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Optimal Allocation of DG using Hybrid Optimization Technique for Minimizing the Power Loss

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Abstract: *In recent days, the utility grids (renewable resources) facing critical issues in the power generation system due to continuous load development. The traditional power grids are incapable of generating necessary power supply with respect to the load demand. The other issue in the distribution network is power loss during the transmission of generated power. In order to overcome these issues, the Distributed Generation (DG) is utilized in power generation system to maintain the system steadiness, and reject the distribution system bottleneck to satisfy the load demand. This research paper proposed a methodology for placing the DG in appropriate location and fixe the issue of the size of DG units in the distribution system to minimize the power loss and enhance the voltage profile. Additionally, Hybrid optimization methodology is employed for optimal DG reconfiguration. This proposed hybrid methodology is the combination of Binary Particle Swarm Optimization (BPSO) and Kinetic Gas Molecule Optimization (KGMO). The proposed BPSO-KGMO computes the optimal DG placement and size, based on the various control parameters like voltage profile, power loss and cost are considered in the fitness function to find the appropriate placement of DG. which helps to minimize the power losses and enhance the voltage steadiness. The proposed BPSO-KGMO methodology is simulated in IEEE 69 bus system and the efficiency of the proposed BPSO-KGMO methodology is evaluated and compared with the Genetic algorithm, Stud Krill Herd algorithm BPSO algorithm in terms of four test cases.*

Index Terms: Binary Particle Swarm Optimization (BPSO), and Kinetic Gas Molecule Optimization, Distributed Generation (DG), Optimal Placement, Power loss, Voltage Profile.

I. INTRODUCTION

The renewable DG units such as photovoltaic cells, wind energy conversion system are widely used as an alternative energy resources to solve the problem in existing energy resources and environment concerns [1]. The DG is a minimal amount of power production systems which are directly connected with the meter or distribution network that can produce 3-10000 kW from the renewable energy resources [2] [3]. To reduce the consumption of fossil fuel in electricity production, the renewable energy sources based DGs are developed. It helps to minimize the power loss, continuous power supply for load demand and avoids the toxic carbon emissions [4]. The DG helps to eliminate the power loss and improve the voltage profile in the distribution and transmission lines. The DG helps to support and attain the real power along with the reactive power compensation and it is the responsible for the efficient power and energy reliability [5] [6]. The voltage reliability and the steadiness of the power generation system directly depends on the appropriate position and size of DG [7]. When the DG is integrated with the system, the distribution system changed in the form of passive network to an active network. When the DG is fixed in a random or unfair position that leads to more power loss and reduce the voltage profiles [8].

The DG units are used as a synchronous generator in hydro-power system, geothermal power system and combustion turbines, wind turbines with power electronics [9] that helps to improve the stability enhancement, minimization of power loss and improvement of voltage profile [10]. During the peak time periods, DG delivers the power in accordance with the load demand which helps to minimize the cost of power [11]. The size, position, and configuration of the hardware components of the DG is decided based on the cost of the power [12] and power distribution loss [13]. The growth of machineries and variants in the load demand plays important role in the development of power generation and management [9]. To solve the problems in electrical network, it is an important consideration to discover the appropriate location of each DG to solve problems [14]. The major shortcoming of the above methodologies was inadequate reactive power support. The reactive power is generated from the DG units when it connected to any of the bus in the network [22]. The assimilation of DG in the existing power generation system at a non-optimal location leads to increase in loss of power and reduction in voltage profile [15]. Because of the above reasons, it is necessary to determine a methodology that can be more consistent with the power loss and voltage profile [16].

In this paper, network reconfiguration is implemented based on the hybrid optimization methodology which comprises Binary Particle Swarm Optimization (BPSO) and Kinetic Gas Molecule Optimization (KGMO). The BPSO and KGMO algorithms update their velocity and positions in different way. Both of the algorithms help to discover the appropriate position of the DG in the power generation system. During the preparation process (initialization) of BPSO, the initial solution is reconstructed into binary code and particle position can take the values 0 or 1.

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Subsequently, those vectors drawn from the n-dimensional binary space (B) into the real numbers (F) that means a particle's location must belong to binary space. The output of the BPSO algorithm is given to the KGMO algorithm for further development and the output of the KGMO algorithm is given to BPSO algorithm. This cyclic process is repeated for every iteration and checks whether the feasible solution is obtained based on the fitness function. The main objective of this research work is to minimize the power loss and scale up the voltage profile in the power system with the help of fixing the DG in an appropriate place. This algorithm is applied on IEEE 69-bus Radial Distribution Network (RDN), and then it has been verified by proposed hybrid BPSO-KGMO methodology. This proposed work gives an efficient performance over the distributed system compared to other traditional techniques.

