APPLICATION OF PARTICLE SWARM OPTIMIZATION AND SIMULATED ANNEALING TECHNIQUES FOR OPTIMAL LOCATION AND SIZING OF DISTRIBUTED GENERATORS

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ABSTRACT

Distributed Generators (DGs) are generators that produce electrical power from quite a few modest energy resources. Some could be referred to as on-site generation, dispersed generation, embedded generation, decentralized generation or distributed energy. These DGs are located in metropolitan locations if you want to minimize the losses in transmitting the energy. In order to identify the size of the distributed generators, an optimization technique is required if the location has been determined. In this study, Fast Voltage Stability Index (FVSI) is applied to figure out the appropriate location for the DGs while Evolution Random Number and hybrid Particle Swarm Optimization (PSO) and Simulated Annealing (SA) were used as the optimization technique to identify the suitable size of the distributed generators. In order to conduct validation process, the IEEE test system is utilized in this study. The results show the viability of using the proposed method over genetic algorithm.

1. INTRODUCTION

From twenty century until now, more than 99% of electricity is generated from large power plants in industrial countries. Most of these countries used coal as their primer source of energy [1]. Another type of energy sources are natural gas, nuclear reactors, hydropower and steam. This type of power plant is popularly known as centralized generation. Even though, some of these types of sources succeed in balancing the supply with demand, but the energy has to transmit over a long distance before it reaches to the consumer due to safety purpose. Other than that, it is due to the pollution created by the power plant. Because of it a location and amount of pollution created, losses are unavoidable [2]. Thus the performance or efficiency of these power plants is at average value. The only power plant that can be near to the cities is the combined cycle plants that burn natural gas or gasifies coal [3].

With such complication and green issues, decentralized generation has become more important and popular among the developed country. Decentralized generation or distributed generation is a local generation of heat and electricity in the distribution grid. A group of DG unit can form a virtual power plant, being centrally controlled and behaves as a single power plant towards the grid [4]. As a result, it reduces the amount of energy lost in power lines because the electricity is generated within the area as the load or perhaps even in the same building. Moreover, widely use of this method will reduce the size and number of power lines that must be constructed [5-6].

However, there are still some problems arise in managing these new decentralized generators. The fundamental problem is the linking between active power injection and the voltage profile in the grid. In high voltage grids, an active power injection will affects the frequency at nominal level. On the other hand, in low-voltage grids, the active power injection will affect the voltage profile throughout the grid. Thus, a suitable and exact location of the DGs is very important.

Another fundamental is the size of the distributed generators. Distributed generation units such as photovoltaic panels (PV cells) and Combined Heat and

Power (CHP) are non-dispatchable. There is almost no inertia in the energy sources which is needed for stability reasons. The only methods that succeed in solving these particular problems are by using the genetic optimization algorithm. Genetic Algorithm (GA) is a search algorithm that is based on the hypothesis of natural selection. The GA is an evolutionary population –based search process that begins with a very large set of initial candidate solution. GA was used to for optimal and sizing of DG using linear programming to confirm the optimization results [7]. GA was used to minimize power losses and power profile in the DG [8]. An improved GA, neuro-genetic algorithm was recently used in [9], for optimal placements of DG, the outcomes of their study indicate a reduction in the active power losses. The different hybrid model is being used to optimize DG systems, for instance, particle swarm optimization and GA were used for optimal location and sizing of DG, the presented work considers power loss and improved voltage stability [10]. In a similar work [11], PSO and GA were applied for DG optimization, the purpose of the work is to reduce power loss and obtain better voltage stability and security drawbacks of the radial distributed system. The fuzzy optimal theory was applied to condensed multi optimization objective problem into a single objective problem. One study considers reducing real power losses, operating costs and enhancing the voltage stability, which becomes the objective function [12]. Although, it is known that injection of the DG system into a power distribution network has impacted on power, but PSO algorithms are very efficient in handling the DG placement and sizing problems. This paper tends to introduce one aspect which is the optimum generation capacity of the DGs which is not being considered in the previous.

