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ORIGINAL RESEARCH

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Reliability and efficiency enhancement of a radial distribution system through value-based auto-recloser placement and network remodelling

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Abstract

The electric distribution system (EDS) is prone to faults leading to power interruptions. The present energy market demands that electricity utilities invest more in different measures to improve the performance of the EDS. The approach proposed here details a composite dual-phased methodology to improve the reliability and efficiency of the power delivered by the EDS. In the first phase, the optimal allocation of auto-reclosers (AR) is undertaken by employing a newly formulated algorithm. The determination of the total number and location for AR placement is based on the economic analysis of two factors, i.e., AR investment-maintenance cost and total benefit earned in terms of reliability improvement due to AR placement. The analysis also takes into account the impact of power outages on different load types, the load growth rate, and the inflation rate. Further, to enhance the efficiency of the AR-incorporated EDS, the technique of Radial Distribution System Remodelling is employed in the second phase. This method searches for a radial configuration that delivers power at minimum line losses. These phases comprising complex combinatorial operations are aided by a fresh hybrid of the Sine Cosine Algorithm, Krill Herd Algorithm, and a genetic operator of Differential Evolution. The results obtained from its application on the IEEE 69-bus distribution test system prove the credibility of the suggested formulation.

Keywords: Auto-recloser placement, Load flow, Metaheuristic optimization algorithm, Power loss minimization, Reconfiguration, Reliability assessment

1 Introduction

The push for rapid modernisation of the power sector has amplified the need for reliability and efficiency to be the critical benchmarks of a healthy Electric Distribution System (EDS). However, nearly 80% of the total power outages occur because of failures in the distribution of power to the end customers. This adversely affects the reliability and efficiency of the EDS [1]. Power from the EDS is supplied to the customers through Electric Utility Companies (EUC). Depending on the quality and quantity of power delivered to the customers during a time period, the EUC may generate profits or incur losses because of penalties [1, 2]. Therefore, maintaining the efficiency and reliability of the power provided by an EDS is of utmost importance to the EUC. Several approaches have been adopted by the EUC to deal with these concerns, such as network remodelling, placement of protective devices, etc.

Radial Distribution System Remodelling (DSRM) is a well-recognized tool that is often used by EUC. In DSRM, the sequential power flow arrangement through buses in an EDS is altered by varying the closed/open states of its sectionalizing and tie switches in such a way that all the buses are energized without forming any loops in

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the network [3]. By applying DSRM in an EDS several objectives can be fulfilled, such as reduction of system losses [3, 4], thereby improving system loading capability, enhancing voltage level at each bus [5], improving system reliability [6], delaying system expansion by using the available infrastructural facilities in the most efficient and optimum arrangement, and mitigating Total Harmonic Distortion [7].

DSRM is a non-linear non-differentiable optimization problem comprising of extremely complicated combinative operations. To solve DSRM, several metaheuristics optimization algorithms have been explored and presented in the literature, e.g., Ant Colony System [8], Adaptive Particle Swarm Optimization [9], Quantam Firefly Algorithm [10], Fireworks Algorithm [11], Enhanced Genetic Algorithm [12], Genetic Algorithm [13], etc. Application of metaheuristic techniques on power system problems is easy and convenient compared to classical numerical methods, because the conversion of problem equations according to the optimization simulation model is not required. Heuristic methods such as those formulated in [2, 14] have also been employed to analyse DSRM.

Protective switchgears such as auto-reclosers (AR), automatic sectionalizers, fuses, etc. are installed in an EDS to reduce the number of customers affected by power interruptions. These devices are capable of promptly detecting and isolating the fault-affected sections after which power flow is re-established to the healthy network [15, 16]. It is realized that optimally placing these protective devices in EDS can improve the reliability of the networks considerably. In [15–17], methodologies capable of recognizing the type, location, and number of protective devices such as AR, fuses and switches, and the coordination among them are proposed. The task of optimal allocation of automatic switches in pre-routed radially distributed networks is exhibited in [18–20], while a solution approach with simultaneous placement of wind turbine/switches and system remodelling using a Modified ABC optimization algorithm is given in [21]. A value-based planning analysis for finding the optimal number and location of automatic sectionalizers is introduced in [1], whereas in [22], a methodology is implemented for reliability improvement by optimal placement of AR. In addition, factors such as equipment damage reduction and risk of tripping due to heavy loading are also considered. An approach to find the optimal locations of AR using the cross-entropy method and the Monte Carlo method is presented in [23], where the objectives considered are reliability enhancement, minimization of the costs, and the occurrence of voltage sags. Reference [24] puts forward a combined process of an analytical method and PSO algorithm to determine the number and location of AR and switches, such that the reliability of the system can be enhanced. A complete placement procedure of circuit breakers and switches to improve reliability is provided in [25], while in [26], the AR placement problem considering the effect of manoeuvre points is proposed. Reference [27] presents a dual method where both reconfigurations of the distribution system and auto-recloser placement are considered such that the efficiency, as well as reliability of the system, are improved.

1.1 Contribution of the paper

Although a lot of research has been done on the placement problem of automatic switches in an EDS, only limited studies have been done on the optimal placement of AR.

The scope of solving the optimal allocation of AR in an EDS as a remedy for improving system reliability acts as a motivation to take up this task. Furthermore, it is observed that there is a void in the literature where the efficiency quotient of the AR-installed EDS is investigated and provisions for its enhancement are undertaken. So a new composite methodology is formulated in this paper to improve the reliability and efficiency of an EDS.

The proposed methodology has two phases:

In Phase I, the optimal number and location for ARs are detected with the aid of a newly formulated AR allocating algorithm and a cost–benefit analysis. The cost–benefit analysis considers the investment cost, maintenance cost, load growth rate, inflation rate, cost of unsupplied energy to various types of customers (viz. residential, commercial, industrial customers), and the profit earned by the EUC that is due to AR installation in the system. Such analysis also considers the Cumulative Present Value of the maintenance cost and the profit earned by the EUC for the complete working lifespan of the installed ARs. By doing so these finances are reflected in the first year of the AR allocation by the EUC. Thus, based on the total prospective expenditure and benefits, the optimal number and location for AR placement can be identified.

In Phase II, the AR-incorporated EDS (as obtained in phase I) is remodelled in such a fashion that the overall system line losses are reduced, while keeping all the system nodes energized in a radial configuration and without disturbing the coordination among the installed ARs.

