased to 1500, the estimated LOLE is found to be 9.381. The higher the number of iterations, the higher the accuracy of reliability estimations. The accuracy of SMCS estimations can be further improved by employing a tighter COV value. However, the computation time will be significantly increased when the number of simulation years increases.

As can be seen in Table 5.10, the mean of the estimated LOLE is the largest in ESA. Thus, the ESA outperforms the intelligent search ability of GA and BPSO. The standard deviation of the estimated LOLE provides an idea of the consistency of the adequacy evaluation algorithm. The standard deviation is lowest in ESA. Hence, the ESA can provide consistent and invariable estimations for system adequacy indices. Moreover, the bias is positive and lowest in ESA and highest in BPSO. On the other hand, BPSO has the highest variability in the estimations. This may have happened due to the trapping of swarm particles in local search areas.

The computational time is lowest in the ESA and highest in the BPSO. The structure of the PIS algorithms is similar except for the population guiding mechanism. Hence, the complexity of different population guiding mechanisms is the reason for the above differences in overall adequacy evaluation time. In BPSO, the positions of the following iteration generators are obtained using the Sigmoid transformation function [135]. However, in the ESA, the dynamic mutation probabilities can be used to determine the status of the following iteration generators without using the Sigmoid function. This may be the main reason for differences in the computational times between the ESA and BPSO. The computational efficiency of GA and ESA is approximately the same.

The estimations of the SMCS cannot be directly compared with those of PIS methods because the event sampling mechanisms are different in each method. In SMCS, events are sampled from the system event space, and the adequacy indices are computed by statistical inference. Hence, in SMCS, both success and failure events are sampled. On the other hand, PIS methods try to find the most probable system failure events that affect the system's adequacy. Hence, PIS methods always provide estimations smaller than the exact values. This is explained by the positive bias shown in PIS methods. However, Table 5.10 shows that the accuracy, precision, and computational efficiency of the ESA are higher than those of the SMCS for the given stopping criterion. The accuracy and precision of the SMCS can be improved by increasing the simulation years, but it will require a significantly large computational time. Moreover, the bias of the estimations obtained by SMCS is the lowest among all the methods. As the number of simulation years increases, the bias reaches zero as the estimations are obtained by statistical inference.

Table 5.11 shows the estimated LOLE of the renewable integrated RTS for different solar and wind penetration levels. The ESA and SMCS results are compared

in Table 5.11. When considering a renewable integrated power system, the proposed ESA-based adequacy evaluation framework provides results close to the SMCS. Therefore, the ESA can be used as a successful tool for finding failure events of renewable integrated system event space.

TABLE 5.11: LOLE OF RENEWABLE INTEGRATED RTS FOR DIFFERENT SOLAR AND WIND GENERATION LEVELS

Renewable Capacity (MW)		LOLE (hours/year)	
		ESA	SMCS
Wind	100	7.83	8.45
	200	6.62	7.76
Solar	100	7.05	7.08
	200	5.31	5.40
Wind & solar	100	7.40	7.70
	200	5.78	6.33

When the power system is highly reliable, SMCS may not be converged for a tight COV of LOLP. The event space of a reliable power system mostly consists of system success events. In this scenario, PIS methods such as ESA become more efficient because PIS methods can find most of the system failure events.

5.6 Conclusion

This chapter proposes a new population-based random search guide mechanism called ESA for the adequacy evaluation of composite power systems. Then, the results of the proposed ESA are compared with those of GA, BPSO, and SMCS to investigate the application of PIS methods on the adequacy evaluation of composite power systems. The proposed algorithm provides more consistent and accurate estimations for adequacy indices in significantly less time than SMCS. Moreover, the computational and sampling efficiency of the proposed ESA is higher than that of GA and BPSO.

In this particular application, PIS methods such as GA, BPSO, and ESA are used to scan and find out a set of most probable failure events that contribute significantly to system reliability indices rather than attempting to find a single optimal or near-optimal solution. Therefore, the convergence of these algorithms may not guarantee the accuracy of the solution. In this work, the accuracy of the solution provided by the proposed algorithm is checked by comparing it with the solution of a well-established method, i.e., SMCS, instead of checking the convergence of the proposed ESA.

However, PIS methods cannot provide exact adequacy indices because the enumeration of every system failure event is computationally intractable. Hence, the adequacy indices obtained by the PIS methods are always somewhat less than the exact values. On the other hand, in SMCS, the estimated indices are somewhat larger or smaller than

the exact values. Thus, a small error margin is acceptable in the adequacy estimation of composite systems. Therefore, the proposed ESA is able to provide acceptable estimations for composite system adequacy indices. The ESA is proposed considering the application, i.e., event sampling. Therefore, it might not be applicable for general optimization tasks.

Moreover, an ESA-based adequacy evaluation framework is proposed to estimate the adequacy indices of wind and solar-integrated composite systems. The proposed adequacy evaluation framework is applied to the IEEE RTS. It can be seen that the proposed system adequacy evaluation framework can provide accurate estimations for system adequacy indices in a more computationally efficient manner. The impact of integrating renewables on the adequacy of composite systems is analyzed. The contribution of wind and solar generation to the composite system adequacy is quantified by calculating the respective equivalent capacity values with respect to a conventional generator. It is found that in the RTS, 125 MW of wind capacity or 215 MW of solar capacity provides the same reliability improvement as a 50 MW hydro generator. The results show that if renewables are integrated into less reliable parts of the system, the overall reliability improvement becomes high.

Finally, an ESA-based generation system adequacy evaluation framework was proposed for evaluating the adequacy of renewable rich power generation systems. The proposed ESA-based generation system adequacy evaluation framework is validated by the results of SMCS. It is shown that the proposed adequacy evaluation framework can provide accurate estimates for system adequacy indices. Moreover, the results of ESA are compared with those of GA and BPSO. The ESA tends to provide more robust estimates than GA and BPSO. The generation system adequacy is evaluated for different wind and solar penetration levels. The results show that the proposed ESA is applicable for evaluating the adequacy of both generation and composite systems.

CHAPTER 6

DISTRIBUTION SYSTEM ADEQUACY EVALUATION

Integration of renewable power sources into power systems has become a continuously increasing trend. Incisively, solar power integration into power distribution systems has been increasing over the last decade [19]. Integration of solar power generation causes the injection of harmonics into the system as well as system voltage deviations [19]. Hence, the stability and adequacy of power distribution systems are affected by distributed solar generation.

The integration of variable power sources, such as solar power, increases the complexity of distribution system adequacy evaluation because of the intraday variation of solar generation. Moreover, AC-OPF analysis should be incorporated into the adequacy evaluation framework to consider the system voltage variations due to the solar generators. In power system adequacy evaluation, AC-OPF is a time-consuming nonlinear optimization problem [10]. Thus, the integration of AC OPF analysis into conventional reliability evaluation methods such as MCS significantly increases the computational time, especially when estimating the annual adequacy indices.

