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# An overview on reliability assessment in power systems using CI approaches

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**Abstract:** A Computational Intelligence (CI) approach is one of the main trending and potent data dealing out and processing instruments to unravel and resolve difficult and hard reliability crisis and it takes an important position in intelligent reliability analysis and management of data. Nevertheless, just few little broad reviews have recapitulated the current attempts of Computational Intelligence (CI) in reliability assessment in power systems. There are many methods in reliability assessment with the aim to prolong the life cycles of a system, to maximize profit and predict the life cycle of assets or systems within an organization especially in electric power distribution systems. Sustaining an uninterrupted electrical energy supply is a pointer of affluence and nationwide growth. The general background of reliability assessment in power system distribution using computational intelligence, some computational intelligence techniques, reliability engineering, literature reviews, theoretical or conceptual frameworks, methods of reliability assessment and conclusions was discussed. The anticipated and proposed technique has the aptitude to significantly reduce the needed period for reliability investigation in distribution networks because the distribution network needs an algorithm that can evaluate, assess, measure and update the reliability indices and system performance within a short time. It can also manage outages data on assets and on the entire system for quick and rapid decisions making as well as can prevent catastrophic failures. Those listed above would be taken care of if the proposed method is utilized. This overview or review may be deemed as valuable assistance for anybody doing research.

**Key words:** computational intelligence, power system

## List of abbreviations

CI: Computational Intelligence
AI: Artificial Intelligence
SI: Swarm Intelligence
AIS: Artificial Immune System
ANN: Artificial Neural Networks
EC: Evolutionary Computing
FS: Fuzzy System
ES: Expert Systems
MAS: Multi-Agent System
DAI: Distributed Artificial Intelligence
GA: Genetic Algorithm
SVM: Support Vector Machine
PLM: Product Lifespan Management
DG: Distributed Generator
RBF: Radial Basis Function
T&D: Transmission and Distribution
RCAM: Reliability Centred Asset Management
FMEA: Failure Mode and Effect Analysis
SAIDI: System Average Interruption Duration Index
RNN: Recurrent Neural Network
ETAP: Electrical Transient and Analysis Program
ECOST: Expected Interruption Cost
CAIFI: Customer Average Interruption Frequency Index
CAIDI: Customer Average Interruption Duration Index
SAIFI: System Average Interruption Frequency Index
ATC: Available Transfer Capability
MTBF: Mean Time Between Failure
MTTF: Mean Time to Failure
LOLP: Loss of Load Probability
LOLF: Loss of Load Frequency
ENS: Energy Not Supplied.
LOLD: Loss of Load Duration
MTTI: Mean Time to Instability
ENLC: Expected Number Load Curtailment
ELC: Expected Load Curtailment
HL: Hierarchical Levels
ASAI: Average Service Availability Index
IEEE: Institute of Electrical and Electronic Engineers
BUGF: Belief Universal Generating Function
LOLE: Loss of Load Expectation
EUL: Expected Unsupplied Load
EUE: Expected Unsupplied Energy
SVM: Support Vector Machine
ESS: Energy Storage System
EPS: Electric Power System
MLRBF: Multilabel Radial Basis Function

## 1. Background of the research

With the advancement in technology, demand for electricity is growing and upgrading must track this advancement in the reliability and quality of the electricity generated termly, the electric power system's reliability and quality [91]. Power is the fundamental need for the development of any nation. Accessibility to electricity has been the most commanding medium of initiating advancement and social transformation all over the globe. The development of modernization, enhancement in the manufacturing industry, agriculture, and improvement in the pattern or standard of living of the individuals solely rely on the sufficient and constant power supply [27]. The lack of energy intensifies poverty especially in developing countries [16]. A nation where an erratic power supply is occurring will surely stay behind in her social and economic actions. The predicament in this sector is well marked in the sense that it affects both the ordinary and the wealthy and is necessary to every element of the nation [64]. Presently, about 1.3 billion to 1.6 billion people in the world, many of whom live in remote areas, have no electricity [40]. With the fast development of the economy of the world, power demand is rising significantly; energy catastrophes and environmental problems are imminent [70].

Electrical power is generated to a large capacity in thermal, hydro-electric and nuclear power stations. These power stations are located at far distances from the load centres /consumers. This condition has necessitated transmission [26].

