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Multi Objective Optimization Framework to Provide Reactive Power Support to the Local Distribution Grid Using a Heuristic Approach.

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Abstract: - Reactive power support to the local distribution grid becomes mandatory as it highly impacts the network's voltage profile and active power loss. Reactive power support improves the performance and efficiency of the grid. However, higher compensation to the line increases losses, deteriorates the voltage profile, and occupies the investment cost. The location of these reactive power compensators (RPC) also influences the network's performance. This paper presents a multi-objective strategy for optimal reactive power compensation to get techno-economic benefits. An objective function, which includes technical and economic criteria, has been formulated. The proposed MOF includes weighted distributed objectives that are minimized to get a trade-off solution. The proposed MOF has been minimized using three different heuristic algorithms, i.e. TLBO, GA and PSO. The proposed strategy has been tested on 56 buses 11 KV Gurukul distribution network located at Bhavnagar, Gujarat, India. NR load flow has been utilized to investigate losses and bus voltages.

Keywords: Reactive Power Compensator(RPC), Multi Objective Function(MOF). Genetic Algorithm(GA), Particle Swarm optimization(PSO), Teaching Learning Based Algorithm(TLBO), Active Power Loss, Voltage Profile Improvement.

I. INTRODUCTION

The addition of a Power Compensator can reduce the inductive reactance component of the line loading, hence minimizing reactive losses and making the capacitor a source of reactive power. Since power distribution systems are the last point of contact between consumers and the bulk power system, they represent an important research topic. However, in a distribution network, reactive power flows invariably result in significant power losses. Reactive power flow losses might become much more significant at high loads. Additionally, these fluxes cause a substantial voltage drop in some distribution network locations. Distribution businesses should strive to optimize their operations by reducing losses and raising voltages at various buses. Using devices that achieve efficient voltage control, reactive power management, and power factor control is crucial to ensure minimal loss and appropriate voltage levels at various distribution network locations. One of the essential pieces of equipment needed to accomplish these goals is the shunt capacitor. Distribution engineers must choose the best position and size of capacitors to be put at various load levels to minimize loss, enhance voltage profile, and adjust power factor to the greatest extent possible under various operational limitations. Therefore, one of the main concerns of electric power utilities is always the best approach to allocating capacitors in electrical distribution networks. Significant contributions to the capacitor placement strategy for voltage control and subsequently loss prevention have been made by a number of writers. The primary difficulties with this approach are, Location for capacitors, Deciding on the right CB size, The use of CBs to fulfill the necessary goals of power flow management, voltage regulation, and loss reduction. The benefits of varying capacitive volt-amp reactive (VARs) in response to load variations have been known since the 1940s. Before the 1950s, there was a trend toward minimizing loss at the substation by placing capacitors. However, because pole-mounted equipment was more readily available and the arrangement made financial sense, the trend shifted to installing capacitors closer to the loads on primary distribution feeders after that time.

II. LITERATURE REVIEW

Several researchers employed classical techniques [1–3] to address the issue of optimal capacitor placement. Khodr et al. introduced a methodology based on mixed integer linear optimization [4] to determine the best location and size of static and switched shunt capacitors in a radial distribution system. Jabr utilized the mixed integer linear programming (MINP) [5] method to achieve the optimal arrangement of fixed and switched-type capacitors in a

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radial distribution network. This research aimed to reduce the expenses related to capacitor banks, peak power, and energy losses while meeting specific physical and technical limitations. Franco et al. have developed a multi-objective MILP strategy [6] based on Pareto principles. This technique aims to solve the problem of optimally allocating voltage regulators and capacitors in radial distribution networks. Oliveira et al. suggested a mixed integer nonlinear programming (MINLP) approach [7] to reconfigure capacitor allocation to minimize energy losses in radial electrical networks. Wu et al. developed a method based on loop analysis [8] to determine the most efficient size of a capacitor in order to minimize power loss in distribution networks during everyday operation. Segura et al. presented an interior point technique (IPM) [9] for solving the optimal capacitor placement problem in radial distribution networks.

The optimal placement problem of capacitors in a radial distribution system for variable load levels is regarded as a nonlinear optimization problem with a non-differentiable objective function.

This is because the costs of the capacitors change discretely while the system load changes continuously throughout the day. Hence, the conventional optimization methods are inadequate for effectively solving optimal capacitor placement problems.

Neagle and Samson [10] proposed an approach for the best distribution of capacitor banks (CBs) to compensate for reactive power. Cook [11] presents a novel approach considering energy loss, peak power loss, and demand reduction (KVA).

Grainger and Lee [12] introduced a novel approach in which certain feeder sections have distinct wire diameters. Lee SH and Grainger JJ [13] further discuss the issue by incorporating switching and fixed capacitor banks into a radial distribution network model. In their study, the authors introduced an approach that integrates the cost of CBS to identify cost-effective alternatives. In their study, the authors presented a strategy for reactive power compensation in the primary distribution network that allows for continuous monitoring.

Ulinuha et al.[14] proposed using Evolutionary-Based Algorithms to optimize large distribution systems with different types of nonlinear loads. This technique achieves the best scheduling of Load Tap Changers and switched shunt capacitors to reduce energy loss, improve the voltage profile, and incorporate harmonics. Various methodologies, including previously utilized analytical and interactive methods [15, 16], have been introduced for this objective. Nevertheless, these methods required significant processing resources, prompting the development of alternative approaches that employed heuristic techniques and reduced issue formulations. When seeking outcomes that better represented the reality of the problem, conductors with different sections and non-uniformly distributed loads were considered [17]. Ziari et al.[18] introduced a modified discrete Particle Swarm Optimization (PSO) method to determine the optimal placement and rating of fixed and switching capacitor banks throughout the distribution network. Taher and Bagherpour proposed a hybrid honey bee colony optimization (HBCO) technique [19] to optimally place shunt capacitor banks in the IEEE-25 and IEEE-37 bus test systems. The suggested MOF integrates loss minimization while ensuring that buses' total harmonic distortion (THD) remains within an acceptable range. In their study, Szuvovivski et al. [20] present a system for assigning CBs and VRs to regulate bus voltage, reactive power demand, and power factor. Genetic algorithms (GA) and optimal Power Flow (OPF) have been employed to determine the optimal solution. The recommended technique has been implemented for three distinct load levels: Light, Middle, and Heavy. The global criterion approach transforms a multi-objective function into a single-objective function. A 70-bus test system is employed to evaluate the methodology.