To tackle the combinatorial processes presented in both phases, a novel hybrid meta-heuristic optimization technique named Mutated Krill Herd Sine Cosine Algorithm (μ-KHSC) is used. The proposed framework is applied to the IEEE 69-bus radial distribution test system to validate its potential.

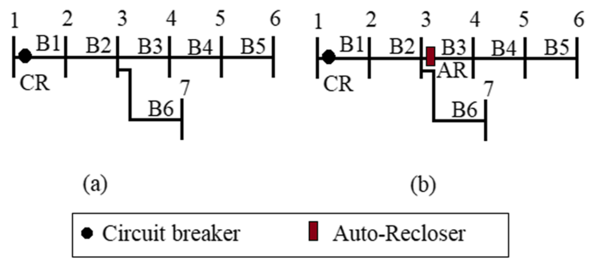

Fig. 1 Single line diagram of a seven-node system

Table 1 Power interruptions caused by a fault at B4 based on Fig. 1a

	Load nodes	Interruption duration per year due to the faults at B4
Load nodes lying upstream to the faulty branch, B4	2, 3, 4, 7	$\lambda_{B4}.\delta t_{B4}$
Load nodes lying downstream to the faulty branch, B4	5, 6	$\lambda_{B4}.\delta p_{B4}$

The remainder of the paper is organized as follows: The major aspects of reliability evaluation are discussed in Sect. 2, and Sect. 3 describes the suggested approach in detail. Section 4 focuses on the development of the new hybrid algorithm, while numerical findings are reported in Sect. 5. Finally, Sect. 6 concludes the paper by showcasing its contributions.

2 Reliability assessment of a radial distribution system

"The ability of a component or system to perform required functions under stated conditions for a stated period of time", is termed reliability [2]. There are three fundamental indices employed to analyse the reliability of a system, i.e., frequency of failure in a year (λ), average downtime per failure (δ) and outage duration per annum (γ) [2]. The average downtime per failure δ_j, due to faults in the *j*th branch is of two types:

- δp_j is the mean time needed to isolate and repair the faulty branch *j*.
- δt_j is the mean time needed to disconnect the faulty branch *j* from the healthy network by turning off its sectionalising switches.

The interruptions caused by failures result in decreasing the reliability of a system. Interruptions can broadly be classified as momentary and sustained. Momentary interruptions are those power outages which last for less than five minutes, whereas outages which exist for more than five minutes are referred to as sustained interruptions [28].

Placement of automation-enabled protective devices, such as auto-reclosers, helps mitigate the total number of loads affected by the failures. Such impact of AR placement is described below with the help of a dummy network shown in Fig. 1.

Referring to Fig. 1a, when a fault occurs at B4, on sensing the fault, the circuit breaker CR at the feeder node trips the circuit causing power interruption in the whole network. The EUC fault repair team then detects the failure point and opens the sectionalizing switch of that faulty branch for further repair actions. Eventually, CR is closed and power is restored to the remaining healthy network.

Thus, the power interruption duration for each of the loads connected to nodes 2, 3, 4, and 7 is equal to the detection and isolation of the faulty branch B4 by switching action. However, the loads at nodes 5 and 6 lying downstream of the failure point suffer an interruption equal to the duration required for the fault to be repaired and reconnected to the system.

The durations of power interruptions caused at each load node due to fault at B4 are listed in Table 1.

In Table 1, λ_{B4} is the frequency of occurrence of failure events at branch segment B4, δt_{B4} is the average switching time of the sectionalizing switch at B4, and δp_{B4} is the average repair time needed for any repair action at B4.

In Fig. 1b, an AR is assumed to be allocated at the branch segment B3. The effect of a similar scenario of fault occurrence at B4 is analyzed. When a sustained fault occurs at B4, on sensing the fault, the AR automatically trips the circuit before CR detects the fault. By doing so, the loads connected at nodes 2, 3, and 7 are protected from the power outage that had occurred in the previous case. The load at node 4 faces an interruption for the switching period required to disconnect the faulty branch B4, whereas the loads at node 5 and 6 lying downstream of the faulty branch are disconnected from the power supply until the fault is completely repaired and B4 is connected back to the live network.

The nodal power interruptions due to a fault at B4 in the presence of AR are summarized in Table 2.

The significance of the presence of AR in reducing power interruption duration to a great extent is manifested by the analysis as displayed in Tables 1 and 2.

Although AR inclusion in the system improves reliability by mitigating power outages, this comes at the cost of a large expenditure from the EUC side in the form of the AR investment and maintenance costs. So practically it is infeasible to install ARs in large numbers for the

Table 2 Power interruptions caused by faults at B4 in presence of AR placed at B3 based on Fig. 1b

	Load nodes	Interruption duration per year due to the faults at B4
Load nodes lying upstream to AR as well as the faulty branch, B4	2, 3, 7	No interruption
Load node lying downstream to AR but upstream to the faulty branch, B4	4	$\lambda_{B4}.\delta t_{B4}$
Load nodes lying downstream to the faulty branch, B4 as well as AR located at B3	5, 6	$\lambda_{B4}.\delta p_{B4}$

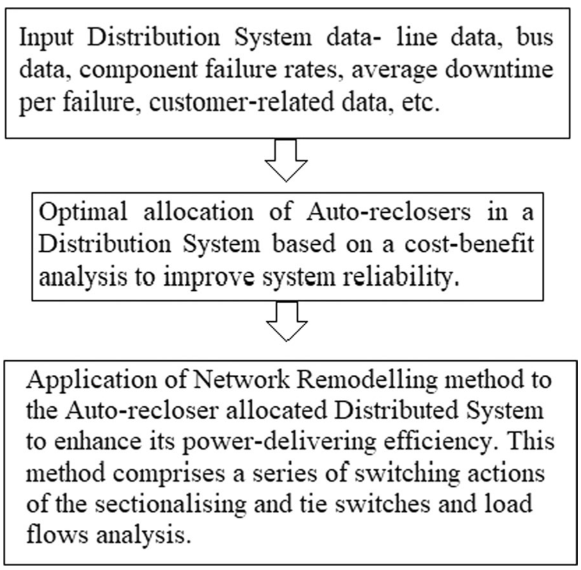

Fig. 2 Proposed schema

EUC. Thus, EUC often seeks a balanced solution where both conditions, i.e., the benefit provided to the customers by cutting down the power interruptions and AR investment-maintenance costs incurred by the EUC, are satisfied.