In distribution system adequacy evaluation, the system's ability to cater to consumer demand using the existing network is quantified. This is done by estimating the distribution system reliability indices such as EENS, SAIDI, and SAIFI [25].

6.1 Application of Evolutionary Swarm Algorithm for Adequacy Evaluation of Distribution Systems

In PIS methods such as GAs or PSO algorithms, the system (generation, composite, or distribution) event space is explored to find the most probable system failure events. Then, each system event that is found by the PIS algorithm is evaluated to identify the respective load curtailment associated with the event. In composite system adequacy evaluation, event evaluation is done by DC-OPF analysis [71–73, 77, 78]. However, due to the considerable resistance of distribution feeders, AC-OPF analysis should be used to evaluate the distribution system events. Further, the effect of DGs on feeder voltage levels is considered in the AC-OPF analysis. In PIS methods, most of the evaluated system events are failure events, and hence, the computational time required for reliability evaluation can be further reduced compared to SMCS [6, 40]. Thus, PIS methods can be used to evaluate the reliability of power distribution systems similarly to power generation or composite systems.

When PIS methods are used to identify the distribution system failure events, the system reliability indices can be directly derived, considering the respective load curtailments and probabilities of events. In previous chapters, the proposed ESA is utilized

to evaluate the adequacy of composite power generation and transmission systems. In this work, the said algorithm is utilized for evaluating the reliability of power distribution systems as illustrated in Figure 6.1.

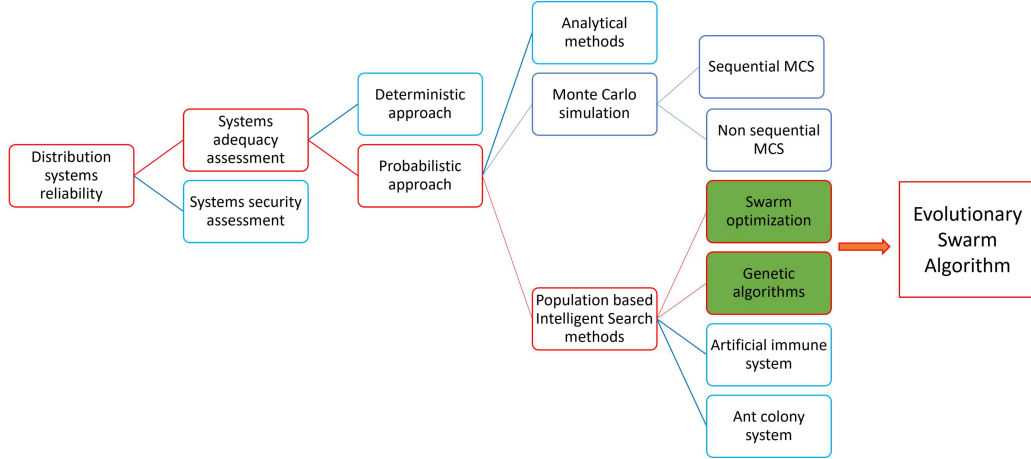


Fig. 6.1: The selection of distribution system adequacy evaluation framework

6.1.1 System Event Evaluation Using AC-OPF Analysis

The population of system events that is generated using the PIS operators should be evaluated to identify failure events and respective load curtailments. AC-OPF analysis is used in this work to evaluate the distribution system events while considering feeder voltages. This work uses a tailored OPF formulation based on the classic formulation presented in [115, 140]. The typical objective of the classic OPF formulation is to reduce the total generation cost. However, in this work, the required objective is to minimize the total load curtailments considering the DG inputs, node voltages, and power angles. The optimization problem can be formulated as follows.

$$\text{minimize } f = [x] \quad (6.1)$$

$$P_{gi} + C_{Pi} - P_{load,i} - P_i(V, \delta) = 0 \quad (6.2)$$

$$Q_{gi} + C_{Qi} - Q_{load,i} - Q_i(V, \delta) = 0 \quad (6.3)$$

$$H_{load,i} \times C_{Pi} - C_{Qi} = 0 \quad (6.4)$$

$$0 \leq P_{gi} \leq P_{gi}^{Max} \quad (6.5)$$

$$Q_{gi}^{Min} \leq Q_{gi} \leq Q_{gi}^{Max} \quad (6.6)$$

$$0 \leq C_{Pi} \leq P_{load,i} \quad (6.7)$$

$$0 \leq C_{Qi} \leq Q_{load,i} \quad (6.8)$$

$$V_i^{Min} \leq V_i \leq V_i^{Max} \quad (6.9)$$

$$-\pi \leq \delta \leq +\pi \quad (6.10)$$

In the above formulation, $[x]$ is the total load curtailment of the system, P_{gi} and Q_{gi} are active power and reactive power generation at node i , C_{Pi} and C_{Qi} are active and reactive load curtailment at node i , $P_{load,i}$ and $Q_{load,i}$ are active power and reactive power demand at node i , $P_i(V, \delta)$ and $Q_i(V, \delta)$ are active and reactive power going out from node i , $H_{load,i}$ represents the relationship between $P_{load,i}$ and $Q_{load,i}$, P_{gi}^{Max} and Q_{gi}^{Max} are maximum active and reactive power generation at node i , Q_{gi}^{Min} is the minimum reactive power absorption of the generators at node i , V_i is the voltage at node i , V_i^{Min} and V_i^{Max} are minimum and maximum allowable voltages at node i and δ is the power angle at nodes.

6.1.2 Modeling of Distribution Transformers and Feeders

The distribution transformers and feeders are modeled using 2-state Markov models as illustrated in Figure 2.1. According to the unit failure rate λ and repair rate μ , the forced outage rate can be calculated using 6.11.

$$Forced\ Outage\ Rate = \frac{\lambda}{(\lambda + \mu)} \quad (6.11)$$

The forced outage rates of system components can be used to calculate the probability of system events. Figure 6.2 shows a sample system event. The event probability can be calculated using 6.12. The calculated event probability represents the fitness of the event.