III. PROBLEM FORMULATION

The problem of optimal reactive power compensation has been investigated to find a cost-effective solution for improving system performance indicators. This involves determining a reactive power compensator's right location and size for an ideal distribution system. The proposed technique has been tested on a 56-bus 11KV distribution network in Bhavnagar, Gujarat. This complex optimization problem is non-convexed, multi-objective, and non-linear. It involves a weighted distributed multi-objective function minimization type. The proposed M.O.F. was reduced using three distinct heuristic techniques, namely Genetic Algorithm (G.A.), Teaching-Learning-Based Optimization (TLBO), and Particle Swarm Optimization (PSO), implemented in MATLAB.

The primary objective of this problem is to determine the most efficient dimensions and capacity of the Reactive Power Compensator (R.P.C.) to minimize active power loss in the distribution network while improving the voltage profile. An initial analysis was conducted using a loss-sensitive analytical approach to narrow down the search area for the optimization problem. This approach identified the prospective locations of candidate buses that are both sensitive to loss reduction and experiencing poor voltage regulation. Fig.2 displays the Geographic Information System (G.I.S.) map and single-line diagram of the 56bus 11kv Gurukul distribution network. Fig.1 depicts a schematic representation of the proposed approach for the optimization problem. The 11kv Gurukul network is an urban feeder responsible for providing electricity to the city region. The network parameters are displayed in Table 1. The N.R. load flow approach has been utilized to assess several network performance metrics. The network voltage profile and branch losses are depicted in Fig.5 and Fig.4, respectively.

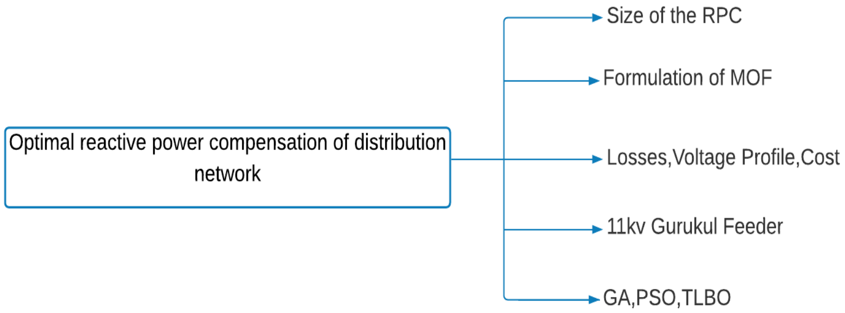

Fig. 1 Problem Formulation for ORPC problem

Table 1 Network data of gurukul network

1	Name of the feeder	Gurukul
2	Type of feeder	URBAN
3	Feeder voltage level	11 kv
4	Total length of feeder	8.39 KM
5	Type of conductor	55MM2 AAAC

