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Optimal Solar plant placement using holomorphic embedded power Flow Considering the clustering technique in uncertainty analysis

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Abstract

Increasing energy consumption and reducing fossil energy reserves and its environmental consequences can lead to the use of clean and renewable energy sources such as solar energy. With an inappropriate placement of these units, the system losses is increased and voltage profile will be decreased, So the system efficiency will be decreased. Choosing the best placement of these power plants affects the amount of production of energy and its cost, and consequently amount of the emissions of pollutants. The purpose of this study is to find the best place of solar photovoltaic (SPV) plant to increase energy efficiency by reducing losses and improving voltage profiles. It is crucial task due to the stochastic variation of the PV output power which is related to the solar irradiance variations. In this paper, an improved clustering method with a non-iterative flow approach named as holomorphic embedding method (HEM) are used to solve the problem under the uncertainty condition. It is developed on the base of a tip how it possible to reduce the computation time of calculations. Achieving the mentioned goals has been made faster and easier by reducing the considered scenarios and by using the holomorphic load flow algorithm. Obtaining the solution is possible by using the particle swarm optimization (PSO) algorithm. The decision is based on converting the multi-objective function to a single-objective one. These objective functions are considered to have the lowest line loss and the lowest voltage deviation. The proposed approach is able to include a variety of possible scenarios in the problem analysis and it is applied on IEEE 14-bus test system by considering uncertainty of solar irradiance. Best results are obtained from the placement of PV unit in bus number 3 with operation at -0.27 Pf.

Keywords: Solar power plant; Holomorphic embedded load flow; Uncertainty; Clustering algorithm

1. Introduction

Relying on fossil fuel resources and the negative impact of these resources on the environment has increased the need to use the potential of renewable energy sources. There is a lot of potential in using renewable energy sources like being cheap and harmless. These include solar energy, wind and geothermal. Among them the photovoltaic technology (PV) is one of the fastest renewable energy technologies in growing all over the world. The integration of a PV unit offers significant benefits to the power system. These benefits include lower maintenance costs, no moving parts, less required space and less vulnerability. Due to these advantages, PV plants are more widely used among renewable energy sources. However, due to the

