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Research Article

Chance-Constrained Optimization of Photovoltaic System Allocation considering Power Loss, Voltage Level, and Line Current

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Changes are emerging that will significantly alter structure and operation of this century's distribution networks, and photovoltaic (PV) systems will play greater role in energy sector, with implications for power system reliability. Considering uncertainties in solar irradiance and electrical loads and incorporating them into the optimization problem within an appropriate methodology is becoming increasingly important in reshaping distribution networks. In this paper, uncertainty scenarios are handled with Monte Carlo Simulation (MCS) under genetic algorithm (GA) and differential evolution- (DE-) based optimization, and probability distribution functions (pdf) of bus voltages and line current are obtained to be used in chance-constrained stochastic programming. This present study focuses on investigating impact of uncertainties in PV system operating under different irradiance scenarios on power loss with probabilistic constraints in distribution networks instead of precise deterministic limits to contribute more efficient and reliable use of energy. By combining meta-heuristic optimization and MCS technique under one framework, this paper contributes to knowledge base of how to allocate PV plants within distribution networks under chance-constrained strategy. In order to show the effectiveness of the proposed methodology, obtained optimization results are tested using MCS under set of uncertainty conditions and network constraints are evaluated for limit violation probabilities. The effectiveness of this method is investigated based on comparative results of two different optimization methods through probabilistic analysis and simulation.

1. Introduction

Nowadays, all countries in the world are making great efforts to cope with global warming along with the need for energy [1]. As a result of the high demand for electricity, there is a demand for renewable energy generation and planning studies that take into account the probabilistic issues that come with it. Conventional centralized generation units can aid to some extent in transmitting electricity over large areas due to environmental and cost concerns. Within the scope of these challenges, reducing power losses and keeping bus voltages and line currents within the required limits are becoming crucial issues due to technical and economic reasons [2]. In the event that the load voltages and line current flows violate their related bounds, the electricity demand cannot be efficiently supplied. The increase in power losses caused by voltage drops causes voltages to violate their corresponding bounds while transferring energy to meet demand in the electricity distribution network [3]. On the other hand, with the widespread penetration of photovoltaic systems, managing the associated uncertainties that pose significant risks to system reliability is a major challenge. These issues have a negative impact on system security and reliability [4]. Besides the production of high-efficiency generation technologies, such as high-efficiency solar cells for more utilization of solar energy, the need to optimize the reduction of power losses in active distribution networks has led researchers to investigate the optimal arrangement of distributed generation (DG) systems [5–12]. In the context of photovoltaic plants integrated distribution systems, it is important to assess the power loss, bus voltage limits, and line current carrying capacities. This evaluation becomes more complex due to uncertainties in the solar irradiance and load demand. To address this challenge, electricity grid plans can be developed using a stochastic framework. These plans aim to ensure that the necessary energy is supplied to electrical loads. In that manner, planning photovoltaic systems with probabilistic constraints in active distribution networks instead of precise deterministic limits can contribute to more efficient and reliable use of energy.

A number of different strategies have been researched and put into practice in an effort to tackle the issue of loss reduction [13–15]. The loss reduction software package selection, the issue description, the utilized procedure, and the reached outcome are important criteria for those strategies that vary from one another. The optimal capacity and allocation of DG units have been handled by taking into account the approach for alleviating distribution power losses and boosting voltage profile in [16]. The decrement in line current flows and the usage of present distribution feeders in case of any loading situations can be observed as the advantages by the optimal distribution power loss minimization. In that manner, the methodologies based on optimal DG placement and size for minimizing losses have been presented in [17, 18]. On the other hand, the load variation is another crucial issue for planning of the distribution network. As a result of these variations, the operating characteristics of the distribution network fluctuate. Alleviation of power loss and improvement of voltage profile have been taken into account by optimal coordination of DG and voltage regulation devices considering variation of demand in [19]. In [20], energy loss minimization has been considered together with the reconfiguration of distribution grid under various electricity consumption levels to perform the DG planning. Optimal planning has been carried out for mitigating power losses and managing voltages with the consideration of low, medium, and high loading conditions in the presence of DG allocation in [21]. The power losses have been optimized by taking into account both the DG allocation and capacity in the distribution grids with varying electrical consumption in [22]. The aforementioned approaches disregard the temporal fluctuations of renewable energy and include only single demand or load variation conditions.

The optimization procedure of loss minimization without considering renewable energy systems might not depict the desired outcomes due to the uncertainties of demand and generation [23, 24]. In [25], it is shown that the variation of DG penetration level has a significant effect on the power loss and voltage profile and it is stated that the penetration is not a static metric. In [26], the optimal renewable unit placements and capacities for alleviating energy losses have been determined using analytical methodology by considering the variations in load and renewable power output under different scenarios. In this regard, the minimization of energy loss has been considered with the optimal renewable sites in [27]. In [28], a meta-heuristic optimization algorithm is applied to reduce energy losses in sizing PV and energy storage system considering uncertainties of demand and generation. The loss minimization in the planning framework has been dealt with the optimal PV system and voltage regulation device coordination in [29]. The inclusion of optimally located renewable energy sources can be used as an advantage both in terms of reducing power losses and improving voltages [30–33]. When the variability of demand is superimposed on the variability of output power intermittent renewable generation, the optimal placement of these units in the distribution system becomes a challenge optimization problem [34–37]. In [34], it is stated that the scenario-based stochastic optimization method with the inclusion of power loss can lead to higher benefits from renewable-based DG and reduced green gas emission. In [35, 36], this problem is optimally considered in the DG-incorporated distribution grids by taking into account the combination of heuristic and stochastic methodologies. However, the chance-constrained approach has not been handled in these studies. In [37], an iterative-based probabilistic approach is presented to minimize average loss with and without consideration of background harmonics. It is clear that power loss minimization plays an extremely significant role in the provision of consistent and steady power backup to the customers as a result of the assessment up to this point. However, there is a gap in published research on loss minimization under the framework of stochastic optimization with chance constraints under different uncertainty conditions. In light of this, this present study focuses on investigating the impact of uncertainties in PV output power operation under different irradiance scenarios on power loss minimization with a chance-constrained probabilistic optimization environment. The proposed approach has been compared with the existing research in the literature by considering the subjects taken into account in this study in Table 1. As presented in Table 1, the important gaps have been observed in the previous literature based on various criteria. These criteria can be classified by considering the inclusion of meta-heuristic optimization methods, load uncertainty, renewable uncertainty, chance-constrained objective function, Monte Carlo Simulation, and different solar irradiance scenarios (low, medium, and high irradiances) in the methodologies. The novelty of this present study is to consider all these criteria in the proposed approach by filling the literature gaps.

In this paper, the uncertainty scenarios are handled with MCS under the GA-based optimization, and the pdf of bus voltages and line current are obtained to be used in chance-constrained stochastic programming. The uncertainties of the loads and different solar irradiance scenarios are introduced into the GA optimization within an integer programming problem for the optimal allocation of PV plants in the distribution system. In addition, the same methodology is adapted to the DE optimization technique to compare the optimization results. In order to demonstrate effectiveness of the proposed methodology, the obtained optimization results are tested under the set of uncertainty conditions. By combining meta-heuristic optimization and MCS technique under one framework, this paper contributes to the knowledge base of how to allocate PV plants within

Table 1: Comparison of the proposed approach with the existing research in the literature.

References	Meta-heuristic optimization methods	Load uncertainty	Renewable uncertainty	Chance-constrained objective function	Monte Carlo Simulation	Different solar irradiance scenarios
[18]	✓					
[19]	✓	✓				
[20]	✓	✓				
[21]		✓				
[22]	✓	✓				
[23]	✓	✓	✓			
[24]	✓	✓	✓			
[26]		✓	✓			
[27]	✓	✓	✓			
[28]	✓	✓	✓			
[29]	✓	✓	✓			
[30]	✓	✓	✓			
[33]	✓	✓	✓			
[36]	✓	✓			✓	
[37]		✓	✓	✓	✓	
In this study	✓	✓	✓	✓	✓	✓

distribution networks under chance-constrained strategy. The effectiveness of proposed stochastic optimization method has been presented by the simulation results by considering chance-constrained programming in IEEE 33 bus and IEEE 69 bus distribution networks under different solar irradiance scenarios.

The remaining parts of this paper are organized as follows. Section 2 illustrates the load flow analysis methodology contemplated in this study. Section 3 demonstrates the uncertainty modelling taken into account in the present paper. Section 4 gives the heuristic and stochastic featured optimization planning framework proposed in this paper. Section 5 presents the case studies considered in the current study. Section 6 illustrates the results and discussion drawn from the proposed approach. Finally, Section 7 provides the general conclusions determined in this paper.

2. Load Flow Analysis

The incorporation of renewable PV systems in distribution grids remains prominent as a result of rising electrical loads. In that manner, the bus voltages, line current flows, and losses can be considered while making use of the PVs in these grids. At the same time, the variability of electrical demands and solar radiation-dependent PV power outputs can have an impact on the technical parameters of the distribution network. The analysis of load flow is indispensable for examining these parameters in the grid. In the present article, the load flow analysis, which is based on backward and forward sweep [38], has been considered to examine the parameters of the grid. This approach has been demonstrated as follows:

$$\begin{aligned} \mathrm{DV}_B^{\mathrm{iter}+1} &= (\mathrm{BCBV})(\mathrm{BIBC}) I_{B,inj}^{\mathrm{iter}}, \\ V_B^{\mathrm{iter}+1} &= V_B^{\mathrm{init}} - \mathrm{DV}_B^{\mathrm{iter}+1}, \end{aligned} \tag{1}$$

where $\mathrm{DV}_B^{\mathrm{iter}+1}$ is the vector demonstrating the iteratively changes of bus voltages, $I_{B,\mathrm{inj}}^{\mathrm{iter}}$ is the vector illustrating the injection currents associated with PVs and electrical loads at the present iteration, V_B^{init} is the vector illustrating the initial bus voltages, $V_B^{\mathrm{iter}+1}$ is the vector depicting the bus voltages at another iteration, BIBC is the matrix illustrating the relations between bus and line currents, and BCBV is the matrix demonstrating the relations between line currents and bus voltages, respectively.

3. Uncertainty Modelling

In this article, the beta distribution with a stochastic structure has been used to generate solar radiation conditions [39]. The expression of this distribution is demonstrated as follows:

$$f\left(\mathrm{Srad}_b^{\mathrm{cr}}\right) = \begin{cases} R\left(\mathrm{Srad}_b^{\mathrm{cr}}, \alpha, \beta\right), & \begin{array}{l} 0 \le \mathrm{Srad}_b^{\mathrm{cr}} \le 1, \\ \alpha \ge 0, \beta \ge 0, \end{array} \\ 0, & \text{else}, \end{cases} \tag{2}$$

where

$$R\left(\mathrm{Srad}_b^{\mathrm{cr}}, \alpha, \beta\right) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \left(\mathrm{Srad}_b^{\mathrm{cr}}\right)^{\alpha-1} \left(1 - \mathrm{Srad}_b^{\mathrm{cr}}\right)^{\alpha-1}, \tag{3}$$

where $\mathrm{Srad}_b^{\mathrm{cr}}$ is the radiation considered for the PV system at bus b of distribution system for the $\mathrm{cr}^{\mathrm{th}}$ state. The variables of beta expression, which are α and β, can be obtained in terms of deviation (σ) and mean (μ) as follows:

$$\begin{aligned} \beta &= (1-\mu)\left(\frac{\mu - \mu^2 - \sigma^2}{\sigma^2}\right), \\ \alpha &= \frac{\mu\beta}{1-\mu}. \end{aligned} \tag{4}$$

The injected PV output powers can be determined with respect to the radiation as follows:

$$P_{b,\mathrm{inj}}^{\mathrm{PV,cr}} = P_b^{\mathrm{PV}}\mathrm{Srad}_b^{\mathrm{cr}}, \tag{5}$$

where P_b^{PV} is the installed power of renewable PV system. This power will be optimally integrated at bus b of distribution system in the planning.

In the present research, the states of electrical demand have been produced by considering the expression of normal distribution [39] as illustrated in the following:

$$f\left(P_{\mathrm{Dem},b}^{\mathrm{cr}}\right) = \left(\frac{1}{\sigma_{\mathrm{Dem},b}\sqrt{2\pi}}\right)\exp\left(-\frac{P_{\mathrm{Dem},b}^{\mathrm{cr}} - P_{\mathrm{Dem},b,\mathrm{avrg}}}{2\left(\sigma_{\mathrm{Dem},b}\right)^2}\right), \tag{6}$$

where $\sigma_{\mathrm{Dem},b}$ illustrates electrical load standard deviation, $P_{\mathrm{Dem},b,\mathrm{avrg}}$ demonstrates the mean of load consumption, and $P_{\mathrm{Dem},b}^{\mathrm{cr}}$ depicts the load power at bus b of the distribution network for the $\mathrm{cr}^{\mathrm{th}}$ state.

4. Planning Framework

The chance constraints have been considered while optimally minimizing the expected power losses. GA [40] methodology has been carried out with the integer framework in the distribution network. The optimization problem has been dealt with probabilistic structure considering variabilities of electrical load and PV output powers. The bus voltages and line currents have been regarded as the chance constraints. The GA methodology jointly with MCS approach has been implemented for optimal execution of power loss minimization.

