

Application of Artificial Intelligence in Adequacy Evaluation of Power Systems

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The expansion of modern power systems is accelerating due to the rapid integration of components such as generators, transformers, and transmission lines. As a result, the number of system events in a power system exponentially increases. With the increase in system events, using traditional analytical and simulation methods for evaluating the adequacy of power systems has become computationally intractable. Further, integrating renewable power on a large scale requires accurate modeling. Over the past two decades, Artificial Intelligence (AI) techniques have been applied to improve the efficiency of power system adequacy evaluation. Branches of AI widely used in power system adequacy evaluation include machine learning methods and AI-based optimization algorithms. This chapter offers a much-needed summary of AI applications for assessing power system adequacy. The applications of AI methods, including genetic algorithms, particle swarm optimization, ant colony optimization, neural networks, and support vector machines, in power system adequacy evaluation are investigated. The transformation of traditional adequacy evaluation frameworks into novel AI-based frameworks is discussed, highlighting the contribution of AI. Further, several case studies demonstrate the enhanced computational efficiency of AI-based adequacy evaluation approaches compared to conventional methods.

Keywords: Artificial Intelligence; Genetic Algorithms; Machine Learning; Neural Networks; Optimization; Power System Adequacy.

1. Introduction

Evaluating power system adequacy is crucial in planning, designing, and operating electrical power systems. It quantitatively evaluates the ability of power systems to meet consumer demand, considering component outage data (e.g., generators, transmission lines) and system configuration. The power system adequacy is quantified by estimating adequacy indices, such as Loss of Load Probability (LOLP), Loss of Load Expectation (LOLE), Expected Energy Not Supplied (EENS), System Average Interruption Duration Index (SAIDI), etc.¹. Evaluating the adequacy of entire power systems is computationally infeasible due to the complexity of modeling. Therefore, the adequacy of power systems is separately assessed for power generation systems, composite power generation and transmission systems, and power distribution systems¹. The adequacy evaluation of these subsystems involves three main steps: system event sampling, event evaluation, and estimation of adequacy indices. Traditionally, analytical and simulation methods are used to perform these tasks¹⁻³.

When quantifying the adequacy of power systems, it is necessary to evaluate the system events. A system state or event can be considered a collection of the status of generators, transmission lines, transformers, consumer demand, etc. Fig. 2 illustrates a sample system event for the composite generation and transmission system shown in Fig. 1. G1 and G2 are power generators connected to Bus A and B, respectively. T1, T2, and T3 are transmission lines. L1 and L2 are consumer demand at Bus A and C, respectively.

A given power system has a significant number of system events. Some of the events might satisfy consumer demand, while others might not. If consumer demand is satisfied, the system state is considered a success state. Otherwise, it will be a failed state. The adequacy indices of a system can be determined using the load curtailment of events and the ratio of success to failed events. However, exploring and evaluating the whole system state space is computationally intractable. Hence, different state sampling methods are used to sample events from the system state space. The load is modeled using the annual load curve. After that, the sampled events will be evaluated by considering the load model to determine the associated load curtailment. Once the system failure probability and load curtailments are calculated, system adequacy indices can be estimated according to the sampling method employed.

The complexity of existing power systems is continually increasing due

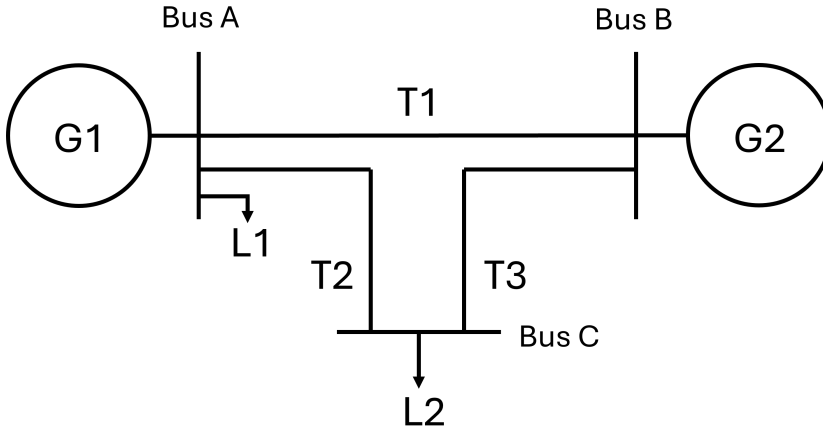


Fig. 1. Simplified illustration of a composite power system.