Feeder Section	F1	F2	F3	F4	F5	F6
Status	1	1	0	0	0	1
Probability	1-FOR(F1)	1-FOR(F2)	FOR(F3)	FOR(F4)	FOR(F5)	1-FOR(F6)

Fig. 6.2: A sample system event

$$\begin{aligned}
\text{The Event Probability} &= [1 - FOR(1)] \times [1 - FOR(2)] \\
&\times [FOR(3)] \times [FOR(4)] \times [FOR(5)] \\
&\times [FOR(6)] \times [1 - FOR(7)]
\end{aligned} \tag{6.12}$$

6.1.3 Modeling of Annual Load

In this work, the chronological load variation is taken into account instead of considering a fixed load. The normalized Sri Lankan daily load curve is used to derive the load curve of RBTS. This is done by multiplying the normalized load curve by the peak load of the RBTS Bus-2 system. The annual load curve consists of 8760 load values. If the recorded system failure events are evaluated with those load values, the computational time will be enormous. Hence, the load is modeled considering only the daily demand variations. The normalized daily load curve is shown in Figure 6.3

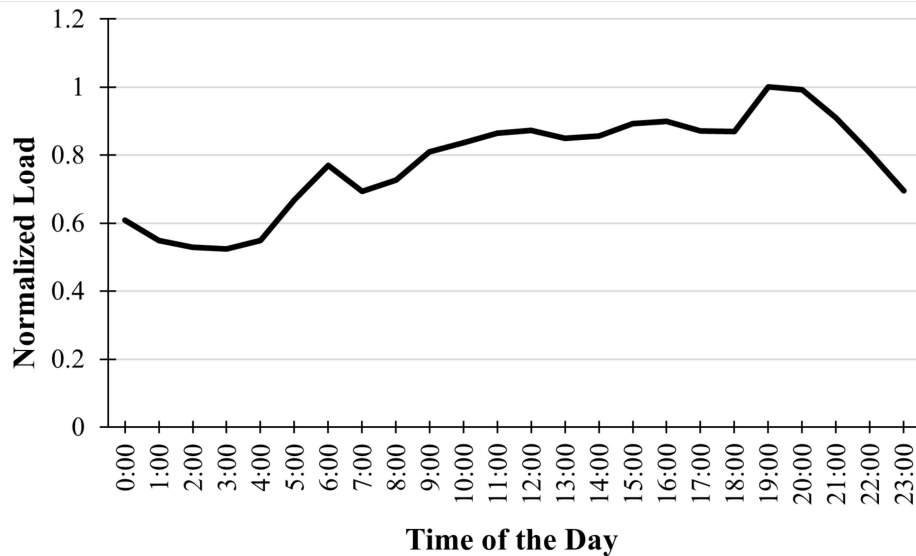


Fig. 6.3: Normalized intra-day load curve

6.1.4 Modeling of Solar Power Generation.

Residential solar power integration to the distribution system is modeled using historical solar power generation data. This work uses historical solar power generation data from Buruthakanda Solar Farm, Sri Lanka, to model the daily solar power generation. Solar power is also modeled similarly to the load for preserving the intraday relationship between the load and renewable power generation. The normalized daily solar power variation is shown in Figure 6.4. A data set of a sunny day is considered in this work to identify the maximum reliability improvement.

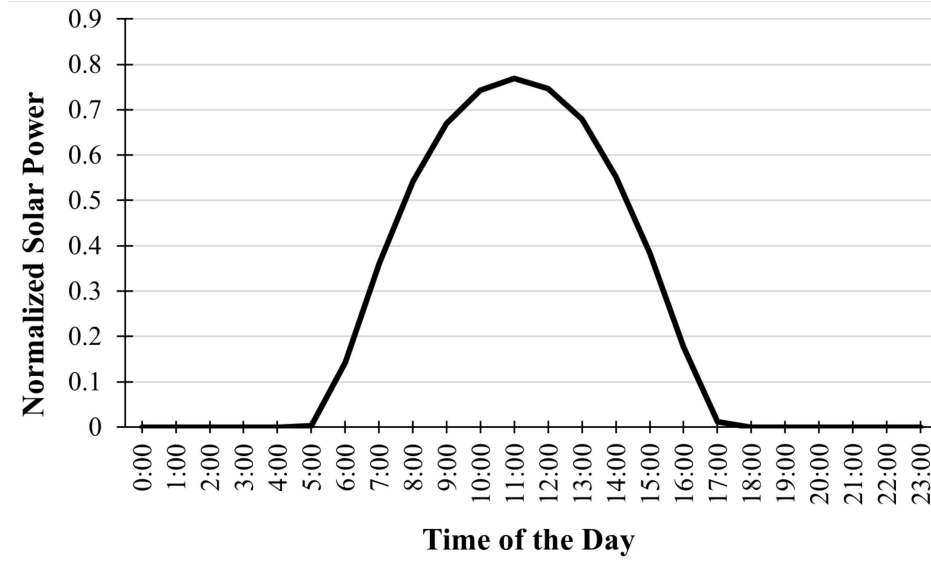


Fig. 6.4: Normalized intra-day solar power generation

6.1.5 Estimation of Distribution System Reliability Indices

Different types of reliability indices can be used to quantify the distribution system reliability. The most popular indices are SAIDI, SAIFI, and EENS. The analytical or simulation methods use various methods to estimate the aforementioned reliability indices, and those methods cannot be used with PIS methods. Therefore, novel methods are needed to estimate the distribution system reliability indices in a PIS-based framework. The SAIDI, SAIFI, and EENS estimations can be described as follows.

$$SAIDI = 8760 \times \sum_{i=1}^n \frac{P_{ei} \times N_{ei}}{N} \quad (6.13)$$

Where n is the total number of events, P_{ei} is the probability of failure event i , N_{ei} is the number of affected customers in event i and N is the total number of customers.

$$SAIFI = \sum_{i=1}^n \frac{F_i \times N_{ei}}{N} \quad (6.14)$$

Where F_i is the Frequency of load curtailment at i^{th} failure event.

$$F_i = P_{ei} \times \left(\sum_{j=1}^m (1 - b_j) \times \mu_j - \sum_{j=1}^m b_j \times \lambda_j \right) \quad (6.15)$$

Where b_j indicates the state of the distribution line/transformer j , μ_j and λ_j are the repair rate and failure rate of the distribution line/transformer, respectively.

$$EENS = \sum_{i=1}^n LC_i \times P_{ei} \times 8760 \quad (6.16)$$

Where LC_i is the load curtailment in failure event i .

6.2 Modified RBTS Bus-2 Distribution System

This section describes the RBTS Bus-2 distribution system used to apply the proposed PIS-based distribution system adequacy evaluation framework. A network diagram of the RBTS Bus-2 distribution system is shown in Figure 6.5. The tie lines are closed to obtain the maximum reliability benefits of solar power integration. The maximum peak load of the RBTS Bus-2 is 20 MW. The peak reactive power demand is considered as 9.686 MVar by taking the power factor of residential, commercial, and small users as 0.9. The system consists of 22 Load Points (LPs) .