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seasonal and daily variation of the solar irradiance and weather conditions, there is a challenge to incorporate the PV farms in the power system. This causes an uncertainty in in the production of these plants. So, there is some errors in short-term and long-term network scheduling. It is mandatory to consider the uncertainty of PV units for efficient planning in the power system. In these cases find the best sit and size of the SPV plant has a great importance. By defining various technical and economic goals, these problems can be modeled by an optimization problem whose analysis approach is based on mathematical techniques and using meta-heuristic algorithms. However, modelling of the devices has the most importance in defining the optimization problem. This issue is even more important when uncertainty is also involved in finding the optimal solution of the problem. The integration of uncertainty modeling techniques in definition of the optimization problem minimizes the amount of error in performing calculations and achieving the optimal solution. Using uncertainty modeling methods and problem analysis with the help of intelligent algorithms can facilitate the selection of the appropriate solution by considering the key criteria. In various sources, some techniques for dealing with uncertainty have been mentioned. Among the researches which were conducted in field of the problem, the followings can be mentioned: for example, Jayavarma and Joseph [1] have a study using PSO for Optimal placement of solar PV in a radial distribution system. With minimization of total active power loss, the developed algorithm has been tested in terms of certainty condition. They concluded that optimal placement of the SPV not only reduces the loss but also improves the voltage profile. Ansari and Syal [2] have examined and evaluated a PSO based technique for optimal placement of solar based DG in distribution system for minimizing losses and THD. The proposed method was found to be robust with high efficiency for the minimization of loss and harmonic. Also Calculation of the objective functions were based on Newton-Raphson (NR) load flow analysis. Sirat and Parsa [3] have implemented the proposed method for loss minimization through the allocation of DGs Considering the stochastic nature of those units. As a result, they found that the reliability of the system and voltage profile of buses were improved. In that paper three different kinds of DGs were included which were wind turbine, solar panels and biomass generator. Also the utilized calculations was based on forward-backward power flow. Mawgoud et al. [4] have a study on the Optimal Implementation of photovoltaic and battery energy storage in distribution networks. In that paper the slime mould algorithm (SMA) was implemented to determine the best size and location of photovoltaic alone or with battery energy storage in radial distribution system (RDS). Total active loss during 24-hours was used as an objective function. It was based on the probabilistic for PV output. The results have shown the integration of PV and BES reduces the system power loss and increase the system capacity. Kai zou et al. [5] have proposed a novel distribution systems expansion planning strategy encompassing renewable DG systems, which the system uncertainties such as load demand, wind speed and solar radiation were accounted by using the probabilistic models. TRIBE PSO and OO algorithms was developed to obtain optimal solutions. Jain et al. [6] have examined an effective cumulative performance index, utilizing voltage profile improvement, loss reduction and voltage stability index (VSI) for optimal siting and sizing of multiple distributed generators by using PSO. The system loss was minimized considering constant power as well as voltage dependent load models. Chakraborty et al. [7] have proposed an effective method based on the Harris hawks optimization (HHO) algorithm to select the optimum capacity, number, and site of solar-based DGs to reduce real power losses and voltage deviation.they observed that the overall performance of the systems is enhanced when additional DGs are installed. Also a practical size of DG has been suggested considering the stochastic and sporadic nature of solar irradiance. Suresh and Belwin [8] have presented an optimal placement of DGs which is based on Dragonfly algorithm. The objective functions which are discussed in that paper include voltage profile increment, voltage regulation improvement, power losses reduction and economic benefits increment. ODA et al. [9] have studied an optimal planning of distribution system considering integrated photovoltaic-based DG and DSTATCOM under the uncertainties of loads and solar Irradiance. The considered optimization problem was defined as multi-objective function including the cost reduction, the voltage profile, and stability index improvement And Modified Ant Lion Optimizer (MALO) is proposed to solve the stochastic problem. Fathi and Ghiasi [10] have used genetic (GA) and (PSO) algorithms to address the placement of wind and photovoltaic generators simultaneously. The network losses reduction was applied as the objective function to optimize the location and capacity of DGs in the network. Kabir et al. [11] have discussed the optimal placement of large scale photovoltaic units . They addressed the location and sizing issues of the PV units properly to reduce reactive power losses. The presentation of the optimization algorithm is based on exact loss formula and perturbation and observation (P&O) method. On the whole, it has been realized that most existing work on the optimal DG planning have considered different functions to be minimized such as power loss, THD, voltage variation, cost of energy and function to be maximized such as profit, reliability, power quality and voltage profile. For more details see [12]. From the literature in this field, it can be concluded that, various techniques for solving the optimal placement of PV units are generally divided in four categories; 1-analytical methods, 2-conventional optimization methods, 3-metaheuristic optimization algorithms, 4-hybrid approaches [13]. This categorization is based on different point of views like different objective functions and the goal addressing type for PV plants allocation. All of these approaches have their advantages and drawbacks. In this regard, to seek the optimal PV location, the solar irradiance and its stochastic behaviour are incorporated into planning model in this paper. because it affects the PV output power. Also to model the uncertainty of sun irradiance, the beta probability distribution function is used. Moreover two criteria for reducing active power losses and improving the voltage profile are applied and finally PSO is used to solve the optimization problem. The proposed method encompasses an approach which is used to reduce the time of calculations in the modeling of the uncertainty and load flow calculations. It is the salient features of this research compared to other articles in this field. With consideration of the uncertainty conception in the problem analysis, the possible scenarios are reduced with a clustering algorithm. In the meantime to find the state variables in the system, The holomorphic load flow algorithm is used in optimization problem analysis. Besides time reduction methods of the calculations, a PSO methodology is proposed for optimal placement of solar based DG sources for real power loss reduction and voltage profile improvement in distribution system. By using the proposed method, the system losses must be reduced as much as possible. Also the voltage profile must be increased. The paper is organized as follows. In first section, the problem formulation for optimum SPV plant placement is introduced. Second section is composed of performance modeling of solar power generation system. In third section, the solving procedure is proposed. Section fourth, basic mechanism of PSO is presented, and also states an improved clustering method. In fifth section, the proposed method is tested in IEEE14-bus distribution systems. Finally some relevant conclusions are drawn. The contributions of this paper can be described as:

1) A fast and efficient load flow approach is used for the computation of objective functions.

