Hybrid Allocation of Capacitor and Distributed Static Compensator in Radial Distribution Networks Using Multi-Objective Improved Golden Ratio Optimization Based on Fuzzy Decision Making

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ABSTRACT In this paper, multi-objective reactive power compensation based on optimal and simultaneous allocation of capacitors and distribution static compensator (DSTATCOM) in radial distribution networks based on fuzzy decision making is proposed with the aim of reducing power losses cost, reactive investment cost and reducing voltage deviations considering power loss reduction factor (PLRF) to identify candidate buses. Optimal location and size of reactive resources is determined based using multi-objective improved golden ratio optimization algorithm (MOIGROM) inspired by Fibonacci series and improved using nonlinearly inertia weight strategy. This method is performed on a 13 bus distribution network, 69 and 118 buses IEEE standard networks in various scenarios including capacitor allocation only, DSTATCOM allocation only and optimal and simultaneous capacitor and DSTATCOM allocation (hybrid allocation). The simulation results showed that the hybrid allocation has less power losses and voltage deviations in different scenarios using fuzzy decision making based on Pareto front set. Also the impact of different loading conditions on problem solution cleared that with increasing the load level, especially during the heavy load, the power losses and voltage deviations of the networks increase and vice versa. In addition, the advantage of the MOIGROM method over the other methods is confirmed.

INDEX TERMS Radial distribution network, optimal capacitor and DSTATCOM allocation, power loss reduction factor, fuzzy decision making, multi-objective improved golden ratio optimization algorithm.

I. INTRODUCTION Part of the power system losses flow in the distribution grid is due to the reactive power, so by installing parallel capacitors in the network feeders, reactive power can be generated at the consumption site and reduce losses [1]. The capacitors are able to reduce the lines flow from the location of capacitors to power plants by reducing the reactive power demand of generators. As a result, losses and loads on distribution lines, transformers and transmission lines are reduced. By installing parallel capacitors, some of the capacity of generators and substations and transmission and distribution lines can be released. The capacitor reduces the induced current, which in turn increases the total voltage of the path from the capacitor installation to the voltage source in a radial system. Capacitors have become widely applied in radial distribution networks because of their lower cost, lower losses, lower maintenance costs and more cost-effectiveness than the other reactive power compensators and methods like distributed generation [2]. The capacitors can be reduce power and energy losses and improve voltage quality by reducing the voltage deviations [2], [3]. In addition, in recent years, D-FACT devices named distribution static compensator (DSTATCOM) is used in transmission and distribution
networks to control reactive power factor and reactive generation [4], [5]. This type of equipment is a combination of electronic power circuits and control systems with the aim of improving power quality. Single line diagram of 2-bus distribution system with D-STATCOM is presented in Figure 1. Static reactive compensator is also used in distribution and transmission networks to control the power factor and reactive power generation. The DSTATCOM controller, as a fast-response controlled source, is able to reduce the oscillations of active and reactive power, compensate for the harmonic currents drawn by variable loads, and be effective in flicker voltage and voltage regulators. Using parallel voltage source converter (VSC), power quality issues such as unbalanced load, voltage drop, voltage fluctuations and unbalanced load are also solved.

DSTATCOM converter has the ability to quickly and seamlessly generate capacitive or inductive reactive power. DSTATCOM is one of the powerful compensation devices that inject current into the network to reduce losses and voltage deviations. The DSTATCOM converter is capable to generate fast and uninterrupted of reactive power [4], [5]. Therefore, in order to take advantage of capacitors and DSTATCOM in distribution networks, the optimal location and size of these reactive sources must be properly determined. Incorrect sitting and sizing of these devices not only can’t improve the network characteristics, it may even lead to increase in network losses and wasted system costs.

The problem of reactive resource allocation in distribution networks has been categorized in previous studies based on analytical, numerical programming, heuristic and artificial intelligence methods [6], [7]. The analytical method is a simple method for solving the capacitor allocation problem that requires all assumptions, such as the non-change of load that the operator has considered in developing the algorithm. Numerical programming is a method based on formulating mathematical problems and solving those using logical operations. Numerical programming methods are iterative-based methods that are intended to maximize or minimize the objective function of a problem. The heuristic methods are based on suggestions and definite rules that those developed based on experience and judgment and also provided rapid and practical approaches to reducing search space and resulting in near-optimal solution. Artificial intelligence methods are a kind of heuristic methods that examines all possible solutions to choose the best one. Artificial intelligence-based optimization methods have also been used to optimally allocate reactive resources, especially capacitors in the distribution network [6], [7]. In [8], capacitor allocation with reconfiguration is presented in distribution network using mixed integer non linear programming with the aim of reducing energy loss cost for different loading. In [9], capacitor placement and reconfiguration is studied with hybrid shuffled frog leaping in distribution network to reduce the cost of energy losses. In [10], the location and size of capacitors in radial distribution networks is determined using the oppositional krill herd algorithm with the objective of power losses reduction for different load types as single objective optimization. In [11], the optimal capacitor placement in the radial networks is proposed by cuckoo search algorithm for power losses minimization and voltage profile improvement as multi-objective optimization based on weighted coefficient method. In [12], determination of optimum site and size of capacitors in distribution networks is evaluated using plant growth optimization for reducing power losses and improving voltage profile using weighted coefficient method. In [13], the multi-objective optimal allocation of capacitors in distribution networks is investigated using a hybrid honey bee colony algorithm with the aim of reducing power losses and harmonic with weighted coefficient method. In [14], the optimal placement of capacitors in distribution networks is studied using particle swarm optimization algorithm to reduce the power losses as single objective optimization. In [15], teaching-learning based optimization (TLBO) method is presented with the objective of minimizing the power losses and energy costs using optimal capacitor placement in radial distribution network. In [16], the optimal sizing of the capacitor in the network for loss reduction, voltage stability improvement and increase the net saving of the network is presented using artificial bee colony (ABC) algorithm based on weighted coefficient method. In [17], the optimal placement of capacitors in the distribution network to reduce the losses and increasing net saving is presented using improved harmony search algorithm (HSA). In [18], the site and size of capacitors in the network are evaluated using the aim of losses reduction and maximizing the financial benefit of using the capacitors. In [18], gravitational search algorithm (GSA) is used to solve the problem and locate the capacitors, optimally. In [19], the optimal location of capacitors in the distribution network using bacterial foraging optimization (BFO) algorithm for reducing power losses as single objective is presented. In [20], the optimal allocation of DSTATCOM along with distributed generation in the networks using PSO is studied with the objective of power losses minimization and voltage profile improvement as multi objective optimization using weighted coefficient method. In [21], the multi-objective and optimal placement of DSTATCOM in distribution networks is proposed using immune
algorithm (IA) power loss reduction and network current and voltage improvement with weighted coefficient method. In [22], the optimal placement of DSTATCOM along with DG in the networks is applied for reducing power losses using cuckoo optimization algorithm (COA) as single objective optimization. In [23], the multi-objective allocation of DSTATCOM in load variations condition in distribution networks to reduce power losses and voltage deviations based on weighted coefficient method. In [24], optimal allocation of DSTATCOM is determined with the objective of power loss minimization and voltage stability improvement using whale optimization algorithm (WOA) based on weighted coefficient method.