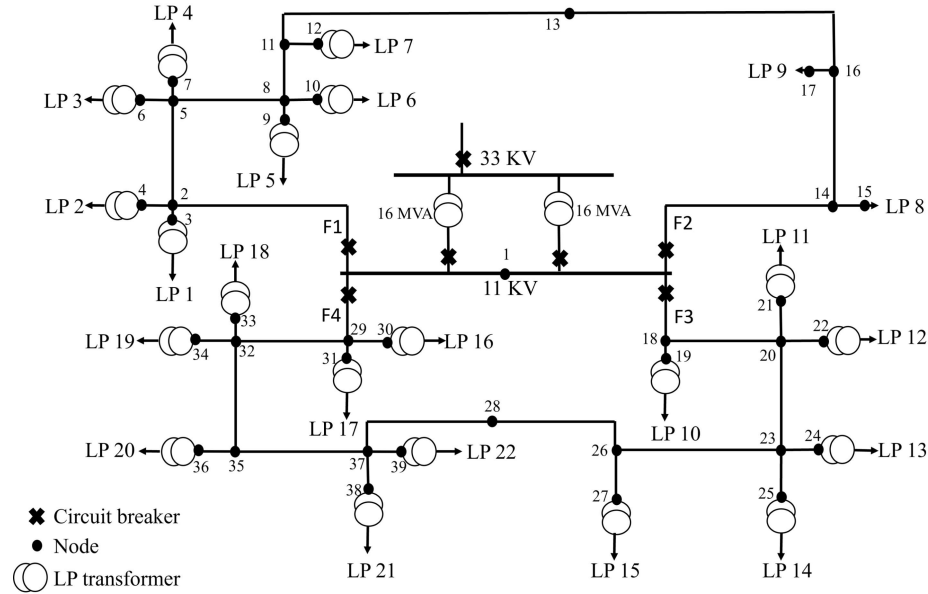


Fig. 6.5: RBTS Bus-2

It should be noted that the RBTS Bus-2 system does not define the feeder section parameters such as line resistance, reactance, and current capacity. Hence, appropriate parameters are selected for feeder sections as shown in Table 6.1 considering the apparent power flow. Aluminum Conductor Steel Reinforced lines are used as 11 kV overhead feeders according to the BS 215 part 2: 1970 standard. The respective code names of the lines are *Lynx*, *Raccoon*, and *Mole*, which have current ratings of 528 A, 324 A, and 98 A. The impedance and current ratings are obtained from a cable manufacturer, *SICAB*.

In this work, the following assumptions have been made to reduce the complexity of AC-OPF analysis.

- Fuses and disconnects are perfectly reliable.
- The outage rates of distribution transformers and feeder sections are considered.
- The whole distribution system fails if node 1 is isolated.
- The feeder voltage can be deviated between 0.94 pu and 1.06 pu. This range is defined according to the Grid Code of Sri Lanka.
- Node 1 voltage is 1 pu. This is defined according to the current practice in Sri Lanka.
- Solar penetration to the grid curtails when the feeder voltage is greater than 1.06 pu.
- The distribution line capacity is sufficient for the peak load requirements.
- The outage rates of solar inverter systems are neglected.
- The power factor of the residential, commercial, and small user loads is considered 0.9.

6.3 Validation of The Proposed ESA-based Distribution System Reliability Evaluation Framework

Results obtained from the proposed reliability evaluation framework shown in Figure 6.6 are compared with those of SMCS, a well-established benchmark method. It is assumed that solar integration is 50% of the load demand and injected into the system from all LPs. A laptop with Intel Core i5-1135G7 Processor, 16 GB memory, and 256 GB SSD storage is used in this work. SMCS is conducted considering 150 years of distribution system operation. The respective simulation time is 229 hours. In this study, a tight coefficient of variance is not used for the convergence criteria of the SMCS as it requires a huge computational time. The interior-point algorithm facilitated by the "fmincon" nonlinear programming solver in MATLAB is used to solve the AC OPF problem. Table 6.2 tabulates the validation results.

It can be seen that the results of ESA are very close to those of SMCS. Given that both ESA and SMCS are probabilistic reliability evaluation methods, small deviations in the estimated reliability indices can be accepted. Hence, the proposed ESA-based reliability evaluation framework can be used to evaluate the reliability of power distribution systems.

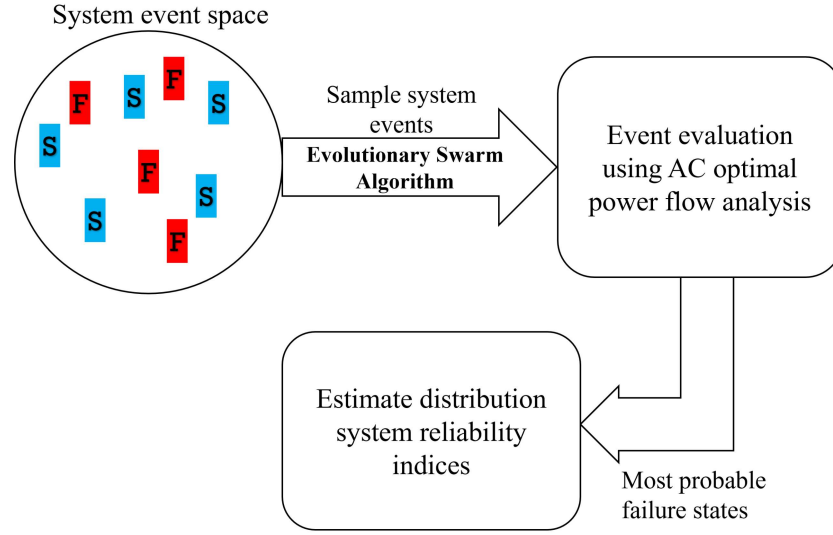


Fig. 6.6: Proposed distribution system adequacy evaluation framework

The computational time of SMCS is significantly higher than that of the ESA-based algorithm, as can be seen in Table 6.2. This is due to the limitation of the sampling mechanism in SMCS. In SMCS, the system events are chronologically organized and evaluated. Hence, both success events and failure events are evaluated using the AC-OPF analysis. Then, the system reliability indices are estimated using statistical inference. This consumes a significant amount of time due to the complexity of the non-linear optimization problem. However, in PIS methods such as ESA, only the system failure events are considered and evaluated. Thus, the computational efficiency of the proposed method is higher than that of SMCS.

6.4 Additional Application Studies

In this section, two additional application studies are conducted on the RBTS Bus-2 distribution system. Firstly, the influence of solar integration on the reliability of power distribution systems is investigated. Secondly, the impact of dynamic tap changing on the reliability of power distribution systems is analyzed.

6.4.1 The Impact of Solar Integration on the Reliability of Power Distribution Systems.

In this section, solar power is injected into different load points. Then, the respective reliability improvement is identified. Table 6.3 shows the reliability variation of the system in terms of EENS, SAIDI, and SAIFI for different cases. Solar integration is zero in case study 1. In case studies 2, 3, and 4, the total solar penetration is 3.5 MW.