2) The integration of an improved k-means clustering algorithm with the PSO handles various constraints imposed by uncertainty while decreasing the number of scenarios in optimizing procedure.

3) Solar photovoltaic (PV) optimally injects active and reactive power into the system to minimize the active power loss and voltage deviation(VD).

4) The optimum number of clusters is chosen based on Dunn’s validity index.

6) Prototype selection for the clustering is based on Minmax linkage.

2. PROBLEM FORMULATION

Problem definition of the optimal SPV plant allocation is considered by following assumptions:

1- The power system is considered to be balanced

2- Active and reactive power of load is constant.

3- The output of SPV plant is an uncertain variable due to uncertainty of the solar irradiance.

In this paper, SPV is considered as negative loads which its bus ID is considered as PQ bus. The best placement and size of PV plant should be achieved without violating any constraints and these constraints should be checked through load flow analysis at each iteration. Also fundamental objective functions such as line losses, and voltage profile enhancement are examined. In subsequent sub-section, objective functions and constraints are described. In this paper, change in total active loss and minimum voltage value has been used to compare various approaches. The following conditions have been incorporated in the algorithm to obtain the desired result.

(I) The injected power os SPV plant is calculated by using (15) and its placement is generated by swarm operation.

(II) All the bus locations except the slack bus, is tried for optimal location for PV plant placement.

(III) The effect of SPV is considered as negative load at the buses.

2.1. Objective Functions

The optimization problem is formulated as a non-linear constraint problem with power losses reduction and voltage profile improvement as objective functions. These objectives are more important in large-sized feeders especially during peak time. The total real power loss and the deviation of bus voltages from the nominal voltage magnitude minimization formulation are given by equations below [13]:

$$P_{loss} = \sum_{k=1}^{Nl} g_k (V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j)) \tag{1}$$

$$VD = \sum_{i=1}^{Nb} |V_i - V_{ref}| \tag{2}$$

where g_k is the conductance of branch k; V_i and V_j are the magnitude of voltages at sending and receiving bus, respectively; δ_i is the phase angle at ith bus; Nb is the number of buses and Nl denotes the number of lines. In this paper, The objective function to be minimized to derive the best SPV plant allocation for minimum power losses and enhanced voltage profile using PSO is formulated as:

$$\min(F_{obj}) = w_1.P_{loss} + w_2.VD \tag{3}$$

Subject to the following constraints:

$$V_{min} \le Vi \le V_{max} \tag{4}$$

$$P^{PV}{}_{min} \le P^{PV} \le P^{PV}{}_{max} \tag{5}$$

$$Q^{PV}{}_{min} \le Q^{PV} \le Q^{PV}{}_{max} \tag{6}$$

$$P^{Gi}{}_{min} \le P^{Gi} \le P^{Gi}{}_{max} \tag{7}$$

$$Q^{Gi}{}_{min} \le Q^{Gi} \le Q^{Gi}{}_{max} \tag{8}$$

Where P_{PV} and Q_{PV} represent active and reactive power generation by SPV respectively; and P_{Gi} represents active power generation at ith bus.

In equation (3), Weight coefficient method is used to convert real power loss reduction and voltage profile improvement into a single double objective formulation. w_1, w_2 are the weighting factors of active loss and voltage deviation respectively however, $w_1+w_2=1$. If $w_1=1$, $w_2=0$, the single objective optimization is real power loss .Otherwise, the voltage deviation is treated as the single objective optimization.