Investigation of the studies showed that the optimal and simultaneous allocation of capacitors and DSTATCOM in distribution networks is not well addressed. Because designers and operators of distribution networks are interested in using different equipments to compensate reactive power in distribution networks. So one of the attractive areas could be the contribution of these equipments together in compensation of the network and improving its characteristics. In addition, these reactive resources should be installed in the best buses of the network with optimal size and contribution of these equipments in compensation must be determined optimally using powerful optimization method. Investigation of literature review showed that most studies in optimization of reactive sources are as single objective or multi-objective based on weighted coefficients. The studies showed that the optimal allocation of capacitors or DSTATCOM in distribution networks is done as single objective optimization and using single objective algorithms considering the cost of power losses and reactive sources cost (single objective). On the other hand, reducing the voltage deviations of the network is one of the important features of the operation of distribution networks, which is not considered as a part of the objective function in reactive resource placement. The studies have shown that if voltage deviations are considered as part of the objective function, multi-objective optimization is solved based on weight coefficients, which is not an accurate method for solving multi-objective optimization problems because adjusting weight coefficients is one of the challenges. Using of weighted coefficients method in solving multi-objective optimization problems avoids achieving the accurate solution and correct compromises between different objectives due to choosing coefficients based on trial and error and their non-optimality. One of the best ways to solve multi-objective optimization problems is to use Pareto front approach based on fuzzy decision making method that should be used to solve the reactive power compensation problem for precise compromise between different objectives. Also, the use of high-speed and high-precision optimization methods to obtain a global solution has always been an appropriate field for previous studies.

In this paper, optimal and simultaneous allocation of DSTATCOM and capacitors (hybrid allocation) is proposed with objective of reducing power losses cost, reactive investment cost and reducing voltage deviations as multi-objective optimization based on fuzzy decision making for 13 bus (Khodabandehloo for Iran), 69 and 118 bus IEEE radial distribution networks. Power loss reduction factor (PLRF) is presented to reduce search space and to identify candidate buses for reactive resource installation. A new algorithm named multi-objective improved golden ratio optimization method (MOIGROM) inspired by the Fibonacci series [25] is presented to determine the decision variables including optimal location and size of reactive resources. In this study the superiority of the MOIGROM is proved compared to multi-objective golden ratio optimization method (MOGROM) and multi-objective particle swarm optimization (MOPSO). It should be noted that the hybrid allocation is implemented on Khodabandehloo feeder for first time. In addition, this paper assumes that the network operator has no cost constraints for reactive sources application but reactive power constraints in the grid are fully satisfied like in order to understand more accurately the effect of compensator sources on power losses and voltage deviations of distribution networks like [10]. The effect of each reactive source includes capacitor and DSTATCOM is evaluated on improvement of characteristics of the distribution network separately and their capabilities have been compared technically and economically. Also simultaneous use of both reactive sources including capacitor and DSTATCOM and the contribution of each equipment is investigated in improving the characteristics of the networks.

The highlights of this paper are as follows:

- Hybrid allocation of capacitor and DSTATCOM in compensation of radial distribution networks, simultaneously
- Using of multi-objective improved golden ratio optimization method (MOIGROM) to solve the problem
- Applying fuzzy decision making to determine the best solution of Pareto front approach
- Evaluation of different loading conditions on problem solution
- Comparison of the MOIGROM performance with MOGROM and MOPSO

The structure of the paper is as described, in Section II, PLRF, objective function and problem constraints is presented. In section III, MOIGROM formulation and applying it in problem solution is presented. In section IV, the simulation results and discussion and conclusions are described in section V.

II. PROBLEM FORMULATION

Fuzzy multi-objective allocation of capacitors and DSTATCOM in radial networks is proposed with the objective function of minimizing the power losses cost, reactive investment cost and reducing voltage deviations using MOIGROM considering PLRF. In this paper multi-objective improved golden ratio optimization algorithm (MOIGROM) is used for optimal and simultaneously allocation of capacitor and
DSTATCOM in radial distribution networks based on Pareto front set and fuzzy decision making.

A. POWER LOSS REDUCTION FACTOR (PLRF)
In this study, the PLRF is used to determine the candidate buses for reactive resource installation [17]. Based on this factor, the search space is significantly reduced and the computation time is also declined in the optimization process. Using this factor, instead of searching the algorithm for all network buses to determine the best location for reactive sources, the algorithm considers sensitive buses in view of losses for this purpose. In other words, before optimization, the PLRF factor study is performed on the base network and the sensitive buses are determined in terms of losses. The number of these buses is given to the optimization program. The optimization algorithm then selects the optimal location of the reactive resources from these buses. In this way, the search space of the algorithm is reduced and the algorithm achieves the optimal solution faster. So, the best candidate buses are selected by PLRF factor for installing reactive sources. The equation of the PLRF is defined as follows.

$$PLRF(m) = \frac{\phi(m) - \phi_{\text{min}}}{\phi_{\text{max}} - \phi_{\text{min}}}$$

where, $\phi(m)$ is reduction in active loss at bus m, $\phi_{\text{min}}$ is the minimum reduction in active loss and $\phi_{\text{max}}$ is maximum reduction in power loss. The buses with bigger PLRF are selected as candidate sites for reactive resource installation.