The electrical generating stations, electrical transmitting stations and electrical distribution stations are the main constituents of electrical power systems [27]. Transmission lines transmit bulk electrical energy from electrical generating stations to receiving end stations without supplying any consumer en route. The electrical transmission system of an area (or state) is called the grid. A distribution line directly supplies consumers at short intervals along the line. The worry of a scheme operator is now changing toward distributing the outcomes of stability evaluation in actual periods or near genuine moments [63].

"Reliability is the ability of a system to perform its desired functions under the stated conditions within which it was designed to operate. Provided this perception, power system reliability is the ability of a power system to convey electricity to all points of consumption at acceptable benchmarks and in the quantity aspired" [30]. One of the most common expenditures of power providers is the maintaining cost of assets, for instance, espousing preventive appraises or measures commonly known as preventive maintenance. Preventive maintenance appraises or measures would have consequences on the reliability of the scheme by extending the life span of an asset and recuperating the situation of an asset [4]. Usually, "preventive maintenance is the eagerness of failures and embracing of essential preventive actions before they happen or occur." The major purposes of preventive maintenance are to influence the work of evaluation servicing, amendment and to avert equipment breakdown in an operating state [80]. Reliability may also reduce the period of electrical energy supply disruptions. Preventive maintenance actions could avert the real cause of the breakdown in the system. As a result, in cost-effectual expenditure, preventive maintenance should be employed where the reliability advantages overshadow the price of executing the preventive maintenance [6, 49, 50, 60, 66] and [81]. Power system reliability is split into two, adequacy and security. Adequacy means the capability of a system to satisfy energy demands of customers and the load with no infringement of steady-state limits for all particular component outage events. This contains generating amenities essential to generate sufficient power, transmission and distribution apparatus necessary to convey electrical energy to genuine consumer load points. Adequacy is therefore associated with static conditions that do not include system dynamic and transient disturbances. "Security refers to the ability of a system to withstand various dynamic or transient disturbances". Security is therefore related to responses of the system to whatever perturbations it is subjected to. These include both local and prevalent interruptions and unforeseen abrupt loss of generators, transmission elements, or loads that may lead to transient, dynamic or voltage unsteadiness in the system, cascading outages or system split [3, 21, 32, 77] and [97]. When there is a failure in the systems it may lead to unnecessary linger times for both consumers and the utility or the service provider. These periods may be the outcome of waiting for an asset to be restored, waiting on products for the subsequent stage, or consumers waiting for entire products. Adopting predictive factors to decide likely breakdowns will avert hindrances because preventive maintenance could be finished before total breakdown occurs [20]. Also, the early detection of faults or high impedance faults in distribution power systems would improve the reliability of power supply [96]. Findings have revealed that maintenance improves reliability of an element that will ultimately show on the whole system because the power system is composed of various interrelated elements [28, 29, 78] and [82]. In ancient times, the distribution segment of a power system obtained the lowest concentration of the contribution to reliability preparation and planning than have generation and transmission sectors and therefore, the distribution segments have been the frailest connection between the source of energy supply and the consumer point of consumption. This is because that generation and transmission segments are extremely financially demanding and failures in these sectors would have extensive disastrous economic outcomes to both energy providers and consumers [46].

Artificial intelligence is the simulation of human intelligence processes, especially computer systems. "AI has the ability of taking big data, boiling it down and making sense out of it". A biggest bewilderment issues is all the diverse words that are employed as nearest in meaning for AI like deep learning, machine learning, cognitive computing, etc. The catalogue is expending every day. Bearing it in mind, these words are not interchangeable, but they are usually employed in that system [38]. As innovation is essential, artificial intelligence (AI) is grown with the aid of improved computer devices and utilized to decide all the mentioned setbacks for huge electrical power systems [68] and correctness because of widespread and gigantic system data managing. Integrating AI will increase the dynamic managing of electrical power system networks by harmonizing supply and demand. "And computational Intelligence (CI) is defined as a study of adaptive mechanism to facilitate intelligent behaviour in difficult, vague and varying environments. These adaptive devises comprise artificial intelligence paradigms that show the ability to learn or adapt to new situations, to generalize, abstract, discover and associate." There are various types of CI paradigms such as Swarm Intelligence (SI), the Artificial Neural Network (ANN), Artificial Immune System (AIS), Evolutionary Computing (EC), Fuzzy System (FS) [63]. In a good judgment these metaheuristic methods offer an efficient and intelligence-based pruning or truncation of state space. Artificial Intelligence (AI) methods or approaches have called for more concentration to deal with difficult, complex and challenging situations in electrical power systems in which evaluation of reliability is a type of representative use [14]. Hybrid Systems, an approach or technique at times may likely not be adequate to successfully unravel the real planet problems. [95] Olajuyin and Olubakinde said, the artificial neural network is part of artificial intelligence. It is an attempt to form machines that function like human brains by creating these machines using apparatus that performs like biological neurons. Neural networks are interconnected neural computing basics that have the ability to reply to input stimuli, adapt and learn the environment. It can be trained to solve various problems that are not easy to solve with the human brain and ordinary computers. After the neural networks have been trained, they have the ability to make forecasting and prediction.

