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Evolutionary PSO based optimal sizing and placement of solar PV distributed generation for voltage and power efficiency enhancement.

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Abstract

The solar photovoltaic continues to be one of the most exploited renewable energy resource globally. It is being utilized both on small scale and large scale applications. In the recent times grid tied solar PV is gaining popularity. Integration of solar power to the main grid can either bring positive or negative impacts depending on how they are sized and where they are located. This paper looks at finding the optimal size and location of solar PV which is a type 1 distributed generation using evolutionary particle swarm optimization (EPSO) technique. The IEEE 30 bus system is utilized with the objective of reducing power loss as well as improve voltage profile. This methodology and its associated results was compared with other algorithms applied by other authors results and the superiority of this methodology is evident.

1. INTRODUCTION

Power from solar photovoltaic (PV) can be utilized as distributed generation (DG) when connected in the distribution system. Distributed generation have many advantages over centralized power generation such as reduction in power losses, improved voltage profile, system stability improvement, pollutant emission reduction and relieving transmission and distribution system congestion. Due to deregulation of power system, many power companies are investing in small-scale renewable energy resources such as wind, solar photo-voltaic, micro, mini and small hydros, combined heat and power (CHPs) and hybrid of these to meet the active power demand (MW) as well as to earn a profit [1]. The addition of distributed generation (DG) in this case solar PV in power system offers a number of advantages such as reduces power losses and voltage improvement in the power system. This improvement will however depend mainly on how well these units are sized and located within the power system. This is because integrating DG units especially for large scale installations, may impact the distribution system negatively if they are not optimally sized and placed. The negative impacts are for instance excess voltages and over currents that may exceed the line's thermal limit, harmonic problems, noticeable voltage flicker and instability of the voltage profile of some of the customers. In addition, the bi-directional power flows can lead to voltage profile fluctuation and change the short circuit levels. Negligible effects can be observed in the network with a low penetration level and serious effects normally results from sizeable penetration level. Therefore, optimal placement and sizing of DGs is necessary so as to address these problems and to minimize overall system losses and improve voltage profiles [1, 2]. Several approaches for optimal placement and sizing of DGs have been proposed in literature. Conventional mathematical approaches have been used as shown by [3, 4]. However these methods have been found to display less robustness especially when solving complex problem because they are based on laws of classical mathematics [1]. More suitable technique based on nature inspired algorithms have also been applied by a number of different researchers. Syahrial Shaddiq et al [5] applied the particle swarm optimization (PSO) technique and [6] compared PSO with the bat algorithm (BA) and Improved Analytical (lA), [7] and [8] compared a number of algorithms including PSO, genetic algorithm (GA) and evolutionary programming (EP). Each of these methods have their own advantages and disadvantages. For example for the case of PSO determination of the inertia weights to improve convergence has been a problem. A number of PSO variations are based on the method used in determining these constants as shown by [9]. PSO however has an advantage over evolutionary techniques such as GA and EP in the sense that the population search space will always remain the same throughout unlike the evolutionary techniques where the process of mutation and crossover produces new populations leading to more search space and also less fit solutions might be produced as a result. Hybrid solutions have also been proposed for example [10] compared PSO with PSO-GA hybrid. This approach is good however a direct hybrid in this way is simply taking the properties of PSO and GA both positive and negative. Not always will this lead to the best solution. The Evolutionary particle swarm optimization (EPSO) addresses the main shortcoming of PSO by applying the strengths of evolutionary techniques. The inertia weights after each iteration undergo replication and mutation which are properties of an evolutionary method to obtain the best solution.

2. POWER FLOW AND OBJECTIVE FUNCTION FORMULATION

2.1 Background on Power Flow

The main objective of the power flow is to determine the steady state conditions of a power system. It mainly involves finding the power system operating condition based on a particular of system parameters of a given that the system parameters are known in advance [11]. Load flow is very importance and usually provide the starting point for other power system analysis such as transient stability, short circuit (of faults) analysis and contingency analysis [12, 13]. The power system is modeled by an equivalent electric circuit which consists of generators, transmission network and distribution network. Load flow studies provide an appropriate analytical approach to determine different bus voltages, their phase angles, active and reactive power flows in all the lines, generators, transformer loadings and load under steady state conditions [14].
Four quantities are associated with each bus which are the voltage magnitude ($|V|$), voltage phase angle (δ), real (active) power (P) and the reactive power (Q) [11].
Depending on the parameters specified in a particular bus the system buses are generally classified into three types as summarized in table 1.

