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Deployment Of Distributed Energy Resources In Distribution Systems Using Fuzzified Improved Particle Swarm Optimization

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Abstract:
This paper presents an improved particle swarm optimization (IPSO) predicated fuzzy stochastic long term approach for determining optimum location and size of distributed energy resources (DERs). An opportune coalescence of several objectives is considered in the objective function. The point estimation method is used to model the uncertainties associated with long-term load forecasting. Reduction of loss and power purchased from the electricity market, loss reduction in peak load level, and reduction in voltage deviation are simultaneously considered as the objective functions. All the four objectives are solved individually and the results from the individual optimizations are fuzzified and designed to be commensurable with each other, then they are introduced to an IPSO algorithm in order to obtain the solution which maximizes the value of integrated objective function. The experimental results show that proposed IPSO method was indeed capable of obtaining higher quality solution. Simulation results for IEEE30 bus network are represented to show the effectiveness of the proposed method.

Keywords: Distributed energy resources (DERs), fuzzy optimization, loss reduction, improved particle swarm optimization (IPSO), stochastic programming, and voltage deviation reduction.

I. INTRODUCTION

The uncertainties associated with load forecasting and equipments' unavailability affect the system operation and orchestrating decisions. Applying a felicitous method for modeling these uncertainties in orchestrating phase, one can reduce the peril of the decisions as well as the stochastic cost of operation. Ignoring the uncertainties in orchestrating process leads to a high peril, and renders the stochastic preserving gained by applying the decisions non optimal. In this paper an incipient methodology to solve the perplexed quandary of finding optimal location and size of distributed Energy resources (DERs) are presented that considers the uncertainties associated with load forecasting.

In the proposed stochastic orchestrating scheme, the stochastic characteristics of load magnification are simulated utilizing the point estimation method. Each possible system state is represented by a scenario, and a scenario reduction approach, is employed to decrement the number of engendered scenarios. The IPSO is a population based stochastic optimization technique. In IPSO each potential solution is assigned a randomized velocity and the potential solution is called as particle. Each particle change their position by flying around a multi dimensional space, adjusts its trajectory towards its own previous best position and the global best position at each step. The advantages of IPSO are easy to execute, and provide fast convergence for many optimization problems. IPSO has been successfully applied in many research and application areas.

Restructuring of puissance systems has caused an incrementing interest in DERs. Prosperous application and ecumenical propensity to DERs have led to the emergence of incipient technologies in this area. Moreover, the incrementing cognizance on environmental issues have motivated the application of DERs even more.Many benefits are gained by emplacement of DERs, yet they may cause some troubles in operation of distribution systems if they are installed without exhaustive consideration. Therefore, special care should be taken in locating and sizing of DERs. A wide range of benefits, from loss reduction to voltage profile amelioration, can be gained by placement of DERs in distributed systems. Therefore the realm of study of distribution systems is replete with the works on solving the quandary of DER placement with different objective functions. In the most consequential benefits of DER are modeled in economic terms. A set of indices are proposed in for modeling and quantifying of the technical benefits of DERs.

II. MOTIVATIONS AND CONTRIBUTIONS

1) **Developing a Long Term Stochastic Load Model for DER Placement Considering Stochastic Load Magnification:** A long-term stochastic model for system uncertainties is presented in this paper that is suited for application along with IPSO algorithm. The results of the case studies show the indispensability of stochastic modeling of the

quandary. Some other studies in the literature have considered the stochastic nature of the load and system components, but uncertainties are modeled in just one hour or just one year. In orchestrating quandaries, it is compulsory to model the uncertainties in the entire orchestrating horizon.

2) **Considering System Operation in Orchestrating Phase for Different System States:** In this paper, the output power is scheduled for each load level to evade the in convenient repudiation of more optimal solutions. In contrast, the anterior works considered the output power of DERs to be fine-tuned at the maximum rated value, while the load varies at each bus. This may render some optimal solutions infeasible due to violation of some constraints, such as voltage magnitude limits in some load levels, while in most of the other load levels there is no violation.

