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Modeling of Adverse Weather Events in an Integrated Reliability and Power Quality Assessment of Distribution System Using Stochastic Diffusion Process

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Abstract

This paper presents the modeling of adverse weather events and their impact on the integrated reliability and power quality assessment of power distribution systems. With respect to previous works, stochastic modeling of adverse weather events is integrated into the Monte Carlo Simulation approach and its impacts on reliability and voltage sag indices are highlighted. In this paper, the aleatory and epistemic uncertainty are modeled into sampling of Time to Failure (TTF) using the Stochastic Diffusion Process. The Stochastic Diffusion Process, including the Jump diffusion is used to model the impact of adverse weather events on permanent and temporary failure rates. The proposed method is applied to the modified IEEE 34 node test feeder, and three case studies have been performed to investigate the impact of various uncertainties and adverse weather events. Numerical results for the IEEE 34 node test feeder are presented to quantify adverse weather impacts on both reliability and voltage sag indices.

Author Keywords. Adverse Weather Events, Distribution System, Monte Carlo Simulation, Reliability, Stochastic Diffusion Process, Voltage Sag Indices.

Type: Research Article

1. Introduction

Power distribution system reliability and power quality studies are critical for consumers to ensure supply continuity and quality (Short 2005). With the increased penetration of Distributed Energy Resources (DERs), power distribution systems are subject to a variety of uncertainties, necessitating the development of more efficient methods for modeling the uncertainty. There are two types of uncertainty: aleatory uncertainty and epistemic uncertainty (Awadallah and Milanović 2013). Aleatory uncertainty is associated with randomness, whereas epistemic uncertainty is associated with a lack of data or model simplifications. To model aleatory uncertainty with probability distribution functions, Monte Carlo Simulation (MCS) methods are commonly used.

In general, distribution system reliability is assessed using MCS methods that account for aleatory uncertainty (Conti and Rizzo 2019). Similarly, as reported in Baptista, Rodrigues, and da Silva (2016), MCS methods are used to assess voltage sag in distribution systems. However, so far, distribution system reliability and power quality assessments have been performed independently. Furthermore, there is a growing interest in integrated reliability and power quality studies during the planning phase. In this context, very little literature is available on integrated reliability and power quality analysis of power distribution systems as reported below.

It is evident that the primary cause of the occurrence of voltage sag events is short circuit faults, and the faults are characterized by type, location, resistance, and phases. Apart from short circuit faults, the other causes of voltage sag are transformer energisation, motor starting, adverse weather events etc. The impact of adverse weather events on distribution system reliability assessment is well studied in Huda, Nazmul, and Živanović (2019), where failure rates take into account the scaling factors of adverse weather conditions. In addition, the effect of high wind conditions on reliability indices has been investigated (Costa, Venturini, and da Rosa 2019). The above-mentioned models, however, do not account for the epistemic uncertainty associated with the adverse weather conditions.

In Leal (2014), short circuit analysis has been integrated into the MCS method to evaluate the reliability and power quality indices without and with Distributed Generation (DG). The integrated reliability and power quality algorithm has been validated by the IEEE 34 node test feeder and the results demonstrate the importance of conisdering voltage sags from a reliability perspective. Then, the impact of network geometric model characterized by different overhead geometric configurations has been studied on integrated reliability and power quality assessment of distribution systems in da Rosa et al. (2016). Furthermore, the impact of different protection schemes and network geometric models on reliability and power quality indices has been investigated for different alternatives (Bolacell, Venturini, and da Rosa 2018). It is observed that the protection schemes and geometric models have a considerable impact on the reliability and voltage sag performance of the distribution systems.

Gautam, Piya, and Karki (2020) developed an aggregated reliability and power quality model that employs a graph theory approach to identify protection system operations and DERs. The findings demonstrate the effect of DERs on the reliability and voltage sag indices. Recently, the impact of loadability and economic factors, on the assessment of integrated reliability and power quality has been investigated (Bolacell et al. 2020a). The findings demonstrate the selection of alternative protection schemes while taking thermal limits, voltage degradation, and economic considerations into account. In addition, three short circuit indices are developed as part of an integrated distribution system reliability and power quality assessment (Bolacell et al. 2020b). These indices aid in determining the protection system settings during the planning phase, and the effect of network geometry on these indices is also investigated.

It is clear from the literature on integrated reliability and power quality assessment of distribution systems that only aleatory uncertainty has been addressed in terms of reliability and power quality performance. To the best of our knowledge, the preceding literature has not taken into account the modeling of epistemic uncertainty into TTF sampling in MCS methods. Furthermore, the modeling of adverse weather events while accounting for aleatory and epistemic uncertainty has yet to be addressed. This paper proposes a modified Integrated Reliability and Power Quality Assessment (IRPQ) approach for modeling aleatory and epistemic uncertainty with more accuracy.

The main contributions of the paper are:

Evaluation of the impact of aleatory and epistemic uncertainty modeling on integrated reliability and power quality assessment of distribution systems.