Therefore, in this study, an efficient particle swarm optimizing technique will be used to identify the optimum generation capacity of the DGs and its location to provide the maximum power quality improvement using a standard IEEE-69 bus system's is a simulation based program that determines the best solution involving certain problems. PSO is defined as a stochastic, population-based computer problem-solving algorithm; it is a kind of swarm intelligence that is based on social-psychological principles and provides insights into social behavior, as well as contributing to engineering application. PSO was created by observing the behavior of nature. The hypothesis is that 'individual members of the school can profit from the discoveries and previous experience of all other members of the school during the search for food'. Therefore, in detail explanation PS approach utilizes a cooperative swarm of particles, where each particle represents a candidate solution, to explore the space of possible solutions to an optimization problem. Each particle is randomly or heuristically initialized and then allowed to 'fly'. At each step of the optimization, each particle allowed to evaluate its own fitness and the fitness of its neighboring particles.

2. METHODOLOGY

In this paper, there are two different objectives that need to be solved, which are the location of the DGs and the optimal size or capacity of the DGs. Therefore, to determine the absolute location to place the DGs, an algorithm called Fast Voltage Stability Index (FVSI) will be used. Although, the method was used in different engineering optimization methods, for instance, fast voltage stability index (FVSI) based technique for congestion management assessment was used [13], a novel line stability index for voltage stability analysis and contingency ranking in power system using fuzzy based load flow [2].

2.1 FVSI Technique

FVSI is a technique that indicates the stressfulness of a line in the transmission system. In the technique, the reactive power at the certain bus is increased until it reaches the instability point. At that particular point, load that is connected to the bus is being defined as the maximum load ability. It is formulated based on a line or a bus. FVSI is proposed from the existing technique. The formula of FVSI is as follows:

$$FVSI_{ij} = \frac{4Z^2 Q_j}{V_i^2 X} \tag{1}$$

Z is the line impedance

X is the line reactance
Q_j is the reactive power at the receiving end
v_i is the sending end voltage

FVSI is used to sort the index with the highest value on top of the index. Then a total of 5 instability points are taken to be the best candidate for DGs placement. The following steps are being implemented in order to calculate the index:

1. Run the load flow program using Newton Raphson method for the base case.
2. Evaluate the FVSI value for every line in the system.

Gradually increase the reactive power loading at a chosen load bus until the load flow solution fails to give the results. Calculate FVSI values for every load variation.

2.2 Evolution Random Number

In this paper, a technique called Evolution Random Number is used to generate a set of random number. This technique is an adaptation from the Evolution Programming (EP) which evolved new set of data for each iteration in order to meet the desired objectives

Figure 1 shows the process of FVSI. This is because some particles that are generated would probably exceed its dimension space because the number is generated randomly between [0, 1] in uniform distribution. Therefore, with this adaptation, a fitness will be calculated when a set of random number is generated. If the fitness exceeds the maximum fitness, a new set of random number will be generated. This process will continue until the objective fitness has been achieved, as shown in Figure 2.

2.3 PSO and SA Technique

PSO technique is applied by considering it in as a search space. A swarm on N particles is randomly initialized and assign to a certain position randomly in the search space or D-dimensional hyperspace. Each particle is a candidate solution for the optimization problem. Summary of the techniques is shown in Figure 3.

For better understanding, let x be a particle's position and v denote the particle velocity over a search space. Each x in the search is scored by scoring function that obtains a score (fitness value). The fitness value represents how good the particle solves the problem.