In case study 2, solar power is equally injected into the LPs that are located near the substation, i.e., nodes 3, 4, 15, 19, 21, 30, and 31. On the other hand, in case study 3, solar power is equally injected into nodes 10, 12, 17, 25, 27, 38, and 39, which are located far from the substation. Solar capacity is uniformly distributed into all LPs in case study 4.

The results show that solar power integration can improve the distribution system reliability. Case studies 2, 3, and 4 show reliability improvement of 2.02%, 5.02%, and 3.87%, respectively over case study 1.

When 3.5 MW of solar capacity is uniformly distributed among the LPs that are located far from the substation, as in case study 3, the reliability improvement is greater than that of case studies 2 and 4. When a feeder section is failed, the other side of the ring tends to supply the load. Hence, due to the resistance and reactance of the feeder sections, some nodes located far from the substation may have low voltages below the specified range. Thus, the load of the LPs located far from the substation will be curtailed. When solar is integrated into those nodes, the node voltage will be improved, and load curtailment will be minimized. This can be clearly seen when there is a feeder section failure. Figures 6.7 and 6.8 show the LP voltages and load curtailments in the daytime when feeder sections 10 and 24 fail. The node voltages and load curtailments are observed with and without solar integration.

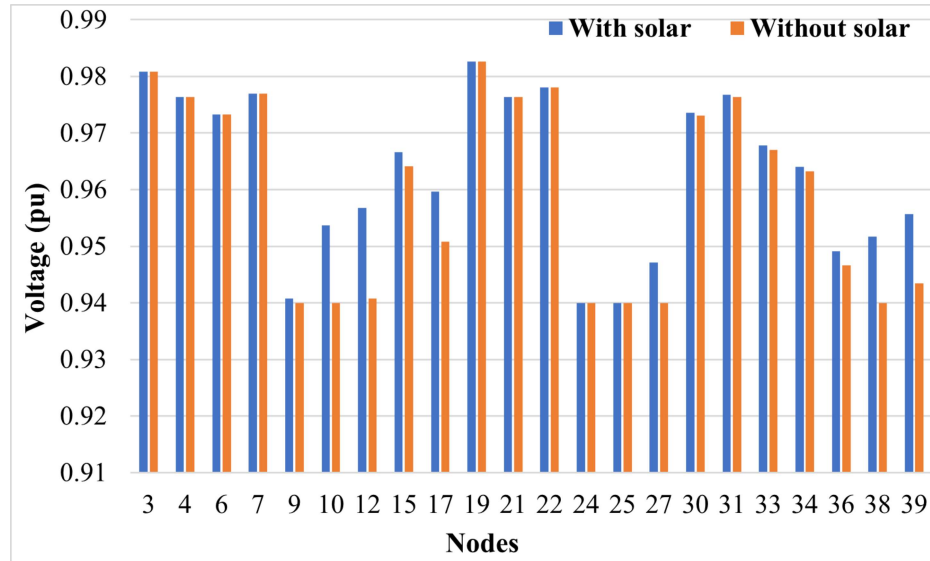


Fig. 6.7: Daytime load point voltages when feeder sections 10 and 24 fail

Figures 6.7 and 6.8 show that solar integration can completely avoid the load curtailment in nodes 9, 10, 27, and 38. Further, the load curtailment in nodes 24 and 25 is reduced by 10.4% and 90.6%, respectively. The load curtailment of node 25 is significantly reduced than node 24 because, in case study 3, solar is injected into node

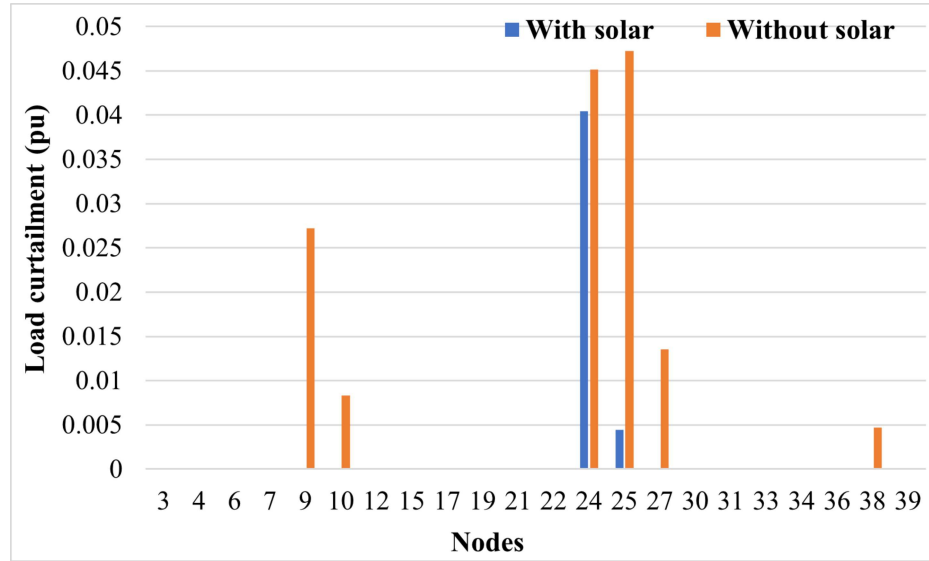


Fig. 6.8: Daytime load point load curtailment when feeder sections 10 and 24 fail

25. In fact, the nighttime load curtailments cannot be reduced in this manner due to the unavailability of solar.

It can be seen that solar power integration can improve the distribution system's reliability in the daytime. However, the peak load occurs at nighttime, as shown in Figure 6.3. Thus, solar power integration cannot improve the overall system reliability levels significantly compared to a diesel generator. When case study 4 is repeated by replacing solar with diesel generators, the EENS is found to be 9.75 MWh per year, which is a 10.7% improvement to the solar integrated scenario. Thus, power generators with high plant factors can significantly improve distribution system adequacy.

6.4.2 The Impact of Dynamic Tap Changing on the Reliability of Power Distribution Systems.

Since the ESA-based distribution system adequacy evaluation framework considers voltage levels of system nodes, it can be used to identify possible ways to improve the distribution system reliability.

In countries such as Sri Lanka, the 132/33 kV, 132/11 kV, and 33/11 kV step-down power transformers are utilized in distribution substations. The voltage of the secondary winding (33 kV or 11 kV) is kept constant at 1 pu by using on-load tap changers. However, when the feeder end voltage is significantly low, the taps are changed manually to improve the voltage levels. This process can be automated to improve the system's reliability level. Power transformer taps can be changed dynamically, considering the voltage levels of LPs.

