Reliability Performance Optimization and Voltage Sag Mitigation for Radial Distribution Systems with Distributed Generations

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ABSTRACT

This paper proposes an innovative approach aimed at optimizing reliability indices by considering voltage sag and integrating distributed generations. An objective function is formulated to enhance reliability and mitigate voltage sag by minimizing the failure rate, repair time, and fault rate of each distributor segment. The formulation incorporates constraints on indices and decision variables to ensure reliability. To solve the optimization problem, the Improved Elephant Herding Optimization (IMEHO) method is proposed and applied to a sample radial distribution system. The results obtained using IMEHO are compared with those from the arithmetic optimization algorithm (AOA) and the teaching-learning-based optimization (TLBO) techniques. Additionally, the paper provides statistical inferences to evaluate the performance of the proposed method against the comparison techniques. Overall, the paper contributes to the field by introducing a novel optimization strategy tailored to enhance reliability indices and mitigate voltage sag in distribution systems with distributed generations. The comparative analysis and statistical inferences offer insights into the effectiveness and performance of the IMEHO algorithm in addressing the optimization problem at hand.

1. INTRODUCTION

The reliability of power supply has long been a primary concern for consumers who now demand both quality and continuity. Distribution systems are expected to consistently deliver rated power and frequency [1], maintaining a uniform sinusoidal voltage. However, the presence of nonlinear loads within the distribution network and various system events, including motor starting, capacitor switching and different types of faults, can significantly impact power quality [2]. The three main power quality issues that most customers are concerned about are voltage sags, momentary outages and sustained outages. These issues affect customers differently, with residential consumers typically experiencing momentary and sustained interruptions, while commercial and industrial clients are more concerned about voltage sags and momentary interruptions. The root cause of these power quality issues, especially in the distribution system, is utility power system faults. While faults are inevitable, their impact on customers can be mitigated [3].

Customers experience interruptions when electricity is unavailable during one or more outages, making interruptions a notable power-quality event. These interruptions can vary in duration, with short interruptions automatically terminated by switching or automatic reclosing [2]. Longer interruptions, lasting three minutes or more according to official IEC criteria, are considered extended outages. To assess the reliability of the power grid, the frequency and duration of prolonged interruptions are stochastically predicted. Many utilities monitor their performance using reliability indices, and regulators often require utility performance reports on reliability. The prevailing regulatory trend today is performance-based rates, which either reward or penalize superior performance. This paper contributes to improving the distribution system's reliability by incorporating simple power quality issues, such as voltage sag. Specifically, the paper focuses on voltage sags caused by faults. It's worth noting that voltage sags frequently lead to load outages, negatively impacting the reliability indices of distribution systems.

Voltage sags are garnering attention due to their adverse effects on various equipment used in current process control, as these devices are vulnerable to voltage sags. The malfunction or failure of equipment caused by voltage sags can lead to expensive production interruptions or work stoppages, consequently impacting reliability levels [4]

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Analytical evaluations of voltage sag performance in distribution networks are discussed in [5]. The connection between distributed generation and power quality is explored in [6], with a focus on the direct effects of rising wind energy usage on distribution networks' power reliability and quality [7].

A method for optimization was developed by Mishra and Bhandakkar [8] to find the best position and capacity for DG facilities. Network reconfiguration was efficiently addressed through a GA-based solution [9], with the aim of improving distribution networks' power as well as reliability. Optimal power system reconfiguration, as discussed in [10], demonstrated improvements in reliability and power quality, including a reduction in propagating voltage sag (Nsag) and other reliability indices. The use of PSO was proposed in [8] to significantly reduce overall power loss in systems, enhance reliability indices, and improve voltage profiles by selecting the optimal location, size, & number of DGs. Balasubramaniam and Prabha [11] studied power quality problems, their causes, and applicable norms and standards. Divya et al. [12] addressed power quality problems by optimizing the placement of DGs in the DS. Eltamaly et al. [13] utilized an appropriate distribution of photovoltaic systems to tackle power quality and reliability issues. Mallappa et al. [14] employed hybrid optimization techniques to improve power quality in a grid-integrated PV system. The Residual Denoising Convolutional Auto-Encoder proposed in [15] served as an unsupervised learning-based technique for diagnosing Power Quality Disturbance. Ferroresonance, causing overvoltages and overcurrents, was explored in low-voltage power factor correction systems [16]. Chang et al. [17] presented a hybrid detection method for time-varying harmonics & interharmonics using the synchrosqueezing wavelet transform. In Saket et al. [18], a municipal waste water-based technology for producing electricity is described. The flow duration curve (FDC) and the Gaussian distribution technique are used to assess the reliability of the micro-hydro-photo-voltaic hybrid power system. Comparative analysis of the resent work for voltage sag and reliability indices is summarized in Table1.

Table 1. Comparing different methods with related literature reviews

Authors	Year	Contributions	Minimize	Optimization approach Used
Ngampraser and Rugthaicharoenc heep [19]	2024	Power distribution system's voltage sag by employing Tabu Search.	Voltage sags	Tabu Search
Thang et al. [20]	2023	GA-based MOO to address the optimization issue, which aims to minimize both the test system's SARFIX and D-Statcom's investment.	Voltage sags	GA
Mohtasham and Jalilian [21]	2022	The phase angle jump is determined using a novel approach that takes into account the Clarke zero component and a classification procedure for multilevel stress drops	Multi-level voltage sag	Clarke's transformation
Turiza et al. [22]	2022	The application of deep convolutional neural networks and fault analysis to the characterization of voltage drops.	Reliability indices and voltage sag	Convolutional neural networks
Shakeri et al. [23]	2022	Describe a novel technique to reduce pollution of the sensitive harmonic loads sector, taking into account the financial losses caused by voltage drops.	Voltage sag	Non-dominant Sorting Genetic Algorithm
Wang et al. [24]	2021	Presents an evaluation method using "knee points" to obtain an approximate VTC.	Voltage sag	-
Shin et al. [25]	2021	This paper uses PSCAD/EMTDC simulations to evaluate voltage drops in the power DS using SFCL as a function of fault location.	Voltage sag	-
Chen et al. [26]	2020	Provides insurance against voltage drop based on a severity index that includes liability, period, premium, and indemnity.	Voltage sag	-
Nguyen and Bach [27]	2019	A comparative analysis of the voltage dip mitigation capabilities of DVRs and D-Statcoms in distribution networks.	Voltage sag	GA

The propagation of voltage drops and their impact on reliability indices, specifically the SARFI, has been given limited attention. Voltage dips and interruptions are typically associated with power quality issues, often resulting from faults in the power system and the necessary switching operations to isolate damaged sections. Voltage sags at various load points negatively affect reliability. The paper's primary contributions are emphasized;

- Development of a strategy for reliability enhancement accounting voltage sag.
- Application of IMEHO algorithm for optimization employing Lampinen's criteria for handling inequality constraints.
- Accounting impact of DGs on indices and voltage sag.
- The performance of IMEHO is superior than other the two methods based on statistical inferences.