In this review, reliability assessment using computational intelligence approaches would be employed but to be specific, a Recurrent Neural Network (RNN) algorithm is chosen from the different types of computational intelligence approaches. The recurrent neural network is a type of artificial neural network in which the past output is fed as an input to the current step. Traditionally, in neural networks, all the inputs and outputs are independent of each other, but in cases like when it is required to predict the next word of a sentence, the previous words are required and hence there is a need to remember the previous words. The RNN have an internal memory which remembers all information about what has been calculated [92] and [93] Recurrent neural networks produce predictive results in sequential data that other algorithms can't. Monte Carlo would be reinforced with the recurrent neural network to carry out the reliability assessment

## 2. Different computational intelligence technique that could be applied

### 2.1. Artificial Neural Network

"Artificial Neural Network (ANN) is biologically motivated systems that change a set of inputs into a set of outputs by a network of neurons, where each neuron produces one output as a function of inputs". "Artificial neural networks (ANNs) could be described as being very simple arithmetic computing units (nodes) attached together in a highly parallel network of interrelated layers and as being able with this kind of structure to symbolize functions and to learn these functions from examples" [2, 25, 39] and [60].

### 2.2. Fuzzy logic

Fuzzy system was grown in 1965 and have been used in solving difficult problems. They are deemed as arithmetical ways of unfolding pensiveness in linguistic expressions instead of precise arithmetical depiction.

Fuzzy systems perform some decisions similar to that of man's brain with unvarying, acceptable reasoning and they are constant. Convinced and fairly accurate information and data will generate precise solutions. Therefore, this skill can be applied in machines to execute or carry out work like human beings [68].

### 2.3. Artificial Immune System

The Artificial Immune System (AIS) combines the features of erudition and reminiscence to decipher a particular difficulty that examines the use of the immune systems to solve calculation predicaments or issues from mathematics, science and engineering. The Artificial Immune System uses an associative retrieval system, memory and learning to solve classification, optimization and recognition tasks. There are four familiar algorithms used in the AIS which are immune network, clonal selection, dendritic cell and negative selection algorithms. General use parts of the Artificial Immune System (AIS) are stated as pattern recognition, roles approximation, anomaly discovery, network safety and noise forbearance. In power system operations, the Artificial Immune System (AIS) has been applied to voltage stability [69].

### 2.4. Expert System

The Expert System (ES) embodiment is momentarily cleared by the name given. Expert systems are computer-based applications that are sufficient in offering expert service in bordered specific areas and resolve difficult jobs separately. The singular attribute of the system is that it takes into account the ambiguity of the data and rules. The modular structure of the expert system is composed of the following: the reasoning mechanism or inference engine user interface and the knowledge base [41].

### 2.5. Multi-Agent System

The Multi-Agent System (MAS) has originated from Artificial Intelligence (AI), particularly from Distributed Artificial Intelligence (DAI). Hence the Multi-Agent System is deemed as a sub-discipline of artificial intelligence. Distributed Artificial Intelligence has been employed to

Condition Monitoring, but the agent skills have a universal approval and its function to diverse parts rose speedily due to the agent's ability to work on dispensed unwrap surroundings such as the Internet. Software with many operational attributes is an intelligent agent [42]

### 2.6. Genetic Algorithm

A genetic algorithm (GA): it is a population-based stochastic investigate modus operandi motivated by ordinary fruition. A genetic algorithm has become an efficient substitute for this category of "nonsmooth" issues. The other basis for using genetic algorithms is because of the huge range of elucidation room. The intrinsic targeted search mechanism of genetic algorithms assists to attain stupendous meeting feat by pruning the elucidation room and shunning substandard clarifications [51].

### 2.7. Support Vector Machine

A Support Vector Machine (SVM) study majorly centres on the algorithm elucidation and representation development. The reason of algorithm remedy is to pact with a restrained optimization issue by taking the suitable algorithm. The crises of replica development consist of optimization of replica factors, feature vector extraction, kernel function selection and unbalanced samples. The afore-revealed issues expressly influence the representation accurateness [76].