G1 = 100 MW (Available) G2 = 0 MW (Unavailable)
T1 = Available T2 = Available T3 = Unavailable

Fig. 2. A sample state of the composite system, illustrated in Fig. 1.

to the rapid integration of components such as generators, transformers, and transmission lines. As a result, the number of system events in a power system exponentially increases. If a generating system has x power generators, the state space size will be 2^x . Integrating renewable power in large proportions demands accurate renewable power modeling. Further, renewable power generators have various power output levels, significantly increasing the system state space size. With the increase in system events, using traditional analytical and simulation methods to evaluate power system adequacy is computationally intractable.

AI is a branch of computer science that focuses on implementing in-

telligent machines capable of performing tasks that typically require human intelligence. These tasks include reasoning, learning, problem-solving, perception, language understanding, and decision-making. Different approaches to AI include Machine Learning (ML), Deep Learning (DL), computer vision, and AI optimization.

Over the past two decades, Artificial Intelligence (AI) techniques have been applied to power system studies. One of the main objectives of applying AI techniques is to reduce the computational time required to estimate different indices, such as voltage regulation, loss of load probability, reserve capacity, and capacity credit. Furthermore, AI technology has been used to improve the accuracy of system modeling. This chapter summarizes AI applications in the adequacy evaluation of power systems, including system state sampling, state evaluation, and estimation of adequacy indices.

2. System State Sampling

When a subsystem, i.e., generation, composite generation, transmission, or distribution, is considered for adequacy evaluation, different state sampling mechanisms can be utilized. Accordingly, suitable methods for estimating adequacy indices will be selected.

In traditional simulation approaches, such as Monte Carlo Simulation (MCS), events are randomly sampled from the system state space. Then, statistical inference is used to estimate the loss-of-load indices. However, the accuracy of the estimated indices depends on the number of sampled events. The larger the number of sampled events, the higher the accuracy of adequacy indices. On the other hand, the computational burden tends to increase when a substantial proportion of events are sampled.

Although population-based meta-heuristics are used to find minima or maxima in most applications, these methods are utilized in power system state sampling to explore system events. Several AI optimization methods, such as Genetic Algorithms (GAs), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO), are used to find a set of system failure events or a set of system success events.

In the literature, meta-heuristics are used in two approaches to sample system events. One such approach is to reduce the size of the system state space by exploring and removing system success events. This is illustrated in Fig. 3. The shrunk state space is then sampled using the MCS⁴⁻⁶. The MCS is expected to converge quickly because the available state space is largely occupied by system-failure states. When estimating system

adequacy indices, pruned success events are reintroduced into the algorithm. In ⁵, authors show that when compared to Non-Sequential Monte Carlo simulation (NSMCS), the intelligent state space pruning-based MCS methods can reduce the computational time required for convergence by approximately 50-90 %

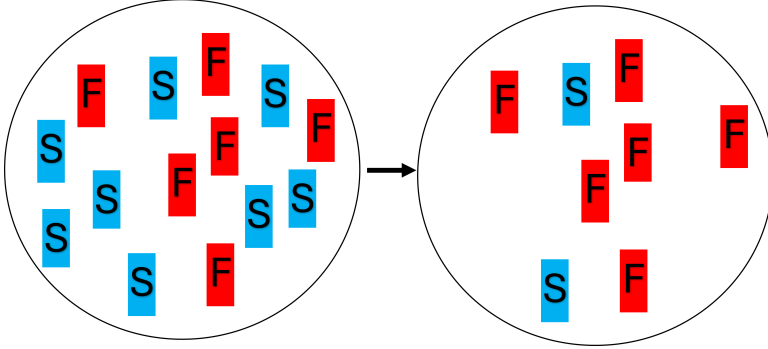


Fig. 3. Pruning the system state space by removing the success states

The MCS-PIS adequacy evaluation framework proposed in ⁵ is described below.

- (1) A set of system events is generated randomly.
- (2) Calculate the probability of each event and record that as the fitness of the event.
- (3) Events with significantly high fitness values e.g., *events probability* $> 1e^{-10}$ are filtered for evaluation.
- (4) The filtered events are evaluated using the Optimal Power Flow (OPF) analysis. Generally, composite and distribution system events are evaluated using DC-OPF and AC-OPF, respectively.
- (5) Events with zero load curtailment, i.e., success events of the system, are recorded, and the fitness of failure system events is assigned to a minimal value, e.g., $1e-20$. Thus, they will not appear in future generations.
- (6) If the algorithm has reached a predetermined number of iterations, go to step 9. Otherwise, go to the next step.
- (7) A new event population is generated by applying intelligent search-based operations.
- (8) Repeat steps 2-7.