The research aimed to achieve its objectives by integrating Distributed Generators (DGs) at various load points and optimizing a newly developed objective function. Section-2: Presents an overview of the reliability indices utilized in the study. Section-3: Explains the methodology employed for calculating the number of interruptions and assessing voltage sag occurrences. Section-4: Describes the problem definition. Section-5: Offers an overview of Improved Elephant Herding Optimization (IMEHO). Section-6: provides a complete overview of the research findings along with a detailed analysis of them. Section-7: Summarizes the main findings, implications, and contributions of the research.

2. RELIABILITY INDICES AND POWER QUALITY

The introduction of new power quality measures provides utilities with tools that are similar to reliability indices. These measures serve various purposes, including identifying areas for maintenance, upgrading circuits, monitoring regional performance, and reporting to regulatory bodies. One prominent indicator in this field is SARFI, as mentioned in previous studies [28, 29]. SARFI calculates the average count of specified RMS measurement events per customer served within a defined assessment period. This indicator plays a crucial role in providing insights into the reliability and power quality performance of the distribution system. To calculate the SARFI for the overall system, the total anticipated number of sags (N_{sag}) resulting from various system failures is utilized, as referenced in [30]. All system buses ($\mathrm{N_{bus}}$) serving the customers connected in the evaluation area are considered.

$$\mathrm{SARFI} = \frac{\sum \mathrm{N_{sag}}}{\mathrm{N_T}} \tag{1}$$

where, N_{sag} is the number of consumers that suffered a short-term voltage deviation as a result of all possible fault during the evaluation time. The number of customers the system component under evaluation serves is N_T. Using the different voltage sag ranges from 0 to 1 p.u., the number of sags in $SARFI$ can be determined. Three customer-oriented reliability indices, known as $SAIFI$, $SAIDI$ and$CAIDI$ are commonly used by utilities [31].

$$\mathrm{SAIFI} = \frac{\sum \lambda_{\mathrm{sys,i}} \mathrm{N_i}}{\sum \mathrm{N_i}} \tag{2}$$

$$\mathrm{SAIDI} = \frac{\sum \mathrm{U_{sys,i}} \mathrm{N_i}}{\sum \mathrm{N_i}} \tag{3}$$

$$\mathrm{CAIDI} = \frac{\sum \mathrm{U_{sys,i}} \mathrm{N_i}}{\sum \lambda_{\mathrm{sys,i}} \mathrm{N_i}} \tag{4}$$

$AENS$, one of the most essential reliability indices that is energy-based, is defined as follows:

$$\mathrm{AENS} = \frac{\sum \mathrm{L_i} \mathrm{U_{sys,i}}}{\sum \mathrm{N_i}} \tag{5}$$

The following are expressions for calculating $\lambda_{\mathrm{sys,i}}$ and $\mathrm{U_{sys,i}}$ for each load point:

$$\lambda_{\mathrm{sys,i}} = \sum \lambda_{\mathrm{k}} \tag{6}$$

$$\mathrm{U_{sys,i}} = \sum \lambda_{\mathrm{k}} \mathrm{r_k} \tag{7}$$

3. CALCULATION OF THE NUMBER OF INTERRUPTIONS AND VOLTAGE SAGS

The propagation of voltage drops in a system is influenced by the nature and location of the fault. Buses located farther from the fault experience less severe voltage drops [32]. Line faults are primary contributors to voltage sags, and fault analysis is a key tool for calculating both symmetrical and asymmetrical faults. By conducting fault analysis, it is possible to identify the system branches that contribute significantly to sag exposure. To calculate the expressed yearly number of line faults, use the formula below.

$$f_{total} = \sum_{p=1}^{4} \sum_{k=1}^{N_L} L_k \lambda_{k\_fault} \tag{8}$$

where, p stands for the fault type, e.g. three-phase (LLL), line-to-ground (LG), line-to-line-to-ground (LLG), and line-to-line (LL).

L_k- k^{th} distributor segment's length

N_L - all distributor segments up until the failure point

λ_{k_fault} - k^{th} distributor segment's fault rate

This paper calculates sag values due to various types of faults at specific load points.

$$N_{sag} = \sum_{i=1}^{N_{bus}} \sum_{f=1}^{total} \begin{cases} 1\ if \quad 0.10\ p.u. < V_i < 0.90\ p.u. \\ 0\ \ otherwise \end{cases} \tag{9}$$

where, N_{sag} is voltage sags per year

A continuous interruption exists when a fault-related voltage drop at any load point is smaller than 0.10 p.u. The total yearly interruptions can be calculated as follows:

$$N_{int} = \sum_{i=1}^{N_{bus}} \sum_{f=1}^{total} \begin{cases} 1 \; if \;\; V_i < 0.1 \, p.u. \\ 0 \; otherwise \end{cases} \tag{10}$$

The power quality index can be calculated using relation (1) and relation (9) to determine the interruptions. These interruptions, resulting from relation (10), are combined with interruptions caused by outages of various distribution segments due to factors such as aging, environmental effects, accidents, etc. The reliability indices are then obtained from (2) to (5). To account for the different impacts of various voltage drops on the costs associated with customer interruptions, weighting variables were developed for economic analysis.

4. PROBLEM DEFINITION

The objective function is defined as follows with the purpose of enhancing reliability while considering voltage sags:

$$\mathrm{F} = \sum_{\mathrm{k=1}}^{\mathrm{N_c}} (\alpha_{\mathrm{k}}/\lambda^2_{\mathrm{k_{failure}}} + (\gamma_{\mathrm{k}}/\lambda^2_{\mathrm{k_{fault}}}) + \sum_{\mathrm{k=1}}^{\mathrm{N_c}} \beta_{\mathrm{k}}/\mathrm{r_k} + \sum_{\mathrm{k=1}}^{\mathrm{N_c}} \mathrm{CIC} + \mathrm{ADCOST(EENSO - EENSD)} + \sum_{\mathrm{k=1}}^{\mathrm{N_c}} C_{RP} \tag{11}$$

where,

$$\mathrm{CIC} = \lambda_{\mathrm{k}} \times \mathrm{r_k} \times \mathrm{L_i} \times \mathrm{C_{p_k}} \tag{12}$$

$$\mathrm{CIC} = \mathrm{CIC_1} + \mathrm{CIC_2} + \mathrm{CIC_3} + \mathrm{CIC_4} \tag{13}$$

$$\lambda_{\mathrm{k}} = \lambda_{\mathrm{k\_failure}} + \lambda_{\mathrm{k\_fault}} \text{ (Sustained interruptions)} \tag{14}$$