2.2. Holomorphic Embedding Approach

In this section power flow technique is described. This is based on holomorphic embedding approach. In power system networks analysis, Due to the repetitive nature, the traditional load flow solutions such as Gauss-Seidel(GS) and Newton Raphson (NR) methods are not appropriate. To overcome this problem, the power flow should be done in an especial manner that does not depend on repetition and size of the calculations. In this paper, the applied power flow technique is based on the concept of the continued analytical function. It is used to obtain load flow solutions, objective functions and constraints for the optimization process. This method is named as the holomorphic embedding approach. It is a recursive and non-iterative mathematical tool to solve the load flow equations [14-16].The Holomorphic Embedding Method (HEM) was applied to the load flow problem by Trias in 2012 [14]. It is based on the construction of a Padé approximant (continued analytical function) [14], and has the following properties: It is guaranteed to find a solution if it exists; it will find only the feasible solution; and will unequivocally signal if no solution exists through oscillations in the rational approximation values of the voltage power series. It reaches this by means of advanced concepts in algebraic geometry and complex analysis [14]. On the HEM formulation, the voltages at all buses and the reactive power at the PV buses are expressed as Maclaurin series of a complex embedding parameter s [14]. The foundation is based on properties of holomorphic functions and the analytic continuation properties of HEM. It is guaranteed that, if an operable solution exists at a given loading level, the correct voltage solution will be obtained by using the Padé approximants of the holomorphic series as long as the correct germ solution(s=0) is used. The germ solution for the HEM is not analogous to the initial estimate of the solution in the NR method and will be obtained by evaluating a set of equations [14]. Table 1. shows the equations for different type of bus in conventional HEM. For power flow calculation of a power grid having PV buses, the admittance matrix Y_{ik} is decomposed to a series admittance matrix $Y_{ik,tr}$ and a shunt admittance matrix $Y_{i,sh}$. $Y_{ik,tr}$ is for the admittances between different buses, while $Y_{i,sh}$ is for the admittances of shunt components and off-nominal tap transformers. For more detail See [14-16]. The germ solution can be obtained by plugging s = 0 into expressions on the 3 rd column of Table 1, while the final solution of PFEs can be achieved with s = 1.

Table 1. The equations for different type of bus in HEM

Type	Original PFEs	HEM
SL	$V_i(s) = V_i^{SL}$	$V_i(s) = 1 + (V_i^{SL} - 1)s$
PQ	$\sum_{k=1}^{N} Y_{ik} V_i(s) = \frac{S_i^*}{V_i^*}$	$\sum_{k=1}^{N} Y_{ik} V_k(s) = \frac{sS_i^*}{V_i^*(s^*)} - sY_{i,sh} V_i(s)$
PV	$P_i = \mathrm{Re}(V_i \sum_{k=1}^{N} Y_{ik}^* V_k^*)$ $\lvert V_i \rvert = \lvert V_i^{sp} \rvert$	$\sum_{k=1}^{N} Y_{ik} V_k(s) = \frac{s(P_i - jQ_i(s)}{V_i^*(s^*)} - sY_{i,sh} V_i(s)$ $\lvert V_i(s).V_i^*(s^*) \rvert = 1 + (\lvert V_i^{sp} \rvert^2 - 1)s$

After the load flow study, the node voltages and the branch currents are known, Therefore, P and Q at the receiving end of each line can easily be calculated and, hence by using the equations (1)-(3), the objective function can be calculated. The solution, at which the value of the F_{obj} is minimum, is considered as the best solution of the problem.

3. SPV modelling

In conventional load flow studies, it is assumed that the output power of SPV is constant regardless the sun irradiance variations at that installation location. The nature of SPV plant is such that its output powers are dependent on some factors like solar irradiance, temperature, moisture content and atmospheric composition. Moreover, these conditions have significant effects on the power generation of the SPV plant and finally on the load flow solutions and convergence ability. Since, the model of the SPV plant has more importance in optimization problem, In this paper, For the optimal placement resolution problem, the following model is provided.

3.1. Probability model of PV unit

The output power of SPV plant is mainly related with light intensity during a time period. Therefore, any random variations in solar radiation can lead to uncertainty in the output power of PV unit. In this way, Solar irradiance must be defined as a random variable. It has been stated in various literatures that, the sun irradiance satisfies the Beta distribution function. It is as follows:

$$f(r') = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} (r')^{\alpha-1} (1-r')^{\beta-1} & ,0 \le r' \le 1 \\ 0 & ,\text{otherwise} \end{cases} \tag{9}$$

$$\beta = (1-\mu)(\frac{\mu(1-\mu)}{\sigma^2} - 1) \tag{10}$$

$$\alpha = \frac{\mu\beta}{(1-\mu)} \tag{11}$$

where α and β are the shape parameters of the Beta distribution, which are both positive. $\Gamma(\circ)$ is defined as the gamma function, r' is defined as the random variable of solar irradiance, $f(r')$ is defined as the beta distribution function of r', μ and σ are defined as the mean and standard deviation of r'. For more details refer to [17-18,25]. To calculate the output power of PV, we can apply equation (12).