The objective function has been demonstrated as follows:

$$E\left(P_{\mathrm{Loss}}\right) = \frac{1}{\mathrm{Tcr}}\sum_{\mathrm{cr}=1}^{\mathrm{Tcr}}\sum_{b=1}^{\mathrm{TNB}}\sum_{\substack{e=1\\e>b}}^{\mathrm{TNB}}\left|V_b^{\mathrm{cr}}\right|\left|V_e^{\mathrm{cr}}\right|\left|Y_{\mathrm{be}}\right|\cos\left(\theta_b^{\mathrm{cr}} - \theta_e^{\mathrm{cr}} - \delta_{\mathrm{be}}\right), \tag{7}$$

where Tcr is the total amount of states for uncertainty in the planning phase, TNB is the total bus number in the distribution energy grid, $|V_b^{\mathrm{cr}}|$ and θ_b^{cr} are the voltage absolute and angle values of bus b in the $\mathrm{cr}^{\mathrm{th}}$ state of planning, $|Y_{\mathrm{be}}|$ and δ_{be} are the admittance absolute and angle values in the b^{th} row and e^{th} column of the related matrix, and $E(P_{\mathrm{Loss}})$ is the expected value of power losses. The objective function has been subjected to the chance constraints as follows:

$$\begin{aligned}\Pr\left\{V_b^{\min} \le V_b^{\mathrm{cr}} \le V_b^{\max}\right\} \ge \lambda_V\, \mathrm{cr} &= 1,\cdots \mathrm{Tcr},\\ b &= 1,\cdots \mathrm{TNB},\\ \Pr\left\{I_{\mathrm{nl}}^{\mathrm{cr}} \le I_{\mathrm{nl}}^{\max}\right\} \ge \lambda_I \quad \mathrm{cr} &= 1,\cdots \mathrm{Tcr},\\ \mathrm{nl} &= 1,\cdots \mathrm{TNL},\end{aligned} \tag{8}$$

where $V_b^{\min}$ and $V_b^{\max}$ are the minimum and maximum bounds of voltage at bus b, $I_{\mathrm{nl}}^{\mathrm{cr}}$ is the line flow current value for the line between buses b and e at the $\mathrm{cr}^{\mathrm{th}}$ state, $I_{\mathrm{nl}}^{\max}$ is the maximum bound of line flow current, λ_V and λ_I are levels of confidence corresponding to the bus voltages and line flow currents, and TNL depicts the total line numbers in the distribution network.

By considering the limit violation of constraints, the objective function has been converted to the augmented structure by handling the method of the penalty function.

$$\begin{aligned}f^{\mathrm{augform}} &= \frac{1}{\mathrm{Tcr}}\sum_{\mathrm{cr}=1}^{\mathrm{Tcr}}\sum_{b=1}^{\mathrm{TNB}}\sum_{\substack{e=1\\e>b}}^{\mathrm{TNB}}\left|V_b^{\mathrm{cr}}\right|\left|V_e^{\mathrm{cr}}\right|\left|Y_{\mathrm{be}}\right|\cos\left(\theta_b^{\mathrm{cr}} - \theta_e^{\mathrm{cr}} - \delta_{\mathrm{be}}\right)\\ &\quad + \mathrm{ck}_V\sum_{b=1}^{\mathrm{TNB}}\left|\psi_V^b - \left(1-\lambda_V\right)\right| + \mathrm{ck}_I\sum_{\mathrm{nl}=1}^{\mathrm{TNL}}\left|\psi_I^{\mathrm{nl}} - \left(1-\lambda_I\right)\right|,\end{aligned} \tag{9}$$

where

$$\begin{aligned}\psi_V^b &= 1 - \Pr\left\{V_b^{\min} \le V_b^{\mathrm{cr}} \le V_b^{\max}\right\}, \quad \begin{aligned}\mathrm{cr} &= 1,\cdots \mathrm{Tcr},\\ b &= 1,\cdots \mathrm{TNB},\end{aligned}\\ \psi_I^{\mathrm{nl}} &= 1 - \Pr\left\{I_{\mathrm{nl}}^{\mathrm{cr}} \le I_{\mathrm{nl}}^{\max}\right\}, \quad \begin{aligned}\mathrm{cr} &= 1,\cdots \mathrm{Tcr},\\ \mathrm{nl} &= 1,\cdots \mathrm{TNL},\end{aligned}\end{aligned} \tag{10}$$

where ψ_V^b and ψ_I^{nl} illustrate the limit violation probabilities for bus voltages and line currents and ck_V and ck_I demonstrate the factors for penalizing the constraints in case of violation in this study. The limits of constraints are sustained while considering the minimization of total distribution grid power losses from the viewpoint of (9). The factors for penalizing the constraints are performed in case the limit violation is observed [41]. The more proper outcome is optimally investigated by GA when the violation of constraints gives rise to the bigger values in augmented structure.

This study implements the chance-constrained optimization to determine optimal allocation of PV systems in distribution network considering power loss, voltage level, and line current under stochastic programming framework. In this study, the decision variables are the optimal bus allocations for the predefined PV system output powers. The optimal PV placement buses in distribution energy grid are depicted as follows:

$$X = \left(x_1^{\mathrm{PV}}, \cdots, x_b^{\mathrm{PV}}, \cdots, x_{\mathrm{TPV}}^{\mathrm{PV}}\right), \tag{11}$$

where

$$x^{\mathrm{PV,min}} \leq x_b^{\mathrm{PV}} \leq x^{\mathrm{PV,max}}, b = 1, \cdots, \mathrm{TPV}, \tag{12}$$

where x_b^{PV} is the bus number for the optimally allocated PV system, $x^{\mathrm{PV,min}}$ and $x^{\mathrm{PV,max}}$ are the minimum and maximum values for the buses, at which PVs are optimally allocated, and TPV represents the total PV system allocation buses. The block diagram of the proposed methodology is demonstrated in Figure 1.

The framework of the stochastic optimization process is depicted in Figure 2.

The prominent phases of the planning methodology for optimally allocating the PVs are demonstrated as follows:

(1) Enter the distribution network parameters.
(2) Enter the installed PV power outputs that will be allocated.
(3) Enter the states of solar irradiance and electrical demands produced from the probabilistic distribution functions.
(4) Enter the beginning population that demonstrates the PV allocation buses in a random manner.
(5) Initiate MCS approach considering the cr$^{\mathrm{th}}$ state (cr = 1,…, Tcr). Carry out phase 8, in case cr is bigger than Tcr.
(6) Extract the electricity demand and calculate the solar irradiance-dependent PV output powers for the cr$^{\mathrm{th}}$ state.
(7) Calculate the bus voltages and line currents on the distribution network by carrying out load flow approach considering the cr$^{\mathrm{th}}$ state.
(8) Plot the functions of stochastic distributions for bus voltages and line currents on the distribution network.
(9) In this phase, the functions of stochastic distributions for the voltages and line currents are considered in terms of limit violation. The integrals of functions of stochastic distributions are evaluated on the ranges, where the bounds are surpassed [42]. An illustrative example of a probability distribution function for the quantification of chance constraints in the distribution network is shown in Figure 3. As shown in Figure 3(a), B is the shaded pdf region where the confidence level of bus voltage is maintained. However A and C are pdf regions where the bus voltage limits of the distribution network parameters are exceeded. While the shaded region D in Figure 3(b) can be the pdf region where the confidence level of line current is maintained, E is the pdf region in which the line current constraint is violated.
(10) At this stage, the constraints on the fulfilment of the technical limitations are checked from a probabilistic point of view according to the confidence level specified. If the pdf integrals, where the bounds of bus voltages and line currents are violated, are not greater than $1 - \lambda_V$ and $1 - \lambda_I$, these stochastic constraints are maintained.
(11) Handle the chance constraints associated with bus voltages and line currents. This step is performed while determining the objective function by considering every chromosome.
(12) In case the constraints are not maintained, utilize the factor for penalizing the constraints in obtaining the value of objective function.
(13) In case the criteria of optimally planning process are maintained, the optimal PV allocations are printed out. If they are not maintained, return to phase 4.
(14) In terms of examining the constraints for limit violation, implement the testing of optimal PV allocation.

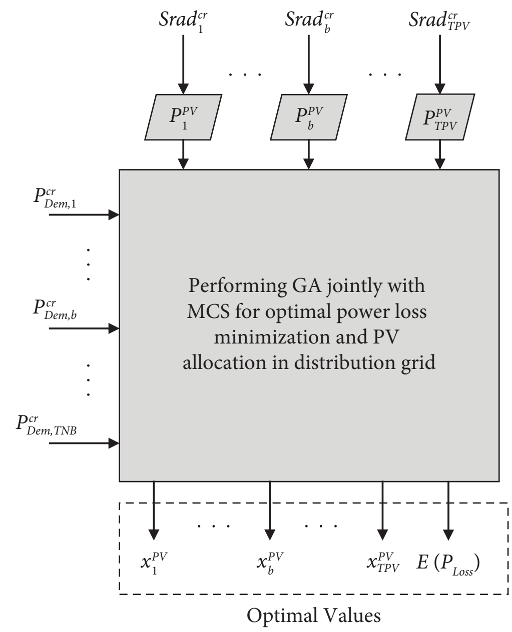


Figure 1: The block diagram of the proposed methodology in this study.

In the optimization process, the PV installed capacity to be placed in the distribution network is entered. The states of solar irradiance and electrical power demands are generated from probability distribution functions. Then, the initial population of PV bus allocation is randomly initialized by the GA framework at the upper level of the problem. At the lower level of the problem, probability distribution functions for voltages and line currents in the distribution network are determined with the help of load flow under MCS, and then probabilities of constraint violations are obtained. During the GA process, PV bus allocations are iteratively generated according to the objective function in which the violation cases are included.

In order to demonstrate effectiveness of the proposed methodology, the obtained optimization results are tested under the set of uncertainty conditions. The implementation of testing of optimal PV allocation outcomes is demonstrated in Figure 4.

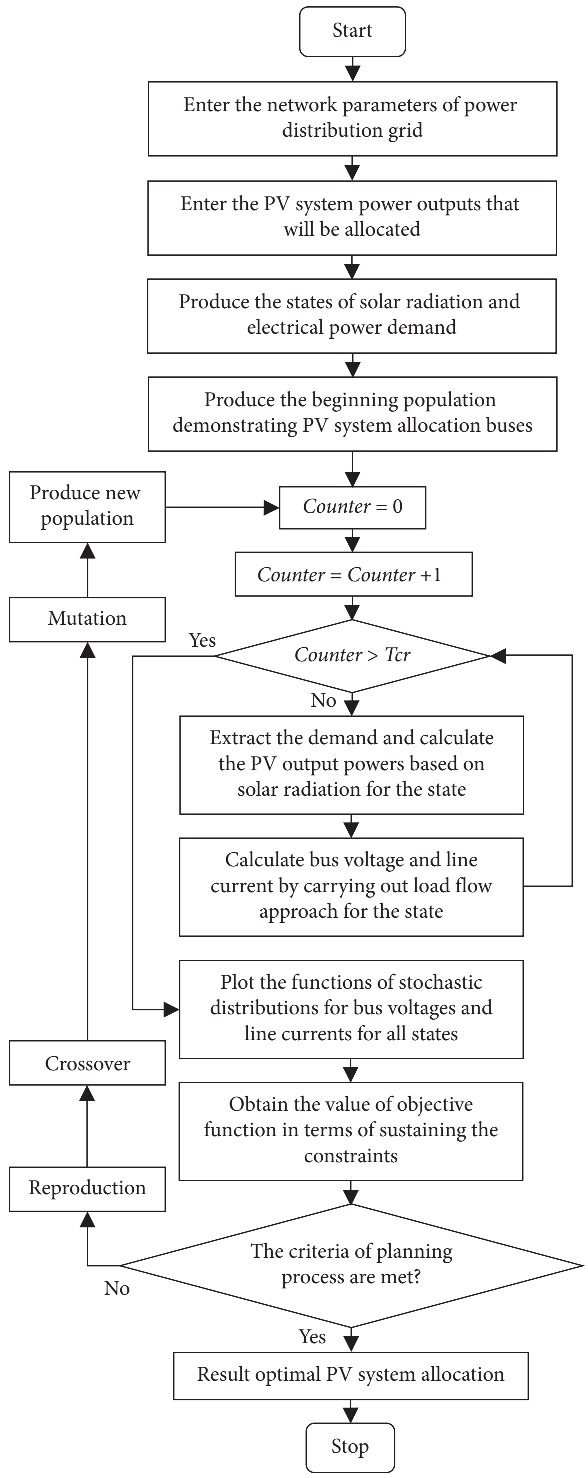


Figure 2: The framework of stochastic optimization in this study.

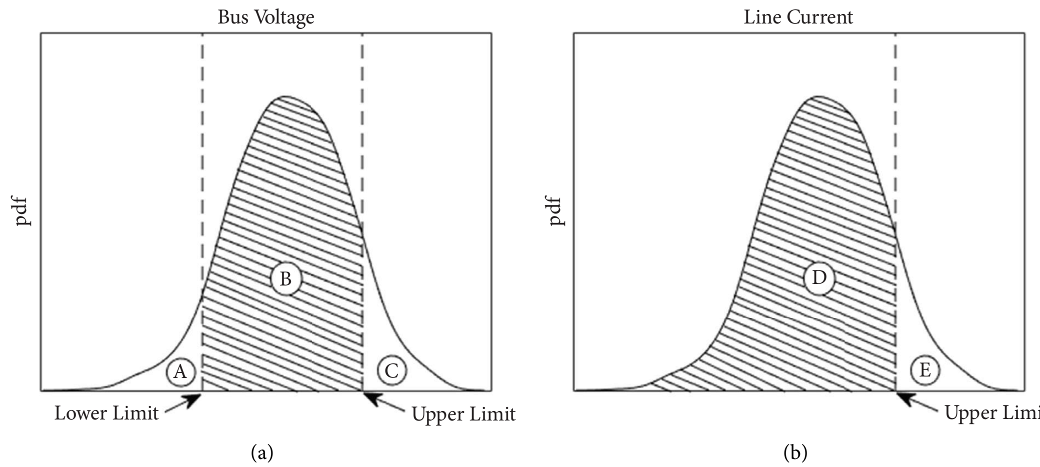


FIGURE 3: The pdf for (a) bus voltage and (b) line current on the distribution network.