Thus the optimal number and location of AR placement in the system play a vital role for both EUC and the customers.

3 Problem composition

In the proposed schema as illustrated in Fig. 2, a merger of two kinds of power system problems of planning and operation is addressed. The task of optimum allocation of AR to improve system reliability is a planning problem, while DSRM is an operational problem and is implemented to minimize system power losses.

3.1 Phase I: Optimum placement of auto-reclosers

The presence of AR in a radial EDS can reduce the power interruptions caused by failures in the network. Accordingly, their optimum placement plays a significant role in enhancing system reliability.

In this study, the number and location for AR installation depend on an economic analysis of the prospective expenditure and the profit that will be earned because of AR placement in the system. This analysis takes into account the load growth, inflation and interest rates, and also the effect of the unsupplied energy on different types of loads such as industrial, commercial and domestic loads.

The total expenditure (*TE*) on AR installation by an EUC is divided into investment cost (*TIC*) and maintenance cost (*TMC*), as:

$$TE = TIC + TMC \tag{1}$$

The expressions for the total investment cost and total maintenance cost are given respectively as:

$$TIC = AR^{NM} * AR^{IC} \tag{2}$$

$$TMC = AR^{NM} * AR^{MC} \tag{3}$$

where AR^{NM} is the total number of AR, AR^{IC} and AR^{MC} are the investment cost and maintenance cost of a single AR, respectively.

The profit earned by the EUC due to the improvement in reliability in one year can be stated as:

$$PSE = CUE^{NOAR} - CUE^{AR} \tag{4}$$

where PSE is the profit due to the supplied energy, whereas CUE^{NOAR} and CUE^{AR} are the costs of the unsupplied energy in the absence and presence of AR, respectively. Equation (4) represents the fact that the incorporation of AR in an EDS will increase the amount of supplied energy to the customers, resulting in a rise in revenue earned by the EUC.

The unsupplied energy *EENS* and the cost of unsupplied energy *CUE* [15] are evaluated respectively as:

$$EENS = \sum_{a=1}^{nbus} Ld_a \cdot \gamma_a = \sum_{a=1}^{nbus} Ld_a \cdot \left(\sum_{b=1}^{bn} \lambda_b \delta_b \right) \tag{5}$$

$$CUE = \sum_{e=1}^{cont} \sum_{f=1}^{alp_e} Ld_f \cdot \lambda_e \cdot C_{ef}(\delta_e) \tag{6}$$

where *nbus* and *bn* are the total numbers of system load nodes and branch segments, respectively. *cont* is the maximum number of contingencies, alp_e is the number of affected load points due to contingency e, Ld_f is the total load connected at load point f, λ_e is the frequency of occurrence of the eth contingency, and $C_{ef}(\delta_e)$ is the customer interruption cost obtained using sector customer damage functions (SCDFs) [15] as displayed in Table 3. SCDF has non-linear representations which depend on the type of load affected at the fth load point due to an interruption of duration δ_e caused due to contingency e.

To consider the overall expenditure and profits that will be earned by the EUC for the entire life span of the installed ARs, an assessment based on Cumulative Present Value (CPV) is performed [1]. CPV converts all the future expected expenses and benefits into the first year of their operation, which helps in realizing the actual impact of the placement of any devices.

The investment of an AR is a single time expenditure, whereas the maintenance and the profit earned take place every year over the working lifespan of the installed AR. So CPV is applied only on the yearly maintenance cost as in (3) and the yearly profit earned as in (4). CPV of TMC and PSE are shown as:

$$TMC^{CPV} = TMC\left(\frac{1-Z^{\eta}}{1-Z}\right) \tag{7}$$

$$PSE^{CPV} = PSE\left(\frac{1-Z^{\eta}}{1-Z}\right) \tag{8}$$

$$Z = \frac{(1+IFR)(1+LGR)}{(1+ITR)} \tag{9}$$

In the above equations, IFR, LGR and ITR are the inflation, load growth and interest rates, respectively. η is the total working life span of an AR.

The objective of this phase is to maximize the total expected profit (TEP) from installing these protective devices in EDS and can be formulated as:

$$TEP = PSE^{CPV} - TMC^{CPV} - TIC. \tag{10}$$

Table 3 Customer interruption cost

Customer type	Interruption duration (h) and cost (USD/kW)	
	1 h	4 h
Industrial	9.085	25.16
Commercial	8.552	31.317
Residential	0.482	4.914

3.2 Phase II: Radial distribution system re-modelling

Radial DSRM is an optimization technique that is often applied by an EUC to maintain a network with healthy characteristics. Application of DSRM offers possibilities to find network configurations where the line current magnitudes are lower compared to the base configuration. As the current magnitude reduces, the line resistive losses (I^2R losses) also reduce [4], thereby improving the efficiency of the overall EDS.

In the DSRM technique used in this study, a linkage matrix lkg is formed using the line data and the open/close status of the sectionalizing and tie switches of the radial EDS. The size of the linkage matrix is $bn \times nbus$, and the matrix can be populated as:

$$lkg_{pq} = \begin{cases} -1, & \text{when } q \text{ is sending end node in } p\text{th branch} \\ 1, & \text{when } q \text{ is receiving end node in } p\text{th branch} \end{cases} \tag{11}$$

In (11), the terms -1 and 1 are used to represent the respective sending and receiving end nodes in a particular branch. As these values are for representation purposes only, they can be replaced during simulation by any other values for convenience.

According to the linkage matrix, if a column has multiple cells with value '1', it corresponds to a loop in the system. Such a configuration is neglected considering it to be a meshed one. Thus, the linkage matrix identifies a radial configuration of the network and ensures the correct direction of current flow throughout all the remodelling phases.

The DSRM method deploys a Kirchhoff's formulation based on the Sweep Algorithm [29] to analyze the network parameters. This load flow method, also known as the Backward/Forward sweep method, is based on the direct application of Kirchhoff's voltage and current laws (KVL and KCL). The equations involved in the load flow are:

$$NC_l = \left(\frac{ALD_l + jRLD_l}{NV_l}\right)^{*}, \quad l = 1, 2, \ldots, nbus \tag{12}$$

where NC_l is the nodal current flowing through the lth node, ALD_l is the active load of the lth node, RLD_l is the reactive load of the lth node, and NV_l is the nodal voltage across the lth node.

$$LC_k = LC_{k+1} + NC_{k+1}, k = 1, 2, \ldots, bn \tag{13}$$

where LC_k is the line current flowing through the kth branch

$$NV_{m+1} = NV_m - \left\{LC_m \times (LRs_m + jLRc_m)\right\}, \quad m = 1, 2, \ldots, bn; \tag{14}$$

where LRs_m and LRc_m are the line resistance and reactance of the mth branch, respectively.