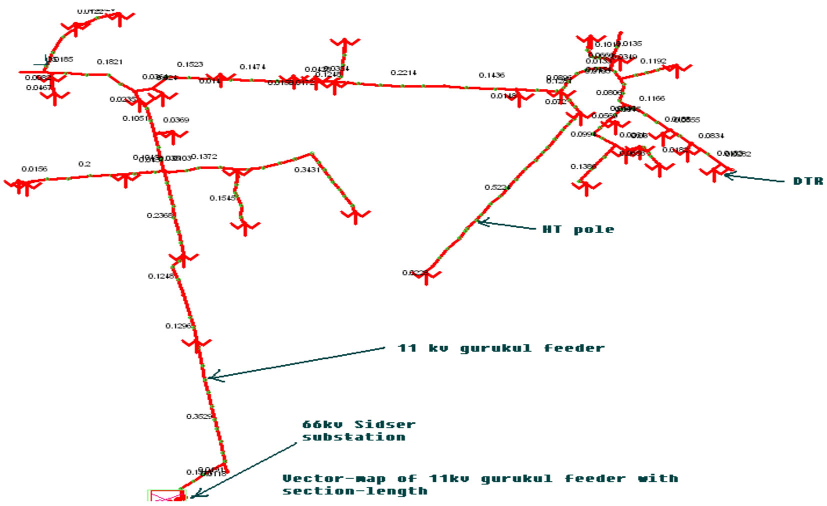

Fig. 2 G.I.S Map of 56 bus gurukul distribution network

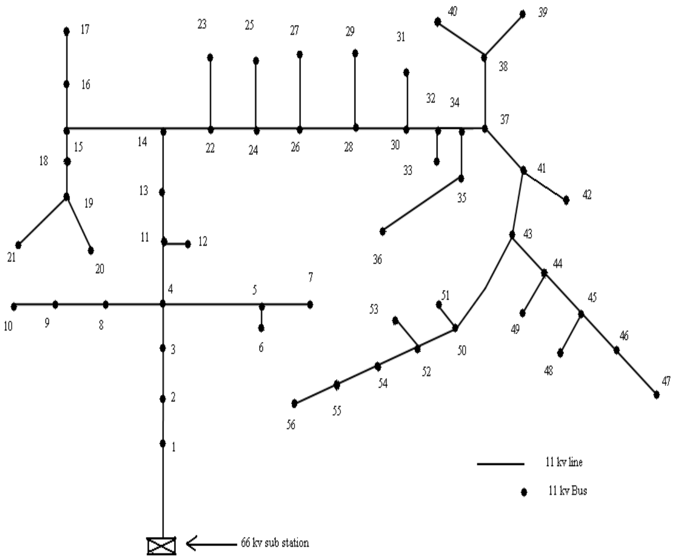

Fig. 3 Single line diagram of 56 bus gurul network

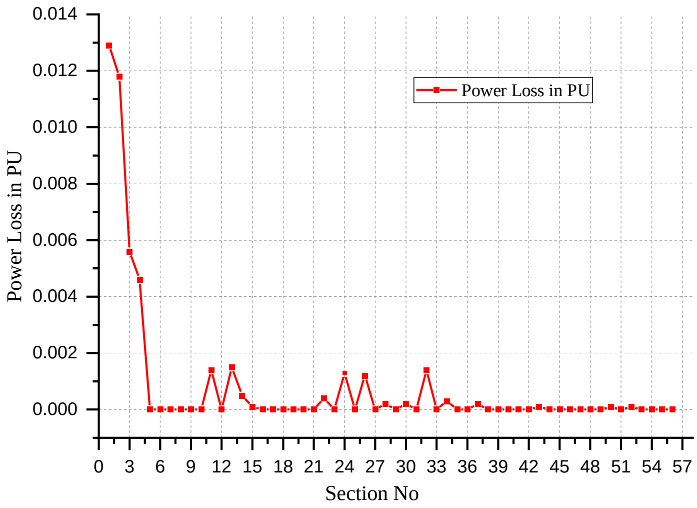

Fig. 4 Power loss across each line section of the network

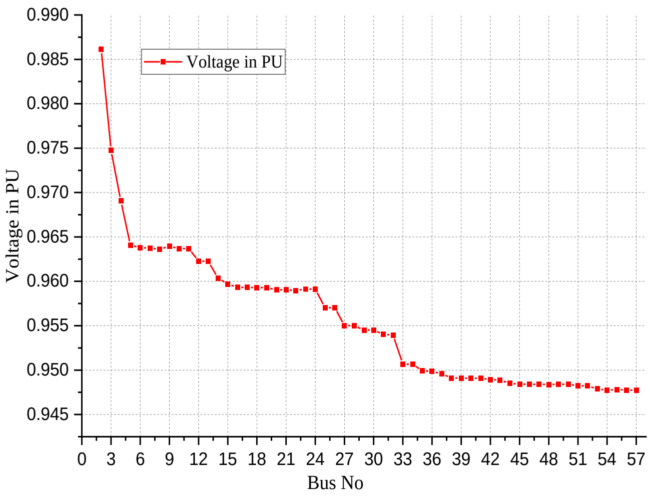

Fig. 5 Voltage profile of the network

A. Potential location for RPC deployment using sensitivity analysis

Sensitivity analysis is used to identify the optimal location for capacitors in a radial distribution system. Assessing these potential places aids in narrowing down the search area during optimization methods. Placing capacitors at those locations necessitates using sensitivity analysis as the most effective method for minimizing actual power losses in the system. The Loss Sensitivity Factor (LSF) is calculated to identify potential locations for placing Capacitor bank. Additionally, there is a load connected between k, with an adequate power of $P_{k+1,eff}$ + $jQ_{k+1,eff}$. Furthermore, Sensitivity analysis is used to identify the optimal location for capacitors in a radial distribution system. Assessing these potential places aids in narrowing down the search area during optimization methods. Placing capacitors at such locations necessitates using sensitivity analysis as the most effective method for minimizing actual power losses in the system. The Loss Sensitivity Factor (LSF) is calculated to identify potential locations for placing Capacitor bank.

The active power loss in the line section between buses k and k+1 is calculated by,

$$P_{Loss\,k,k+1} = R_{k,k+1} * \frac{P^2{}_{k+1,eff} + Q^2{}_{k+1,eff}}{|V_{k+1}|^2} \text{..........................(1)}$$

Now, the LSFs can be obtained with the help of following equation,

$$\frac{\partial P_{Loss\,K,K+1}}{\partial Q_{k+1,eff}} = \frac{2 * Q_{k+1,eff} * R_{k,k+1}}{|V_{k+1}|^2} \text{..........................(2)}$$

LSFs are computed from load flows using the (1) and (2),and values aresorted in decreasing order for all line sections of the given system. LSFs determine the order in which buses are considered for RPC installation. The buses with lower voltage [v < 0.96p.u] will be chosen for RPC installation from the sequence of LSFs. An optimization algorithm is used to determine the appropriate size of RPC at candidate buses. The potential locations which are consider for placement of RPC are 4,32,24,26,13,11,37,34.

IV. METHODOLOGY

Optimal sizing of CBs have been addressed using three different heuristic algorithms i.e. GA,TLBO and PSO.

A. Optimal sizing of RPC using GA

The optimal size has been determined using a real-time Genetic Algorithm (RGA). The genetic algorithm is an iterative method that begins with a collection of randomly created solutions called the initial population. The objective function and fitness are computed for every solution in the set. Selection operators produce a group of selected populations by using these fitness functions. The solution in the pool is used to employ the crossover and mutation operators to generate novel solutions. The procedure is executed iteratively, with a predetermined number of solutions in the pool of the selected population. The solution optimizes with each iteration until the optimal solution is achieved. The GA selection technique involves choosing reasonable solutions from the initial population to create offspring. The selection process involves randomly choosing good solutions from the initial population, with a bias towards the most fit individuals. Table 2 shows algorithm specific parameters using GA approach. Fig.6 shows the flowchart of RPO problem using GA.

Table 2 Algorithm specific parameters of GA

Sr no	Component of Genetic Algorithm	Method
1	Crossover Probability	0.95
2	Mutation Probability	0.2
3	No. of Population	80
4	No of generation	50

5	Selection Method	Stochastic Uniform
6	Crossover Method	Arithmetic
7	Mutation Method	Adaptive feasible
8	Termination Method	Maximum generation
9	Objective function	Min[Active Power loss]
10	Nos of Population	100

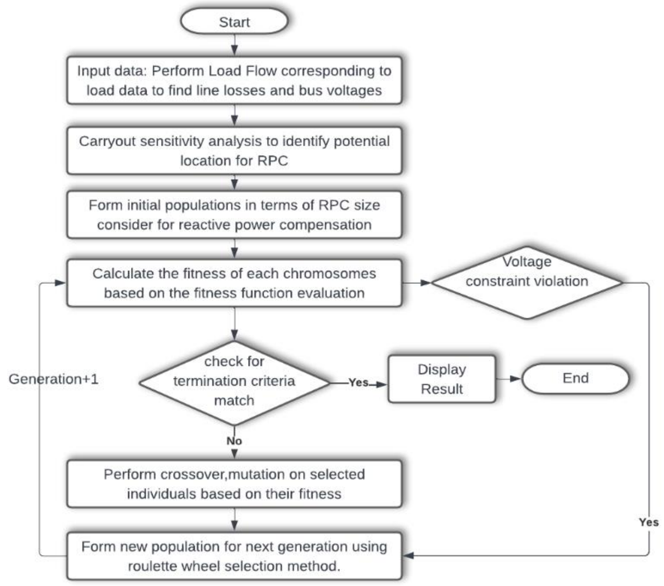

Fig. 6 Flow chart of GA to solve RPO problem

Result of optimal sizing using GA

Fig.7 shows the convergence graph of the objective function wherein the objective function converges to a minimum value with an increase in the number of generations.

