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Optimal Placement of Distributed Generators with Regard to Reliability Assessment using Virus Colony Search Algorithm

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Abstract- The integration of distributed generation (DG) resources is growing day by day in electricity grids. There are many reasons which persuade the operators to utilize DGs such as restrictions on the construction and development of transmission lines and distribution network, transition of traditional power systems to restructured electricity markets, the competitive conditions in wholesale and retail markets, the implication of economic and environmental issues in the production of electrical energy, increasing the system reliability and customer satisfactory level. The reliability improvement capability of power systems by utilization of these units has attracted the attention of many electrical engineering experts and power system planners and operators. Reliability plays a prominent role in the satisfaction of all power industry participants, especially the consumers of the electricity. In this paper, the effect of distributed generation units on the power system reliability has been investigated. Therefore, the virus colony search (VCS) algorithm is employed to determine the optimal placement and size of distributed generators subject to improve the reliability indices. The simulation is carried out on a 34-bus IEEE test network. The optimization results are also compared with the results of both genetic algorithm (GA), particle swarm optimization (PSO) algorithm, differential evolution (DE) algorithm, multi-objective particle swarm optimization (MOPSO) algorithm, modified shuffled frog leaping algorithm (MSFLA), gravitational search algorithm (GSA), biogeography-based optimization (BBO) algorithm, hybrid big bang-big crunch (HBB-BC) algorithm and glowworm swarm optimization (GSO) algorithm.

Keywords- Distributed Generation, Virus Colony Algorithm, Optimal placement and sizing, Reliability, Distribution Network.

1. Introduction

The use of low-capacity electrical power plants was reduced when the construction of large-scale power plants was prospering. However, due to the development of small-scale power generation technologies and restructuring of the electricity industry as well as environmental issues the deployment of low-capacity generation technologies has boomed again. In a restructured deregulated power system, small-scale power plants produce power in any location. The reasons of incremental utilization of distributed generations may include the following items:

- Reduction in power losses
- Postponement of the necessity of transmission and distribution network expansion
- Preventing the lines' capacity from congestion
- Increasing the reliability of energy supply
- Improving the voltage profile
- Reducing the environmental adverse impacts by using renewable energy sources

Distributed generation (DG) sources will have a crucial role in supplying the consumers' demand in power systems in the future. Hence the optimal location of these sources is very important and may have a significant economic implication in a long-term period. Determining the number, location, size, and type of these sources in the power system are the scope of many studies. The appropriate selection of DGs can cause the reduction of electrical losses and improvement in voltage profile and reliability of the system [1-2].

Several studies have been conducted so far to determine the placement of DG units in the distribution networks, in which the reduction of the cost associated with losses, reliability, and construction of generation units are considered as the goal of designing [3-6]. In [7], the placement of distributed generators in a distribution network feeder is solved by the genetic algorithm with the goal of reduction of losses. In [8], the purpose of the study is to find the location of distributed generators using the multi-objective PSO algorithm with two objectives of minimizing operational cost and emission, which is modeled for a specified number of DG units. In [9], in addition to study the effect of DG units on the ohmic losses and on the distribution network capacity, a heuristic algorithm is suggested to find the approximate solution of DG units' locations in order to reduce the system losses. The placement of DG units on the feeders in the form of a multi-objective optimization is modeled and solved in [10]. An analytical method for locating DG units to reduce losses is presented in [11]. In [12], the problem of renewable resources placement for a predetermined number of DG units with the goals of reducing operational costs, emission, and losses along with optimizing the voltage profile is carried out. In this work, the combined ant colony optimization and artificial bee colony algorithm (ACO-ABC algorithm) is applied. In [13], the genetic algorithm is employed to obtain the best placement and price of bilateral contract between private distributed generation entities and distribution company. The proposed model can provide the maximum profitability for the DGs owners and the lowest cost for Disco. In reference [14], in order to minimize the active losses of the network, the bee colony algorithm is applied. The authors in [15] have conducted a study to find the places for installation of DGs using PSO subject to minimize the losses. In this survey the loads are considered as fix power voltage-variant loads. In [16], the multi-objective PSO algorithm is used to optimize the problem of economical-environmental placement of DGs contemplating fuel price variations and air pollution concerns. Carmen et al. in [17] have evaluated the implication of presence of DGs on the system reliability as well as active power losses and voltage profile. Besides, in this work, the genetic algorithm is employed to find the best location and the optimum size of installation so that the operational condition remains stable. Sudipta et al. in [18], by using an iterative approach in addition to Newton-Raphson method, have made a study to determine the best placement and sizing of DGs. In [19], the Tabu search algorithm is utilized to determine the optimum size of DGs and reactive power resources in a distribution grid. In this study, the objective function encompasses active power losses, the flow rate of lines, and the cost of reactive power compensation. In [20], a hybrid method has been investigated which evaluates the optimum installation location using the genetic algorithm and explores the optimum size of the DG employing PSO algorithm. The authors in [21], have applied a voltage sensitivity index to determine the best DG placement. At first, the best location is found, and then the active and reactive power of the rest of units is adjusted so that the voltage stability index remains within its permissible boundaries. In [22], a dynamic programming approach for DG placement problem based on genetic algorithm is proposed. In [23], an innovative approach for DG placement and sizing is represented. In this approach, the flow rate capability is maximized and the voltage stability margins are observed. In [24], the same work is addressed while the objective is the reduction of active power losses in distribution network. In addition, in a similar work in [25], the reliability indices are incorporated, which indicates that utilization of DGs can improve reliability and security of the distribution grid.