$$P_{PV} = \begin{cases} P_{rated} \times (\frac{r^2}{r_{STD} \times r_C}) & , r \le r_C \\ P_{rated} \times (\frac{r}{r_{STD}}) & , r_C < r \le r_{STD} \\ P_{rated} & , r \ge r_{STD} \end{cases} \quad (12)$$

4. Solving procedure

In this section, the proposed approach is explained. Owing to the randomness of PV output power, the power flow analysis should be done under the uncertainty condition. In this case, the planning of the power system is also affected by uncertainty. Consequently, Planing procedure will be difficult to implement in real conditions. To deal with this matter, the probability power flow must be used. In this paper, the main steps of solving procedure can be summarized as follows:

1. Solar irradiance modelling by beta probability density function and obtaining the output power of PVs.
2. Generating scenarios.
3. Decreasing the number of generated scenarios by using the improved K-means clustering method.
4. Optimizing the objective function by using the PSO algorithm.
6. Recording the optimal results.

This method depends on repeated random sampling for calculating the results so that uses PSO algorithm to find the optimal solution of the problem by considering the uncertainty of the output power of SPV plant.

4.1. Scenario Generation

The following procedure is used for generating different scenarios. This method is the general designation for stochastic simulation using the random numbers.

For uncertainty analysis caused by SPV power, the Latin Hypercube Sampling(LHS) method is used. It has two stage namely sampling and composition. At the sampling stage, The following steps are applied for uncertain variable which is related to the optimization problem:

1. The sun irradiance cumulative distribution function (CDF) is divided into 1000 periods.
2. A random number is generated by uniform probability distribution function, $U_i \in (0,1)$
3. The cumulative probability of the sample in step 2 is calculated by equation (13) in every period.

$$Prob_i = (\frac{1}{1000})U_i + (\frac{i-1}{1000}) \quad (13)$$

4. The value of the random variable xi is calculated by inverse cumulative distribution function(ICDF)

$$x_i = F^{-1}(Prob_i) \quad (14)$$

5. Steps 2 to 4 are repeated 1000 times for each random variable.

In this paper, The output power of PV unit is calculated by fitting random variable to Beta distribution for scenario s. When it comes to deal with uncertainties in an optimization problem, the predicted SPV power during the single period can be calculated as [19]:

$$\hat{P} = \xi\{P\} = \sum_{\omega=1}^{Ns} \pi_\omega P_\omega \quad (15)$$

where P_ω, π_ω are generated power of PV and its probability in scenario ω respectively and Ns is the number of scenarios.

In the proposed method, considering the superior features of the pso algorithm and the need to reduce the computational time involved in the optimization process, using of the pso algorithm and the clustering technique is considered.

4.2. PSO Algorithm

The PSO algorithm is one of the evolutionary Computation (EC) techniques. It is a population-based and self-adaptive technique introduced originally by Kennedy and Eberhart in 1995 [20]. It handles a population of individuals, in parallel, to probe capable areas of a multidimensional space where the optimal solution is searched. PSO algorithm is described in more detail in [6-18,20]. For the purpose of the solution encoding it should be noted that, Form the technical standpoint, it is supposed that the photovoltaic system is equipped with current inverter, So it is capable of injecting both P and Q and it is molded as PQ bus in load flow equations. Also to facilitate the simulation, it is supposed that active and the reactive power demands are constant.