Case studies 1, 2, 3, and 4 conducted in subsection 6.4.1 are repeated, assuming

that power transformer taps are dynamically changed based on the voltages of nodes of the distribution system. Thus, the node one voltage may also vary between 0.94 pu and 1.06 pu. Table 6.4 shows the respective improvement of EENS of the system. The results show that the system's reliability improvement due to solar integration is insignificant when dynamic tap changing is applied.

It can be observed that when power transformer taps are dynamically changing, the system reliability is improved by 31.2% when solar is not integrated. Further, when solar is integrated (case studies 2, 3, and 4), the reliability improvement obtained by dynamic tap changing is 30%.

In dynamic tap changing, 11 kV bus voltage is allowed to vary within the permitted range. Hence, more power can be transferred to the feeders without curtailing the loads due to low voltages at LPs. The importance of this mechanism can be showcased by simulating a feeder section fault. The voltages and load curtailments associated with system load points are obtained when feeder sections 10 and 24 are failed. The total solar capacity of the system is kept at 3.5 MW, and it is uniformly distributed among the LPs that are located far from the substation, as in case study 3. Figures 6.9 and 6.10 show the daytime and nighttime LP voltages and load curtailments without dynamic tap changing. Figure 6.11 shows the daytime and nighttime LP voltages with dynamic tap changing.

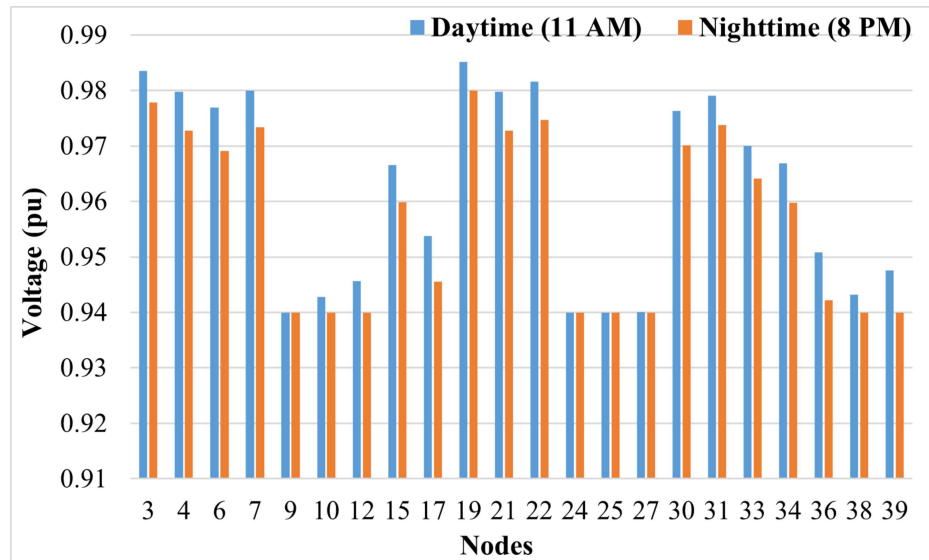


Fig. 6.9: Voltage of load points without dynamic tap changing during a feeder section failure

According to Figures 6.9 and 6.10, voltage violations in several LPs can be seen when there are feeder section failures in the system. Especially, the load curtailment is significantly high at nighttime due to the night peak of the load curve and the absence of solar power. Figure 6.11 shows that dynamic tap changing can maintain the LP

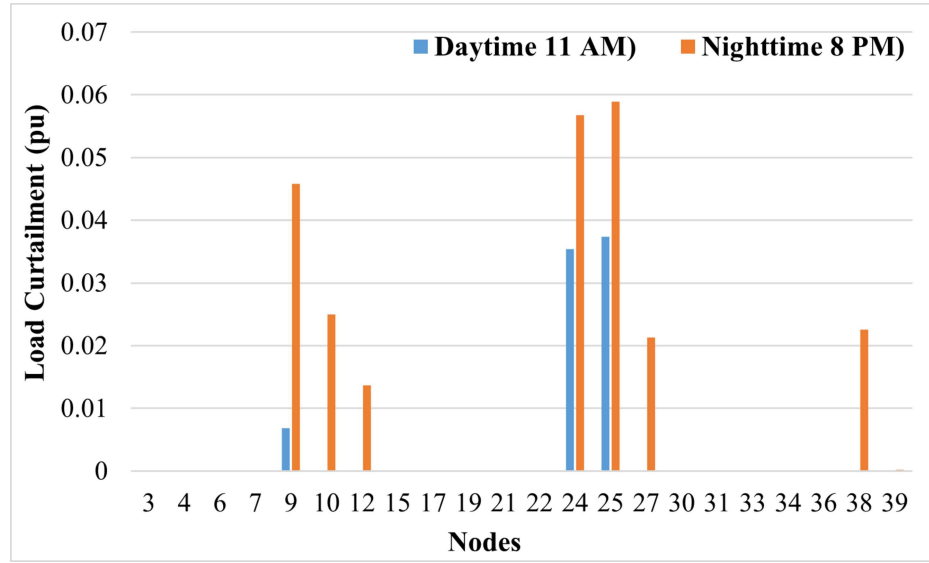


Fig. 6.10: Load curtailment of load points without dynamic tap changing during a feeder section failure

voltages within the range specified in the grid code. Hence, the load curtailment is zero. When an LP located far from the substation is subjected to load curtailment due to voltage drop, node 1 voltage can be increased to provide more power to the far end. These case studies show that the reliability of distribution systems can be maximized by implementing a dynamic tap-changing mechanism that operates according to the LP voltages. This can be realized by continuously measuring the voltages of LPs and changing the power transformer taps dynamically.

6.5 Conclusion

In this work, a novel ESA-based framework is proposed for evaluating the adequacy of power distribution systems. The proposed methodology is based on the PIS of system failure events for estimating system reliability indices. AC-OPF is used for evaluating distribution system events. The results of the proposed reliability evaluation framework are compared with those of SMCS. It is found that the proposed method can accurately estimate system adequacy indices with significantly improved computational efficiency. Then, a case study is conducted to evaluate the impact of integrating solar power on the reliability of power distribution systems. Results show that distributed solar power generators can improve system reliability by improving the node voltage levels, especially when they are placed far from the substation. Further, it was found that the system reliability can be improved by changing the taps of power transformers, considering the LP voltages.