- (9) Begin the MCS. Sample events from the pruned system state space.
- (10) Evaluate the sampled system states. In generation systems, the available generation capacity and consumer demand are compared. For composite and transmission systems, OPF analysis is used to evaluate the states.
- (11) Calculate the adequacy indices using the statistical inference. Note that these indices are obtained for the pruned system state space. Repeat steps 9-11 until MCS converges.
- (12) Estimate the final adequacy indices considering the whole state space. E.g., $LOLP_{PIS-MCS} = LOLP_{MCS} \times (1 - Ps)$ Where $LOLP_{MCS}$ is the LOLP estimated using the MCS. Ps is the sum of the probability of occurrences of pruned states.

Although the application of MCS is reduced in this approach, the state evaluation burden remains unchanged in the adequacy evaluation of composite or distribution systems that use OPF analysis. This is mainly due to two reasons. Success events in the state space are significantly higher in practical systems. Hence, exploring and removing system success events requires substantial computational time. Secondly, the MCS method combined with OPF requires considerable computational time despite reducing the state space. However, the computational efficiency of generation system adequacy evaluation can be improved by this method because it does not involve OPF analysis.

In addition, meta-heuristics are used to discover system failure events. Then, the sampled events can be evaluated, and the adequacy indices can be estimated. This method substantially reduces the computational burden of evaluating composite and distribution system adequacy by significantly minimizing the application of OPF analysis ⁷⁻¹⁰.

In either method, the basic structure of the algorithm is the same. The framework below is used in the latter approach, where system failure events are explored in the event space.

- (1) A set of system events is generated randomly.
- (2) Calculate the probability of each event and record that as the fitness of the event.
- (3) Events with significantly high fitness values e.g., $events\ probability > 1e^{-10}$ are filtered for evaluation.
- (4) The filtered events are evaluated using the OPF analysis. Generally, composite and distribution system events are evaluated using DC-OPF and AC-OPF, respectively.

- (5) Failure events of the system are recorded along with the respective load curtailments, and the fitness of successful system events is assigned to a minimal value, e.g., 1e-20. Thus, they will not appear in future generations.
- (6) If the algorithm has reached a predetermined number of iterations, stop the algorithm. Then, the system adequacy indices will be estimated using the recorded system failure events and respective load curtailments. Otherwise, go to the next step.
- (7) A new event population is generated by applying intelligent search-based operations.
- (8) Repeat steps 2-7.

Intelligent search-based, or meta-heuristic operators, are unique to each AI optimization algorithm. These operators create a new event population with many failure events, i.e., solutions. Table 1 tabulates the Population-based Intelligent Search (PIS) operators used in different AI optimization algorithms.

Table 1. PIS operators used in different AI optimization algorithms

PIS Algorithm	Operators
Genetic Algorithm ⁹	Selection Crossover Mutation
Particle Swarm Optimization ¹⁰	Position and Velocity Initializer Updater Evaluator
Ant Colony Optimization ⁷	Path Explorer Pheromone Updater Pheromone Evaporator
Evolutionary Swarm Algorithm ¹⁰	Selection Dynamic Mutation
Evolutionary Particle Swarm Optimization ⁸	Position and Velocity Initializer Adaptive Recombination Operator Evaluator

In meta-heuristic-based power system adequacy evaluation frameworks, system events are represented as an array, as shown in Fig. 4. The availability of each component — generator, transmission line, and transformer— is expressed in binary form. Similar elements are grouped to simplify the

calculations involved with adequacy indices.

G1	G2	T1	T2	T3
1	0	1	1	1

Fig. 4. A sample event/ state representation for the composite system shown in Fig. 1.

When considering the PIS methods used to evaluate the adequacy of power systems, hybrid techniques such as the Evolutionary Swarm Algorithm (ESA) provide accurate estimates in a computationally efficient manner¹⁰. This is mainly due to the problem-specific nature of the algorithm. Unlike traditional algorithms such as GAs or PSO algorithms, ESA was proposed to explore the most probable system events in a state space¹⁰. The features of GAs and PSO are combined in ESA to explore the most probable system failure events rapidly. The convergence curve of the ESA is compared with those of other PIS methods in Fig. 5¹⁰. In¹⁰, the authors show that ESA requires significantly less time to evaluate the composite system adequacy than Sequential MCS (SMCS). The computational time of ESA is reduced by 31.24% and 90.24%, respectively, compared to GA and BPSO for the Expected Duration of Load Curtailments (EDLC) tolerance level of 1.5%.