Modeling of Adverse Weather Events including aleatory and epistemic uncertainties using the Stochastic Jump Diffusion Process based MCS.

Three case studies are performed on the modified IEEE 34 node test system to quantify the impact of different uncertainty and adverse weather events. The efficiency of the improved method in handling various uncertainties over the other techniques is confirmed by the results.

This paper is organized as follows. Section 2 presents an overview of the types of uncertainty, the Stochastic Diffusion Process, modeling of TTF including aleatory and epistemic uncertainty, reliability and power quality indices of power distribution systems. Section 3 presents the modeling of adverse weather events, network fault scenarios model, and the proposed algorithm of Stochastic Diffusion Process-based MCS for integrated reliability and power quality assessment. Section 4 presents the comparison of results between Sequential MCS (SMCS), and the proposed method for the modified IEEE 34 node test system. Section 5 presents the conclusions and future scope of the research work.

2. Background

2.1. Types of uncertainty in power system reliability analysis

In the context of power system reliability analysis, the TTF of a power system component represents the aleatory uncertainty (Awadallah and Milanović 2013) and is usually sampled by the exponential probability distribution function in the MCS method as shown below:

$$TTF = -\frac{1}{\lambda_k} * \ln(U) = -X_k * \ln(U) \quad (1)$$

where λ_k represents the failure rate of k^{th} branch and U is the uniform random number sampled using uniform probability distribution between [0, 1].

Furthermore, the TTF of a power system component depends on the failure rate of the respective component, which is usually evaluated from historical data and is constant throughout the sampling process in the MCS method. Thus, the failure rate represents the epistemic uncertainty and should be accounted in the reliability analysis. In this paper, both the aleatory and epistemic uncertainty are modeled more accurately using the Stochastic Diffusion Process, explained in detail in the following sections.

2.2. Stochastic diffusion process

In this section, the problem formulation follows the approach presented in Zárate-Miñano and Milano (2016). The stochastic differential equation usually defines the Stochastic Diffusion Process (SDP). A general form of single-dimensional SDP is:

$$dX = a(X,t) * dt + b(X,t) * \ dW_t, \qquad t \in [0,T] \quad (2)$$

where X is the stochastic process (TTF) and W_t is a Weiner process, also known as Brownian motion. The numerical solution of (2) is as shown in Equation (3), and the terms $a(X,t)$ and $b(X,t)$ are called drift and diffusion coefficients of the SDP.

$$X_{t+1} = X_t + a(X,t) * \ dt + b(X,t) * dW_t \quad (3)$$

Therefore, the expression to sample TTF considering uncertainty is:

$$TTF = -X_{t+1} * \ln(U) \quad (4)$$

2.3. Modeling of TTF using Stochastic Diffusion Process

In this section, the problem formulation follows the approach presented in Manohar and Atla (2021). The Stochastic Diffusion Process can be generated in different ways by considering the probability distribution function of a random variable. A Stochastic Diffusion Process representing the Weibull distribution has been developed to model the uncertainty of a random variable.

The probability distribution function of the Weibull distribution is given by:

$$f(t;\ \alpha,\beta) = \frac{\beta}{\alpha} * \left(\frac{t}{\alpha}\right)^{\beta-1} * \exp\left(-\left(\frac{t}{\alpha}\right)^{\beta}\right) \tag{5}$$

where α is the scale parameter and β is the shape parameter.

The drift coefficient is considered as proportional to the probability distribution function of Weibull distribution. Therefore, the drift coefficient representing the random variable, TTF is expressed as Equation (6):

$$(X,t) = \left[\frac{\beta}{\alpha} * \left(\frac{t}{\alpha}\right)^{\beta-1} * \exp\left(-\left(\frac{t}{\alpha}\right)^{\beta}\right)\right] * X_t \tag{6}$$

Equation (7) represents the derived expression for the diffusion coefficient $b(X,t)$:

$$b(X,t) = \sqrt{\left[\frac{\beta}{\alpha} * \left(\frac{t}{\alpha}\right)^{\beta-1} * \exp\left(-\left(\frac{t}{\alpha}\right)^{\beta}\right)\right]} * X_t \tag{7}$$

Thus, the expression to sample TTF in the proposed method is determined by substituting Equation (6) and Equation (7) into Equation (4) and is given by:

$$\begin{aligned} TF = -X_t * [1 + &\left\{\left[\frac{\beta}{\alpha} * \left(\frac{t}{\alpha}\right)^{\beta-1} * \exp\left(-\left(\frac{t}{\alpha}\right)^{\beta}\right)\right]\right\} * dt \\ &+ \left\{\sqrt{\left[\frac{\beta}{\alpha} * \left(\frac{t}{\alpha}\right)^{\beta-1} * \exp\left(-\left(\frac{t}{\alpha}\right)^{\beta}\right)\right]}\right\} * dW_t] \times ln\,(U) \end{aligned} \tag{8}$$