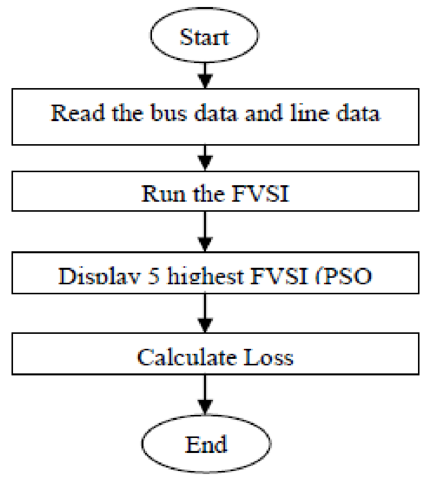

Fig.. 1. Flow Chart of FVSI Technique

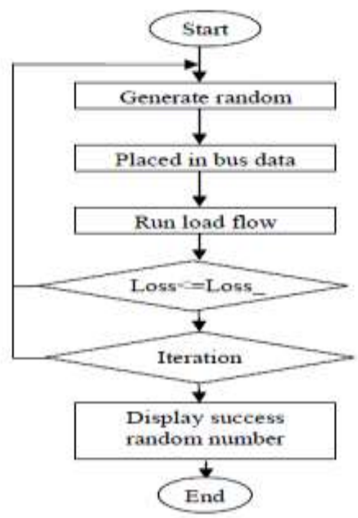

Fig. 2: Process of determining suitable candidate.

The best previous position of a particle is *Pbest*. The index of the best particle among all particles in the swarm is *Gbest*. Each particle records its own personal best position (*Pbest*) and knows the best position found by all particles (neighbour) in the swarm (*Gbest*).Then, all the particles in the search space will update their velocity and position and this process is continuing until the optimal position is found, Figure 3 shows the techniques used to model the PSO, while the rules for updating the velocity and position are given in Equation 2 and 3 respectively.

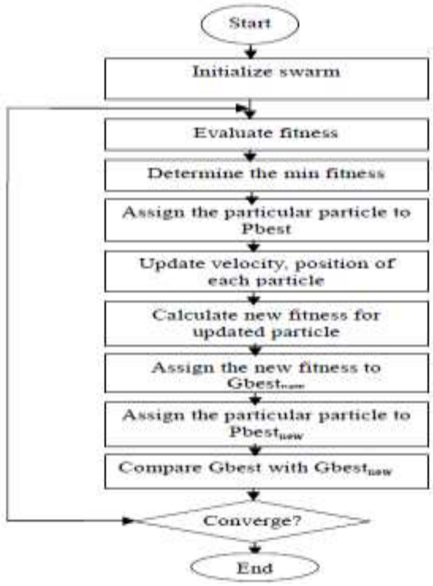

Fig..3 . General Flow Chart of the PSO

$$v^i = wv_i^k + c_i Rand()^{\cdot}(Pbest_i^k - x_i^k) + c_2 Rand()^{\cdot}(Gbest_i^k - x_i^k) \quad (2)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (3)$$

where w is an inertia weight, c_1 and c_2 are the acceleration constant and *Rand( )* is a random number between 0and 1. In this paper, constant c_1 and c_2 are set to1.43 while the weight inertia is set to 0.7.The methodology used in this section is adopted from [12], [14]–[18] with modifications. Consider the minimization problem of an objective function $F(x)$ on the Boolean cube B^n: $min\ \{ F(x) | x \in B^n \}$.

In order to find the global optimum $F_{opt} = F(x_{opt})$ SA algorithm was applied with the following features. Denote by $N(x)$ a neighborhood of the point x and assume that it contains all neighboring points $y \in B^n$ with Hamming distance $d(x,y) \leq 2$. A randomized neighborhood $N_p(x)$ with probabilistic threshold p, $0<p<1$, is a subset of $N(x)$. Each $y \in N(x)$ is included in $N_p(x)$ randomly with probability p and independently from other points. It is clear that $N_p(x)$ may range from being empty for arbitrary threshold $0<p<1$ to including all points from $N(x)$.

Consider a finite sequence $\{x_t\}$, $1 \leq t \leq k$ with property $x_{t+1} \in N(x_t)$. An ordered set $\varphi = \{(i_k,j_k),(i_{k-1},j_{k-1}),\ldots,(i_{k-l+1}, j_{k-l+1})\}$ is called a SA list if vectors x_t and x_{t+1} differ by coordinates (i_t,j_t). The constant l is called the length of the SA list. Note that i_t and j_t are defined as equal if the vectors x_t and x_{t+1} are differed by exactly one coordinate. By definition, $i_t = j_t = 0$ if $x_{t+1} = x_t$.