2.1. *Evolutionary Swarm Algorithm*

In ESA, selection and dynamic mutation operators have been utilized to generate a new set of system events from the existing set, which has already been evaluated. The primary goal of the above-mentioned PIS operators is to provide a new set of system events, including a sizable number of system failure events with a higher probability of occurrence.

The selection operator is the same as that in GAs. Roulette wheel selection is used to select system events with a high probability of occurrence, which is considered an event's fitness. However, unlike the traditional mutation operator, the dynamic mutation operator assigns different mutation probabilities for each array cell, representing the availability of system components. The dynamic mutation operator can be expressed using 1.

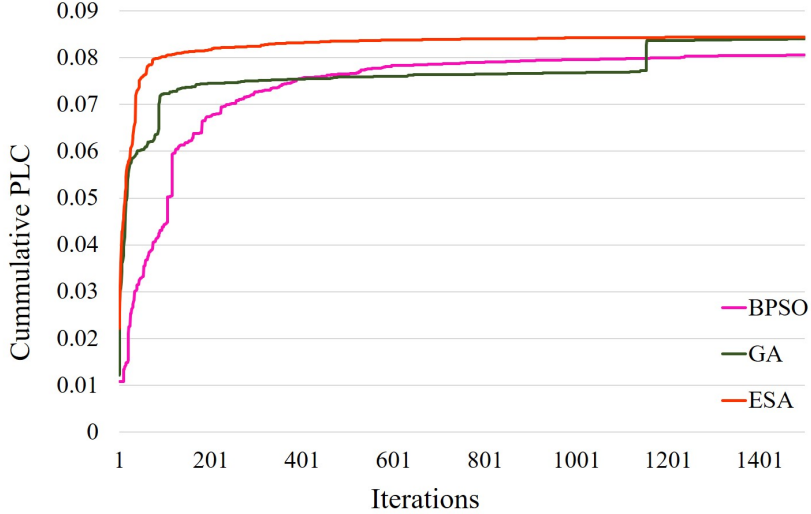


Fig. 5. The evolution of Probability of Load Curtailment (PLC) over computational iterations ¹⁰.

$$P_i^{(K+1)} = Pm + r^{K+1} \times |p.b_i^K - X_i^K| \quad (1)$$

$P_i^{(K+1)}$ is the dynamic mutation probability of i^{th} component (e.g., generator) for $(K+1)^{th}$ iteration. Pm is a constant that provides a permanent mutation probability that avoids premature algorithm convergence. r^{K+1} is a random number uniformly distributed between 0 and 1. It adds randomness to the event exploration. $p.b_i^K$ is the state of i^{th} component of the event, which has the highest fitness value up to K^{th} iteration. X_i^K is the status of i^{th} component of the selected event at K^{th} iteration. Similarly, the mutation probability of components is computed for every cell within the array. This calculation is then extended to the entire set of events that are generated at K^{th} iteration.

Thereafter, the status of each component is updated using 2 where r is a random number uniformly distributed between 0 and 1. This applies to all the events selected for the dynamic mutation operation. $\neg$ denotes negation, which is the operation of interchanging true and false in a logical statement.

$$X_i^{(K+1)} = \neg X_i^K \text{ if } r < P_i^{(K+1)}, \quad X_i^K \text{ else} \quad (2)$$

2.2. Case Studies

2.2.1. Adequacy Evaluation of a Small Power System

In this case, both NSMCS and ESA¹⁰ are used to evaluate the reliability of the composite system shown in Fig. 1. Thus, their computational efficiencies in evaluating system reliability can be assessed.

In NSMCS, system events are randomly sampled. Component availability at each event depends on its respective Forced Outage Rate (FOR). Then, the events are evaluated to distinguish between success and failure. The LOLP can be estimated using the proportion of failure states. The adequacy indices are repeatedly computed until they converge to an acceptable Coefficient of Variation (COV)¹¹. The basic structure of NSMCS is shown below.