2.4. Reliability and Power Quality Indices

The reliability performance of an electrical distribution system is examined in terms of two important metrics, which are the System Average Interruption Frequency Index (SAIFI), and System Average Interruption Duration Index (SAIDI) (*IEEE Std 1366-2012*). These indices are calculated from the average load point outage frequency (λ_i) and outage duration (U_i) of the distribution system and are expressed as follows:

$$SAIFI = \frac{\sum_{i=1}^{n_{LP}} N_{C,i} * \lambda_i}{\sum_{i=1}^{n_{LP}} N_{C,i}} \tag{9}$$

$$SAIDI = \frac{\sum_{i=1}^{n_{LP}} N_{C,i} * U_i}{\sum_{i=1}^{n_{LP}} N_{C,i}} \tag{10}$$

where n_{LP} represents the number of load points (LPs), $N_{C,i}$ represents the number of customers at LP - *i*.

The power quality performance of an electrical distribution system is examined in terms of an important index that is the System Average RMS variation Frequency Index (SARFI) (*IEEE Std 1564-2014*):

$$SARFI_x = \frac{\sum_{i=1}^{n_{LP}} N_{C,i} * N_i^x}{\sum_{i=1}^{n_{LP}} N_{C,i}} \tag{11}$$

where N_i^x is the number of voltage sag events with magnitudes below *x* percent occurred at the load point-*i.*

3. Proposed Methodology

This section presents the proposed methodology, including the modeling of adverse weather events considering both aleatory and epistemic uncertainty. A brief explanation about the adverse weather events model, network fault scenarios model, and modified Integrated Reliability and Power Quality algorithm are detailed in this section.

3.1. Modeling of adverse weather events

A jump diffusion process usually models the discrete random events associated with the stochastic process. The jump diffusion process is driven by jump amplitude, duration, and the number of jumps in the period of interest. In this paper, the impact of Cyclone events on sampling of TTF considering both aleatory and epistemic uncertainty is modeled by the integration of the jump diffusion process into SDP. The aleatory uncertainty is modeled by the Weiner process (W_t) and the epistemic uncertainty is modeled by the Liu canonical process (N_t). The mathematical representation of the Stochastic Jump Diffusion Process (SJDP) is shown below (Chirima, Chikodza, and Hove-Musekwa 2019):

$$dX = a(X,t) * dt + b(X,t) * dW_t + \xi * dN_t \tag{12}$$

where ξ is the jumps amplitude and N_t represents the Liu canonical process which follows an uncertain normal distribution with a mean (μ) and standard deviation (σ) as shown below (Liu 2015):

$$\Phi(x) = \left(1 + exp\left(\frac{\pi(\mu - x)}{\sqrt{3} * \sigma}\right)\right)^{-1} \tag{13}$$

In this paper, the adverse weather events considered are the occurrence of cyclone events. In general, cyclone events are characterized by high winds and lightning conditions. Therefore, the impact of wind and lightning on the failure rates is to be quantified in terms of the scaling factors of the failure rate during normal weather conditions. The failure rate models during high wind and lightning conditions considered in this study are as follows (Huda, Nazmul, and Živanović 2019):

$$\lambda_{wind}\big(w(t)\big) = \left(1 + \alpha_W\left(\frac{w(t)^2}{w_{critical}^2} - 1\right)\right) * \lambda_{norm} \tag{14}$$

$$\lambda_{lightning}\left(N_g(t)\right) = \left(\beta_L * N_g(t) + 1\right) * \lambda_{norm} \tag{15}$$

where, $w(t)$ --> wind speed at time *t*

$w_{critical}$ --> critical wind speed over which failure rate increased

λ_{norm} --> constant failure rate during normal weather conditions

$N_g(t)$ --> ground flash density at time *t*

α_W and β_L --> scaling parameters for wind and lightning respectively.

The historical data of the occurrence of cyclone events at a specific location is collected to model the parameters of the jump diffusion process. The number of Cyclone events that occurred during the time duration T is modeled using a Poisson process with an occurrence rate of $\lambda_{cyclones}$

$$N_{cyclones} \sim poisson(\lambda_{cyclones}) \tag{16}$$

The magnitude of the wind and lightning events is sampled using a random number generated using a normal distribution with a mean (μ_ξ^W, μ_ξ^L) and standard deviation ($\sigma_\xi^W, \sigma_\xi^L$) shown below:

$$\begin{gathered} \xi^W \sim normal\left(\mu_\xi^W, \sigma_\xi^W\right) \; and \; \xi^L \sim normal\left(\mu_\xi^L, \sigma_\xi^L\right) \\ \xi = \xi^W + \xi^L \end{gathered} \tag{17}$$

The duration of the cyclone events is sampled using an uncertain normal random variable with the following inverse uncertainty distribution for mean cyclone event duration ($\mu_{cycones}$) and standard deviation ($\sigma_{cyclones}$) (Liu 2015):

$$dN_t \sim \Phi_t^{-1}(U) = \mu_{cycones} + \frac{\sigma_{cyclones} * \sqrt{3}}{\pi} * ln\left(\frac{U}{1 - U}\right) \tag{18}$$