3) **Application of Fuzzy Optimization Approach to Satisfy Different Objectives Simultaneously in DER Placement:** So many studies have been conducted to reduce the cost of loss in distribution systems. Reduction of voltage deviation in order to reach a more flat voltage profile has additionally been the subject of many studies in distribution systems. In this paper, the reduction of loss and power purchased from the electricity market, loss reduction in peak load level, and reduction in voltage deviation are considered simultaneously as the objective functions. These objectives are first Fuzzified and then integrated and introduced to a IPSO Algorithm in order to obtain the solution which minimizes the value of integrated objective function.

4) **Developing Adoptive Membership Functions:** Fuzzy approach has been applied in anterior works, such as (for capacitor placement), but membership functions were predefined. This paper presents a method to find the felicitous membership functions in Fuzzification process of objective functions. A method is withal presented in order to make these objectives commensurable with each other.

5) **Improved Economic Modeling***:* Profit maximizations considered one of the objective functions, while in order to justify the investment on DER installation compared to the other investment opportunities, the benefit to cost ratio (BCR) is considered as a constraint whose value should be more preponderant than a predefined value. This predefined value should be calculated predicated on the other investment opportunities. The proposed method is tested on IEEE-30 bus radial distribution test system. The simulation results show the efficacy of the proposed method in DER orchestrating quandaries and the essentiality of stochastic modeling. The rest of this paper is organized as follows. In Section II, an overview of the IPSO algorithm is presented. The long term scenario generation and reduction procedures are described in Section III. The proposed method is presented in Section IV. The simulation results are presented and discussed in Section V. The conclusions are drawn in Section VI.

III. IMPROVED PARTICLE SWARM OPTIMIZATION

Considering the expeditious magnification in quandary dimensions and great appeal to expeditious optimization algorithms in recent years, heuristic algorithms predicated on arbitrary search are widely used in lieu of the overall search in quandary space. Heuristic methods may be habituated to solve some combinatorial multi objective optimization quandaries. These methods are called keenly intellective, because the peregrinate from one solution to another is done utilizing rules predicated upon human reasoning. Heuristic algorithms may search for a solution only inside a subspace of the total search region. Albeit, they are able to give a good solution for certain type of quandaries in a plausible computational time, they do not thoroughly assure to reach the ecumenical optimum. The most paramount advantage of heuristic methods lies in the fact that they are not inhibited by restrictive posits about the search space like continuity, actuality of derivative of the objective function, etc. Several heuristic methods can be addressed, such as tabu search (TS), simulated annealing (SA), genetic algorithms (GAs), and particle swarm optimization (PSO). Each one has its own pro and cons which make them possible to apply to the congruous quandaries; in this paper IPSO method is culled as a keenly intellective optimization method. The system is initialized with a population of arbitrary solutions and searches for the optimal solution by updating generations.

In 1995, [14] Kennedy and Eberhert first proposed the IPSO method, inspired by social behaviour of organisms such as fish schooling and bird flocking. It is a population based stochastic optimization technique. In a IPSO the potential solution called particles, fly around in a multi-dimensional search space. The individual particles move towards the position of their own previous best performance and their neighbours best performance.In this process it searches optima by updating iterations. In every iteration,each particle is updated by following two 'best'values. The first one is best solution it has achieved so far, this is called 'pbest'. Another value is the best value obtained so far by any particle in the population. This value is called global best, "gbest".

Expedition is weighted by an arbitrary term, along with separate desultory numbers being engendered for expedition toward p-best and g-best. This incipient technique for nonlinear optimization involves simulating gregarious deportment among individuals (particles) flying through a multidimensional search space, where each particle represents a single intersection of all search dimensions. The particles evaluate their positions relative to a goal (fitness) for any iteration, and particles in a local neighborhood share memories of their best positions, and then use those memories to adjust their own velocities for subsequent positions. In IPSO ith particle Xi is defined as a potential solution in Dimensional space, where $X_i = x_{i1}, x_{i2}, \ldots, x_{iD}$. Each particle also maintains a memory of its previous best position and a velocity along each dimension represented as $P_i = P_{i1}, P_{i2} \ldots, P_iD$, $Vi = V_{i1,} V_{i2} \ldots, V_{iD}$. At each iteration, the $P = [P_1, P_2, P_i, P_n]$ vector of the particle will be adjusted with the best fitness in the local neighborhood. This adjustment will be done using a factor g-best and with the best fitness of the population by a factor p-best. Velocity adjustment along each dimension, can be defined by (1), where it is used where it is used to compute a new position for the particle.