- (1) Initialize F (Number of failure events) = 0, T (Total number of sampled events) = 0, E (loss of energy) = 0.
- (2) For all the components, i.e., generators and transmission lines in the system, determine the availability of components considering their FORs.
- (3) Rebuild the system using the available components. Then, evaluate the sampled event and estimate the respective load curtailment LC . For example, in composite systems, conduct a DC OPF.
- (4) If $LC > 0$ then $F = F + 1$ which means the sampled event is a failure event,
 $E = E + LC$,
 $T = T + 1$.
 Else $T = T + 1$.
- (5) Calculate,
 $LOLP = F/T$
 $LOLE = LOLP \times 8760$
 $LOEE = (E \times 8760)/T$
- (6) Repeat steps 2–5 until the convergence criterion is satisfied.

FORs of the system components are shown in Table 2. The reactance of transmission lines is considered as 0.12 PU. These values are selected based on component data from the Roy Billinton Test System¹. The generating capacities of generators 1 and 2 are 100 MW and 50 MW, respectively. The L1 and L2 loads are 80 MW and 20 MW, respectively. It is assumed that the transmission lines have sufficient capacity to carry the system's maximum load, i.e., 100 MW.

Table 2. Outage data of system components

Component	FOR	Repair rate/ year	Failure rate/ year
G1	0.01	198	2
G2	0.01	198	2
T1	0.00114	876	1
T2	0.00114	876	1
T3	0.00114	876	1

NSMCS and ESA are executed using a laptop with an Intel 1135G7 processor and 16 GB RAM. The NSMCS is stopped when the COV of an adequacy index, such as the Probability of Load Curtailments (PLC), reaches a predetermined value. In this work, NSMCS was stopped when the COV of PLC is less than $5e-5$. The number of iterations in ESA is fixed to 200. The event population size is fixed to 10. The algorithms' outcomes are shown in Table 3.

Table 3. PLC, EENS and computational time of NSMCS and ESA

Algorithm	PLC	EENS (MWh)	Computational time
ESA	0.0100	4424.3	0.35 seconds
NSMCS	0.00993	4391.3	14.04 hours

When considering a real power system, many system failure events exist. Hence, a PIS algorithm might not be able to capture all of these system failure events. Therefore, adequacy indices such as PLC and EENS estimated using PIS methods are always smaller than the exact values. However, if the most probable system failure states are captured, PIS methods can provide close estimations of system adequacy indices. Fig. 6 shows the cumulative number of failure states explored by the ESA over the 200 iterations. Figs. 7 and 8 show the convergence curves of PLC and EENS over computational iterations.

It can be seen that the curve shown in Fig. 6 converges after the 75th iteration. This does not mean that the adequacy indices are converged. If most probable system states are captured early in the first few iterations, adequacy indices converge faster. Figs. 7 and 8 show that the PLC and EENS indices converged just after the 10th iteration, in which 19 system failure events were identified. Thus, less than 0.35 seconds are required

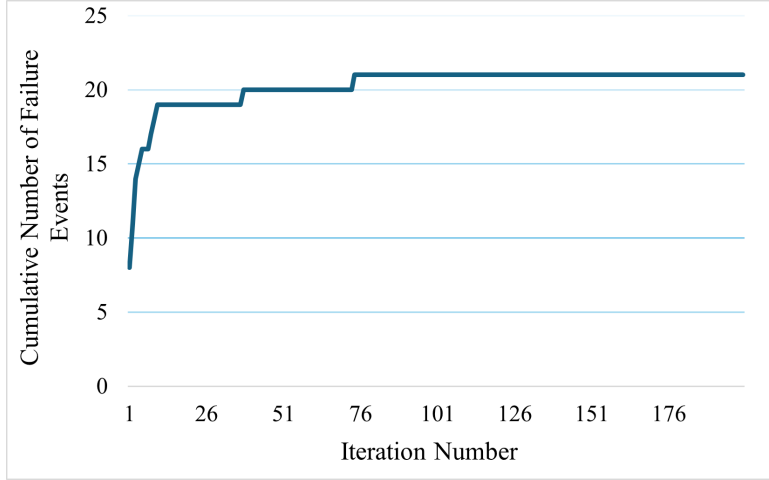


Fig. 6. The cumulative number of system failure events captured by ESA over computational iterations