As it is obvious in the literature, several studies have been addressed solution for the optimal location of the distributed generators. However, the impact of presence of DG resources on the reliability indices and reliability-oriented placement of DGs in the power system are rarely investigated [26]. Hence, in this paper, at first, the effect of distributed generation units on reliability is modeled. Then by the employment of the VCS algorithm, the optimal locations of them are investigated subject to improve the system reliability on a 34-bus IEEE test network. In this study, the optimal placement of distributed generation considering reliability indices are performed on a distribution grid. In this study, the novel optimization algorithm of virus colony search is employed. Furthermore, many practical constraints are imposed to obtain a more realistic simulation. All aforementioned items make an adequate distinction for this study. In addition, in order to evaluate the effectiveness of the adopted algorithm, the results of optimizations are compared with some common algorithms such as GA [27], PSO [28], DE [29], MOPSO [30], and some novel algorithm such as MSFLA [31], GSA [32], BBO [33], HBB-BC [34], GSO [35].

2. Formulation of the Problem

2.1. The load flow equations

The load flow in a distribution grid can be obtained based on the equations discussed below in accordance with the Fig. 1.

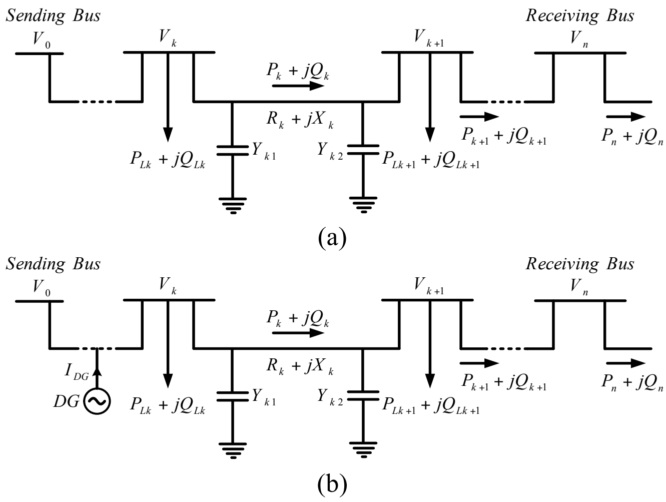

Fig. 1. A single-line diagram of a feeder (a) without DG (b) with DG

$$P_{loss,k} = \frac{R_k}{|V_k|^2}\left\{P_k^2 + \left(Q_k + Y_k |V_k|^2\right)^2\right\} \tag{1}$$

$$Q_{loss,k} = \frac{X_k}{|V_k|^2}\left\{P_k^2 + \left(Q_k + Y_{k1}|V_k|^2\right)^2\right\} - Y_{k1}|V_k|^2 - Y_{k2}|V_{k+1}|^2 \tag{2}$$

$$\begin{aligned} P_{k+1} &= P_k - P_{loss,k} - P_{Lk+1} \\ &= P_k - \frac{R_k}{|V_k|^2}\left\{P_k^2 + \left(Q_k + Y_k|V_k|^2\right)^2\right\} - P_{Lk+1} \end{aligned} \tag{3}$$

$$\begin{aligned} Q_{k+1} &= Q_k - Q_{loss,k} - Q_{Lk+1} \\ &= Q_k - \frac{X_k}{|V_k|^2}\left\{P_k^2 + \left(Q_k + Y_{k1}|V_k|^2\right)^2\right\} - Y_{k1}|V_k|^2 - Y_{k2}|V_{k+1}|^2 - Q_{Lk+1} \end{aligned} \tag{4}$$

$$\begin{aligned} |V_{k+1}|^2 &= |V_k|^2 + \frac{R_k^2 + X_k^2}{|V_k|^2}\left(P_k^2 + Q_k^2\right) - 2\left(R_k P_k + X_k Q_k\right) \\ &= |V_k|^2 + \frac{R_k^2 + X_k^2}{|V_k|^2}\left(P_k^2 + \left(Q_k^2 + Y_k|V_k|^2\right)^2\right) - 2\left(R_k P_k + X_k\left(Q_k + Y_k|V_k|^2\right)\right) \end{aligned} \tag{5}$$

In the above equation, P_k represents the active power of k^{th} bus, Q_k denotes the reactive power of k^{th} bus, $P_{loss,k}$ is the active power losses at the k^{th} bus, $Q_{loss,k}$ shows the active power losses at the kth bus, R_k indicates the resistance of the branch between the k^{th} and $k+1^{th}$ buses. X_k defines the reactance of the line between the sending and receiving buses, Y_k expresses the parallel admittance of the k^{th} bus, V_k means the voltage magnitude at bus k. The active power losses when a DG is installed according to Fig. 1.b. can be calculated by Eq. (6) as below:

$$P_{DG,loss} = \frac{R_k}{V_k^2}\left(P_k^2 + Q_k^2\right) + \frac{R_k}{V_k^2}\left(P_G^2 + Q_G^2 - 2P_kP_G - 2Q_kQ_G\right)\left(\frac{G}{L}\right) \tag{6}$$

Where P_G shows the injected active power to the distribution grid by DG, Q_G denotes the injected reactive power to the distribution grid by DG, G represents the distance between the electrical supply point (source) to the location of DG in km, and L is the length of feeder from the feeding point to the k^{th} bus [36-37].