Thus, the expression to sample TTF in the proposed method including adverse weather impacts is determined by adding the jump diffusion term into Equation (8) and is given by Equation (19):

$$TF = -X_t * [1 + \left\{\left[\frac{\beta}{\alpha} * \left(\frac{t}{\alpha}\right)^{\beta-1} * \exp\left(-\left(\frac{t}{\alpha}\right)^{\beta}\right)\right]\right\} * dt + \left\{\sqrt{\left[\frac{\beta}{\alpha} * \left(\frac{t}{\alpha}\right)^{\beta-1} * \exp\left(-\left(\frac{t}{\alpha}\right)^{\beta}\right)\right]}\right\} * dW_t + \xi * dN_t] \times ln\,(U) \quad (19)$$

3.2. Network fault scenario modeling

In general, voltage sag events exhibit stochasticity and the primary cause of them in distribution systems is the occurrence of unbalanced network faults like LG, LL, LLG, and LLLG. In the voltage sag assessment approach, the network fault scenarios are characterized by four important uncertainties, i.e., fault type, affected phases, fault location, and fault resistance (Bolacell et al. 2020b).

1) *Fault type:*

In the MCS method, the type of the network fault is sampled using the uniform probability distribution function shown below:

$$f_{type} \sim uniform[0, 1] \quad (20)$$

Table 1 presents the probability of occurrence for identifying the different types of faults sampled using Equation (20). In this paper, the probability of occurrence of various types of faults in the system is assumed to be the same as in literature (Bordalo, Rodrigues, and da Silva 2006).

Sl. No.	Fault Type	Probability (%)	Cumulative Probability (%)	Sampling range
1	**LG**	81	81	(0.00-0.81]
2	**LL**	10	91	(0.81-0.91]
3	**LLG**	6	97	(0.91-0.97]
4	**LLLG**	3	100	(0.97-1.00]

Table 1: Fault Types Probability

2) *Fault affected phases:*

In the MCS method, the phases affected for a specific network fault is sampled using the uniform probability distribution function shown below:

$$f_{phase} \sim uniform[0, 1] \quad (21)$$

Table 2 presents the probability of occurrence for identifying the different phases affected for a specific type of fault sampled using Equation (21). In this paper, the probability of occurrence of different phases is assumed to be the same as in literature (Bordalo, Rodrigues, and da Silva 2006).

Sl. No.	Fault Type	Fault Phase	Probability (%)	Sampling range
1	**LG**	A->G	33.33	(0.00-0.33]
		B->G	33.33	(0.33-0.66]
		C->G	33.33	(0.66-1.00]
2	**LLG**	AB->G	33.33	(0.00-0.33]
		BC->G	33.33	(0.33-0.66]
		CA->G	33.33	(0.66-1.00]
3	**LL**	AB	33.33	(0.00-0.33]
		BC	33.33	(0.33-0.66]
		CA	33.33	(0.66-1.00]
4	**LLLG**	ABC->G	100	(0.00-1.00]

Table 2: Fault Phases Probability for a Fault Type

3) *Fault location:*

The location of the sampled fault type on the distribution line section is usually sampled using the uniform probability distribution multiplied by the length of the line section as shown below:

$$f_{loc} \sim uniform[0,1] * l_B \tag{22}$$

where, $\boldsymbol{l_B}$ is the length of the line section or branch.

4) *Fault resistance:*

The fault resistance is usually sampled using the Weibull distribution function and its cumulative distribution function is given by:

$$f_{res} = 1 - exp\left(-\frac{R}{\alpha_R}\right)^{\beta_R} \tag{23}$$

where, $\beta_R > 0$ and $\alpha_R > 0$ are the shape and scale parameters respectively and *R* is the fault resistance in ohms.

3.3. Modified integrated reliability and power quality assessment

The flowchart of the modified Integrated Reliability and Power Quality Assessment for power distribution systems are summarized in this section:

Flowchart:

The flowchart of the modified Integrated Reliability and Power Quality Assessment for power distribution systems is presented in Figure 1.

4. Case Study and Results

The modified IRPQ algorithm is implemented in Visual C++ and validated using modified IEEE 34 node test system from (Bolacell 2016). Three different case studies have been analyzed, which is listed as follows:

Case – 1) Base Case - Only Aleatory Uncertainty

Case – 2) Both Aleatory and Epistemic Uncertainty

Case – 3) Impact of Cyclones modeled as Aleatory and Epistemic Uncertainty

The description of the test system along with the numerical results are discussed in this section.

