International Journal of Electrical, Electronic and Communication Sciences
ISSN: 2517-9438
Vol:15, No:8, 2021

Slime Mould Optimization Algorithms for Optimal Distributed Generation Integration in Distribution Electrical Network

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***Abstract*—**This document proposes a method for determining the optimal point of integration of distributed generation (DG) in distribution grid. Slime mould optimization is applied to determine best node in case of one and two injection point. Problem has been modeled as an optimization problem where the objective is to minimize joule loses and main constraint is to regulate voltage in each point. The proposed method has been implemented in MATLAB and applied in IEEE network 33 and 69 nodes. Comparing results obtained with other algorithms showed that slime mould optimization algorithms (SMOA) have the best reduction of power losses and good amelioration of voltage profile.

***Keywords*—**Optimization, distributed generation, integration, slime mould algorithm.

I. Introduction

NOWADAYS, electrical energy is fed into the power grid from large power plants, and centralized operation allows for optimized production management for the benefit of customers. With the increase in energy consumption due to industrialization, population growth and then urbanization associated with the respect of ecological constraints, decentralized production from renewable energies is developing in many countries provided that their natural and sometimes random fluctuations are accepted [1]. DG is a small-scale power generation that is close to the end of the load and uses energy sources such as photovoltaic solar energy, wind turbines, fuel cells, gas turbines, etc. [2]. DG connected to the distribution system has a significant impact on energy losses, voltage profile, system stability and thus the overall quality of power supplied to customers. Some of the reasons for the growing interest in DG are:

- The DG is small and requires less space for installation.
- DGs are located close to consumers, thus minimizing transmission and distribution losses and thus the cost of electricity transmission.
- The installation time is much less and the investment risk associated with the installation of the plant is less.
- The overall power quality of the system is improved with the installation of DG.
- The DG uses mainly renewable energy sources to protect the environment [2].

In order to have the advantages mentioned above, we need to choose the optimal size and location of the DG, while connecting it to the distribution system. Different methodologies have been used to optimally allocate the appropriate size and location of the DGs. These methodologies include analytical tools, optimization methods or algorithms based on artificial intelligence.

In [3] the bee colony method associated with Newton Raphson was used to integrate a DG into the distribution network.

In [4] a newly developed adaptive Particle Swarm Optimization (PSO) algorithm, known as Phase Particle Swarm Optimization (PPSO), based on the modeling of particle control parameters with a phase angle (θ) transforming the standard PSO into an independent, self-adaptive and parametric metaheuristic optimization algorithm was used to determine the optimal placement and sizing of the DG in the radial distribution network. The optimal placement of three different types of renewable energy resources using target optimization algorithms was presented in [5]. A hybrid approach for optimal placement of multiple types of DGs was discussed in [6].

In [7], a new uniform voltage distribution algorithm (UVDA) based constructive reconfiguration is implemented along with reconfiguration of distribution network to find out optimal site and size for a DG unit.

In [8] a hybrid artificial colony algorithm of bees and ants was used for optimal DG placement and sizing. In [9], the optimal setting and size of different DGs was determined taking into account the harmonic distortion of the system. In [10] the method of sensitivity to loss reduction and voltage improvement is used to determine the best location for DG connection.

In [11], the harmonic search algorithm is used to place the

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DG optimally using a multi-objective approach. In [12], a combination of the Genetic Algorithm (GA) and the PSO algorithm are used to find the optimal location and size of DG in the distribution network. The optimal location and sizing of DG in a distribution network using the GA is discussed in [13]. In [14], DG units are placed on the buses that are most sensitive to voltage collapse when the load increases, by calculating a factor called Voltage Sensitivity Index (VSI). In [14] a new discrete OSP and OPF algorithm has been presented for the coordination of DG units. However, in this research work, SMOA is proposed to determine the optimal allocation and size of DG units in the radial distribution system to minimize total losses and have a normalized grid voltage. The choice of this algorithm is justified first by [15] which has shown that SMOA is an algorithm that is best optimized when the problem is complex and with high dimensions. This efficiency has been demonstrated most recently by [16] which used complex mathematical functions and applied several metaheuristic algorithms looking for the minimum. Reference [16] concluded that SMOA is more efficient than other metaheuristics.

The rest of the document is organized as follows. Section II provides the method for calculating active power losses in the distribution system; the problem formulation and the optimization algorithm including the SMOA will be described in Section II. The implementation of this algorithm will be presented in Section III. The results of DG placement and sizing in the distribution network obtained by this algorithm and the discussion are presented in Section IV through a case study on the IEEE 33 node and 69 nodes radial network.

II. Methods

A. Presentation of IEEE Networks

Our study will focus on distribution networks that are characterized by a radial configuration. We have taken the standard IEEE 33 and 69 nodes. Figs. 1 and 2 show the standard IEEE 33 and 69 node networks.

The number of nodes is taken as pop size of the problem. Figs. 1 and 2 show the test system. The characteristics of the networks are given in [17] and [18].