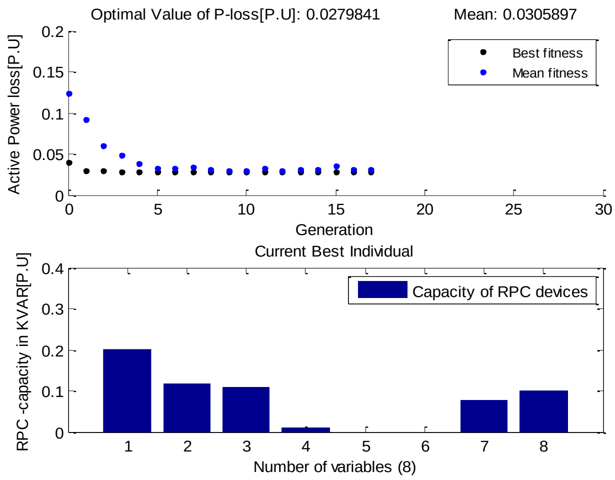

Fig. 7 Convergence curve of MOF using GA

Table 3 shows the optimal size of RPC given from GA corresponding to the potential locations. Table 4 shows the comparison of various network performance parameters before and after optimal placement of RPC.

Considerable voltage improvement and loss reduction can be seen after implementing the proposed strategy, as shown in Fig.8 and Fig.9

Table 3 Optimal size of RPC using GA approach

Bus No	4	32	24	26	13	11	37	34
KVAR in P.U	0.202	.118	.109	.011	0	0	.0178	.101

Table 4 Network performance parameters comparison using GA approach

Types of Quantity	**Before**	**After**
Total Active Power Loss in KW	109.75	69.75
Total Reactive Power Loss in KVAR	42.25	28.15
Tail End Voltage in KV	10.54	10.42
Voltage Deviation Index	0.04507	0.03443