$$V_i = w.v_{i-1} + C_1 \times rand\,(0, 1) \times (x_{igbest} - x_i) + C_2 \times rand(0, 1) \times (x_{ipbest} - x_i) \quad (1)$$

$$X_{i+1} = x_i + v_i \quad (2)$$

Where w: inertia weight factor, often decrease linearly from about0.9 to 0.4 during a run. C_1,$C2$: acceleration constants. *Rand (0, 1)*, random number between 0 and 1. X_{igbest} : The best particle among all individuals in the population. *Xipbest* : The best history of position of particle x_i.
The constants C_1 and C_2 represent the weighting of the stochastic acceleration terms that pull each particle *xi* toward Xi_{gbest} and Xi_{pbest} positions. According to the literature $c1$, $c2$ were often set to be 2.05. A suitable selection of inertia weight w in(1) provides a balance between global and local explorations, thus requiring less iteration to find a sufficiently optimal solution. As it is originally developed, w often decreases linearly from about 0.9 to 0.4 during optimization process. The inertia weight w can be set according to

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{iter_{max}} \times iter \quad (3)$$

where i_{termax} is the maximum number of iterations (generations),while i_{iter} is the current number of iterations. Like GA,PSO is initialized by a population of random solutions with some advantages. It has memory to support the knowledge of good solutions by all particles. PSO has constructive cooperation between particles in order to share their information.

IV. PROBLEM FORMULATION

The aim of operation and planning in deregulated power systems is to maximize the social welfare through minimization of costs of the network, while the electric power is delivered to the customers with sufficient quality and reliability. Because of the high investment cost of DERs, there is considerable risk in their application. Therefore the optimal placement and sizing of DERs are the most important steps to be performed considering various aspects of distribution networks. The objectives of this study are loss minimization, reduction of power which should be purchased from electricity market, loss reduction at the peak load level and improvement of voltage profile of the power system through proper application of DERs.

A. Objective Fuzzification:

Each objective in fuzzy domain is associated with a membership function. The membership function specifies the degree of satisfaction of the objective. In the crisp domain, the objective is either satisfied or violated, indicating membership values of unity and zero, respectively. On the contrary, fuzzy sets consider varying degrees of membership function values from zero to unity. The present work considers the following objectives for the DER placement problem. Maximization of the saving by minimization of the energy loss, power purchased and loss at the peak load level due to the application of DERs. Minimization of the voltage deviation at network buses before continuing further in this section let us return to the stochastic long term load model and find out how one can use it for DER placement. In each scenario we have 12 load levels representing four different load blocks of the three years of study horizon, each with a chance of occurrence. Each scenario itself has a probability. Combining the load levels of the scenarios, the total load probability density function (PDF) is obtained. The load PDF is divided into equal sections each with an occurrence probability. The centers of these sections are introduced to the optimization algorithm as the load levels.The membership function consists of lower and upper bound values along with a strictly monotonically decreasing and continuous function are described in the following.

B. Membership Function for the Net Saving:

The net saving at *k*ith load level due to application of DER in a distribution system is given as the following (it should be noted that load levels are in fact the stochastic load levels that along with line outages reflect the system states in each

$$N_s = \sum_{yr}^{N_{yr}} K_p\, T^{peak}\, L\, R_{yr}^{peak} - \sum_{i=1}^{N_{der}} K_{inv}^{DER}\, P_i^{DER.max} + \sum_{k=1}^{N_k} [K_{E\,\rho k}\, L\, R_k + K_{E\,\rho k} \sum_{i=1}^{N_{der}} P_{i,k}^{DER} - \sum_{i=1}^{N_{der}} K_k^{DER}\; P_{i,k}^{DER}] \quad (12)$$