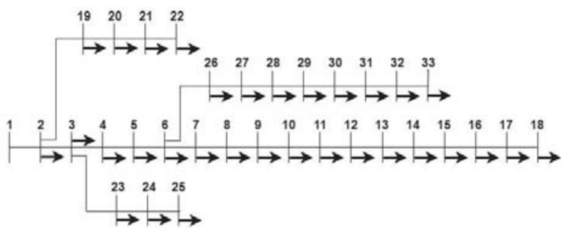

Fig. 1 Structure of the IEEE 33 Node Network [17]

For the IEEE 33 nodes, the system has 33 buses and 32 sections with a total real and reactive power demand of 3802.19 kW and 2694.60 kVAr respectively. It is supposed that all nodes are available.

For the IEEE 69 nodes, the system has 69 buses and 68 sections with a total real and reactive power demand of 3802.19 kW and 2694.60 kVAr respectively. It is supposed that all nodes are available.

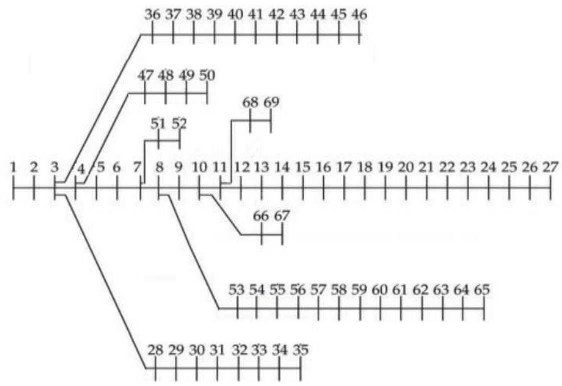

Fig. 2 Structure of the IEEE 69 Nodes Network [18]

B. Formulation of the Problem

Four elements are necessary to solve an optimization problem: Definition of the parameters; Choice of the objective function with its constraints; Choice of the model; Choice of the optimization algorithm.

C. The Parameters

We want to work with the IEEE network. The network parameters are those of the IEEE network. We are going to take a distribution network because the energy to be injected is a DG which is generally produced next to the loads and can only be injected into a distribution network. An electrical network consists of the nodes to which generators or loads can be connected and the power lines connecting the nodes. At the level of a node, 4 values are needed: The active and reactive power; the voltage module and its phase. These 4 values are given by (1)-(3) which constitute the power flow equations.

$$P_{i+1} = P_i + P_{L,i+1} - R_{i,i+1} * \left(\frac{P_i^2 + Q_i^2}{V_i^2} \right) \quad (1)$$

$$Q_{i+1} = Q_i + Q_{L,i+1} - X_{i,i+1} * \left(\frac{P_i^2 + Q_i^2}{V_i^2} \right) \quad (2)$$

$$|V_{i+1i}| = \sqrt{\left(V_i^2 - 2*\left(R_{i;i+1} * P_i + X_{i,i+1} * Q_i\right) + \left(R_{i,i+1}^2 + X_{i,i+1}^2\right) * \left(\frac{P_i^2 + Q_i^2}{V_i^2} \right) \right)} \quad (3)$$

However, we want to point out that, these are the real values and therefore the modules. This is why we do not have the phase equation of the voltage.

We want to inject energy into a network by minimizing joule losses and keeping voltages within the acceptable range. Joule losses are caused by line resistances. The formula is given in (4) [3]:

$$P_{loss,i} = R_{i,i+1} * I_i^2 = R_{i,i+1} * \left(\frac{P_i^2 + Q_i^2}{V_i^2}\right) \quad (4)$$

D. Function Objective

Our function objective is related to the sum of the joule losses in the distribution network [3].

$$P_{Loss,T} = \sum_{i=1} P_{loss,i} \quad (5)$$

It is necessary to minimize these losses, then if we let F_{obj} to be the objective function:

$$F_{obj} = \min(P_{loss,T}) \quad (6)$$

P_i and Q_i are respectively the active and reactive power at node i; V_i is the voltage of node i; N is total number of nodes; $R_{i,i+1}$: line resistance between node i and node i +1; $X_{i,i+1}$: line reactance between node i and node i + 1; Since we want to keep the node voltage stable we will have constraints.

E. Constraints

Injecting energy into an electrical grid can create power surges at certain nodes. It is then necessary to limit the voltage on the network by using constraints.

Constraints are related to network parameters that need to be constantly monitored [5]. One of the parameters is the voltage of the nodes, then the maximum power to be injected

$$\forall i \in [1\,;N] V_{min} \leq V_i \leq V_{max} \quad (7)$$

$$P_{min} \leq P_{inj} \leq 0.4 * P_{Tload} \quad (8)$$

where, V_{min} and V_{max} are the minimum and maximum limits of the voltages of the ith bus. These values are respectively equal to 0.95 pu and 1.05 pu according to [19]. P_{inj} is the power of the DG at the node that we can inject. The maximum value of P_{inj} is fixed at 0.4 * P_{Tload} because the power injected must not exceed 40% of the total power load [20].