Table 1: Power system buses classification

Bus	**Known Parameters**	**Unknown Parameters**
Slack	$\|V\|$ and δ	P and Q
Generator	P and $\|V\|$	Q and δ
Load	P and Q	$\|V\|$ and δ

2.2 Main Power Flow Equations and Solutions

The load flow Mathematical formulation (known as the power flow equation) as given by equation 1 [12, 15].

$$\frac{P_i - jQ_i}{V_i^*} = V_i \sum_{j=0}^{n} y_{ij} - \sum_{j=1}^{n} y_{ij} V_j \qquad j \neq i \tag{1}$$

The main parameters are obtained from this equation. These resulting equations are non-linear and must be solved by iterative techniques using numerical (iterative) methods only [16, 15, 17]. The main iterative methods used in power flow studies are:

1. Gauss Siedel method
2. Newton Raphson method
3. Fast decoupled method.

The Newton Raphson technique is the most successful power flow calculation method because it has superior convergence characteristics and is less likely to diverge even in large systems [12, 18, 19]. The active and reactive power at any bus i in a power system as derived from 1 can be given the the equations 2 and 3. gives:

$$P_i = \sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \cos\left(\theta_{ij} - \delta_i + \delta_j\right) \tag{2}$$

and;

$$Q_i = -\sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \sin\left(\theta_{ij} - \delta_i + \delta_j\right) \tag{3}$$

2.3 Calculation of Line Flows and Losses

After running load flow by Newton Raphson method, the losses in the system can be obtained the following simple procedure [12]. Give two busses (i,j) in any power system, the complex power from bus i to j, S_{ij} can be calculated as:

$$S_{ij} = V_i I_{ij}^* \tag{4}$$

Also the complex power from bus j to i, S$_{ji}$ can be obtained as;

$$S_{ji} = V_j I_{ji}^* \tag{5}$$

Since these buses are connected through a transmission line, then the power loss in line $i \rightarrow j$ is the algebraic sum of the power flows determined

$$S_{Lij} = S_{ij} + S_{ji} \tag{6}$$

The total power loss in the whole network can then be determined by the summation of the losses in all the branches i.e:

$$\sum S_{Lij} \tag{7}$$

The real part of equation 7 gives the total active power loss while the imaginary part will give the reactive power loss. Therefore the objective functions for active and reactive power loss minimization are;

3. EVOLUTIONARY PARTICLE SWARM OPTIMIZATION (EPSO)

3.1 EPSO Background

This is a hybrid algorithm that was developed to gather the best qualities between PSO and GA [20]. Tuning of the parameters which is the determination of the best algorithm parameters to give the best solution is the main weakness of the classical PSO algorithm. Evolutionary PSO tries to addresses this main weakness by ”mutating” the weight parameters in progression with successive iterations. This is to say that the weight parameters evolve toward the best values as the algorithm progresses. The EPSO uses the same particle movement rule as that used to update the particle position in PSO. The particle will be moving towards its personal best (pBest) which describes the best solution that it achieved so far by that particle, as well as towards the global best solution (gBest) which is the best among the individual best solutions of each particle (pBest). The main difference of the EPSO algorithm is that the gBest position is ”disturbed” hence the particles are not only aiming for the gBest that has already been found but also in the region around the gBest. These disturbance means that a better solution than the already obtained gBest is possible [21]. The EPSO algorithm follows the following steps after each iteration; [22, 21].

- **Replication** - each particle is replicated r times.
- **Mutation** - each particle has its weight parameters (ω, c_1 and c_2 mutated.
- **Reproduction** - each mutated particle will generate an offspring through the process of recombination, according to the particle movement rule.
- **Evaluation** - each offspring has its fitness evaluated.

- **Selection** - by stochastic tournament, the best particles survive to form a new generation, composed of a selected descendant from every individual in the previous generation

3.2 EPSO Algorithm

Figure 1 shows the flow diagram of the EPSO algorithm showing how the evolutionary concepts of GA are combined with those of PSO. The following steps were followed:
Step 1: *Initialization of particles and constants:*
Initialize *N* particles to represent $X_{i,k}$ where *i* = 1 ,2, 3 , ... , *N*. Other parameters that are initialized include the weights (ω_i, c_i), mutation weights (τ_ω, τ_{ci}), slight noise disturb (τ_{gBest}) and the probability of choosing the best particle during selection step constant p_{luck}.
Step 2: *Definition of objective function, pBest and gBest:*
Each of these initialized particles is stored as $pBest_i$ and its associated fitness is labelled as F_pBest_i. The best fitness value and the corresponding particle will be stored as $gBest$ and F_gBest respectively.
Step 3: *Setting the initial iteration counter:* i.e. set k = 1.
Step 4: *Performing Replication:*
Each of the initialized particles is replicated R times. Therefore there will be formed R new particles as:

$$X_{i,k}^r = X_{i,k} \qquad \textit{Where r=1, 2 , . . . , R} \tag{8}$$

Step 5: *Performing Mutation:*
Each particles will have its weights mutated as follows:

$$\begin{aligned} \omega_{i,k+1}^r &= \omega_{i,k}^r + \tau_\omega N(0,1) \\ c_{i,k+1}^r &= c_{i,k}^r + \tau_{ci} N(0,1) \end{aligned} \tag{9}$$