This paper is organized as follows. Section II provides a brief description of the related works. Section III focuses on BPSO methodology. In section IV, comparative analysis of resultant voltage of proposed and existing system is discussed. Section V gives a summary of this paper.

II. Literature review

S. Ray et al. [17] presented the methodology for discovering the appropriate position of Remote Control Switch (RCS) in a RDS. With the help of Differential Search (DS) algorithm, they found the appropriate number and position of the RCS which leads to improve the reliability of the RDS. The DS algorithm used the Brownian-like random-walk technique for repositioning the RCS from one place to another place. This method considers the location of the RCS and it fails to explain the required number of DG units. Prakash, and Lakshminarayana [18] presented a methodology for distribution network to discover the optimal DG placements. This method considered power loss and voltage stability as the important issue of the distribution network. To solve these issues, it used the multiple DG units in the distribution network in appropriate size and position. They have used Particle Swarm Optimization (PSO) Algorithm as an evolutionary algorithm for discovering the appropriate place and configuration of DG. However, this method only focused on the power loss issue as a single objective, which leads to produce the low convergence rate.

P. Chiradeja, et al. [19] presented Differential Evolution (DE) algorithm with the intention of discovering the suitable position for the multiple DG's in the distribution network. By assigning the multiple DGs in the proper position of the network leads to improve the efficiency of the distribution network. However, in this DE algorithm the modification of parameters is indispensable and identical parameters may not assure the global optimal resolution.

A.A.Z. Diab and H. Rezk [20] presented soft computing multiple optimization technique to find out the appropriate placement of DG and the value of the capacitor in the RDS. They have considered three optimization technique, including the Grey Wolf (GWO), Dragonfly (DFO) and Moth-Flame (MFO). The main objective of this method is to minimizing of the total cost by reducing the power loss and improving the voltage profile. Initially, this method identified optimal candidate buses for the capacitor placements with the help of loss sensitivity factor subsequently each of the evolutionary algorithm was used for discovering the optimal size of the capacitor and the positions. However, the computation complexity of their proposed algorithm is very high compared to the traditional optimization algorithm.

Tri Phuoc Nguyen et al. [21] presented Chaotic Stochastic Fractal Search (CSFS) algorithm with the intention of discovering the appropriate position and the ability of the DG units. This process integrated chaos with the SFS algorithm in order to improve the capabilities of the traditional SFS algorithm. At first their system, optimized all the decision parameters and the second method considered as comparative method that makes the changes in decision parameters. However, this method does not discuss the reconfiguration process of the RDS in their proposed methodology.

III. BPSO Algorithm

Particle Swarm Optimization (PSO) is the one of the most computationally efficient evolutionary algorithm that provides improved performance compared to Genetic Algorithm and other traditional evolutionary algorithms in DG placement complications.

In order to discover the appropriate placement of DG, numerous researches have been done based on the optimization issues, which are discrete in nature and categorized as combinational optimization difficulties. The general PSO methodology is not suitable for finding the appropriate placement of DG in power production system because of continuous property of PSO. In this paper, the Binary version of the PSO algorithm is utilized and considered as an alternative solution for the different kind of optimization issues. The Binary Particle Swarm Optimization (BPSO) is utilized in this paper for discovering the variables from the appropriate space which makes the power system become convenient. The typical IEEE 69-bus RDN is used to find out the result of the proposed BPSO-KGMO methodology.

The BPSO creates the set of initial particles bit strings and constrains the velocity value in the interval of [0 1]. Hence, in this paper, the BPSO algorithm is utilized to improve the steadiness of the distribution network system by minimizing the power losses.

In PSO, the position and the velocity of every particle at the iteration k in the search space are described by X_k^i and V_k^i. The velocity of the particle I in the iteration $k+1 P_{ibest}^i$ is obtained from the following Eq. (1).

$$V_{k+1}^i = \omega . V_k^i + C1.R1\left(P_{ibest}^i - X_k^i\right) + C2.R2\left(P_{global}^i - X_k^i\right) \tag{1}$$

Where $R1$ and $R2$ are the random functions and $C1, C2$ are the training coefficients. ω is the inertia weight factor. ω can be obtained from the following Eq. (2).

$$\omega = \omega_{\max} - \{((\omega_{\max} - \omega_{\min}) - k_{\max})\} \times k \quad (2)$$