III. Overview of SMOA

A. Approach to Feeding

To model the approach behavior of viscous mould in the form of a mathematical equation, the following rule is proposed to mimic the contraction mode [16]:

$$\overrightarrow{X(t+1)} = \begin{cases} \overrightarrow{X_b(t)} + \overrightarrow{vb}.(\overrightarrow{W}.\overrightarrow{X_A}(t) - \overrightarrow{X_B(t)}), r \prec p \\ \overrightarrow{vc}.\overrightarrow{X(t)}, r \geq p \end{cases} \quad (9)$$

where $\overrightarrow{vb}$ is a parameter with a range of $[-a, a]$, $\overrightarrow{vc}$ decreases linearly from one to zero. t represents the current iteration, $\overrightarrow{X_b}$ represents the individual location with the highest odor concentration currently found, $\vec{X}$ represents the location of slime mould, $\overrightarrow{X_A}$ and $\overrightarrow{X_B}$ represent two individuals randomly selected from the swarm, $\overrightarrow{W}$ represents the weight of slime mould. [16]

The formula of p is as [16]:

$$p = \tanh\left|S(i) - DF\right| \quad (10)$$

where $i \in 1,2,\dots,n$, $S(i)$ represents the fitness of $\vec{X}$, DF represents the best fitness obtained in all iterations.

The formula of $\overrightarrow{vb}$is as:

$$\overrightarrow{v_b} = [-a, a]$$

$$\overrightarrow{W(smellindex(i))} = \begin{cases} 1 + r.\log(\frac{bF - S(i)}{bF - wF} + 1), condition \\ 1 - r.\log(\frac{bF - S(i)}{bF - wF} + 1), others \end{cases} \quad (13)$$

$$a = \operatorname{arctan}h(-(\frac{t}{\max\_t}) + 1)$$

The formula of $\overrightarrow{W}$ is listed as:

$$Smellindex = sort(S) \quad (12)$$

where $condition$ indicates that $S(i)$ ranks first half of the population, r denotes the random value in the interval of $[0,1]$, bF denotes the optimal fitness obtained in the current iterative process, wF denotes the worst fitness value obtained in the iterative processcurrently, $SmellIndex$ denotes the sequence of fitness values sorted (ascends in the minimum value problem).

B. Wrap Food

The mathematical formula for updating the location of slime mould is:

$$\overrightarrow{X^*} = \begin{cases} rand(UB - LB) + LB, rand \prec z \\ \overrightarrow{X_b(t)} + \overrightarrow{vb}(\overrightarrow{W}.\overrightarrow{X_A(t)} - \overrightarrow{X_B(t)}), r \prec p \\ \overrightarrow{vc}.\overrightarrow{X(t)}, r \geq p \end{cases} \quad (13)$$

whereLB and UB denote the lower and upper boundaries of the search range, $rand$and $r$denote the random value in [0,1]. [16]

C. Grabble Food

The value of $\overrightarrow{vb}$ oscillates randomly between $[-a, a]$ and gradually approaches zero as the iterations increase. The value of $\overrightarrow{vc}$ oscillates between [-1,1] and tends to zero eventually.

IV. Implementation of Optimization Algorithms

The implementation of the algorithm to our injection optimization problem is given by the flowchart in Fig. 3. Flowchart in Fig. 3 allows us to write a program in MATLAB R2018b. The computer used is the AMD A4-5000 APU with Radeon (TM) hd GRAPHICS computer with 1.5 GHz frequency and 4.00 GB RAM.