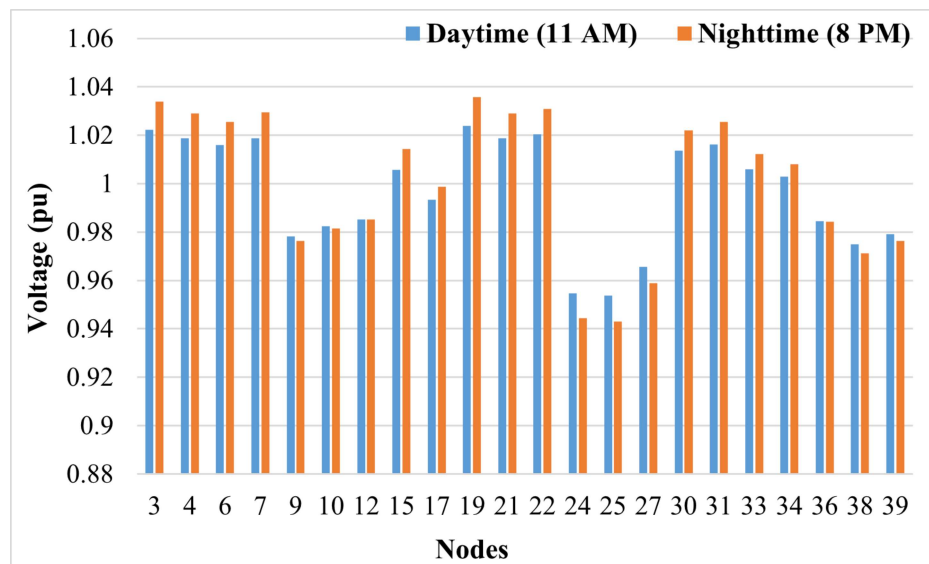


Fig. 6.11: Voltage of load points with dynamic tap changing during a feeder failure

TABLE 6.1: RBTS BUS-2 FEEDER SECTION PARAMETERS

Feeder Sec- tion No.	Starting Node	Ending Node	Conductor Code Name	Resistance (pu)	Reactance (pu)	Forced Outage Rate
1	1	2	Lynx	0.012	0.016	2.78E-05
2	1	14	Raccoon	0.027	0.018	2.78E-05
3	1	18	Lynx	0.012	0.016	2.78E-05
4	1	29	Lynx	0.013	0.017	2.97E-05
5	2	3	Mole	0.164	0.017	2.23E-05
6	2	4	Mole	0.218	0.023	2.97E-05
7	2	5	Lynx	0.012	0.016	2.78E-05
8	5	6	Mole	0.218	0.023	2.97E-05
9	5	7	Mole	0.164	0.017	2.23E-05
10	5	8	Raccoon	0.027	0.018	2.78E-05
11	8	9	Mole	0.218	0.023	2.97E-05
12	8	10	Mole	0.205	0.022	2.78E-05
13	8	11	Raccoon	0.022	0.014	2.23E-05
14	11	12	Mole	0.218	0.023	2.97E-05
15	11	13	Raccoon	0.029	0.019	1.85E-05
16	13	16	Raccoon	0.029	0.019	1.85E-05
17	14	15	Squirrel	0.110	0.022	2.97E-05
18	14	16	Raccoon	0.022	0.014	2.23E-05
19	16	17	Squirrel	0.110	0.022	2.97E-05
20	18	19	Mole	0.164	0.017	2.23E-05
21	18	20	Lynx	0.013	0.017	2.97E-05
22	20	21	Mole	0.205	0.022	2.78E-05
23	20	22	Mole	0.218	0.023	2.97E-05
24	20	23	Raccoon	0.022	0.014	2.23E-05
25	23	24	Mole	0.205	0.022	2.78E-05
26	23	25	Mole	0.218	0.023	2.97E-05
27	23	26	Raccoon	0.027	0.018	2.78E-05
28	26	27	Mole	0.164	0.017	2.23E-05
29	26	28	Raccoon	0.029	0.019	1.85E-05
30	29	30	Mole	0.205	0.022	2.78E-05
31	29	31	Mole	0.164	0.017	2.23E-05
32	29	32	Lynx	0.012	0.016	2.78E-05
33	32	33	Mole	0.164	0.017	2.23E-05
34	32	34	Mole	0.218	0.023	2.97E-05
35	32	35	Raccoon	0.027	0.018	2.78E-05
36	35	36	Mole	0.218	0.023	2.97E-05
37	35	37	Raccoon	0.022	0.014	2.23E-05
38	37	38	Mole	0.218	0.023	2.97E-05
39	37	39	Mole	0.205	0.022	2.78E-05
40	37	28	Raccoon	0.029	0.019	2.97E-05

TABLE 6.2: EENS (MWH PER YEAR), SAIDI, SAIFI AND COMPUTATIONAL TIME (HOURS) OF RBTS BUS-2

Method	EENS	SAIDI	SAIFI	Time
SMCS	11.53	0.7948	0.1297	229
ESA	11.93	0.765	0.137	6.75

TABLE 6.3: EENS (MWH PER YEAR), SAIFI AND SAIDI OF RBTS BUS-2 FOR CASE STUDIES 1, 2, 3 AND 4

Cases	EENS	SAIFI	SAIDI
(1) No solar	11.36	0.7701	0.1407
(2) Solar connected near the substation Nodes 3, 4, 19, 21, 30, 31, 15	11.13	0.7700	0.1407
(3) Solar connected far from the substation Nodes 10, 12, 17, 25, 27, 38, 39	10.79	0.7647	0.1366
(4) Solar connected to all load points	10.92	0.7685	0.1395

TABLE 6.4: EENS (MWH PER YEAR), SAIFI AND SAIDI OF RBTS BUS-2 FOR CASE STUDIES 1, 2, 3 AND 4 CONSIDERING DYNAMIC TAP CHANGING

Cases	EENS	SAIFI	SAIDI
(1) No solar	7.78	0.5655	0.1019
(2) Solar connected near the substation Nodes 3,4,19,21,30,31,15	7.66	0.5170	0.079
(3) Solar connected far from the substation Nodes 10,12,17,25,27,38,39	7.65	0.5310	0.0957
(4) Solar connected to all load busses	7.64	0.5221	0.0944

CHAPTER 7

CONCLUSION

Power system adequacy evaluation is a challenging task in power system planning. Different adequacy evaluation methodologies have been proposed over the decades for evaluating the adequacy of generation, composite generation and transmission, and distribution systems. The rapid development of computer processing capabilities promoted simulation-based adequacy evaluation methods over analytical methods. Further, renewable power generation and power storage can be conveniently integrated into the simulation methods without a complex modeling process.

7.1 Concluding Remarks

The adequacy evaluation of power generation systems is not as complex as that of composite systems or distribution systems because the optimal power flow analysis is not required for HL1 studies. Hence, both analytical methods and simulation methods can be used to evaluate the adequacy of power generation systems. The accuracy of renewable power models significantly affects the accuracy of reliability indices estimated using the adequacy evaluation framework. The chronological simulation of renewable power generation is a computationally challenging task. Therefore, sequential simulations require more computational time to estimate the reliability indices.