Where $k_{\max}$ is the number of the maximum iteration. Once the number of iterations is assigned, at each iteration the position of each candidate particle gets updated using Eq. (3).

$$X_{k+1}^{i} = X_{k}^{i} + V_{k+1}^{i} \quad (3)$$

The updated particles are not in the form of binary numbers; it is not suitable for solving the problem which is considered in this paper. In order to convert the particles as binary values, the following logistic transformation $S(V_k^i)$ is utilized which is written in Eq. (4) and (5).

$$S(V_{k+i}^{i}) = sig\,mod\,e(V_{k+i}^{i}) = \frac{1}{1+\exp(V_{k+i}^{i})} \quad (4)$$

If rand $\alpha S(V_{k+i}^{i})$ then: $X_{k+1}^{i} = 1;$ (5)

Else: $X_{k+1}^{i} = 0;$

The function $S(V_k^i)$ is a sigmoid that controls the changes in particle's updation, and the parameter rand is quasi random number which is selected randomly from a uniform distribution in [0, 1]. Eq. (6), (7) and (8) describe the limits of the particle's dimension.

$$1 \alpha B_i \alpha B_{\max} \quad (6)$$

$$0 \alpha P_i \alpha P_{\max} \quad (7)$$

$$T_i = \{1, 2, \ldots.. T_f\} \quad (8)$$

IV. KINETIC GAS MOLECULE OPTIMIZATION

With the intention of providing the efficient solution for handling the non-linear problems, a swam based evolutionary algorithm namely Kinetic Gas Molecule Optimization (KGMO) utilized in this paper. The KGMO discover the solution based on the behavior of gas molecule theory [23]. The gas molecules in the KGMO are act as an agent in the search area to discover the optimal solution based on the kinetic energy of gas molecule as control parameter [24], [25]. Let's consider the set of agents (gas molecules) where each of the agents has its own location. The location of the i^{th} agent is comes with its own velocity presented in Eq. 9.

$$X_i = (x_i^1, \ldots., x_i^d, \ldots v_i^n) \text{ for } (i = 1, 2, \ldots, N) \quad (9)$$

Where the notation N represents the total number of agents and each agents are differentiated and identified based on the location and its identity indicated by i. The velocity of the each agent is represented by v_i^d which is presented in Eq. 10, where i represents the agent's ID and d indicates dimension of the i^{th} agent.

$$V_i = (v_i^1, \ldots v_i^d, \ldots, v_i^n), \text{ for } (i = 1, 2, \ldots, N) \quad (10)$$

The basic definition of KMGO based on the kinetic energy presented in Eq. 11.

$$k_i^d(t) = \frac{3}{2} N b T_i^d(t), \qquad K_i = (k_i^1, \ldots. k_i^d, \ldots, k_i^n), \quad \text{for } (i = 1, 2, \ldots, N) \quad (11)$$

Where the notation b indicates the Boltzmann constant. The symbol $T_i^d(t)$ represents the temperature of agent and the notation t indicates the time.

The velocity of each agent is updated based on the Eq. 12.

$$v_i^d(t+1) = T_i^d(t) w v_i^d(t) + C_1 rand_i(t)(gbest^d - x_i^d(t)) + C_2 rand_i(t)(pbest_i^d(t) - x_i^d(t)) \quad (12)$$

Where the notation $T_i^d(t)$ represents the converging area of agent molecules minimize exponentially with respect to time which is computed using Eq. 13.

$$T_i^d(t) = 0.95 \times T_i^d(t-1) \quad (13)$$

The vector $pbest_i = (pbest_i^1, pbest_i^2, \ldots.., pbest_i^n)$ indicating the best position of each iteration of the i^{th} agent and $gbest^1 = (gbest^1, pbest^2, \ldots.., pbest^n)$ is the best position of the entire molecules in the container. Each of the candidate particles has their own position and the velocity, where initialization of position and velocity is done by randomized manner within the respective ranges. The $[-v_{\min}, v_{\max}]$ is represented as the limits of the gas molecule velocity. If $|v_i| > v_{\max}$, then $|v_i| > v_{\max}$.w is represents the inertia weight which impacts on the gas molecule's resistance to slow its movement. The $rand_i(t)$ represents the uniform random variable of the interval $[0,1]$ at time t, utilized for a given randomized distinctive of the searching algorithm. The C_1, C_2 are acceleration constants. The mass m of each gas molecule is the randomized number within the range $0 < m \le 1$. In order to simulate the various kinds of gases with different executions, the random number is utilized.

