TELKOMNIKA Indonesian Journal of Electrical Engineering
Vol. 13, No. 2, February 2015, pp. 247 ~ 256
DOI: 10.11591/telkomnika.v13i2.7026

Optimal Placement and Sizing of Distributed Generation Units Using Co-Evolutionary Particle Swarm Optimization Algorithms

Alireza Kaviani-Arani
Department of Electrical Engineeing, Majlesi Branch, Islamic Azad University, Isfahan, Iran
Shahid Rajaee Center, Department of Technical and Vocational Education in Isfahan Province
E-mail: A.Kaviani@iaumajlesi.ac.ir, A.Kaviani@etvto.ir

Abstract

Today, with the increase of distributed generation sources in power systems, it's important to optimal location of these sources. Determine the number, location, size and type of distributed generation (DG) on Power Systems, causes the reducing losses and improving reliability of the system. In this paper is used Co-evolutionary particle swarm optimization algorithm (CPSO) to determine the optimal values of the listed parameters. Obtained results through simulations are done in MATLAB software is presented in the form of figure and table in this paper. These tables and figures, show how to changes the system losses and improving reliability by changing parameters such as location, size, number and type of DG. Finally, the results of this method are compared with the results of the Genetic algorithm (GA) method, to determine the performance of each of these methods.

Keywords: *optimal size and location, distributed generation (DG), co-evolutionary particle swarm optimization (CPSO), system losses*

1. Introduction

The simplest and the most general definition of distributed generation sources include the source that is connected directly to distributed (the client). Usually these resources are referred to as small-scale power plants. There are various definitions for distributed generation source in view of different institutes. From the perspective of the International Energy Agency (IEA), DG refers to the source that can meet customer requirements on-site, and help distribution network in energizing. In the view of CIGRE, DG refers to a resource that is facing features: It's not established a centralized, it's not centralized dispatching, it's usually connected to the distribution network and its value is usually less than 50MW to 100MW. In the view of Power Research Institute, DG is the power of a few KW to 50MW.

Use the DG in power system can have advantages such as: reduce losses; improve voltage profiles, increased reliability, lower THD and power system improvement quality. In addition, the small size of this resource is another advantage that it's a very short time of installation and be in place. A number of available distributed power generation technologies in the world are: fuel cells, wind turbines, solar powerhouses, geothermal powerhouses, micro-turbines and so on.

Therefore, it looks essential to determining distributed generation units to achieve these benefits. So far, several methods have been proposed such as minimizing costs, improve voltage profiles, low THD, increased system reliability, minimizing system losses and etc. to DG determine the optimal location and size. In each of these methods, several optimization algorithms are used to achieve the desired goal. In [1] to [7] references, it is used GA to improve the voltage profile and minimizing the losses, in reference [12], reduce the cost has been to basis of accounting, in [8],[9] references, it is used ACO algorithm to reduce losses and improve voltage, in reference [13], it is used GA in order to eliminate the shortcomings system voltage with DG, in [10, 11] references, it has used fuzzy logic for minimizing losses, and finally, in [14] reference, it's used Tabu Search Algorithm for this purpose (determining the optimal location and size of DG). In this paper, it is presented a method to determine the number, location and size of DG with the goal of minimizing losses and improving reliability systems that in which is

Received November 14, 2014; Revised December 29, 2014; Accepted January 12, 2015

used Co-evolutionary Particle Swarm Optimization algorithm (CPSO) for optimization procedure.

2. Evaluation and Selection of Indicators for DG Installation

Installation of DG without the study will have a negative effect in distribution networks, so to avoid the negative impact of DG on system parameters; it should be exist comprehensive and total standards for control, installation and placement of these units [15]. However, according to which choose of following purposes, it will be specified target function:

2.1. Losses Reduction Indicator

Lines are important in conditions of heavy loads, so that its cost will impose to consumer’s form of energy by higher prices. It is obvious that losses in line are effects of power transmission in transmission lines. Thus by using DG, we can reduce the amount of power transmission in lines and therefore it will be reduced losses. In any case, according to the power and location of DG there is also the possibility of increasing the losses lines.

