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Optimization of reactive power using dragonfly algorithm in DG integrated distribution system

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ABSTRACT

This study proposes, a swarm intelligence Memory based new Multi-Objective Dragonfly (MMOD) algorithm. Analyze to optimize active power loss, total investment on reactive power sources and total voltage variations in distribution systems. MMOD algorithm is implemented for a number of cycles repeatedly and in each cycle dragonflies are made to memorize available Pareto-optimal solutions. The memorized Pareto-optimal solutions are used as initial solutions and only the remaining swarm is reinitialized. Usefulness of the MMODA algorithm is established by solving MORPD problem in the two cases. Cases are standard IEEE- 30 bus test system and another IEEE-69 bus radial distribution systems integrated with DGs and RPS units system. Comparing MORPD results for IEEE 33 bus are more suitable for Power loss 11.42986 kW, voltage profile 0.094375pu and reactive power capacity $599.8718k with respective other algorithm like NSGA-II, MODE, MODA, and MDE algorithm. Similarly for IEEE-69 bus radial distribution system found Power loss minimum 4.3964 kW, voltage profile 0.05474pu reactive power capacity $553.061k.

1. Introduction

Keeping in view the continuously increasing economic growths, environmental aspects, enhanced reliability of the power services, better power quality and independency from conventional energy sources and inclusion of renewable energy sources have become a must of present power industries. As a result, penetration of Dispersed Generation (DG) using Renewable Energy Sources (RESs) is increasing continuously. The high efficiency of DGs can be achieved by installing it near load end. DGs include hydro-electric plants of mini/ micro scale, wind turbines, fuel cells, solar energy and biomass etc. To achieve reliable power supply with enhanced reliability dispersed generation are preferred now a days.

The impact analysis of DGs integration is an important part of power network planning [1–2]. The DGs preferred to integrate on distribution side for obtaining improved stability/voltage profile, minimizing both active as well as reactive power loss and cost effectiveness as well [3–6].

In literature various algorithms/ methodology has been reported for Reactive Power Optimization (RPO) or reactive power dispatch. The problem formulation of this include optimal placement of reactive power sources such as FACTS controllers, bank of capacitors etc., optimal settings of generator voltage sand/or reactive power, use of tap-settings of regulating transformers [4–5]. Carpentier has formulated optimization of reactive power as a sub-problem for optimal power flow (OPF) [7].

The R/X ratio is for any distribution system is high with radial configuration, results reactive power management significantly [8–12]. Therefore, reactive power management is extremely important for DGs with radial distribution system (RDS) for providing reliable and high quality power to consumer end with economic consideration. For this problem of RPO in a distribution system researchers initially attempted with modeling as a constrained single-objective problem which further attempted by population based single-objective optimization (SOO) algorithms [12–16] and further as multi-objective optimization (MOO) problem.

The common used method of solving a multi-objective RPO (MORPO) problem was to convert MORPO problem into a sub number of

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SOO problem by implementing weighted sum method [9-10,14-15] or fuzzy optimization method (FOM) [8,11]. The limitation with these methods are found to simplify the MORPO problem significantly and producing results for MOO, but unable to provide adequate options for the decision maker [17–18]. The major drawback found with these, inefficacy to provide solution for the problem where confecting objectives were involved while converting MOOO of MOO problem into SOO problem. Also, the solution achieved using such conversion is relative weight sensitive applied in formulating the combined function [19].

Subsequently, MOO was used as MORPO. In presence of conflicting objectives MORPO may fail provide optimization results for such problems. [20]. Instead of offering only one optimized solution, the MOO methods provide many solutions known as Pareto optimal solutions [17,20,21]. The Pareto or un-dominated solutions characterize the compromises of best possibility among the involved objective functions.

This paper presents, Memory based Multi-Objective Dragonfly (MMOD) algorithm to solve MORPO problem formulated with radial distribution system. The DGs units are able to deliver power of real and reactive nature both [3]. The minimization functions for MORPO total investment on RPS units, loss of active power and variations in total voltage, with control variables reactive power outputs of the RPS and DGs units integrated in RDS respectively. In the developed Memory based Multi-Objective Dragonfly algorithm, the MOD algorithm is implemented repetitively utilizing the Pareto-optimal solutions available and re-initializing only the residual population.

Dragonfly algorithm (DA), first put forward by Mirjalili in 2014 is a recently developed heuristic algorithms, which is motivated by the unique swarming behavior of dragonflies. DA is found to provide better performance as compared to several existing swarm based algorithms, which are available in the literature [22–23]. Efficacy of the developed MMOD algorithm has been established by solving the MORPO problem in IEEE 33-bus and IEEE 69-bus radial distribution systems penetrated with DGs and RPS units at optimal locations [24].

The main contributions and novelty of this work are as follows

- MMOD algorithm is a conceptually very simple metaphor-less and algorithm-specific parameter-less optimization algorithm
- MMOD algorithms proposed to solve single objective and multi-objective RPD problems.
- RPD solved for minimization of active power losses, total voltage variation and total investment on RPS Units.
- MMOD algorithms applied to solve single and multi-objective OPF in IEEE 33- RDS and IEEE 69-RDS.
- MMOD algorithms found to provide better solutions (voltage profile, minimization of power loss and minimization of RPS units total investment) as compared to solutions by other EC/SI based techniques.

The paper organization is as follows: Section1 details brief introduction of single as well as multi objective optimization problems. In Section2 details the problem formulation of multi objective optimization with two objectives function and system constraints and mathematical Modeling of NSGA-II, MOD, MODE and MMOD EC/SI based techniques. The proposed MMOD algorithms applied to solve single and multi-objective OPF in IEEE 33- RDS and IEEE 69-RDS.Multi objective memory based algorithm is presented in Section 3 .Details the results and discussion are provided in Section 4.

2. Multi-objective RPO

The various objectives in radial distribution systems with DGs for RPO are minimization of active power loss and voltage deviation improving profile of the voltage in the system total initial investment and running costs of RPS units satisfying both constraint of equality and inequality constraint [5,21]:

2.1. Objective functions of RPO problem

2.1.1. Loss minimization of active power

Distribution system power loss P_L of active nature can be obtained by adding up losses of all the lines (nl) and is expressed as below Eq. (1).

$$f_1 = P_L = \sum_{k=1}^{nl} G_k \left[V_i^2 + V_j^2 - 2V_i V_j \cos\theta_{ij} \right] \tag{1}$$

Here G_k is the conductance of k^{th} line; $V_i\angle\theta_i$is voltage at terminal bus i and$V_j\angle\theta_j$is the voltage at terminal bus j of k^{th} line. $\theta_{ij} = \theta_i$- θ_j.

2.1.2. Minimization of variations in total voltage

The voltage profile of RDS is improved by minimizing the total voltage variations TV_V. The improvement in voltage profile can be attained at various load buses by subtracting from the variations in voltage magnitudes $|V_i|$ to reference voltage V_i^{ref}(1.0 Pu) and minimizing it which is calculated from formulae given below:

$$f_2 = TV_V = \sum_{i=1}^{LB} \left| V_i - V_i^{ref} \right| \tag{2}$$

In (2), LBindicates the total load buses of distribution system.