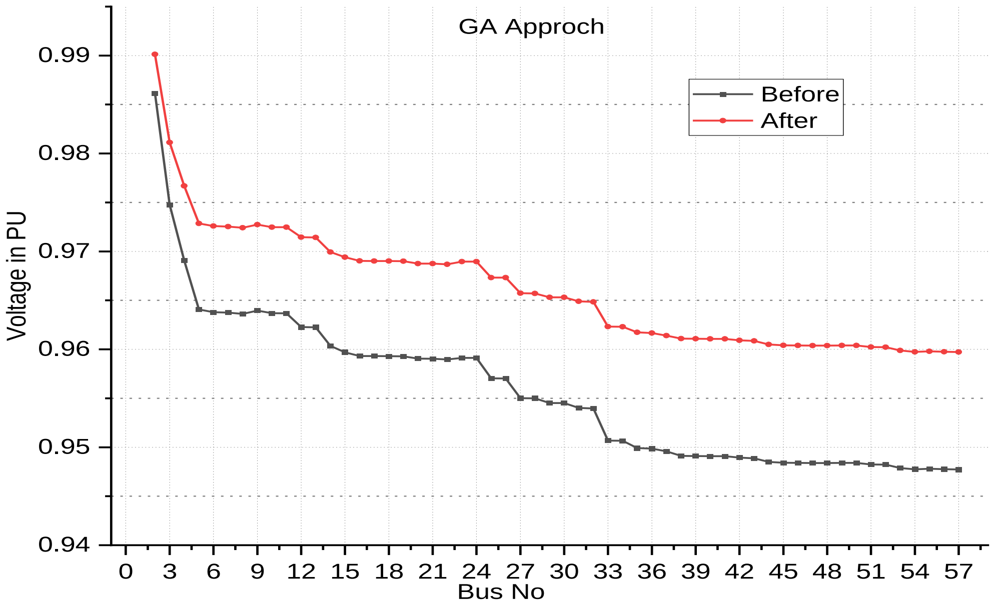

Fig. 8 Comparison of voltage profile using GA

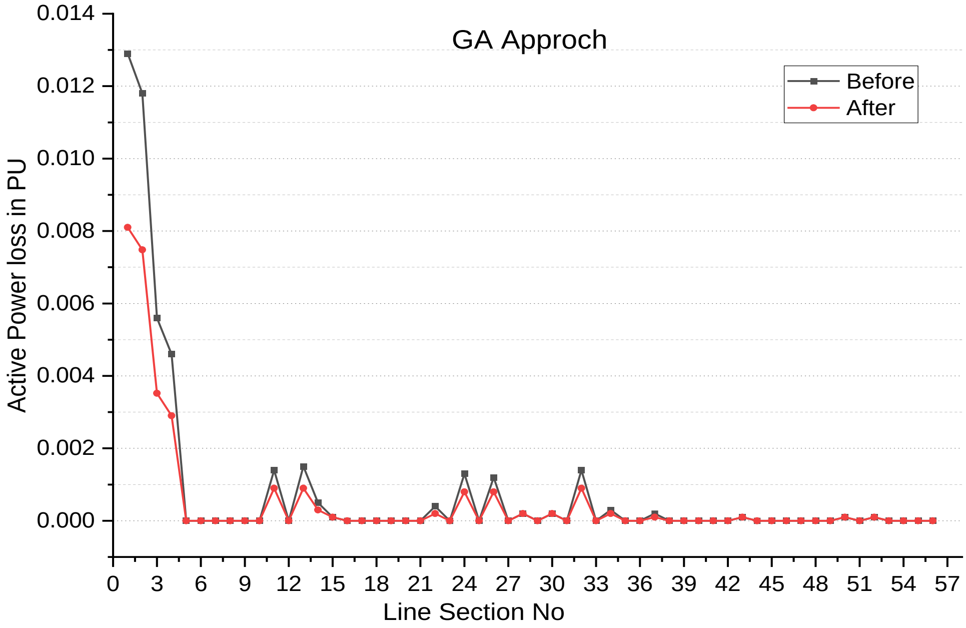

Fig. 9 Comparison of Power loss using GA approach

B. Optimal sizing of RPC using PSO

Particle Swarm Optimization [21] is a computational technique that draws inspiration from the behavior of flocks of birds, schools of fish, and herds of animals. These groups can adapt to their environment, locate plentiful food, and evade predators by utilizing tactics that involve exchanging knowledge. This behavior gives them an advantage in terms of evolution. The PSO was inspired by flock behavior and was developed as an optimization tool for complicated mathematical problems. When a group of birds flies over an area, they must find a place to land. Figuring out where the entire group should land is challenging since it depends on different aspects, such as finding enough food while minimizing the danger of predators. From this perspective, the bird's motion can be seen as choreography; the birds move in perfect synchronization until they find the best place to land, and then the entire flock lands simultaneously. In the given scenario, the flock's migration occurs only when all swarm members can exchange information. Otherwise, each animal would settle at a different location and time. The challenge of identifying the optimal landing location is an optimization problem.

An optimization problem aims to identify the variable, represented by the vector $X = [x_1, x_2, x_3, ..., x_n]$, that minimizes or maximizes the function f, based on the given optimization formulation f(X). However, the function f(X) is referred to as a fitness or objective function. It assesses the quality of a position X, specifically the desirability of a landing point as perceived by a bird. This evaluation is based on multiple survival criteria. Each particle in a swarm of P particles is associated with a position vector $X_{mi} = [x_{m1}, x_{m2}, x_{m3}, ..., x_{mn}]$ and a velocity vector $V_{mi} = [V_{i1}, V_{i2}, Vi3, ..., V_{mn}]$ at iteration m. The Equation(3) is utilized to update these vectors along the j dimension.

$$v_i^{n+1} = W * v_i^n + C_1 k_1^n (P_{b1}^n - P_i^n) + C_2 K_2^n (G_b^m - P_i^m) \ldots\ldots\ldots\ldots\ldots(3)$$

Where,

W=Partical's Motion

P_{b1}^n = Particle's personal best position at iteration m.

P_i^n= Particle's current position at iteration m.

$C1$, C2 = Individual-cognition parameters.

k_1^m, K_2^n= random value parameters at iteration m[0 ,1].

After updating of velocities for all the particle, move the particle to their new location,

$P_i^{m+1} = P_i^m + V_i^{m+1}$……………………………………(4)

In the Present analysis, the population vector or solution vector of RPC size between the lower and upper bound becomes Swarm particles. Active power loss becomes a fitness function. Furthermore, it is used to find personal best and global best solutions in each iteration. The PSO-algorithm specific parameters are shown in Table 5. Fig.10 shows operational flow chart to solve optimal sizing problem using PSO.

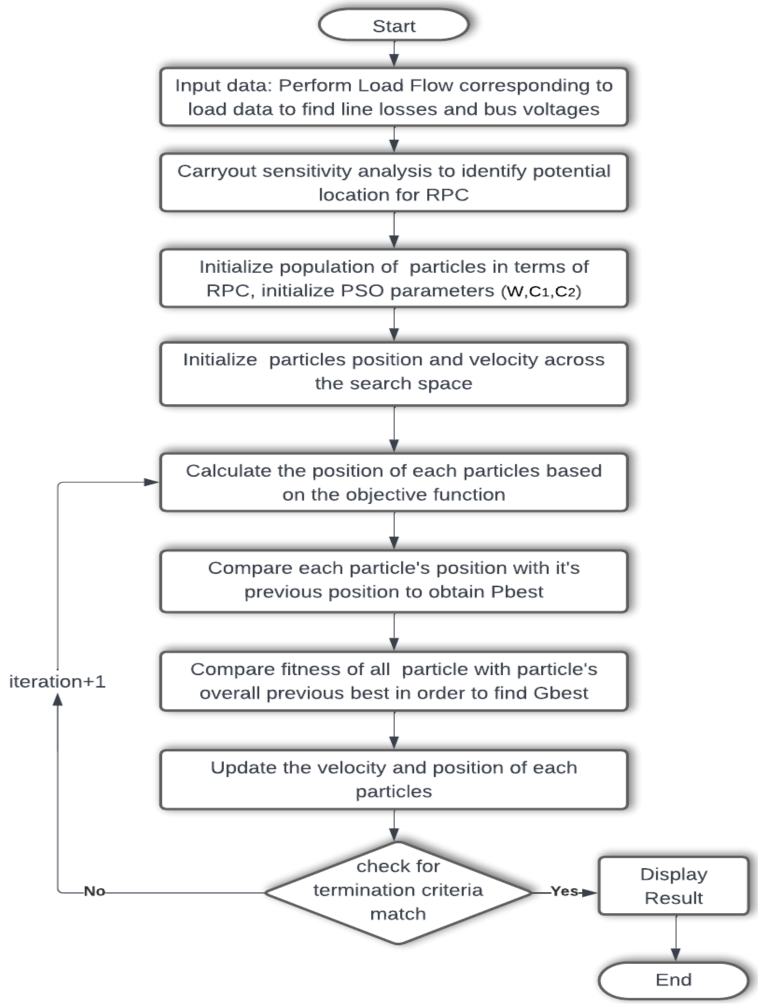

Fig. 10 Flowchart of PSO for RPO

Table 5 Algorithm specific parameters of PSO

W(Weight)	.65
C1(Acceleration constants)	1.65
C2(Acceleration constants)	1.75

Results of optimal sizing problem using PSO

The Table 6 displays the optimum size of the RPC that match to the prospective locations. The Table 7 displays the comparison of several network performance attributes before and after the appropriate placement of RPC. The

Fig.12 and Fig.13 demonstrate a substantial increase in voltage and a decrease in power loss following the implementation of the suggested technique. The graph in Fig.11 illustrates the convergence of the objective function, showing how it approaches the minimal value as the number of generations grows.