B. OBJECTIVE FUNCTION
The objective function of the problem is considered as minimization of power losses cost and reactive resources installation and active power purchasing cost as well as voltage deviations minimization in the distribution network [10], [18] and [26].

$$f_1 = Total\_cost = K_p \times \sum_{i=1}^{N_{\text{branch}}} R_i \times |I_i|^2 \times T + K_d \times N_d + K_{di} \times \sum_{i}^{N_d} Q_{di} + K_c \times N_c + K_{ci} \times \sum_{i}^{N_d} Q_{ci}$$

where, $f_1$ is the total power loss, $R_i$ is the $i^{th}$ branch resistance, $|I_i|$ is amount of current in branch i and $N_{\text{branch}}$ refers to the number of network branches. $K_p$ (0.06 $S$) is cost of per kW power loss, $T$ is time in hours (8760 hours), $K_d$ (1600 $S$) and $N_d$ refer to cost of per installation of DSTATCOM and number of compensated buses using DSTATCOM. $K_{di}$ (5.3 $S/kVAR$) and $Q_{di}$ are cost of per kVAR and value of DSTATCOM installed reactive power in kVAR, respectively. Also, $K_c$ (1000 $S$) and $N_c$ refer to cost per installation of capacitor and number of compensated buses using capacitor. $K_{ci}$ (3 $S/kVAR$) and $Q_{ci}$ are cost of per kVAR and value of capacitor installed reactive power in kVAR, respectively.

The objective function of voltage profile improvement due to reduction of voltage deviations is defined as follows [26].

$$f_2 = Voltage\_Deviation(\text{VD}) = \sqrt{\frac{1}{N_{\text{bus}}} \sum_{m=1}^{N_{\text{bus}}} (v_m - v_p)^2}$$

where, $v_p$ is average voltage of network buses and $N_{\text{bus}}$ indicate the number of buses. Fuzzy multi-objective solution is described in detailed in Section III.

The objective function of the problem must be optimized in the following equality and inequality constraints.

C. OPTIMIZATION PROBLEM CONSTRAINTS
Equality constraints are as follows:

- Load flow constraint

In this study, back-forward method is used for distribution network load flow. The active power injected into the network by post should be equal to the active power lost in the lines plus the active power consumption by the load. Also, the reactive power injected to the network along with the sources reactive power should be equivalent to the reactive power lost in the lines plus reactive power consumption by the load [5], [18] and [20].

The active ($P_{\text{loss}}(t)$) and reactive ($Q_{\text{loss}}(t)$) losses in line i are calculated as follows:

$$P_{\text{loss}}(i) = \frac{(P_{m,m+1}^2 + Q_{m,m+1}^2)}{|V_m|^2} \times R_{m,m+1}$$

$$Q_{\text{loss}}(i) = \frac{(P_{m,m+1}^2 + Q_{m,m+1}^2)}{|V_m|^2} \times X_{m,m+1}$$

$$P_{\text{Swing}} = \sum_{i=1}^{N_{\text{branch}}} P_{\text{loss}}(i) + \sum_{m=1}^{N_{\text{bus}}} P_{\text{load}}(m)$$

$$Q_{\text{Swing}} + \sum_{b=1}^{N_{\text{bus}}} Q_{\text{loss}}(b) = \sum_{b=1}^{N_{\text{bus}}} Q_{\text{loss}}(b) + \sum_{q=1}^{N_{\text{bus}}} Q_{\text{load}}(m)$$

where, $R_{m,m+1}$ and $X_{m,m+1}$ represents the ohmic and reactance resistance between the buses $m$ and $m+1$, respectively. $P_{\text{Swing}}$ and $Q_{\text{Swing}}$ are the active and reactive power of the slack bus. $P_{\text{load}}(m)$ and $Q_{\text{load}}(m)$ refer to the network active and reactive load connected to the bus $m$, $N_b$ is the number of installed reactive resources in the network and $\sum_{b=1}^{N_{\text{bus}}} Q_{\text{loss}}(b)$ is total reactive size installed in the network.

Non-equality constraints are as follows:

- Voltage constraint

The voltage range of the network buses should be within the minimum and maximum range as bellow:

$$V_m^{\text{min}} \leq V_m \leq V_m^{\text{max}}$$
where, $V_{min}^i$ and $V_{max}^i$ are the minimum and maximum voltages in bus $i$. These values in the distribution networks are 0.9 and 1.1 p.u., respectively.

- **Compensation constraint**
  The reactive power injected into each network bus by reactive resources must be less than its effective reactive power.

- **Total reactive power constraint**
  The reactive power transferred to the network must be less than or equal to 75% of the total reactive power required by the network load.

$$\sum_{b=1}^{N_{bs}} Q_{rs}(b) \leq \frac{3 \times \sum_{m=1}^{N_{bus}} Q_{load}(m)}{4}$$

(10)

- **Power factor constraint**
  The power factor of the network must be as follows between the minimum and maximum values.

$$PF_{\min} \leq PF \leq PF_{\max}$$

(11)

- **Line capacity constraint**
  The complex power capacity of each line of network must be less than or equal to its permissible value.

$$S_{Li} \leq S_{Li(rated)}$$

(12)

- **Compensator constraint**
  Reactive power injected into the network by reactive sources is considered as discrete units of 50 kVar [10], [15]:

$$Q_{rs,\min} \leq Q_{rs} \leq Q_{rs,\max}$$

(13)

### III. PROPOSED OPTIMIZATION METHOD

#### A. GOLDEN RATIO OPTIMIZATION ALGORITHM (GROM)

The growth of Creatures or physical phenomena such as tornadoes depends on their former conditions as a golden ratio based on the Fibonacci series, which improves their efficiency. Based on Fibonacci series, a series of numbers is generated where the sum of the two preceding numbers equals the next such that the ratio between the two integers is 1.618 called the golden ratio ($\phi$) [25]. Figure 2, shows the golden ratio in nature.

Fibonacci series numbers are presented as 1, 1, 2, 3, 5, 8, 13, 21, 34, 55, 89, 144, 233, 377, 610, 987, 1597, 2584, 4181, from the third number on, the numbers are equal to the sum of their two previous numbers.

Fibonacci numbers are calculated by a golden number, which is equal to summation of two preceding numbers [25]:

$$x_n = \phi^n - (1 - \phi)^n$$

(14)

$$x_0 = \frac{(1.618034 \ldots)^6 - (1 - 1.618034 \ldots)^6}{\sqrt{5}} = 8$$

(15)

Accordingly, the GROM is inspired to solve optimization problems. Each solution should be considered a vector and the solution should move in the best possible direction.