2.2. Voltage of Profile Improvement Indicator

One of the advantages of using DG is improve the voltage profile and maintain voltage in acceptable range in the consumer’s terminal. By using DG, because amount of active and reactive power loads is provided by voltage profile, it will be reduced electricity in the transmission line and therefore strengthen of voltage range for consumer.

2.3. Increase in System Loading Indicator

One other advantages of using DG is reduction of active and reactive power transition from the transmission lines (Overall apparent power). This works leads to increase of transmission lines capacity and therefore it will be preventing construction and development of new lines and other installations such as transmission and distribution substations and therefore reduces costs the related to them.

2.4. Reliability Indicator

Improving the reliability of the system is one of the objectives of using distributed generation. But this does not mean that we should look to it as an independent objective because if we use DG to any reason, it will affect reliability. Of course maybe we can know in total, all these objectives for a distribution network as subset of the system's reliability.

2.5. Voltage Stability Indicator

In the network, voltage stability is associated with the system's ability to provide the needed reactive power of network. In other words, most of reactive power reserve in system resulted a higher degree of voltage stability in the system.

2.6. Environmental Indicator

With utilization of DG and electrical energy production, it will be more less the emissions of greenhouse gases and other environmental pollutants compared with traditional technologies. We can use resources that are optimal in this respect according to percent of emissions of DG. But it is not considered as important indicators in our country.

Now, with regards to the materials above by targeting the two targets to reduce losses and improve reliability, all indicators are provided. Because reduced losses and improved reliability are more consistent with the philosophy of using distributed generation. The objective function is defined as the sum of this two indicators (Reduce losses and improve reliability). Thus our objective function is a multi-objective function (Multi-purpose) that is major difference with the single indicator objective function that we will discuss them in the following.

3. Model of Losses Reduction Indicator

We need reduction in power losses for operation efficiently of network. Losses in distribution system are calculated from the Equation (1), (2).

$$P_L = \sum_{i=1}^{n}\sum_{j=1}^{n} A_{ij}(P_iP_j + Q_iQ_j) + B_{ij}(Q_iP_j - P_iQ_j) \quad (1)$$

$$A_{ij} = \frac{R_{ij}\cos(\delta_i - \delta_j)}{V_iV_j} \quad , \quad B_{ij} = \frac{R_{ij}\sin(\delta_i - \delta_j)}{V_iV_j} \quad (2)$$

P_L : Power losses
P_i : Active power at bus i
Q_i : Reactive power at bus i
V_i : Bus voltage i
δ_i : Phase angle of bus i

The objective of solving the problem is minimizing the total power losses so that the first part of the objective function is as follows:

$$F_1 = P_L = \sum_{i=1}^{N_{sc}} \mathrm{Loss}_k \quad (3)$$

The constraints governing issue is as follows:
Power balance constraint

$$\sum_{i=1}^{N_{sc}} P_{DGi} = \sum_{i=1}^{N_{sc}} P_{Di} + P_L \quad (4)$$

Range of active and reactive power produced by the DG

$$Q_{DGi}^{min} \le Q_{DGi} \le Q_{DGi}^{max} \quad (5)$$

$$P_{DGi}^{min} \le P_{DGi} \le P_{DGi}^{max} \quad (6)$$

Range of network losses

$$\sum \mathrm{Loss}_k(\mathrm{withDG}) \le \sum \mathrm{Loss}_k(\mathrm{withoutDG}) \quad (7)$$