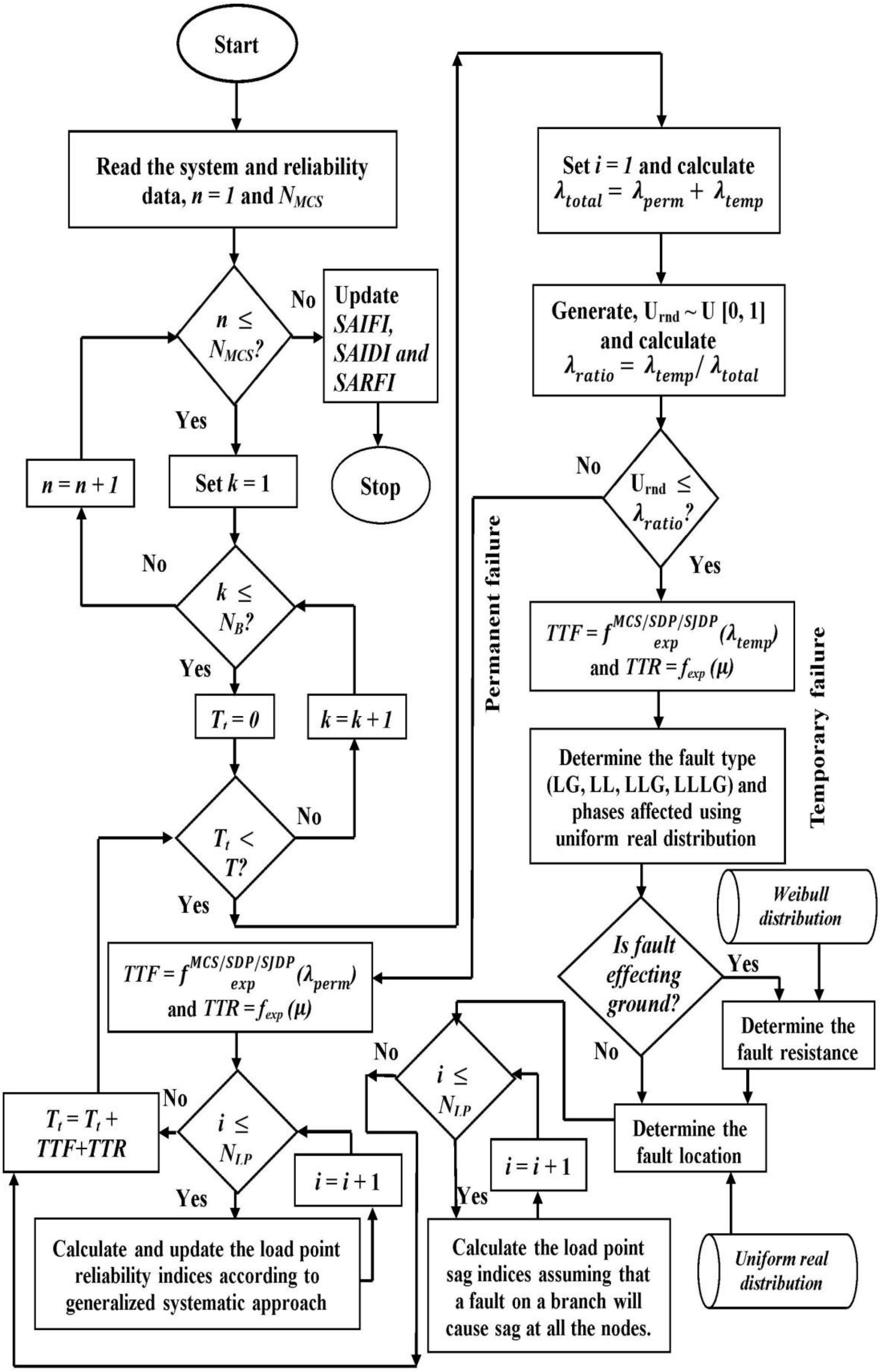

Figure 1: Flowchart of Modified Integrated Reliability and Power Quality Assessment

4.1. Test system

An unbalanced 24.9 kV modified IEEE 34 node test distribution system (Bolacell 2016) is considered to validate the proposed method and evaluate the impact of adverse weather events, as shown in Figure 2.

The test system consists of 34 nodes, 1 transformer, 2 voltage regulators, 2 shunt capacitors, 6 unbalanced spot loads, and 19 unbalanced distributed loads. The reliability data, line lengths, average load data, and customers' data are considered from Bolacell (2016).