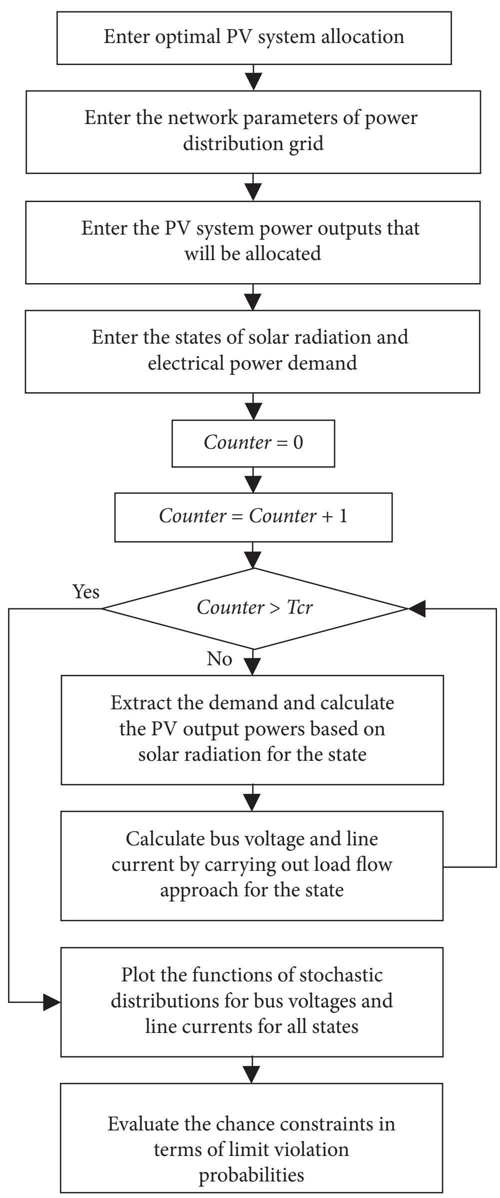


FIGURE 4: The implementation of testing the optimization outcomes.

In the verification phase of the obtained optimization results, the optimal PV system allocations and distribution network parameters are first input to the test algorithm. Then, MCS is applied using the uncertainty sets generated for electricity consumption and solar irradiance and the network constraints are evaluated in terms of limit violation probabilities.

5. Case Studies

In the proposed stochastic programming, the optimization results are compared for possible long-term solar irradiance conditions under three different profiles as low, medium, and high. The frequency distributions of solar irradiances for these scenarios are shown in Figure 5.

6. Results and Discussion

In the optimization process, the size of population, maximum iteration, rate of crossover, and objective function tolerance have been considered as 30, 200, 0.8, and 10^{-6} for GA. The stochastic optimization has been implemented on the PC possessing the CPU of 2.80 GHz.

6.1. IEEE 33 Bus Distribution Network. The planning simulations have been carried out on the 33 bus distribution network [43], which is demonstrated in Figure 6.

The electricity demand states of distribution network are illustrated in Figure 7. The standard deviation of electricity demands is 10% in terms of the mean of these demands.

The MCS stage of the optimization procedure has been carried out with 1000 scenarios according to the probability distributions of solar irradiance and electrical load. The total number of PV systems has been considered to be 12 in the test network. The installed power of each PV system has been regarded as 400 kW. The minimum and maximum values for the buses, at which PVs will be optimally allocated, are 2 and 33, respectively. The level of confidence for the bus voltages and line flow currents is taken as 0.8 in the chance-constrained programming.

6.1.1. Results of GA for Single Run of Stochastic Optimization Framework. The GA methodology jointly with MCS approach has been performed for scenarios 1–3. The optimal PV allocations are demonstrated in Table 2.

As seen in Table 2, the optimal PV system allocations demonstrate variability among the scenarios. It is worthy to note that these optimal PV allocations are the decision variables that have been determined by minimizing the power losses and meeting the chance constraints in all scenarios. These PV placements among the scenarios have been obtained by taking into account different limitation impacts of chance constraints on the objective function values. Therefore, the chance constraints and various solar radiation profiles in the scenarios have important role in the optimal PV allocations and power losses. The optimally evaluated distribution grid power losses are shown in Figure 8 in an iterative manner.

In the base case, PV systems are not allocated and only variations in electricity demands are considered and the total power loss in the grid is 211.31 kW. By using stochastic planning, the power losses have been cut down to 80.69 kW in scenario 1, 70.38 kW in scenario 2, and 66.65 kW in scenario 3. The percentages of decrements in these losses have been achieved at 61.81%, 66.69%, and 68.46% for scenarios 1–3 when compared with the base case. The total power loss in scenario 1 is greater than that in the other scenarios due to the limitations imposed by the chance constraints associated with the bus voltages. In scenario 1, the optimal PV allocation has led to higher power loss when compared to the other scenarios since the voltage profile is less due to the lower solar radiation conditions in this scenario. The comparatively less voltage profile has given rise to the limitation impact by the chance constraints. As the solar radiation levels get higher in other scenarios, the voltage profile also has the improvement in the distribution system. This improvement provides the reduction in power losses and chance constraint limitations. In scenarios 2 and 3, the total grid losses are alleviated more than those in scenario 1 as the levels of solar irradiance rise and the impact of chance constraints reduces in these scenarios.

6.1.2. Comparison between GA and DE for Single Run of Stochastic Optimization Framework. The proposed optimization issue in all scenarios has also been handled by the DE methodology for comparing the optimization results obtained in the GA. In this paper, DE methodology has been modified to handle the integer variables since the proposed problem has discrete framework. This modification has been achieved by implementing the approach presented in [44]. The optimal PV system placements, corresponding power losses, convergence iterations, and simulation times are presented in Table 3. The optimally obtained power losses are iteratively demonstrated in Figure 9.

As illustrated in Table 3 and Figure 9, the advantages of GA-based algorithm when compared to DE have been seen. The optimal power losses have been obtained as 81.8917 kW, 70.994 kW, and 67.0895 kW in the corresponding scenarios by using DE algorithm. The number of iterations for the convergence is 102, 132, and 147 by the GA algorithm, whereas that is 200 with the DE approach in scenarios 1, 2, and 3, respectively. Moreover, the simulation times are 935.36, 1246.11, and 1363.53 seconds for the GA, while those are 4424.73, 4366.11, and 4470.92 seconds by the DE algorithm. Therefore, the stochastic power loss minimization by optimal PV allocation can be remarkably dealt with by the GA-based algorithm thanks to the aforementioned advantages. In addition, the optimal power losses obtained by the corresponding PV placements have been alleviated by the influences of solar radiation levels and chance constraint limitations in scenarios 1 through 3 for both algorithms.

6.1.3. Comparison between GA and DE for 10 Runs of Stochastic Optimization Framework. The 10 independent runs of both GA and DE optimization algorithms have been considered to compare the algorithm performances. These

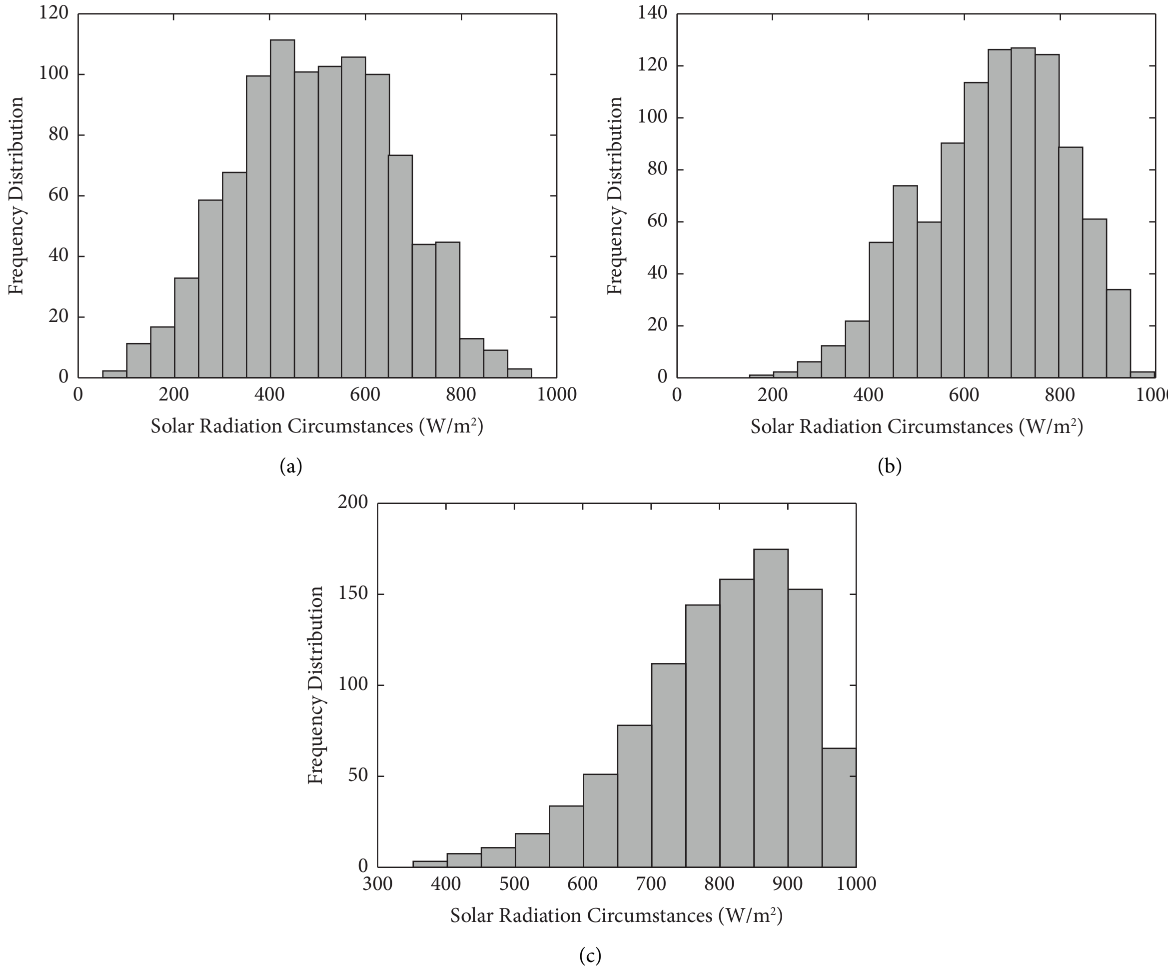


Figure 5: The frequency distributions of solar irradiances in (a) scenario 1 (low), (b) scenario 2 (medium), and (c) scenario 3 (high).

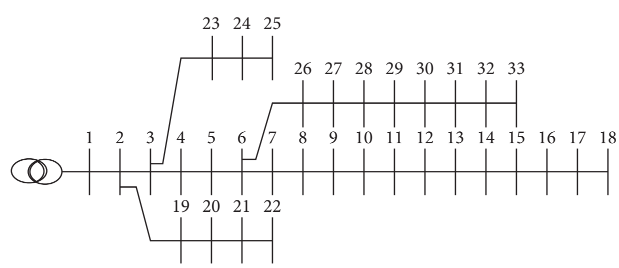


Figure 6: The 33 bus distribution network [43].

independent runs have been performed for all scenarios. Table 4 illustrates the optimal power loss, PV allocation buses, iterations, and simulation times for the corresponding 10 runs in all scenarios.

As seen in Table 4, the proposed GA methodology has the advantages in comparison with DE. The improvements have been generally observed by the aid of GA approach in terms of the power losses, corresponding PV allocation buses, iterations, and elapsed times. The GA and DE runs, at which the best optimization results have been obtained, are shown with the bold values in Table 4. The best GA outcome has been seen at 8th run of GA in scenario 1, and the best results have been observed at 3rd runs of GA in scenarios 2 and 3. The best DE optimization results have been determined at 2nd, 10th, and 3rd runs of DE in scenarios 1, 2, and 3, respectively. The optimal power losses and PV allocations have been determined by both GA and DE in all scenarios. The power losses have been reduced by the rising solar radiation in scenarios 1 through 3.

The determined best optimal power losses among 10 runs are presented in Figure 10 in an iterative manner. As shown in Figure 10, the proposed GA approach's superiority has been observed in comparison with DE. With the GA algorithm, the power losses have been determined as 80.6008 kW,

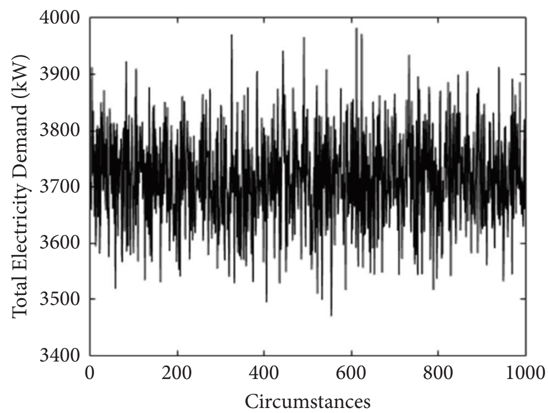


Figure 7: The total electricity demand states in the 33 bus distribution grid.

Table 2: The optimal PV system allocations.

Scenarios	PV allocation buses					
Scenario 1	6	7	9	12	14	18
	24	25	28	30	31	32
Scenario 2	7	8	13	17	21	23
	24	25	26	29	30	32
Scenario 3	5	8	12	16	19	21
	23	24	25	28	30	33

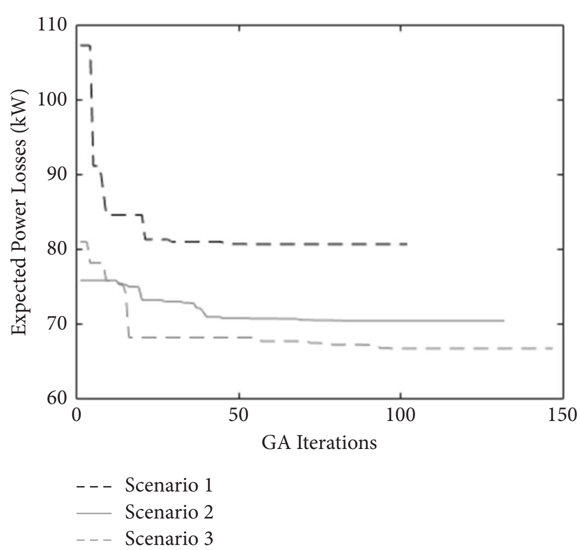


Figure 8: The optimally evaluated distribution network power losses.

Table 3: Results of algorithms for single run of stochastic optimization framework in the 33 bus distribution system.