2.1.3. Minimization of RPS units total investment

Minimization of the total investment TC_{RPS}on RPS units can be achieved by minimizing the RPS unit's total capacity as follows:

$$f_3 = TC_{RPS} = \sum_{i=1}^{NQ} C_{RPSi} |Q_{RPSi}| \tag{3}$$

Here, NQ is total number of units of RPS connected to RDS, C_{RPS} represents the investment for RPS devices per kVAR and Q_{RPSr} represents the reactive power requirement from i^{th} Reactive Power Source. If C_{RPS}=$1k, eq (3) turns out to be the function of the total capacity of RPS units.

2.2. Constraints

2.2.1. Constraints of equality

In RPO problem, the constraints of equality are the typical balance equations of power [21] and are given as:

$$\begin{cases} P_{gi} + P_{DGi} - P_{li} = V_i \sum_{j=1}^{N_{bus}} V_j \left(G_k \cos\theta_{ij} + B_k \sin\theta_{ij} \right) \\ Q_{gi} + Q_{DGi} + Q_{RPSi} - Q_{li} = V_i \sum_{j=1}^{N_{bus}} V_j \left(G_k \sin\theta_{ij} + B_k cos\theta_{ij} \right) \end{cases} \tag{4}$$

Where P_g and Q_g represent power outputs of generators of real and reactive nature, P_{DG} and Q_{DG} represent the real natured and reactive natured power outputs of DG, and $P_l$and Q_l represent the real and reactive natured power load at bus i. Q_{RPSi} is the reactive power of the RPS units on bus i. Susceptance value B_k of line k in the N_{bus} distribution system.

2.2.2. Constraints of inequality

(i) **Transmission capacity Constraints of Buses and Feeder**

For maintaining voltage profile of system voltage of any bus I should be within specified limits. Mathematically,

$$V_i^{min} \le V_i \le V_i^{max}, \quad i = 1,\ 2, \ldots LB \tag{5}$$

Where, V_i^{min}represents lower threshold or limit and V_i^{max} represent upper threshold or limit respectively. In addition to this, the power flowing through any line must be below its maximum limit, which can be expressed as:

$$S_k \le S_k^{max}, \quad k = 1,\ 2, \ldots nl \tag{6}$$

Where S_k^{max}denotes the maximum loading limit of kth branch.

(i) **Constraints for DGs and RPS units**

In this paper, the DGs considered are of Type III, which are able to inject the real as well as power reactive. Hence, the constraints on power reactive delivered by the RPS and by DGs are as [21]:

$$Q_{DGi}^{min} \le Q_{DGi} \le Q_{DGi}^{max} \quad i = 1,\ 2, \ldots NDG \tag{7}$$

$$Q_{RPSi}^{min} \le Q_{RPSi} \le Q_{RPSi}^{max} \quad i = 1,\ 2, \ldots NQ \tag{8}$$

Where, *NDG* stands for the number of DGs. The MOO problem is formulated as (9)-(12).

$$\text{Minimize F} = [f_1\ f_2\ \ f_3] \tag{9}$$

Subject to

$$\text{Constraints of Equality}\ \mathrm{g}(\mathrm{x}, \mathrm{u}) = 0 \tag{10}$$

$$\text{Constraints of Inequality}\ \mathrm{h}(\mathrm{x}, \mathrm{u}) \le 0 \tag{11}$$

and

$$\text{Variable bounds} ub_j \ge u_j \ge lb_j,\ j = \ 1,\ 2 \ldots n \tag{12}$$

Here ub_j and lb_j are the upper and lower bounds of j^{th} decision or control decision variable respectively and n is no. of decision variables. Different objectives of MORPO problem are given as

$f_1 = P_L(x,\ u)$,$f_2 = TV_V(x,\ u)$, and $f_3 = \mathrm{TC}_{RPS}(x,\ u)$

Here, the dependent variables $x$are expressed as

$$x^T = [V_1 \ldots., V_{LB}, S_1, \ldots., S_{nl}] \tag{13}$$

and independent or control variables $u$are expressed as

$$u^T = [Q_{DG1}, Q_{DG2}, \ldots Q_{DGNDG},\ Q_{RPS1}, Q_{RPS2}, \ldots Q_{RPSNQ}] \tag{14}$$

The equality and inequality constraints for the multi objective RPO problem are as given in Eqs. (4)–(8), while the variable bounds are shown by Eq. (12). All the solutions which are within the variable bounds and also satisfy various inequality and equality constraints form a feasible space for decision variables. Equality constraints are basically power balance equations which are satisfied when applying any load flow technique.

To apply inequality constraints and solve RPO problem using EC/SI technique, the concept of penalty function (PF) is applied, in which the objective function is modified by adding terms proportional to only the violated dependent variables ($V_i$and S_i) in order to discard any unfeasible solution. The modified or extended objective function of the problem can be expressed as follows:

$$F_1 = f_1 + \lambda_v \times \sum_{i=1}^{LB} \Delta V_i + \lambda_S \times \sum_{i=1}^{nl} \Delta S_{li} \tag{15}$$

$$\text{or} \quad F_1 = f_1 + PF \tag{16}$$

$$Similarly \quad F_2 = f_2 + PF \tag{17}$$

$$F_3 = f_3 + PF \tag{18}$$

$$\text{Where } PF \ = \ \lambda_v \times \sum_{i=1}^{LB} \Delta V_i + \lambda_S \times \sum_{i=1}^{nl} \Delta S_i \tag{19}$$

Where λ_V and λ_S are the penalty factors corresponding to limit violation of the dependent variables.

$$\Delta V_i = \begin{cases} \left|V_i^{min} - V_i\right| & if V_i < V_i^{min} \\ \left|V_i - V_i^{max}\right| if V_i \rangle V_i^{max} & \\ 0 \quad if \quad V_i^{min} \le V_i < V_i^{max} & \end{cases} \tag{20}$$

$$\Delta S_i = \begin{cases} \left(S_{li} - S_{li}^{max}\right)^2 if S_{li} > S_{li}^{max} \\ 0\ if \quad S_{li}^{min} \le S_{li} < S_{li}^{max} \end{cases} \tag{21}$$

The concept of Pareto front or set of optimal solutions in the space of objective functions in multi-objective optimization problems (MOOPs) stands for a set of solutions that are non-dominated to each other but are superior to the rest of solutions in the search space. In multi-objective optimization algorithm, there is tradeoff between the two conflicting objective functions and the two objectives are to be considered simultaneously. In this paper, the Pareto optimal solutions achieved using different MOO algorithms are also compared with those of Reference Pareto- optimal solutions. The MOO algorithm providing the results very close to that of Reference POF is considered as the superior one. The purpose of a Pareto diagram is to separate the significant aspects of a problem from the trivial ones. By graphically separating the aspects of a problem, a team will know where to direct its improvement efforts. Reducing the largest bars identified in the diagram will do more for overall improvement than reducing the smaller ones.

MMOD algorithm solves the MORPO problem by minimizing the DGs and RPS unit's reactive power integrated in the RDS and these control variables are continuous by nature.