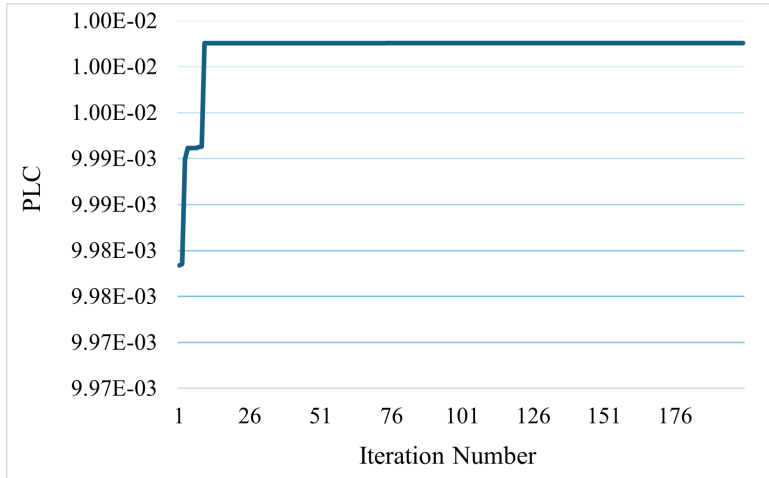


Fig. 7. PLC over computational iterations

to get acceptable results from the ESA, demonstrating that the ESA can sample system failure events with a high probability of occurring in a few iterations.

As shown in Table 3, the PLC and EENS estimated by NSMCS are smaller than those of the ESA. Thus, NSMCS could not converge for the

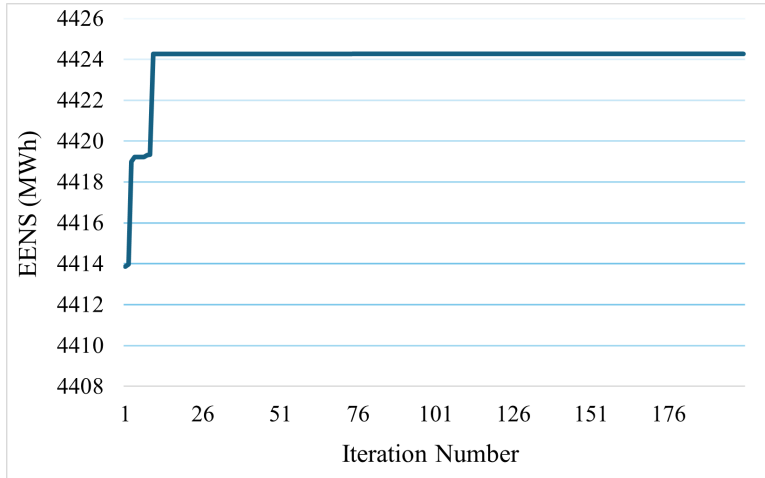


Fig. 8. EENS over computational iterations

given COV of PLC, which further requires computational time. The results clearly show that ESA provides accurate results as NSMCS within significantly less time. Thus, ESA's computational efficiency is remarkably higher than that of NSMCS. The main reason behind this is the limited use of DC OPF in the ESA-based adequacy evaluation framework.

NSMCS evaluated 5140000 events using DC OPF, and ESA only evaluated 2000 events, i.e., event population size $\times$ number of iterations. Thus, the utilization of OPF analysis is minimal in ESA-based adequacy evaluation frameworks.

2.2.2. Adequacy Evaluation of Roy Billinton Test System (RBTS)¹²

This case study compares the computational efficiency of PIS and SMCS methods. In SMCS, the number of simulation years is fixed at 500 while maintaining the PLC coefficient of variation below $1e^{-2}$. MATLAB is used to implement the PIS and SMCS methods in a single-core processing environment. The DC OPF analysis is conducted using the linear optimization function "linprog." A system with an Intel Core i7-8750H processor and 8 GB of RAM is used in this work.

In the adequacy evaluation of RBTS, the total number of iterations, i.e., new generations, for GA, BPSO, and ESA is set to 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 4. Annual composite system adequacy indices and the respective evaluation time are shown in Table 4.

Table 4. 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. 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

In SMCS, accurate estimates of system adequacy indices can be obtained by using 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 4 and 5 show the computational time associated with each PIS method and SMCS. When comparing computational time, PIS methods are more efficient than SMCS. Compared with the SMCS, ESA can estimate the system adequacy indices in a significantly shorter time. The main reason is the difference in the sampling mechanisms between 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 conducted for both successful and failed system events. This significantly increases the computational time. Moreover, when the system is more reliable, the probability

of sampling failure events decreases, and the simulation may not converge even with 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, thereby drastically reducing computational time.