![Figure 2. Golden ratio in nature and physical phenomena [25].](image)

- **First phase**
  
  **Step 1**: Average population value of the algorithm is evaluated and the objective function value is computed for each population member. Worst solution is identified in terms of the objective function. If the average solution is better than the worst one, it is replaced. This eliminates the far-fetched average solutions, thus increasing the convergence speed of the algorithm.

  **Step 2**: Random vector is considered for population vector. Average population numbers are used to determine the direction and amplitude of the motion of the new vector. The three vectors including the selected vector, the random vector and the mean vector are compared to determine the direction of the new vector. Therefore, the best vector with the best value of the objective function is chosen as the main vector [25].

$$F_{best} > F_{medium} > F_{worst}$$

(16)

$$\bar{X}_i = \bar{X}_{medium} - \bar{X}_{worst}$$

(17)

The Fibonacci series and the golden ratio equation are then used to determine the range of motion in the direction of the main vector. The following Fibonacci equation is then used for global and local search [25]:

$$F_i = GF \times \frac{\phi^T - (1 - \phi)^T}{\sqrt{5}}$$

$$GF = 1.618 \& T = \frac{t}{t_{max}}$$

(18)

To evaluate the entire search space, a random move for new solution is considered that the update equation is as follows [20]:

$$X_{new} = (1 - F_i) \times X_{best} + rand \times F_i \times X_i$$

(19)

The constraints of the variables are evaluated and replaced if the objective function of the new solution is better than the previous one [25].

$$X^i = X^i_{new} \text{ if } F_{testpoint\_new} < F_{testpoint}$$

$$X^i = X^i_{old} \text{ otherwise}$$

(20)

- **Second phase**
  In this phase, each population of the algorithm tries to achieve the best value of the objective function and avoids...
approaching a bad solution. The best solution based on the golden ratio is determined as follows [25].

\[ X_{new} = X_{old} + rand \times \left( \frac{1}{GF} \right) t \times (X_{best} - X_{worst}) \quad (21) \]

**B. IMPROVED GOLDEN RATIO OPTIMIZATION ALGORITHM (IGROM)**

A nonlinearly inertia weight strategy [26] is used for Eq. (22) to improve the GROM capability in global and local discovery. Search capability is tuned by variations the \( W \) value. The \( W \) declined nonlinearly from \( W_{max} \) to \( W_{min} \). Big value of \( W \) is suitable for global discovery search and small \( W \) is suitable for local discovery search. This strategy is defined as follows:

\[ W = W_{min} + \left( \frac{1 + \cos(\frac{\pi t}{\text{\( t_{max} \)})}}{2} \right) \times (W_{max} - W_{min}) \quad (22) \]

where, \( W_{max} \) and \( W_{min} \) are max and min values of \( W \), respectively. \( t_{max} \) is maximum number of iterations and \( \chi \) is a constant that is positive (here \( \chi = 10 \) [26]).

Eq. (22) is rewritten based on decreasing inertia weight strategy as follows:

\[ X_{new} = (W_{min} + \left( \frac{1 + \cos(\frac{\pi t}{\text{\( t_{max} \)})}}{2} \right) \times (W_{max} - W_{min})) \times X_{old} + rand \times \left( \frac{1}{GF} \right) t \times (X_{best} - X_{worst}) \quad (23) \]

The solutions are then updated and one with better objective function is replaced with old one [25]:

\[ X^{i} = X^{i}_{new} \quad \text{if} \quad F^{i}_{testpoint} < F^{i}_{testpoint_{new}} \]
\[ X^{i} = X^{i}_{old} \quad \text{otherwise} \quad (24) \]

**C. MULTI-OBJECTIVE IMPROVED GOLDEN RATIO OPTIMIZATION ALGORITHM (MOIGROM)**

In this paper Pareto front optimal approach is used for implementing the multi-objective optimization based GROM (MOIGROM), that is formulated as minimization problem as follow [27]:

\[
\begin{align*}
\text{minimize} & : \quad F(\mathbf{x}) = f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_o(\mathbf{x}) \\
\text{subjected to} & : \quad g_s(\mathbf{x}) \geq 0, \quad s = 1, 2, 3, \ldots, z \\
& : \quad h_s(\mathbf{x}) = 0, \quad s = 1, 2, \ldots, y \\
& : \quad L_s \leq x \leq U_s 
\end{align*}
\]

where, \( o \) is objective numbers, \( y \) and \( z \) are inequality and equality constraint numbers respectively, and \([L_s, U_s] \) is the boundary of variable \( x \).

The Pareto front optimization method allows comparing search space of multi-objective between two solutions. In the MOGOA method, an archive is created to store and retrieve the best Pareto solution. Investigation of the best and worst Pareto objectives to obtain the best solution a roulette wheel is applied as follows:

\[ RW_{Pr,k} = \frac{\delta}{NU_{ps,k}} \quad (29) \]

where, \( \delta \) refers to a constant number (more than 1) and \( NU_{ps,k} \) is Pareto solution numbers in area \( k \).

In this paper fuzzy decision making is used to determine the optimum solutions from the Pareto set method. Membership function is presented for objective of \( \sigma \) to solve the Pareto sets as follows [27]:

\[
\mu_{\xi_\sigma} = \begin{cases} 
\frac{f_{\sigma} - f_{\sigma_{\sigma_{\min}}} \quad f_{\sigma} \leq f_{\sigma_{\sigma_{\min}}} \\
\frac{f_{\sigma_{\sigma_{\max}} - f_{\sigma_{\sigma_{\min}}} \quad f_{\sigma_{\sigma_{\min}}} \leq f_{\sigma} \leq f_{\sigma_{\sigma_{\max}}} \\
0 \quad f_{\sigma} \geq f_{\sigma_{\sigma_{\max}}} 
\end{cases} \quad (30) 
\]

where, \( F_{\sigma_{\sigma_{\min}}} \) and \( F_{\sigma_{\sigma_{\max}}} \) refer to minimum and maximum level of objective \( \sigma \).

The \( \mu_{\xi_\sigma} \) for solution \( \beta \) is formulated as follows:

\[
\mu_{\xi_\beta} = \frac{\sum_{\sigma=1}^{o} \mu_{\xi_\sigma}^\beta}{\sum_{\sigma=1}^{o} \mu_{\xi_\sigma}^\beta} \quad (31) 
\]

where, \( o \) refers to objective function numbers and \( m \) clear solution numbers.

**D. IMPLEMENTATION OF MOIGROM IN PROBLEM SOLUTION**

The steps of the MOIGROM implementation in solving the fuzzy multi-objective allocation of reactive resource as shown in Figure 3 are as follows:

**Step 1):** Determine parameters of the MOIGROM including maximum iteration and population number as well as apply network data including line impedance, bus data (active and reactive load power required).