2.2. The constraints and restrictions

2.2.1. The power equality constraint

The active and reactive equality of the grid are expressed as the following equations:

$$P_{Grid,j} + \sum_{i=1}^{N_{DG}} P_{i,j}^{DG} = P_{D,j} + P_{Loss,j} \tag{7}$$

$$Q_{Grid,j} + \sum_{i=1}^{N_{DG}} Q_{i,j}^{DG} = Q_{D,j} + Q_{Loss,j} \tag{8}$$

Where $P_{Grid,\,j}$ and $Q_{Grid,\,j}$ show the absorbed active and reactive power from the substation at the j^{th} loading level respectively. $P_{D,j}$ and $Q_{D,j}$ represent the demanded active and reactive power by the loads from the substation at the j^{th} loading level respectively. $P_{i,j}^{DG}$ is the generated active power by the i^{th} DG at the j^{th} loading level respectively.

2.2.2. voltage constraints on buses

The voltage magnitude at all buses must be restrained within the permissible range. V_{min} and V_{max} are the lower and lower boundaries for voltage of buses.

$$V_{min} \le V_{i,j} \le V_{max} \tag{9}$$

2.2.3. The thermal stability margins of the lines

The flow rate at each branch is not allowed to violate from the permissible limit. In Eq. (10), S^{max} denotes the thermal capacity of the line in MVA.

$$\left|S_{i,j}\right| \le \left|S_i^{\max}\right| \tag{10}$$

2.2.4. The generation capacity of DGs

The active power generation of DGs and the power factor of them have specific boundaries as below [38-39]:

$$P_{min}^{DG} \le P_{i,j}^{DG} \le P_{max}^{DG} \tag{11}$$

$$pf_{min}^{DG} \le pf_{i,j}^{DG} \le pf_{max}^{DG} \tag{12}$$

$$Q_{i,j}^{DG} = P_{i,j}^{DG} \times tan\left(cos^{-1}(pf_{i,j}^{DG})\right) \tag{13}$$

2.3. Types of utilized DG technologies

2.3.1. Proton-exchange membrane fuel cells

In recent years, the fuel cell technology as a kind of distributed generation resource has assumed more importance. Nowadays, the proton-exchange membrane fuel cell (PEMFC) is the most prevalent type of fuel cell technology utilized as distributed generation. This technology many advantages such as high efficiency and power density, long lifespan, low wear and tear rate, and being capable of proper operation within the temperature of 40-80. The last advantage mentioned causes the ability of fast startup speed. Fig. 2 illustrates the polarization curve of voltage and current in a stack of a fuel cell. As the current flow increases in a fuel cell, the voltage at both terminals of it will be decreased. In accordance with current-voltage characteristics of PEMFC, three operational zones can be defined for a fuel cell. In the ohmic region, the voltage of fuel cell decreases linearly as the current increases. This region is the practical operational zone of a fuel cell. In the concentration region, where the current exceeds the upper bound, the voltage of Fuel cell drops. Hence, the long-term operation in this condition must be avoided because it incurs serious damages to the equipment due to lack of hydrogen.

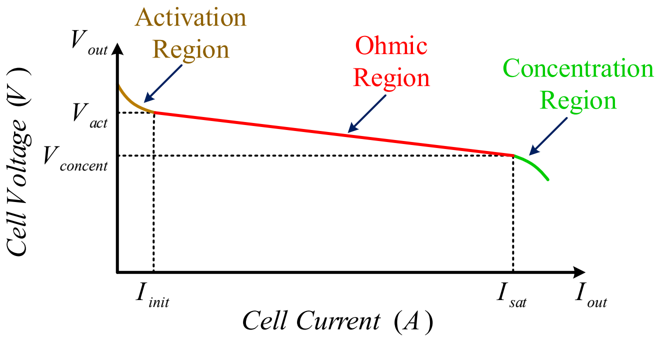

Fig. 2. The I-V curve of fuel cell

The equations pertaining to current-voltage characteristics of PEMFC are displayed in the following:

$$V_{FC} = E_{Nernst} - V_{act} - V_{ohm} - V_{concent} \tag{14}$$

$$V_{act} = A \times log\frac{i_{FC} - i_n}{i_o} \tag{15}$$

$$V_{ohm} = R_m(i_{FC} - i_n) \tag{16}$$

$$V_{concent} = b \times log\left(1 - \frac{i_{FC} - i_n}{i_{lim}}\right) \tag{17}$$

$$E_{Nernst} = \alpha_1 + \alpha_2\left(T - 298.15\right) + \alpha_3 T\left(ln(p_{H2}) + 0.5ln(p_{O2})\right) \tag{18}$$

$$P_{fc} = N_{cell} \times \left[E_o - b \cdot log\left(\frac{I_{FC}}{A_{cell}}\right) - r \cdot \frac{I_{FC}}{A_{cell}} - m \cdot e^{\left(\frac{n \cdot I_{FC}}{A_{cell}}\right)}\right] \times I_{FC} \tag{19}$$