Equations (12) and (13) represent the backward stage and Eq. (14) represents the forward stage. This set of equations is repeated until the convergence criteria are reached.

After the load flow problem has converged, the following two equations are used to obtain the total line resistive loss of the system:

$$RL_n = LC_n^2 \cdot LRs_n, \quad n = 1, 2, \ldots, bn \tag{15}$$

$$RL_{total} = \sum_{n=1}^{bn} RL_n \tag{16}$$

where RL_n is the line resistive loss of a branch segment and RL_{total} is the total line resistive loss of the overall system.

3.3 Problem objective

The objective functions to be optimized using the proposed framework are:

$$\text{Maximize} \{f_1(\alpha) = TEP\} \tag{17}$$

$$\text{Minimize}\{f_2(\beta) = RL_{total}\} \tag{18}$$

where α and β are two single row matrices. α represents the set of AR^{NM} number of branches where auto-reclosers are to be installed, while β denotes the open/close statuses of all the bn number of the sectionalizing switches and tn number of the tie switches present in the EDS. In the matrix β, the open status of the switches is shown by zero and closed is shown by one.

To generate α, a new algorithm is formulated as listed in Table 4, which also shows an example that employs the new algorithm to generate a set of branches for AR allocation based on the EDS depicted in Fig. 1a.

In Table 4, tp is the total number of power flow paths in a radial EDS configuration, pb is the possible set of branch segments in every power flow path suitable for AR placement. These are carefully selected by studying the given EDS configuration. pb is a matrix with the number of rows being tp.

3.4 Problem constraints

1. Radiality constraint: The EDS should be radial in nature and have no loops.
2. Power continuity constraint: All load nodes in the EDS should be connected to the feeder for power supply.

Table 4 Pseudocode for AR allocation and an example of its application based on Fig. 1a. The bold words are highlight the functionality which is to be taken in each step of the algorithm

Algorithm for AR location determination	Example
Enter values of tp, pb by examining the configuration of the EDS.	$tp = 2$
Initialize α as a zero row matrix of size tp	$pb = \begin{bmatrix} B2 & B3 & B4 & B5 \\ B2 & B6 & 0 & 0 \end{bmatrix}$
$sb = 0$	$\alpha = [0 \quad 0]$
$iter = 1$	
while $iter <= tp$ % Condition no. 1	When $iter = 1$, let $sb = B3$.
Randomly select a branch from row $iter$ of matrix pb and store it in sb	2nd condition is True, so $\alpha = [B3 \quad 0]$.
if $iter == 1$ % Condition no. 2	$iter = iter + 1 = 2$
$\alpha(1, iter) = sb$	
$iter = iter + 1$	When $iter = 2$, 1st condition is true.
else	Let $sb = B6$.
if $[\{\alpha(1, 1{:}iter-1) \cap sb\} = null]$	2nd condition is False.
%Condition no. 3	3rd condition is True, so
$\alpha(1, iter) = sb$	$\alpha = [B3 \quad B6]$
$iter = iter + 1$	
else	$iter = iter + 1 = 3$
$sb = 0$	
$iter = iter$	When $iter = 3$, 1st condition is false.
end % Condition no. 3	
end % Condition no. 2	The algorithm ends here.
end % Condition no. 1	
	So $\alpha = [B3 \quad B6]$

3. Nodal voltage boundary constraint [35]:

$$NV_{j,\min} \le |NV_j| \le NV_{j,\max}, \quad j = 1, 2, \ldots, nbus \tag{19}$$

4. Line current boundary constraint [35]:

$$LC_i \le LC_{i,\max}, \quad i = 1, 2, \ldots, bn \tag{20}$$

5. Maximum allowable power flow limit constraint [35]:

$$S_{ij} \le S_{ij}^{\max}; \quad i \ne j;\ i, \quad j = 1, 2, \ldots, nbus \tag{21}$$

6. Protection devices coordination constraint: To prevent miscoordination of the allocated protective devices, alignment of multiple ARs in the same power flow path is prevented.

3.5 Problem assumptions

1. Fault analysis is done only for sustained interruptions [30].
2. All switches, circuit breakers, ARs are considered to be perfectly reliable.

3. Only one fault occurs at a time and before its incidence, any earlier fault has been repaired [21].
4. All protective devices are in proper coordination [21].
5. Only peak load is considered in this study.
6. The failure rates, line currents and system loads are considered to be constant [21].
7. A circuit breaker along with an overcurrent relay is placed at the substation.

4 Optimization algorithms used

4.1 Krill Herd algorithm

The Krill Herd Algorithm (KHA) [31] is a well-established optimization technique that mimics the behavior of an aquatic species known as Krill, which live in herds. The position of each Krill individual (Z) represents a possible solution when the algorithm is applied to solve a problem. The closer the position of the Krill to its food, the better is the fitness of the solution (Fit). The algorithm is influenced by three types of movements each Krill individual performs, i.e., (1) the tendency to be nearer to the herd ($m1$); (2) motion to search food ($m2$); and (3) arbitrary movement ($m3$).

The formulation of the algorithm is presented below.

4.1.1 The tendency to be nearer to the herd of Krill

$$
\begin{aligned}
& m1_i^{iter} = m1^{\max}(M1 + M2) + M3, \quad i = 1, 2, \ldots, tki \\
& M1 = \left(\sum_{j=1}^{ngb} Fit_{ij} \cdot Z_{ij} \right) \\
& M2 = (cf_{best} \cdot Fit_{ibest} \cdot Z_{ibest}) \\
& M3 = wi \cdot m1_i^{iter-1}
\end{aligned} \tag{22}
$$

$$
Fit_{ij} = \frac{Fit_i - Fit_j}{Fit_{worst} - Fit_{best}}, \quad j = 1, 2, \ldots, ngb \tag{23}
$$

$$
Z_{ij} = \frac{Z_i - Z_j}{\left\| Z_i - Z_j \right\| + e} \tag{24}
$$

$$
cf_{best} = 2\left(rand + \frac{iter}{iter_{\max}} \right) \tag{25}
$$

$$
snd = \frac{1}{5tk} \left(\sum_{j=1}^{tki} \left\| Z_i - Z_j \right\| \right) \tag{26}
$$

where $m1^{\max}$ is the highest induced speed, cf_{best} guides the $i$thKrill towards the global solution, and wi is the inertia of the induced movement due to the presence of the other Krill which lie between 0 and 1. e is a small positive number, tki is the total number of Krill individuals, ngb is the number of neighbors the ith krill has and is determined using sensing distance snd given in (26). $iter$ and $iter_{\max}$ are the present and the maximum number of iterations, respectively.