Finally, let $N_p(x_t,\varphi)$ be a set of points $y \in N_p(x_t)$ which are not forbidden by the tabu list φ. Obviously, $N_p(x_t,\varphi)$ may be empty for nonempty set $N_p(x_t)$. Now SA algorithm can be written as follows:

SA algorithm

1. Initialize $x_0 \in B^n$, $F^* := F(x_0)$, $\varphi := \varnothing$, $t := 0$.
2. While a stopping condition is not fulfilled do
   2.1. Generate neighborhood $N_p(x_t, \varphi)$.
   2.2. If $N_p(x_t, \varphi) = \varnothing$ then $x_{t+1} := x_t$,
   else find x_{t+1} such that $F(x_{t+1}) = min\ \{F(y), y \in N_p(x_t,\varphi)\}$.
   2.3. If $F(x_{t+1}) < F^*$ then $F^* := F(x_{t+1})$.
   2.4. Update the SA list φ and the counter $t := t+1$.

3. RESULTS AND DISCUSSION

The loading condition was applied on bus 6, bus 30 and bus 40. Thus the optimization process will determine the optimal location and sizing of the DGs. Several cases as below were conducted in order to observe the characteristic of the load when DGs are installed and when several adjustments were made in the optimization process. **Case A**: Losses with respect to loading value with DGs being installed

Case B: Losses with respect to number of population (N) per swarm

Case C: Losses with respect to number of swarm

3.1 CASE A: Losses with Respect to Loading Value with DGs Being Installed

In case A, a total of five (5) swarms and a population of 20 particles for each swarm are being considered to determine the optimal location of DGs. By observing this data (Figs. 4-6 and Tables 1-3), adding DGs in the system could decrease the total line loss in the system by 29% for loading value of 10MVAR. However, location of optimal DGs varies as the loading condition increases or decreases. Below are the data for different busses under the same loading condition.

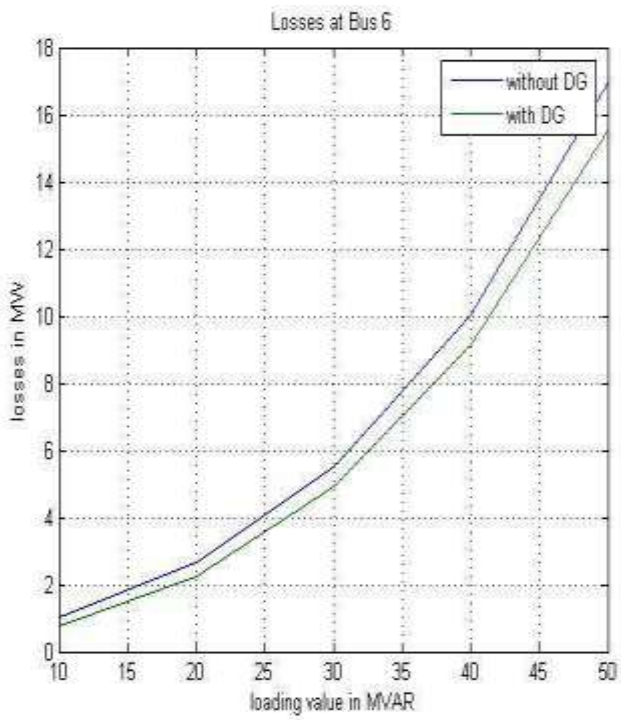

Fig. 4. Losses in the System when DGs are Being Installed for Loading Condition at Bus 6.