Where P_{fc} introduces the active power output of the PEMFC in Watt. E_0 is thermodynamic potential difference of fuel cell, which indicates the reversible voltage of fuel cell. V_{FC} expresses the fuel cell voltage; E_{Nernst} shows the produced voltage through chemical process; V_{act} represents the voltage drop due to chemical reaction of anode and cathode; V_{ohm} denotes the voltage drop due to permeating of proton through solid electrolyte and passing the electron from the intrinsic resistance; $V_{connect}$ shows the voltage drop due to transmission of gases due to chemical reactions; i_{fc} indicates the delivering current of fuel cell; i_n displays the interior current; i_o is the exchanged current; i_{lim} is the limited curren; R_m represents the membrane and connectors' resistance, and b is the coefficient of mass transmission. In addition, E_o denotes the standard potential of O_2-H_2 chemical reaction in volt. I_{fc} is the output current of the fuel cell in ampere, N_{cell} shows the number of series cells, and A_{cell} states the surface of each cell in cm^2. Besides, the coefficient of α corresponds with the type of fuel cell, T is the operation temperature, p_{H2}, and p_{O2} indicate the hydrogen pressure and oxygen pressure at input respectively. Finally, η_{FC} is the efficiency of the fuel cell, P_{aux} is the auxiliary power, P_{H2} is the generated power by hydrogen, $\dot{m}_{H2}$ represents the consumption rate of hydrogen and ΔH shows the rate of change of hydrogen enthalpy [40].

$$\eta_{FC} = \frac{P_{FC} - P_{aux}}{P_{H2}} \tag{20}$$

$$P_{H2} = \dot{m}_{H2} \Delta H \tag{21}$$

2.3.2. Micro-turbine

The micro-turbines are of small combustion turbines which can have higher efficiencies than diesel generators by heat recovery of exhausted gases. Micro-turbines are counted as fast-response units which are capable of tracking the loads' variations within their maximum and minimum operational boundaries. They can also be used as quick-start units as reserve capacity. In the considered micro-turbine model, the fuel cost (by a quadratic function), and operation and maintenance costs are included.

$$FC_t^{MT} = \sum_{G=1}^{N_{MT}} \left(f_{1G} + f_{2G} P_{G,t}^{MT} + f_{3G} (P_{G,t}^{MT})^2 \right) \tag{22}$$

In the above equation, P_G^{MT} shows the output power of the micro-turbine. In addition, f_{1G}, f_{2G}, and f_{3G} are the coefficients pertaining to micro-turbine. The exhausted gases of the micro-turbine correspond with the consumed fuel. The emitted gases are approximated by a quadratic function. In this study, the implication of emission of micro-turbines is neglected [41].

3. Evaluating the Reliability of Distribution Systems

In general, the methods of the reliability evaluation of distribution networks can be classified into two major categories of analytic and simulation approaches. In analytical methods, which has many applications in engineering studies corresponded with distribution network reliability, the feeders and related equipment are modeled mathematically as series or parallel components, and the relevant indices can be calculated in a relatively short time. In the simulation methods, the actual model of the stochastic behavior of the system must be simulated. Then through an iterative simulations procedure, the more precise results of parameters and indices can be achieved. It should be noted that the evaluation based on this method requires a lot of computational time [42].

The results of the reliability evaluation of distribution networks are provided in the form of the load points (local) indices and the whole system indices. The reliability indices of the load points are: the mean failure rate that is defined by λ (f/yr), the average interruption duration defined by r (h), the annual average interruption duration which is symbolized by U (h/yr), the energy not supplied that is abbreviated as *ENS* (kWh/yr). The indices are calculated using the following equations:

$$\lambda_s = \sum_{i=1}^{n} \lambda_i \tag{23}$$

$$U_s = \sum_{i=1}^{n} \lambda_i \cdot r_i \tag{24}$$

$$r_s = U_s / \lambda_s \tag{25}$$

$$ENS_s = P \cdot U_s \tag{26}$$

Where λ_i is the occurrence rate of failures at the i_{th} mode, r_i denotes the required time to resupply the considered load points after the incidence of a failure in the i_{th} mode, and P expresses the average consumption rate at the load point (at the distribution power station) [43].

To have a more tangible view of the network status, the indices pertaining to reliability of power systems which describe the behavior of the whole feeder are employed. In the following parts, some of the most commonly used indices are expressed. Nevertheless, various methods are proposed for modeling and evaluating the reliability of distribution networks and further researches and studies in this area are ongoing.

3.1. System Average Interruption Frequency Index (in terms of occurrence per year)

This index is the average number of each customer's interruptions during a year and is obtained by dividing the total number of customers' interruptions in one year to the total number of customers.

$$SAIFI = \sum_{i=1}^{n} \lambda_i \cdot N_i \Big/ \sum N \tag{27}$$

The *SAIFI* is a criterion to determine how many long-term interruptions have occurred during a year for each customer. For the constant number of consumers, the only way to improve this parameter is to reduce the number of long-lasting interruptions that have been occurred.

3.2. System Average Interruption Duration Index (In terms of hour per year)

This index shows the average interruption duration of each customer per year and is calculated by dividing the sum of all durations of customers' interruptions in one year to the total number of network customers.

$$SAIDI = \sum_{i=1}^{n} U_i \cdot N_i \Big/ \sum_{i=1}^{n} N_i \tag{28}$$

The *SAIDI* is a criterion that shows how many long-lasting interruptions have been occurred for each customer within a year. For the constant number of consumers, the only way to improve *SAIDI* is to diminish either the number or the duration of long-lasting interruptions that has been occurred. By reduction of each one of these two factors, the reliability will be improved. In another word, it can be said that the reduction of these parameters will increase the reliability.