Step 6: *Performing Reproduction:*
Each particles together with their replicas will generate offspring in a similar manner as that of the classical particle swar optimization (PSO) as follows:
For the initial particles;

$$\begin{aligned} V_{i,k+1} = w_{i,k} * V_{i,k} + c_{1,i} * \left(pBest_i - X_{i,k}\right) + c_{2,i} * \left(pBest_i - X_{i,k}\right) \\ X_{i,k+1} = X_{i,k} + V_{i,k+1} \end{aligned} \tag{10}$$

For the replica particles;

$$\begin{aligned} V_{i,k+1}^r = w_{i,k}^r * V_{i,k}^r + c_{1,i}^r * \left(pBest_i - X_{i,k}^r\right) + c_{2,i}^r * \left(pBest_i - X_{i,k}^r\right) \\ X_{i,k+1}^r = X_{i,k}^r + V_{i,k+1}^r \end{aligned} \tag{11}$$

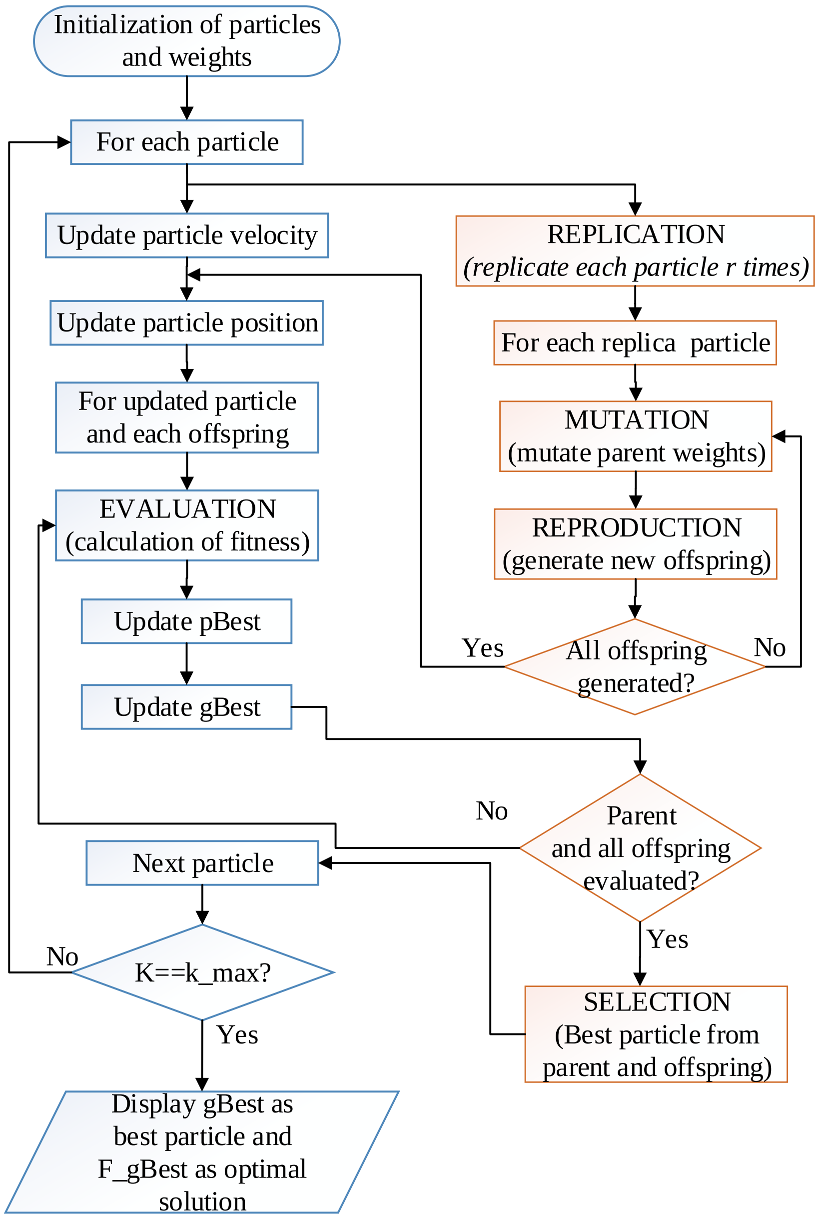

Figure 1: Evolutionary Particle Swarm Optimization Flowchart.