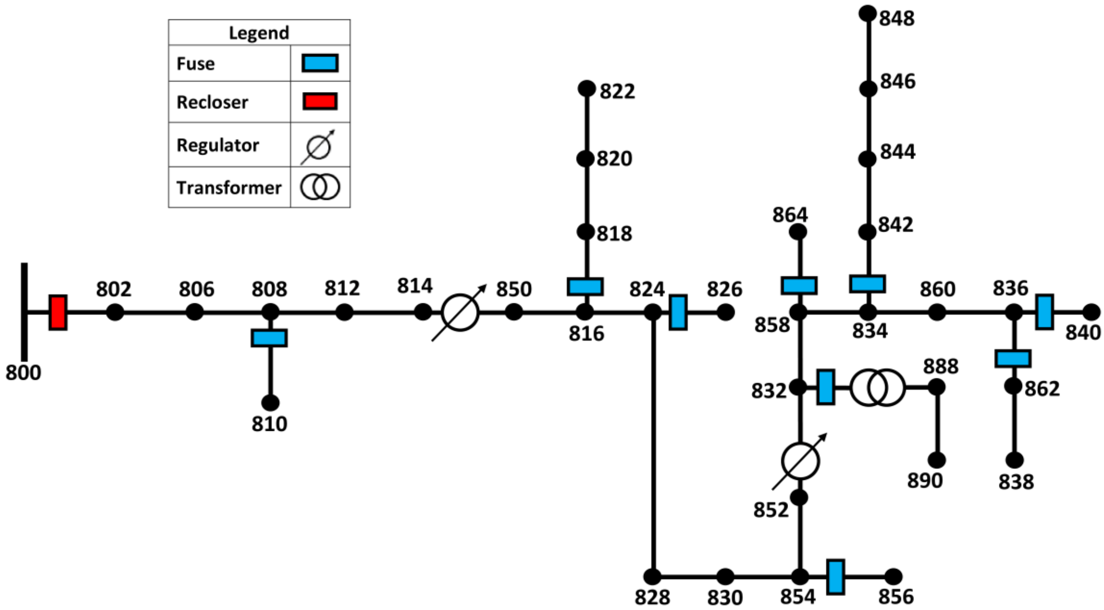

Figure 2: Modified IEEE 34 Node Test Distribution System (Bolacell 2016)

4.2. Adverse Weather Events Model – Data and analysis

In this paper, it is assumed that the cyclone data of Bay of Bengal is overlapped on IEEE test system to find the adverse weather impacts. The historical cyclone events occurrence data from 2000 to 2020 of the Bay of Bengal is accessed from Knapp et al. (2018). The cyclone events dataset consists of the attributes like the year of the event, date and time of occurrence, maximum wind speed (knots), latitude and longitude of the start of the cyclone center, and the landfall data. A total of 75 cyclone events data is recorded for 21 years in the Bay of Bengal and the test system is assumed to be selected at the identified site in this research work. The number of cyclone events recorded at the location is 18; thus, the cyclone events occurrence rate ($\lambda_{cyclones}$) evaluated is given by 0.85714 events/yr.

Figure 3 shows the number of cyclone events occurred year wise from 2000 to 2020. It is observed that a maximum of 3 events occurred during 2009. Figure 4 shows the total duration (hours) of each cyclone event that affects the site of interest. Figure 5 shows the maximum wind speed of each cyclone event recorded at the site of interest. The critical wind speed ($w_{critical}$) is assumed to be 34 knots and for the wind speeds above critical speed, the failure rate is evaluated using Equation (14). Figure 6 shows the average ground flash density of each cyclone event recorded, and the failure rate due to lightning is estimated using Equation (15).

Table 3 presents the estimated jump diffusion parameters based on historical cyclone event data. These parameters are used in the Stochastic Jump Diffusion Process to simulate adverse weather events.

Parameters	Values
$\lambda_{cyclones}$(events/yr.)	0.85714
μ_{ξ}^{W}(f/yr.)	2.5751
σ_{ξ}^{W}(f/yr.)	2.9657
μ_{ξ}^{L}(f/yr.)	3.2283
σ_{ξ}^{L}(f/yr.)	1.6092
$\mu_{cyclones}$ (yr./event)	0.012
$\sigma_{cyclones}$ (yr./event	0.0054

Table 3: Estimated Jump Diffusion Parameters – Cyclone Events

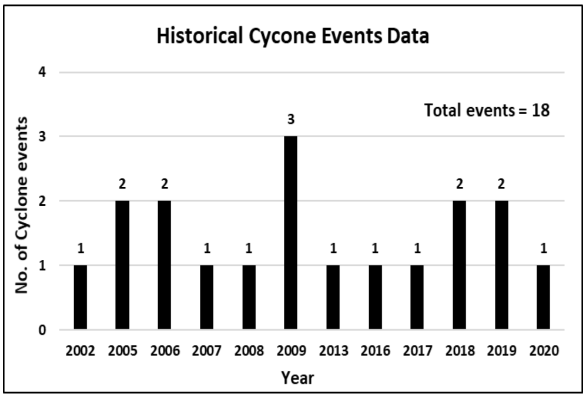

Figure 3: Historical Cyclone Events Data (Knap et al. 2018)

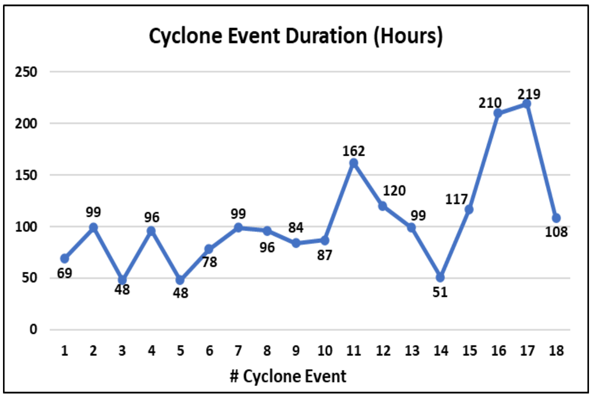

Figure 4: Duration of Cyclone Events (Knap et al. 2018)