Where, K_p is a factor to convert peak power loss reduction to dollar (\$/*kw*); *T Peak* is the duration of peak load hours);LRP_{earyr} is the power loss reduction at peak load level at year*yr* due to application of DERs (*kw*); *KE* is a factor to convert energy losses to dollar (\$/*kwh*); ρ_k is the probability of k_{th}load level; LR_k is the reduction in power loss at k_{th} load leveldue to application of DERs (*kwh*); *N*DER is the number ofDERs; *P*DER*i,k* is the power output of i_{th} DER at k_{th} load level(*kwh*); $PDER_k$ is the cost of operation and maintenance of DER at k_{th} load level(\$/*kwh*); $KDER_{inv}$ is the cost of investment of DER (\$/*kw*); and *P*DER,max*i* is the maximum capacity of i_{th}DER (*kw*).

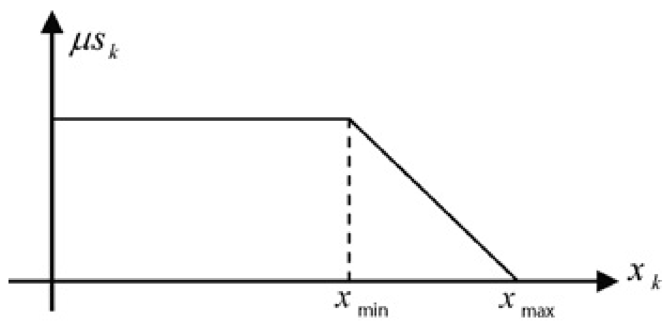

Fig. 3. Membership functions of saving.

Considering a positive profit for application of DERs, for net saving in (13), we have Ns > 0 that means

$$\sum_{k=1}^{N_k}[K_{E\rho k}\, LR_k + K_{E\rho k}\sum_{i=1}^{N_{DER}} P_{i,k}^{DER}] + \sum_{yr}^{N_{yr}} K_p T^{peak}\ L\, R_{yr}^{peak} - \sum_{k=1}^{N_k}\sum_{i=1}^{N_{DER}} K_k^{DER}\, P_{i,k}^{DER} \geq 0 \quad (13)$$

Membership function for the net saving (profit)is given in Fig. 3. Based on this figure one can reach the following equations

$$(\sum_{K=1}^{N_K} K_K^{DER}\, P_{i,k}^{DER}) / \sum_{K=1}^{N_K}\lfloor K_E\rho_K LR_K + K_E\rho_K\sum_{i=1}^{N_{DER}} P_{i,k}^{DER}\rfloor + \sum_{yr}^{N_{yr}} K_P\, T^{peak} LR_{yr}^{peak} \leq 1 \quad (14)$$

$$x_k = \sum_{K=1}^{N_K}\sum_{i=1}^{N_K} K_K^{DER}\, P_{i,k}^{DER} / \sum_{K=1}^{N_K}\lfloor K_E\rho_K LR_K + K_E\rho_K\sum_{i=1}^{N_{DER}} P_{i,k}^{DER}\rfloor + \sum_{yr}^{N_{yr}} K_P\, T^{peak} LR_{yr}^{peak} \quad (15)$$

$$\mu s_k = \frac{(x_{max}-x_k)}{x_{msx}-x_{min}} \text{ for } x_{min\leq}x_k \leq x_{max} \quad (16)$$

$$\mu s_k = 1 \text{ for } x_k \leq x_{min} \quad (17)$$

$$\mu s_k = 0 \text{ for } x_k \geq x_{max} \quad (18)$$

In this paper, x_{max} is assumed to be 1.0; in order to achieve $x_{min}$the proposed method is once performed without consideration of voltage improvement as one of the objectives. The value of x_{min} is determined based on the maximum profit to cost ratio. It means if the maximum profit to cost ratio achieved is 0.6,x_{min} will be 0.375. The x_{min} of 0.375 means unity membership value is assigned if the savings is 37.5% or more, and the x_{max} of 1.0 means zero membership value is assigned if the profitis zero percent of the cost or has a negative value.