Definition for the best so far (global best, gBest) is done by introduction for random noise disturbance as shown below;

$$gBest_k = gBest_k + \tau_{gBest} N(0,1) \tag{12}$$

Step 7: *Evaluation:*

Here the fitness (objective) function is calculated used both the original (parent) and the offspring (mutated) particles. The fitness functions obtained are stored as F(i,:) and

Fr(i,:) for the initial and offspring respectively.
Step 8: *Updating pBest and gBest:*
The fitness functions obtained in step 7 above is used in updating the stored values of $pBest_k$ and $gBest_k$ respectively.
Step 9: *Selection:*
Here a stochastic competition process is undertaken between all the produced offspring together with their parents. This is done to determine which of them will survive to the next generation. This stochastic tournament is done as follows:

- The best particle after replication / mutation and the parent (non-mutated) particles is determined.

- This is the particle that survives to the next generation with a probability of p_{luck} while the other particles survive with a probability of (1-p_{luck})/R.

Step 10: *Termination criterion test:*
If the termination criterion is met then go to ***step 11*** else go to ***step 4.***
Step 11: *Ending the Algorithm:*
The values obtained after the termination criterion is met are stored as $gBest$ for the best particle (best size of the SPV) and F_gBest as the most optimal solution (in this case minimum active power loss, minimum reactive power loss or optimal voltage magnitudes)

4. TEST SYSTEM RESULTS AND DISCUSSIONS

The Evolutionary particle swarm optimization was used with the aim of ascertaining the most appropriate size and location of the solar photovoltaic (SPV) in the IEEE 30 bus system Figure 2.
The aim of the optimization was to minimize the total active power loss and improve the voltage profile in the system. Each of these objectives was carried out separately. Different possibilities based on the number of optimal locations and their corresponding sizes were considered. The optimal sizes and locations were different in the case of active power and reactive power minimization objectives. For active power loss minimization the optimal bus locations in order of priority were buses 5, 7, 30, 24. The optimal sizes corresponding active power losses are as shown in table 2.

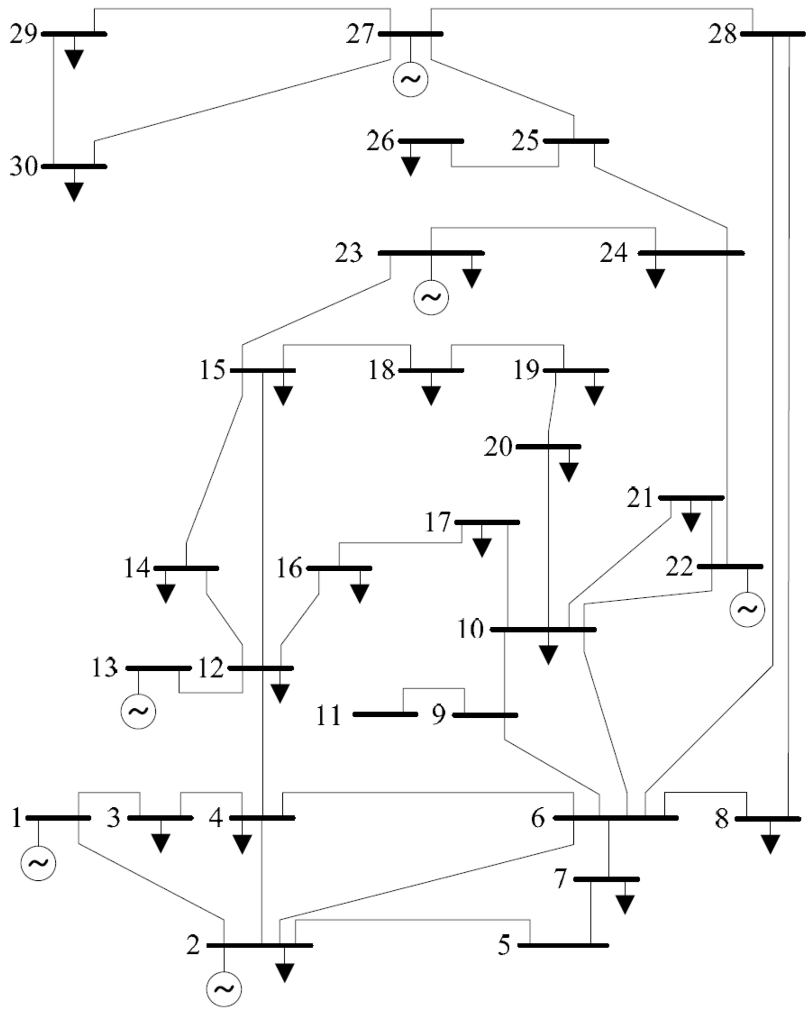

Figure 2: *IEEE 30 bus system single line diagram*

Case	Location	Size	Total Losses	% Reduction
Base	-	-	17.5569	-
One SPV	5	46.8917	11.4827	34.59
Two SPVs	5	24.8002	11.2960	35.70
	7	23.5998		
Three SPVs	5	17.8793	10.5928	39.67
	7	19.2923		
	30	18.9022		
Four SPVs	5	14.9398	10.3013	41.32
	7	14.7411		
	30	13.8744		
	24	12.9413		