3. System State Evaluation

The evaluation of system states/events in composite and distribution systems requires OPF analysis to determine the load curtailment associated with the event. Several Machine-Learning (ML) methods have been proposed in the literature to classify system events. Hence, these methods are applied to the adequacy evaluation of composite and distribution systems. By considering data on available or unavailable generation, load, unavailable transmission capacity, and generation reserve capacity as input features, it is possible to predict whether a bus will experience load curtailment. Artificial Neural Network ¹³, Support Vector Machine ¹⁴, K Nearest Neighbor ¹⁵, Fisher Linear Discriminant ¹⁶, and transfer learning ¹⁷ methods are widely utilized in the literature for event classification.

Furthermore, in ¹⁸, Kohonen self-organizing map, K-means, and K-medoids methods are used to reduce computational time without sacrificing the accuracy of adequacy indices. These methods can be incorporated into different adequacy evaluation frameworks, including analytical, MCS, and PIS-based methods. After the classification process, only system failure events are evaluated using OPF analysis, thereby reducing computational burden. The implementation of the ML Classifier is shown below.

- (1) Input/output training data set is generated using MCS or PIS methods.
- (2) Identify the most essential features. Linear or logistic regression models, random forests, and XGBoost methods can be used to quantify feature importance.
- (3) Train an ML classification model using the selected features.
- (4) Evaluate the accuracy of the ML classifier.

A sample set of input features to the ML algorithm is tabulated in Table 6 for the composite system illustrated in Fig. 1.

The adequacy evaluation framework can be structured as follows.

- (1) Sample system events using MCS or PIS-based method.
- (2) Classify the sampled events using the ML classification model.

Table 6. A Sample Set of Input Features to the ML Classifier

Generation Reserve (MW)	Unavailable Generation (MW)	TX Line 1 Availability	TX Line 2 Availability	TX Line 3 Availability	Event Status
50	0	1	1	1	Success
0	150	1	0	0	Failure
70	0	1	0	0	Failure
20	50	0	0	0	Failure
0	100	1	0	0	Failure
50	0	0	1	1	Success
0	150	0	0	1	Failure
0	150	0	1	1	Failure

- (3) Evaluate the failure events using the OPF analysis and calculate the load curtailments.
- (4) Estimate the adequacy indices. In MCS, statistical inference is used, whereas in PIS-based methods, failure event probabilities are used to estimate adequacy indices.

The main drawback of the methods mentioned above is the need to train ML models. When the power system changes, these ML models should be retrained, a time-consuming process. Thus, the reliability evaluation time during the training stage should be larger than the values reported in ^{13–15}.

OPF analysis is an optimization problem, and AI optimization methods can be utilized instead of linear or nonlinear programming. The PIS approaches overcome the limitations of the conventional OPF approaches in modeling nonconvex cost functions, discrete control variables, etc. However, applying PIS methods is challenging for large systems due to the significant number of variables.

The sampled system states are analyzed in state evaluation to identify the associated load curtailments. In composite systems, DC OPF analysis evaluates the sampled system states. Minimizing the cost of load curtailment is the main objective of the optimization problem. The DC OPF is explained below ².

$$\text{Min } f = \sum_{i=1}^k Y_i C_i \quad (3)$$

$$\sum_{i=1}^k G_i + \sum_{i=1}^k C_i = \sum_{i=1}^k L_i \quad (4)$$

$$|[A].[P]| \leq [T_{limit}] \quad (5)$$

$$0 \leq G_x \leq Gmax_x \quad (6)$$

$$0 \leq C_i \leq L_i \quad (7)$$

Y_i and C_i are the cost of load curtailment and the curtailed load at the i^{th} bus. The total number of buses in the transmission system is N . The power generation and demand at the i^{th} bus are G_i and L_i . The transmission line power flows are represented using A . Net bus injection is represented by P . The transmission line capacity is expressed by T_{limit} . G_x is the power output of x^{th} generator that has a peak generation of $Gmax_x$.

After evaluation of a system event, if $\sum_{i=1}^k C_i > 0$, then the state is labeled as a failure state, and $\sum_{i=1}^k C_i > 0$ is the total load curtailment associated with the event.

In the literature, rather than being used to evaluate power system adequacy, PIS algorithms have been used to minimize power generation costs through OPF analysis^{19–23}. GAs¹⁹ and innovative PIS methods such as Hybrid Harris Hawk Optimization²⁴, Sunflower Optimization Algorithm²¹, Crow Search Optimizer²², and Differential Evolution Algorithm²⁰ are used in this aspect. Hence, there exists a need to investigate the application of AI optimization methods in power system reliability-based OPF analysis, where load curtailment is minimized.