According to [26], the location of the gas molecule is updated for each unit of time interval based on the Eq. 14.

$$x_{t+1}^{i} = \frac{\sqrt{2(\Delta k_i^d)}}{m}(t+1) + v_i^d(t+1) x_i^d \quad (14)$$

The minimum fitness function is found using Eq. 15 and 16.

$$pbest_i = f(x_i) \text{ if } f(x_i) < f(pbest_i) \tag{15}$$

$$gbest_i = f(x_i) \text{ if } (x_i) < f(gbest_i) \tag{16}$$

Every gas particles attempt to adjust its place (x_i^d) based on the distance between the current place and $pbest_i^d$,and the distance between the current place and $gbest_i$.

V. OPTIMAL DG ALLOCATION

The integration of DG into the distributed systems have an impact on the frequency, stability of the distribution system, voltage regulation and protection discrimination. Improper choice of position and configuration of DG causes more power loss. By optimal placement of DGs, distributed system take benefits of improving the reliability of supply. DG could be considered as one of the maintainable elections to diminish some of the problems such as, poor power quality, high power loss and low reliability. The maximum value of DG makes the less power loss for a particular bus. Each DG unit has their own active and reactive power as output. The output value of DG must be in the range of minimum and maximum of active power and reactive power which is given in Eq. (17) and (18).

$$p_{DG,i}^{\min} \leq P_{Dg,i} \leq P_{DG,i}^{\max} \tag{17}$$

$$Q_{G,\min} \leq Q_G \leq Q_{G,\max} \tag{18}$$

Where $P_{Dg,i}$ and Q_G is nominal active power and reactive power of DG, $p_{DG,i}^{\min}$ and $P_{DG,i}^{\max}$ are minimum and maximum range of DG's active. The block diagram for the optimal placement in IEEE 69-bus system is shown in below Fig. 1.

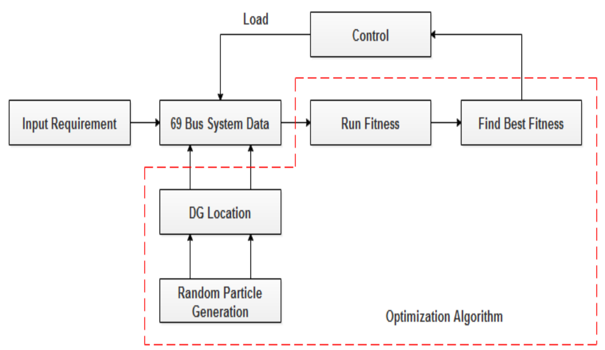

Fig. 1 Block diagram of optimal placement in IEEE 69-bus system.

1. Initialize the process with common control factors.
2. For the considered IEEE 69 bus radial distribution system, the data from line and bus are examined.
3. The random particle generation is considered as initialization process for the evolutionary progress. Subsequently, verification has been done by analysing the load flow.
4. Then, compute the fitness function that comprises of a set of control parameters like voltage profile, power loss and cost.
5. From the data, discover the optimal fitness values that are given to system data, which will be processed again for the next iteration.
6. The similar verification has been done by analysing the load flow with the proposed hybrid optimization to discover the best fitness values.
7. The fitness values of the proposed hybrid optimization algorithm computed for random position for employing DG, and it manages the values of active power and reactive power.
8. From the best values, DG will be optimally located with the help of the proposed BPSO-KGMO methodology, and multi-objectives are evaluated with proper placement of DG.

A. Reconfiguration using hybrid BPSO-KGMO

The initial progress of DG reconfiguration is completely based on continuous search spaces. The proposed BPSO-KGMO is used for real value optimization issues once the real-binary transformation process is completed. The $Q_{G,\min}$ and $Q_{G,\max}$ are lowest and highest range of DG's reactive power. In order to decide the size of the DG, the volume of the distribution network based on the load plays an important role. Similarly, the position of the DG also considered as primary role in order to reduce the power loss. The process of reconfiguration in the distribution network system performed by using hybrid BPSO-KGMO for handling the operation of switches. This hybrid BPSO-KGMO is used to overcome the concern over the selection of sectionalizing switches. The sectionalizing of switches has two states, one is open and another one is close. The open and close states of the switches are defined by two different conditions such as 0 and 1. The flowchart of proposed hybrid BPSO-KGMO methodology is presented in Fig. 2.

Initially, the BPSO algorithm begins with the initialization progress where the position and velocity of the particles are generated by swarm values which is in the form of dimensional matrix. The computation of fitness function made with the help of updated velocity in randomized value. The output of the BPSO algorithm is given to KGMO algorithm to update the solution. If the updated solution is optimal which is used for optimal switch configuration else the updated solution given back to BPSO algorithm in order to make further improvements in the solution. This cycle will repeat until the optimal solution gets obtained. Like this, the proposed BPSO-KGMO method is developed to simulate the IEEE 69 Bus distribution network.