Maintenance costs are represented by the first three terms in objective function (11). The first two terms represent the cost of reducing failure and fault rates across the distribution network. The third term refers to the cost of changing the repair times in the distribution segments. The utility must spend more on corrective and preventive maintenance when the values of these components are lower to achieve its goals [33]. These concepts represent Duane's reliability growth model [34]. The fourth component is concerned with the costs of consumer interruptions. If the load is sensitive to interruptions, both momentary and continuous interruptions have an economic impact. For each load point, the total cost of interruptions can be calculated by adding the cost of all section outages. In this way, the price of each interruption caused by a customer can be determined. The incremental cost of power supplied by DGs connected at different load points is dealt with in the fifth term. It is the sum of the ADCOST in rupees per kWH and the power supplied by the DGs. The DGs considered in this study are standby units. The connected DGs are treated as standby units in this situation. The average downtime and failure rate of the DG used in this study is 13.25 hours and 0.50 failures per year, respectively. For the system under consideration, the DG switch has a failure rate of 0.10/ year and a recovery time of 0.50 hours. The reliability model used here is from [35]. In the event of faults or outages, the uninterruptible backup power supplies (UPS) will provide power for a very short time until the standby DGs connected to the load points are ready to supply the power. The utility's cost of reward or penalty is the subject of the sixth term. The utility is paid or otherwise penalized when its reliability falls below a certain threshold. As a result, the objective function strikes a balance between the costs associated with DGs, maintenance, customer interruptions, and rewards and penalties. By reducing fault rates in different parts of the distribution system, failure rates in the distribution system, and repair times, this objective function aims to enhance the reliability and power quality index concerned with voltage sag. The use of DGs in combination with an emergency power system UPS makes this possible. Minimizing the objective function given in relation (11) leads to the best result.

(i) Decision variables constraints

$$\lambda_{\mathrm{k\_failure,min}} \leq \lambda_{\mathrm{k\_failure}} \leq \lambda_{\mathrm{k\_failure,max}} \tag{15}$$

$$\lambda_{\mathrm{k\_fault,min}} \leq \lambda_{\mathrm{k\_fault}} \leq \lambda_{\mathrm{k\_fault,max}} \tag{16}$$

$$\mathrm{r_{k,min}} \leq \mathrm{r_k} \leq \mathrm{r_{k,max}} \tag{17}$$

$$\mathrm{k} = 1, \dots \dots \dots \dots \dots, \mathrm{N_c}$$

where,

$\lambda_{\mathrm{k,max}}$ & $\lambda_{\mathrm{k,min}}$ - maximum and minimum failure rate of the k^{th} segment

$\mathrm{r_{k,max}}$ & $\mathrm{r_{k,min}}$ - maximum and minimum repair time of the k^{th} segment

(ii) Inequality constraints for the energy & customer-based indices

$$\mathrm{SAIDI_t} \geq \mathrm{SAIDI} \tag{18}$$

$$\mathrm{SAIFI_t} \geq \mathrm{SAIFI} \tag{19}$$

$$\mathrm{CAIDI_t} \geq \mathrm{CAIDI} \tag{20}$$

$$\mathrm{AENS_t} \geq \mathrm{AENS} \tag{21}$$

$$\mathrm{SARFI_t} \geq \mathrm{SARFI} \tag{22}$$

$$\mathrm{R} = \frac{\mathrm{SAIFI}}{\mathrm{SAIFI_t}} + \frac{\mathrm{SAIDI}}{\mathrm{SAIDI_t}} + \frac{\mathrm{CAIDI}}{\mathrm{CAIDI_t}} + \frac{\mathrm{AENS}}{\mathrm{AENS_t}} \tag{23}$$

where, $SAIFI_t$, $SAIDI_t$, $CAIDI_t$, $AENS_t$ and $SARFI_t$ - are each of the indices' target/threshold values.

5. MATHEMATICAL MODELING OF IMPROVED ELEPHANT HERDING OPTIMIZATION (IMEHO) METHOD FOR THE SOLUTION OF PROPOSED FORMULATION [36]

The EHO (Elephant Herding Optimization) algorithm formulates optimization strategies by drawing inspiration from the behavior of elephant herds. This approach adopts a multidimensional strategy that integrates insights from various fields or viewpoints to enhance the optimization process. By referencing "elephant herding behavior" the algorithm leverages collective behaviors observed in groups of elephants, including coordination, collaboration, and other social aspects, to inform its optimization strategies. This multidimensional approach allows the algorithm to explore diverse perspectives and adapt its strategies accordingly, contributing to its effectiveness in solving optimization problem.

5.1 Bionics Perspective (Simulating Elephant Movement): Velocity Strategy

The approach involves mimicking the movement patterns of elephants in a bionic manner. The proposed global velocity strategy implies a coordinated movement of the algorithmic agents, akin to how elephants move as a group. This could enhance the overall efficiency and effectiveness of the algorithm. Assign a set of velocity V_j to each elephant when it initializes its location. The following is the procedure for setting the elephant's beginning location and speed:

$$U_j = U_{min} + (U_{max} - U_{min})rand_1 \tag{24}$$

$$V_j = V_{min} + (V_{max} - V_{min})rand_2 \tag{25}$$

$$V_{max} = (U_{max} - U_{min}) * 0.20 \tag{26}$$

$$V_{min} = -V_{max} \tag{27}$$

where,

U_j & V_j - j^{th} elephant position and speed.

U_{max} & U_{min} - higher and lower positional bounds.

V_{max} & V_{min} - higher and lower velocity bounds.

Equation (28) updates the elephant's speed at each generation in the following manner:

$$V_{new,cl,j} = W_i * V_{cl,j} + AC * \left(U^* - U_{cl,j}\right)rand_3 \tag{28}$$

$$W_i = 0.90 - \frac{k}{k_{max}} * 0.70 \tag{29}$$

$V_{new,cl,j}$ & $V_{cl,j}$ - j^{th} elephant speed of new and old clan cl.

W_i - inertia weight falls linearly: $W \in [0.20, 0.90]$

AC - acceleration coefficient.

$U_{cl,j}$ - j^{th} elephant position in clan cl.

U^* - $U_{cl,j}$ elephant learning goal.

$rand_1$, $rand_2$ & $rand_3$ – random digits between 0 and 1.

5.2 Learning Perspective (Improving Information Exchange): Learning Strategy

Each elephant in the EHO algorithm performs the clan update phrase based on its current location and the herd's matriarch's location. Every member of the clan contributes information that updates the matriarch's status. However, it is noted that this approach may lead to falling into a local optimum. To address this issue, a new learning strategy is proposed, dividing all the elephants into three groups. The best elephant (U_{gbest}) in the elephant herd, is the first type of elephant. The second group is called U_{pbest}, and it consists of the matriarchs of each clan. The final group of elephants is referred to as U_{other}.

The herd's finest elephant should venture outside of its tribe and pick up knowledge from other matriarchs. In this case, we'll suppose that it updates itself based on all the matriarchs' data. The position of the herd's best elephant, U_{gbest}, can be modified as follows:

$$V_{new,gbest} = W_i * V_{gbest} + IF * \left(U_{center} - U_{gbest}\right) \tag{30}$$

$$U_{new,gbest} = U_{gbest} + V_{new,gbest} \tag{31}$$

$$U_{center} = \frac{1}{n_{cl}} \sum_{i=1}^{n_{cl}} U_{pbest,cl} \tag{32}$$

where,

$V_{new,gbest}$ & V_{gbest} - new and old velocity for elephant U_{gbest}.