Scenarios	Algorithms	Power losses (kW)	PV allocation buses	Iterations	Time (seconds)
Scenario 1	GA	80.69	6, 7, 9, 12, 14, 18, 24, 25, 28, 30, 31, 32	102	935.36
	DE	81.8917	15, 32, 12, 24, 33, 25, 10, 29, 8, 17, 28, 27	200	4424.73
Scenario 2	GA	70.38	7, 8, 13, 17, 21, 23, 24, 25, 26, 29, 30, 32	132	1246.11
	DE	70.994	25, 12, 32, 21, 10, 23, 26, 18, 24, 29, 7, 31	200	4366.11
Scenario 3	GA	66.65	5, 8, 12, 16, 19, 21, 23, 24, 25, 28, 30, 33	147	1363.53
	DE	67.0895	23, 4, 24, 11, 21, 33, 31, 25, 2, 28, 17, 8	200	4470.92

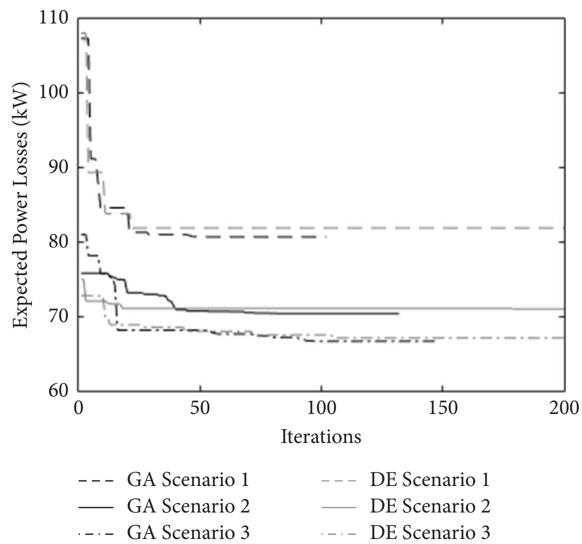


Figure 9: Iterations of algorithms in case of a single run in the 33 bus distribution system.

Table 4: Results of algorithms for 10 runs of stochastic optimization framework in the 33 bus distribution system.

Scenarios	Runs	Algorithms	Power losses (kW)	PV allocation buses	Iterations	Time (seconds)
Scenario 1	1	GA	81.18845	17, 8, 23, 25, 32, 24, 13, 30, 7, 28, 33, 16	172	1529.044
		DE	81.89172	15, 32, 12, 24, 33, 25, 10, 29, 8, 17, 28, 27	200	4455.618
	2	GA	80.68997	30, 31, 18, 25, 6, 28, 24, 7, 9, 32, 12, 14	102	925.0102
		DE	**80.79174**	**25, 24, 12, 17, 7, 29, 8, 26, 30, 16, 32, 31**	**200**	**4303.456**
	3	GA	80.76082	11, 24, 14, 33, 9, 7, 32, 28, 30, 6, 25, 18	135	1170.512
		DE	80.94892	15, 18, 32, 9, 25, 24, 11, 6, 33, 26, 29, 30	200	4353.887
	4	GA	80.6172	18, 28, 24, 8, 26, 7, 31, 12, 33, 30, 25, 15	151	1307.531
		DE	81.58163	13, 31, 15, 24, 16, 6, 9, 26, 7, 25, 30, 33	200	4358.224
	5	GA	80.88062	6, 18, 27, 11, 24, 33, 14, 31, 25, 30, 9, 7	112	979.7276
		DE	81.26418	24, 14, 30, 33, 17, 11, 28, 25, 7, 32, 12, 6	200	4375.681
	6	GA	80.76594	28, 24, 9, 7, 32, 30, 31, 25, 11, 26, 15, 18	139	1208.576
		DE	81.13645	17, 32, 30, 14, 7, 13, 24, 26, 25, 28, 9, 33	200	4349.562
	7	GA	81.18845	17, 8, 23, 25, 32, 24, 13, 30, 7, 28, 33, 16	172	1446.726
		DE	81.35108	12, 8, 18, 9, 14, 33, 32, 25, 29, 27, 24, 30	200	4364.901
	8	GA	**80.60079**	**33, 15, 8, 30, 31, 28, 7, 24, 6, 18, 25, 12**	**105**	**914.902**
		DE	81.22338	33, 30, 32, 9, 10, 29, 26, 17, 14, 25, 8, 24	200	4390.024
	9	GA	80.68997	30, 31, 18, 25, 6, 28, 24, 7, 9, 32, 12, 14	102	980.4589
		DE	81.15259	30, 25, 32, 17, 29, 7, 6, 24, 14, 11, 10, 33	200	4418.767
	10	GA	81.25007	17, 7, 24, 30, 11, 12, 31, 23, 25, 29, 32, 15	127	1107.407
		DE	81.37312	18, 29, 5, 10, 26, 32, 24, 30, 12, 14, 33, 25	200	4432.145

Table 4: Continued.

Scenarios	Runs	Algorithms	Power losses (kW)	PV allocation buses	Iterations	Time (seconds)
Scenario 2	1	GA	70.38690	30, 25, 29, 23, 26, 7, 21, 24, 8, 32, 13, 17	132	1085.535
		DE	70.99402	25, 12, 32, 21, 10, 23, 26, 18, 24, 29, 7, 31	200	4210.81
	2	GA	70.37624	6, 13, 21, 25, 17, 30, 29, 8, 23, 7, 32, 24	128	1112.944
		DE	70.9224	23, 28, 25, 20, 24, 30, 33, 9, 26, 6, 13, 16	200	4197.457
	3	GA	**70.34734**	**24, 7, 25, 17, 21, 31, 8, 13, 32, 29, 6, 23**	**156**	**1350.513**
		DE	70.69013	13, 24, 26, 20, 33, 7, 8, 32, 23, 17, 29, 25	200	4228.313
	4	GA	70.39349	23, 32, 21, 25, 9, 29, 26, 17, 24, 13, 7, 31	106	918.533
		DE	70.80245	32, 17, 25, 29, 9, 24, 27, 13, 7, 33, 23, 20	200	4238.582
	5	GA	70.45252	24, 23, 6, 7, 31, 21, 25, 33, 13, 8, 29, 17	131	1135.114
		DE	71.05788	23, 32, 16, 27, 25, 9, 24, 6, 29, 14, 33, 22	200	4197.864
	6	GA	70.60315	22, 7, 33, 17, 9, 13, 23, 24, 31, 29, 25, 6	141	1224.547
		DE	70.68907	13, 29, 8, 30, 25, 31, 21, 24, 7, 23, 16, 27	200	4345.649
	7	GA	70.72217	17, 13, 21, 3, 32, 29, 25, 26, 7, 8, 24, 31	125	1078.431
		DE	70.90593	15, 23, 6, 21, 8, 7, 28, 24, 33, 25, 13, 31	200	4201.741
	8	GA	70.47606	23, 25, 7, 30, 26, 21, 32, 8, 17, 13, 31, 24	91	799.0024
		DE	71.25464	29, 18, 24, 20, 33, 13, 7, 8, 28, 25, 23, 26	200	4333.079
	9	GA	70.35796	21, 23, 31, 17, 26, 7, 32, 25, 24, 29, 13, 8	132	1086.863
		DE	70.90343	29, 22, 23, 5, 25, 26, 31, 8, 14, 17, 24, 30	200	4399.946
	10	GA	70.44946	31, 20, 29, 24, 25, 17, 7, 14, 23, 6, 32, 8	137	1194.988
		DE	**70.64786**	**29, 31, 7, 20, 8, 13, 33, 18, 23, 24, 25, 26**	**200**	**4412.595**
Scenario 3	1	GA	66.81752	25, 24, 2, 23, 33, 16, 30, 12, 8, 21, 5, 6	167	1435.939
		DE	67.0895	23, 4, 24, 11, 21, 33, 31, 25, 2, 28, 17, 8	200	4315.394
	2	GA	66.40316	28, 5, 8, 12, 23, 21, 25, 32, 2, 24, 16, 30	145	1259.962
		DE	67.15949	23, 10, 24, 25, 8, 19, 18, 6, 29, 32, 30, 20	200	4314.125
	3	GA	**66.40316**	**25, 28, 30, 21, 2, 16, 32, 5, 23, 8, 24, 12**	**144**	**1237.924**
		DE	**66.55941**	**2, 5, 24, 30, 12, 31, 8, 25, 16, 21, 23, 28**	**200**	**4416.606**
	4	GA	66.40316	21, 32, 28, 23, 30, 12, 25, 8, 5, 24, 16, 2	166	1440.995
		DE	66.85096	27, 17, 24, 3, 23, 8, 31, 21, 7, 12, 25, 30	200	4293.368
	5	GA	66.8767	16, 8, 28, 26, 23, 25, 30, 24, 22, 32, 12, 19	108	941.324
		DE	67.19499	21, 11, 3, 2, 18, 24, 25, 7, 8, 33, 28, 30	200	4301.227
	6	GA	66.61077	11, 25, 8, 24, 28, 16, 2, 21, 5, 33, 23, 30	81	707.1047
		DE	66.90454	23, 33, 8, 25, 16, 31, 24, 5, 2, 28, 21, 11	200	4428.746
	7	GA	66.70066	16, 30, 28, 21, 32, 19, 24, 3, 5, 12, 8, 25	140	1205.368
		DE	66.81706	19, 8, 5, 30, 25, 24, 21, 23, 28, 15, 33, 12	200	4324.598
	8	GA	66.78352	16, 33, 21, 3, 12, 28, 25, 2, 5, 30, 24, 8	125	1080.636
		DE	67.0154	6, 10, 2, 25, 21, 23, 31, 32, 17, 8, 24, 26	200	4330.636
	9	GA	66.65544	8, 30, 28, 21, 19, 33, 24, 12, 25, 23, 16, 5	81	711.0599
		DE	66.81642	28, 24, 6, 10, 31, 23, 2, 32, 8, 16, 25, 21	200	4294.741
	10	GA	66.65544	33, 25, 23, 12, 5, 30, 19, 16, 8, 24, 28, 21	142	1269.396
		DE	67.16666	24, 33, 8, 28, 23, 5, 13, 22, 15, 25, 30, 2	200	4309.311

The bold values represent the best optimization results of GA and DE.

70.3473 kW, and 66.4032 kW for scenarios 1, 2, and 3, respectively. On the other hand, those have been obtained as 80.7917 kW, 70.6479 kW, and 66.5594 kW in all scenarios with DE approach. The proposed algorithm converges to the optimal solutions at 105, 156, and 144 iterations, while the DE algorithm converges to the optimal results at 200 iterations in scenarios 1, 2, and 3, respectively. In addition, the GA method gives the optimal outcomes at 914.90, 1350.51, and 1237.92 seconds, whereas the DE algorithm shows these results at 4303.45, 4412.59, and 4416.60 seconds. As a result, the GA-based methodology has also advantages in the best optimal results when compared to DE.

The evaluated best PV system allocations among 10 runs of both GA and DE algorithms are iteratively shown in Figure 11 for all scenarios. The PV placements have converged to their corresponding optimal buses as seen in Figure 11. It is clearly shown in Figure 11 that the best optimal PV placements have been achieved at the different sites by applying GA and DE with stochastic optimization framework on the distribution system. For both methodologies, these best PV allocations have been obtained so that the power losses have been minimized and the chance constraints have been satisfied. These best placements have been influenced by the chance constraint and solar radiation levels in the scenarios. This in turn has also resulted in the changes of power losses among the scenarios.

The statistical analysis of algorithms' performance has been conducted for observing the executions of GA and DE methodologies. The corresponding analysis is presented in Table 5. As seen in Table 5, the outcomes have been given based on 10 independent runs of optimization algorithms. The improvements have been determined in best, average,

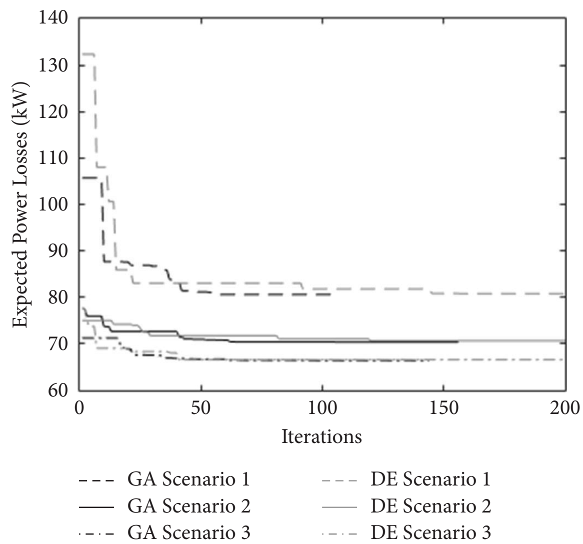


Figure 10: Best power losses in algorithms for 10 runs of stochastic optimization framework in the 33 bus distribution system.

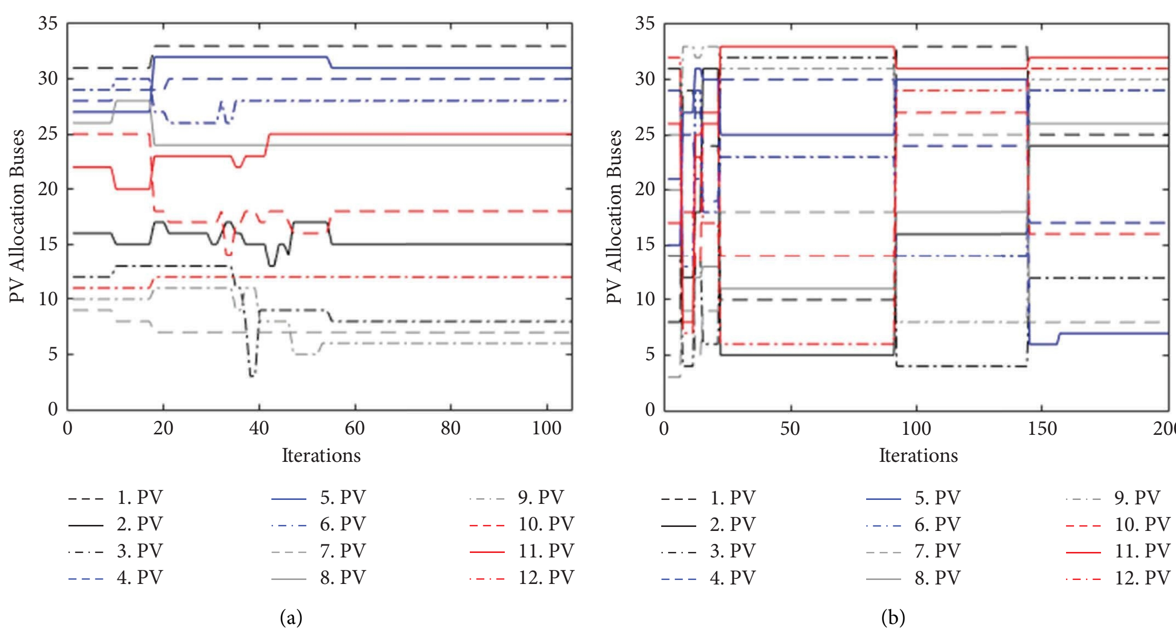


Figure 11: Continued.