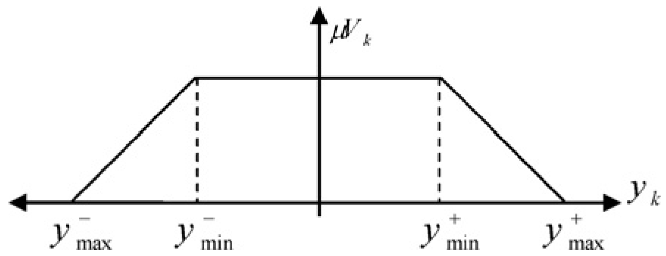

Fig.4. Membership functions of node voltage deviation.

C. Membership Function for the Node Voltage Deviation:

Basic purpose of this membership function is that the deviation of nodes voltage should be minimized. At k_{th} load level of the load duration curve, let us define

$$y_k = \max\left(abs\left(v_n - v_{i,}\right)\right) for\ i = 2,3,\dots N_B \quad (19)$$

where, $V_{i,k}$ is the voltage magnitude of node i at k_{th} load level in per unit and V_n is the nominal voltage magnitude that is equal to one in per unit. It should be noted that it is for the case that the substation is located at bus 1. The less the maximum value of nodes voltage deviation, the high the assigned membership value and vice versa.

$$\mu V_K = (Y_{max}^+ - y_k)\backslash(y_{max}^+ y_{min}^+)\ y_k \geq 0$$
$$(y_{max}^+ - y_k)\backslash(y_{max}^- - y_{min}^-)\ y_k \leq 0 \quad (20)$$

$$\mu\ V_K = 0 \text{ for} Y_K \geq or Y_{max}^+ \text{or} Y_K \text{ or} \leq\ Y_{max}^- \quad (21)$$

$$\mu\ V_K = 1 \text{ for} Y_{min}^- \leq\ \ or Y_{\min}^+ \quad (22)$$

Fig. 4 shows the membership function for maximum node voltage deviation defined. Based on Fig. 3 and taking into account $y^{-max} \leq yk \leq y^{+max}$ we have In this paper, y^{+min} and y^{+max} are considered to be 0.05 and 0.10, respectively. Y−min and y^{-max} are assumed −0.05 and −0.10, respectively. Considering Vn = 1, y^{+min} = 0.05 means the minimum system voltage will be 0.95 p.u. and it means that if the minimum system voltage is greater than or equal to0.95 p.u. the membership value is one. Similarly, y+max = 0.10means the minimum system voltage allowed will be 0.90 p.u. and if the minimum system voltage is less than or equal to 0.90p.u., the assigned membership value will be zero.

D. Fuzzy Formulation for Several Objectives:

The two fuzzified objectives described in the previous section are dealt with by integrating them into a fuzzy satisfaction objective function *F*, through appropriate weighting factors (*K*)as

$$\text{Max } F = K_1 \times \mu s_k + K_2 \times \mu V_k \quad (23)$$

K_1 and K_2 are weighting factor considered in this paper for investigation of the impact of each one of objectives in planning of the DERs. K1 = 0 and K2 = 1 means that only improving voltage profile is considered as the objective of optimization and vice versa; while K_1 = 0.5 and K_2 = 0.5means that these two objectives are assumed to be equally important. The weighting factors can be determined according to the preferences of the operators.