4.1.2 The motion to search food

$$
\begin{aligned}
& m2_i^{iter} = fs(F1 + F2) + F3 \\
& F1 = \left(cfd \cdot Fit_{i,fd} \cdot Z_{i,fd} \right) \\
& F2 = \left(Fit_{i,ibest} \cdot Z_{i,ibest} \right) \\
& F3 = wfd \cdot m2_i^{itr-1}
\end{aligned} \tag{27}
$$

$$
cfd = 2\left(1 - \frac{iter}{iter_{\max}} \right) \tag{28}
$$

$$
Z_{fd}^{iter} = \frac{\sum_{i=1}^{tki} Z_i^{iter} \cdot \frac{1}{Fit_i^{iter}}}{\sum_{i=1}^{tki} \frac{1}{Fit_i^{iter}}} \tag{29}
$$

where fs is the foraging speed, cfd is the food coefficient which tends to decrease gradually, Z_{fd}^{iter} is the food position at the $iter$th iteration which is updated with the movement of the ith Krill.

4.1.3 Arbitrary movement

$$
m3_i^{iter} = m3_{\max} \cdot r \cdot \left(1 - \frac{iter}{iter_{\max}} \right) \tag{30}
$$

Equation (30) is designed to ensure a gradual decrease in the random movement of each Krill as the number of iterations increases. $m3_{\max}$ is the highest speed of diffusion whereas r is a random vector whose value lies between −1 and 1.

The following equations are used to update the location of the ith Krill after each iteration:

$$
\frac{dZ_i}{dt} = m1_i + m2_i + m3_i; \quad i = 1, 2, \ldots, tki \tag{31}
$$

where tki is the total number of Krill.

$$
Z_i^{iter} = Z_i^{iter-1} + \frac{dZ_i}{dt} \left\{ cns \sum_{k=1}^{tv} up_k - lw_k) \right\} \tag{32}
$$

where cns is a constant between 0 and 2, tv is the total number of variables involved, up_k and lw_k are the upper and lower bounds of the$k$th variable, respectively.

4.2 Sine cosine algorithm

The Sine Cosine Algorithm (SCA) [32] is a metaheuristic optimization algorithm that brings forward an amalgamation of a few trigonometric functions such as sine and cosine functions and several other random variables to push a problem towards its global solution.

The randomly generated solutions PS are updated using the following equation:

$$Z_i^{iter} = \begin{cases} Z_i^{iter-1} + \alpha \cdot \sin(\beta) \cdot \left|\delta \cdot Z_{best}^{iter-1} - Z_i^{iter-1}\right|, & \sigma < 0.5 \\ Z_i^{iter-1} + \alpha \cdot \cos(\beta) \cdot \left|\delta \cdot Z_{best}^{iter-1} - Z_i^{iter-1}\right|, & \sigma \geq 0.5 \end{cases} \quad (33)$$

Here $\alpha, \beta, \delta, \sigma$ are random numbers, β lies in $[-2, 2]$ whereas α, δ, σ lie in the range $[0, 1][0, 1]$. Z_{best}^{iter-1} is the best candidate solution obtained in the $(iter - 1)$th iteration.

4.3 The mutation operator of differential evolution

Out of the multiple mutation strategies of the Differential Algorithm presented in [33], "DE/ran-to-best/1", is considered here. This strategy, unlike the others, enhances both global and local searches. It introduces a targeted approach towards the solution with the highest fitness as well as randomness from randomly selected available solutions. The strategy is provided below:

$$\begin{aligned} Z_{i,\mu}^{iter} =& Z_i^{iter} + cfr \cdot \left(Z_{best}^{iter-1} - Z_i^{iter}\right) + cfr \cdot \left(Z_{i,rd1}^{iter} - Z_{i,rd2}^{iter}\right); \\ & i = 1, 2, \ldots, \text{NK}; \quad iter = 1, 2, \ldots, iter_{\max}; \end{aligned} \quad (34)$$

where Z_{best}^{iter-1} is the solution with the best fitness in the $iter - 1$ th iteration, Z_i^{iter} is the ith solution in the $iter$ th iteration which is being mutated. $rd1$ and $rd2$ are two exclusive random numbers between 1 and NK (but excluding the value of the index i). $Z_{i,rd1}^{iter}$ and $Z_{i,rd2}^{iter}$ are the $rd1$ th and $rd2$ th solutions respectively from the $iter$ th iteration, whereas cfr is a controlling factor.

4.4 Mutated Krill Herd sine cosine algorithm

The Mutated Krill Herd Sine Cosine algorithm (μ-KHSC) is a unification of the above-mentioned algorithms and strategy namely, the Krill Herd (KHA) [31], the Sine Cosine (SCA) [32], and mutation operator of Differential Algorithms [33]. KHA is itself a powerful optimization tool but occasionally fails to reproduce the same optimal solution at different runs as it gets caught in local optima. The merger of SCA and mutation operator of DE render μ-KHSCA with a perfect blend of robustness, exploration, and exploitation capabilities.

The flowchart of the μ-KHSC algorithm is demonstrated in Fig. 3.

4.5 Application of μ-KHSC algorithm

The new hybrid algorithm μ-KHSC is applied to the proposed twofold framework. Every candidate solution $\vec{Z}_j$ portrays:

- the selected set of AR branch locations α when applied in Phase I- Optimal placement of AR where the objective is shown in (17).
- a radial configuration β that is applied in Phase II-DSRM where the objective is clarified by (18).

The fitness of each Krill individual in Phase I and Phase II is evaluated using (10) and (16), respectively. Each solution is verified in such a way that it adheres to the constraints provided in Sect. 3.4. If any solution violates any boundary limits, then the solution is fixed to the limit which is violated.

To simplify the understanding of the complete optimization process, a step-by-step approach of Phase I (Optimal placement of AR) of the methodology is provided below, where Steps 1 to 4 fall under initialization of the optimization process.