In *Case A*, active power losses P_L and total voltage variations TV_V were minimised. In *Case B,* active power losses P_L and total investment on reactive power source units TC_{RPS} were minimised, whereas in *Case C*, active power losses P_L, total voltage variations $TV_V$and total investment on RPS units TC_{RPS} were minimised. In all the three cases, besides voltage constraints, feeder loading constraints were also considered. Once solutions are achieved by Pareto-optimal or non-dominated approach, the best preferred or compromised solution is extracted from these by utilizing membership function of fuzzy logic based approach [14-15,20].

3. MOO algorithms

With the development of various EC/ SI algorithms like Genetic Algorithm, Differential Evolution, Dragonfly Algorithm etc., these techniques are being implemented for solving a variety of engineering optimization problems.

3.1. Non-Sorting genetic algorithm-ii

In the Non-Sorting Genetic Algorithm-II (NSGA-II), the Pareto optimal set and the corresponding Pareto frontier are achieved based on elitist non-dominated sorting genetic algorithm as proposed by Deb [25, 26]. In each cycle of NSGA-II [25], the initial parent population is generated and is sorted on the basis of the rank and crowding distance. Then, tournament selection is applied to select individuals, which form a mating pool. The crossover and mutation operators are applied to generate the off-spring populations. After that, the old set of solutions and newly created solutions are combined.

The non-dominated sorting is carried out to assign fitness values to all the individuals of the combined population. At last, elitist sorting is done to select the individuals with better fitness, which become the parent individuals for next generation. These steps are repeated for a pre-defined number of generations. In the last generation, a niche strategy is used to select the members of the last front that are located in the least crowded region in the front [26]. When NSGA-II terminates, non-dominated solutions of the final population are the approximate Pareto frontier of multi-objective space [25]. Once, the non-dominated solutions are obtained, the preferred solution is extracted out of the

Pareto-optimal solutions using fuzzy membership [15].

3.2. Multi-objective differential evolution

Multi Objective Differential Evolution (MODE) algorithm is an expansion of DE algorithm, which can be implemented for solving MOO problems. Differential evolution [27] is a population-based stochastic search algorithm, wherein DE variants perturb the population members (*NP*) with the scaled difference of the randomly selected and distinct population members. The optimization process utilizes mutation, crossover and selection operators [5,28].

In MODE algorithm, each trail vector is compared only with its target vector from which it is derived. In case the trail vector dominates the target vector, it replaces the target vector for the next generation; otherwise, the target vector survives in the population. The stopping criterion used is the attainment of a pre-defined number of maximum generations. After the last generation, non-dominated sorting is performed to remove the dominated solutions [20]. Once, the Pareto-optimal solutions are obtained, the preferred solution is extracted out of the Pareto-optimal solutions using fuzzy membership [15].

3.3. Multi-objective functions dragonfly algorithm

Dragonfly algorithm (DA) is a recently proposed optimization algorithm based on the static and dynamic swarming behavior of dragonflies. Due to its simplicity and efficiency, DA has received interest of researchers from different fields. However it lacks internal memory which may lead to its premature convergence to local optima. To overcome this drawback, we propose a novel Memory based Multi-objective Dragonfly algorithm (MODA) for solving numerical optimization problems.

Multi-Objective Dragonfly (MOD) Algorithm is an extension of DA which is capable of solving MOO problems successfully. Small predators which occurs in nature are the Dragonflies, all small insects are haunted by these Dragonflies [22–23].Two main stages in a dragonfly's lifecycle are nymph and adult. A dragonfly spends the major part of its lifetime as nymph, and after metamorphism it turns into adult [23].For migration and hunting purpose these Dragonflies swarm. The earlier it is called static or feeding swarm, while afterwards itis named as the migratory or dynamic swarm [23].

The two swarming behaviours, namely hunting and migration are same as the main parts of optimization procedure, namely exploration and exploitation used in any meta-heuristic algorithm. These are considered by mathematical modeling of social behavioural interaction of dragonflies in finding the ways for searching the food, and keeping away from enemies when swarming statistically or dynamically [23]. For solving MOO problems using the DA algorithm, an archive is used for storing and improving the best estimate of the Pareto optimal solutions during the optimization process. The archive is updated regularly in each iteration. In case the archive becomes full during optimization, a mechanism [23] is used to manage the archive.

3.3.1. Modeling of artificial dragonflies

behavior of the dragonflies is summarised as steps mentioned, Cohesion (C_i), Food source (F_i) attraction, Alignment (A_i),Separation (S_i) and Distraction outwards an enemy (E_i) [23]. Mathematically, these steps are expressed as:

$$S_i = -\sum_{j=1}^{N} X - X_j \tag{22}$$

$$A_i = \frac{\sum_{j=1}^{N} v_j}{N} \tag{23}$$

$$C_i = \frac{\sum_{j=1}^{N} X_j}{N} - -X \tag{24}$$

$$F_i = X^+ - X \tag{25}$$

$$E_i = X - - - X \tag{26}$$

Here X shows current individuals position, X_j is jth adjacent individual's position, N is the number of adjacent individuals. v_j is velocity of j^{th} neighbouring individual. X^+denotes positions of food source, while X^-denotes the positions of the enemy. For position updating of an artificial dragonfly in the search space and to simulate the movements of dragonflies, two vectors, namely the step vector (ΔX) to provide the direction of movement and the position vector (X) are to be considered. The step vector ΔX_{t+1}at $(t+1)^{th}$ iteration can be calculated as:

$$\Delta X_{t+1} = (sS_i + aA_i + cC_i + fF_i + eE_i) + w\Delta X_t \tag{27}$$

Here s expresses weight of separation, a shows weight of alignment, c is the weight of cohesion, f shows factor of food, e indicates factor of enemy, w shows weight of inertia, and t denotes the iteration count. Once step vector ΔX is determined, the position vectors X is to be found out as follows:

$$X_{t+1} = X_t + \Delta X_{t+1} \tag{28}$$

In absence of neighbouring solution, random walk (Le'vy flight) updates the position of dragonflies. X (position vectors) are computed as:

$$X_{t+1} = X_t + Le^{'}vy(d) \times X_t \tag{29}$$

The neighbourhood area is enlarged and in the final stage of optimization, the swarm become one group only. This converges in the most favourable search space region and diverges in outward non-promising areas of the search space.

3.3.2. MOD algorithm for RPO problem

In following steps summary of MODA (MOD Algorithm) is given to solve problems of RPO:

i Data fetching and reading of the RDS.
ii Setting up of maximum number of iterations as IT^{MAX}.
iii Initial population generation of *NP* dragonflies X_i $(i = 1, 2 \ldots NP)$ randomly in lower and upper bounds of control variables.
iv Set the step vectors ΔX.
v Set MOD iteration count $IT = 1$.
vi Power flow (BFSPF) program of Back and forward sweep for every individual is run [29,30] to compute various objective functions.
vii Determine the extended or augmented objective functions F_1, F_2 and F_3 using (16) – (18).
viii Obtain the un-dominated solutions.
ix Update the archive.
x Select a food source $X^+$and an enemy $X^-$from the archive.
xi Modify factors *s, a, c, f, e* and *w*.
xii Determine the values of *S, A, C, F,* and *E* using (22) to (26).
xiii Update the radius of neighborhood.
xiv If least one dragonfly is nearby to dragonfly, then update step vector and position vector using (27) and (28) respectively. Otherwise, update only the position vector applying (29).
xv Considering the bounds at lower and upper levels of decision variables, modify new position vector.
xvi If $IT < IT^{MAX}$ go to step *vi* by putting $IT = IT+1$ or otherwise go to step *xvii*.
xvii End if got the best compromised solution by Pareto-optimal *NP** as obtained in step *xv* [15].