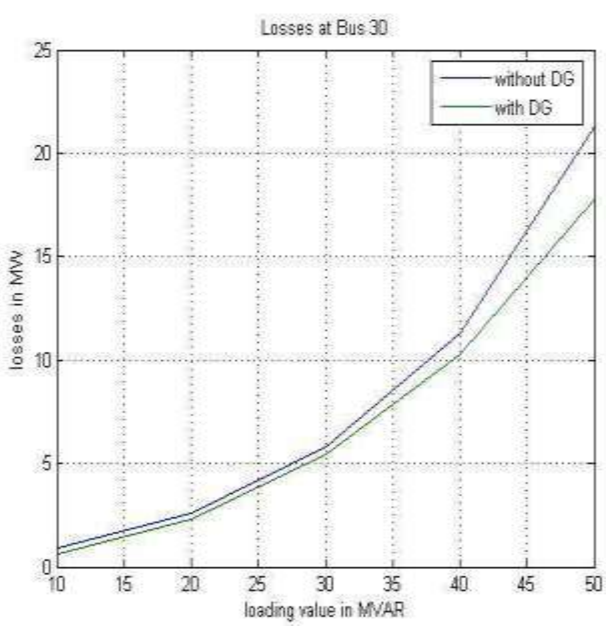

Fig.5. Losses in the System with DGs at Bus 30

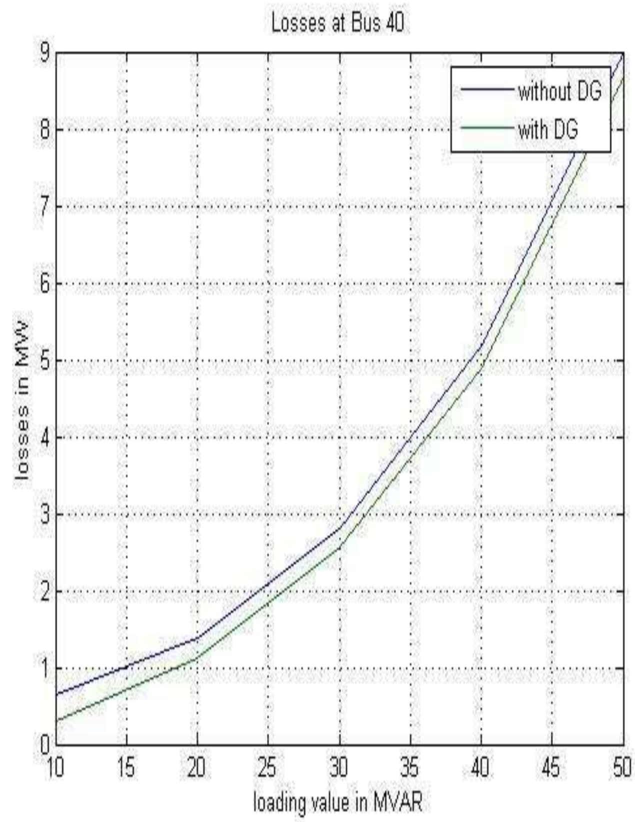

Fig. 6. Losses in the System with DGs at Bus 40

Table 2 and Table 3 showed the different optimal location of the DGs in the system based on the loading condition at different buses.

CASE B: Losses with Respect to Number of Population (N) Per Swarm

Number of population is defined as the candidate value of the DGs capacity. PSO needs a small population in order to meet the objective. However, this is different from Genetic Algorithms (GA). GA will require large genes (> 100) in order to achieve the same objective. This will give PSO+SA the advantage to converge faster than GA. However, increasing the number of populations at a suitable value will decrease the number of iterations thus shortening the optimization process as shown in Figs 7-8. Below are the data that was taken when loading condition is at bus 30 (Table 4-5). If a loading value of 50 MVAR is taken as the reference it can be seen that as the population increase to 60, optimization process needs only 6 iterations in order to converge thus reveal the optimal capacity of the DGs.