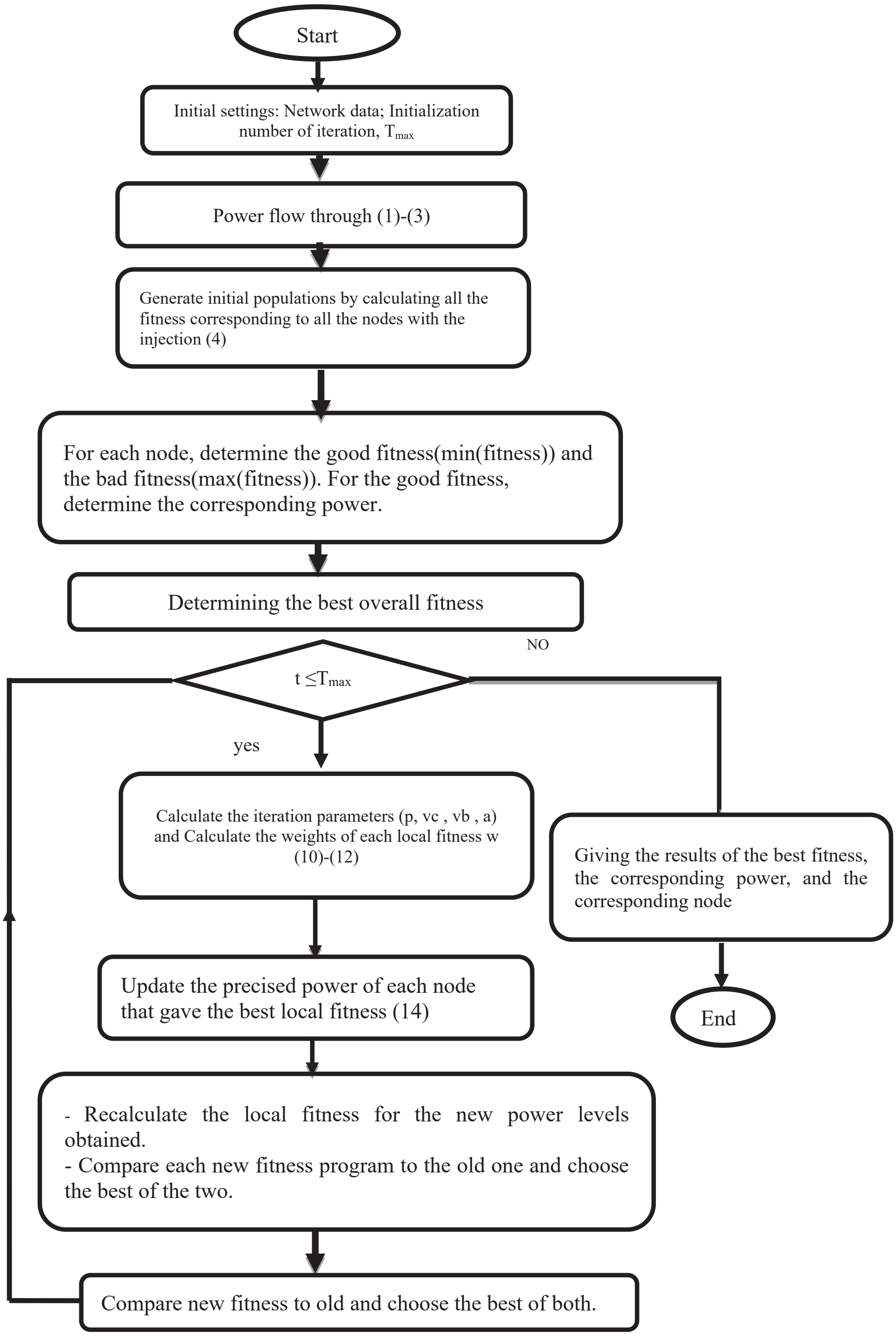

Fig. 3 Flowchart of the Method by the SMOA

V. Voltage Regulation

The injection of the DGs can cause overvoltage in the network. This is why it is necessary to regulate this voltage by keeping it between the values 0.95 pu and 1.05 pu [19]. For this purpose, reactive energy regulation is used. In [21], a voltage regulation according to the reactive power is proposed. It keeps the voltage within a desired range. The regulation scheme is shown in Fig. 4.

Algorithm 1 Pseudo-code of SMOA [16]

Initialize the parameters $popsize$, $Max\_iteraition$;
Initialize the positions of slime mould $X_i (i = 1,2, \dots, n)$;
While ($t \leq Max\_iteraition$)
    Calculate the fitness of all slime mould;
$Updatebe\ the\ Fitness, X_b$
    Calculate the W by (13);
    For$eachsearchportion$
    $Updatep, vb, vc$;
    $Update\ positionsb\ y$ (14);
    End For
    $t = t + 1$;
End While
Return $be\ the\ Fitness, X_b$;

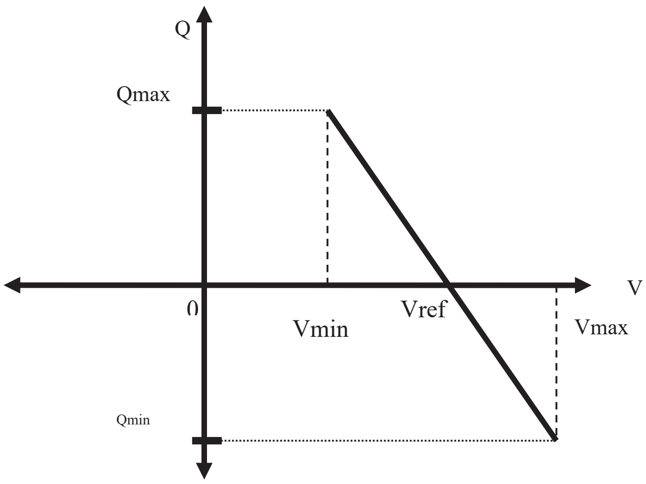

Fig. 4 Schematic diagram of voltage regulation

From Fig. 4, (16) can be deduced

$$Q = \begin{cases} Q_{max} V_{bus} \leq V_{min} \\ \frac{Q_{max} - Q_{min}}{V_{min} - V_{max}} \quad (Vi - Vref) \\ Q_{min} V_{bus} \geq V_{max} \end{cases} \quad (16)$$

VI. Results and Discussion

The results will be presented according to the IEEE network. We used two IEEE networks of 33 and 69 nodes.

A. IEEE-33 Bus System Results

Maximum iteration: 25; Number of DG unit: 1 and 2. Fig. 5 shows the variation of active power losses at each node of the IEEE 33 node network, when power is injected. The curve is given as a function of the nodes.