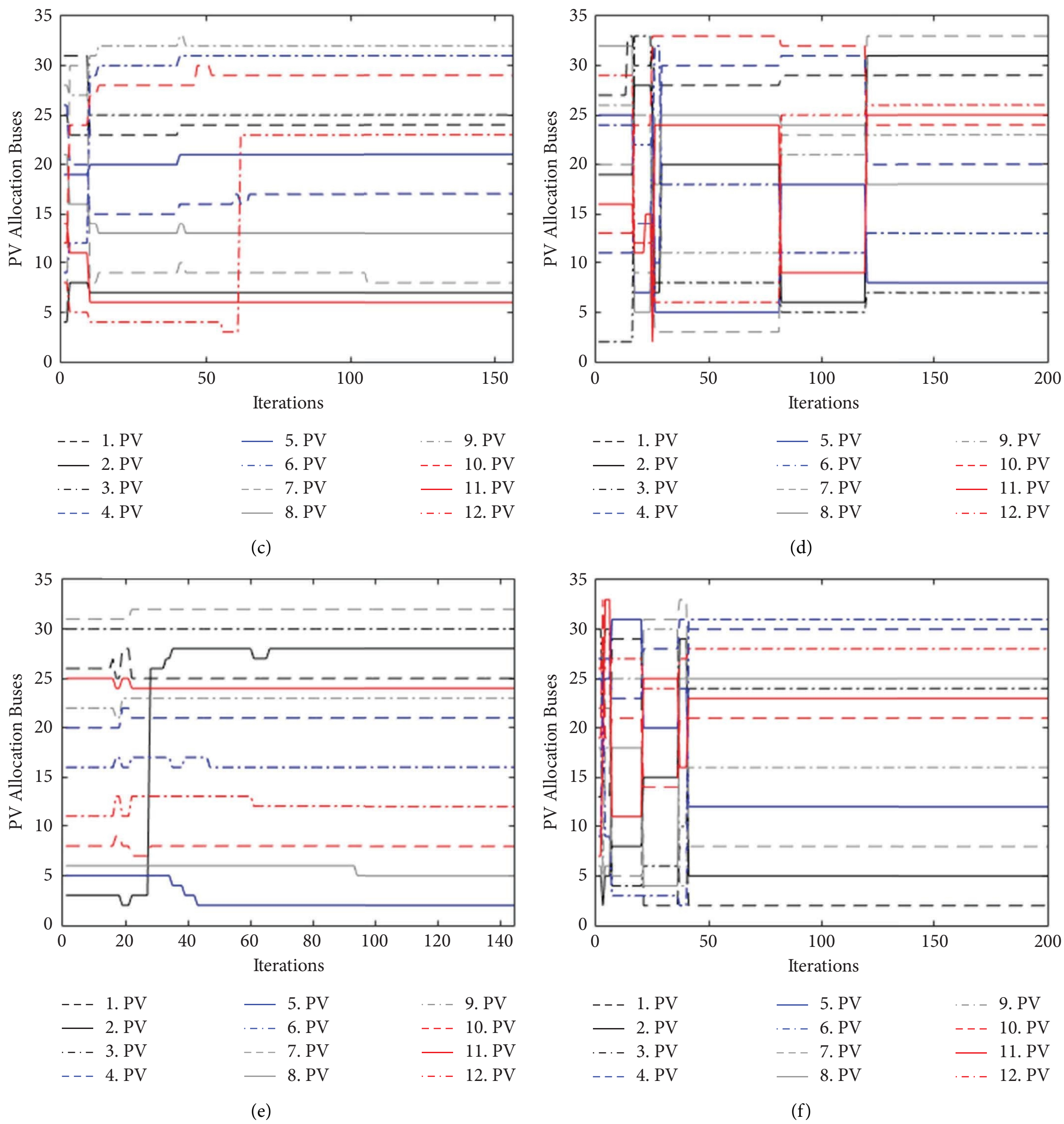


Figure 11: PV allocation convergence curves for; (a) scenario 1 in GA, (b) scenario 1 in DE, (c) scenario 2 in GA, (d) scenario 2 in DE, (e) scenario 3 in GA, (f) scenario 3 in DE for the 33 bus distribution system.

and worst values of objective function by implementing the GA method in all scenarios. These findings illustrate that the proposed GA approach has presented more improved behavior in comparison with DE. Moreover, the GA methodology has given smaller standard deviation values than DE in all scenarios. The near-optimal outcome represents the one with the lower standard deviation [45, 46]. In that manner, the GA-based optimization is more successful than DE since it has the smaller standard deviation.

6.1.4. Validation of Optimization Results. In this study, the robustness of the best results obtained from the optimization results using GA and DE with 1000 samples in each of three different scenarios is tested under the uncertainty sets considering low, medium, and high irradiance cases. In the test results obtained using the load flow under MCS, it is observed whether the bus voltages and line currents will violate the chance constraints. Table 6 shows the violation probabilities of bus voltages in all scenarios for both GA and DE.

As can be seen in Table 6, the boundary violation in the chance constraints of bus voltages is observed in the base case. In all scenarios, including the base case, no violations of the chance constraints of line currents were observed. In scenarios 1–3, the best optimal PV placements for both algorithms were able to significantly reduce the violations. The violation of the chance constraints for bus voltages was achieved at the desired confidence level with the optimal PV

Table 5: Statistical analysis for GA and DE algorithms in the 33 bus distribution system.

Scenarios	Algorithms	Best power losses (kW)	Average power losses (kW)	Worst power losses (kW)	Standard deviation
Scenario 1	GA	80.6008	80.8632	81.2501	0.2518
	DE	80.7917	81.2715	81.8917	0.3103
Scenario 2	GA	70.3473	70.4565	70.7222	0.1199
	DE	70.6479	70.8868	71.2546	0.1885
Scenario 3	GA	66.4032	66.6310	66.8767	0.1766
	DE	66.5594	66.9575	67.1950	0.2039

Table 6: The probabilities of limit violations for GA and DE in the 33 bus distribution system.

Buses	Base case	The probabilities of limit violations					
		GA			DE		
		Scenario 1	Scenario 2	Scenario 3	Scenario 1	Scenario 2	Scenario 3
1	—	—	—	—	—	—	—
2	—	—	—	—	—	—	—
3	—	—	—	—	—	—	—
4	—	—	—	—	—	—	—
5	—	—	—	—	—	—	—
6	0.7151		—	—	—	—	—
7	0.9999	0.0011	—	—	0.0011	—	—
8	0.9999	0.0352	0.0042	—	0.0351	0.0042	—
9	0.9999	0.0713	0.0128	0.0010	0.0710	0.0128	0.0010
10	0.9999	0.1025	0.0305	0.0049	0.1022	0.0305	0.0049
11	0.9999	0.1149	0.0306	0.0049	0.1145	0.0305	0.0049
12	0.9999	0.1148	0.0359	0.0058	0.1144	0.0358	0.0058
13	0.9999	0.1579	0.0559	0.0145	0.1574	0.0558	0.0145
14	0.9999	0.1741	0.0742	0.0182	0.1735	0.0741	0.0183
15	0.9999	0.1738	0.0845	0.0203	0.1732	0.0844	0.0203
16	0.9999	0.1909	0.0843	0.0203	0.1729	0.0842	0.0203
17	0.9999	0.1912	0.0948	0.0277	0.1906	0.0946	0.0277
18	0.9999	0.1913	0.0947	0.0308	0.1908	0.0943	0.0308
19	—	—	—	—	—	—	—
20	—	—	—	—	—	—	—
21	—	—	—	—	—	—	—
22	—	—	—	—	—	—	—
23	—	—	—	—	—	—	—
24	—	—	—	—	—	—	—
25	—	—	—	—	—	—	—
26	0.9958	0.0002	—	—	0.0002	—	—
27	0.9999	0.0016	—	—	0.0016	—	—
28	0.9999	0.0331	0.0039	—	0.0330	0.0039	—
29	0.9999	0.0987	0.0192	0.0027	0.0872	0.0191	0.0027
30	0.9999	0.1248	0.0316	0.0064	0.1111	0.0315	0.0064
31	0.9999	0.1704	0.0448	0.0139	0.1536	0.0447	0.0139
32	0.9999	0.1701	0.0526	0.0142	0.1534	0.0525	0.0162
33	0.9999	0.1702	0.0526	0.0161	0.1696	0.0523	0.0183

allocations for each bus of the distribution network. The confidence level of 0.8 in scenario 1 is almost maintained. Moreover, in scenarios 2 and 3, confidence levels of 0.9 and 0.95 were achieved, respectively.

In Figure 12, the voltage at bus 33 and the line current between buses 1 and 2 are presented as an example of the cumulative distribution functions for the base case and scenarios 1 to 3. Bus 33 is prominent in terms of being the far end bus in the distribution grid. The line between buses 1 and 2 is also important with regard to feeding this grid. By the best optimal PV allocation, the improvements in technical parameters have been observed compared to the base case as seen in Figure 12. The increase in solar irradiance gives rise to the enhancements in cumulative distribution functions. It is clear from Figure 12 that the cumulative distributions for bus voltages have a shift to the right hand side, whereas those for line currents possess the shift to the left hand side in scenarios 1 through 3 when compared with the base case. These shifts demonstrate the improvements in bus voltages and line currents.

Variations in electrical demand and PV systems have a significant impact on the constraints of power network.

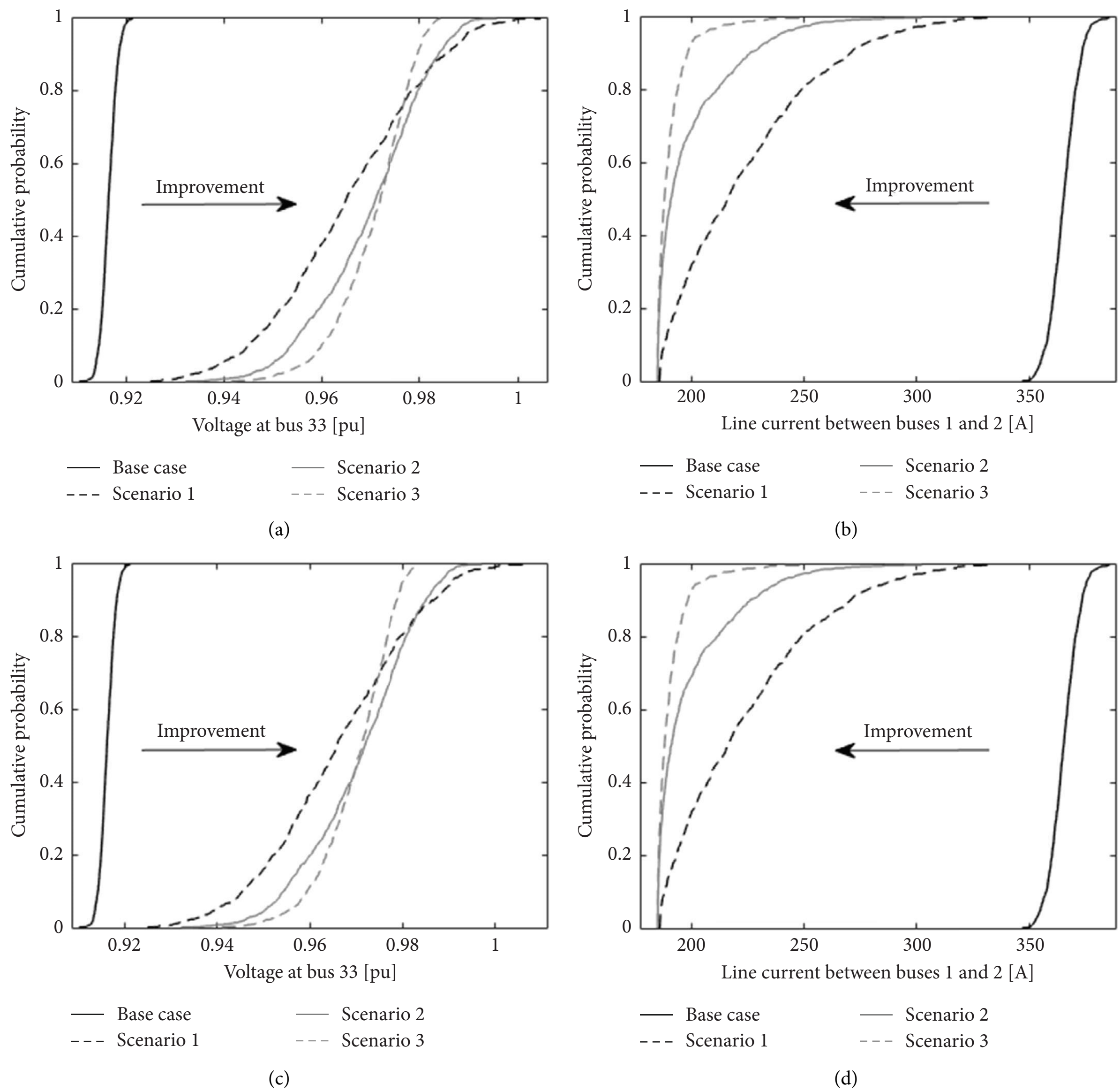


Figure 12: The cumulative distribution functions of (a) bus voltage for GA, (b) line current for GA, (c) bus voltage for DE, (d) line current for DE in the 33 bus distribution system.

When distribution networks with renewable energy sources are planned to incorporate the effects of these probabilistic behaviors, it may be possible to maximize the expected benefits. The chance constraint approach is an effective method for incorporating this random behavior into the optimization problem. As a result, the problem of minimizing power losses in distribution networks by considering the uncertainties arising from photovoltaic systems together with the uncertainties of the load is of great importance in terms of the most efficient use of available energy.