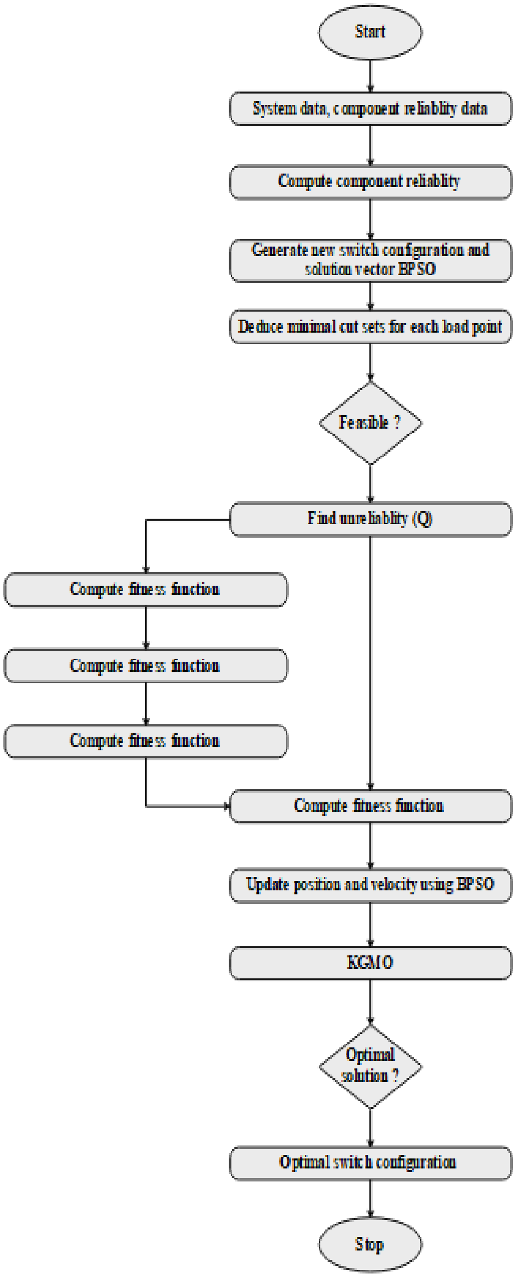

Fig. 2 Flow chart of proposed BPSO-KGMO method

B. Optimal DG placement using hybrid BPSO-KGMO

The steps of optimal DG placement using hybrid BPSO-KGMO is given as follows:

Step 1 (Input System Data and Initialize): There are various inputs given in the PSO initialization. Those are line data (resistance and impedance), bus data (type of the bus, voltage and angle), generator data (real and reactive power) and load data (real and reactive power). During the initialization progress the size of the population of the particles and iterations are set, the velocity and position of the particles are randomly generated. Initially, there is a need to allocate number of iteration count $k = 0$ and then start the process.

Step 2 (Computation of Objective Function): The computation of the objective function given in Eq. (1) is approved by "Forward Backward Sweep Method"

Step 3 (Calculate *pbest* *pbest*): The objective value of each particle is compared with its individual best. This individual best is taken as current *pbest* , when the objective value is smaller than the *pbest* as well as the corresponding position is recorded.

Step 4 (Calculate *gbest*): The candidate particle that has the lowest own best is *pbest* , and allocate the value of this *pbest* as the current best value $(gbest)$.

Step 5 (Updation): The position and the velocity of each particle are updated with the help of Eq. (1) and (2) respectively.

Step 6 (Check Convergence Criterion): when the count of iteration reaches the threshold value, go to Step 8. Otherwise, set iteration index $k = k+1$, and go back to Step 2.

Step 7 (KGMO initialization): The optimal values from the BPSO such as DG location and size are given as the input to KGMO for finding the optimal position and size. The KGMO received the DG location and size from the BPSO to identify the excellence of the solution.

Step 8 (Replacement): A candidate particle is elected from n (number of solution particle) randomly, when the excellence of updated particle solution in the elected particle is better than the existing solution, then the existing solution is replaced by the updated particle solution.

Step 9 (Creation of new solution): The inferior solution is rejected based on the probability (Pa) and the new solutions are generated using Eq. (3).

Step 10 (Termination): In this study, the stopping criterion is set to the tolerance value of $1e^{-6}$ and maximum generation of 100 iterations. The iteration stopped, when reaching the stopping criterion, and the result of KGMO is obtained.