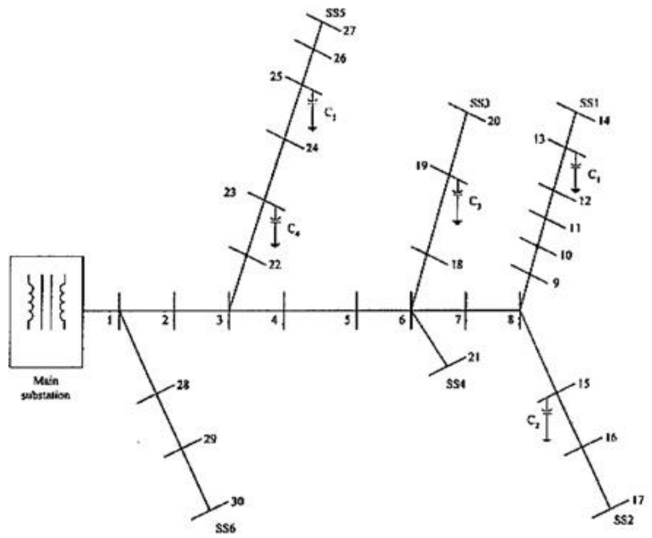

Fig.5. IEEE 30-bus distribution system.

V. SIMULATION BASED RESULTS

In order to test the effectiveness of the proposed method, IEEE 30-bus distribution system including 22 load points, six auxiliary substations and a main feeder [26] is chosen. This system is shown in Fig. 5.The load pattern in the peak load level of the present year is shown in Table I. Both real (*kW*) and reactive (*kVAR*) loads are specified. The base value of voltage and power are 23 (*kV*)and 100 (*MVA*), respectively. After scenario aggregation ten load levels are considered, each with an occurrence probability. These load levels are presented at peak load levels for the sake of accuracy. The PSO parameters are presented in Table III. It is assumed that the size of DERs varies in 100 (*kW*) steps. The investment and operation costs of DERs are borrowed.

A. Fuzzy Optimization Problem Considering Several Objectives, Deterministic Case

Before testing the proposed stochastic method, a deterministic version of the proposed method is tested on IEEE 30-bus distribution system in this subsection. The solution of this deterministic problem can be compared with the solution of stochastic problem to show the necessity of the stochastic modeling of the problem. The values of the load and energy growth rates are considered to be 0.08. The load model with nine levels is used for the three-year time horizon. Table IV shows these load levels and the regarding time durations.The proposed stochastic approach can be simply modified for Deterministic problem by substituting the probability of load levels (ρk) with load level durations of Table IV. In order to find the maximum attainable profit, which as discussed earlier is an important factor in construction of membership functions, firstly the voltage deviation is omitted from the objective function and the maximum profit found is \$1389923.00. Now we can find the suitable membership function regarding to profits and solve the problem. Table V shows the optimal solution of the deterministic problem.Fig. 6 shows the voltage profile for compensated and uncompensated systems for the peak load level of the present year. As can be seen in this figure, voltage deviation is lower for compensated system, which demonstrates that the algorithm can effectively mitigate the voltage deviation while the value of profit is still acceptable comparing with the maximum attainable profit gained in previous case study

B. Fuzzy Optimization Problem Considering Several Objectives, Stochastic Case

In this case study the proposed stochastic approach is used to find the best solution of the optimization problem considering several objectives. In order to find the shape of membership function of the first part of the objective function, initially the stochastic problem is solved considering the profits the objective function to find the maximum attainable value of profit. Table VI show the results of placement problem for the single objective problem. As can be seen in this table the maximum attainable profit with the minimum acceptable *BCR*is \$6658313.10. At the next stage the stochastic problem is solved considering all the objectives shows convergence characteristic for the stochastic problem by PSO. This figure depicts the change in the BCR of the best solution (g-best) versus iterations of the algorithm. As it can be seen, the PSO have rapid convergence characteristic.

C. Statistical Analysis of the Results

Since the algorithm used here is a heuristic optimization algorithm and the stochastic nature of the system has been taken into account, the results derived from the proposed method might vary in each run. In order to investigate the effect of these factors, statistical analysis of the results is discussed in this subsection. The proposed algorithm is run50 times to find the best solution to the problem discussed in case study B (stochastic case with both objectives included).Table VIII shows the results of the statistical analysis. The PSO parameters are considered to be fixed in all runs. As can be seen the standard deviation of the solutions is very low. This shows the robustness of the proposed algorithm against some factors such as initial population of PSO algorithm. Another study is also conducted to analyze the effects of an increase in the degree of uncertainty associated with system loads. The standard deviation of peak load and energy growth is changed from 2% to 5% and the results are presented in Table IX. As can be seen in this table the value of the profit decreases as the degree of uncertainty increases. It is also interesting that as the degree of uncertainty increases, the maximum value of voltage deviation (19) increases with one exception.