3.3.3. *Memory based MOD algorithm*

In the memory based MOD algorithm developed in this paper, the MOD algorithm is implemented for few previously-decided iterations say IT^{MAX} and solutions by Pareto-optimal approach are stored. Further next to this cycle of MMOD algorithm, MOD algorithm is implemented again making use of the stored Pareto-optimal solutions NP^* as the initial population and re-initializing residual population only. This procedure is repeated for a pre-defined say, M cycles. In every next cycle of MMOD algorithm, better values of preferred solutions are achieved.

As a final step of MMOD algorithm, a fuzzy membership based mechanism is implemented to determine the preferred solution from the Pareto-optimal solutions available at last. Flowchart of the MMOD algorithm is depicted in Fig. 1.

3.3.4. *MMOD algorithm for RPO problem*

Proposed MMOD solution algorithm to solve the MORPO problem has been summarised in following steps:

i Read the RDS data.
ii Set the maximum iterations count (IT^{MAX}) for MOD algorithm and the number of cycles M for MMOD algorithm.
iii Initialize the population randomly within the upper and lower bounds of the control variables.
iv Set MMOD cycle count $m = 1$.
v Initialize step vectors ΔX.
vi Apply MOD algorithm for IT^{MAX} iterations (step *v.* to *xvii.* Of MOD algorithm) to obtain the set of Pareto-solutions NP^*.
vii If $m \langle M$ then put $m = m + 1$ and move to step *viii*. Otherwise jump to step *x*.
viii In step *vi* Pareto-optimal solutions NP^* are obtained which is further used as the initial population of NP^* dragonflies and reinitialize the rest of the population i.e. NP - NP^*.
ix Go to step *vi*.
x Stop. Find the best compromised solution from the POS applying the fuzzy membership based mechanism [15].
xi Choose the control variables setting of the preferred solution.

Setting of Control variables in accordance with preferred solution

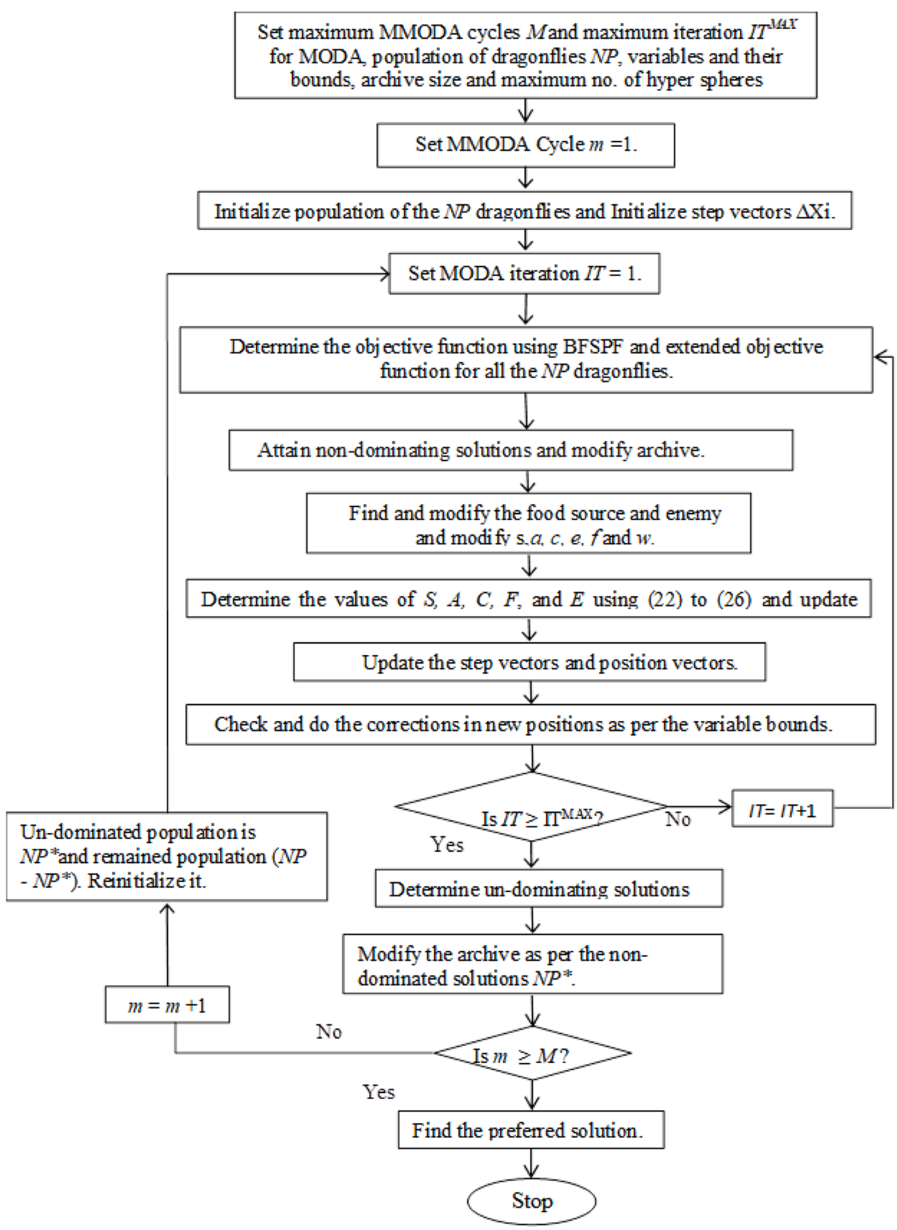

Fig. 1. Flowchart for MMOD Algorithm.

will provide the optimised objective functions values at various RDS operating conditions.