3.3. Average Energy Not Supplied Index (AENS)

The average energy not supplied index is obtained by dividing the total not supplied energy in a system to the number of customers.

$$AENS = ENS \Big/ \sum N \tag{29}$$

These criteria seem very convenient to evaluate the way of performing the main tasks of the distribution system and to evaluate the fulfillment of customers' needs and objectives, which can be calculated for an entire system or some of its components [44]. In this paper, the possibility of occurrence of a fault in all lines have been examined and the number of the points that will be affected regard to the corresponded areas (which will be determined respect to the circuit breaker's location) is identified, and the reliability indices are calculated in each of the load points. The noticeable point is that in the simulation of each fault, the impact of network structure, the presence of disconnecting switches, and the possibility of feeding the unsupplied loads from the main source or other sources should be modeled correctly.

4. Combined Objective Function

In this paper, the combined objective function is imposed to find the optimal location of the distributed generators which is composed of three important reliability indices including system average interruption frequency index (*SAIFI*), system average interruption duration index (*SAIDI*), and average energy not supplied index (*AENS*) as well as the costs of distributed generation units. In Eq. (30), W_i determines the weighting factor of each index.

$$OF = w_1 \cdot \frac{SAIFI}{SAIFI_T} + w_2 \cdot \frac{SAIDI}{SAIDI_T} + w_3 \cdot \frac{AENS}{AENS_T} + w_4 \cdot \frac{C_{DG}}{C_{DGT}} \tag{30}$$

The purpose of this problem is to minimize the combination of these indices. Different amounts of weighting factor in the objective function are selected according to experiences and trial and failure tests. The DG cost index can be calculated as shown in below:

$$C_{DG} = C_{Installation} + \left(\sum_{t=1}^{T_{yr}} 1/(1+r)^t \right) \times C_{O\&M} \tag{31}$$

Where $C_{Install}$ denotes the DG installation cost, $C_{O\&M}$ declares the DG operation and maintenance cost, r indicates the interest rate, and T_{yr} shows the whole duration of the study [45].

5. Virus Colony Search Algorithm

The virus colony search (VCS) algorithm is a novel heuristic algorithm, which is a nature-inspired optimization method and is adopted of the way viruses behave. VCS is originated by Mu Dong Li, Hui Zhao, Xing Wei Weng and Tong Han in 2016 [46]. In this algorithm, the diffusion and infection of a host cell which is selected by a virus is simulated. The virus has invaded to the host cell to remain alive and to be propagated in the environment. The Fig. 3 demonstrates the paradigm of general growth of viruses.

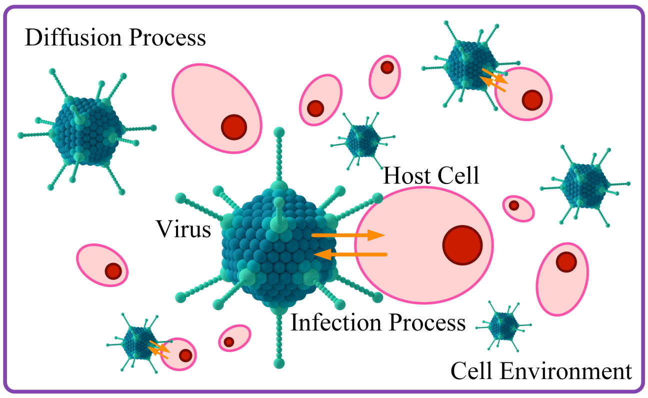

Fig. 3. The diagram of growth of viruses in the cell environment.

5.1. Virus Diffusion

A virus is a small infection factor that can only be remained alive in the living cells of other organisms. The origins of the evolution of viruses' lives are unknown yet, but they generally have two processes for survival and growth. They find the host cells randomly and infect them in order to receive their needed nutritious materials. In this process, the Gaussian random walk method is employed to stimulate the random behavior of diffusion phenomenon. This method has good performance in reaching global optimum. The diffusion behavior of viruses can be modeled by Eq. (32) as below:

$$V'_{pop} = Gaussian(G^g_{best}, \tau) + (r_1 \cdot G^g_{best} - r_2 \cdot V_{pop_i}) \tag{32}$$

In the above equation, i represents a random value derived from [1, 2, 3, …, N], N shows the population size. G^g_{best} is the best solution for the generation of g. In addition, r_1 and r_2 are random variables within [0,1]. τ represents the standard deviation which can be obtained by Eq. (33).

$$\tau = log(g)/g \cdot (V_{pop_i} - G^g_{best}) \tag{33}$$

The term of ($r_1 \cdot G^g_{best} - r_2 \cdot V_{popi}$) prevents the search direction to trap in local optimums. V_{popi} denotes the i^{th} current position of virus V_{pop}. The term of $log(g)/g$ reduce the size of Gaussian jumps as the generation increases. It will improve the algorithm performance. As the Eq. (32) declares, new infectious individuals will be generated around the best global solution. As the generation increases, the term of $log(g)/g$ will be decreased gradually.