$U_{new,gbest}$ - is elephant U_{gbest} new position.

IF – impact factor between [0,1].

n_{cl} - is the number of clans.

The second sort of elephant (U_{pbest}) best indicates the status of the matriarchs. It ought to encourage its members to take advice from the herd's finest elephant. Here, it updates itself based on the data provided by the elephant U_{gbest}.

$$V_{new,pbest} = W_i * V_{pbest} + AC * \left(U_{gbest} - U_{pbest}\right) * rand_4 \tag{33}$$

$$U_{new,pbest} = U_{pbest} + V_{new,pbest} \tag{34}$$

$V_{new,pbest}$ & V_{pbest} - new and old velocity for elephant U_{pbest}.

$U_{new,pbest}$ - is elephant U_{pbest} new position.

IF – impact factor between [0,1].

Their matriarch will teach the other elephants (U_{other}). They update themselves by the following matriarch within the same clan:

$$V_{new,other} = W_i * V_{other} + AC * \left(U_{pbest} - U_{other}\right) * rand_5 \tag{35}$$

$$U_{new,other} = U_{other} + V_{new,other} \tag{36}$$

$V_{new,other}$ & V_{other} - new and old velocity for elephant U_{other}.

$U_{new,othert}$ - is elephant U_{other} new position.

$rand_4$ & $rand_5$ – random digits between 0 and 1.

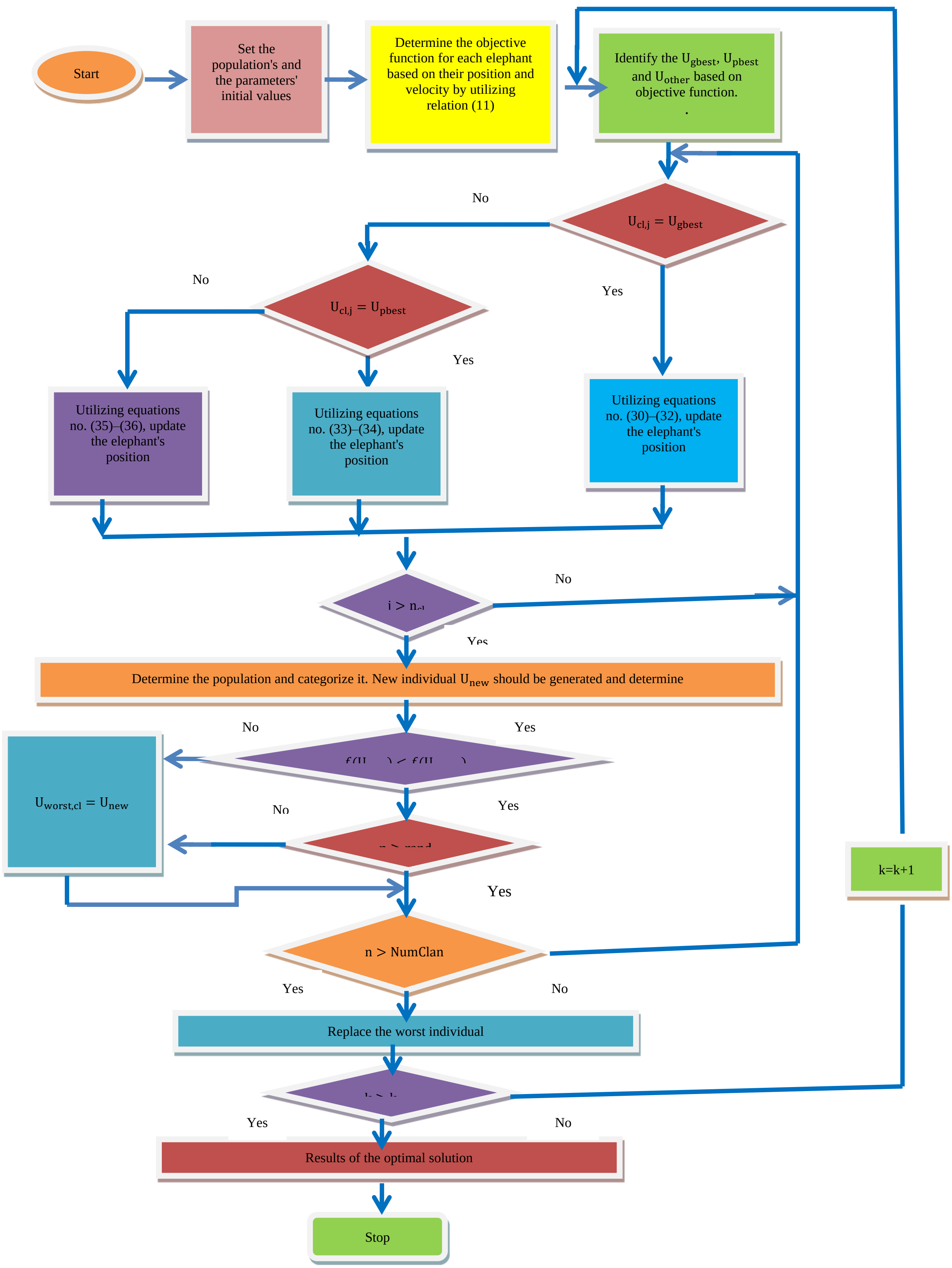

Fig. 1. IEHO technique process flow for resolving the given problem.

5.1. Algorithmic Perspective (Enhancing Separation Operator): Separation Strategy

Assess the newborn calf first. It can be changed if the new fitness value is superior to the old one. If not, a probability value, represented by (p), will determine whether or not the original elephant is replaced. To create a random number rand_6, a judgement operation will be performed in this case. The original elephant will be replaced if its worth exceeds (p),. In this case, the individual selection process is based on a minor probability occurrence. It preserves the population's variety while enhancing the algorithm's performance.

$$U_{\mathrm{worst,cl}} = \begin{cases} U_{\mathrm{new}} & if\ f(U_{\mathrm{new}}) < f(U_{\mathrm{worst}}) \\ U_{\mathrm{new}} & p \geq \mathrm{rand}_6 \end{cases} \tag{37}$$

5.2. Evolutionary Perspective (Incorporating Elitism): Elitism Strategy

Elitism is a strategy commonly used to preserve the best-performing solutions from one generation to the next. It involves selecting a certain percentage or number of the best individuals (solutions) and directly transferring them to the next generation without any modifications. The idea is to maintain the best solutions found so far and ensure that they are not lost during the process.

The IMEHO approach of the suggested technique is demonstrated using the flowchart in Fig. 1.