Table 1: Percentage of Loss Reduction, Values in MW and Candidate Bus under Loading Condition at Bus 6
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Load Value	***LOSS W/O DGs***	***LOSS WITH DGs***	***(%)***	***X1***	***X2***	***X3***	***X4***	***X5***
10	1.0412	0.738	29.12	BUS 57	BUS 58	BUS 38	BUS 60	BUS 7
				9272	0.781	0.6275	0.8124	0.6143
20	2.6671	2.2526	15.54	BUS 57	BUS 38	BUS 58	BUS 37	BUS 60
				1.5285	0.5674	0.1912	1.3753	0.7523
30	5.5247	4.9466	10.46	BUS 57	BUS 38	BUS 37	BUS 38	BUS 39
				1.3221	0.2469	0.2454	0.0801	1.3093
40	10.0202	9.1128	9.06	BUS 38	BUS 57	BUS 57	BUS 58	BUS 39
				0.6145	0.893	0.966	0.6987	1.4411
50	8.9867	8.6668	3.56	BUS 38	BUS 57	BUS 57	BUS 39	BUS 58
				0.5461	1.0015	0.6786	0.5756	0.9146

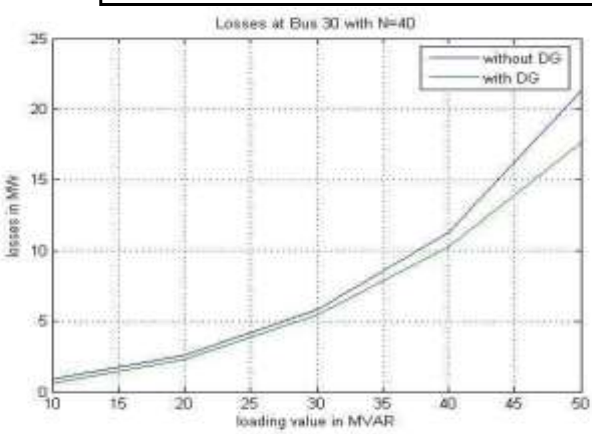

Fig.7: Losses in the System when Number of Population is Increase to 40.

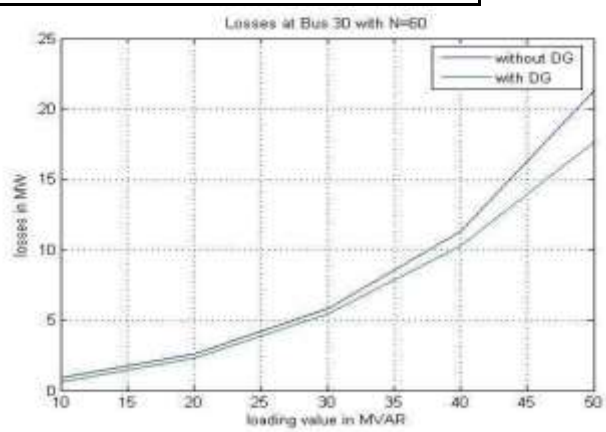

Fig. 8. Losses in the System when Number of Population is Increase to 60

Table 2: Percentage of Loss Reduction, Values in MW and Candidate Bus under Loading Condition at Bus 30 with Number of Iteration.

BUS NO: 6 (N=20)								
Load Value	***LOSS W/O DGs***	***LOSS WITH DGs***	***(%)***	***X1***	***X2***	***X3***	***X4***	***X5***
10 (1 iter)	0.9122	0.6472	29.01	BUS 30	BUS 57	BUS 58	BUS 60	BUS 7
				0.805	0.200	0.258	1.701	0.915
20 (1 iter)	2.5792	2.3001	10.81	BUS 38	BUS 57	BUS 57	BUS 39	BUS 58
				1.632	0.168	1.030	0.873	0.247
30 (1 iter)	5.7942	5.4551	30.53	BUS 30	BUS 57	BUS 29	BUS 58	BUS 60
				1.731	0.747	0.392	-0.0945	0.909
40 (1 iter)	11.32	10.29	40.78	BUS 30	BUS 29	BUS 57	BUS 58	BUS 60
				1.9876	0.8932	7.503	5.525	1.144
50(1 iter)	21.30	17.83	16.34	BUS 30	BUS 29	BUS 57	BUS 58	BUS 60
				14.29	5.850	1.993	4.993	14.29

Table 4. Percentage of Loss Reduction, Value in MW and Candidate Bus under Loading Condition at Bus 30 with N=40.