Range of line loading

$$|I_{ij}| \le |I_{ij}|^{max} \quad (8)$$

4. Calculate the Reliability Index

4.1. Unit Unavailability

It is defined the probability of failure in some time intervals during the work in the next as the unavailability of unit and it is known as the unit forced removal rate (*FOR*) in applications of power systems [16]. This parameter is defined based on the ratio of the two units value as follows:

$$\mathrm{FOR} = \frac{\lambda}{\lambda+\mu} = \frac{r}{m+r} = \frac{r}{T} = \frac{f}{\mu} = \frac{\sum[\text{down time}]}{\sum[\text{down time}] + \sum[\text{up time}]} \quad (9)$$

That λ is expected failure rate, μ is expected repair rates, m is mean time to failure ($MTTF = 1/\lambda$), r is mean time to repair ($MTTR = 1/\mu$), $m+r$is mean time between failures ($MTBF= 1/f$), f is frequency period and T is since period.

$$FOR = \frac{MTTR}{MTTR + MTTF} \tag{10}$$

In connection with the production equipment with relatively long duty cycle, FOR parameter is a probabilistic estimates which shows that the production unit will not be able to next time load service under similar circumstances.

4.2. Energy Index Reliability (EIR)

Area under the load curve shows the consumed energy during a specific period and can be used to calculate not feeding energy due deficiency in manufacturing capacity. This parameter is defined the ratio of energy lost due to manufacturing defects and total requirement energy for feeding the network. It's independent of time to define this parameter for the defined period in the load curve and is usually considered for a day, a month or a year. Any manufacturing defect causing loss of load power still be obtained its probability from the following equation:

$$\begin{aligned} &\Pr ob = \binom{n}{m} (U)^m (A)^{n-m} \\ &A = 1 - U \\ &\binom{\mathrm{n}}{\mathrm{m}} = \frac{\mathrm{n}\,!}{(\mathrm{n}\text{-}\mathrm{m})!\ \mathrm{m}!} \end{aligned} \tag{11}$$

That m is number of units that have been damaged, *n* is the total number of units, *U* isunit not available and *A* is availability of units. Probable energy loss in a Power failure is E_k P_k. The total od this multiplies is the total energy lost or hope lost energy.

$$LOEE = \sum_{k=1}^{n} E_k P_k \tag{12}$$

That P_k is possibility of exit production unit with a capacity of Q_k and E_k is energy lost due to the production unit failure with a capacity of Q_k. This parameter can be normalized by using the total energy under the load curve that is defined by *E*.

$$LOEE_{p.u.} = \sum_{k=1}^{n} \frac{E_k P_k}{E} \tag{13}$$

The amount of $LOEE_{p.u.}$is the ratio between potential energy lost due to corruption unit and the total required energy to feed the network load. Index of reliability energy *EIR* is defined as follows:

$$EIR = 1 - LOEE_{p.u.} \tag{14}$$

5. Objective Function the Problem

By combining the phrase above, objective function to determine the size and location of DG resources are provided as follows:

$$F_{Total} = w_1 F_1 + w_2 F_2, \qquad \sum_{i}^{n} w_i = 1 \tag{15}$$

$$F_{Total} = w_1 F_{1,pu} + w_2 F_{2,pu} \tag{16}$$

w_1 and w_2 parameters are weighting coefficients that are an indication of their relative importance.

6. Particle Swarm Optimization (PSO)

PSO is an evolutionary computation technique with the mechanism of individual improvement, population cooperation and competition, which is based on the simulation of simplified social models, such as bird flocking, fish schooling and the swarming theory (Kennedy and Eberhart, 1995). In PSO, it starts with the random initialization of a population (swarm) of individuals (particles) in the search space and works on the social behavior of the particles in the swarm. Therefore, it finds the global best solution by simply adjusting the trajectory of each individual towards its own best location and towards the best particle of the swarm at each time step (generation). However, the trajectory of each individual in the search space is adjusted by dynamically altering the velocity of each particle, according to its own flying experience and the flying experience of the other particles in the search space.