6. RESULTS AND DISCUSSIONS

The developed approach was implemented on an 8-bus, 7-segment radial distribution system to enhance system reliability and power quality, specifically focusing on voltage sag and subject to inequality constraints [33, 35]. The objective function of the optimization algorithm considers costs related to distributed generators (DGs), maintenance, customer disruptions, and rewards or penalties. There are seven loading stations in the radial system, labelled LP-2 to LP-8 in Fig. 2. Various parameters for each component of the radial distribution system, including current, lowest practical failure rate, repair times, average load, consumers at load points, and cost coefficients, were calculated as detailed in [35, 37]. Table-2 shows the length of segments of the radial distribution system with failure rate, fault rate, average repair time, minimum failure rate, minimum fault rate, and minimum repair time [35]. Table-3 shows the interruption cost (C_{p_k}) for the sample radial distribution system at various load points. The weighting for the different voltage drop value ranges shown in Table-4 is used to calculate the total contribution to customer interruption costs based on sustained and temporary interruptions. Table-5 gives average load and the customers' number at various load points [35].

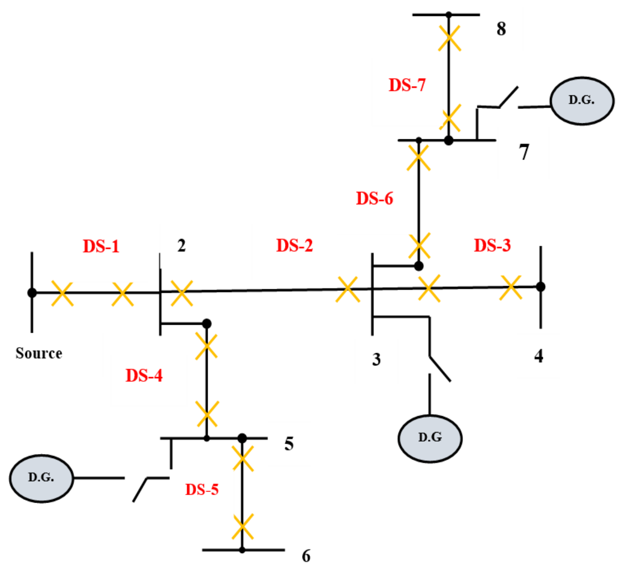

Fig. 2. Radial distribution network, single-line scheme with seven distributions.

Table 2. System information for a representative radial distribution network

Distributor segment (DS)	DS-1	DS-2	DS-3	DS-4	DS-5	DS-6	DS-7
$\lambda^0_{k\_failure}$ / $year$	0.4000	0.2000	0.3000	0.5000	0.2000	0.1000	0.1000
$\lambda^0_{k\_fault}$ / $year$	4.5000	2.2500	3.3000	5.6000	2.2500	1.1000	1.1000
Average repair time r^0_k (h)	10.0000	9.0000	12.0000	20.0000	15.0000	8.0000	12.0000
$\lambda_{\mathrm{k\_failure,min}}$ / year	0.2000	0.0500	0.1000	0.1000	0.1500	0.0500	0.0500
$\lambda_{\mathrm{k\_fault,min}}$/year	2.2500	0.5600	1.1000	1.1200	1.6800	0.5500	0.5500
$r_{k,min}(h)$	6.0000	6.0000	4.0000	8.0000	7.0000	6.0000	6.0000
Length (km)	0.8300	2.0800	3.0300	1.7300	2.9800	2.7800	3.6300

Table-3. Costs of interruptions of radial distribution networks at load points

DLP	#DLP2	#DLP3	#DLP4	#DLP5	#DLP6	#DLP7	#DLP8
Cost of Interruptions (Rs./kW)	15.00	13.00	17.00	20.00	20.00	12.00	14.00

Table 4. Weighting factors for various voltage drops and associated CICs (customer interruption charges)

Event of category	Economic analysis weighting	CIC
Interruption	1.00	CIC_1
Sag when the voltage is at or below 50%	0.80	CIC_2
Minimum voltage sag from 50% and 70%	0.40	CIC_3
Minimum voltage sag from 70% and 90% between	0.10	CIC_4

Table 5. Average load, and total number of consumers at load locations for a radial distribution network

DLP	#DLP2	#DLP3	#DLP4	#DLP5	#DLP6	#DLP7	#DLP8
Load average Li (KW)	1000.00	0700.00	0400.00	0500.00	0300.00	0200.00	0150.00
Number of clients, Ni	200.00	150.00	100.00	150.00	100.00	250.00	050.00

Table 6. For a radial distribution network, the cost coefficients αk, βk and γ_k

DS	DS-1	DS-2	DS-3	DS-4	DS-5	DS-6	DS-7
α_k **Rs.**	240.00	300.00	180.00	120.00	240.00	285.00	300.00
β_k **Rs.**	400.00	360.00	200.00	200.00	320.00	240.00	220.00
γ_k **Rs.**	1500.00	2000.00	1250.00	900.00	1500.00	1850.00	2000.00

Table 6 presents a breakdown of cost coefficients associated with the failure rates, fault rates, and repair times of individual segments within the distribution network [35]. These coefficients are used to quantify the economic impact of failures, faults, and repair activities on the overall cost analysis. Table-7 shows a reactance component for a radial distribution network. Table-8 provides a percentage breakdown of the various fault categories observed in the radial distribution network. This table provides an understanding of the distribution and relative frequency of the various fault types, which is essential for fault analysis, mitigation strategies, and system maintenance.

Table 7. Reactance component for a radial distribution system

Component	Generator (pu)	Feeder (pu/km)
Positive sequence	0.600	0.230
Negative sequence	0.600	0.230
Zero sequence	0.000	0.276

Table 8. The percentage of various fault types in a radial distribution network

Type of faults	LG	LLG	LL	LLL
Percentage of occurrence (%)	73.00	17.00	6.00	4.00

There could be a maximum of 1000 generations. In the program described, several sets of randomly generated selection factors were used as input. These selection factors were used to determine which elephant clan should be selected or included in the solution. The selection process was based on evaluating the values of an objective function. Feasible and infeasible solution vectors were determined based on whether they met all inequality constraints. Feasible solutions are those that satisfy all specified conditions, while infeasible solutions do not satisfy one or more conditions. As stated in Section-5, Lampinen's approach using relation (37) was used to update the population or elephant position [38]. According to equation (29), the inertia weight (W) falls gradually and has a range of $\mathrm{W} \in [0.20, 0.90]$. The global and local search capabilities are balanced by using inertial weight. The optimal value of the objective function $(\mathrm{F} = 507597.5)$ was found for the impact factor $(\mathrm{IM} = 0.60)$, acceleration coefficient $(AC = 1.55)$, and probability $(p = 0.10)$. Due to the convergence of the solution of the objective function, the simulation procedure was terminated after 608 generations. For the optimal values of the parameters IMEHO, AOA and TLBO [36, 39, 40], a visualization of the objective function and the iterations can be seen in Fig. 3.