6.2. IEEE 69 Bus Distribution Network. The planning simulations have been performed on the 69 bus distribution network [43], which is demonstrated in Figure 13. The distribution system electricity demand states are presented in Figure 14. For this distribution system, the standard deviation of electricity demands is 10% in terms of mean of these electricity demands.

Based on the probability distributions of solar irradiance and electrical loads, the MCS stage of the optimization methodology has been performed with 1000 states in all scenarios. The total number of PVs has been regarded as 12 in the distribution system. The installed power of each PV system has been considered as 400 kW. The minimum and maximum values for the buses, where PV systems will be optimally placed, are 2 and 69, respectively. The confidence level for the bus voltages and line currents is considered as 0.8 in the chance-constrained programming.

6.2.1. Comparison between GA and DE for Single Run of Stochastic Optimization Framework. For scenarios 1–3, the GA optimization methodology together with MCS has been

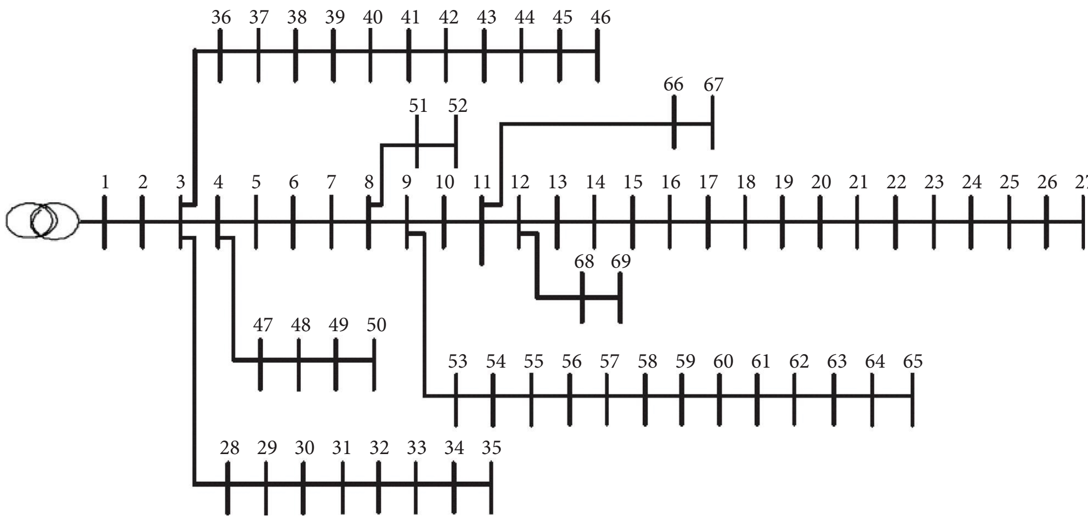


Figure 13: The 69 bus distribution network [43].

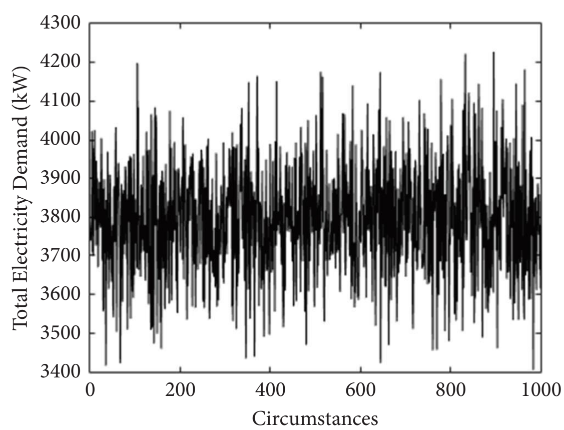


Figure 14: The total electricity demand states in the 69 bus distribution grid.

carried out. The optimization problem has also been implemented by the DE methodology for comparing the results determined in the GA approach. The optimal PV system allocations, expected power losses, convergence iterations, and simulation times are presented in Table 7.

For both methodologies, the variabilities of optimal PV system placements among the scenarios are illustrated as seen in Table 7. It is worthwhile mentioning that these optimal PV bus allocations have been obtained by minimizing the power losses and meeting the chance constraints in all scenarios. The optimal PV placements and power losses can be affected by the limitation impact of chance constraints based on different solar irradiance scenarios. The optimal distribution network power losses are iteratively demonstrated in Figure 15.

For the base case, PV systems are not placed and only variations in electricity loads are considered and the total power loss in the distribution network is 191.7302 kW. By applying the GA methodology, the power losses have been decreased to 79.8442 kW in scenario 1, 73.2466 kW in scenario 2, and 69.1757 kW in scenario 3, respectively. These power losses have been decreased by 58.36%, 61.80%, and 63.92% for scenarios 1–3 in comparison with the base case. Due to the limitations imposed by the chance constraints related with the bus voltages, the total power loss in scenario 1 is greater than that in the other scenarios. Since the voltage level is less due to the lower solar irradiance conditions in scenario 1, higher power loss has been obtained by the optimal PV placement in this scenario when compared with the other scenarios. The limitation effect of chance constraints is increased by the comparatively less voltage level in scenario 1. The distribution system voltage profile is improved when the solar irradiance levels increase in scenarios 2 and 3. The power losses and chance constraint limitations are minimized by this improvement. Since the solar irradiance levels increase and the impact of chance constraints decreases in scenarios 2 and 3, the total distribution network power losses are minimized in these scenarios more than those in scenario 1.

The advantages of GA optimization methodology have been observed in comparison with DE as presented in Table 7 and Figure 15. The optimal power losses have been determined as 80.1766 kW, 73.9686 kW, and 69.5418 kW in scenarios 1–3 by using the DE approach. The number of iterations for the convergence is 110, 124, and 140 by GA methodology, while that is 200 for DE in scenarios 1–3, respectively. In addition, the simulation times are 2131.394, 2402.663, and 2712.684 seconds for GA, while these are

Table 7: Results of algorithms for single run of stochastic optimization framework in the 69 bus distribution system.

Scenarios	Algorithms	Power losses (kW)	PV allocation buses	Iterations	Time (seconds)
Scenario 1	GA	79.8442	62, 61, 16, 65, 59, 60, 57, 23, 50, 64, 67, 63	110	2131.394
	DE	80.1766	50, 64, 65, 61, 21, 68, 66, 8, 60, 59, 62, 63	200	9251.708
Scenario 2	GA	73.2466	64, 60, 19, 63, 58, 67, 2, 40, 61, 49, 69, 62	124	2402.663
	DE	73.9686	61, 62, 64, 59, 7, 69, 46, 5, 22, 10, 63, 60	200	9129.139
Scenario 3	GA	69.1757	64, 38, 60, 61, 48, 62, 36, 63, 66, 22, 50, 8	140	2712.684
	DE	69.5418	58, 50, 2, 8, 12, 64, 41, 23, 61, 48, 62, 63	200	9348.287

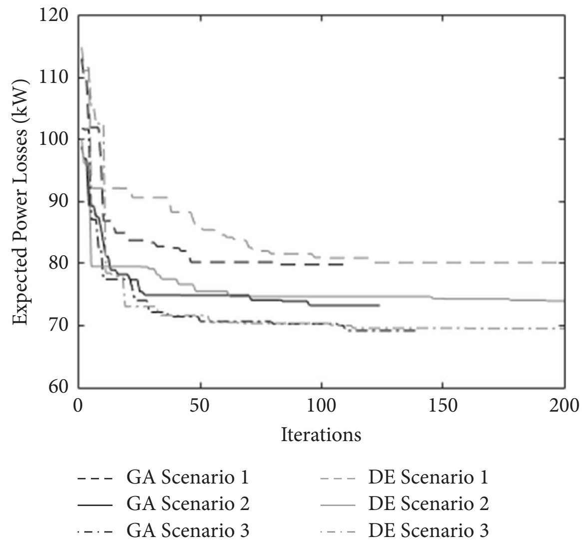


Figure 15: Iterations of algorithms in case of a single run in the 69 bus distribution system.

9251.708, 9129.139, and 9348.287 seconds by the DE approach. As a result, GA-based methodology can handle the stochastic power loss minimization in both less simulation times and less number of iterations when compared with the DE approach. In addition, the total power losses determined by the GA approach have been improved more than those obtained by DE. For both algorithms, the optimal power losses have been minimized in scenarios 1 through 3.

6.2.2. Comparison between GA and DE for 10 Runs of Stochastic Optimization Framework. The 10 runs of both GA and DE optimization methodologies have been taken into account for comparing the algorithm performances. For all scenarios, these 10 independent runs have been implemented. The expected optimal power losses, PV allocation buses, iterations, and simulation times are presented in Table 8 by considering the 10 runs in all scenarios.

The proposed GA approach has the advantages when compared to DE as shown in Table 8. With regard to the power losses, PV allocation buses, iterations, and simulation times, the improvements have been generally determined by GA methodology. The GA and DE runs, where the best optimization outcomes have been observed, are shown with the bold values in Table 8. The best GA optimization results have been obtained at 9th run of GA in scenario 1, 5th run of GA in scenario 2, and 7th run of GA in scenario 3, respectively. The best DE optimization results have been determined at 10th runs of DE in scenarios 1 and 2, and the best result has been seen at 4th run of DE in scenario 3. In scenarios 1 through 3, the power losses have been reduced by the increasing solar irradiance for both algorithms.

The obtained best expected optimal power losses among 10 runs are iteratively shown in Figure 16. The proposed GA methodology's advantages have been determined when compared to DE as presented in Figure 16. The best optimal power losses have been obtained as 79.8339 kW, 72.2470 kW, and 68.8709 kW taking into account GA approach for scenarios 1, 2, and 3, respectively. However, the best optimal power losses have been determined as 79.9527 kW, 73.0363 kW, and 69.2797 kW for all scenarios using the DE methodology. The proposed GA methodology converges to the best optimal results at 105, 126, and 120 iterations, whereas the DE approach converges to the best optimal solutions at 200 iterations for scenarios 1, 2, and 3, respectively. Moreover, the GA optimization methodology presents the best optimal results at 2034.513, 2441.415, and 2325.157 seconds, while the DE approach gives the best optimal solutions at 9267.212, 9226.335, and 8977.042 seconds. Therefore, the proposed GA optimization methodology has the superiority for the best optimal solutions in comparison with DE.

The best optimal PV system allocations for both GA and DE methodologies are presented in Figure 17 for all scenarios in an iterative manner. As seen in Figure 17, the best PV

Table 8: Results of algorithms for 10 runs of stochastic optimization framework in the 69 bus distribution system.