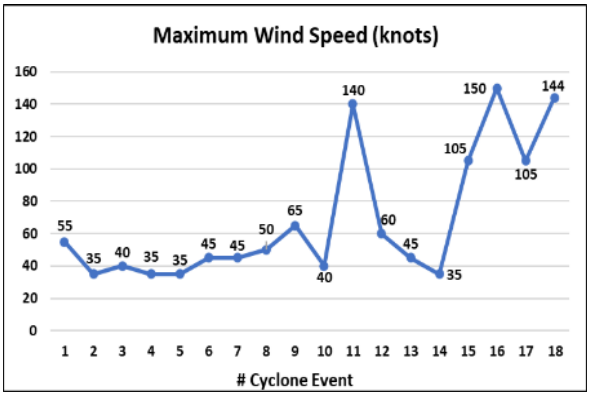

Figure 5: Maximum Wind Speed of Cyclone Events (Knap et al. 2018)

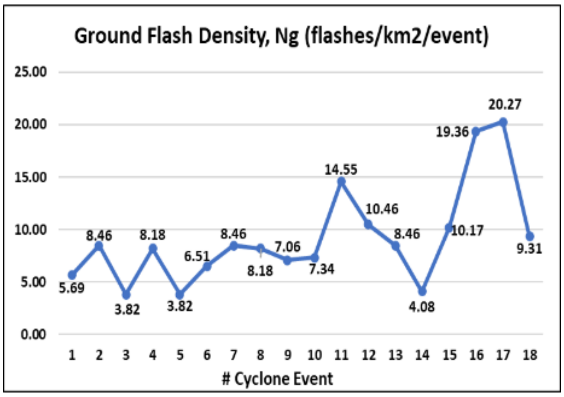

Figure 6: Ground Flash Density of Cyclone Events (Knap et al. 2018)

4.3. Results and discussions

This section presents the simulation results of the modified integrated reliability and power quality assessment algorithm for the IEEE 34 node test system. Three case studies are performed to study the impact of uncertainty and adverse weather events on reliability and power quality indices described as follows:

Case – 1) Base Case - Only Aleatory Uncertainty

Case 1 represents the simulation of IRPQ assessment using the MCS method that considers only aleatory uncertainty in TTF sampling. Table 4 presents the reliability and power quality indices evaluated using the MCS method for 5000 simulation years (Bolacell et al. 2016).

Method	Monte Carlo Simulation		
Index	SAIFI (interruptions/yr./cust.)	SAIDI (hours/yr./cust.)	SARFI (events/yr./cust.)
Value	0.80832	3.43586	4.2928

Table 4: Reliability and Power Quality Indices – MCS

MCS			
Sl. No.	Fault Type	No. of Faults Simulated	Estimated Probability (%)
1	LG	17464	81.36
2	LL	2097	9.77
3	LLG	1259	5.87
4	LLLG	644	3.00
	Total	21464	

Table 5: Number of Simulated Faults – MCS

Table 5 presents the different types of faults simulated using the MCS method. The simulated probabilities of different fault types are found to be similar to the probabilities in Table 1. In all cases, the main assumption considered in this paper is that a fault on a branch will cause the voltage sag event at all nodes of the test system.

Case – 2) Both Aleatory and Epistemic Uncertainty

Case 2 represents the simulation of modified IRPQ assessment using the SDP_MCS method that considers both aleatory and epistemic uncertainty in TTF sampling. Table 6 presents the reliability and power quality indices evaluated using the SDP_MCS method for 5000 simulation years.

Method	Stochastic Diffusion Process Based Monte Carlo Simulation		
Index	SAIFI (interruptions/yr./cust.)	SAIDI (hours/yr./cust.)	SARFI (events/yr./cust.)
Value	0.82173	3.50307	4.2762

Table 6: Reliability and Power Quality Indices – SDP_MCS

SDP_MCS			
Sl. No.	Fault Type	No. of Faults Simulated	Estimated Probability (%)
1	LG	17396	81.36
2	LL	2124	9.93
3	LLG	1227	5.74
4	LLLG	634	2.97
	Total	21381	

Table 7: Number of Simulated Faults – SDP_MCS

Table 7 presents the different types of faults simulated using the SDP_MCS method. The simulated probabilities of fault types are found to be similar to the probabilities in Table 1.

Case – 3) Impact of Cyclones modeled as Aleatory and Epistemic Uncertainty

Case 3 represents the simulation of modified IRPQ assessment using the SJDP_MCS method that considers the impact of cyclone events in TTF sampling. Table 8 shows the reliability and power quality indices calculated using the SDP_MCS method over a period of 5000 simulation years. There is a significant increase in the reliability and power quality indices when compared to Cases 1 and 2.