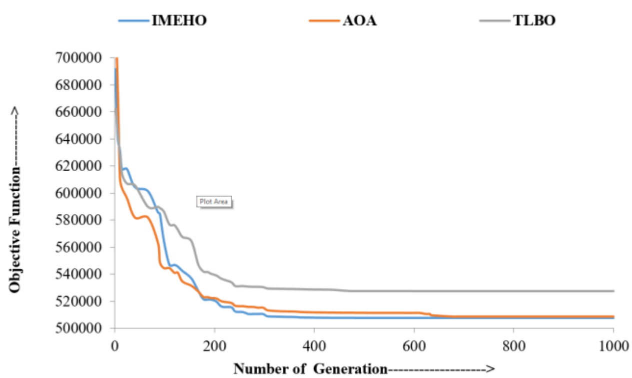

Fig. 3. Convergence of the objective function for a radial distribution system with the approaches IMEHO, AOA and TLBO as a function of the number of generations.

A comparison of the failure rates in the base case without and with optimization using the approaches IMEHO, AOA and TLBO is shown in Fig. 4. In Fig. 5, fault rates under base case conditions with and without optimization utilizing IMEHO, AOA, and TLBO techniques are shown. The repair times with the approaches IMEHO, AOA and TLBO are shown in Fig. 6 for the base case with and without optimization.

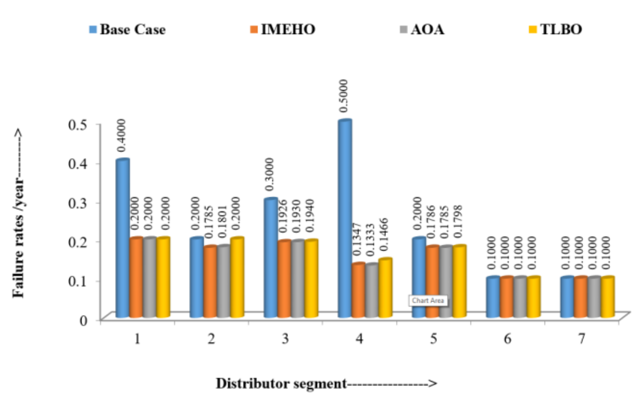

Fig. 4. Comparison of IMEHO algorithm with AOA, and TLBO algorithm-based failure rates for the radial distribution system.

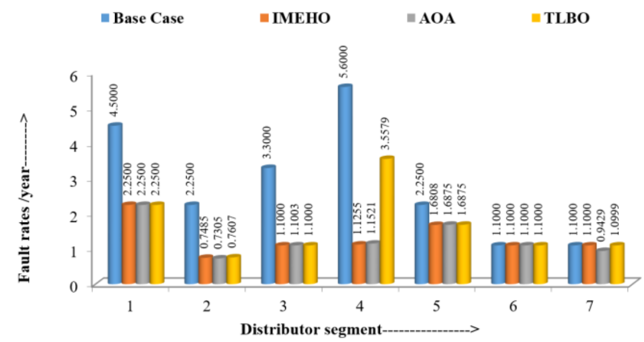

Fig. 5. Comparison of IMEHO algorithm with AOA, and TLBO algorithm-based fault rates for the radial distribution system.

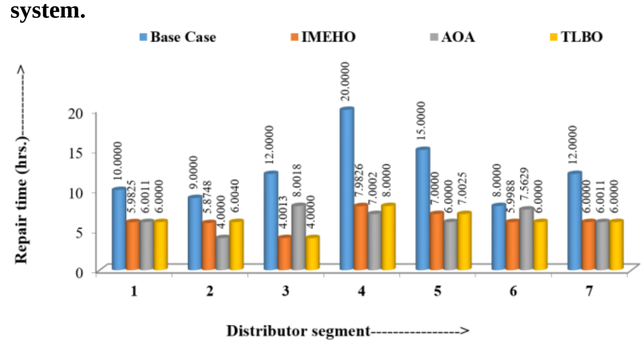

Fig. 6. Comparison of IMEHO algorithm with AOA, and TLBO algorithm-based repair time for the radial distribution system.

Fig. 7 shows a comparison of the IMEHO approach with the AOA & TLBO approach for a radial distribution system based on SARFI, SAIDI (h/customer), SAIFI (interruptions/customer), AENS (kW/customer), CAIDI (h/customer interruption), and total reliability (R). Fig. 8 shows a comparison of a radial distribution system's maintenance costs, customer interruption costs, incremental costs to be paid while generators are connected, reward/penalty costs, and the objective function using the IMEHO algorithm, the AOA algorithm, and the TLBO algorithm.

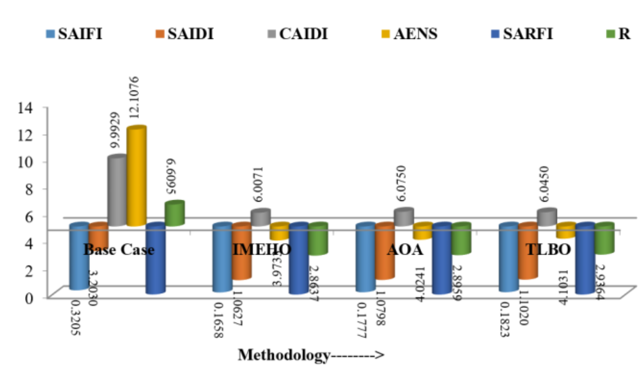

Fig. 7. Comparison of IMEHO techniques with AOA, & TLBO algorithm-based power quality indices and reliability for a radial distribution system.

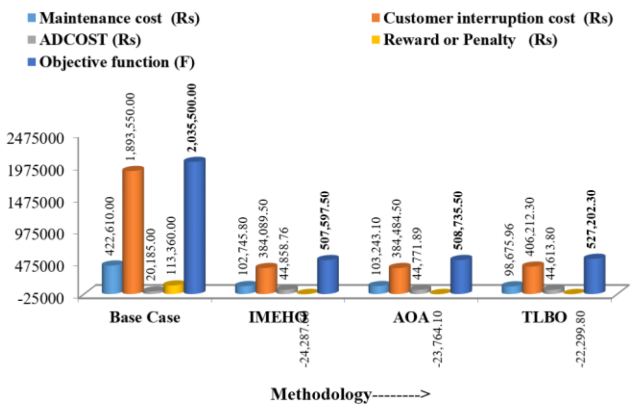

Fig. 8. Comparison of IMEHO technique with AOA, &TLBO algorithm based on customer interruption costs, maintenance costs, ADCOST, reward or penalty costs and objective function for a radial distribution network.

Table 9 compares various optimization strategies based on multiple criteria, including the objective function, overall reliability, number of iterations, and computation time required to reach convergence. The objective function represents the optimization goal or criterion being considered. Table-10, on the other hand, compares the IMEHO with the AOA and TLBO techniques. Statistical inference, referenced as [41], is employed to evaluate and contrast various optimization techniques' performance. This comparison is based on multiple statistical derivatives or parameters of the objective function used in the study. To ensure statistical robustness and reliability, 20 runs of each optimization method were performed. This allows for a comprehensive evaluation of the optimization techniques and their performance variability across multiple executions. Based on the statistical parameter values presented in Table-10, the preference or superiority of the IMEHO technique, particularly when using Lampinen's technique, is demonstrated for the created objective function. The IMEHO technique, with the specific modifications or enhancements proposed by Lampinen, outperformed the AOA and TLBO techniques in terms of the objective function and other related metrics.