4. Results and discussion

To demonstrate the efficiency of the developed MMOD algorithm, this algorithm is employed for solving RPO problem of IEEE 33-bus and IEEE 69-bus radial distribution(RD) systems [24] penetrated with units of DGs and RPS in optimal locations as reported in [24].Performance of MMOD algorithm is assessed through NSGA-II [17,19,26] MODE [20, 27-28], MOD and modified DE [15] algorithms for taken problem of MORPO and results are compared for the cases A, B and C of radial distribution systems as follows:

Case A: P_L and TV_V Minimization
Case B: P_L and TC_{RPS} Minimization
Case C: P_L, TV_V and TC_{RPS} Minimization

EC/ SI and MMOD algorithms generate Pareto-optimal fronts (POF). To validate it MORPO to RPO problem conversion takes place with single objective function and a reference POF is generated In next step SOO algorithm like GA, DE or so are applied. In this paper, for getting Reference Pareto-front modified DE (MDE) algorithm [15] is applied. The single objective function of RPO problem which is obtained by converting MORPO problem by taking weighted sum of the normalized objective functions is P_{LN}, TV_{VN} and TC_{RPSN} as given below:

$$Minimize\ W \times P_{LN} + (1 - W) \times TV_{VN}\ \text{in}\ Case\,A \quad (30)$$

$$Minimize\ W \times P_{LN} + (1 - W) \times TC_{RPSN}\ \text{in}\ Case\,B \quad (31)$$

$$Minimize\ W_1 \times P_{LN} + W_2 \times TV_{VN} + W_3 \times TC_{RPSN}\ \text{in}\ Case C \quad (32)$$

Where, W_1, W_2 and W_3 are the weighing factors. After getting random values which lies between 0 and 1 of weighing factor W number is homogeneously distributed between 0 and 1. In (25), W_1, W_2, and-$W_3$are estimated by 0.33, 0.33 and 0.34 times the randomly placed numbers are generated between 0 and 1 respectively. For instance, to attain 30 non-inferior solutions, a single objective EC technique, say MDE is to be implemented 30 times with varying weighing factors between 0 and 1.

As discussed in Section 3, the MORPO problem is resolved by reducing reactive outputs of DGs and RPS. In this paper, assumed control variables are continuous in nature. In three cases of two radial distribution systems, at various load buses the lower limit and upper limit of voltage magnitude are considered to be 0.95pu and1.05purespectively. Besides constraints on voltage of load buses and feeder capacity is also taken into problem. Algorithmic implementations are done in MATLAB versionR2017a on Core i7with hard disk of 2.9 GHz, and 4GB of RAM.

4.1. RDS of IEEE 33-Bus

Three distributed generators of rating 794.8 kW, 1069 kW and 1029 kW are placed optimally at different buses of nos. 13, 24 and 30 respectively and IEEE 33-bus RDS is penetrated as considered reported in [24,30-31]. In addition, three shunt reactive power sources are also carried by RDS and placed optimally at bus nos. 8, 18 and 30 as given in and is shown in Fig. 2 [24,30-31]. Without installing DGs and RPS unit's active power losses are 210.98 kW and 72.83 kW, respectively, whereas the variations in total voltage are 1.8044pu and 0.6340pu, respectively. RDS is able to deliver real as well as reactive power [3] with integrated DGs. The threshold of upper and lower sides of output reactive powers DGs and RPS units are shown in Table 1.

In IEEE 33-bus RDS with three DGs and RPS units 6 decision variables are obtained. To determine reactive powers best values, MMOD algorithm is applied. Output of DGs and optimal usage of RPS units for the three cases of MORPO. Various trials were taken with different parameter setting of MMOD algorithm. The best results achieved and included here are for the dragonfly's population size NP=100, number of MMOD cycles M = 5, no. of MOD iterations IT^{MAX} equal to 100 and archive size =70. For MOD algorithm, taking NP=100, and archive size=70, the maximum iterations =500 (5 × 100).

4.1.1. Case A: P_L and TV_V minimization

With constraints on the load buses and feeder capacity voltage magnitude, MDE, MODE, MOD, MMOD and NSGA-II algorithms are implemented for optimization of reactive power as given in IEEE 33-RDS. The achieved POFs are with the Reference POF obtained by MOO algorithms and MDE algorithm as per [15] and shown in Fig. 3. It is visible in Fig. 3, that the obtained POF is closer to the reference POF.

The preferred or best compromised solution (BCS) as achieved using MMOD algorithm for the minimum P_L and minimum TV_V

Table 1
Control variables limits.

Parameter	Values
$Q^{min}_{DG13}/Q^{min}_{DG24}$ $/Q^{min}_{DG30}$	0.0kVAR
Q^{max}_{DG13}	400kVAR
$Q^{max}_{DG24}/Q^{max}_{DG30}$	600kVAR
$Q^{min}_{RPS8}/Q^{min}_{RPS18}/Q^{min}_{RPS30}$	0.0kVAR
$Q^{max}_{RPS8}/Q^{max}_{RPS18}$	450kVAR
Q^{max}_{RPS30}	600kVAR

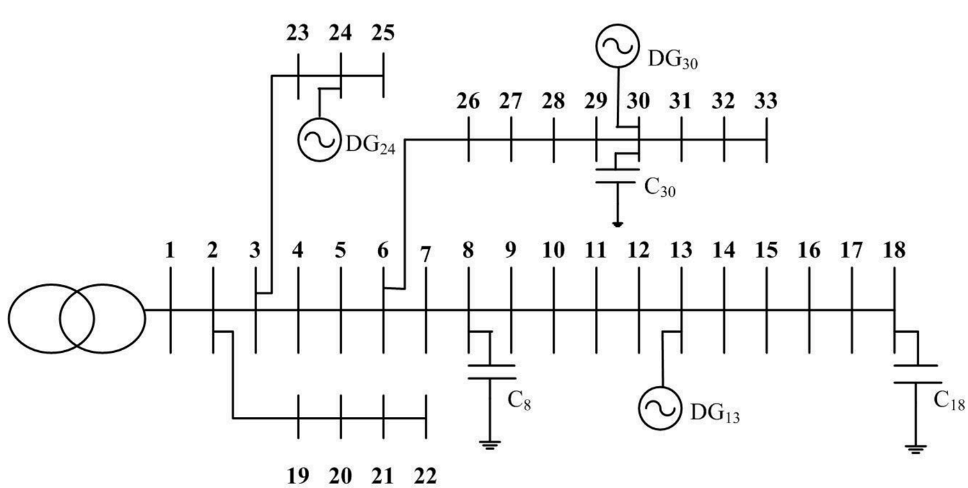

Fig. 2. IEEE 33-bus RDS Single line diagram.

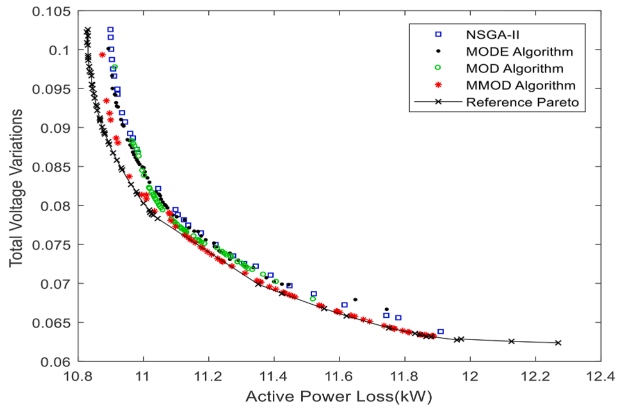

Fig. 3. POFs for P_L and TV_V minimization in IEEE 33-RDS (*Case A*).