Method	Stochastic Jump Diffusion Process Based Monte Carlo Simulation		
Index	SAIFI (interruptions/yr./cust.)	SAIDI (hours/yr./cust.)	SARFI (events/yr./cust.)
Value	1.43704	6.21955	7.6266

Table 8: Reliability and Power Quality Indices – SJDP_MCS

Table 9 presents the different types of faults simulated using the SJDP_MCS method. It is observed that there is an increase in the number of faults compared to Cases 1 and 2 because of cyclone events.

SJDP_MCS			
Sl. No.	**Fault Type**	**No. of Faults Simulated**	**Estimated Probability (%)**
1	**LG**	30963	81.20
2	**LL**	3766	9.88
3	**LLG**	2286	5.99
4	**LLLG**	1118	2.93
	Total	38133	

Table 9: Number of Simulated Faults – SJDP_MCS

Comparison of results

Table 10 compares the reliability and power quality indices of the three cases. The results conclude that ignoring the epistemic uncertainty leads to underestimation of distribution system reliability and power quality performance.

	Case-1: Only Aleatory Uncertainty	**Case-2: Both Aleatory and Epistemic Uncertainty**		**Case-3: Both Aleatory and Epistemic Uncertainty including Cyclone events**	
	MCS	**SDP_MCS**	**Error (%)**	**SJDP_MCS**	**Deviation (%)**
SAIFI	0.80832	0.82173	-1.66	1.43704	-77.78
SAIDI	3.43586	3.50307	-1.88	6.21955	-80.88
SARFI	4.2928	4.2762	0.387	7.6266	-78.35

Table 10: Comparison of Indices - Methods

Furthermore, it is observed that the adverse weather events have very significant impact on the reliability and power quality indices. Figure 7 illustrates the number of faults simulated in all the methods. It is observed that the there is an increase in the faults due to the occurrence of adverse weather events.

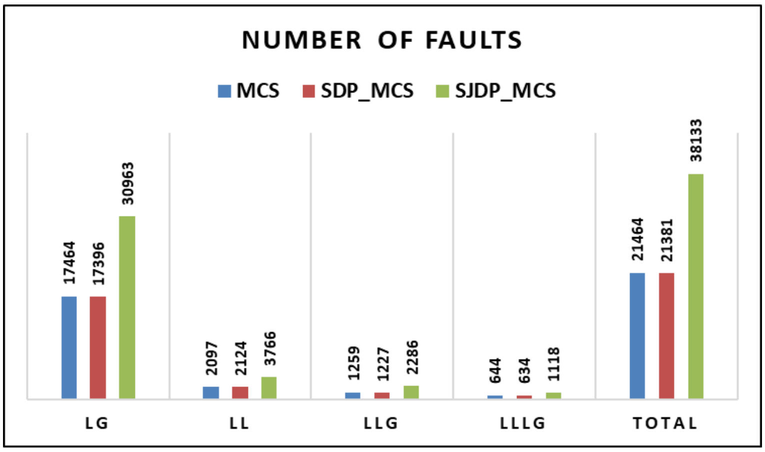

Figure 7: Number of Faults Simulated – MCS, SDP_MCS and SJDP_MCS

The analysis concludes that the proposed method, incorporating aleatory and epistemic uncertainty into TTF sampling, yields more accurate indices values. Furthermore, adverse weather events have been observed to decrease the reliability and power quality in the system. Finally, the modified IRPQ assessment algorithm has more innovatively modeled the various uncertainties and adverse weather events.

5. Conclusions and Future Scope

This research illustrates the application of the Stochastic Diffusion Process for modeling aleatory and epistemic uncertainty in integrated reliability and power quality assessment of power distribution systems. The aleatory and epistemic uncertainty is modelled into the drift and diffusion coefficients of the Stochastic Diffusion Process that describes TTF sampling. Furthermore, the adverse weather events are modelled into SDP with the integration of the Jump diffusion process. The parameters of the Jump diffusion process are estimated from the historical cyclone events data collected for a specific location. The efficacy of the proposed method in handling uncertainty is validated by the modified IEEE 34 node test system. Three different case studies have been performed to investigate the impact of aleatory and epistemic uncertainty and adverse weather events on TTF sampling during the permanent and temporary failures.

Numerical results reveal that the improved method is capable of modeling any uncertainty associated with TTF. It is concluded that aleatory and epistemic uncertainty have a significant impact on distribution system reliability and power quality indices. Furthermore, considering the adverse weather parameters in reliability analysis demonstrated the decrease in system reliability as expected. It is concluded that there is a need to implement reliability and power quality improvement alternatives in order to quantify distribution system performance in terms of supply continuity and quality. Further, the proposed method is better suited for modeling various uncertainties associated with DERs and performing integrated reliability and power quality analysis more effectively.

As regards to future research, the Stochastic Diffusion Process can be used to model the various uncertainties associated with Energy Storage Systems and Electric Vehicles.

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