BUS NO: 30 (N=40 & Swarm=5)								
Load Value	***LOSS W/O DGs***	***LOSS WITH DGs***	*(%)*	***X1***	***X2***	***X3***	***X4***	***X5***
10 (1 iter)	0.912	0.648	28.9	BUS 30	BUS 37	BUS 38	BUS 60	BUS 37
				1.248	-0.052	0.458	1.519	1.436
20 (1 iter)	2.579	2.294	11.024	BUS 30	BUS 37	BUS 58	BUS29	BUS 60
				1.485	0.152	0.812	1.559	1.052
30 (1 iter)	5.794	5.471	5.581	BUS 57	BUS 58	BUS 38	BUS 60	BUS 7
				1.220	0.854	0.471	0.775	0.371
40 (1 iter)	11.32	10.24	9.52	BUS 50	BUS 29	BUS 57	BUS 58	BUS 60
				9.790	4.380	0.726	-2.086	3.243
50 (1 iter)	21.30	17.62	17.3	BUS 38	BUS 29	BUS 57	BUS 58	BUS 50
				13.78	16.75	1.872	6.062	13.78

Table 5: Percentage of Loss Reduction, Value in MW and Candidate Bus under Loading Condition at Bus 30 with N=60.

BUS NO: 30 (N=60 & Swarm=5)								
Load Value	***LOSS W/O DGs***	***LOSS WITH DGs***	*(%)*	***X1***	***X2***	***X3***	***X4***	***X5***
10 (1 iter)	0.912	0.647	28.9	BUS 30	BUS 57	BUS 58	BUS 60	BUS 7
				0.712	0.466	0.424	0.492	0.618
20 (1 iter)	2.579	2.299	10.8	BUS 30	BUS 57	BUS58	BUS29	BUS 60
				1.479	0.673	0.756	0.828	0.751
30 (1 iter)	5.794	5.469	5.794	BUS 30	BUS 57	BUS 29	BUS 58	BUS 60
				5.743	0.635	0.635	0.673	1.369
40 (1 iter)	11.32	10.26	9.41	BUS 30	BUS 29	BUS 57	BUS 58	BUS 60
				9.559	0.849	2.265	0.849	2.780
50 (1 iter)	21.30	17.68	17.0	BUS 29	BUS 57	BUS 58	BUS 50	BUS 60
				17.12	12.88	4.148	4.148	5.658

3.2 CASE C: Losses with Respect to Number of Swarm

In this paper, swarm can be defined as the optimal location of the DGs in the IEEE 69 bus system. A number of the swarm can become one of the factors to minimize loss in the system. In this case, swarm is increased from 5 to 6 and 7 swarms in order to see how the system reacts in terms of loss minimization (Figs.9-10). A total of 30% of loss reduction is being experienced even though the convergence takes a several time. Tables 6-7 showed the percentage of loss reduction, value in mw and candidate bus under loading condition at bus 30 with swarm values 6 and 7 the data clearly indicates minimal loss when the simulation carried out with DGs.

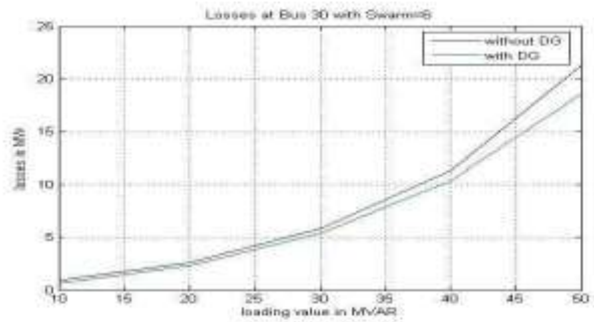

Fig. 9. Losses when the Number of Swarm is increased to 6.