Table 6 Optimal size and location of RPC using PSO approch

Bus No	4	32	24	26	13	11	37	34
KVAR in P.U	0.2073	0	0.1136	0	0	0	0	0.2841

Table 7 Performance parameter using GA approach

Types of Quantity	Before	After
Total Active Power Loss in KW	109.75	70.06
Total Reactive Power Loss in KVAR	42.25	28.15
Tail End Voltage in KV	10.42	10.55
Voltage Deviation Index	0.0450	0.03405

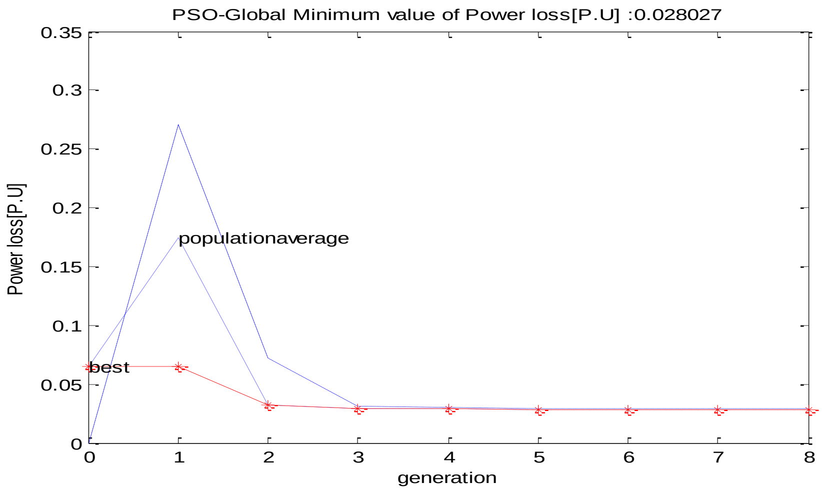

Fig. 11 Convergence curve of MOF using PSO

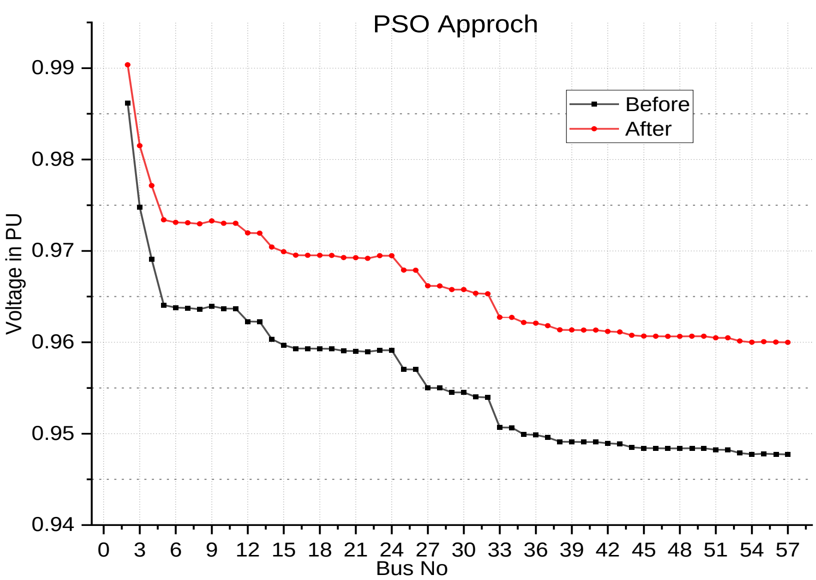

Fig. 12 Voltage profile comparison chart using PSO approach

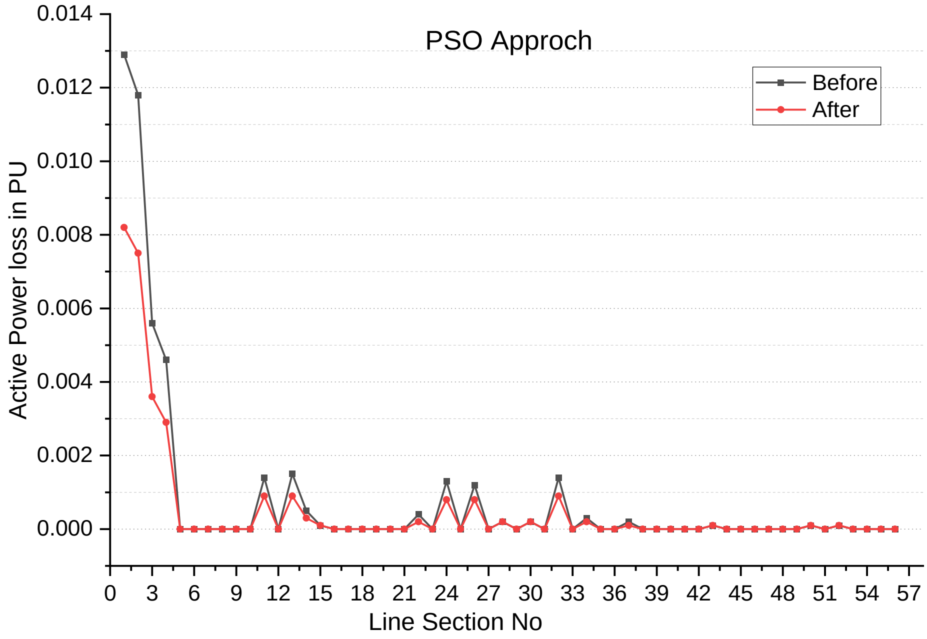

Fig. 13 Power loss comparison chart using PSO approach

C. Optimal RPC sizing using TLBO

Rao et al. [22,] and Rao and Patel [23] have proposed a teaching-learning process optimization approach that is influenced by the impact of a teacher on the performance of students in a classroom. This strategy involves studying a population of learners and considering different themes provided to the learners as diverse design variables. The learner's output is then evaluated as the fitness value for the optimization problem. The teacher is widely regarded as the most optimal solution for the entire population. The optimal solution refers to the most favourable value of the objective function, while the design parameters are the specific parameters that are used in the objective function of the given optimization problem. The TLBO algorithm consists of two distinct phases: the 'Teacher phase' and the 'Learner phase'. Rao et al. [22, 23] extensively analyse the functioning of both of these stages. The functioning of the TLBO algorithm is elucidated in a manner analogous to the teacher and learner stages. The TLBO algorithm has been utilized to address optimal sizing problems, where the learner class consists of the population of problem variables, specifically the size of the RPC. The student's ranking is determined by evaluating the objective function. The individual who achieves the minimum value of the goal function will assume the role of a teacher for other