By observing Fig. 5 we notice the variations of losses in the network when injecting one and two DGs. The blue curve shows the evolution of losses at each node when a DG is injected. Node 7 represents the node with the optimum losses, i.e., 107.12 kW. Similarly, the black curve shows the evolution of losses, when two DGs are injected into the network. Nodes 7 and 12 represent the optimal injection points with the same value of minimum losses which is equal to 76.4 kW. It can be seen that the injection of two DGs reduces losses even more since the percentage of reduction according to Table I is 63.79% while it is 49.23% when injecting one DG.

To be sure of the convergence of the method, we traced the convergence curve in both cases with the IEEE 33 node network. This is to be sure about the convergence criterion. Fig. 6 shows the convergence curve in the case where one and two DGs are injected.

The maximum number of convergences has been set at 25. Because we had noticed that beyond this number, there were not too much variation in values.

We can see from Fig. 6 that in both cases there is a convergence of the method. This convergence is much more rapid with higher numbers of DGs injected.

After that we observed the voltages in the network. Since the injection of a DG into a network creates disturbances. The curve in Fig. 7 shows the different voltages at the nodes without injection and with injection without regulation.

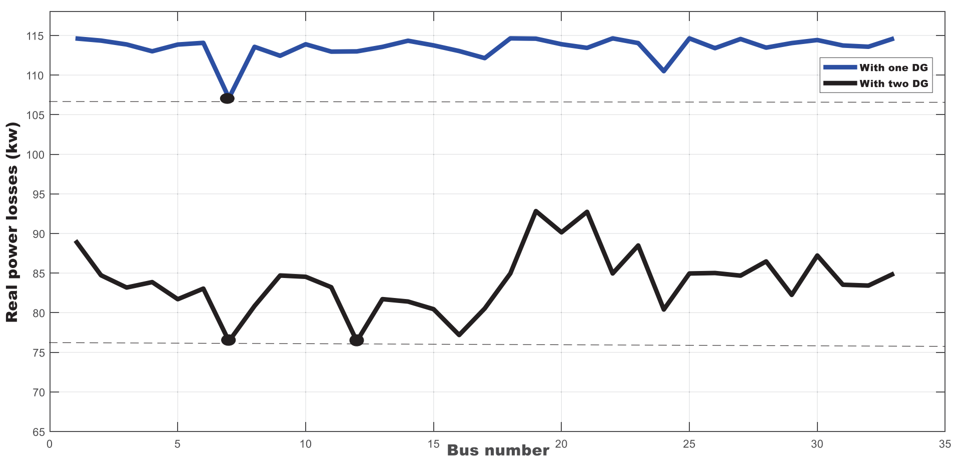

Fig. 5 Evolution of losses at each node of IEEE 33 networks

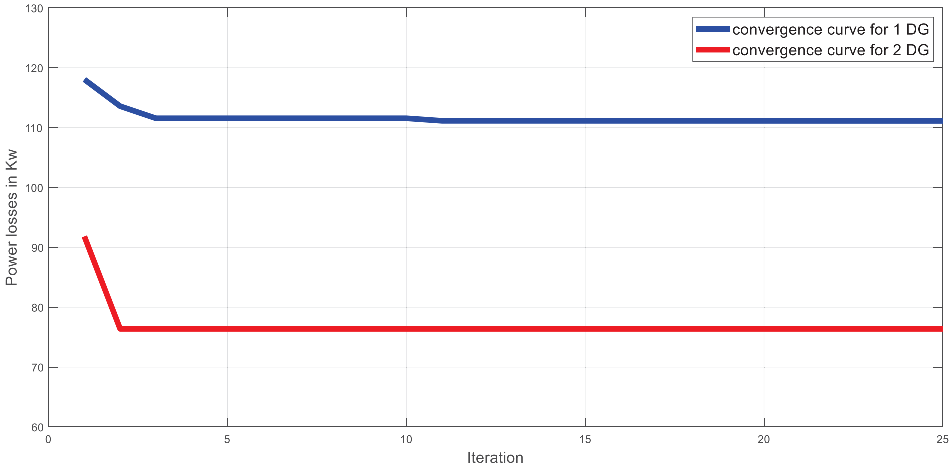

Fig. 6 SMOA Convergences curves in 33 Bus System

TABLE I
COMPARISON OF VALUES FOR THE IEEE 33 NODE NETWORK

Number of DG	Technique	DG installation		Power loss	
		Size (kVA/P.F)	Bus	Value (kW)	Percentage
	Without DG	-	-	211	-
1 DG	Algorithm bee colony [3]	9700/1	7	109.12	48.28
	Fire fly algorithm [22]	1190/1	30	116.7	44.69
	Moth-Flame optimization [2]	2590/1	6	111.02	47.38
	PSO [6]	2590/1	6	111.03	47.37
	SMOA (Proposed)	5020/1	7	107.12	49.23
2 DG	Fire fly algorithm [22]	1013/1 612/1	30 14	96.9	54.08
	Moth-Flame optimization [2]	851.6/1 1157.5/1	13 30	87.17	58.69
	PSO [6]	850/1 1160/1	13 30	87.17	58.68
	SMOA (Proposed)	172/1 1050.4/1	14 62	76.4	63.79