Table 9. Compares the algorithms of IMEHO with the methods of AOA and TLBO based on the objective function, overall reliability, iterations and computation time

Sr. No.	Methodology	Overall Reliability	Objective Function (F)	No of Iteration	Computational Time (Second)
1	**IMEHO**	**2.863689**	**507597.5**	**608**	**765**
2	AOA	2.895902	508735.5	765	916
3	TLBO	2.936356	527202.3	894	1178

Table 10. Compares the algorithm IMEHO, with AOA and TLBO approach using statistical inference of the objective function for a radial distribution network in twenty runs.

Optimization methods	Arithmetic mean $(\bar{F})$	Median (m)	Standard deviation (σ)	Best (F_{best})	Worst (F_{worst})	Convergence frequency (f)	Level of confidence (γ)	Value chosen for the engineering application (c)	Standard error (ϵ)	Confidence interval (μ)	Length of confidence interval L
IMEHO	**508976.8**	**508481.3**	**1439.52**	**507597.5**	**512635.6**	**12**	**0.95**	**2.0452**	**657.55**	**508342.15≤ μ ≤ 509638.16**	**2698.54**
AOA	516167.3	514629.5	7017.43	508735.5	531246.5	10	0.95	2.0452	3209.20	512958.10≤ μ ≤519376.50	13126.9
TLBO	539640.0	538241.5	9625.53	527202.3	558373.6	08	0.95	2.0452	4401.95	535238.05≤ μ ≤544041.95	18005.7

7. CONCLUSIONS

A novel methodology has been developed to enhance the reliability of the distribution network and optimize an objective function based on specific parameters. The mentioned parameters, including fault rate, outage rate, and repair time, are crucial in determining the performance of the distribution network in the presence of voltage sags. The optimization process involves determining the ideal values for these indices, particularly in radial distribution systems, as various power quality indices rely on these fundamental parameters. The placement of DGs in the radial distribution system has been identified as a key factor in improving reliability indices and the power quality index for voltage.

Additionally, optimized values for customer interruption costs, maintenance costs, additional energy for DGs, and reward or penalty values have been obtained. Furthermore, the IMEHO technique is highlighted as performing better than AOA and TLBO methods based on statistical inferences such as computation period, convergence frequency, and objective function etc.

REFERENCES

[1] de Almeida, A.T.; Moreira, L.; and Delgado, J. 2003. Power quality problems and new solutions", ISR – Department of Electrical and Computer Engineering University of Coimbra, Pólo II 3030-290 Coimbra (Portugal): 1-9, DOI:10.24084/repqj01.004.

[2] Bollen, M.H.J. 2000. Understanding power quality problems: voltage sags and interruptions. Wiley-IEEE Press, Inc. *(Book*).

[3] Short, T. A. 2005. Distribution reliability and power quality. CRC Press: Inc. *(Book*).

[4] 1159-1995 – "IEEE Recommended practice for monitoring electric power quality". IEEE Press, 1995, DOI: 10.1109/IEEESTD.1995.79050.

[5] Wang, J.; Chen, S.; and Lie, T.T. 2005. System voltage sag performance estimation. IEEE Transactions on Power Delivery, 20(2): 1738-1747, DOI: 10.1109/TPWRD. 2004. 834341.

[6] Yang, Y.; and Bollen, M. 2008. Power quality and reliability in distribution networks with increased levels of distributed generation. Elforse Inc. (Project report).

[7] Mendoza, J.E.; López, M.E.; Coello, C.A.C.; and López, E.A. 2009. Microgenetic multiobjective reconfiguration algorithm considering power losses and reliability for medium voltage distribution network. IET Generation, Transmission & Distribution 3(9): 8251-840. DOI: 10.1049/iet-gtd.2009.0009.

[8] Mishra, A.; and Bhandakkar, A. 2014. Selection of optimal location and size of distributed generation in distribution system using particle swarm optimization. International Journal of Engineering Research & Technology (IJERT) 3(1): 2008-2013.

[9] Gupta, N.; Swarnkar, A.; and Niazi, K.R. 2014. Distribution network reconfiguration for power quality and reliability improvement using genetic algorithms. International Journal of Electrical Power and Energy Systems 54: 664-671. https://doi.org/10.1016/j.ijepes.2013.08.016.

[10] Shareef, H.; Ibrahim, A.A.; Salman, N.; Mohamed, A.; and Ai, W.L. 2014. Power quality and reliability enhancement in distribution systems via optimum network reconfiguration by using quantum firefly algorithm. International Journal of Electrical Power and Energy Systems 58: 160-169. https://doi.org/10.1016/j.ijepes.2014.01.013.

[11] Balasubramaniam, P.M.; and Prabha, S.U. 2015. Power quality issues, solutions and standards: A technology review. Journal of Applied Science and Engineering 18(4): 371-380. https://doi.org/10.6180/jase.2015.18.4.08.

[12] Divya, S.; Shivakumar, S.B.; and Ananthapadmanabha, T. 2019. Optimal allocation of renewable distributed generation with large penetration to mitigate power quality issues. International Journal of Electrical Engineering & Technology (IJEET) 10(3):10-15.

[13] Eltamaly, A.M.; Mohamed, Y.S.; El-Sayed, A.H.M.; Mohamed, M.A.; and Elghaffar, A.N.A. 2020. Power quality and reliability considerations of photovoltaic distributed generation. Technology and Economics of Smart Grids and Sustainable Energy 5(25): 1-21. https://doi.org/10.1007/s40866-020-00096-2.

[14] Mallappa, P.K.B.; Garcia, H.M.; and Quesada, G.V. 2021. Power quality enhancement in a grid-integrated photovoltaic system using hybrid techniques. Applied Sciences 11(21): 10120. https://doi.org/10.3390/app112110120.

[15] Liu, J.; Tang, Q.; Qiu, W.; Ma, J.; Qin, Y.; and Sun, B. 2021. Automatic power quality disturbance diagnosis based on residual denoising convolutional auto-encoder. Applied Sciences 11(16): 7637. https://doi.org/10.3390/app11167637.

[16] Kutija, M.; and Pravica, L. 2021. Effect of harmonics on ferroresonance in low voltage power factor correction system—a case study., Applied Sciences 11(10): 4322. https://doi.org/10.3390/app11104322.

[17] Chang, G.W.; Lin, Y.L.; Liu, Y.J.; Sun, G.H.; and Yu, J.T. 2021. A hybrid approach for time-varying harmonic and interharmonic detection using synchrosqueezing wavelet transform. Applied Sciences 11(2):752. https://doi.org/10.3390/app11020752.