4.3. k-Means Clustering method

The basic objective in cluster analysis is to discover natural groupings of items based on either their similarities or dissimilarities. k-means method is very popular clustering method with strengths and weaknesses. k-means clustering assigns each item within a data set to a cluster that has its centroid closer to the item than the centroid of any other cluster [22-23]. The primary benefit of k-means clustering is that it performs relatively quickly compared to other clustering methods. The most commonly used variant of the k-means clustering algorithm is summarized as bellows [22]. This algorithm takes two inputs- a set of points to be clustered and the number of clusters to assign the points to.

k-means clustering algorithm

1- Inputs: X,C
2- Initialize : $k \leftarrow 0$; assign each point to starting clusters, $C_1^{\,0},.....,C_C^{\,0}$
3- Repeat
   a. For $i \leftarrow 1,....,C$ do
   b. $\overline{C}_i \leftarrow (\sum_{x \in C_i^k} x)/\left|C_i^{\,k}\right|$
   c. $C_i^{\,k+1} \leftarrow 0$
4- End for
5- For $x \in X$ do
   a. $i \leftarrow \underset{i' \in \{1,....C\}}{\arg\min}(d(x,\overline{C}i'))$
   b. $C_i^{\,k+1} \leftarrow C_i^{\,k+1} \cup x$
6- End for
7- $k \leftarrow k+1$
8- Until $C_i^{\,k} = C_i^{\,k-1}, \forall i = 1,....C$

In step 5, $d(x,x')$ is euclidean distance and used as distance metric.

$$d(x,x') = \sqrt{\sum_{j=1}^{n}(x_j - x'_j)^2} \qquad (16)$$

Important matters in k-means clustering algorithm are the choise of the optimum number of clusters and prototype of each cluster. The first one is based on dunn's validity index and the latter is based on minmax linkage.

4.4. Dunn's validity index

For any number of clusters, the dunn's validation index can be calculated with following formula:

$$D = \min_{1 \le i \le k}\left(\min_{i+1 \le j \le k}\left(\frac{dist(c_i,c_j)}{\max_{1 \le l \le k} diam(c_l)} \right) \right) \qquad (17)$$

Where

$dist(c_i,c_j)$ is distance between clusters c_i and c_j where $dist(c_i,c_j) = \min\ d(x_i,x_j)$, $x_i \in c_i$, $x_j \in c_j$ and $diam(c_l)$ is diameter of cluster c_l where $diam(c_l) = \max\ d(x_{l1},x_{l2})$, $x_{l1},x_{l2} \in c_l$

The k which maximizes D is defined as the optimum number of clusters.

4.5. minmax linkage

This linkage criterion determines a point, which is referred to as the cluster prototype, which can be thought of as a point within the cluster that is most representative of it. Having cluster prototypes is beneficial, Because each prototype allows the cluster to be modeled in capacity-expansion model for system operation [21]. To compute the minmax linkage between two clusters, we first define the maximal distance between any point, x, and the cluster, C, as:

$$d_{x,C}^{\max} = \max_{x' \in C} d(x,x') \qquad (18)$$

In words, $d_{x,C}^{\max}$ is defined as the distance between x and the point in C that is furthest from x. We then define the minmax radius of the cluster, C, as:

$$r(C) = \min_{x \in C} d_{x,C}^{\max} \qquad (19)$$

The point, x_C, that minimizes (19) is defined as the prototype of the cluster, C. The prototype has the property that it has the minimal maximal distance to C [21].

5. Results & Discussion

The effectiveness of the proposed approach is demonstrated on IEEE 14-bus test system. It is shown in Figure 1. The test system data is given in [24]. PSO parameters are presented in Table 2. To facilitate the simulation, only one SPV plant is considered for the optimization procedure. In the test system, bus 1 has been considered the slack bus and is not considered for the SPV placement.

Table 2. PSO parameters [20].

C_j	W_{max}	W_{min}	Max iteration	Particle Number
2	0.9	0.4	100	100

A simple PSO based method to solve for optimal location of SPV plant has been executed to optimize the fitness function, which is defined in (3). The number of scenarios related to sun irradiance uncertainty was 1000 and it reduced to 30 scenarios by the applied clustering algorithm. With the placement of one SPV plant, the results are presented in Tables 3-4. The minimum voltage of the system at the base case is 1.0035 p.u. As it shown in table 3, its value at the new case in [1], [2] and this paper, are 0.9103 p.u.,1.01 p.u., and 1.0249 p.u., respectively. Variations of the minimum voltage are - 9.28%, 0.647%, and 2.13% with respect to PV unit placement in the system. The results show that the minimum voltage is increased more as compared with its value at new case in references [1] and [2]. Similarly, the results show that in this paper, the real power loss is reduced by-63.26%, as compared with its value in the base case. While in the reference [1] it is increased by 43.81%. This indicates that 0.0849 p.u. of real power can be saved as compared to when the existing network topology is used. It is indeed decreased by -96.84% as compared with its value in reference [2]. It can be concluded that the proposed approach presented in this paper was able to achieve a suitable voltage profile, because it provides more minimum voltage value within the system compared to other methods in this table. Also with the Comparison of the reduction in real power loss, the result provided by proposed method is acceptable, Since, the conditions in [1] are deterministic and the second objective function in [2] is different from what is considered in this article.