It is essential to study the prevailing Monte Carlo simulation methods to propose possible improvements to the power system adequacy evaluation framework. Hence, several case studies have been conducted to identify the Monte Carlo simulation sampling mechanism. Capacity credit of wind and solar generation is evaluated using non-sequential Monte Carlo simulation. The impact of pumped hydro storage on the adequacy of generation systems is evaluated using sequential Monte Carlo simulation. This preliminary work revealed the limitations and possible improvements of Monte Carlo simulation methods. Considering the results of the preliminary studies and the literature, we proposed novel renewable power modeling and system reliability evaluation methods that can be applied to all three HLs of power system reliability evaluation. The main contributions are listed below.

- A novel renewable power generation methodology that is compatible with non-sequential Monte Carlo Simulation is proposed. The proposed renewable power generation models reflect the diurnal and seasonal power variations. Further, the intermittent nature of the renewable power is modeled using Kernel Density Estimation-based probability distribution functions. The relationship between renewable power generation and load can be easily implemented into the adequacy evaluation framework. The results show that the proposed adequacy

evaluation algorithm provides accurate estimations of reliability indices when compared to sequential Monte Carlo simulation. The impact of increasing renewables on the adequacy of power generation systems is analyzed for different proportions of wind and solar. It is found that when the system's renewable proportion is increased, the reliability is decreased significantly. Further, the importance of modeling seasonal variations of renewable power is investigated. The results of this study show that the accuracy of power system reliability indices is significantly dependent on the accuracy of renewable power models. In fact, the renewable power generation models should be compatible with the adequacy evaluation methodology. More accurate and sophisticated renewable power models can be used in generation system adequacy evaluation because HL1 reliability evaluation does not need huge computational power. The results show that the proposed Kernel density estimation-based renewable power generation models can represent the actual variations of wind and solar power generation.

- When a power system becomes more complex (e.g., interconnected systems), the system event space increases exponentially. The transmission system risk is evaluated using DC optimal power flow analysis which is a time-consuming optimization problem. Hence, the composite system adequacy evaluation procedure should be computationally efficient. In this work, a novel evolutionary swarm algorithm is proposed for evaluating the adequacy of the composite system. The proposed algorithm significantly outperforms Monte Carlo simulation in terms of computational time. Moreover, the accuracy of reliability indices and computational efficiency of the proposed algorithm are compared with those of the genetic algorithm and particle swarm optimization. It is found that the sampling efficiency and computational efficiency of the proposed algorithm are higher than those of the genetic algorithm and particle swarm optimization. In fact, the proposed evolutionary swarm algorithm can be applied to evaluate the adequacy of generation systems.
- The integration of rooftop solar power into distribution systems has become a popular trend in the last decade. Thus, the reliability and stability of power distribution systems tend to vary significantly. The over-voltage and under-voltage situations that occur due to solar integration decrease the reliability of distribution systems. Therefore, AC optimal power flow analysis is required to evaluate the reliability of the distribution system. AC optimal power analysis is a nonlinear optimization problem that requires huge computational time when applied to a large event space. The Monte Carlo simulation is not ideal for such an application due to the nature of event sampling. In Monte Carlo simulation, both success events and failure events are evaluated, and the reliability indices are es-

estimated using statistical inference. Hence, both success events and failure events are evaluated using AC optimal power flow. It is an extremely computationally inefficient process. On the other hand, the proposed evolutionary swarm algorithm mostly evaluates system failure events, and those events are used to estimate the system reliability indices. Hence, the proposed evolutionary algorithm is an ideal method for evaluating the adequacy of power distribution systems with distributed solar generators. The proposed evolutionary swarm algorithm is utilized with AC optimal power flow analysis to evaluate the adequacy of power distribution systems. The developed algorithm can identify feeder voltage variations and respective load curtailments. The impact of solar integration on the adequacy of distribution systems is analyzed. A dynamic tap-changing methodology is proposed for power transformers to manage voltage variations in feeders. It is found that dynamic tap-changing can maintain the feeder voltages within the range specified in the grid code.

7.2 Future Studies

The results of this study have shown that population-based intelligent search methods can significantly reduce the time required to evaluate the adequacy of power systems. The nature of the sampling mechanism of these meta-heuristic algorithms limits the chronological modeling of power system components. Although the chronological modeling of conventional generators and load is not a must, energy storage that has limited energy output should be modeled chronologically in the adequacy evaluation algorithm. Further studies can be conducted to integrate energy storage models into the ESA-based adequacy evaluation framework.

Power system adequacy evaluation consists of three steps: event sampling, event evaluation, and reliability indices calculation. In this work, an AI-based optimization method called the Evolutionary Swarm algorithm is used for state sampling. The event evaluation task is done by applying the optimal power flow analysis on the sampled events. The optimal power flow analysis is a complex optimization problem that requires a significant amount of computational power. The computational cost can be reduced by simplifying the algorithm by removing unwanted and redundant equality and inequality constraints. Moreover, AI-based optimization algorithms can be used to find the solution instead of linear or non-linear optimization methods. Hence, it can be seen that AI can solve and simplify most of the processes of power system adequacy evaluation. Future studies could implement a power system adequacy evaluation framework that incorporates AI algorithms for both event sampling and evaluation tasks.

Furthermore, the proposed adequacy evaluation frameworks can be utilized to optimize solar capacities, battery storage, and diesel generators connected to microgrids.

In addition, the use of AC-OPF in distribution system reliability evaluation allows accurate estimation of PV hosting capacities of feeders. Utilities can use such algorithm-based software to find out the PV hosting capacities more conveniently.

7.3 Insights and Recommendations for Policy Makers and Power System Planners

- The capacity credit of the renewable power farms should be considered when integrating renewables into the grid. This is needed to obtain the maximum reliability benefit of the renewable additions.
- With the increased renewable energy proportion in the grid, system planners should use accurate renewable power models that demonstrate the diurnal, seasonal, and intermittent nature of renewables. The capacity credit of renewable generators depends on the correlation between the load and renewable power generation. Hence, the correlation between load and renewable generation should be modeled.
- The simulation studies show that integrating PHS into the grid significantly reduces the system failure rate. The impact of the duck curve on the power system can be solved with an energy storage system.
- The computational burden of traditional analytical and simulation power system reliability evaluation methods can be drastically reduced using novel AI-based methods. System planners can obtain accurate system reliability indices in a time-efficient manner. These time-efficient algorithms are advantageous when reliability indices are needed for several scenarios.
- System planners and policymakers can identify the less reliable areas of the system when integrating more generators or energy storage. The failure rates of the load points/ buses can be used when upgrading the power system.
- Utility companies can adopt Internet of Things technology to enhance power quality. For e.g., the load point voltages can be measured, and power transformer taps can be changed accordingly. This can significantly enhance the solar hosting capacity of the feeders.

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LIST OF PUBLICATIONS ORIGINATED FROM THE THESIS

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