[18] Saket, R.K.; Bansal, R.C.; and Anand, K.S. 2007. Reliability evaluation of micro hydro-photo-voltaic hybrid power generation using municipal waste water. GMSARN International Journal 1: 13-20.

[19] Ngamprasert, P.; and Rugthaicharoencheep, N. 2024. Optimization technique for voltage sag with integration of photovoltaic energy distributed generation", GMSARN International Journal 18: 414-420.

[20] Thang, L.M.; Hieu, D.T.; Le-Duc, T.; and Khanh, B.Q. 2023. GA based multi-objective optimizing size and location of one d-statcom for global voltage sag mitigation in distribution system. GMSARN International Journal 17: 1-7.

[21] Mohtasham, M.B.; and Jalilian, A. 2022. Classification of multi-stage voltage sags and calculation of phase angle jump based on clarke components ellipse. Electric Power Systems Research 205: 107725. https://doi.org/10.1016/j.epsr.2021.107725.

[22] Turiza, S.; Ramos, G.; and Celeita, D. 2022. Voltage sags characterization using fault analysis and deep convolutional neural networks. IEEE Transactions on Industry Applications 58(3): 3333-3341. DOI: 10.1109/TIA.2022.3162569.

[23] Shakeri, S.; Khajouei, J.; Esmaeilie, S.; Yoon, K.H.; Chai, H.S.; and Koochi, M.H.R. 2022. Improving the area of harmonic pollution and vulnerability to voltage sag for compatible and reliable operation of sensitive harmonic loads. IET Generation, Transmission & Distribution 16(19): 3951-3965. https://doi.org/10.1049/gtd2.12579.

[24] Wang, Y.; Yang, H.; Yang, Y.; and Xiaog, X. 2021. Practical tables for tolerance assessment of adjustable speed drives under voltage sag. IET Generation, Transmission & Distribution 15(25): 2250-2261. https://doi.org/10.1049/gtd2.12175.

[25] Shin, J.W.; Kim, J.C.; Lee, H.; Yoon, K.H.; Chai, H.S.; and Kim, J.S. 2021. Impact of SFCL according to voltage sags based reliability. IET Transactions Applied Superconductivity 31(5): 5600905. DOI: 10.1109/TASC.

2021.3064525.

[26] Chen, Y.Z.; Xiaoi, X.X.; Wang, Y.; Zhang, H.Y.; Li, H.X.; and Wang, Q. 2020. Severity index-based voltage sag insurance for high-tech enterprises. IET Generation, Transmission & Distribution 14(24): 5992-5999. https://doi.org/10.1049/iet-gtd.2020.0518.

[27] Nguyen, M.V.; and Bach, K.Q. 2019. A novel comparison on ‘‘central improvement” of voltage dips in 16 bus distribution system by d-statcom and dvr. GMSARN International Journal 13: 74-80.

[28] EPRI TP-113781. 1999. Reliability benchmarking application guide for utility/customer PQ indices. Electric Power Research Institute, Palo Alto, CA.

[29] Sabin, D.D.; Grebe, T.E.; and Sundaram, A. 1999. RMS voltage variation statistical analysis for a survey of distribution system power quality performance. EEE Power Engineering Society. Winter Meeting (Cat. No.99CH36233). DOI: 10.1109/PESW.1999.747390.

[30] Brooks, D.L.; Dugan, R.C.; Waclawiak, M.; and Sundaram, A. 1998. Indices for assessing utility distribution system RMS variation performance. IEEE Transactions on Power Delivery 13(1): 254-259. DOI: 10.1109/61.660886.

[31] Billinton, R.; and Allan, R.N. 2013. Reliability evaluation of power systems. Springer Science & Business Media, Inc. (Book).

[32] 493-2007 – IEEE Recommended practice for the design of reliable industrial and commercial power systems, 2007, DOI: 10.1109/IEEESTD.2007.380668.

[33] Kela, K.B.; and Arya, L.D. 2014. Reliability optimization of radial distribution systems employing differential evolution and bare bones particle swarm optimization. Journal of The Institution of Engineers (India), Series B 95(3): 231-239. https://doi.org/10.1007/s40031-014-0094-z.

[34] Ebling, C.E. 2019. An introduction to reliability and maintainability engineering. Tata Waveland Press, Inc. (Book).

[35] Arya, R.; Choube, S.C.; and Arya, L.D. 2012. Reliability evaluation and enhancement of distribution systems in the presence of distributed generation based on standby mode. International Journal of Electrical Power and Energy Systems 43(1): 607-616. https://doi.org/10.1016/j.ijepes.2012.05.045.

[36] Li, W.; Wang, Gai-Ge; and Alavi, A.H. 2020. Learning-based elephant herding optimization algorithm for solving numerical optimiation problems. Knowledge-Based Systems 195: 105675. https://doi.org/10.1016/j.knosys.2020.105675.

[37] Kela, K.B. 2018. Strategies for Reliability Enhancement of Electrical Distribution Systems. PhD Thesis.

[38] Singh, P.; Arya, R.; Titare, L.S.; Purey, P.; and Arya, L.D. 2023. Value aided optimal load shedding accounting voltage stability consideration employing crow search algorithm with modification based on Lampinen’s criterion. Applied Soft Computing 143: 110391. https://doi.org/10.1016/j.asoc.2023.110391.

[39] Agushaka, J.O.; and Ezugwu, A.E. 2021. Advanced arithmetic optimization algorithm for solving mechanical engineering design problems. PLoS One 16: 1-29. https://doi.org/10.1371/journal.pone.0255703.

[40] Singh, P.; Titare, L.S.; and Arya, L.D. 2014. Mitigation of transmission losses with voltage stability consideration using TLBO. 2014 Power and Energy Systems: Towards Sustainable Energy 1-5. DOI: 10.1109/PESTSE.2014.6805260.

[41] Arya, L.D.; Singh, P.; and Titare, L.S. 2012. Optimum load shedding based on sensitivity to enhance static voltage stability using DE. Swarm and Evolutionary Computation 6: 25-38. https://doi.org/10.1016/j.swevo.2012.06.002.

ABBREVIATIONS

SAIFI	System average interruption frequency index.
SAIDI	System average interruption duration index.
SARFI	System average rms variation frequency index.
CAIDI	Customer average interruption duration index.
AENS	Average energy not supplied.
ADCOST	Additional cost.
DGs	Distributed generators.
DS	Distributed system.
F	Objective function.
L_i	i^{th} load point's average load connection.
$\lambda_{sys,i}$	Rate of system failure at the i^{th} load point.
N_i	Number of clients at the load point i^{th}.
$U_{sys,i}$	Duration of the annual outage at the i^{th} load point.
λ_k	k^{th} distributor segment failure rate.
r_k	Average distributor segment repair time.
s_i	Set of distributor segments.
k_{max}	Maximum number of generations.
k	Current number of generation .
p	Probability between 0 and 1.
IM	Impact factor between 0 and 1.
AC	Acceleration coefficient.
DLP	Distributor load points.
CIC	Customer interruption cost.