## 3. Reliability engineering

Reliability engineering is composed of the methodical submission of occasion-pleased engineering techniques and principles all through a product lifespan and this is an indispensable constituent of a high-quality Product Lifespan Management (PLM) program. The purpose of reliability engineering is to estimate the intrinsic reliability of a process or product and identify prospective spots for reliability enhancement. Practically, all breakdowns may not be eradicated out of a work/design, an additional purpose of reliability engineering is to discover the main probable breakdowns and also recognize suitable deeds to alleviate the consequences of those breakdowns [37].

The reliability engineering action could be a continuing procedure commencing at the conceptual stage of product design or proposals and ongoing throughout all stages of a product's lifespan or lifecycle [8, 17, 24] and [37].

## 4. Literature review

In this section, the existing relevant literatures on power system reliability assessment would be considered with the aim of reviewing the reliability assessment effectively, and the various modeling techniques that have been used in the past related studies would be presented.

Faiz and Eran 2009 [22] methodology was based on combining a fuzzy logic scheme and an expert system to present a superior means of assessment creation with projecting maintenance in prognostic Maintenance of Asset Management administration.

Lina, Ron and Roland, 2011 [52], proposed a technique for evaluating the consequence of dissimilar maintenance approaches on the reliability of cost and the system. This technique correlated reliability assumption with the knowledge acquired from information and realistic understanding of part malfunctions and maintenance procedures but failed to put into consideration the life cycles of transformers and other components, which are very vital in achieving a higher level of reliability in power systems.

Hossein and Hamed, 2018 [36], provided an evaluation of the renowned parts in big data methodical proceeds in the region of electrical systems. They carried out many nomenclatures of the accessible, the misplaced constituents in the methods and structures are related through big data questionings in electrical systems. They afforded categorizations and concise conversations on the technological techniques, investigate panoramas and employed divisions for big energy data investigation.

Hao *et al.*, 2011 [31], presented an assessment on dissimilar advances of planning and instructing radial basis function networks. The modern expanded algorithm was initiated for intending dense RBF networks and executing well-organized teaching procedure. However, it was a review article that showed how it could be applied to power systems

Fangxing and Nura, 2008 [23], modelled the impact of a distributed generation (DG) on the network of distribution systems to evaluate reliability by employing an inclusive, sequential Monte Carlo simulation replica. Due to utility-attached allocated generation, the generation is characteristically inaugurated in the neighbourhood of the customers. However, the technique was employed to examine the effect of the DG on distribution networks only, not on the entire reliability of a distribution network, and the components on distribution networks were not considered in their study.

Jonathan and Nal, 2019 [45], presented Markov Chain Monte Carlo techniques that facilitate Bayesian deduction to produce illustrations from the subsequent delivery greater than representation factors. However, this was to strengthen both Marko Chain and Monte Carlo. But it was not used to estimate the life span of components.

Michallis and Petros, 2019 [58], introduced an incline-supported learning technique to robotically become accustomed to Markov Chain Monte Carlo suggestion distributions to obstinate objectives. They described the greatest entropy regularized intention purpose, submitted to as universal swiftness calculate that could be energetically managed above the factors of the application distribution via stochastic slope optimization but this was not used in power systems and was to hybridize Markov and Monte Carlo.

Brunette *et.al.*, 2009 [11], reviewed the artificial intelligence centring on personified artificial intelligence. He also reflected replicas of artificial perception, the philosophical commentary on artificial intelligence and agent-based artificial intelligence as well as finalized that there was no harmony and that the accomplishments were scanty. But his write up discussed the general perceptions and general idea of machine learning and artificial intelligence.

Juan, 2010 [83], presented a tactic to calculate the methodological situation of electrical energy transmission and distribution (T&D) networks and to describe connected asset management strategies. The investigation is based on a tactic forenamed Reliability Centered Asset Management (RCAM) that relies on the thoroughness of the situation and the significance of the assets in the network as the drivers for their administration.

Xufeng and Joydeep, 2010 [75], employed a hybrid algorithm based on Failure Mode and Effect Analysis (FMEA) and fuzzy simulation to decide fuzzy reliability performance indices of distribution systems. This method obtained fuzzy expected values and their discrepancies of reliability indices and the credibility of reliability indices meeting particular goals but cannot also account for the remaining life of a distribution transformer and they did not work on any of the aspect of asset management in the course of the study.