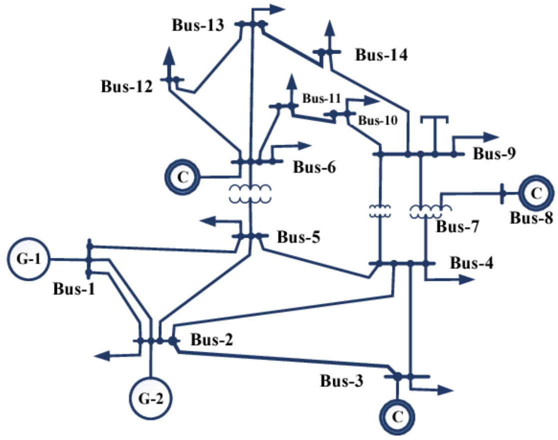

Figure 1. IEEE 14 bus system

Table 4. shows the summary of results in base case before the PV installation and new case after the PV installation. This table shows that the proposed approach has significantly outperformed the active power loss reduction. Although the improvement of

Table 3. Obtained Optimal Scheme

Method	Proposed approach	Method in [1]	Method in [2]
Optimal Bus location	3	2	6
Optimal SPV size(kw)	1550.4*	---	748.1
Real Power Loss(p.u.)	0.0493	0.1930	0.00423
Min Voltage (p.u.)	1.0249	0.9103	1.01

*. PV with Pf of -0.27.

Table 4. Comparison of the object functions

	Base case	New case
Real Power loss (MW)	0.1342	0.0493
Volatge Deviation (p.u.)	0.6667	0.7367

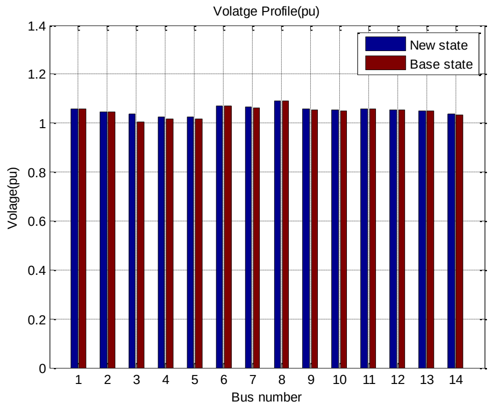

Figure 2. Voltage profile across all the system buses.

Voltage deviation is less, but it should be noted that the optimization is done for two objective functions. It is to be expected in term of multi-objective optimization. However the proposed method minimized power losses and increase in the minimum voltage value effectively with satisfying all constraints. Figure 2 shows the voltage profile across all the system buses. It is also shown that there is an improvement in the voltage profile when the system is fed by PV. The comparison of minimum voltage values proves this claim. From this figure, it is clearly stated that all buses voltage are within the set limit with SPV optimal placement. To verify the efficiency of the proposed approach based on statistical factor, Some trials must be made. The minimum, maximum, mean and standard deviation(SD) of the objective functions are presented in table 5. It is apparent that the system power losses varies from 0.0119 p.u. to 0.1026 p.u., with a mean value of 0.0591 p.u. and SD of 0.0302 p.u. The voltage deviation ranges from 0.6671 p.u. to 0.7374 p.u., with a mean value of 0.7213 p.u. and SD of 02561 p.u. The width of the minimum voltage varies from 1.0036 p.u. to 1.0408 p.u., with a mean value of 1.0212 p.u. and SD of 0.01212 p.u.