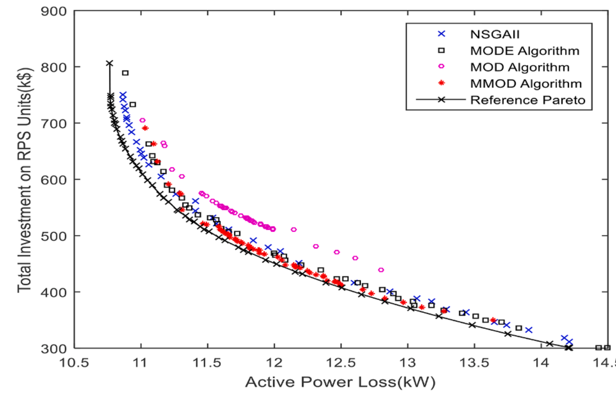

Fig. 4. POFs for P_L and TC_{RPS} minimization in IEEE 33-RDS (*Case B*).

simultaneously along with total investment on RPS units TC_{RPS} are compared with those of MDE and other MOO algorithms in Table 2 and it is clear that the developed MMOD algorithm provides minimum value of active power loss 11.0687 kW and minimum value of the total voltage variations 0.0793pucloser to reference POF. Table 2 shows, the least total investment on RPS units, minimum values of active power loss and good voltage profile when MMOD algorithm is applied. This shows the superiority of MMOD algorithm.

4.1.2. Case B: P_L and TC_{RPS} minimization

With the objectives of minimizing P_L and TC_{RPS} in IEEE 33-RDS, NSGA-II, MODE, MOD, MMOD and MDE algorithms are applied. Reference POF is compared with obtained POFs generated by algorithms as shown in Fig. 4. This is obvious in Fig. 4, the Pareto optimal front achieved using MMOD algorithm shows closeness to reference POF in comparison to those attained from other MOO algorithms. The BC solution as obtained for the minimum P_L and minimum TC_{RPS} simultaneously using MMOD algorithm are compared with those of NSGA-II, MODE, MOD and MDE in Table 3.

Decision variables are optimally set in various MOO techniques, the total voltage variations are determined and listed in Table 3. From Table 3, it is clear that MMOD algorithm provides minimum value of active power losses as 11.5620 kW and minimum value of TC_{RPS} as $521.2723k very close to Reference Pareto. Also, in case of MMOD algorithm, the total voltage variations TV_V value is least. This establishes the improved performance of the proposed MMOD algorithm over other MOO algorithms.

4.1.3. Case C: P_L, TV_V and TC_{RPS} minimization

Here, three objective functions are considered for minimization of MORPO problem. These are loss in active power P_L, variation in total voltage TV_V and RPS units total investment TC_{RPS}. With three parameter functions, NSGA-II, MODE, MOD, MMOD algorithms were employed for reactive power optimization in IEEE 33-RDS. The reference POF and obtained POFs obtained are compared as shown in Fig. 5.

Table 3
Control variables setting for BCS in IEEE 33-bus RDS (*Case B*).

Decision Variables	Method NSGAII	MODE	MODA	MMODA	MDE
Q_{DG13}	262.0402	266.2196	259.9947	275.6601	259.9537
Q_{DG24}	519.0511	521.8735	480.2185	550.0112	539.3594
Q_{DG30}	549.3313	546.9307	529.0573	543.6904	550.0102
Q_{RPS8}	122.8303	103.3851	149.3667	100.0021	100.3041
Q_{RPS18}	100.6313	100.2589	100.0100	100.0110	100.0301
Q_{RPS30}	298.4201	308.6711	307.9197	321.2592	315.7524
P_L	11.5635	11.5980	11.5626	11.5620	11.5393
TC_{RPS}	521.8817	512.3151	557.2964	521.2723	516.0866
TV_V	0.126146	0.128141	0.124384	0.121894	0.128183

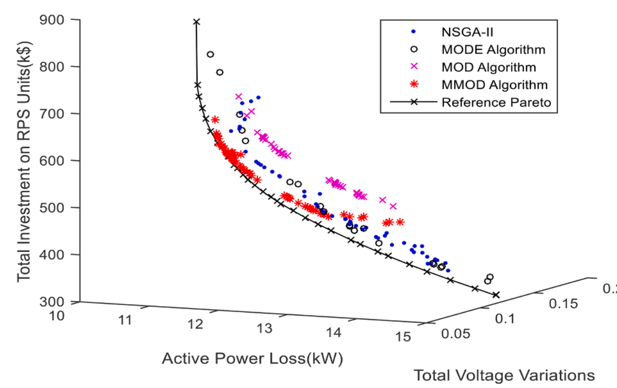

Fig. 5. POFs for P_L, TV_V and TC_{RPS} minimization in IEEE 33-RDS (*Case C*).

As obvious from Fig. 5, that the provided Pareto optimal front by MMOD algorithm and NSGA II shows closeness to reference POF more than obtained by MODE and MOD algorithms. The preferred solution as obtained for the minimum P_L, minimum TV_V and minimum TC_{RPS}

Table 2
Decision variables settings for BCS in IEEE 33-bus RDS (*Case A*).

Decision Variables	Method NSGAII	MODE	MODA	MMODA	MDE
Q_{DG13}	183.6601	196.8164	170.4846	186.1208	163.6554
Q_{DG24}	503.0211	499.2731	480.0627	492.6756	498.5274
Q_{DG30}	454.8102	403.1273	497.3783	499.1809	501.2134
Q_{RPS8}	290.8213	287.6012	294.2970	299.2027	299.9996
Q_{RPS18}	111.0904	101.7925	115.9758	108.8936	118.1273
Q_{RPS30}	525.6614	571.8772	489.7839	463.1778	479.6386
P_L	11.10199	11.0768	11.08689	11.06874	11.07851
TV_V	0.077479	0.078552	0.078184	0.079273	0.078323
TC_{RPS}	927.5731	961.2709	900.0567	871.2741	897.7655

Table 4
Control variables setting for BCS in IEEE 33-bus RDS (*Case C*).

Decision Variables	Method NSGAII	MODE	MODA	MMODA	MDE
Q_{DG13}	290.8231	299.2393	279.2644	301.4737	287.7976
Q_{DG24}	526.095	459.8671	364.7793	521.8753	535.6955
Q_{DG30}	546.1467	497.9784	541.5244	549.5562	549.9988
Q_{RPS8}	100.4428	152.1297	132.8907	131.9614	100.0101
Q_{RPS18}	100.0421	103.3977	104.2023	103.9956	100.0003
Q_{RPS30}	459.5092	383.5961	392.8250	363.9148	358.7841
P_L	11.37487	11.50513	11.46121	11.42986	11.38162
TV_V	0.087124	0.100523	0.103244	0.094375	0.107213
TC_{RPS}	659.9941	639.1235	629.9180	599.8718	558.7945

simultaneously using MMOD algorithm are compared with those of other MOO techniques and MDE in Table 4. It can be observed From Table 4, the developed MMOD algorithm gives the minimum values of P_L as 11.4299 kW, TV_V as 0.0944puand TCRPS as $599.872k, which is close to reference Pareto. This shows MMOD algorithm superiority.

4.2. IEEE 69-Bus RDS

IEEE 69-bus RDS [24,30,31] considered for RPO problem in this paper, is integrated with three DGs of 490, 390 and 1690 kW placed optimally at 11, 18 and 61number buses respectively as reported in [24], These deliver the power of real and reactive nature both [3]. In addition to 3 DGs, the system is integrated with three reactive power sources placed optimally at bus nos. 21, 61 and 64 [24,30–32] as depicted in Fig. 6. With 3 DGs and 3 RPS units in this system, 6 control variables are to be obtained using MMOD algorithm for minimizing total variation in voltage in this RD system, active power loss and total investment on RPS units.