The position and the velocity of the ith particle in the dimensional search space can be represented as $X_i = [X_{i1}, X_{i2}, \ldots, X_{iN}]^T$ and $V_i = [V_{i1}, V_{i2}, \ldots, V_{iN}]^T$, respectively. Each particle has its own best position (*pbest*) $P_i = [P_{i1}, P_{i2}, \ldots, P_{iN}]^T$ corresponding to the personal best objective value obtained so far at time *t*. The global best particle (*gbest*) is denoted by P_g, which represents the best particle found so far at time t in the entire swarm. The new velocity of each particle is calculated as follows:

$$v_{i,j(t+1)} = wv_{i,j(t)} + c_1 r_1 \left(p_{i,j} - x_{i,j(t)}\right) + c_2 r_2 \left(p_{g,j} - x_{i,j(t)}\right),\ j = 1,\ 2,\ \ldots,\ d \tag{17}$$

Where c_1 and c_2 are constants called acceleration coefficients, *w* is called the inertia factor, r_1 and r_2 are two independent random numbers uniformly distributed in the range of [0, 1].

Thus, the position of each particle is updated in each generation according to the following equation:

$$x_{i,j(t+1)} = x_{i,j(t)} + v_{i,j(t+1)},\ j = 1,\ 2,\ \ldots,\ d \tag{18}$$

In the standard PSO, Equation (17) is used to calculate the new velocity according to its previous velocity and to the distance of its current position from both its own best historical position and its neighbors' best position. Generally, the value of each component in V_i can be clamped to the range [$V_{i,min}$, $V_{i,max}$] to control excessive roaming of particles outside the search space [$X_{i,min}$, $X_{i,max}$] Then the particle flies toward a new position according to Equation (18). The process is repeated until a user-defined stopping criterion is reached [17].

6.1. Co-evolutionary Particle Swarm Optimization (CPSO)

6.1.1. Mechanism of Co-evolution

Due to the simplicity of principle and easiness to implement, the penalty function method is the most popular technique to handle constraints. With respect to the main difficulty of setting appropriate penalty factors, Michalewicz and Attia (1994) indicated that a self-adaptive scheme is a promising direction. In the previous work by Coello (2000), a notion of co-evolution was proposed and incorporated into a *GA* to solve constrained optimization problems. In this paper, we will make some modifications on co evolution and incorporate it into *PSO* for constrained optimization problems [17].

The principle of co-evolution model in *CPSO* is shown in Figure 1. In our *CPSO*, two kinds of swarms are used. In particular, one kind of a single swarm (denoted by $Swarm_2$) with size M_2 is used adapt suitable penalty factors, another kind of multiple swarms (denoted by $Swarm_{1,1}$, $Swarm_{1,2}$, …, $Swarm_{1,M2}$) each with size M_1 are used in parallel to search good decision solutions. Each particle B_j in $Swarm_2$ represents a set of penalty factors for particles in $Swarm_{1,j}$, where each particle represents a decision solution. In every generation of co-evolution process, every $Swarm_{1,j}$ will evolve by using *PSO* for a certain number of generations (G_1) with particle B_j in Swarm2 as penalty factors for solution evaluation to get a new $Swarm_{1,j}$. Then the fitness of each particle B_j in $Swarm_2$ will be determined. After all particles in $Swarm_2$ are evaluated, $Swarm_2$ will also evolve by using *PSO* with one generation to get a new $Swarm_2$ with adjusted penalty factors. The above coevolution process will be repeated until a pre-defined stopping criterion is satisfied (e.g., a maximum number of co-evolution generations G_2 is reached).

In brief, two kinds of swarms evolve interactively, where $Swarm_{1,j}$ is used to evolve decision solutions while $Swarm_2$ is used to adapt penalty factors for solution evaluation. Due to the co-evolution, not only decision solutions are explored evolutionary, but also penalty factors are adjusted in a self-tuning way to avoid the difficulty of setting suitable factors by trial and error.