1. For initialization of a set of solutions, the newly developed algorithm as elaborated in Table 4 is rigorously followed. Here each solution represents an EDS where AR are assumed to be allocated at the generated branch locations.
2. Reliability analysis, as explained in Sect. 2, is performed on each solution. Using (5) and (6) provided in Sect. 3.1, the values of EENS and CUE are calculated.
3. The PSE and the CPV of PSE are obtained using (4), (9) and (8).
4. Finally, using (2), (3), (9) and (7), the Total Expected Profit (TEP) of each solution is calculated using (10).
5. The updating procedure of the optimization technique is followed exactly from the flowchart shown in Fig. 3.
6. At the end of all iterations, $Z_{globalBest}$ obtained represents the best set of branch locations for AR placement which provides TEP of $Fit_{globalBest}$ (as shown in Fig. 3).

A similar approach to that discussed above is considered to solve Phase II (DSRM) of the methodology.

5 Numerical analysis

The potency of the suggested methodology for the multi-objective formulation is verified using the IEEE 69-bus test system and the results obtained are shown in this section.

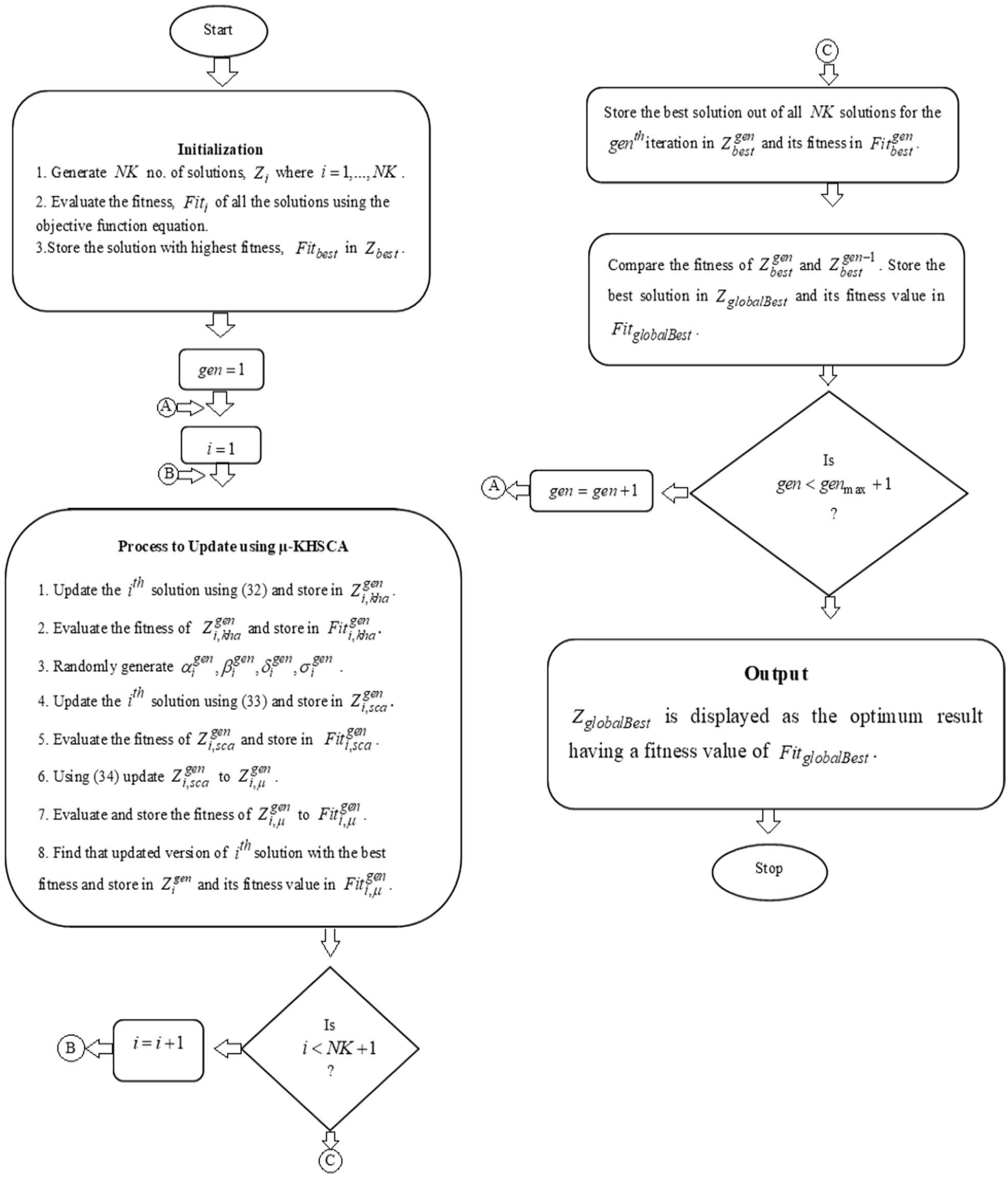

Fig. 3 Flowchart of the µ-KHSC algorithm

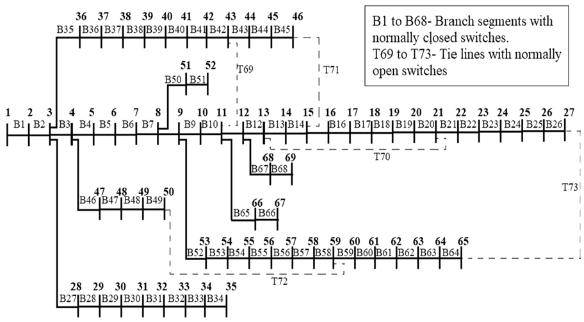

Fig. 4 The IEEE 69-bus test system

Table 5 Different load types and their locations in terms of loads

Load type	Load nodes
Residential load	6, 7, 8, 9, 10, 13, 14, 16, 17, 18, 20, 22, 24, 26, 27, 28, 29, 33, 34, 35, 36, 37, 39, 40, 41, 43, 45, 46, 48, 51, 52, 53, 54, 55, 62, 65, 66, 67, 68, 69
Commercial load	11, 12, 21, 59
Industrial load	49, 50, 61, 64

The test system as displayed in Fig. 4 comprises 69 nodes and five tie lines. Each of the 68 branch segments consists of normally closed sectionalizing switches and each of the five tie lines has normally open tie switches. The total active and reactive loads are 3802.19 kW and 2694.60 kVAr, respectively. The total line resistive loss of the base system is 224.9804 kW. It is assumed that there is a circuit breaker along with an overcurrent relay placed at feeder node 1.