Active power loss P_L and TV_V values without the installed DG is 224.98 kW and 1.8368pu respectively while without RPS units these are 64.45kWand 0.4531pu, respectively. Control variables limits are shown in Table 5. For this system also several trials were taken and the best results achieved and reported here are for the dragonfly's population size NP=100, MMOD cycles $M = 7$, no. of MOD iterations IT^{MAX} equal to 100 and archive size =70. For MOD algorithm, taking NP=100,and archive size=100, the maximum iterations =700 (7 × 100).

4.2.1. Case A: P_L and TV_V minimization

To reduce losses in active power and voltage variations in IEEE 69-RDS, NSGA-II, MODE, MOD, MMOD and MDE algorithms are taken into consideration. The POFs provided by NSGA-II, MODE, MOD and MMOD algorithms are shown along with the RPOF obtained using MDE algorithm [15] in Fig. 7. This is clear from Fig. 7 that the POF achieved through MMOD algorithm is very closer to the POF obtained through other multi-objective EC/SI algorithms.

The BC solution obtained using MMOD algorithm to get the minimum P_L and TV_V at the same time along with the required TC_{RPS} are compared with those of other MOO algorithms in Table 6. As is clear from Table 6, the proposed MMOD algorithm provides the least values of active power losses as 4.0243 kW and the minimum total voltage variations as 0.0460pu which are better than the results of other MOO algorithms. It can also be noted that, in case of MMOD algorithm, that TC_{RPS} is least. This establishes the efficacy of the developed MMOD algorithm.

Table 5
Decision variables limits.

Parameter	Values
$Q_{DG11}^{min}/Q_{DG18}^{min}/Q_{DG61}^{min}$	0.0kVAR
$Q_{DG11}^{max}/Q_{DG18}^{max}$	800kVAR
Q_{DG61}^{max}	1800kVAR
$Q_{RPS21}^{min}/Q_{RPS61}^{min}/Q_{RPS64}^{min}$	0.0kVAR
$Q_{RPS21}^{max}/Q_{RPS64}^{max}$	450kVAR
Q_{RPS61}^{max}	1200kVAR

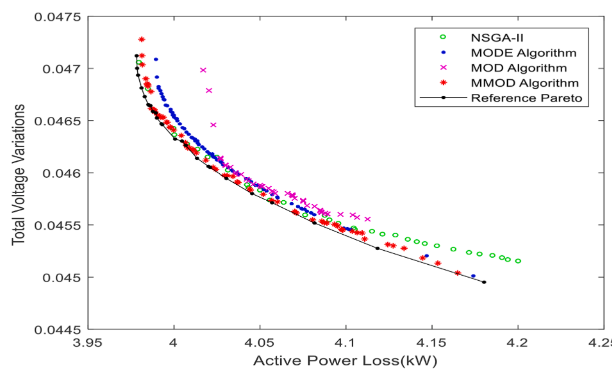

Fig. 7. POFs for P_L and TV_V minimization in IEEE 69-bus RDS (*Case A*).

4.2.2. Case B: P_L and TC_{RPS} minimization

Here, with the objectives of minimizing P_L and TC_{RPS} in IEEE 69-bus RDS, NSGA-II, MODE, MOD, MMOD and MDE algorithms are applied to optimize reactive power. The POFs attained compared in Fig. 8. This is obvious from Fig. 8, the POF achieved using MMOD algorithm is very much close to the RPOF in comparison to those achieved using MOD and

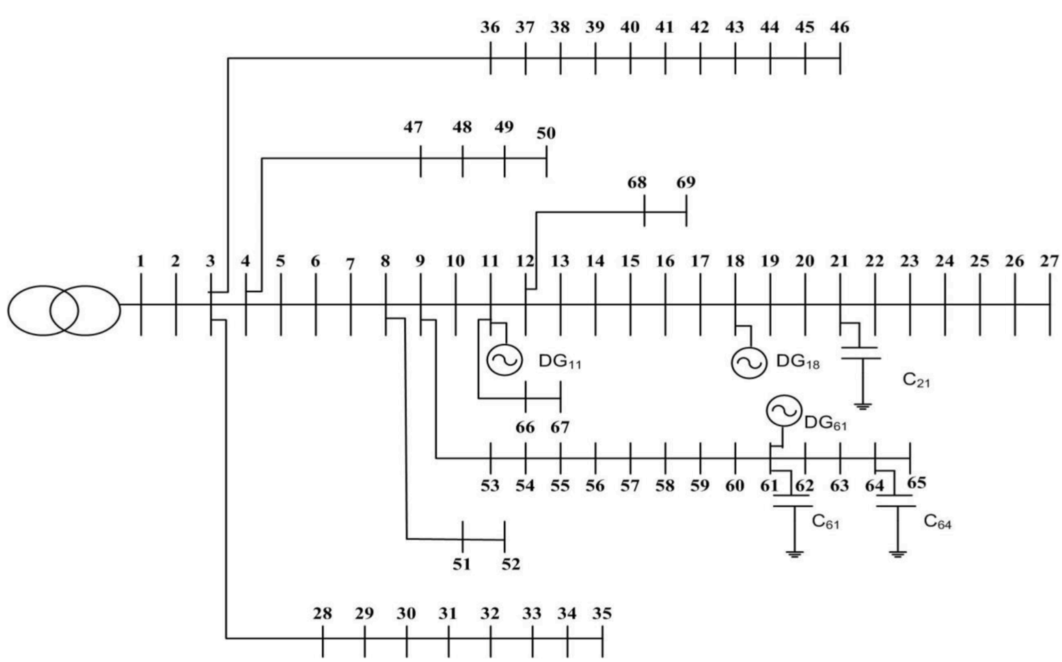

Fig. 6. IEEE 69-bus single-line diagram of.

Table 6
Control variables setting for BCS in IEEE 69-bus RDS (*Case A*).

Decision Variables	Method NSGAII	MODE	MODA	MMODA	MDE
Q_{DG11}	414.2775	404.7490	420.0714	408.5691	409.5789
Q_{DG18}	32.10598	61.29444	48.04072	68.72715	53.94960
Q_{DG61}	437.4554	339.5213	80.48297	779.9575	788.6581
Q_{RPS21}	191.6621	168.7091	178.1455	160.6941	173.9205
Q_{RPS61}	487.6501	611.0860	899.1832	156.1229	150.9739
Q_{RPS64}	265.2003	241.7839	209.3160	254.8650	251.9853
P_L	4.056017	4.018505	4.029932	4.024309	4.030472
TV_V	0.045733	0.046076	0.047069	0.046032	0.048946
TC_{RPS}	944.5125	1021.5790	1286.6447	571.6820	576.8797

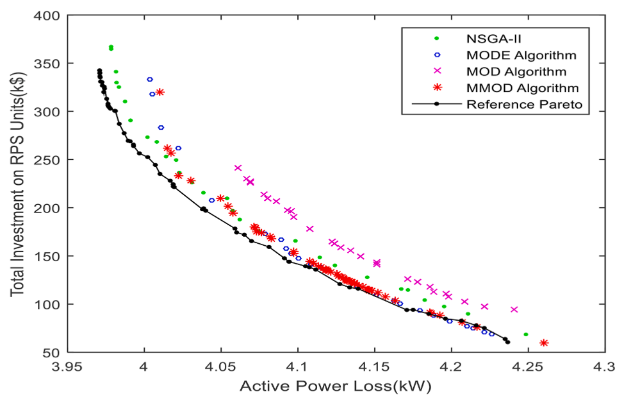

Fig. 8. POFs for P_L and TC_{RPS} minimization in IEEE 69-bus RDS (*Case B*).

other MOO algorithms.