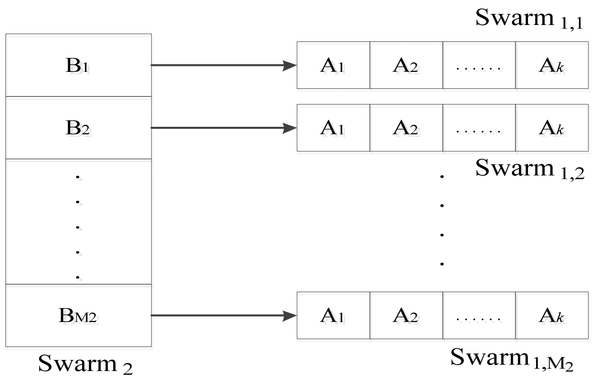

Figure 1. Graphical illustration for the notion of co-evolution

6.1.2. Evaluation function for Swarm1,j

For constrained optimization problems, we design the penalty function following the guidance suggested by Richardson et al. (1989), i.e., not only how many constraints are violated but also the amounts in which such constraints are violated. In particular, the ith particle in $Swarm_{1,j}$in *CPSO* is evaluated by using the following formula:

$$F_i\left(x\right) = f_i\left(x\right) + sum\_viol \times w_1 + num\_viol \times w_2 \tag{19}$$

Where $f_i(x)$ is the objective value of the ith particle, *sum_viol* denotes the sum of all the amounts by which the constraints are violated, *num_viol* denotes the number of constraints violation, w_1 and w_2 are penalty factors corresponding to the particle $B_j$in $Swarm_2$.

The value of *sum_viol* is calculated as follows:

$$\text{sum}_{\text{viol}} = \sum_{i=1}^{N} g_i\left(x\right),\ \forall g_i\left(x\right) > 0 \tag{20}$$

Where N is the number of inequality constraints (here it is assumed that all equality constraints have been transformed to inequality constraints).

6.1.3. Evaluation function for *Swarm₂*

Each particle in $Swarm_2$ represents a set of factors (w_1 and w_2). After $Swarm_{1,j}$evolves for a certain number of generations (G_1), the jth particle B_j in $Swarm_2$ is evaluated as follows.

a) If there is at least one feasible solution in $Swarm_{1,j}$, then particle B_j is evaluated using the following formula and is called a valid particle:

$$P\left(B_j\right) = \frac{\sum f_{\text{feasible}}}{\text{num\_feasible}} - \text{num\_feasible} \tag{21}$$

Where $\sum f_{\text{feasible}}$ denotes the sum of objective function values of feasible solutions in $Swarm_{1,j}$, and *num_feasible* is the number of feasible solutions in $Swarm_{1,j}$. The reason for only considering feasible solutions is to bias the $Swarm_{1,j}$towards feasible regions. Moreover, the subtraction of *num_feasible* in Equation (21) is to avoid $Swarm_{1,j}$ stagnating at certain regions in which only very few particles will have good objective values or even be feasible. Consequently, *Swarm*$_{1,j}$will be encouraged to move towards regions including a lot of feasible solutions with good objective values. In addition, *num_feasible* also acts as a scaling factor when used to divide $\sum f_{\text{feasible}}$.

b) If there is no feasible solution in *Swarm*$_{1,j}$(it can be considered that the penalty is too low), then particle B_j in *Swarm*$_2$ is evaluated as follows and is called an invalid particle.

$$P\left(B_j\right) = \text{Max}\left(P_{valid}\right)\frac{\sum \text{sum\_viol}}{\sum \text{num\_viol}} - \sum \text{num\_viol} \tag{22}$$

Where *Max(P$_{valid}$)* denotes the maximum fitness value of all valid particles in *Swarm*$_2$, $\sum \text{sum\_viol}$ denotes the sum of constraints violation for all particles in *Swarm*$_{1,j}$, and $\sum \text{num\_viol}$ counts the total number of constraints violation for all particles in *Swarm*$_{1,j}$.