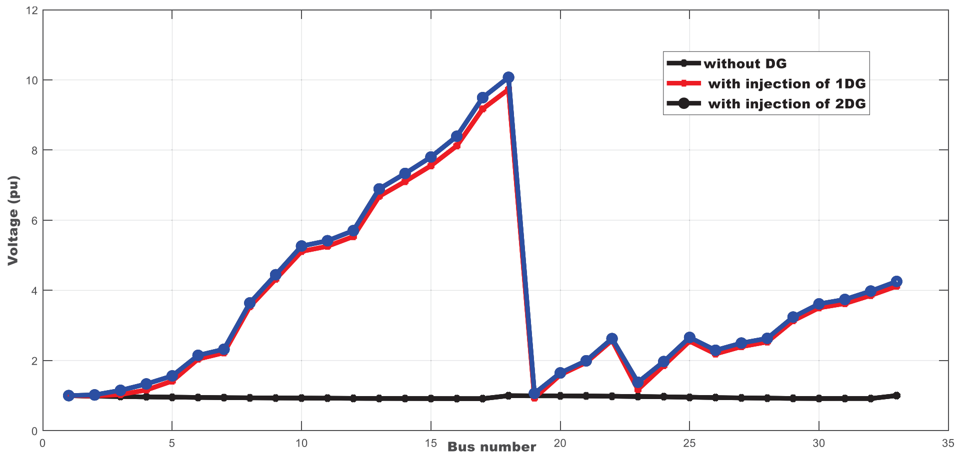

Fig. 7 Bus voltage before and after DG installation in 33 bus system without regulation

We have also plotted the curves which represent the differences between the reference voltage and the voltage curves with injection of one and two DGs with regulation, Fig. 8. These curves are referred to as delta1 and delta2. Equations (17) and (18) show the calculations for delta1 and delta2.

$$delta1 = V_{1DG} - V_{ref} \tag{17}$$

$$delta2 = V_{2DG} - V_{ref} \tag{18}$$

V_{1DG}: node voltage after injection of a DG; V_{2DG}: node voltage after injection of two DGs; V_{ref}: voltage of the node before injection taken as reference.

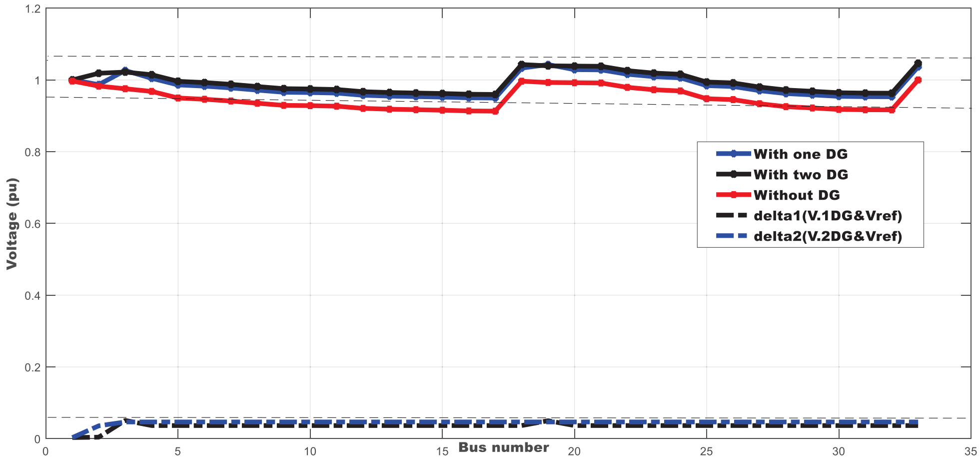

Fig. 8 Bus voltage before and after DG installation in 33 bus system with regulation

The maximum values of delta1 and delta2 are 0.045pu and 0.0365 respectively. And the minimum value is 0.003 for both voltage differences. In view of these deviations, it can be concluded that the regulation was made because the curves are not too different. It can also be seen that both curves during energy injection are between the maximum value of 1.05 pu and the minimum value of 0.95 pu.

It can be said that the energy injection allowed us to improve the voltage, because the minimum value is 0.95 pu, whereas it was about 0.92 pu. Table I gives the values of the other researchers and the values obtained for the IEEE 33 node network in order to make the comparison. In this table, the value of the losses obtained with SMOA is 107.12 kW by injecting a DG with a power equal to 5.02 MW at node 7. And it is equal to 76.38 kW when two DGs with values of 0.172 MW and 1.05 MW are injected at nodes 7 and 12 respectively. Compared to other values in the literature, it can be said that the SMOA allows a considerable reduction in joule losses, especially when two DGs are injected, as the reduction percentages are high and are 49.23% and 63.79% for 1 DG and 2 DGs respectively.