Okorie *et al*., 2015 [62], discussed the reliability of electrical power distribution networks in the investigation of performance indicators of reliability assessment recognized as the SAIFI, SAIDI, CAIFI, CAIDI, Average Service Availability Index (ASAI) and Momentary Average Interruption Frequency Index (MAIFI) etc., but does not recognize the probability histogram of the benchmark reliability. Quantitative reliability assessment of a distribution system was split into two basic sections; appraising the history feat and envisaging the future performance. He examined the existing probabilistic methods which could predict ATC for power system planning (Mojgan *et al*., 2010) [85] and he did not consider how to predict the periods of outages on distribution substations from the historical data outages.

Kezunovic *et al*., 2017 [86], presented novel learning that unlocked many chances to tackle distinctive essential matters on means to efficiently blend network data, weather and climate data in space and a period for the profit of envisaging possibility of electrical power network breakdown in a harsh climate and weather situations

Akhikpemelo, Eyibo and Adeyi, 2016 [87], presented the investigation of diverse studies of electrical distribution system networks with the aid of software called the Electrical Transient and Analysis Program (ETAP). The results obtained from reliability studies provided appropriate benchmarks for assessing the system performance and identifying the weak point of the system however, this cannot adequately take care of impending power outages.

Ulas and Ridvan, 2016 [73], presented the result of reliability indices achieved by an analytical method. A technique is supported by the Monte Carlo simulation approach applied for the estimation of the system reliability performance indices. The reliability indices are assessed for their load points and system's feeders. Reliability performance indices like the SAIDI and SAIFI were decided methodically by employing annual failure information obtained from the observed Distribution Company, and the Monte Carlo simulation supported method was then applied, but one-year outage data was not sufficient to make any sustainable judgment about reliability assessment.

Mohammad *et al*., 2019 [59], introduced an original arithmetical replica to calculate the reliability of electrical power distribution networks.

Hsiang-Hua *et. al*., 2019 [88], investigated a Monte-Carlo-simulation-supported structure to facilitate quick evaluation of loss of load expectation by considering a broad public electrical power system that composed of many origins of conventional and renewable energies. However, no decision was made on how to predict power outages and most of the reliability indices were not evaluated.

Pathomthat *et al*., 2017 [67], determined the system average interruption duration index (SAIDI), the System Average Interruption Frequency Index (SAIFI) and the Expected Interruption Cost (ECOST) that were estimated as indices of the reliability and they determined reactive power loss ($Q_{\mathrm{loss}}$) of power losses and active power loss ($P_{\mathrm{loss}}$) in power system distribution. Collective results were terminated by centring on the sizing and situation of multi-distributed generators that are imperative features which could be affecting power losses and the indices of the reliability but they were silenced on transformer life cycles and asset management. He only evaluated two reliability indices and maintenance was not talked about in the research which may make it difficult to achieve the desired reliability.

Kazemi, 2011 [89], presented a novel approach in his work titled assessment of reliability of an electric power distribution system that employed the progressed reliability improvement technologies. In his assessment of a reliability approach, the general impacts of the intended reliability augmentation elucidations on the maintained disruptions, voltage sags and temporary disruptions witnessed by the consumers, have been put into consideration. It is feasible to lessen the range of variation of the indices of the reliability among different purchasers. However, there were no provision for maintenance of assets; planning and prediction of faults were not incorporated into the design.

Tripathi and Sisodia, 2014 [71], presented probabilistic techniques such as the analytical technique and Monte Carlo Simulation (MCS) approach for the assessment of reliability of composite electrical power systems. The fault tree analysis technique was also discussed and he gave a comparison of all proposed techniques but he did not work on asset management.

Carl J.W., Lina B. and Le Anh T., 2010 [12], worked on quantitative reliability assessment techniques. However, the work offered a brief dialogue on the impacts and the significance of customers' involvement in recuperating system reliability by offering an extra system functioning diffidence from the market viewpoint and ultimately dialogued on the reliability investigation with the aid of a reliability test system and pinpointed the advantage of a universally identified test system.

Leonardo V. *et al*., 2018 [90], developed a Credit Scoring (CS) replica to substitute the pre-risk or pre-danger test of the e-commerce risk managing system - Risk Solution Service (RSS), that is presently one of the commonly employed systems to assess consumers' evasion probability. The replica was expanded on an actual-world dataset offered by a well-recognized German company dealing with monetary solutions.