Obviously, by using Equation (22), the particle in *Swarm*$_2$ that results in a smaller amount of constraints violation of *Swarm*$_{1,j}$ is considered better. Consequently, the search may bias *Swarm*$_{1,j}$ to the region where the sum of constraints violation is small (i.e. the boundary of the feasible region). Moreover, the addition of item *Max(P$_{valid}$)* is to assure that the valid particle is always better than the invalid one to guide the search to the feasible region. In addition, $\sum \text{num\_viol}$ acts as a scaling factor. Figure 2 shows the flow chart of a *CPSO* algorithm.

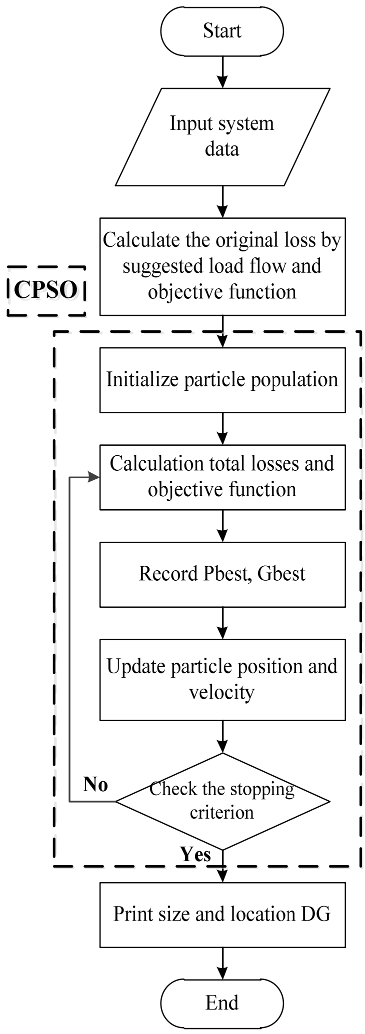

Figure 2. The process computational algorithm (CPSO)

7. Samples Network Study

The proposed method has been applied on a 69 buses test network samples. All network data and Algorithm *CPSO* has been given respectively in Table 1 and 2.

Table 1. Data distribution network sample 69 buses

Network	Active power (MW)	Reactive power (Mvar)	Total active power losses (MW)	Total reactive power losses (Mvar)
69 buses	3.80	2.69	230.0372	104.3791

Table 2. The CPSO algorithm data

CPSO	Population size	Maximum number of repetitions Kmax	C1 = C2	w
	30	100	2	0.4

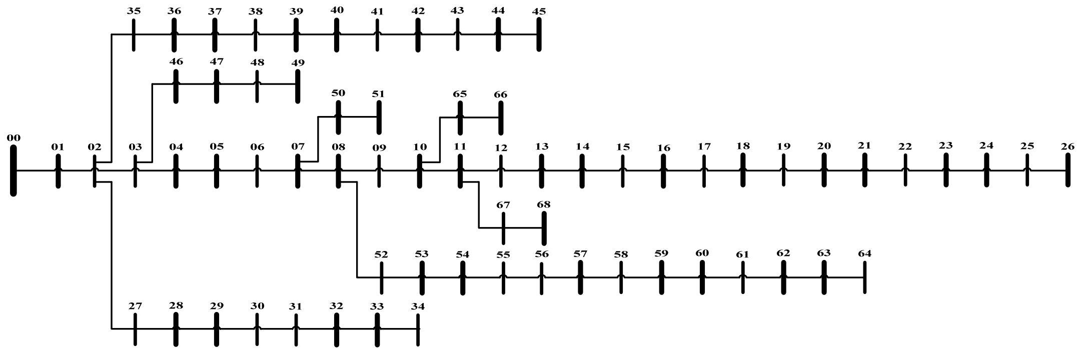

Figure 3. 69 bus distribution network sample

Table 3. *CPSO* results to the samples network

Total real power loss(kW)	Min	Ave.	Max
	80.1933	95.4714	203.2326
Average Time (Sec.)		5.6341	

Convergence characteristic of best the proposed algorithm response is shown in Figure 4. Figure 5 shows total active power losses resulting from the 100 times implementation of *CPSO-OPDG* program.