**Step 2):** After modeling the distribution test network, the backward-forward load flow for the base state is performed and the candidate buses are determined based on the PLFR for reactive sources installation.

**Step 3):** The candidate buses specified in step 2 considered in the optimization program as the default reactive resource installation locations.

**Step 4):** Optimization variables are applied to each population member of the MOIGROM algorithm between their permitted ranges and implemented the load flow. The objective function is defined for each population (the variable set including the location and size of reactive resources).

**Step 5):** Population is updated based on the MOIGROM.

**Step 6):** The load flow is done for new population of the MOIGROM and the objective function is calculated for each new population member. If the objective function value at this stage is less than one obtained in step 4, the solution must be replaced.

**Step 7):** If the convergence condition (minimum objective function and maximum iteration of MOIGROM) is reached go to next step or else go to step 5.

**Step 8):** Stop the MOIGROM and print the results (optimal variables)

**IV. SIMULATION AND RESULTS**

The results of optimal and simultaneously fuzzy multi-objective allocation of capacitors and DSTATCOM is
A. RESULTS OF 13 BUS NETWORK (KHODABANDEHLOO)

The results of optimal placement and sizing of capacitors and DSTATCOM are performed on a network called “Khodabandehloo” for Tehran, Iran country. So far, study of capacitor and DSTATCOM allocation has not been performed on this network. Given the importance of compensating based on reactive resources, 13 bus Khodabandehloo network is presented with the objective of power losses and voltage deviations reduction using the MOIGROM algorithm for 13 bus network in Tehran (Iran country), IEEE 69 and 118 bus networks. The schematics of the 13, 69 and 118 bus networks are shown in Figures 4-6, respectively. The 13 bus network has 12 branches and its data is taken from Ref [29]. In 13 bus network, the total active power consumption is 3.72 MW and reactive power is 2.3 MVar. The total active and reactive load consumption of the 69 bus network is 3.802 MW and 2.696 MVar, respectively. The 69 bus network has 68 branches and its data are extracted from the Ref [30]. The 118 bus network also consists of 118 bus and 117 branches. The total active and reactive load consumption of the 118 bus network is 22.709 MW and 17.041 MVar, respectively [30]. In this paper, the results including the amount of power loss, power loss cost, minimum voltage, voltage deviations, reactive cost, voltage profile curves and power losses of 13, 69 and 118 bus network lines are presented.
selected for this purpose. The PLFR curve for the 13 bus network is presented in Figure 6. According to the PLFR, buses of 7, 4, 12, 9, 10, 13 and 5 are considered as candidate buses for reactive resource placement.

The results of optimal and simultaneously fuzzy multi-objective allocation of capacitors and DSTATCOM are presented with objective of power losses and voltage deviations reduction using MOIGROM method for 13 bus Khodabandehloo network based on PLFR. Simulations are implemented in three scenarios of optimal allocation of capacitors only, DSTATCOM allocation only and simultaneously capacitor and DSTATCOM allocation (hybrid allocation). The simulation results according to Pareto front set for fuzzy multi-objective allocation of each scenarios using MOIGROM showed that the network performance is more improved with the hybrid allocation. In this study, the maximum iterations of algorithms is considered 200 and its population is selected 50 and the performance of MOIGROM method is compared with MOGROM and multi-objective particle swarm optimization (MOPSO) methods. Based on Figures 8-10, the hybrid allocation based on fuzzy multi-objective optimization obtained less power loss and voltage deviations than the other scenarios.

The results of each simulation scenario for the 13 bus network are given in Table 1. As can be seen, the values of power losses and voltage deviations in the hybrid allocation are lower than the other scenarios, indicating better network performance in this scenario. The MOIGROM determines two capacitors in 7 and 12 buses with sizes of 1451 and 1256 kVar and one DSTATCOM in bus 9 with size of 1432 kVar, respectively for installation. The power loss in the hybrid allocation considering MOIGROM, decreased from 175.59 kW to 129.00 kW. Also the network voltage deviations are reduced from 0.0061 p.u to 0.0046 p.u. The minimum voltage also increased from 0.9790 p.u to 0.9846 p.u. In addition, it is obvious that the performance of the MOIGROM is better at reducing power losses and network voltage deviations as well as improving the minimum network voltage than the MOGROM and MOPSO methods. In Hybrid allocation the power loss values for the MOIGROM, MOGROM and MOPSO methods are obtained 129.00, 132.11 and 130.47 kW, respectively. The minimum network voltage for the MOIGROM, MOGROM and MOPSO methods are 0.9846, 0.9844 and 0.9845 p.u, respectively. Therefore the MOIGROM is proposed as a suitable method for sitting and sizing of capacitors and DSTATCOM in distribution networks.

The results of different loadings effect on the implementation of MOIGROM-based hybrid allocation are presented in Table 2. In this study, the light load level is 62.5% of the normal load (results of Table 1, for hybrid allocation) and the heavy load level is 125% of normal load. According to Table 2, it is observed that as the load level increases, the network losses increase and the network voltage is attenuated, and vice versa. The network losses in the light load, normal load and heavy load periods are 55.94, 129 and 199.59 kW, respectively, and the voltage deviation values for these periods are 0.0033, 0.0046 and 0.0051 p.u, respectively using MOIGROM.
TABLE 1. Results of Khodabandehloo 13 bus distribution network.