5.2. The Host Cells Infection

Once a virus infects a host cell, it keeps invading and destroying the host cell until its death. The virus absorbs its essential nutrition from the host cell and metabolizes the harmful substances. This process will be concluded to the gradual death of the cell. Finally, the host cell will convert into a new virus by 'mutation' process. This process is modeled by the adoption of Covariance Matrix Adaptation Evolution Strategy (*CMA-ES*) algorithm which is a stochastic, derivative-free optimization method for nonlinear or non-convex continuous problems. The main steps of this approach are described in below to simulate the interactive relations between host cells and viruses.

a. *Step 1*: *Updating the* H_{pop}

H_{pop} shows the host cell. The update equation can be represented as below:

$$H^g_{pop_i} = X^g_{mean} + \sigma^g_i \times N_i(0, C^g) \quad (34)$$

Where $N_i(0, C^g)$ represents a normal distribution with the mean value of 0 and a $D \times D$ covariance matrix of C^g. Besides, g denotes the current generation, D denotes the dimension of the problem, and $\sigma^g > 0$ is the step size. X^g_{mean} should be initialized by Eq. (35):

$$X^0_{mean} = \sum_{i=1}^{N} V_{pop_i} \Big/ N \quad (35)$$

b. Step 2: The Selection of the Best λ as a Parental Vector.

The center of chosen vector can be calculated based on Eq. (36), in which $\lambda = [N/2]$, and ω_i denotes the recombination weight and i shows the index of the i^{th} best individual. Hence, these two evolution paths are presented to track the changes of the population mean with an exponential decay of the past. In the equations below $\lambda^{-1}_w = \sum_{i=1}^{\lambda} \omega_i^2$.

$$X^{g+1}_{mean} = \frac{1}{\lambda} \sum_{i=1}^{\lambda} \omega_i \cdot V^{\lambda best}_{pop_i} \Big| \omega_i = \ln(\lambda+1) \Big/ \left(\sum_{i=1}^{\lambda} \left(\ln(\lambda+1) - \ln(j) \right) \right) \quad (36)$$

$$p^{g+1}_\sigma = (1-c_\sigma) p^g_\sigma + \sqrt{c_\sigma (2-c_\sigma)\lambda_w} \cdot \frac{1}{\sigma^g} (C^g)^{-0.5} \cdot \left(X^{g+1}_{mean} - X^g_{mean} \right) \quad (37)$$

$$p^{g+1}_c = (1-c_c) p^g_c + h_\sigma \sqrt{c_c (2-c_c)\lambda_w} \cdot \frac{1}{\sigma^g} \cdot \left(X^{g+1}_{mean} - X^g_{mean} \right) \quad (38)$$

The cumulation parameters are set as $c_\sigma = (\lambda_w+2)/(N+\lambda_w+3)$ and $c_c = 4/(N+4)$. h_g usually sets as h_σ=1. But if $\left\| p^{g+1}_\sigma \right\|$ is a large value, h_σ would be equal to 0.

c. Step 3: Updating the Step Size

Updating the step size σ_{g+1} and the covariance matrix C_{g+1} can be calculated by Eqs. (39) to (41), in which $C_\lambda = (\lambda_w - 1).C_1$, where $0 \le C_\lambda \le 1$.

$$\sigma^{g+1} = \sigma^g \times \exp\left(\frac{c_\sigma}{d_\sigma} \left(\frac{\left\| p^{g+1}_\sigma \right\|}{E\left\| N(0,I) \right\|} - 1 \right) \right) \quad (39)$$

$$C^{g+1} = (1 - c_1 - c_\lambda) C^g + c_1 p^{g+1}_c (p^{g+1}_c)^T + c_\lambda \sum_{i=1}^{\lambda} w_i \frac{V\,pop^{\lambda best}_i - X^g_{mean}}{\sigma^g} \cdot \frac{(V\,pop^{\lambda best}_i - X^g_{mean})^T}{\sigma^g} \quad (40)$$

$$d_\sigma = 1 + c_\sigma + 2\max\left\{ 0, (\sqrt{\lambda_w - 1} \big/ \sqrt{N+1}) - 1 \right\} \quad (41)$$

$$c_1 = \frac{1}{\lambda_w} \left(\left(1 - \frac{1}{\lambda_w} \right) \min\left\{ 1, \frac{2\lambda_w - 1}{(N+2)^2 + \lambda_w} \right\} + \frac{1}{\lambda_w} \cdot \frac{2}{\lambda_w (N + \sqrt{2})^2} \right) \quad (42)$$

5.3. Immune Response

Because of the battling feature of host cell's immune system against viruses, only the stronger viruses probably retain its properties to the next generation. In another word, it is more plausible for weaker viruses to be killed by the immune system of host cells. The immune system has an important role in surviving the cell against infection. Hence, following equations are defined to model the virus evolution.

a. Step 1: Evaluation of the performance rank

P_r evaluates the performance rank, N stands for the population size of fitness value of the virus colony V_{pop}, and *rank* (i) indicates the fitness rank of the i^{th} individual.

$$\Pr_{rank(i)} = \left(N - i + 1 \right) \big/ N \quad (43)$$

b. Step 2: The Evolution of Individual V_{pop}

The equation below indicates how an individual evolves. In the following equation, k, i, h are random sets, which must be derived selected from [1, 2, 3, …, N], so that $k \neq i \neq h$ and $j \in$ [1, 2, 3, ..., d]. The parameters r and *rand* expresses random variables within [0, 1]. As the equation below shows, the better individuals pass on their better performance to the next generation.

$$\begin{cases} V_{pop_{i,j}^n} = V_{pop_{k,j}} - rand \cdot (V_{pop_{h,j}} - V_{pop_{i,j}}), & if\ r > \Pr_{rank(i)} \\ V_{pop_{i,j}^n} = V_{pop_{i,j}}, & othrwise \end{cases} \quad (44)$$

The mechanism of new population generation according to processes of diffusion, infection and immune system behaviors may exceed the search boundaries. Therefore, by imposing the following controlling constraints the values will be kept in the permissible range.