The optimal DG location and size are evaluated from the hybrid BPSO-KGMO methodology.

VI. RESULT AND DISCUSSION

The hybrid BPSO-KGMO optimization methodology is implemented in this research and analysed with the standard radial networks comprises of IEEE 69 bus system. DGs are generally placed on a few number of positions, the set of exploratory solutions is discovered from each candidate solution. However, some of the exploratory solutions violate problem constraints and thus become infeasible. These issues are fixed by using BPSO-KGMO algorithm. BPSO-KGMO search algorithm is used in searching within the group to improve search efficiency and avoid early maturing. In the proposed BPSO-KGMO methodology, two important constraints, including the size and position of each DG are found using BPSO-KGMO which recognizes the test system by load flow and appropriate DG placement and DG rating.

The simulation results of proposed BPSO-KGMO algorithm for the distribution network with the DGs not only helps to minimize the loss of distribution network also it enhances the system voltage profile.

The BPSO-KGMO is suitable to search for the best switch combination of distribution network with DG. The effectiveness of the proposed BPSO-KGMO method is investigated in 69-bus test distribution system. This system works with the following configuration, 5 tie-lines, 68 sectionalizing switches and 8 feeders along with open switches are 69-73. The proposed BPSO-KGMO methodology is implemented using MATLAB 2018a software. The simulation of the proposed BPSO-KGMO methodology consists of four scenarios which are considered to analyze the superiority of the proposed technique. The simulated results are compared with the results of other techniques to assess the performance and efficiency of the proposed technique.

Scenario I: The system with reconfiguration only;

Scenario II: The system with reconfiguration and installation of single DG unit;

Scenario III: The system with DG units only;

Scenario IV: The system with reconfiguration and fixing of multi DG units;

For considering scenario 1, in this case, the considered test bus system has only reconfiguration without the presence of DG units. The resultant voltage of the first scenario is expressed in the Fig. 3 and the corresponding values are presented in table 1.

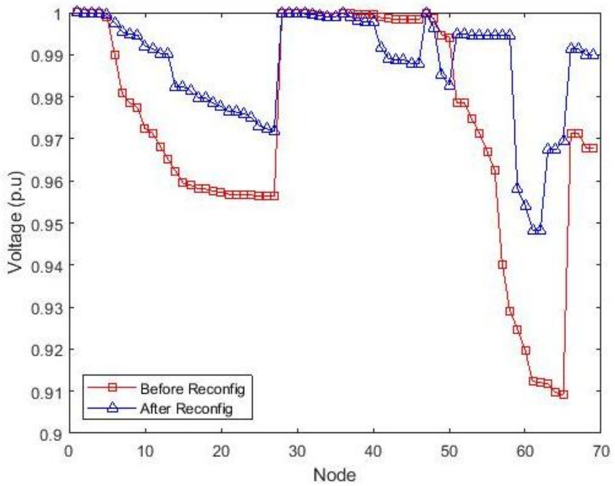

Fig. 3 The resultant data for the first scenario

Table I. Resultant data for first scenario

Comparative analysis of first scenario for 69 Bus Distribution Network		
Items (scenario 1)	**BEFORE Reconfiguration**	**AFTER Reconfiguration**
Tie switches	69 70 71 72 73	3 4 14 19 23
Power loss	224.9804 kW	90.0212 kW
Power loss reduction	-------------	60.587 %
Minimum voltage:	0.90919 pu	0.94947 pu

From the scenario 2, the considered test bus system only has DG units. The comparative analysis of the second scenario is presented in the following table 2.

Table II. Results for second scenario

Comparative analysis of first scenario for 69 Bus Distribution Network		
Items (scenario 2)	**BEFORE Reconfiguration with DG**	**AFTER Reconfiguration with DG**
Tie switches	69 70 71 72 73	62 66 54 55 23
Power loss	224.9804 kW	38.9642 kW
Power loss reduction	-------------	82.6744 %
Minimum voltage:	0.90919 pu	0.94947
Size (location of DG)	4 KW	4 KW (36)

For Scenario 3, the test bus system is carried out with reconfiguration and the inclusion of DG unit. The resultant voltage profile of third scenario is presented in the Fig. 4 and the corresponding numerical results are presented in the table 2 which represents the optimal DG size without the reconfiguration for 69-bus distribution system. It can be concluded that optimal DG allocation with a size of 0.4 MW harnessing a reduction in the total real power loss from 224.6 to 38.9642 kW that shows the 82.6744% of overall reduction. The percentage of improvements in power losses from the base case show better results.