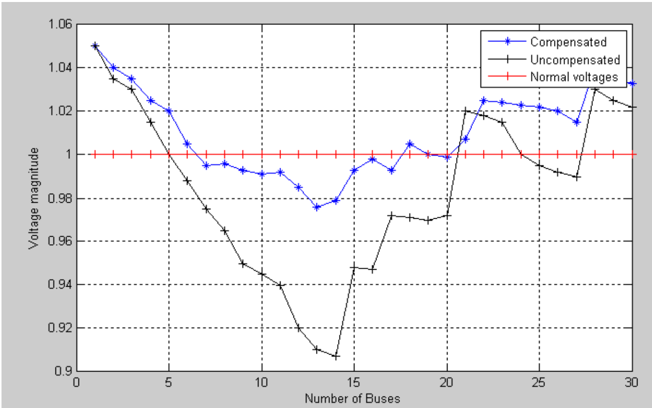

Fig.6. Voltage profile at peak load level for compensated and uncompensated systems at the peak load level of the present year, deterministic case.

TABLE IX Effects of Uncertainties on the Optimal Solution

	$\sigma = 2\%$	$\sigma = 3\%$	$\sigma = 4\%$	$\sigma = 5\%$
3-year Profit (\$)	6255752.6	6255402.5	6254610.1	6254222
Maximum voltage deviation (pu)	0.0412	0.0435	0.0431	0.0442

TABLE X Voltage Deviation at Peak Load Level

	First year	Second year	Third year
Without DER	0.0350	0.0378	0.0381
With DER	0.028502	0.026649	0.025138

The reason may lay under this fact that with increase in these standard deviations the total objective function will definitely decrease, but each objective may show unexpected trend.

feeder for these states is considered to be 1.1 (p.u.). Table X shows the mean

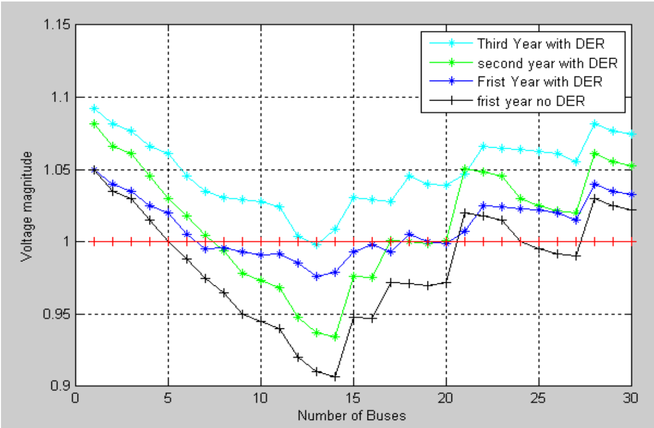

Fig.8. Voltage profile at peak load level of each year for compensated and uncompensated

VI. CONCLUSION

A IPSO based fuzzy stochastic long term optimization methodology considering several objectives was proposed in this paper for optimal placement and sizing of DERs. As the results of case studies showed, ignoring the uncertainties in DER placement problem renders the stochastic saving gained non-optimal.The optimization algorithm simultaneously sought the reduction in power loss; power purchased from the electricity market, power loss at the peak load level, and deviation of the voltage magnitude at the load points. A proper modeling of the economic aspects of the problem was also presented in this paper. Using the proposed algorithm, the optimization problem can be reduced appropriately. The main advantage of proposed algorithm is to achieve faster convergence speed whereas the appropriate performance of system at different loading conditions was guaranteed the justification of investment on DERs. Simulation results demonstrated the effectiveness of developed technique. We have successfully implemented IPSO solution for economic dispatch problem. The algorithm is tested on IEEE30 bus system. The four objectives are solved individually and the results from these individual optimizations are fuzzified and final trade off solution is obtained.

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