Hossein A.H. and Hamed M.R., 2018 [36], provided an evaluation of the discriminated phases in big data methodical improvements in the sphere of electrical power systems. Many nomenclatures were executed on active and omitted elements in the arrangements and techniques connected with big data investigation in electrical power systems and offered holistic delineate categorizations and succinct conversations on the study opportunities, scientific methods and application areas for power big data analytics.

Chanan and Lingfeng, 2007 [14], examined the theoretical foundation of the general reliability assessment procedure and surveyed the responsibility of artificial intelligence techniques in this circumstance. It was employed to enhance the use of MCS but his research cannot answer the question of estimation or prediction of the live span of distribution components and his study was applied to alternative energy sources.

Hongyan L. *et al*., 2011 [35], utilized visual data mining and the Self Organised Map (SOM) to execute and gathering in the circumstance of the Finnish electricity distribution regulation (FEDR) and effectiveness standardization but reliability performance indices in distribution components and life span prediction of components were not dealt with in the study.

Armando *et al*., 2007 [7], presented a new method that can be used for evaluating the reliability of large composite power systems supported by Artificial Neural Networks (ANNs), particularly the Group Method Data Handling known as the polynomial network to decrease the computational attempt needed for sufficient investigation of the operating system states. However, this was applied to evaluate some reliability indices only in transmission and generation components of power systems.

Mauricio and Jorge, 2016 [57], showed a blueprint recognition technique, the Self-Organizing Maps (SOMs) that could be employed to build the Markov replica with the aid of state assignment, however, they did not apply the method to any particular distribution component. They introduced how the method can be used for reliability assessment in a review article.

Mammath *et al*., 2016 [55], discussed a new approach using software reliability forecasting based on a feed forward neural network and also with back-propagation. The approach precisely envisaged the software reliability.

Hector *et al.*, 2016 [33], proposed a Monte Carlo approach, Conditional Monte Carlo with Intermediate Estimations (CMIEs) where he proposed the reduction of the inconsistency of the assessor with the great and trustworthy Markovian system. But they did not apply it to any particular components and some basic reliability indices were not estimated.

Istvan and Laios, 1994 [41] presented an execution of expert systems in the reliability investigation of power networks. The reliability replica employed the approach of Markovian minimal cut sets that permit the reflection of multiple stochastic reliance concerning the state space, like limited repair capacities, common-mode failures (CMF), outage post probabilities and the simultaneous performance of maintenance.

Hongzhou and Hoang, 1997 [34], surveyed and evaluated the representative surviving Monte Carlo reliability, availability, MTBF availability, MTBF simulation of a compound and difficult network and MTTF.

Chanan and Lingfeng, 2008 [15], examined some perceptions on reliability assessment supported by population-based intelligent search, as well as neural network enhanced MCSs were presented. But he applied the method to power systems generally, he did not specify the aspect of the power system, the basic performance indices relevant to distribution system were not evaluated.

Mahind and Patil, 2017 [54], introduced how the intelligence and novel device skills acquired are formulated currently. Present skills are available to the information-supported learning and are accountable for recuperating the intelligence. However, it was just an article review on the general concepts of artificial intelligence and machine learning.

Bolun *et al*., 2017 [10], discussed an original technique supporting the belief universal generating function (BUGF) which was intended to compute the indices of reliability of electrical power systems. As an alternative to giving a sole-worth appraisal outcome, a belief function and a plausibility function were utilized to compute the lesser and higher bounds of the loss of load expectation (LOLE), the Expected Unsupplied Load (EUL), the Loss of Load Probability (LOLP) and the Expected Unsupplied Energy (EUE). The intended method could trail the association of the inventive data very well and maintain it to the time the computation has been finished but the basic reliability indices required in distribution were not dealt with.

Jannie and John, 2017 [43], proposed a method for the calibration of a Markov wear and tear replica supported on historical data for a range of blades and informing the replica about a precise wind turbine blade whenever information is obtainable from assessments and situations observed. This approach was illustrated employing symptomatic data from a database including data from the assessment of wind turbine blades. However, this method was employed in the generation of electrical energy.

Carl *et al*., 2013 [13], aimed at allocating supplies more expenditure-efficiently and to arrest harsh occurrences ignored by the approaches that merely compute mean rates.