Table 5. Statistical analysis of the variable

Variable	Min	Mean	Max	SD
Real Power Loss(p.u.)	0.0119	0.0591	0.1026	0.0302
Voltage Deviation (p.u.)	0.6671	0.7213	0.7374	02561
Min Voltage (p.u.)	1.0036	1.0212	1.0408	0.01212

Considering that the solar irradiance is uncertain, The histogram of solar irradiance is shown in Figure 3. It shows the number of observations for different bucket of solar irradiance. Also, It can be obtained for each hour.

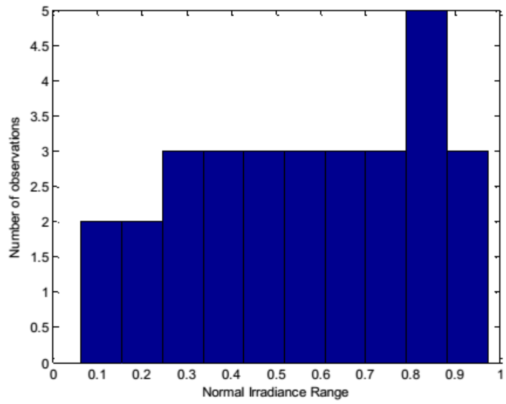

Figure 3. Histogram of solar irradiance

The PDF and CDF of solar irradiance are depicted in Figure 4. It shows the random behavior of the sun radiation and can be statistically described by using the beta distribution function. It should be noted that after the implementation of clustering method, the selected scenarios maintain their original shapes of PDF and CDF. Figure 5 illustrates the output power of the SPV plant. It shows the power injection of SPV plant with its probability of occurrence in all scenarios. Considering this details, the injection power from SPV (MW), at different scenarios of sun irradiance, is depicted in this figure. As can be expected, According to this figure, When the sun irradiance is low, the generation of PV is low too.

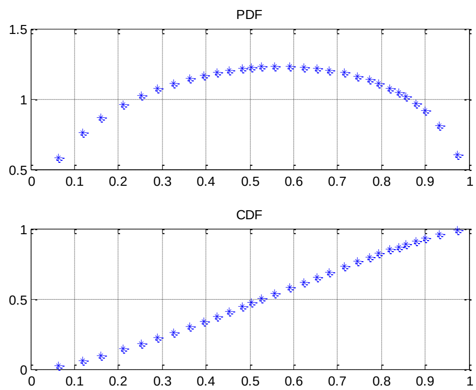

Figure 4. Distribution functions of Solar irradiances

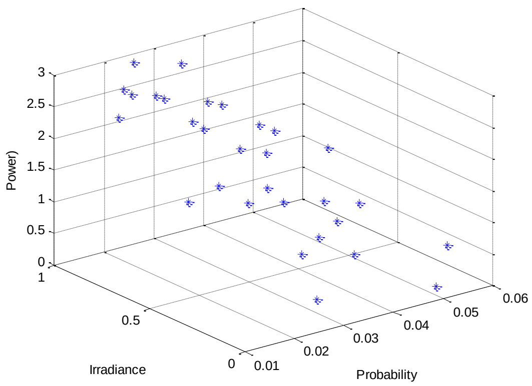

Figure 5. Active power output versus solar irradiance and probability.

6. Conclusions

This paper has presented the results of the proposed approach to the optimal placement of SPV plant in the power system network. The effectiveness of the proposed approach in solving the problem has been demonstrated on IEEE 14-bus test system. A probabilistic method is used for uncertainty modeling. Different scenarios of the SPV output power are generated by beta PDF and LHS approach. Also the HEM method is used for solving the power flow equations involved in the optimal placement of SPV plant. The result of proposed approach can reveal that the time required to calculation is decreased due to the using the HEM load flow and clustering algorithm. Because iterative performance related to conventional power flow programs are eliminated and number of the probable scenarios is decreased by improved clustering algorithm. The results showed that the proposed approach was able to achieve a 63. 26% reduction in real power loss and 2.13 % increase in minimum voltage value. It reveals that the proper placement of SPV in a power system plays a significant role in reducing the total real loss as well as improves the voltage profile within the system. By the results, it can be concluded that the proposed method, performs better or at least similar in comparison with the other methods for the single PV placement problem.

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