Scenarios	Runs	Algorithms	Power losses (kW)	PV allocation buses	Iterations	Time (seconds)
Scenario 1	1	GA	79.8442	62, 61, 16, 65, 59, 60, 57, 23, 50, 64, 67, 63	165	3197.092
		DE	80.1766	50, 64, 65, 61, 21, 68, 66, 8, 60, 59, 62, 63	200	9316.292
	2	GA	79.8442	62, 61, 16, 65, 59, 60, 57, 23, 50, 64, 67, 63	107	2073.265
		DE	80.1766	50, 64, 65, 61, 21, 68, 66, 8, 60, 59, 62, 63	200	8998.135
	3	GA	79.8442	62, 61, 16, 65, 59, 60, 57, 23, 50, 64, 67, 63	128	2480.168
		DE	80.8550	69, 16, 60, 65, 62, 53, 37, 58, 63, 24, 64, 61	200	9103.581
	4	GA	79.9431	69, 59, 58, 61, 63, 62, 65, 64, 50, 15, 24, 60	146	2828.942
		DE	82.7304	62, 61, 16, 10, 12, 21, 64, 31, 65, 60, 63, 9	200	9112.650
	5	GA	79.8442	62, 61, 16, 65, 59, 60, 57, 23, 50, 64, 67, 63	108	2092.642
		DE	80.1766	50, 64, 65, 61, 21, 68, 66, 8, 60, 59, 62, 63	200	9149.151
	6	GA	79.8442	62, 61, 16, 65, 59, 60, 57, 23, 50, 64, 67, 63	130	2518.920
		DE	80.1766	50, 64, 65, 61, 21, 68, 66, 8, 60, 59, 62, 63	200	9094.538
	7	GA	79.9431	69, 59, 58, 61, 63, 62, 65, 64, 50, 15, 24, 60	160	3100.210
		DE	80.8550	69, 16, 60, 65, 62, 53, 37, 58, 63, 24, 64, 61	200	9126.611
	8	GA	79.9008	58, 63, 62, 65, 50, 60, 10, 61, 14, 59, 22, 64	110	2131.394
		DE	82.7304	62, 61, 16, 10, 12, 21, 64, 31, 65, 60, 63, 9	200	9179.141
	9	GA	**79.8339**	**65, 49, 11, 61, 62, 63, 64, 16, 58, 59, 60, 21**	**105**	**2034.513**
		DE	80.1114	62, 63, 18, 58, 64, 65, 66, 60, 49, 56, 61, 23	200	9239.240
	10	GA	79.9331	65, 60, 62, 64, 20, 59, 49, 61, 15, 63, 58, 67	132	2557.673
		DE	**79.9527**	**61, 50, 65, 62, 59, 64, 22, 63, 60, 16, 9, 10**	**200**	**9267.212**
Scenario 2	1	GA	72.6806	59, 63, 61, 65, 48, 62, 50, 60, 21, 11, 69, 49	137	2654.555
		DE	73.2466	64, 60, 19, 63, 58, 67, 2, 40, 61, 49, 69, 62	200	8804.420
	2	GA	72.7266	50, 61, 66, 62, 51, 60, 59, 64, 12, 21, 3, 63	120	2325.157
		DE	73.9686	61, 62, 64, 59, 7, 69, 46, 5, 22, 10, 63, 60	200	8776.501
	3	GA	72.7216	60, 63, 59, 62, 9, 64, 67, 22, 40, 50, 61, 12	160	3100.210
		DE	73.4311	60, 58, 61, 62, 10, 69, 29, 63, 65, 21, 49, 2	200	8841.018
	4	GA	72.8757	69, 49, 62, 64, 52, 60, 50, 59, 22, 61, 37, 63	111	2150.770
		DE	74.5439	2, 64, 50, 7, 12, 8, 62, 21, 55, 59, 63, 61	200	8862.489
	5	GA	**72.2470**	**60, 63, 49, 50, 64, 38, 61, 62, 11, 59, 12, 22**	**126**	**2441.415**
		DE	73.3776	21, 58, 38, 53, 65, 63, 11, 62, 60, 69, 61, 49	200	8777.352
	6	GA	72.7272	69, 59, 65, 63, 62, 2, 60, 11, 49, 61, 50, 21	145	2809.565
		DE	73.0575	62, 37, 61, 65, 60, 63, 11, 50, 64, 21, 12, 8	200	9086.357
	7	GA	72.9295	59, 9, 67, 69, 2, 61, 62, 63, 64, 22, 50, 60	123	2383.286
		DE	73.1616	22, 65, 62, 6, 51, 59, 61, 64, 69, 63, 50, 49	200	8785.458
	8	GA	72.6692	9, 67, 61, 63, 12, 62, 49, 60, 58, 22, 50, 65	101	1957.007
		DE	73.0523	62, 2, 49, 48, 66, 60, 58, 64, 61, 69, 21, 63	200	9060.074
	9	GA	72.4649	59, 50, 19, 60, 10, 49, 63, 8, 68, 64, 61, 62	129	2499.544
		DE	73.3422	4, 12, 49, 60, 63, 20, 64, 58, 48, 62, 61, 69	200	9199.887
	10	GA	72.4932	37, 59, 64, 11, 49, 23, 62, 60, 61, 69, 63, 50	142	2751.436
		DE	**73.0363**	**12, 23, 60, 49, 69, 59, 63, 62, 65, 61, 9, 50**	**200**	**9226.335**
Scenario 3	1	GA	69.2663	24, 64, 62, 59, 10, 4, 50, 9, 49, 36, 63, 61	162	3138.963
		DE	70.7217	61, 67, 59, 62, 38, 28, 53, 21, 64, 30, 2, 63	200	9023.096
	2	GA	69.1757	64, 38, 60, 61, 48, 62, 36, 63, 66, 22, 50, 8	141	2732.060
		DE	69.5418	58, 50, 2, 8, 12, 64, 41, 23, 61, 48, 62, 63	200	9020.443
	3	GA	68.9266	49, 61, 53, 62, 64, 63, 69, 60, 37, 19, 3, 50	138	2673.931
		DE	69.6623	69, 16, 60, 54, 63, 62, 61, 65, 40, 2, 49, 50	200	9234.721
	4	GA	69.0231	53, 48, 66, 63, 50, 61, 64, 20, 62, 49, 59, 2	157	3042.081
		DE	**69.2797**	**60, 17, 69, 63, 64, 62, 28, 49, 9, 48, 2, 61**	**200**	**8977.042**
	5	GA	69.1701	50, 60, 64, 6, 49, 63, 62, 18, 61, 69, 2, 54	113	2189.523
		DE	69.2804	56, 62, 61, 63, 60, 49, 47, 64, 50, 39, 20, 69	200	8993.474
	6	GA	68.9123	64, 4, 49, 8, 63, 58, 61, 62, 22, 50, 2, 12	125	2422.039
		DE	69.3502	60, 36, 50, 61, 62, 66, 2, 63, 64, 17, 8, 29	200	9260.105
	7	GA	**68.8709**	**61, 60, 63, 69, 62, 2, 64, 20, 49, 8, 50, 36**	**120**	**2325.157**
		DE	69.3191	28, 64, 21, 60, 8, 62, 69, 63, 50, 39, 61, 2	200	9042.341
	8	GA	69.2231	28, 22, 67, 63, 62, 61, 49, 55, 64, 50, 59, 4	130	2518.920
		DE	69.2890	49, 23, 62, 2, 69, 60, 50, 61, 64, 63, 7, 51	200	9054.966
	9	GA	69.2469	69, 60, 9, 23, 50, 63, 48, 38, 64, 62, 61, 47	126	2441.415
		DE	70.1427	4, 58, 37, 61, 69, 15, 60, 8, 49, 62, 50, 64	200	8979.913
	10	GA	69.1306	36, 59, 54, 69, 62, 21, 61, 49, 39, 63, 64, 50	149	2887.070
		DE	69.6305	21, 10, 61, 4, 62, 64, 49, 66, 63, 59, 47, 2	200	9010.377

The bold values represent the best optimization results of GA and DE.

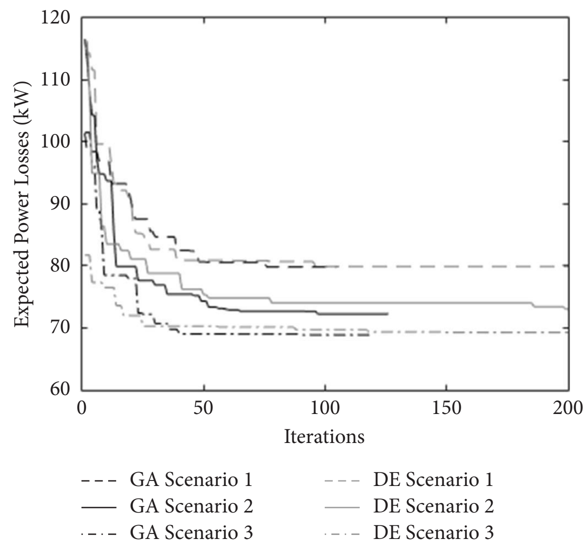
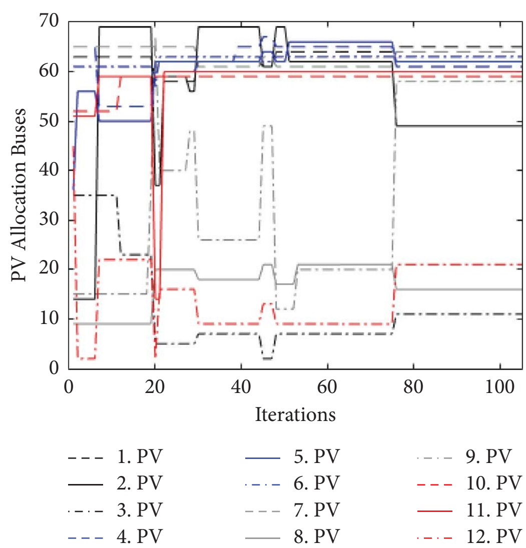
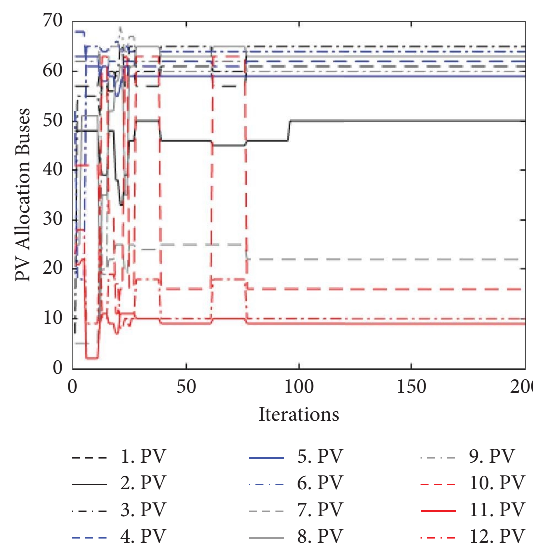


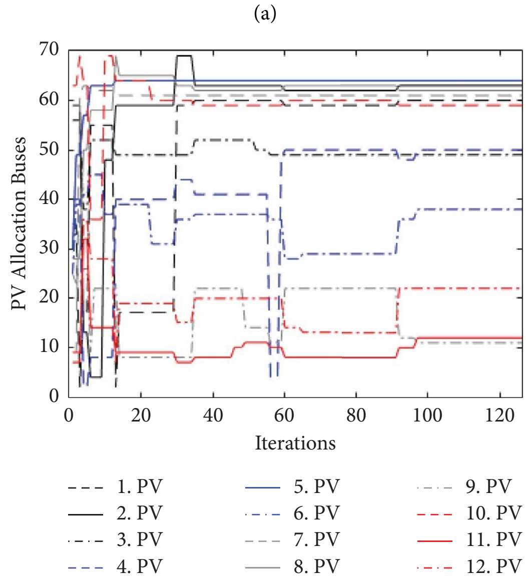
Figure 16: Best power losses in algorithms for 10 runs of stochastic optimization framework in the 69 bus distribution system.



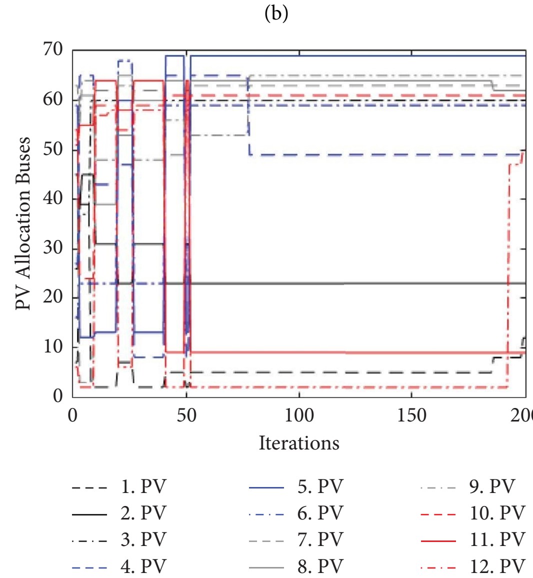
(a)



(b)



(c)



(d)

Figure 17: Continued.

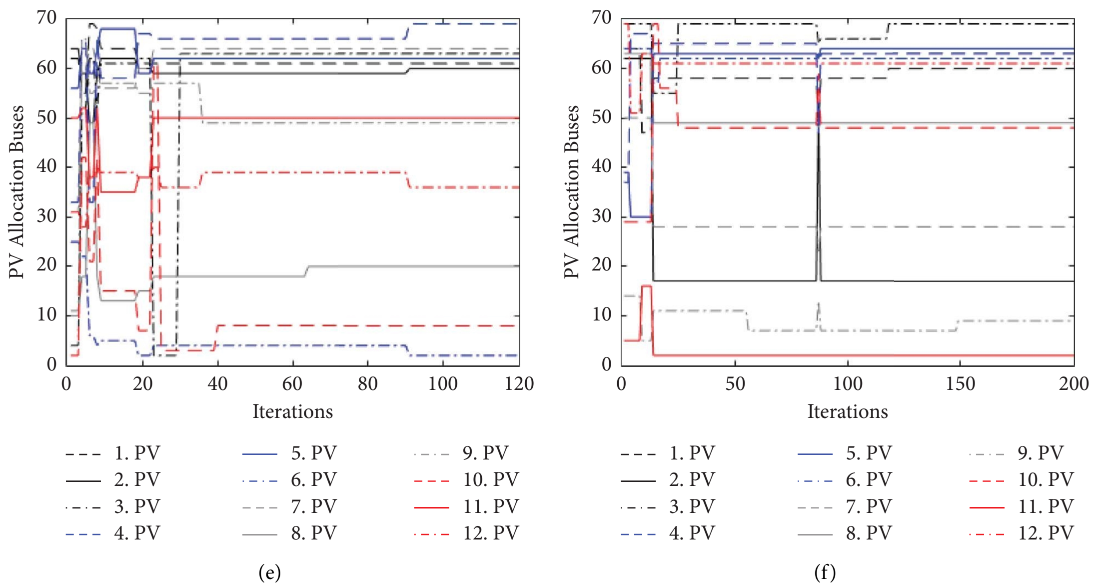


FIGURE 17: PV allocation convergence curves for; (a) scenario 1 in GA, (b) scenario 1 in DE, (c) scenario 2 in GA, (d) scenario 2 in DE, (e) scenario 3 in GA, (f) scenario 3 in DE for the 69 bus distribution system.

allocations have converged to their corresponding buses. The best optimal PV system allocations have been determined at various buses by implementing GA and DE with stochastic optimization framework on the distribution network. These optimal PV placements have been achieved so that the power losses have been alleviated and the chance constraints have been maintained.

In this paper, the simulation studies have been conducted in the direction of stochastic optimization approach for strengthening the distribution network with the execution of useful and optimal PV allocations. These allocations may be utilized for the appropriate supervision of distribution grid. The entire grid performance can be upgraded with optimally placing the PV units by delivering the demands with the help of lines. The various uncertainties of load consumption and PV output powers cause the distribution system to have a complex nature. Hence, the distribution grid parameters can have variabilities. In this concept, the optimal PV system allocation provides the power flow delivery to the demands through the lines. The power loss minimization of entire distribution network can be achieved by this power delivery. With the aim of minimizing the power losses, the optimal PV placements have been properly managed for supplying the lines and demands. Therefore, specifying the allocations of PV systems is inevitable from the standpoint of distribution system loss.

The statistical analysis of algorithms' performance is given in Table 9. The results have been presented by considering 10 independent runs of GA and DE optimization algorithms as shown in Table 9. The improvements have been obtained in best, average, and worst values of optimal power losses by applying GA methodology for all scenarios. In addition, the GA approach has presented lower standard deviation values than DE for all scenarios. It is clearly seen that the proposed GA method has presented more successful results when compared to DE.

6.2.3. Validation of Optimization Results. The validation of best optimization results determined from GA and DE optimization frameworks has been performed under the uncertainty sets considering low, medium, and high irradiance scenarios for presenting the robustness of optimal results. The violations for the chance constraints have been examined for the bus voltages and line currents by taking into account the test results determined with the MCS-based load flow. The violation probabilities of bus voltages are presented in Table 10 by considering all scenarios for both GA and DE.

The violations in chance constraints for bus voltages have been observed in the base case as presented in Table 10. The chance constraint violations for the line currents have not been observed for all scenarios. The violations related with bus voltages have been considerably minimized by the optimal PV system allocations in scenarios 1–3. For both algorithms, the chance constraint violations for bus voltages have been determined at the desired confidence level by considering the optimal PV system placements in the distribution system. For scenario 1, 0.85 confidence level has been maintained. In addition, 0.95 and 0.99 confidence levels have been achieved for scenarios 2 and 3, respectively.