Table 2: *Optimal locations and sizes for active power loss reduction*

The distribution of these losses in each branch is as shown in figures 3 and 4.

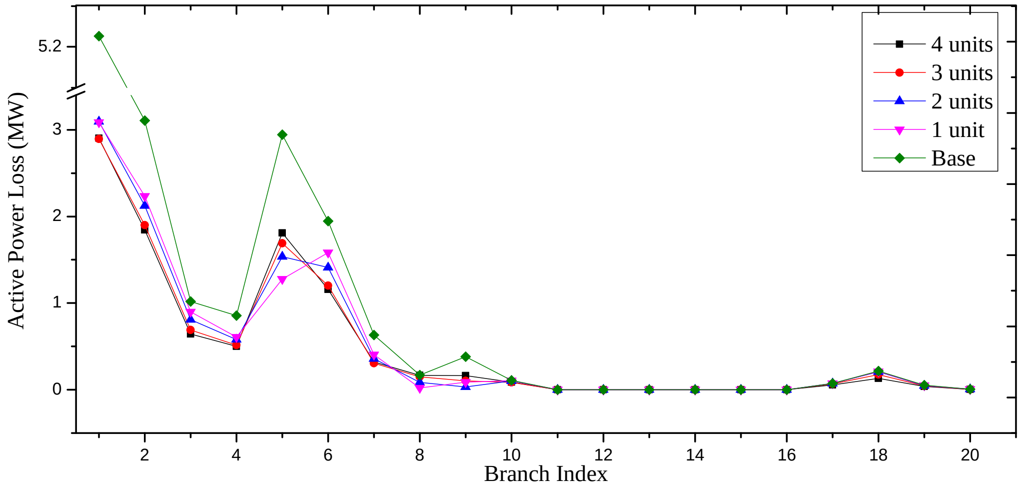

Figure 3: Active power loss between branches 1 and 20

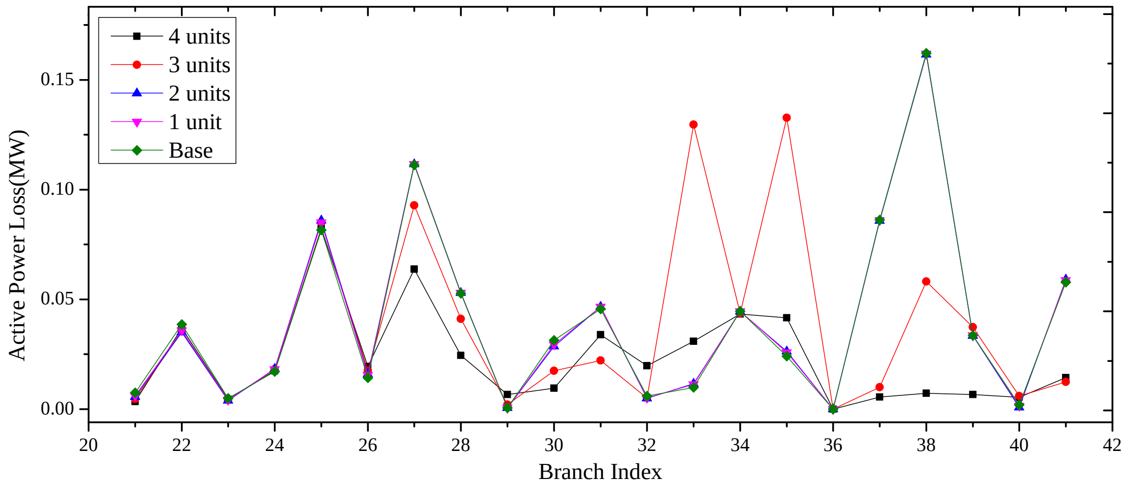

Figure 4: Active power loss between branches 21 and 41

When the objective is changed to reactive power loss reduction the most optimal four locations are 24, 19, 18, 22 in that order or preference. The optimal sizes and the corresponding total reactive power loss is summarized in table 3 which the distribution in each branch is as shown in figures 5 and 6.