Onime and Adegboyega, 2014 [65], executed an assessment of the reliability of power distribution system networks in Nigeria with the Ekpoma network at the Edo state, as a study area. The power outages were categorized based on frequency, types and durations and the outcome estimation demonstrated that power outages occurred in the distribution feeders every day. Supply failure, earth fault, planned or scheduled outages due to maintenance actions and shedding of load were recognized as the major factor of disruptions on the feeders. In this study, load shedding was seen as the main reason for disruptions. The writers proposed a case of the enhancement of reliability on distribution system networks but did not offer suggestions that could bring this enhancement. There were no explanations of the customer performance indices they calculated with benchmark reliability reference. Nevertheless, the system obtained an ASAI figure of 0.6147, which indicated that the reliability fell below expectation.

Adegboye and Dawal, 2012 [1], examined and considered faults that affected representative 11 kV feeders in the Southern region of the Kaduna metropolis. Four outgoing feeders from the 33/11 kV, 30 MVA Coca–Cola and Peugeot injection substation feeders were among them. The reliability of the 11 kV Coca–Cola feeder under observation was evaluated. It was suggested that iron cross-arms should be employed instead of wooden cross arms to reduce unnecessary earth faults because of broken wooden cross-arms. The authors only looked at the feeder in the distribution system and therefore, power failures and faults that occur downstream of the secondary distribution were disregarded.

NEPLAN simulation software helped in evaluating the arrangements of power systems by Uhunmwangho and Omorogiuwa, 2014 [72], a technique that offered assessment and forecasting of distribution system reliability in Choba in the Rivers state as a study area. NEPLAN power system software was used to execute an offline simulation of the distribution system network, judging the outgoing voltage (kV) rating, incoming energy, power outage time and three-phase current rating. The outcome of the calculated reliability indices demonstrated that the distribution system averaged availability was equal to 99.98%, which the authors depicted as very poor because another utility set, ASAI, was equal to 99.99%. It was suggested that the power provider should maintain complete data accounts that have component failures rates, element outage periods and total energy consumed, which would assist in the evaluation of reliability indices like Energy Demanded Not Supplied (EDNS).

Zhong *et al*., 2020 [79], evaluated the reliability of the island Micro Grids with elevated diffusion of renewable distributed generations, putting into consideration power failure outages in the power electronic facilities. The writers assembled a critical method of the integral failure rate of the observed system and applied a customized orientation system, as well as analysed the System Average Interruption Duration Index (SAIDI), System Average Interruption Frequency Index (SAIFI) and Energy Not Supplied (ENS) performance indices.

Jose *et al*., 2020 [44], identified that Micro Grids involved power electronic apparatus for equipment control and protection. His studies measured the effect of power electronic equipment on the reliability of distribution systems with submissions of Micro Grids that are scarce, despite the use of this equipment roughly all over the Micro Grids.

According to Kovalev and Lebedeva, 2019 [47], the reliability evaluation method based on the Monte Carlo simulation is composed of steps that comprise the generation of the power random state computation of reliability indices and minimization of power shortage in power system random states.

Krupenev *et al*., 2020 [48], concluded that the best amalgamation of techniques for estimating the power shortfall of Electric Power Systems (EPSs) is the application of the Sobol sequence

Table 1. Review of some past reliability assessment techniques, authors, titles and their objectives

| **Authors** | **Title** | **Objectives** | **Observation** |
|---|---|---|---|
| Olajuyin *et al*., 2021 [94] | Evaluation of reliability of protective devices in power distribution network. | Statistical package was employed and represented the evaluated failure rates and reliabilities in charts. | They employed statistical package in Excel with analytical analysis. This method cannot generalize, very slow and cannot learn from historical data. |
| Vrana and Johansson, 2011 [74] | Overview of analytical power system reliability assessment techniques. | The condition of the art of analytical power system reliability assessment techniques overview was discussed. | Analytical power system reliability may not be suitable for bulk network and the analysis will take a lot of time. |
| Athraa *et al.*, 2017 [9] | Reliability assessment of power generation systems using intelligent search based on disparity theory. | Disparity evolution was applied to improve the performance of the probability of transformation in a genetic algorithm (GA) by integrating attributes from the concept to the disparity theory. | Their model did not address forecasting of power outages. It is very slow and cannot generalise. |
| Amiri M. *et al*., 2008 [5] | A methodology for analysing the transient availability and survivability of a system with the standby components in two cases. | Eigen vectors, the Markov models and eigen values for assessing transient survivability and the availability of the system were employed. | The components in the power network were analysed but could be used to forecast/predicted when there will outages. Many simplifying assumptions needed to be made to limit the Markov model to a manageable size. |
| Dogan and Chanan, 2018 [19] | Power System Reliability Evaluation using Monte Carlo Simulation and Multi Label Classifier. | They presented a novel technique for assessment of electrical power systems reliability performance indices. In the work, a combination of Monte Carlo Simulation and Multilabel Radial Basis Function classifier was utilized for calculating or assessing system reliability indices. | He applied the method in transmission network and Institute of Electrical and Electronics Engineering (IEEE) Reliability Test System for diverse load levels and however they did not apply the method to distribution network. The major merit of the projected technique is its aptitude of dropping the required time for reliability assessment significantly in distribution network. |