Step. 1. If $x_{i,j} < Low$, then $x_{i,j} = rand \times (Up - Low) + Low$.

Step. 2. If $x_{i,j} > Up$, then $x_{i,j} = rand \times (Up - Low) + Low$.

In the above relationship, *low* and *up* show the lower and upper boundaries respectively. In addition, $x_{i,j}$ denotes the j^{th} dimension of the i^{th} solution. As it is illustrated in Fig. 4, the flowchart describes how to optimize the problem by employing the virus colony algorithm to find the optimal placement of distributed generation sources.

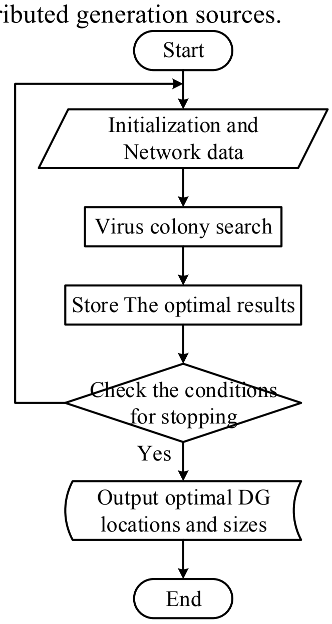

Fig. 4. The flowchart of searching for the optimal location of installation of the DG sources

6. Numerical Study

To display the efficiency of the VCS algorithm, the simulation of the problem is implemented on a 34-bus IEEE standard network that is shown in Fig. 5. This system consists of 33 lines with the total length of 13.5 km and has 34 buses. The detailed data of the target test network including the lines' data, loads' data, etc. are referred to [47-49]. A concise part of the data is presented in Tables 1 and 2 (in appendix at the end of the paper). The failure rate (fault incidence per km) and the duration of maintenance per length unit of the line (per km) are assumed to be identical. The weighting factors values are also chosen as W_1 = 0.31, W_2 = 0.31, W_3 = 0.31 and W_4 = 0.07. The parameters related to the reliability indices and DG costs are also considered as $SAIFI_T$ = 100, $SAIDI_T$ = 10, $AENS_T$ = 350 and C_{DGT} = 1000000.

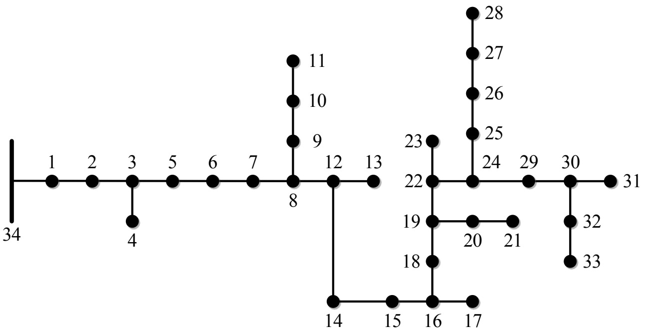

Fig. 5. The diagram of a single-line 34-bus IEEE standard system

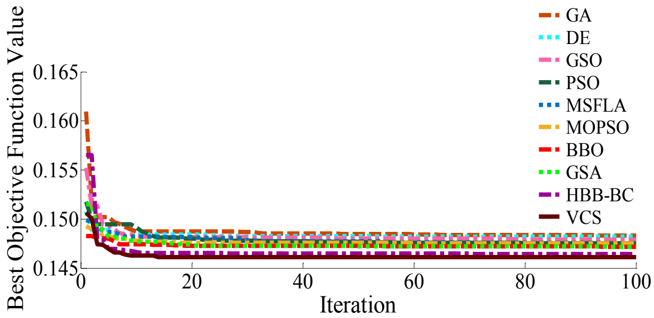

Fig. 6. The comparison of performance of different algorithms

According to the formulation mentioned in section 2 and the optimization algorithm introduced in section 3, the optimization process is executed in order to determine the optimal location to install the distributed generators. Table 3 shows the type, location and capacity of the distributed generators used in this study and the optimized locations for each one by GA, PSO, DE, MOPSO, MSFLA, GSA, BBO, HBB-BC and GSO algorithms as well as crow search algorithm (CSA). The appropriate location for installation of DGs are mentioned in Table 4.

Table 3. The type and installation capacity of the DGs

Type	DG Model	DG capacity	Initial Costs (*$*)	Maintenance cost (*$/yr*)	Operating cost (*$/yr*)
1	PEMFC	300kW	182000	11630	78000
2	PEMFC	500kW	330000	21140	142000
3	MT	700kW	410000	27310	178000
4	MT	1000kW	550000	32240	237000

Table 4. The location of the optimized DGs using the studied algorithms

Type	DG location				
	GA	*DE*	*GSO*	*PSO*	*MSFLA*
DG_1	11	11	11	11	11
DG_2	17	18	17	18	16
DG_3	21	21	20	24	24
DG_4	28	28	28	30	30
Type	DG location				
	MOPSO	*BBO*	*GSA*	*HBB-BC*	*CSA*
DG_1	11	11	11	11	11
DG_2	18	17	17	16	18
DG_3	19	19	19	22	19
DG_4	24	30	30	29	25

The performance of virus colony search algorithm is compared with other evolutionary algorithms such as GA, DE, GSO, PSO, MSFLA, MOPSO, BBO, HBB-BC, and GSA. The results show the priority of this algorithm in terms of accuracy, computation burden and speed. As can be seen in Fig. 6, the objective function is converged to a lower value compared with other types of heuristic methods and reached a better optimal point (minimization).