Case	Location	Size	Total Losses	% Reduction
Base	-	-	67.6861	-
One SPV	24	44.8256	46.0699	31.94
Two SPVs	24	23.7016	43.1672	36.22
	19	25.3943		
Three SPVs	24	21.8163	40.0993	40.76
	19	19.9410		
	18	17.6178		
Four SPVs	24	13.0379	39.8634	41.11
	19	14.9001		
	18	14.9109		
	22	14.8027		

Table 3: *Optimal locations and sizes for reactive power loss reduction*

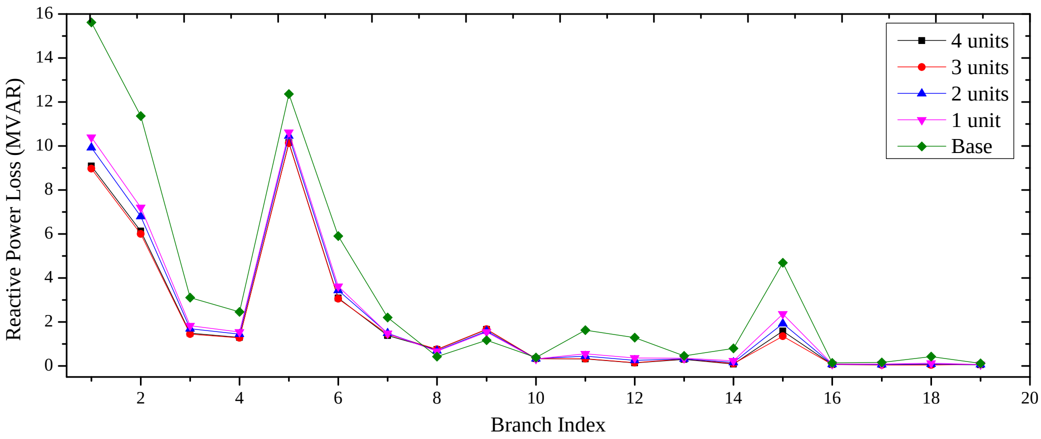

Figure 5: Reactive power loss for branches 1-19

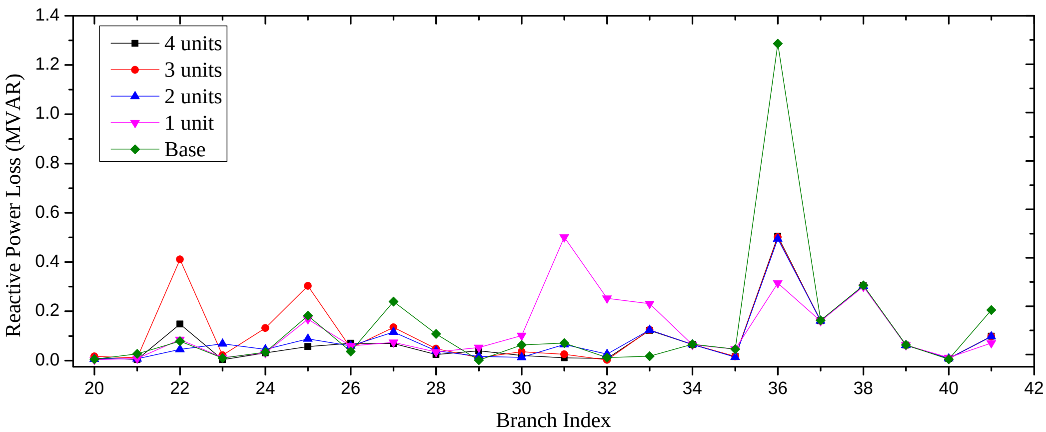

Figure 6: Reactive power loss for branches 20-41

The results obtained with 4 units was compared with those of other authors who used the same system. When the objective was power loss reduction (both active and reactive) the comparison was as summarized in table 4.

Method	**Active Power Loss**		**Reactive Power Loss**	
	MW	**Reduction**	**MW**	**Reduction**
Base Case	17.5569	-	67.6861	-
IPSO [7]	12.1835	30.61 %	45.0811	33.4 %
IPSO-GA [23]	11.6152	33.84 %	44.0708	34.89 %
EPSO (this method)	10.3014	41.32 %	39.8634	41.11 %

Table 4: *Power loss reduction case, comparison with other authors*

The case of voltage profile improvement as the main objective was also carried out. Here the selected buses and their priorities was the same as that of active power loss minimization. The voltage magnitude in each the 30 buses was also compared with that obtained with IPSO [7] and IPSO-GA [23]. This comparison of voltage profile is as shown in figure 7.