4. Estimation of Adequacy Indices

AI optimization or ML methods are not utilized in this stage of adequacy evaluation. This is mainly due to the availability of straightforward formulas for calculating system adequacy indices.

When a PIS method is used to sample system events, the statistical inference method cannot be used to estimate the adequacy indices as in MCS. In hybrid MCS-PIS methods, LOLP and Loss of Load Expectation (LOLE) are estimated as follows^{4–6}.

$$LOLP_{PIS-MCS} = LOLP_{MCS} \times (1 - Ps) \quad (8)$$

Where $LOLP_{MCS}$ is the LOLP estimated using the MCS. Ps is the sum of the probability of occurrences of pruned states.

$$LOLE_{PIS-MCS} = LOLP_{PIS-MCS} \times 8760 \quad (9)$$

On the other hand, in ⁷⁻¹⁰, where PIS methods are utilized for exploring the system failure states, LOLP, LOLE, Loss of Energy Expectation (LOEE), and Loss of Load Frequency (LOLF) are calculated as follows.

$$LOLP = \sum_{i=1}^n State_p_i \quad (10)$$

Where $State_p_i$ is the probability of the system failure state i and n is the total number of system failure states.

$$LOLE = LOLP \times 8760 \quad (11)$$

$$LOEE = \sum_{i=1}^n LC_i \times State_p_i \quad (12)$$

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

$$LOLF = \sum_{i=1}^n Fi \times Perm_i \quad (13)$$

Where $F_i = P_i \times (\sum_{j=1}^m (1 - b_j) \times \mu_j \sum_{j=1}^m b_j \times \lambda_j)$. P_i is the probability of event i . 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. $Perm_i = \binom{LG_1}{n_1} \times \dots \times \binom{LG_i}{n_i} \times \dots \times \binom{LG_n}{n_n}$. LG_i is the length of component group i and n_i is the number of available components in group i . In most cases, similar components exist in a power system. E.g., a power system may have two 50 MW hydro generators with the same repair and failure rates. In PIS-based frameworks, they are grouped in the component arrays as shown in Fig. 9.

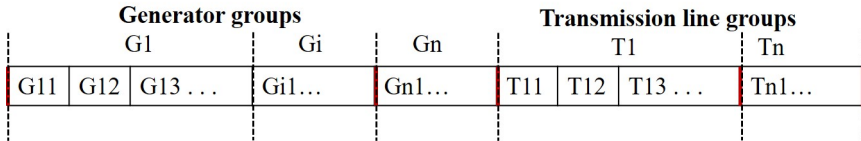


Fig. 9. Grouping similar components.

5. Application of AI Methods for Renewable Power Modeling

The integration of renewable power into power grids has increased rapidly over the last two decades. Therefore, renewable-rich power systems are evident worldwide. In the adequacy evaluation of power systems, renewable power modeling is crucial, especially when there is a large proportion of renewable power in the system. In literature, AI methods are used in renewable power modeling^{11,25,26}. In¹¹, a K-means clustering algorithm is used to model the seasonality of renewable power by categorizing the months into different seasons of the year. In²⁵, the Fuzzy C Means clustering algorithm is utilized to develop time-dependent models for wind and solar generation, exchanged electricity, and load data. Moreover, the correlation between wind and load is modeled using the Fast Global Fuzzy C Means method in²⁶.

6. Conclusion

This chapter delves into the applications of AI in each stage of adequacy evaluation of power systems, considering all relevant aspects. Various AI approaches utilized in the main steps of the system adequacy evaluation procedure are discussed with the aid of examples. First, the application of AI optimization methods, such as GAs, PSO, and ACO, to system event sampling is explored. Two main approaches, i.e., MCS-PIS and purely PIS, are identified, and their respective frameworks are described. Secondly, this chapter explores AI applications for evaluating system events. Specifically, the use of ML methods, including neural networks, to reduce the need for OPF analysis is discussed. Furthermore, prevalent AI-based OPF solvers are identified and presented. Thirdly, the estimation methods of adequacy indices are discussed. Although AI methods are not directly involved in this step, AI-based event sampling and evaluation require new formulas to estimate the system adequacy indices. Finally, the chapter explores the application of AI in renewable power modeling. Overall, the investigations conducted in this chapter reveal that integrating AI methods has significantly enhanced the efficiency of power system adequacy evaluation by directly reducing computational burdens in event sampling and assessment. As modern power systems continue to expand in both generation and transmission capacities, conventional adequacy evaluation algorithms struggle to handle the increasing complexity, underscoring the need for AI integration in large-scale power systems.

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