Three types of loads are considered in this study, i.e., residential, commercial, and industrial, as given in Table 5. The system load data and bus data are obtained from [4].

The values considered for some of the necessary parameters are:

- The average repair time per failure (δp) is 4 h.
- The average restoration or switching time per failure (δt) is 1 h.
- The frequency of failure per km per year (λ) is 0.0650 [20].
- The load growth (LGR), inflation (IFR), and interest rates (ITR) are 5%, 5%, and 8%, respectively [1].
- The total working life span of auto-recloser (η) is 20 years.
- The investment cost of one AR is $14,000.
- The maintenance cost of one AR is 5% of its investment cost.
- The population size and the total number of iterations $iter_{max}$ for μ-KHSC is 25 and 80, respectively.

The complete framework is developed in MATLAB R2014a software in a system having 8 GB RAM, with a core i5 and 2.30 GHz processor. The cost-related values are expressed in US Dollars (USD). The following conversion equation is utilized to convert USD to Indian Rupees(₹):

1 USD= ₹ 79.93

5.1 Phase I: Optimal AR allocation

The application of optimal placement of AR in the test system to maximize the total expected profit as in (17) is carried out in five scenarios where the number of ARs to be allocated is varied from one to five. This concept is undertaken to ease the selection of the optimum number of ARs by the EUC based on a compromise solution where the satisfaction of the customers (through improvement in supplied energy), as well as the EUC benefits, are taken into account.

Branch segments starting from B3 to B68 of the test system, as shown in Fig. 4, are considered suitable candidate locations for the AR placement. The locations for the placement of ARs are determined using the new algorithms explained in Table 4 and Fig. 3.

The results obtained for the five scenarios with varying AR numbers are provided in Table 6, which includes the unsupplied energy (EENS), the cost of unsupplied energy (CUE) as well as the total expected profit for a cumulated period of 20 years. It is observed that as the installed number of ARs increases, the system reliability in terms of supplied energy also improves.

Table 6 Reliability results obtained for five different scenarios of AR placement in the test system using the μ-KHSC algorithm

No. of ARs placed	Branch segments of test case for AR allocation	Unsupplied energy (kWh/year)	Cost of the unsupplied energy ($/year)	Total expected profit for a cumulated period of 20 years ($)
0 Base case	–	18,187.2018	107,863.6574	–
1	B10	15,340.7475	87,826.2270	366,227.6767
2	B10, B35	13,530.8143	75,271.4480	673,819.9401
3	B10, B27, B35	12,204.3642	66,287.5338	893,925.9635
4	B10, B27, B35, B52	10,971.0276	59,849.3838	1,051,660.7297
5	B10, B27, B35, B46, B52	10,452.6971	56,664.7861	1,129,683.4182

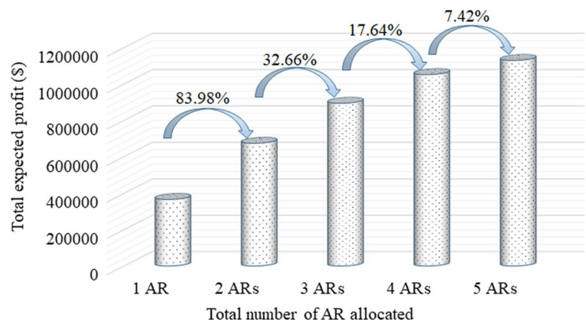

Fig. 5 Percentage improvement in the total expected profit considering five scenarios of AR placement

The percentage improvement in the total expected profit for all the five cases of AR placement is shown in Fig. 5. This pictorial representation in the form of a cylinder bar chart provides the EUC engineers or the decision-makers with a simple analysing solution to decide on the optimum number of ARs to be placed.

From Fig. 5 is it evident that the highest percentage improvement in the total expected profit of 83.98% is obtained when the number of AR (NOA) placed increases from one to two. However, as the NOA increases the percentage improvement gradually decreases, and further drops to a nominal value of 7.42% when the NOA increases from four to five.

Therefore, it is understood that although increasing the NOA alleviates system reliability it does not necessarily improve the overall expected profit earned by the EUC for the working life span of the protective devices.

In this study, based on the analysis provided in Fig. 5, a total of four ARs are selected for optimal allocation in the test system. The optimal AR placement locations which provide a maximum of the total expected profit are branch segments B10, B27, B35, and B52. The corresponding unsupplied energy, the cost of unsupplied energy, and the total expected profit are provided in Table 6.

Table 7 Simulation results obtained by the KHA, SCA, and μ-KHSC algorithm for the optimal placement of four ARs in the IEEE 69-bus test system

Optimization algorithms	Branch segments of test case for AR allocation	Unsupplied energy (kWh/year)	Cost of the unsupplied energy ($/year)	Total expected profit for a cumulated period of 20 years ($)
KHA	B10, B35, B28, B52	11,107.4502	60,825.4557	1,027,746.9539
SCA	B10, B53, B27, B35	11,077.1059	60,414.2438	1,037,821.6508
μ-KHSC	**B10, B27, B35, B52**	**10,971.0276**	**59,849.3838**	**1,051,660.7297**

Bold numerical values represent the best results obtained using the proposed methodology

To present a comparative study between the μ-KHSC algorithm and other optimization techniques, the complete procedure as presented in Fig. 3 is applied to find the optimum solution for the placement of four ARs in the IEEE 69-bus test system (Fig. 4). The comparative study is presented in Table 7.

5.2 Phase II: Distribution system remodelling

In this phase, the DSRM methodology is applied to the AR installed test system as obtained in Phase I. By doing so, the efficiency of the test system is improved by reducing the total line losses as in (18).

The total line resistive losses obtained after applying DSRM are shown in Table 8. It is seen there that there is a reduction of 56.1349% in the line losses when compared to that of the base case of the test system.

A comparison between the simulation results attained by μ-KHSC and other optimization techniques for minimizing line resistive losses using DSRM is given in Table 9. It is noteworthy that μ-KHSC beats all the other algorithms. This confirms the superiority of the hybrid optimization μ-KHSC algorithm developed in this study.