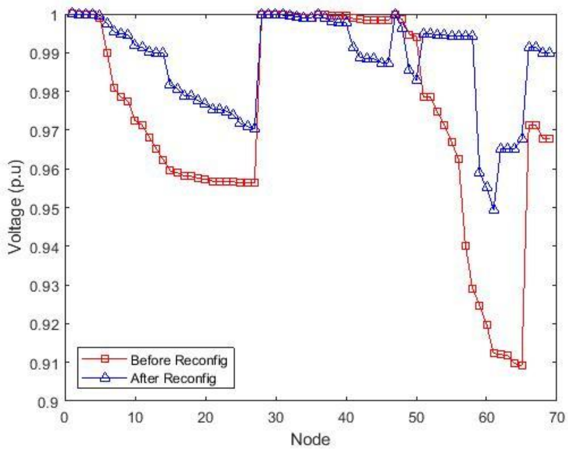

Fig. 4 The result for the second scenario

Table III. Results for third scenario

Simulation Results of 69 Bus Distribution Network		
Items (scenario 2)	**BEFORE DG**	**AFTER DG**
Tie switches	69 70 71 72 72	69 70 71 72 73
Power loss	224.9804 kW	80.9479 kW
Power loss reduction	-------------	64.0062 %
Size of DG	0.1018 MW	4 KW
Minimum voltage:	0.9677	0.94693

Table 3 represents a numerical analysis of the optimal DG size with reconfiguration for the IEEE 69-bus distribution system. By analysing table 3, it can be determined that the bus 39 is finest bus for an appropriate

DG allotment with a size of 0.4 MV that contributes to minimize the total real power loss from 224.6 to 80.9479 kW that shows the 64.0062% of total power loss reduction. However, the total real power loss is reduced more which is happened because of the available of reactive power production source at location of load demand.

The test bus setup consists of reconfiguration with the incorporation of multiple DG units is considered as scenario 4. The numerical analysis of the resultant voltage is depicted in the table 4.

Table IV. Results for fourth scenario

Simulation Results of 69 Bus Distribution Network		
Items (scenario 4)	**BEFORE Reconfiguration with DGs**	**AFTER Reconfiguration with DGs**
Tie switches	69 70 71 72 73	56 11 22 34 48
Power loss	224.9804 kW	28.5472 kW
Power loss reduction	-------------	87.3064 %
Minimum voltage:	0.90919 pu	0.94693 pu
Size (location of DG)	4 KW	4 KW (41 4 67)

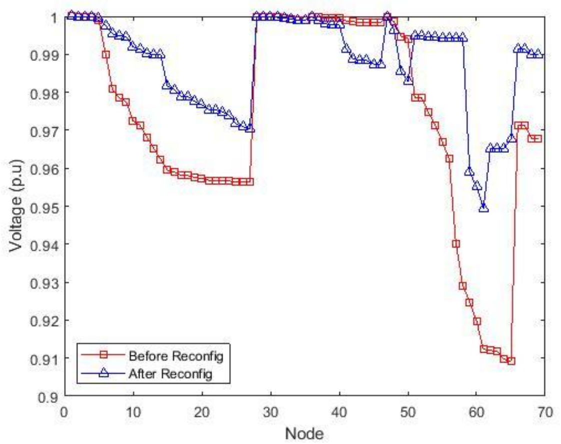

Fig. 5 The resultant voltage for the fourth

Table 4 represents the optimal DG size with reconfiguration of the IEEE 69-bus distribution system. Fig. 5 represents the obtained voltage profile for the fourth scenario with reconfiguration technique. It can be concluded that proposed BPSO-KGMO algorithm minimizes the value of the overall real power loss from 224.6 to 28.5472 kW which indicates 87.3064% of overall power loss reduction. The proportion of growth in total power losses from the general case and considered fourth scenario produces the better results which are depicted in the table 5 and 6.

The improved voltage regulation and power losses minimization is obtained without encountering contrary difficulties in power system process. Moreover, the proposed BPSO-KGMO is efficiently fast and robust in resolving radial distribution systems. Moreover, another benefit of this algorithm is that it updates the multipliers robustly and its resultant outcomes are more fast and accurate. The proposed BPSO-KGMO methodology in this research has achieved notable minimization in terms of real power losses and better enhancement in terms of voltage profile.