The BC solution as achieved using MMOD algorithm for the least value of P_L and TC_{RPS} simultaneously are compared with those of other MOO techniques and reference Pareto optimal solutions in Table 7. From this Table, it can be noted that the proposed MMOD algorithm provides the minimum value of active power loss as4.0727 kW and minimum value of TC_{RPS} of $175.322k, which are closest to the results of Reference Pareto. Also the proposed MMOD algorithm shows the usefulness by providing good profile of voltage. This establishes the usefulness of the proposed MMOD algorithm.

4.2.3. *Case C: P_L, TV_V and TC_{RPS} minimization*

Here, the three objective functions are used to minimize loss in active power, total investment on RPS units and variation in total voltage. The MOO algorithms, NSGA-II, MODE, MOD, MMOD and MDE algorithms were implemented for reactive power optimization in IEEE 69-RDS. Obtained POFs by algorithms are compared and shown in Fig. 9. It is clear from Fig. 9, that the MMOD algorithm generated POF is very closer to the MOO algorithms generated RPOF. Comparison of the BC solutions as obtained for the minimum values of P_L, TV_V and TC_{RPS} simultaneously using MMOD and other MOO techniques and MDE algorithm is given in

Table 7
Control variables setting for BCS in IEEE 69-bus RDS (*Case B*).

Decision Variables	Method NSGAII	MODE	MODA	MMODA	MDE
Q_{DG11}	363.1278	348.2862	385.2924	352.6605	353.9807
Q_{DG18}	190.0551	210.4165	202.327	194.1606	223.7297
Q_{DG61}	1039.053	1033.464	1063.553	1078.18	1049.600
Q_{RPS21}	58.31866	48.99252	35.40065	53.45591	28.5009
Q_{RPS61}	27.4960	25.62532	42.97475	20.0010	22.0263
Q_{RPS64}	129.7965	133.4230	79.80293	101.8659	125.7705
P_L	4.038479	4.043666	4.127757	4.072687	4.079028
TC_{RPS}	215.6111	208.0408	158.1783	175.3228	176.3977
TV_V	0.048112	0.04823	0.048708	0.048541	0.048964

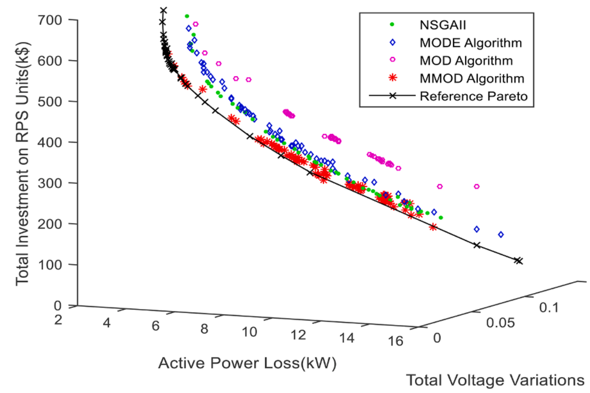

Fig. 9. POFs for P_{LOSS}, TV_V and TC_{RPS} minimization in IEEE 69-RDS (*Case C*).

Table 8
Control variables setting for BCS in IEEE 69-bus RDS (*Case C*).

Decision Variables	Method NSGAII	MODE	MODA	MMODA	MDE
Q_{DG11}	299.8183	279.6382	224.4431	296.4739	299.9995
Q_{DG18}	297.9152	302.6672	333.3952	252.8935	279.904
Q_{DG61}	599.9933	595.789	549.5095	598.4136	599.9989
Q_{RPS21}	20.0492	20.0013	25.4248	30.6742	20.0042
Q_{RPS61}	324.8003	353.6365	286.9264	171.9402	294.1239
Q_{RPS64}	172.4885	166.6963	272.2508	350.4464	244.5164
P_L	4.48107	4.413015	4.657394	4.396351	4.424356
TV_V	0.05729	0.055458	0.058591	0.054737	0.051357
TC_{RPS}	517.3380	540.3341	584.6020	553.0608	558.6445

Table 8. As is obvious from this Table, the proposed MMOD algorithm provides the minimum P_L as 4.3964 kW, minimum TV_Vas0.05474-puandminimum TC_{RPS}as$553.061k, which are better than those obtained using MOD algorithm and the results obtained using other MOO algorithms. This establishes the superiority of the proposed MMOD algorithm.

5. Conclusion

In this proposed work, a new memory-based dragonfly algorithm has been implemented to solve a multi-objective reactive power optimization problem. The competing objectives are the minimization of real power losses, improvement of voltage variation, and investment in RPS units. The memory-based multi-objective dragonfly algorithm uses the existing Pareto-optimal solutions in the next cycle of the MOD algorithm and re-initializes the remaining swarm only. The proposed MMOD algorithm has been successfully implemented to solve the MORPO problem in IEEE 33-bus and IEEE 69-bus radial distribution systems. By comparing the results with those provided by NSGAII, MODE, MOD, and MDE algorithms, it is clear that the proposed algorithm outperforms these methods in terms of solution quality and efficiency. The results and performance metrics demonstrate the efficiency of the recurring MODE algorithm and confirm its potential to solve multi-objective optimization problems in practical power systems. This study can be extended in the future by including a large number of standard buses and more control variables within constraints to improve radial distribution systems. The proposed algorithm improves the initial random population for a given problem, converges towards the global optimum, and provides very competitive results compared to other well-known algorithms in the literature [24]. The results of MODA also show that this algorithm tends to find very accurate approximations of Pareto-optimal solutions with high uniform distribution for multi-objective problems.

CRediT author statement

Himmat Singh: Conceptualization, Methodology, Formal analysis, Investigation, Software, Data curation, Writing-original draft preparation, Visualization, Validation, **Yashwant Sawle:** Methodology, Formal analysis, Investigation, Software, Data curation, Writing-original draft preparation, **Hasmat Malik:** Conceptualization, Methodology, Formal analysis, Investigation, Software, Data curation, Writing-original draft preparation, Visualization, Validation **Shishir Dixit3:** Conceptualization, Methodology, Formal analysis, Investigation, Software, Data curation, Writing-original draft preparation, Visualization, Validation, **Fausto Pedro García Márquez**: Data curation, Writing-original draft preparation, Validation, Writing-reviewing & editing, Supervision.

Declaration of 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.

Data availability

Data will be made available on request.

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