students. The present analysis focuses on the purpose of minimizing losses, where the active power loss of the network is used as an indicator to evaluate each solution to the problem. TLBO made two modifications to the solution population during the teacher and student phases. The operation flow chart of TLBO utilized to address the sizing problem is depicted in Fig.14. The algorithm-specific parameters for Teaching-Learning-Based Optimization (TLBO) are displayed in Table 8.

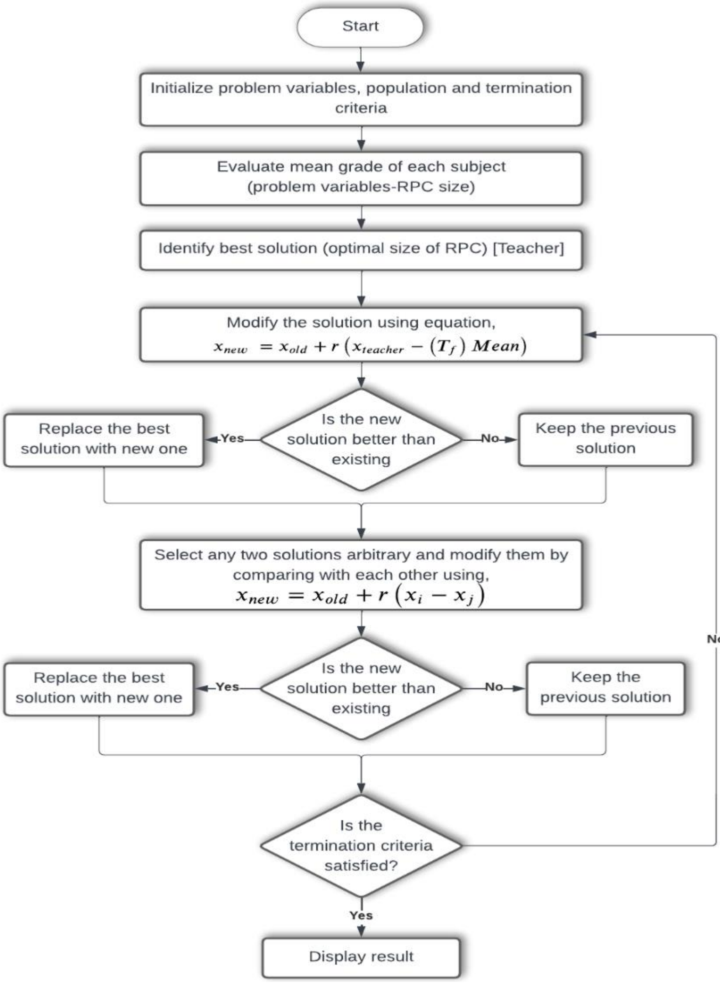

Fig. 14 Flow chart of TLBO to solve RPO problem

Table 8Algorithm specific partakers for TLBO

Nos of subjects(Design variables)	08
Nos of students	10
Name of subject(Design variable)	Capacity of RPC device in kvar
Bound of variables	0 to 0.5 P.U
Value of constant TF	1
Termination Criteria	[Ploss(i+1)-Ploss(i)]<tolerance limit[0.001]
	50 Iterations

Results of optimal sizing problem using TLBO

Fig.15 shows the convergence graph of the objective function wherein the objective function converges to a minimum value with an increase in the number of generations. It shows that objective function converge rapidly to optimal value. Table 9 shows the optimal size of RPC given from GA corresponding to the potential locations.

Table 10 shows the comparison of various network performance parameters before and after optimal placement of RPC. Voltage profile and Power loss comparison graph with TLBO are shown in Fig.16 and Fig.17

Table 9 shows the results of RPO problem; it includes potential locations and corresponding optimal capacity of RPC devices. All three heuristic algorithms have been applied to minimize the proposed MOF index value and retrieve compromised solutions. Fig.18 shows a comparative bar chart for various network performance parameters, i.e., active loss (KW), reactive loss (KVAR) and minimum bus voltage (KV).

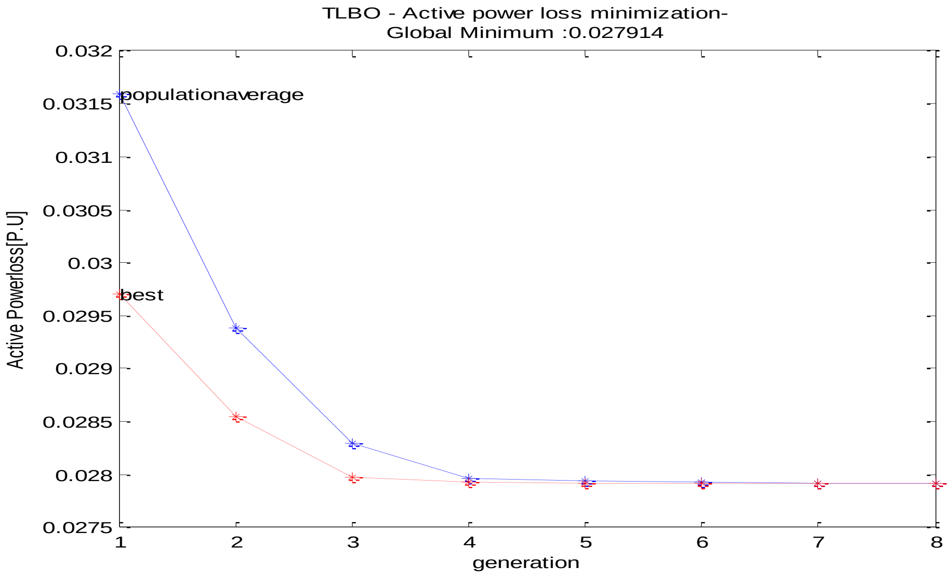

Fig. 15 Convergence curve of MOF using TLBO

Table 9 Optimal size of RPC using TLBO approach

Bus No	4	32	24	26	13	11	37	34
KVAR in P.U	0.1208	0.0175	0	.1082	.1111	0	.0528	.1757