The calculated values for reliability indices are compared in two modes of before/after installation of DGs based on various optimization algorithms which are provided in Table 5. The results indicate the effectiveness and appropriate performance of VCS algorithm to optimize the problem of DG placement and sizing.

Table 5. values of the system reliability indices before and after the installation of DGs

	SAIFI	*SAIDI*	*AENS*	$C_{interruption}$ (*M$*)
Without (DGs)	8.7	92.4	461.4	13.738
GA	2.31	13.23	64.38	2.541
DE	2.15	12.75	62.26	2.398
GSO	1.99	12.27	60.14	2.255
PSO	1.66	11.30	55.90	1.969
MSFLA	1.65	11.26	55.72	1.956
MOPSO	1.64	11.22	55.54	1.943
BBO	1.58	10.92	54.11	1.839
GSA	1.57	10.93	54.11	1.839
HBB-BC	1.41	10.14	50.53	1.579
CSA	1.32	9.75	48.74	1.449

7. Conclusion

The integration of distributed generation sources units in the electrical distribution networks could have great benefits in reducing the outages and improving the reliability of distribution networks. In this paper, by applying the VCS algorithm and modelling the impact of the distributed generation sources on reliability, the numbers and the optimal capacity of these sources are determined on the 34-buses IEEE test network. The results show that the installation of four DGs on buses 11, 18, 19, and 25 not only improves the network reliability indices but also decreases the system interruption cost by 12.239 million dollars compared to the condition of lack of installation of DGs. Regard to the installation, operation, and maintenance costs of DGs, the network operator will be profited by 8.419 million dollars. The results also declare that the advantages corresponded with DG installation are more remarkable compared with employment of other algorithms studied (GA, PSO, DE, MOPSO, MSFLA, GSA, BBO, HBB-BC and GSO). Thus, optimal installation of distributed generators in the distribution networks makes improvement in the reliability indices, especially the energy not supplied index.

Furthermore, the optimized placement and size of DGs provide significant economic benefits. To sum up, the following results can be bolded as the main conclusions of this study:

- The utilization of distributed generation with optimal size can improve the reliability indices of radial distribution networks.
- Although the installation of DGs requires considerable investment, the utilization of them will be led to more economic operation of distribution grid. The reason is that the losses will be mitigated and energy not supplied will be decreased.
- As the more optimum placement and size is determined for DG installation, the operational costs along with losses will be declined and lower loading rate and maintenance rate of equipment will be concluded. This fact is resulted from better load flow and mitigation of voltage volatilities. Thus, the computational tools such as mathematical evolutionary algorithms play a crucial role to achieve this aim.
- In this study it is observed that VCS algorithm has a better performance, accuracy, and speed in comparison with other heuristic algorithms
- In this study, the employed type of DGs are considered to be fuel cell and micro-turbine. To advance this study, other types of DGs such as wind and solar can be employed, which as uncertainty in nature. Therefore, the impact of uncertainties on reliability and economic indices can be investigated. In addition, in a restructured environment, the effect of price variation in different hours can be included in the model.

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Appendix

Table 1. The data of the 34-bus IEEE standard system

Bus Number	Bus Consumer	P (KW)	Q (KVAR)	**Bus Number**	Bus Consumer	P (KW)	Q (KVAR)
1	0	0	0	**18**	1	4	2
2	0	0	0	**19**	0	0	0
3	11	55	29	**20**	0	0	0
4	0	0	0	**21**	0	0	0
5	3	16	8	**22**	90	450	225
6	0	0	0	**23**	3	15	7
7	0	0	0	**24**	1	2	1
8	0	0	0	**25**	6	23	7
9	0	0	0	**26**	0	0	0
10	0	0	0	**27**	83	414	20
11	7	34	17	**28**	9	45	23
12	27	135	70	**29**	17	83	393
13	1	5	2	**30**	41	206	121
14	8	40	20	**31**	16	82	43
15	1	4	2	**32**	13	67	41
16	10	52	23	**33**	0	0	0
17	0	0	0	**34**	6	28	14

Table 2. Lines characteristics of the 34-bus *IEEE* standard network

Line Number	$Bus_{Sending}$	$Bus_{Receiving}$	$\lambda(f/yr)$	**Line Number**	$Bus_{Sending}$	$Bus_{Receiving}$	$\lambda(f/yr)$
1	34	1	0.983	**18**	16	18	14.04
2	1	2	0.65	**19**	18	19	0.04
3	2	3	12.28	**20**	19	20	1.98
4	3	4	2.212	**21**	20	21	4.024
5	3	5	14.29	**22**	19	22	1.867
6	5	6	11.33	**23**	22	23	0.617
7	6	7	0.04	**24**	22	24	2.221
8	7	8	0.118	**25**	24	25	0.107
9	8	9	0.651	**26**	25	26	0.512
10	9	10	18.35	**27**	26	27	1.387
11	10	11	5.236	**28**	27	28	0.202
12	8	12	3.891	**29**	24	29	0.77
13	12	13	1.154	**30**	29	30	1.021
14	12	14	0.32	**31**	30	31	0.328
15	14	15	7.789	**32**	30	32	0.106
16	15	16	0.198	**33**	32	33	1.85
17	16	17	8.891				