Figure 6 shows a comparative study of the nodal voltages obtained before and after applying DSRM in the test system in the form of clustered columns and line graph, respectively. It is apparent from Fig. 6 that

Table 8 Test system configuration with minimum line resistive losses obtained using DSRM and μ-KHSC

Configuration (disconnected branch segments)	Total line resistive losses (in kW)	Increase in efficiency of power supply
Before DSRM T69, T70, T71, T72, T73	224.9804	–
After DSRM B13, B57, B61, T69, T70	98.6877	**56.1349%**

Bold numerical values represent the best results obtained using the proposed methodology

Table 9 Comparison of the minimum line resistive losses for the test system obtained using various optimization algorithms

Optimization algorithm	Least nodal voltage (P.U.)	Line resistive loss (kW)
Base network	0.9092	224.9804
Hybrid PSO [34]	0.9427	99.6704
Improved GA [35]	0.9428	99.6200
SAMCSA [36]	0.9428	99.6200
KHA	0.9483	99.5997
SCA	0.9483	99.6785
μ-KHSC	**0.9494**	**98.6877**

Bold numerical values represent the best results obtained using the proposed methodology

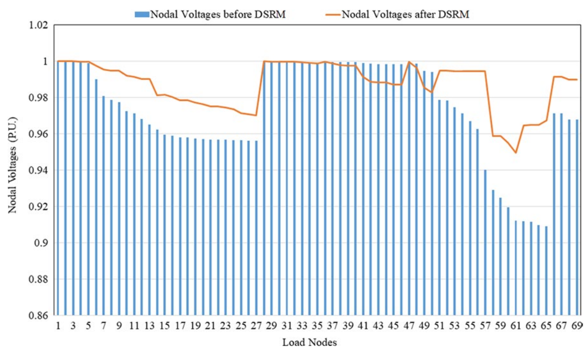

Fig. 6 Comparison of nodal voltages of the test system obtained before and after DSRM using μ-KHSC

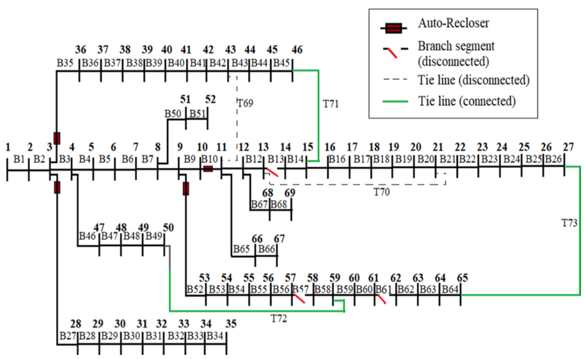

Fig. 7 Final remodelled configuration of the 69-bus test system with optimally allocated ARs

performing DSRM on the test system has significantly improved the nodal voltage levels.

The final remodelled configuration of the 69-bus test system (where the disconnected branches are B13, B57, B61, T69, T70) with four installed auto-reclosers at B10, B27, B35, B52 is outlined in Fig. 7. Results shown in Table 6 reveal the effectiveness of the DSRM methodology

Table 10 Reliability and line resistive loss evaluation results obtained after different phases of the composite methodology

	Base test system without AR	Base test system with AR placed at B10, B27, B35, B52	After DSRM without AR	After DSRM with AR placed at B10, B27, B35, B52
EENS (kWh/year)	18,187.2018	10,971.0276	17,125.6832	10,073.8407
CUE ($/year)	107,863.6574	59,849.3838	101,459.7723	51,469.8135
Reliability Improvement in terms of EENS	–	39.6777%	5.8366%	44.6102%
Total line resistive loss (kW)	224.9804	224.9804	98.6877	98.6877

using the μ-KHSC optimization technique to reduce the system resistive losses. To check if DSRM has any impact on the reliability of the system, reliability assessment is carried out on the AR installed remodelled test system as in Fig. 7, and the results attained are presented in Table 10.

From Table 10 it is observed that the improvement in EENS after the remodelling of the AR installed test system is much higher compared to that obtained after the AR placement in the base test system.

6 Conclusion

A composite dual-phased approach involving auto-recloser placement and Distribution System Remodelling is proposed to improve system reliability and efficiency. To identify the optimum number and location of auto-reclosers to be allocated, a new auto-recloser placement algorithm is introduced (Table 4) and a cost–benefit analysis (Sect. 3.1) is conducted. This analysis takes into account the effect of power outages on various types of customers, the load growth rate, and the inflation rate. A new metaheuristic hybrid optimization algorithm, μ-KHSC, is developed (Sect. 4.4) and employed in both phases of the methodology exploring optimum combinations of branch segments. The simulation results (Sect. 5) obtained corroborate the efficacy and credibility of the proposed approach. The findings of this paper are summarized below.

- A reliability improvement of 39.7% in terms of EENS is obtained when four ARs are optimally allocated in the 69-bus test system.
- The application of DSRM on the AR installed test system provides a significant improvement in system efficiency by reducing the system line resistive losses by 56.1%. Further, it also proves beneficial in elevating the system reliability (considering EENS) by 44.6% when compared to the base case.
- The suggested methodology has positive effects on the up-grading of nodal voltages within the desired limits, as shown in Fig. 6.
- The new hybrid optimization algorithm, μ-KHSC, outperforms the results obtained by KHA, SCA as well as other algorithms present in the literature, validating its superiority.

A similar framework used in the paper may be pursued for the placement of other protective switchgears such as automatic switches and fuses. The study may also be extended for analyzing both momentary and sustained faults.

Abbreviations

EDS: Electric distribution system; AR: Auto-reclosers; EUC: Electric utility companies; DSRM: Radial distribution system re-modelling; μ-KHSC: Mutated Krill

Herd sine cosine algorithm; TE: Total expenditure on AR installation by EUCs; TIC: Total investment cost; TMC: Total maintenance cost; EENS: Unsupplied energy; CUE: Cost of unsupplied energy; SCDF: Sector customer damage functions; CPV: Cumulative present value; PSE: Profit due to the supplied energy; TEP: Total expected profit; IFR: Inflation rate; LGR: Load growth rate; ITR: Interest rate; TEP: Total expected profit; KHA: Krill Herd algorithm; SCA: Sine cosine algorithm; DE: Differential evolution; NOA: Number of AR.

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Author contributions
BG: conceptualization, investigation, software, validation, writing original draft, format analysis, data curation. AKC: visualization, supervision. ARB: Supervision. All authors read and approved the final manuscript.

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Declarations

Competing interest
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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