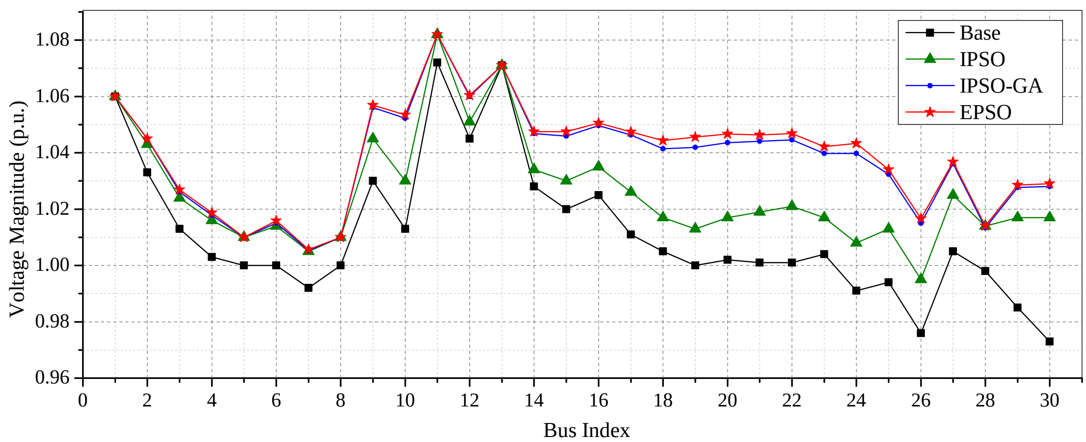

Figure 7: Voltage Magnitude - IEEE 30 Bus

In both cases of results presented above it can be seen that the EPSO algorithm performs best as compared to IPSO and IPSO-GA hybrid. The algorithm is designed to improve the PSO and GA by taking their strong traits and overcoming the weaknesses of each of them.

5. CONCLUSION

In this paper an efficient method of siting and sizing solar PV systems in a power system was investigated. The evolutionary particle swarm optimization (EPSO) was used in this paper. The results obtained was compared with that of particle swarm optimization (IPSO) and GA-IPSO hybrid. The objective function considered were the reduction of power losses and improvement of the voltage profile. The IEEE 30 bus systems was used as the test power system in this work. It was applied in different scenarios with different number of SPVs in the system and the result also compared with other authors who used same system. In all the considered scenarios also its evident that EPSO provides the best response. The performance of EPSO is much better than that of PSO, GA and even that of the GA-PSO hybrid because it only utilizes the strengths of each and not taking all their individual characteristics. This is because some of these individual characteristics are actually shortcomings.

REFERENCES

[1] U. Sultana, Azhar B. Khairuddin, M.M. Aman, A.S. Mokhtar, and N. Zareen, "A review of optimum DG placement based on minimization of power losses and voltage stability enhancement of distribution system," *Renewable and Sustainable Energy Reviews - ELSEVIER*, vol. 63, pp. 363–378, 2 June 2016.

[2] Chandrasekhar Yammani, "A Multi-objective Shuffled Bat Algorithm for Optimal Placement and Sizing of DGs with Load variations ," in *IEEE Region 10 (TENCON) Conference* , Singapore, 22 - 25 Nov 2016.

[3] Chaorui Zhang and Y. andAngela Zhang, "Optimal Solar Panel Placement in Microgrids," in *IEEE International Conference on Smart Grid Communications (SmartGridComm)*, 6 - 9 November 2016, Sydney, Australia.

[4] Mohammed Kdair Abd , Shi Jie Cheng, and Hai Shun Sun , "Optimal Placement and Optimal Mix of RDGs for Improving Voltage Stability and Maximum Loadability Using PSAT," in *IEEE 11th Conference on Industrial Electronics and Applications (ICIEA)*, 5 - 7 June 2016, Hefei, China.

[5] Syahrial Shaddiq, Dian Budhi Santoso, Fikriyan Fajar Alfarobi, Sarjiya , and Sasongko Pramono Hadi, "Optimal Capacity and Placement of Distributed Generation Using Metaheuristic Optimization Algorithm to Reduce Power Losses in Bantul Distribution System, Yogyakarta ," in *IEEE 8th International*

Conference on Information Technology and Electrical Engineering (ICITEE) , Yogyakarta, Indonesia, 6-8 October 2016.

[6] Samir M. Dawoud, Lin Xiangning, Firas M. F. Flaih, and Merfat I. Okba, "PSO Algorithm for Optimal Placement of Multiple SPV Based Distributed Generators in Microgrids," in *IEEE PES Asia-Pacific Power and Energy Conference*, 25 - 28 October 2016 X'ian China.