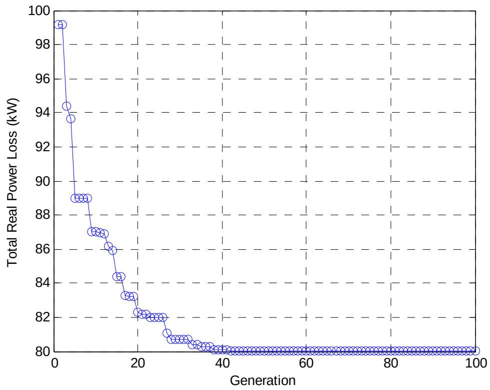

Figure 4. Convergence characteristic of best the proposed algorithm response

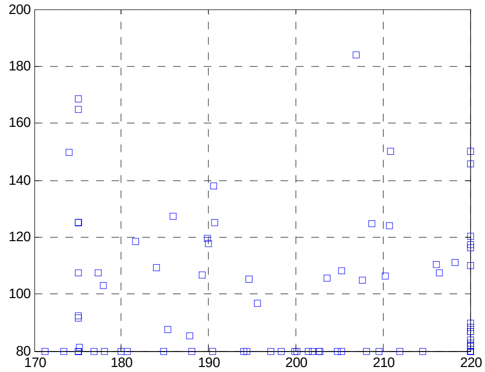

Figure 5. Total active power losses from the 100 times implementation of program *CPSO-OPDG*

Optimum location and size of *DG* for 69 bus system by using *GA* and *CPSO* algorithms is shown in Table 4. As it is shown in Table, loss reduction percentage of active and reactive power in case one *DG* by using the *CPSO* algorithm is equal to 63.05% and 60.28%, while, these two parameters are equal to 61.64% and 58.43% by using the *GA* algorithm. In the case of two *DG*, loss reduction percentage of active and reactive power with using of *CPSO* algorithm is equal to 68.18% and 64.81%, while, it is equal to 63.51% and 60.43% by using the *GA* algorithm. Also in the case of three *DG*, loss reduction percentage of active and reactive power with using of *CPSO* algorithm is equal to 69.19% and 65.81%, but this amount is equal to 67.93% and 64.26% by using the *GA* algorithm. Also it should be mentioned that *CPSO* has this advantage that it can be achieved true optimal solution in the first few repetition, but for *GA* we need to run the algorithm with many repetitions to get the main optimum and non-local answer.

Table 4. *DG* Optimal Placement for 69 buses *IEEE* network using *GA* and *CPSO* algorithms

Method	Bus No.	DG Size (MW)	Bus No.	DG Size (MW)	Bus No.	DG Size (MW)	Ploss (kW)	Qloss (kvar)	Loss Reduction % Real	Reactive
Load Flow Analysis							230.03	104.37		
Heuristic Search	56	1.807					84.93	41.45	63.08	60.29
GA	61	1.500					88.21	43.39	61.64	58.43
	62	0.861	61	0.886			83.91	41.31	63.51	60.43
	62	0.736	18	0.519	61	0.809	73.76	37.31	67.93	64.26
CPSO	56	1.808					84.98	41.47	63.05	60.28
	56	1.724	53	0.519			73.18	36.74	68.18	64.81
	56	1.666	55	0.375	33	0.508	70.87	35.69	69.19	65.81

8. Conclusion

In this paper, it has been used an Evolutionary Intelligent Method for solving the problem of location and optimized size of *DG* resources with multiple objectives. *CPSO* method is very powerful and accurate, as well as is simple on Implementation. About the results of the test network (69 buses *IEEE*) that is done by using two intelligent algorithms *CPSO* and *GA*, it must be said that the simulation shows that loss reduction percentage of active and reactive power with using of *CPSO* algorithm is more and better of the results obtained of *GA* algorithm. Of course, the main advantage *CPSO* algorithm is in the time of obtains optimal values. Because just as mentioned, *CPSO* in the first few repetition; indicates the right answer. But we should be increase the number of these repetitions to find the right optimal solution in the *GA*.