| Only Capacitor Allocation | Base Net | MOPSO | MOGROM | MOIGROM |
|---------------------------|---------|-------|---------|---------|
| Size (kW)/Location (bus) | --      | 770/4 | 1500/7 | 1433/7  |
|                          |         | 1500/7 | 1211/10 | 996/12  |
| Power Losses (kW)        | 175.59  | 137.59 | 137.88  | 136.94  |
| Power Losses cost ($)     | 92290   | 72317  | 72007   | 71979   |
| Reactive cost ($)         | --      | 14268  | 14850   | 14150   |
| Total cost ($)            | --      | 86585  | 86857   | 86079   |
| VD (p.u)                  | 0.0061  | 0.0047 | 0.0047  | 0.0047  |
| Min Voltage (p.u)         | 0.9790  | 0.9837 | 0.9837  | 0.9838  |
| CPU Time (s)              | --      | 757    | 789     | 722     |

| Only DSTATCOM Allocation | Base Net | MOPSO | MOGROM | MOIGROM |
|---------------------------|---------|-------|---------|---------|
| Size (kW)/Location (bus) | --      | 1005/4| 1364/7 | 1386/7  |
|                          |         | 1500/12| 1500/9 | 1229/10 |
|                          |         | 996/12 | 996/12 | 1195/12 |
| Power Losses (kW)        | 175.59  | 136.07 | 136.11  | 134.45  |
| Power Losses cost ($)     | 92290   | 71518  | 71539   | 70668   |
| Reactive cost ($)         | --      | 22965  | 23200   | 22950   |
| Total cost ($)            | --      | 94483  | 94739   | 93618   |
| VD (p.u)                  | 0.0061  | 0.0048 | 0.0048  | 0.0047  |
| Min Voltage (p.u)         | 0.9790  | 0.9837 | 0.9837  | 0.9839  |
| CPU Time (s)              | --      | 885    | 937     | 834     |

| Capacitor and DSTATCOM Allocation, Simultaneously (Hybrid allocation) | Base Net | MOPSO | MOGROM | MOIGROM |
|---------------------------------------------------------------------|---------|-------|---------|---------|
| Size (kW)/Location (bus)                                           | --      | 1199/7 (C) | 1500/4 (C) | 1451/7 (C) |
|                                                                  |         | 1500/12 (C) | 535/9 (C) | 1256/12 (C) |
|                                                                  |         | 1443/10 (D) | 790/10 (D) | 1432/9 (D) |
| Power Losses (kW)                                                  | 175.59  | 130.47 | 132.11  | 129.00  |
| Power Losses cost ($)                                              | 92290   | 67803  | 69437   | 67803   |
| Reactive cost ($)                                                  | --      | 18612  | 22150   | 18878   |
| Total cost ($)                                                     | --      | 86381  | 91587   | 86381   |
| VD (p.u)                                                           | 0.0061  | 0.0046 | 0.0047  | 0.0046  |
| Min Voltage (p.u)                                                  | 0.9790  | 0.9845 | 0.9844  | 0.9846  |
| CPU Time (s)                                                       | 903     | 975    | 852     |         |

* C: capacitor and D: DSTATCOM

TABLE 2. Results of hybrid allocation simulation in different loading for Khodabandehloo 13 bus network using MOIGROM.

| Hybrid allocation | Light Load (Base Net) | Light Load (Optimized) | Normal Load (Base Net) | Normal Load (Optimized) | Heavy Load (Base Net) | Heavy Load (Optimized) |
|-------------------|-----------------------|------------------------|------------------------|-------------------------|-----------------------|------------------------|
| Size (kW)/Location (bus) | 1273/12 (D) | 1318/10 (C) | 1451/7 (C) | 1106/7 (C) | 1314/12 (C) | 1500/9 (D) |
| Power Losses (kW) | 67.60 | 55.94 | 175.59 | 129.00 | 277.09 | 199.59 |
| Power Losses cost ($) | 35531 | 29407 | 92290 | 67803 | 145640 | 104960 |
| Reactive cost ($) | -- | 12619 | -- | 18578 | -- | 22888 |
| Total cost ($) | -- | 36957 | -- | 86381 | -- | 127900 |
| VD (p.u) | 0.0038 | 0.0033 | 0.0061 | 0.0046 | 0.0078 | 0.0051 |
| Min Voltage (p.u) | 0.9870 | 0.9887 | 0.9790 | 0.9846 | 0.9737 | 0.9829 |

The 13 bus network voltage profiles before and after of different allocations using the MOIGROM are shown in Figure 11. It is observed that the voltage deviations of the hybrid allocation are less than the other compensation methods. Also, the power loss curve of the 13 bus network lines is presented using different compensation methods.
in Figure 12. It can be seen that the power losses of the network lines are less using the hybrid allocation than the other methods.

B. RESULTS OF 69 BUS IEEE NETWORK
The results of capacitors and DSTATCOM fuzzy multi-objective allocation on the 69 bus network are implemented using the MOIGROM. The PLFR curve for the IEEE 69 bus network is shown in Figure 13. According to the PLFR curve, buses of 61, 64, 59, 65, 21, 12, 11, 62, 18, 17 and 16 are selected as candidate buses for reactive source installation.

For the 69 bus network, simulations are performed in three scenarios include optimal allocation of capacitors only, DSTATCOM only and optimal and simultaneous fuzzy multi-objective allocation of capacitors and DSTATCOM (hybrid allocation) with the aim of reducing power losses and network voltage deviations using the MOIGROM based on PLFR. The simulation results, similar to results for the 13 bus network according to Figures 14-16, showed that the hybrid allocation has the least losses and voltage deviations. The Pareto front set and fuzzy best solution for different compensation methods using MOIGROM are shown in Figures 14-16. Capability of the MOIGROM is compared with MOGROM and MOPSO methods in problem solution. The superiority of the MOIGROM in achieving the less power loss and voltage deviations proves the better capability of the MOIGROM compared to other methods in 69 bus distribution network compensation.

The numerical results of different compensation methods for 69 bus network are presented in Table 3. The lowest power losses and voltage deviations are obtained in the hybrid allocation and compared to other scenarios. The MOIGROM determined one capacitor in bus 61 with size of 1117 kVar, and one DSTATCOM in buses 64 with size of 677 kVar, respectively. The power loss in the hybrid
allocation is reduced from 224.98 kW to 138.29 kW based on the MOIGROM. The network voltage deviations are decreased from 0.0270 p.u to 0.0185 p.u. The minimum voltage of the network also increased from 0.9092 p.u to 0.9412 p.u. Therefore, the performance of the MOIGROM is better than the MOGROM and MOPSO methods in reducing power losses and voltage deviations of the network as well as improving minimum voltage. In hybrid allocation, the power losses for MOIGROM, MOGROM and MOPSO methods are 138.29, 140.17 and 139.65 kW, respectively and minimum voltage for each algorithms are obtained 0.9412, 0.9410 and 0.9411 p.u, respectively. Therefore, the MOIGROM is desirable algorithm based fuzzy decision making to allocate the reactive sources in the distribution networks, optimally.

The results of different loading conditions on the reactive sources compensation with the hybrid allocation and using MOIGROM is presented in Table 4. According to Table 4, as the load level of the network increases, the voltage of the network increases, and vice versa. The network losses in light load, normal load and heavy load conditions are 49.56, 138.29 and 232.11 kW, respectively. The voltage deviation values for these conditions are 0.0123, 0.0185 and 0.0226 p.u, respectively, using the MOIGROM.