[7] Yusran, Mochamad Ashari, and Adi Soeprijanto, "Optimal Distributed Generation (DG) Allocation for Losses Reduction Using Improved Particle Swarm Optimization (IPSO) Method," *Journal of Basic and Applied Scientific Research*, vol. 2, pp. 7016–7023, 2012.

[8] Ola Badran, Saad Mekhilef, Hazlie Mokhlis, and Wardiah Dahalan, "Optimal reconfiguration of distribution system connected with distributed generations: A review of different methodologies," *Renewable and Sustainable Energy Reviews - ELSEVIER*, vol. 73, pp. 854–867, 2017.

[9] J. C. Bansal,, P. K. Singh, Mukesh Saraswat, Abhishek Verma, Shimpi Singh Jadon, and Ajith Abraham, "Inertia Weight Strategies in Particle Swarm Optimization," in *IEEE Third World Congress on Nature and Biologically Inspired Computing*, Salamanca, Spain, 19-21 October 2011.

[10] Osaloni Oluwafunso Oluwole, "Optimal Allocation of Distributed Generation for Power Loss Reduction and Voltage Profile Improvement," Master's thesis, University of Cape Town, 2016.

[11] Himakar Udatha and Dr. M. Damodar Reddy, "Load flow analysis using real coded genetic algorithm," *International Journal of Engineering Research and Applications (IJERA)*, vol. 4, Issue 2 (Version 1), pp. 522–527, 2014.

[12] H. Saadat, *Power System Analysis*. Mc-Graw Hill, 1999.

[13] Amidaddin Shahriari, Hazlie Mokhlis, and Ab Halim Abu Bakar, "Critical Reviews of Load Flow Methods For Well, Ill and Unsolvable Condition," *Journal of Electrical Engineering*, vol. 63 (3), pp. 144–152, 2012.

[14] Olukayode A. Afolabi, Warsame H. Ali, Penrose Cofie, John Fuller, Pamela Obiomon, and Emmanuel S. Kolawole, "Analysis of the Load Flow Problem in Power System Planning Studies," *Energy and Power Engineering-Scientific Research Publishing* , vol. 7, pp. 509–523, 2015.

[15] Jagpreet Singh and Rajni Bala, “A Case Study: Comparison of Newton-Raphson and Gauss-Seidal Load Flow Solution Techniques in Distributed Transmission and Generation Electricity Networks,” *International Journal of Advance Electrical and Electronics Engineering (IJAEEE)*, vol. 5 (1), pp. 17–26, 2016.

[16] Mr. Rakesh Singh Rathour and Mrs. Deena L. Yadav, “Newton Raphson TCSC Model for Power System Stability Improvement,” *International Journal of Artificial Intelligence and Mechatronics*, vol. 5, pp. 35–40, 2015.

[17] S.K.Salma Sulthana and M.Naga Jyothi, “Newton-Raphson Load-Flow Analysis in Complex form with UPFC,” *International Journal of Engineering Trends and Technology (IJETT)*, vol. 27(1), pp. 33–39, 2015.

[18] Arshdeep Kaur Kailay and Dr. YS Brar, “FACTS Based Power System Optimization by Using Newton Raphson Technique,” *International Journal of Emerging Research in Management and Technology*, vol. 5, pp. 1–7, 2016.

[19] Archita Vijayvargia, Sweety Jain, Sneha Meena, and Vinita GuptaandMahendra Lalwanib, “Comparison between Different Load Flow Methodologies by Analyzing Various Bus Systems,” *International Journal of Electrical Engineering*, vol. 9, pp. 127–138, 2016.

[20] Luis Filipe Couto Azevedo Costa, “Application of Evolutionary Swarms and Autoencoders to Wind-hydro coordination,” Master’s thesis, Faculty of Engineering, University of Porto, 2008.

[21] Adline Bikeri, Christopher Muriithi, and Peter Kihato, “GENCO Optimal Bidding Strategy and Profit Based Unit Commitment using Evolutionary Particle Swarm Optimization illustrating the effect of GENCO Market Power,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 8, 2018.

[22] Vladimiro Miranda, Leonel M. Carvalho, Mauro A. Rosa, Armando M. Leite da Silva, and Chanan Singh, “Improving Power System Reliability Calculation Efficiency With EPSO Variants,” *IEEE Transactions on Power Systems*, vol. 24, pp. 1772 – 1779, Volume: 24, Issue: 4, November 2009.

[23] Julius Kilonzi , “System loss reduction and voltage profile improvement by optimal placement and sizing of distributed generation (DG) using a hybrid of genetic algorithm (GA) and improved particle swarm optimization (IPSO),” Master’s thesis, Department of Electrical and Electronic Engineering, University of Nairobi, 2015.