B. IEEE-69. Bus System Results

The proposed method is tested on a radial distribution system of 69 buses as shown in Fig 2, assuming that the power for all buses in the network is supplied by the substation at Node 1. The total real power and reactive power loads of the 69 radial distribution system are 3.80 MW and 2.69 Mvar respectively [23]. Problem size: 69; Maximum iteration: 150 DG; unit number: 1 and 2.

Fig. 9 shows the evolution of active losses in the IEEE 69 node network with the injection of one and two DGs. The observation of these curves shows that the minimum losses for the injection of a DG are 73.61 kW and are obtained when a power of 0.11 MW is injected at node 64. Similarly, for the injection of 2 DGs we have minimum active losses which are 43.98 kW and are found when injecting a power of 1.015 MW at node 63 or at node 64 and we find the minimum losses which are 43.98 kW. Then, to make sure that we are not limited to the local optimum we have drawn the convergence curves when injecting 1 and 2 DGs.

Fig. 10 shows the convergence curves of the SMAO algorithm. The convergence number was taken at 150.

We notice the different convergences of the curves in Fig. 9. In the case of the injection of one DG, the curve converges at about 60 iterations whereas for the curve of the injection of two DGs, it is much faster.

As with the IEEE 33 node network, the IEEE 69 node network also shows overvoltage after DG injection. We have also regulated the voltage using the reactive power regulation method and we have plotted the curves of the regulated voltages and the reference voltage, i.e., without injection. Then we plotted the deviations between the regulated voltages and the reference voltage.

Fig. 11 shows the different voltages before injecting a DG and after injecting one and two DGs into the IEEE 69 node network with regulation. This figure also shows the differences between the regulated voltages after injection and the pre-injection voltage considered as reference voltage for each node. It can be seen from the curve that the two post-injection regulated curves remain in the range of 0.95 pu and 1.05 pu. The differences between the remaining deviations are between -0.12 pu and 0.06 pu. The values of the deviations remain small. It can then be concluded that voltage regulation has been carried out. In addition, injection after regulation has improved the voltage level according to [19], by eliminating the low voltages before injection and increasing these voltages to a minimum of 0.95 pu.

All values obtained by the SMOA algorithm are shown in Table II. Table II shows that the method described above allows us to have losses with very low values when injecting one or two DGs into the IEEE 69 node network. This translates into very high reduction percentages in column 6 of the table, which is 71.81% when only one DG is injected and 80.45% when two DGs are injected.

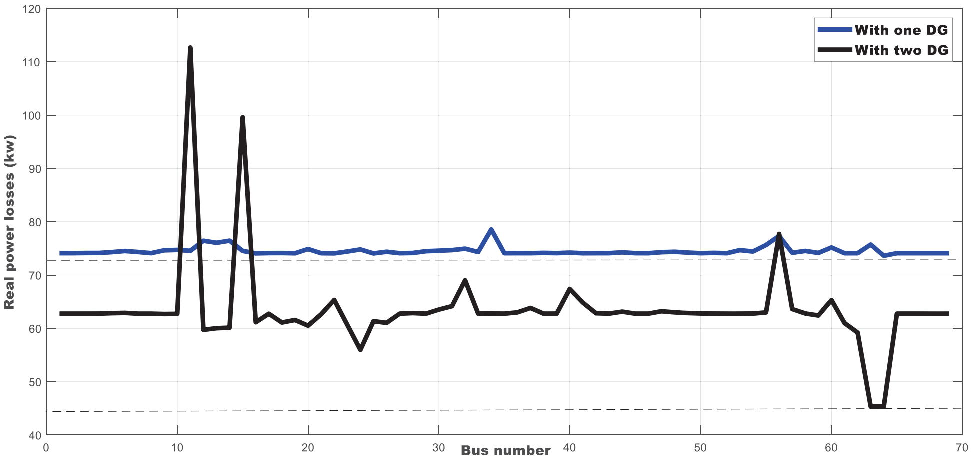

Fig. 9 Evolution of losses at each node for IEEE 60 bus

TABLE II
COMPARISON OF VALUES FOR THE IEEE 69 NODE NETWORK

Number of DG	Technique	DG installation		Power loss	
		Size (kVA/P.F)	Bus	Value (kW)	Percentage
	Without DG	-	-	224.94	-
1 DG	ABC [24]	1900/1	61	83.31	62.96
	GA [13]	1794/1	61	83.42	62.91
	CSA [23]	2000/1	61	83.8	62.74
	SGA [23]	2300/1	61	89.4	60.3
	PSO [23]	13378/1	61	83.8	62.74
	MTLBO [25]	18196/1	61	83.323	62.95
	SMOA (Proposed)	**840.5/1**	**64**	**63.4**	**71.81**
2 DG	GA [26]	1777/1 555/1	61 11	71.79	68.08
	CSA [23]	600/1 2100/1	22 61	76.4	66
	SGA [23]	1000/1 2400/1	17 61	82.9	63.1
	PSO [23]	700/1 2100/1	14 62	78.8	64.97
	MTLBO [25]	519.71/1 1732/1	17 61	71.78	68.09
	ALO [5]	538/1 1700/1	17 61	70.750	68.547
	SMOA (proposed)	**1015/1** **1015/1**	**63** **64**	**43.98**	**80.45**

On the bases of Tables I and II and in comparison with the other results of the literature review, the SMOA gives very high percentages of active loss reduction. The method also converges and convergence is much more rapid as several DGs are injected. This allows us to say that the SMOA is a good algorithm to optimize the injection of DGs into the power grid.