united with the Support Vector Machine (SVM). The acquired outcome enhances the preparation of Electric Power System (EPS) adequacy evaluation and permits solving the issues that create the reliability of Electric Power Systems (EPSs), authenticating the level of hesitation of generating abilities, the arrangement and bandwidth of the electrical power network at a fresh elevated level.

Dogan and Chanan, 2018 [18], presented a novel technique for the assessment of reliability indices in power systems. The Monte Carlo Simulation and Multilabel Radial Basis Function (MLRBF) were combined in the study, a fresh approach was given to assess indices of reliability of power systems. However, they did not apply it to the distribution network, and power outage prediction was not dealt with, apart from the training phase. The outcomes of the case studies show that an MLRBF algorithm provides good classification accuracy in reliability evaluation while reducing computation time substantially.

A reassess of studies that appraise the effect of reliability on power systems when Energy Storage Systems (ESSs) are incorporated was accounted in Mohamad *et al.*, 2018 [61].

## 5. Theoretical/conceptual framework

With many diverse functional prerequisites and changing situations, reliability has diverse meanings to diverse people. The universally received description of reliability describes it as “the characteristic of an item expressed by the probability that it will perform a required function under stated conditions for a stated period of time”. The conceptual framework was explained by equations (1) to (4) below.

$$R(t) = P\big[E \text{ did not fail in time interval } [0,\, t]\big]. \tag{1}$$

Unreliability is a complement of reliability.

The universally accepted explanation of availability describes it as “the characteristic of an item expressed by the probability that it will perform a required function under stated conditions in a stated moment of time”. Mainly, the period intervals when equipment or apparatus are available and the time intervals when apparatus or equipment are unavailable are regarded as:

$$A(t) = P\big[E \text{ did not fail in time } t\big]. \tag{2}$$

Unavailability is a complement of availability. The arithmetical description of reliability is connected to the probability density function $f(t)$, reliability $R(t)$ is the probability that the variable is at least as huge as $t$, as showed in equation (3). For continuous random variables, the connected equation is given as the following:

$$R(t) = \int_{t}^{\infty} f(t)\,\mathrm{d}t. \tag{3}$$

Equation (4) gives the distinct random variable and is given below as the following:

$$R(t_i) = \sum_{i=1}^{i=k} f(t_i). \tag{4}$$

The word reliability is split into two divisions when considering electrical power systems [53] and [84].

## 6. Conclusion

The Computational Intelligence (CI) approach is one of the common potent data processing instruments to unravel and decipher difficult and compound reliability issues, and takes on intelligent reliability assessment and data management. Nevertheless, just few broad overviews have been recapitulated in the current attempts, but using Computational Intelligence (CI) for reliability assessment in power systems would speed up the time of computation of the reliability assessment. Currently, electrical energy is often wasted because, according to the present social belief, its availability is an indisputable right and necessary amenity. Sustaining an uninterrupted electrical energy delivery is a pointer of affluence and nationwide advancement. The general background of reliability assessment, some computational intelligence techniques, reliability engineering, literature reviews, theoretical or conceptual frameworks, conclusions and research gaps were discussed. The anticipated technique has the aptitude to significantly reduce the needed period for reliability investigation in the distribution network because the distribution network needs an algorithm that can evaluate, asses, measure and update the reliability indices and system performance within a short time. It can manage outage data on assets and on the entire system for quick and rapid decision making and also prevent catastrophic failures. Those listed above would be taken care if the proposed method is utilized. Reinforcing the Monte Carlo Simulation or probabilistic methods with recurrent neural networks at the point of the sluggishness of the Monte Carlo Simulation or the probabilistic methods will make the assessment to be faster and it will also compensate for excessive use of memory in the Monte Carlo Simulation method. This method can generalize, learn from history and adapt to a new situation etc.

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