The 69 bus network voltage profile is depicted in Figure 17, before and after implementation of different compensation method using the MOIGROM. It is obvious that the voltage deviations are declined considerably using hybrid allocation and less than the other methods. In addition, Figure 18 shows that the losses of the network lines have significantly decreased using the hybrid allocation and less than the other methods.

C. RESULTS OF 118 BUS IEEE NETWORK

The results of capacitors and DSTATCOM fuzzy multi-objective allocation on the 118 bus network are implemented using the MOIGROM. The PLFR curve for the IEEE 118 bus network is shown in Figure 19. According to the PLFR curve, buses of 70, 104, 78, 68, 106, 108, 65, 31, 69, 67, 89, 64, 103, 101, 42, 46, 58, 30, 23 and 47 are selected as candidate buses for reactive source installation. The simulation results, similar to results for the 118 bus network according to Figures 20-22, showed that the hybrid allocation has the least losses and voltage deviations. The Pareto front set and fuzzy best solution for different compensation methods using MOIGROM
are shown in Figures 20-22. Superiority of the MOIGROM is compared with MOGROM and MOSPSO methods in problem solution. The superiority of the MOIGROM in achieving the less power loss and voltage deviations proves the better capability of the MOIGROM compared to other methods in 118 bus distribution network compensation. The numerical results of different compensation methods for 118 bus network are presented in Table 6. The lowest power losses and voltage deviations are obtained in the hybrid allocation and compared to other scenarios.

The MOIGROM determined five capacitors in buses 31, 47, 70, 78 and 106 with sizes of 1500, 520, 1500, 752 and 1200 kVar, and six DSTATCOMs in buses 23, 58, 64, 89, 101 and 108 with capacities of 1500, 966, 1500, 1433, 1497 and 1299 kVar, respectively. The power loss in the hybrid allocation is reduced from 1298.10 kW to 820.50 kW based on the MOIGROM. The network voltage deviations are decreased from 0.0323 p.u to 0.0169 p.u. The minimum voltage of the network also increased from 0.8688 p.u to 0.9286 p.u. Therefore, the performance of the MOIGROM is

### Table 3. Results of IEEE 69 bus distribution network.

| Only Capacitor Allocation | Base Net | MOPSO | MOGROM | MOIGROM |
|---------------------------|----------|-------|--------|---------|
| Size (kW)/Location (bus)  | --       | 1335/61 | 1500/61 | 1326.8/61 |
| Power Losses (kW)         | 224.98   | 154.80 | 154.89 | 154.47   |
| Power Losses cost ($)     | 118249   | 81362  | 81194  | 81194    |
| Reactive cost ($)         | --       | 7529   | 7667   | 7250     |
| Total cost ($)            | 118249   | 88891  | 88861  | 88444    |
| VD (p.u)                  | 0.0270   | 0.0189 | 0.0189 | 0.0188   |
| Min Voltage (p.u)         | 0.9092   | 0.9408 | 0.9408 | 0.9409   |
| CPU Time (s)              | --       | 1689   | 1722   | 1655     |

### Table 4. Results of hybrid allocation simulation in different loading for IEEE 69 bus network using MOIGROM.

| Capacitor and DSTATCOM Allocation | Base Net | MOPSO | MOGROM | MOIGROM |
|-----------------------------------|----------|-------|--------|---------|
| Size (kW)/Location (bus)          | --       | 1500/12 | 1518/61 | 1500/61 |
| Power Losses (kW)                 | 224.98   | 145.47 | 145.53 | 144.90   |
| Power Losses cost ($)             | 118249   | 76459  | 76490  | 76159    |
| Reactive cost ($)                 | --       | 16170  | 16205  | 16015    |
| Total cost ($)                    | --       | 92629  | 92695  | 92174    |
| VD (p.u)                          | 0.0270   | 0.0187 | 0.0187 | 0.0186   |
| Min Voltage (p.u)                 | 0.9092   | 0.9410 | 0.9410 | 0.9410   |
| CPU Time (s)                      | --       | 1877   | 1935   | 1819     |

### Table 5. Results of hybrid allocation simulation in different loading for IEEE 69 bus network using MOIGROM.

| Hybrid allocation | Light Load (Base Net) | Light Load (Optimized) | Normal Load (Base Net) | Normal Load (Optimized) | Heavy Load (Base Net) | Heavy Load (Optimized) |
|-------------------|-----------------------|------------------------|------------------------|------------------------|----------------------|------------------------|
| Size (kW)/Location (bus) | 946/21 (D) | 257/661 (C) | 1117/61 (D) | 393/65 (C) | 677/64 (C) | 757/59 (C) |
| Power Losses (kW)   | 82.28 | 49.56 | 224.98 | 138.29 | 396.02 | 232.11 |
| Power Losses cost ($) | 43246 | 26050 | 118249 | 72686 | 208150 | 122940 |
| Reactive cost ($)    | -- | 7800 | -- | 10415 | -- | 14885 |
| Total cost ($)       | -- | 33850 | -- | 82600 | -- | 137820 |
| VD (MWh/yr)           | 0.0163 | 0.0123 | 0.0270 | 0.0185 | 0.0346 | 0.0226 |
| Min Voltage (p.u)     | 0.9452 | 0.9596 | 0.9092 | 0.9412 | 0.8834 | 0.9273 |
TABLE 5. Results comparison of 69 bus distribution network.

| Hybrid allocation | MOIGROM (hybrid allocation) | MOIGROM (capacitor allocation) | MOIGROM (DSTATCOM allocation) | GA [31] | DE-PS [32] | FGA [33] | BA [34] | GWO [35] | WCA [35] |
|-------------------|-----------------------------|--------------------------------|--------------------------------|---------|------------|----------|---------|----------|----------|
| Size (kW)/Location (bus) | 1117/61(D) 677/64(C) | 1500/61(C) 397/64(C) 526/59(C) | 1500/61(D) 397/64(D) 526/59(D) | 754/16(D) | 453/31(D) | 150/57(C) 50/58(C) 100/59(C) | 150/59(C) 700/61(C) 800/64(C) | 1150/42/61(D) | 600/16(C) 900/60(C) 1050/61(C) | 600/--(C) 900/--(C) 900/---(C) |
| Power Losses (kW) | 138.29 | 154.47 | 144.90 | 173.23 | 151.37 | 156.62 | 153.36 | 146.74 | 146.73 |
| VD (MW/yr) | 0.0185 | 0.0188 | 0.0186 | -- | -- | -- | -- | -- | -- |
| Min Voltage (p.u) | 0.9412 | 0.9409 | 0.9410 | 0.9399 | 0.9311 | 0.9369 | 0.9278 | 0.9322 | -- |

better than the MOIGROM and MOPSO methods in reducing power losses and voltage deviations of the network as well as improving minimum voltage. In hybrid allocation, the power losses for MOIGROM, MOGROM and MOPSO methods are 820.50, 822.10 and 822.66 kW, respectively and minimum voltage for each algorithms are obtained 0.9286, 0.9284 and 0.9284, respectively. Therefore, the MOIGROM is desirable algorithm based fuzzy decision making to allocate the reactive sources in the distribution networks, optimally.