As with the IEEE 33 node network, we have also regulated the voltage using the reactive power regulation method and we have plotted the curves of the regulated voltages, the reference voltage, i.e., without injection. Then we plotted the deviations between the regulated voltages and the reference voltage.

Fig. 11 shows the different voltages before injecting a DG and after injecting one and two DGs into the IEEE 69 node network with regulation. This figure also shows the differences between the regulated voltages after injection and the pre-injection voltage considered as reference voltage for each node. It can be seen from the curve that the two post-injection regulated curves remain in the range of 0.95 pu and 1.05 pu. The differences between the remaining deviations are between -0.12 pu and 0.06 pu. The values of the deviations remain small. It can then be concluded that voltage regulation has been carried out. In addition, injection after regulation has improved the voltage level according to [19], by eliminating the low voltages before injection and increasing these voltages to a minimum of 0.95 pu.

VI. CONCLUSION

In this work, an algorithm, namely the slime mould algorithm, has been proposed to determine the placement and amount of power of a DG in a distribution network. This algorithm has been tested on IEEE 33 and 69 node networks. We managed the power flow and found the optimal point based on our objective function. The results show that the optimal placement of a generator at one node in a radial distribution network results in minimal active power losses in the network, and the optimal placement of two generators further reduces the power losses considerably. Injection creates overvoltages that have been adjusted using reactive power with the model we have described. This improved the voltage profile in the IEEE power networks by 33 and 69 nodes. Comparison with the other results of the literature review led us to conclude that the algorithm reduces active losses more significantly compared to other algorithms and converges more rapidly as the number of injection points increases.

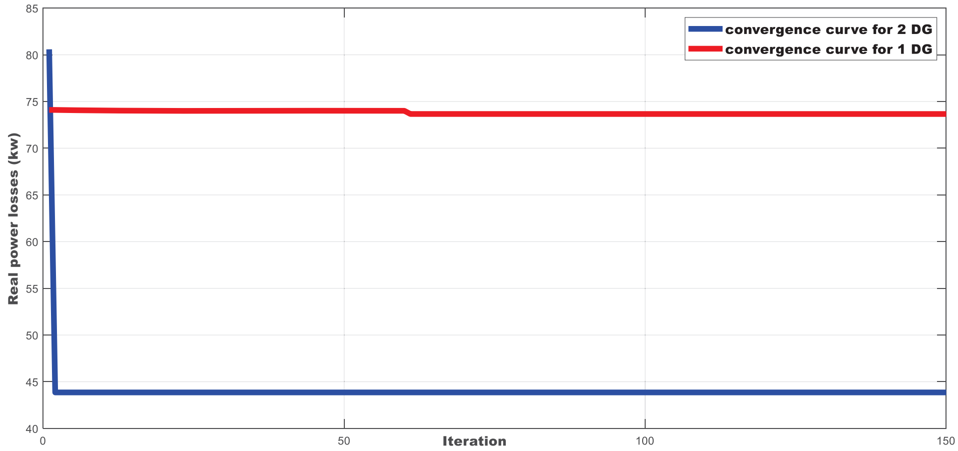

Fig. 10 SMOA convergence curves in 69 bus system

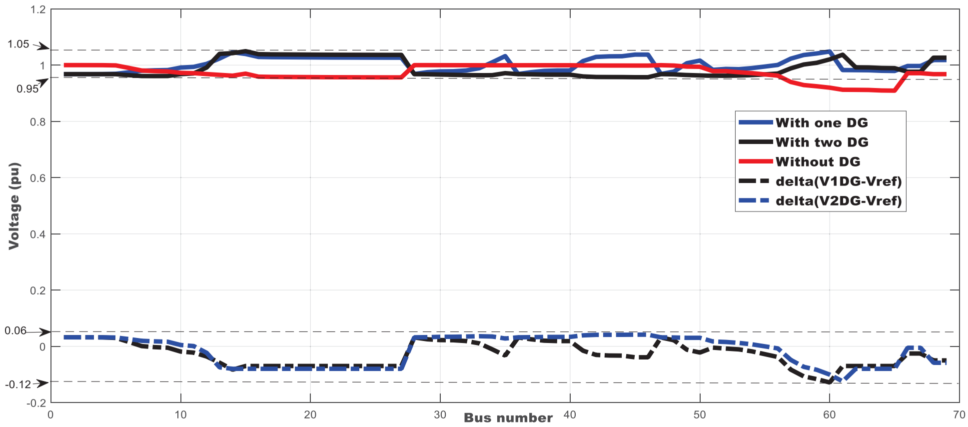

Fig. 11 Bus voltage before and after injection of DG with regulation in 69 bus

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