Table 10 Performance parameters comparison using TLBO approach

Types of Quantity	Before Compensation	After Compensation
Total Active Power Loss in KW	109.75	69.75
Total Reactive Power Loss in KVAR	42.25	27.25
Tail End Voltage in KV	10.56	10.41
Voltage Deviation Index	0.0450	0.0341

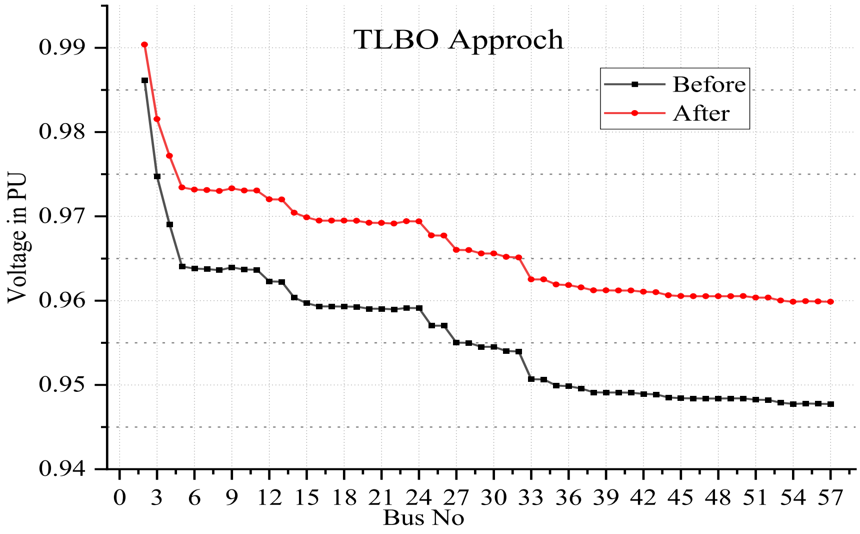

Fig. 16 Voltage profile comparison chart using TLBO approach

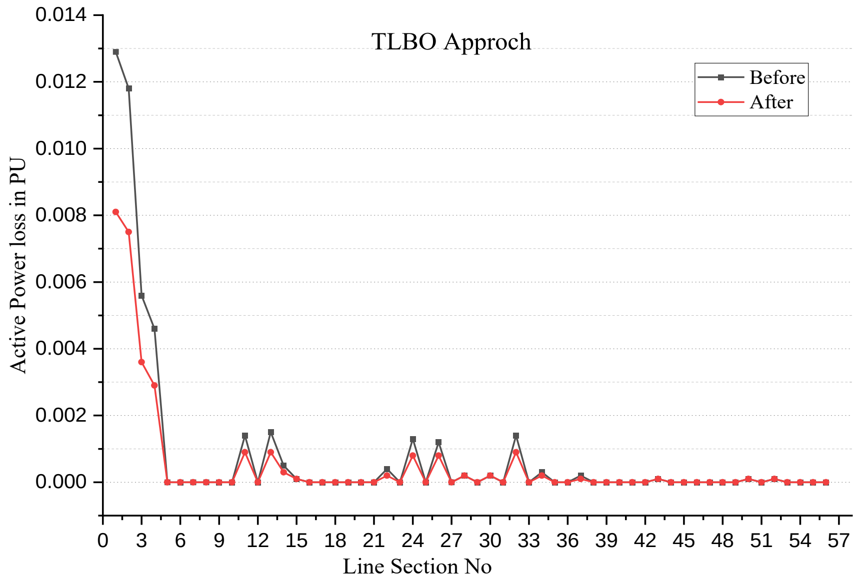

Fig. 17 Power loss comparison chart using TLBO approach

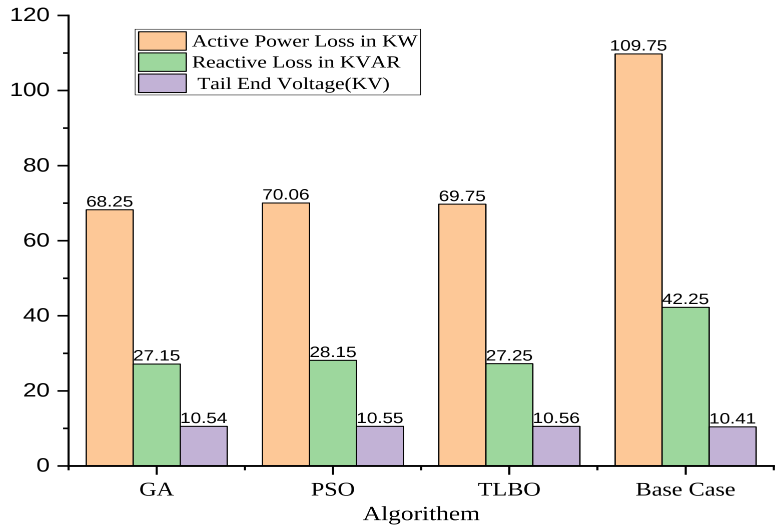

Fig. 18 Comparative analysis of result

V. Conclusion

This paper presents the optimum allocation of RPC (Reactive Power Compensation) to minimize active losses in the distribution grid. Three distinct heuristic algorithms, namely PSO, TLBO, and GA, have minimized the objective function. The outcomes of the optimization methods, namely TLBO, PSO, and GA for the RPO problem, exhibit consistency and comparability. The algorithms consistently yield good outcomes, effectively reducing losses and enhancing voltage. However, GA gives more promising results than TLBO and PSO, which can be seen from the results. The current methodology has been used on a distribution network of 57 buses in Gurukul. The proposed methodology helps the network operator to reap more benefits from the investment made in RPC.

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