The cumulative distribution functions for the voltage at bus 65 and the line current between buses 1 and 2 have been illustrated as the example in Figure 18 for the base case and scenarios 1 through 3. Bus 65 is important with regard to being one of far end buses in the distribution system. The line connecting buses 1 and 2 is the feeder providing power flow in the distribution network. As shown in Figure 18, the improvements in bus voltages and line currents have been observed when compared with the base case by taking into account the optimal PV placements in scenarios 1 through 3. The cumulative distribution functions have been improved by the rise in solar irradiance conditions. It is clearly seen in

Table 9: Statistical analysis for GA and DE algorithms in the 69 bus distribution system.

Scenarios	Algorithms	Best power losses (kW)	Average power losses (kW)	Worst power losses (kW)	Standard deviation
Scenario 1	GA	79.8339	79.8775	79.9431	0.0468
	DE	79.9527	80.7941	82.7304	1.0649
Scenario 2	GA	72.2470	72.6536	72.9295	0.2023
	DE	73.0363	73.4218	74.5439	0.4811
Scenario 3	GA	68.8709	69.0946	69.2663	0.1488
	DE	69.2797	69.6217	70.7217	0.4713

Table 10: The probabilities of limit violations for GA and DE in the 69 bus distribution system.

Buses	Base case	The probabilities of limit violations					
		GA			DE		
		Scenario 1	Scenario 2	Scenario 3	Scenario 1	Scenario 2	Scenario 3
57	0.9548	0.0022	—	—	0.0034	—	—
58	0.9999	0.0234	0.0036	—	0.0295	0.0028	—
59	0.9999	0.0334	0.0074	0.0004	0.0479	0.0059	0.0003
60	0.9999	0.0537	0.0156	0.0013	0.0732	0.0131	0.0013
61	0.9999	0.0948	0.0335	0.0057	0.1211	0.0288	0.0057
62	0.9999	0.0944	0.0335	0.0058	0.1211	0.0288	0.0059
63	0.9999	0.0941	0.0335	0.0059	0.1211	0.0288	0.0059
64	0.9999	0.1052	0.0391	0.0072	0.1207	0.0335	0.0072
65	0.9999	0.0920	0.0390	0.0071	0.1208	0.0332	0.0071

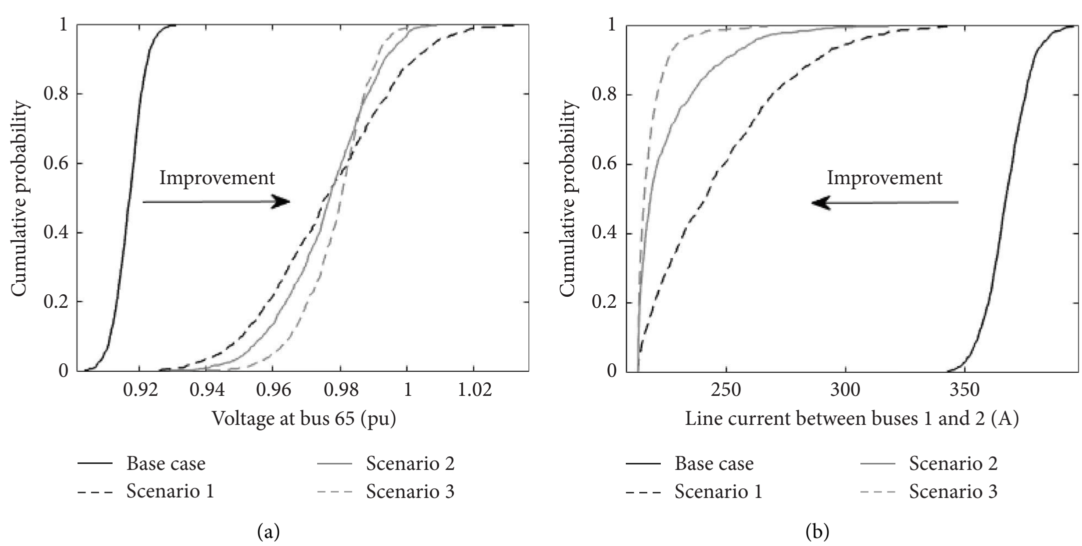
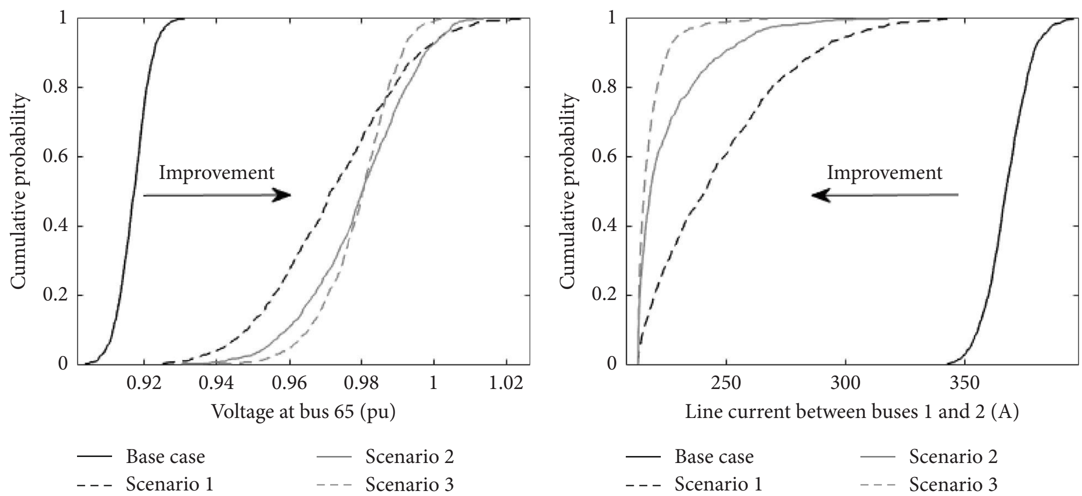


Figure 18: Continued.



(c) (d)

Figure 18: The cumulative distribution functions of (a) bus voltage for GA, (b) line current for GA, (c) bus voltage for DE, (d) line current for DE in the 69 bus distribution system.

Table 11: IEEE 33 bus distribution network data [43].

From	To	PD (kW)	QD (kVAR)	R (ohms)	X (ohms)	Imax (A)
1	2	100	60	0.0922	0.0470	400
2	3	90	40	0.4930	0.2510	400
3	4	120	80	0.3661	0.1864	400
4	5	60	30	0.3811	0.1941	400
5	6	60	20	0.8190	0.7070	400
6	7	200	100	0.1872	0.6188	300
7	8	200	100	1.7117	1.2357	300
8	9	60	20	1.0299	0.7400	200
9	10	60	20	1.0440	0.7400	200
10	11	45	30	0.1967	0.0651	200
11	12	60	35	0.3744	0.1237	200
12	13	60	35	1.4680	1.1549	200
13	14	120	80	0.5416	0.7129	200
14	15	60	10	0.5909	0.5260	200
15	16	60	20	0.7462	0.5449	200
16	17	60	20	1.2889	1.7210	200
17	18	90	40	0.7320	0.5739	200
2	19	90	40	0.1640	0.1564	200
19	20	90	40	1.5042	1.3555	200
20	21	90	40	0.4095	0.4784	200
21	22	90	40	0.7089	0.9373	200
3	23	90	50	0.4512	0.3084	200
23	24	420	200	0.8980	0.7091	200
24	25	420	200	0.8959	0.7010	200
6	26	60	25	0.2031	0.1034	300
26	27	60	25	0.2842	0.1447	300
27	28	60	20	1.0589	0.9338	300
28	29	120	70	0.8043	0.7006	200
29	30	200	600	0.5074	0.2585	200
30	31	150	70	0.9745	0.9629	200
31	32	210	100	0.3105	0.3619	200
32	33	60	40	0.3411	0.5302	200

SB = 100 MVA; VB = 12.66 kV.

Table 12: IEEE 69 bus distribution network data [43].

From	To	PD (kW)	QD (kVAR)	R (ohms)	X (ohms)	Imax (A)
1	2	0	0	0.0005	0.0012	400
2	3	0	0	0.0005	0.0012	400
3	4	0	0	0.0015	0.0036	400
4	5	0	0	0.0251	0.0294	400
5	6	2.6	2.2	0.366	0.1864	400
6	7	40.4	30	0.381	0.1941	400
7	8	75	54	0.0922	0.047	400
8	9	30	22	0.0493	0.0251	400
9	10	28	19	0.819	0.2707	400
10	11	145	104	0.1872	0.0619	200
11	12	145	104	0.7114	0.2351	200
12	13	8	5	1.03	0.34	200
13	14	8	5.5	1.044	0.345	200
14	15	0	0	1.058	0.3496	200
15	16	45.5	30	0.1966	0.065	200
16	17	60	35	0.3744	0.1238	200
17	18	60	35	0.0047	0.0016	200
18	19	0	0	0.3276	0.1083	200
19	20	1	0.6	0.2106	0.069	200
20	21	114	81	0.3416	0.1129	200
21	22	5	3.5	0.014	0.0046	200
22	23	0	0	0.1591	0.0526	200
23	24	28	20	0.3463	0.1145	200
24	25	0	0	0.7488	0.2475	200
25	26	14	10	0.3089	0.1021	200
26	27	14	10	0.1732	0.0572	200
3	28	26	18.6	0.0044	0.0108	200
28	29	26	18.6	0.064	0.1565	200
29	30	0	0	0.3978	0.1315	200
30	31	0	0	0.0702	0.0232	200
31	32	0	0	0.351	0.116	200
32	33	14	10	0.839	0.2816	200
33	34	19.5	14	1.708	0.5646	200
34	35	6	4	1.474	0.4873	200
3	36	26	18.55	0.0044	0.0108	200
36	37	26	18.55	0.064	0.1565	200
37	38	0	0	0.1053	0.123	200
38	39	24	17	0.0304	0.0355	200
39	40	24	17	0.0018	0.0021	200
40	41	1.2	1	0.7283	0.8509	200
41	42	0	0	0.31	0.3623	200
42	43	6	4.3	0.041	0.0478	200
43	44	0	0	0.0092	0.0116	200
44	45	39.22	26.3	0.1089	0.1373	200
45	46	39.22	26.3	0.0009	0.0012	200
4	47	0	0	0.0034	0.0084	300
47	48	79	56.4	0.0851	0.2083	300
48	49	384.7	274.5	0.2898	0.7091	300
49	50	384.7	274.5	0.0822	0.2011	300
8	51	40.5	28.3	0.0928	0.0473	200
51	52	3.6	2.7	0.331	0.1114	200
9	53	4.35	3.5	0.174	0.0886	300
53	54	26.4	19	0.203	0.1034	300
54	55	24	17.2	0.2842	0.1447	300
55	56	0	0	0.2813	0.1433	300
56	57	0	0	1.59	0.5337	300
57	58	0	0	0.7837	0.263	300
58	59	100	72	0.3042	0.1006	300
59	60	0	0	0.3861	0.1172	300
60	61	1244	888	0.5075	0.2585	300

Table 12: Continued.

From	To	PD (kW)	QD (kVAR)	R (ohms)	X (ohms)	Imax (A)
61	62	32	23	0.0974	0.0496	300
62	63	0	0	0.145	0.0738	300
63	64	227	162	0.7105	0.3619	300
64	65	59	42	1.041	0.5302	300
11	66	18	13	0.2012	0.0611	200
66	67	18	13	0.0047	0.0014	200
12	68	28	20	0.7394	0.2444	200
68	69	28	20	0.0047	0.0016	200

SB = 100 MVA; VB = 12.66 kV.

cumulative distribution functions that the right hand side shifts have been obtained in bus voltages and the left hand side shifts have been determined in line currents for scenarios 1 through 3 in comparison with the base case. It can be inferred from these shifts that the bus voltages and line currents have been improved.

The difficulty in planning studies in active distribution networks arises from the intermittent characteristics of the output power of photovoltaic systems with increasing participation rates. A more reliable network can be achieved by considering a large number of possible situations in planning studies. A larger number of samples lead to increased computational difficulty and even to overly conservative decisions or unfeasibility. On the other hand, planning based on worst-case scenarios with low probabilistic probability of realization results in oversized investments. In this manner, the stochastic planning has important role in dealing with the wide range of samples by taking into account the respective probabilities. In this paper, the probabilistic optimization analysis of distribution network has been provided by the uncertainties of solar radiation levels and distribution system load consumption. Hence, the distribution grid technical parameters can be stochastically handled while determining the optimal control variables. In the current study, the optimal PV allocations have gained great importance in terms of considering the probabilistic sample ranges of uncertainties, handling the chance constraints of technical parameters with the specified confidence levels, and minimizing the power losses of distribution system under different scenarios.

7. Conclusions

In this study, power losses, voltages, and line capacities are taken by the chance constraint optimization method in the planning of distribution networks under uncertainties of load and solar irradiance, and the problem of optimal placement of photovoltaic systems, whose penetration level in the grid is increasing day by day, is solved by combining meta-heuristic algorithms such as GA and DE and Monte Carlo Simulation. In the proposed stochastic programming, the optimization results are compared for possible long-term solar irradiance conditions under three different profiles as low, medium, and high. According to the simulation results, distribution grid power losses are optimally minimized in these three scenarios, compared to the scenario with load change but without PV connection. The power loss in the low irradiance scenario is higher than that in the other two scenarios due to the limiting effect of chance constraints related to bus voltages. In the medium and high irradiance scenarios, it is observed that the power loss can be further reduced as the solar irradiance levels are high and the effects of chance constraints are reduced. The findings show that in distribution networks where PV systems with different irradiance uncertainty conditions are connected, violations of the grid voltage are particularly important. At this point, the optimization decisions obtained with the probabilistic grid constraint approach were able to provide quantifiable results. Furthermore, the comparison between MCS-embedded GA and DE algorithms has been made for illustrating the effectiveness of the proposed methodology. The simulation outcomes show that the proposed stochastic GA approach has the superiority. Both GA and DE converge to the optimal solutions. Nevertheless, GA performs in less computational time and iteration in comparison with DE.

Appendix

A. Meaning and Symbols of Parameters

The details of IEEE 33 bus and IEEE 69 bus distribution systems are presented in Tables 11 and 12, respectively.

Data Availability

No data were used to support this study.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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