The 118 bus network voltage profile is depicted in Figure 23, before and after implementaion of different compensation method using the MOIGROM. It is obvious that the voltage deviations are declined considerably using hybrid allocation and less than the other methods. In addition, Figure 24 shows that the losses of the network lines have significantly decreased using the hybrid allocation and less than the other methods.

D. RESULTS COMPARISON WITH LAST STUDIES

In this section, the results of simulated scenarios are compared with some of last studies. In [31], the optimal allocation of DSTATCOM is presented for reducing power losses using GA method. In [32], optimal capacitor allocation with the aim of improving network voltage profile and reducing power losses using differential evolutionary-pattern search (DE-PS) method is evaluated. In [33], optimal allocation of capacitors in 69 bus network is studied with the aim of improving voltage profile and reducing the cost of losses using fuzzy-genetic algorithm (FGA). In [34], allocation of DSTATCOM in 69 bus network with objective of power loss reduction is investigated for allocation of one DSTATCOM using BA. In [34], [35], capacitor placement in 69 bus distribution network using grey wolf optimizer (GWO) and water cycle algorithm (WCA) is investigated. Comparing the results of the scenarios presented in this paper with the GA, DE-PS and FGA methods according to Table 5, it can be seen that the hybrid allocation is achieved power loss equal to 138.29 kW, voltage deviation 0.0185 p.u and also minimum


| TABLE 6. Results of IEEE 118 bus distribution network. |
|--------------------------------------------------------|
| Only Capacitor Allocation                               |
| Base Net                                               |
| voltage value of 0.9412 p.u. Therefore the capability and |
| better performance of the hybrid allocation using MOIGROM |
| is confirmed compared to the other methods. Moreover the |
| obtained results of 118 bus network are compared with the |
| DSTATCOM allocation in [36] in Table 7. In [36], optimal |
| allocation of DSTATCOM with objective of minimizing |
| power loss and costs are presented using bacterial foraging |
| optimization (BFO) algorithm. It is clear that the power loss, |
| voltage value of 0.9412 p.u. Therefore the capability and |
| better performance of the hybrid allocation using MOIGROM |
| is confirmed compared to the other methods. Moreover the |
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| DSTATCOM allocation in [36] in Table 7. In [36], optimal |
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| voltage value of 0.9412 p.u. Therefore the capability and |
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| is confirmed compared to the other methods. Moreover the |
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| better performance of the hybrid allocation using MOIGROM |
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| voltage value of 0.9412 p.u. Therefore the capability and |
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| is confirmed compared to the other methods. Moreover the |
| obtained results of 118 bus network are compared with the |
| DSTATCOM allocation in [36] in Table 7. In [36], optimal |
| allocation of DSTATCOM with objective of minimizing |
| power loss and costs are presented using bacterial foraging |
| optimization (BFO) algorithm. It is clear that the power loss, |
| voltage value of 0.9412 p.u. Therefore the capability and |
| better performance of the hybrid allocation using MOIGROM |
| is confirmed compared to the other methods. Moreover the |
| obtained results of 118 bus network are compared with the |
| DSTATCOM allocation in [36] in Table 7. In [36], optimal |
| allocation of DSTATCOM with objective of minimizing |
| power loss and costs are presented using bacterial foraging |
| optimization (BFO) algorithm. It is clear that the power loss, |
| voltage value of 0.9412 p.u. Therefore the capability and |
| better performance of the hybrid allocation using MOIGROM |
| is confirmed compared to the other methods. Moreover the |
| obtained results of 118 bus network are compared with the |
| DSTATCOM allocation in [36] in Table 7. In [36], optimal |
| allocation of DSTATCOM with objective of minimizing |
| power loss and costs are presented using bacterial foraging |
| optimization (BFO) algorithm. It is clear that the power loss,
In this paper, new hybrid allocation of reactive sources consists of capacitor and DSTATCOM is implemented using the MOIGROM on the distribution network of 13 bus Khodabandehloo, 69 and 118 bus IEEE networks based on multi-objective optimization and fuzzy decision making. The objective function of the problem is considered minimization of power losses cost, reactive investment cost and voltage deviations reduction in the networks. Candidate buses are first determined for capacitor and DSTATCOM installation using power loss reduction factor (PLRF) to reduce computation time and search space for each distribution network and then optimal sitting and sizing of reactive resources are determined using the golden ratio optimization method. Compensation of distribution networks is evaluated by optimal allocation of capacitors only, DSTATCOM only, as well as hybrid allocation using MOIGROM on the 13 bus Khodabandehloo network. Moreover, the results are showed that the network losses for the hybrid allocation using MOIGROM for 118 bus network.

## V. CONCLUSION

In this paper, new hybrid allocation of reactive sources consists of capacitor and DSTATCOM is implemented using the MOIGROM on the distribution network of 13 bus Khodabandehloo, 69 and 118 bus IEEE networks based on multi-objective optimization and fuzzy decision making. The objective function of the problem is considered minimization of power losses cost, reactive investment cost and voltage deviations reduction in the networks. Candidate buses are first determined for capacitor and DSTATCOM installation using power loss reduction factor (PLRF) to reduce computation time and search space for each distribution network and then optimal sitting and sizing of reactive resources are determined using the golden ratio optimization method. Compensation of distribution networks is evaluated by optimal allocation of capacitors only, DSTATCOM only, as well as hybrid allocation using MOIGROM on the 13 bus Khodabandehloo network. Moreover, the results are showed that the network losses for the hybrid allocation using MOIGROM for 118 bus network.

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