So in this context, *CPSO* algorithm is more efficient than genetic algorithm. So in the end, we can be stated that simulation results of the *CPSO* method is more effective compared to other methods used in this field.

References

[1] Tautiva C, Cadena A. *Optimal Placement of Distributed Generation on Distribution Networks.* IEEEPES–TransmissionandDistribution conference and exposition. Latin America. 2008.
[2] Shahinzadeh, Hossein. Effects of the Presence of Distributed Generation on Protection and Operation of Smart Grid Implemented in Iran; Challenges and Solutions. *TELKOMNIKA Indonesian Journal of Electrical Engineering.* 2014; 12(11).
[3] Barker PP, Mello RW. *Determining the Impact of Distributed Generation on Power Systems: Radial Distribution System*. IEEE Summer meeting conference. 2000; 3: 1645-1656.
[4] G Celli, E Ghiani, S Mocci, F Pilo. *A Multi-Objective Formulation for the Optimal Sizing and Sitting of Embedded Generation in Distribution Networks*. IEEE Bologna Power Tech Conference Proceedings, Bologna. 2003; 23-26.
[5] B Kuri, MA Redfern, F Li. Optimization of rating and positioning of dispersed generation with minimum network disruption. IEEE Power Engineering Society General Meeting. 2004; 2: 2074 – 2078.
[6] X Tang, G Tang. *Multi-objective Planning for Distributed Generation in Distribution Network*. Third international conference. Nanjing China. 2008.
[7] Teng JH, Luor TS, Liu YH. *Strategic distributed generator placements for service reliability improvement.* Proc. IEEE Power Engineering Society Summer Meeting, Chicago, USA, 2002: 719–724.
[8] Borges CLT, Falcao DM. Optimal distributed generation allocation for reliability, losses, and voltage improvement. *Int. J. Power Energy Syst*. 2006; 28(6): 413–420.
[9] CLT Borges, DM Falcao. *Impact of Distributed GenerationAllocation and Sizing on Reliability, Losses, and Voltage Profile.* IEEE Bologna Power Tech Conference Proceedings, Bologna. 2003; 2.
[10] C Wang, MH Nehrir. Analytical approaches for optimal placement of distributed generation sources in power systems, *IEEE Transactions on Power Systems*. 2004; 19(4): 2068–2076.
[11] T Gozel, MH Hocaoglo, U Eminoglu, A Balikci. *Optimal Placement and Sizing of DistributedGeneration on Radial Feeder with Different Static Load Models*, IEEE International conference. 2005.
[12] DT Le, MA Kashem, M Negnevitsky, G Ledwich. *Optimal distributed generation parameters for reducing losses with economic consideration*, IEEE General meeting. 2007.
[13] Rau NS, Wan YH. Optimum location of resources in distributed planning, *IEEE Trans. Power Syst.*, 1994; 9(4): 2014–2020.
[14] Nara K, Hayashi Y, Ikeda K, Ashizawa T. Application of tabu search to optimal placement of distributed generators, *IEEE Power Engineering Society Winter Meeting*. 2001; 918-923.
[15] Shahinzadeh, Hossein, Ayla Hasanalizadeh-Khosroshahi. Implementation of Smart Metering Systems: Challenges and Solutions. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2014; 12(7).
[16] Shahinzadeh, Hossein, Mohammad Moien Najaf Abadi, Mohammad Hajahmadi, Ali Paknejad. Design and Economic Study for Use the Photovoltaic Systems for Electricity Supply in Isfahan Museum Park. *International Journal of Power Electronics and Drive Systems (IJPEDS).* 2013; 3(1): 83-94.
[17] He Q, Wang L. An effective co-evolutionary particle swarm optimization for constrained engineering design problems. *Engineering Applications of Artificial Intelligence*. 2007; 89-99.