The table 5 shows the comparison tables for all cases along with existing systems. Table 6 shows the comparison for final scenario. The performance and efficiency of distribution network reconfiguration are comprehensively determined by the proficient searching methodology. The proposed BPSO-KGMO is a swarm intelligence optimization algorithm. The principle of BPSO-KGMO is simple, robust and easy to achieve the optimal solution. The proposed BPSO-KGMO algorithm not only reduce the power loss, it also helps to enhance the voltage.

Table V. Comparison table for all scenarios

Base case	**Stud Krill Herd Algorithm (SKHA) [22]**	**BPSO Algorithm**	**BPSO-KGMO**
Scenario 1 (Only Reconfiguration)	Tie switch = 69 18 13 56 61 Power loss = 99.35 Power loss reduction = 55.85 % Min voltage = 0.9428	Tie switch = 14 56 61 69 70 Power loss = 98.5952 Power loss reduction = 56.1761 % Min voltage = 0.94947	Tie switch =3 4 14 19 23 Power loss = 90.0212 kW Power loss reduction =60.587 % Min voltage =0.94947 pu

Scenario 2 (Only DG)	Tie switch = 69 70 71 72 72 Power loss = 86.77 Power loss reduction = 61.43 % Min voltage = 0.9697	Tie switch = 69 70 71 72 73 Power loss = 82.1119 Power loss reduction = 63.488 % Min voltage = 0.9494	Tie switch = 69 70 71 72 73 Power loss = 80.9479 Power loss reduction = 64.0062 % Min voltage =0.94693
Scenario 3 (Reconfiguration with single DG)	Tie switch = 69 18 13 56 61 Power loss = 51.30 Power loss reduction = 77.2 % Min voltage = 0.9619	Tie switch = 40 60 5 30 6 Power loss = 46.9193 kW Power loss reduction = 79.137 % Min voltage = 0.94693	Tie switch = 62 66 54 55 23 Power loss = 38.9642 kW Power loss reduction = 82.6744 % Min voltage =0.94947
Scenario 4 (Reconfiguration with multi DGs)	Tie switch = 69 17 13 58 61 Power loss = 40.30 Power loss reduction = 82.08 % Min voltage = 0.9736 DG size (location) = 1.0666(61), 0.3525 (60), 0.4527 (62)	Tie switch = 17 14 48 13 36 Power loss = 35.9239 kW Power loss reduction = 84.026 % Min voltage = 0.95907 DG size (location) = 0.4(21), 0.4(32), 0.4(63)	Tie switch = 56 11 22 34 48 Power loss = 28.5472 kW Power loss reduction = 87.3064 % Min voltage = 0.94693 pu 4 KW (41 4 67)

Table VI. Comparison table for final scenario

Base case	Genetic Algorithm with capacitor placement [23]	Stud Krill Herd Algorithm (SKHA) [22]	BPSO Algorithm	BPSO-KGMO
Scenario 4 (Reconfiguration with multi DGs)	Power loss = 99.742 Min voltage = 0.95814 DG size (location) = 0.4(60), 0.4 (62), 0.4 (64)	Power loss = 99.742 Power loss reduction = 69.0967 % Min voltage = 0.95814 DG size (location) = 1719.0677 [61], 370.8802 [17] 527.1736 [11] DG size (location) = 61/1719.0677 17/370.8802 11/527.1736 61/1719.0677 17/370.8802 11/527.1736 61/1719.0677 17/370.8802 11/527.1736	Power loss = 35.9239 kW Power loss reduction = 84.026 % Min voltage = 0.95907 DG size (location) = 0.4(21), 0.4(32), 0.4(63)	Power loss = 28.5472 kW Power loss reduction = 87.3064 % Min voltage = 0.94693 pu (location) = 4 KW (41 4 67)

VII. CONCLUSION

In this research work, BPSO-KGMO algorithm is applied to resolve optimal distribution network reconfiguration and optimal DG employment in order to attain the minimized power loss and to improve the voltage profile. Initially, the proposed BPSO-KGMO algorithm identified an optimal candidate bus for finding the appropriate placement of DG. The control parameters like voltage profile, power loss and cost are considered in the fitness function to find the appropriate placement of DG. To demonstrate the efficiency of the proposed BPSO-KGMO algorithm, it is compared with genetic algorithm (GA) and harmony search algorithm (HAS) in terms of power loss reduction and voltage profile. The proposed BPSO-KGMO algorithm achieved 87.30% of power loss reduction which is better result compared to the GA and HAS. The proposed BPSO-KGMO methodology was made positive impact on voltage profile and power loss reduction. In the future work, the cost of the DG parameter can be considered for the optimization problem to further minimize the power loss and improve the voltage profile.

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