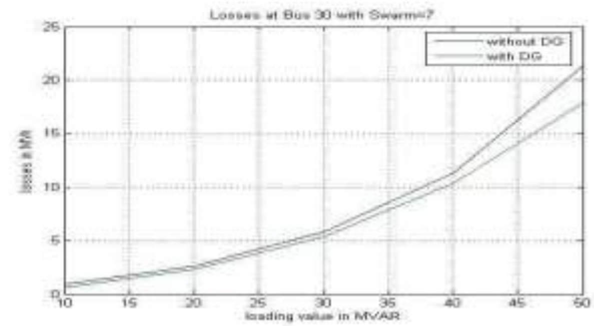

Fig. 10. Losses when Number of Swarm is Increase to 7.

Table 6. Percentage of Loss Reduction, Value in MW and Candidate Bus under Loading Condition at Bus 30 with Swarm=6.

BUS NO: 30 (Swarm=6 & N=20)									
Load Value	***LOSS W/O DGs***	***LOSS WITH DGs***	*(%)*	***X1***	***X2***	***X3***	***X4***	***X5***	***X6***
10 (1 iter)	0.912	0.637	30.4	BUS30	BUS57	BUS58	BUS60	BUS7	BUS61
				0.712	0.466	0.424	0.492	0.618	0.81
20 (1 iter)	2.579	2.297	10.8	BUS30	BUS57	BUS58	BUS29	BUS60	BUS7
				1.479	0.673	0.756	0.828	0.751	0.35
30 (1 iter)	5.794	5.351	7.6	BUS30	BUS57	BUS29	BUS58	BUS60	BUS 7
				5.743	0.635	0.635	0.673	1.36	0.89
40 (1 iter)	11.32	10.35	8.5	BUS30	BUS29	BUS57	BUS57	BUS58	BUS 7
				9.559	0.849	-2.265	0.849	2.780	3.73
50 (1 iter)	21.30	18.58	12.9	BUS30	BUS29	BUS57	BUS 58	BUS60	BUS7
				5.746	11.67	4.284	-2.075	11.67	0.15

Table 7: Percentage of Loss Reduction, Value in MW and Candidate Bus under Loading Condition at Bus 30 with Swarm=7.

BUS NO: 30 (Swarm=7 & N=20)										
Load Value	***LOSS W/O DGs***	***LOSS WITH DGs***	*(%)*	***X1***	***X2***	***X3***	***X4***	***X5***	***X6***	***X7***
10 (1 iter)	0.91	0.63	30.	BUS30	BUS57	BUS58	BUS60	BUS7	BUS61	BUS29
				0.31	0.33	0.45	0.20	0.59	0.89	0.75
20 (1 iter)	1.27	2.27	11.	BUS30	BUS57	BUS58	BUS29	BUS60	BUS7	BUS 61
				1.27	0.18	-0.11	1.34	0.84	1.25	1.10
30 (1 iter)	5.79	5.35	7.5	BUS30	BUS57	BUS29	BUS58	BUS60	BUS7	BUS61
				3.44	-1.08	3.64	1.41	-0.53	-0.55	1.82
40 (1 iter)	11.3	10.3	8.5	BUS30	BUS29	BUS57	BUS58	BUS60	BUS7	BUS60
				5.57	2.70	0.67	0.49	0.55	0.68	0.88
50 (1 iter)	21.3	17.8	16.	BUS30	BUS29	BUS57	BUS58	BUS60	BUS7	BUS61
				15.9	3.95	2.09	4.52	0.66	2.17	3.55

4 CONCLUSION

By introducing DGs in the system, it helps the system by reducing line loss reduction and enhanced the utility system reliability. Moreover, this paper presents a whole new method and approach based on the PSO algorithm for solving the optimal location and sizing of the DGs. Every case gives different critical buses and capacity, which then reduce the total line losses. This stresses the importance of DGs and its optimal location and sizing. An extension to this work, economic factor will be taken into consideration. Even though minimization of loss is part of the cost benefit, other issues will arise which will for the optimal cost benefit of the consumers and country.

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