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Research Paper

AC-DC Distribution Network Planning Under Extreme Events

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Abstract— *The increasing integration of photovoltaic (PV) panels and electric vehicles (EVs), both direct current (DC) sources and loads, has introduced significant transformations in modern distribution networks (DNs). Consequently, the DN now accommodates both alternating current (AC) and DC loads and generators. To effectively manage this evolving structure, the implementation of an AC-DC distribution network (ADDN) has emerged as a promising solution. However, due to the random nature of load demands and the variable output of renewable distributed generations (DGs), the network may face challenges such as line loading violations and bus voltage constraint breaches, posing significant operational risks. To address these uncertainties, the K-means algorithm has been employed for uncertainty modeling. Additionally, extreme events characterized by high costs but low probabilities of occurrence have been incorporated into the analysis. This paper investigates the AC-DC distribution network planning (ADDNP) under such conditions, focusing on minimizing the financial impact of extreme events. The average value at risk (AVaR) criterion has been applied to identify and manage these high-impact scenarios. The proposed model is validated on a 13-bus DN, considering varying confidence levels and voltage tolerance values, demonstrating its effectiveness in mitigating operational risks.*

Keywords—AVaR, AC/DC loads, AC/DC generators, constraints, uncertainties, violation.

NOMENCLATURE

Indices

n, n' Index of buses
sc Index of scenarios
so Index of sources
tr Index of years

Parameters

α Confidence level
$\mathbb{C}^{AC}, \mathbb{C}^{DC}$ AC and DC network equipment (types of equipment)
C_s Energy cost of source
C_{con} The cost of each line conductor
Dis The distance between buses
I_d Interest rate
N_{li} Number of lines connected to the bus
Nt Total number of network buses
P_l Real power demand
Pr Probability of a scenario
X^{mn}, X^{mx} Minimum and maximum limit of the variable X

Set

ϑ_b Set of total network buses
ϑ_s Set of total network sources
ϑ_t Set of total years
ϑ_{sc} Set of total scenarios

Variables

A_{str} Matrix indicating AC or DC buses (types of buses)
$AVaR$ Average value at risk
C_t Total planning costs
$C_{dam\_lo\_ac/dc}$ Cost of damage caused by AC/DC line overload
C_{dam_uov} Cost of damage caused by violation of bus voltage
C_{ic} Investment cost of network equipment
C_{line} Investment cost of network lines
C_{mc} Maintenance cost of network equipment
C_{oc} Operation cost of the network
C_{oper} Optimal operating cost
C_{vsc} Investment cost of converters
$E(X)$ Expected value of the variable X
L_{lo} Damage cost rate caused by violation of line loading
M_{mo} Modulation index of the converter
M_{str} Matrix indicating the connection or non-connection between buses
P_s Real power of source
P_{cal}, Q_{cal} Calculated real and imaginary power
P_{inj}, Q_{inj} Injected real and imaginary power
P_{tr}, Q_{tr}, S_{tr} Real, imaginary, and apparent power flow through a line between buses
Q_{str} Matrix indicating AC or DC lines between buses (types of network lines)
V, θ Bus voltage magnitude and angle
V_{uo} Function of damage caused by violation of bus voltage
OF Objectives of the problem

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1. INTRODUCTION

Recently, distribution networks (DNs) have experienced a growing integration of direct current (DC)-based distributed generation (DG) and DC loads. Connecting these resources and loads to the network requires converters, which increases investment costs. As a solution, implementing AC-DC distribution network planning (ADDNP), which accommodates both alternating current (AC) and DC sources and loads, can prove effective. However, the random nature of renewable energy generation, load demands, and electric vehicle (EV) usage introduces risks to the network, potentially affecting its stability and operation [1–4].

In the following, the studies conducted in the field of AC-DC distribution network (ADDN) are presented. In [5, 6], the decision variables of the ADDNP problem include bus type and network line type (AC and DC). The objective is to determine these variables. In [5], uncertainties in load demand and the power of renewable resources are modeled using Monte Carlo simulation (MCS), while [6] implements ADDNP without considering these uncertainties. In [7], the optimal location and capacity of EVs and renewable energy sources in the non-deterministic ADDNP problem are determined. In [8], AC-DC distribution network expansion planning that considers dynamic investment is discussed. The multi-stage scenario tree method is employed to model the uncertainty in load demand and the power of renewable energy sources. In [9], AC-DC distribution network expansion planning is conducted to determine the optimal location and capacity of converters and the types of lines (AC and DC). The multi-scenario method is utilized to model the uncertainty of load and the power of renewable sources. In [10], deterministic AC-DC distribution network expansion planning is presented, considering the N-1 security criterion for both AC and DC lines. In [11], the ADDNP at the low voltage (LV) level is discussed. This paper is solved through a bi-level planning model. In [12], a bi-level model is presented to identify the optimal number and location of photovoltaic (PV) and energy storage in the ADDN. In [13], the optimal location of DGs in the DC distribution network has been determined. In [14], the DC distribution network planning is addressed with the goal of determining the capacity and number of PVs. Additionally, the impact of the number of installed PVs on the network has been analyzed. In [15], the planning of DC distribution lines and energy storage in the distribution network is conducted. Uncertainty in the output power of PVs and load has been modeled using the robust optimization method. In [16–21], the field of AC-DC microgrid planning is explored. Among the decision variables in this problem are the types of feeders (AC or DC) [16, 21], the capacity of renewable resources [16, 17], [19, 20] and energy storage devices [17–20]. Uncertainty in load demand and the power of renewable resources has been modeled using the robust optimization method [16, 20] and the Taguchi arrays method [18]. In [22], the DC microgrid planning with the aim of integrating renewable sources, DC loads, and energy storage devices is discussed. In [23], the ADDNP considering risk is presented. In this study, risk is modeled as a constraint, ensuring that the risk limitation is consistently satisfied. The problem determines the bus type and network line type, as well as the optimal scheme of the network with the objective of minimizing costs. In planning problems that do not consider risk, the result is unrealistic and leads to non-optimal planning. Therefore, it is essential to identify and apply risk factors to these problems. In risk analysis, one method employed for risk evaluation is the average value at risk (AVaR). AVaR is a rational measure of risk that has several favorable characteristics and convexity [24, 25].

Due to the uncertainty in load demand and the output power of renewable resources, deterministic ADDNP is considered unrealistic and inefficient. This uncertainty leads to violations of constraints, such as bus voltage and line loading. These violations cause risks within the network. Therefore, it is essential to identify and manage these risk factors. The advantages and disadvantages of studies conducted on ADDNP are summarized in Table 1. According to this table, among the studies conducted in the field of ADDNP, only reference [23] discusses planning with consideration of risk. In this paper, the risk associated with the violation of the technical constraints of the problem is not modeled. Specific modeling has been used to express risk, and it is treated as a constraint (which has always been satisfied in the problem). Therefore, in the following paper, the risk caused by the violation of these technical constraints has been modeled. The cost of damage resulting from these violations has then been calculated and added to the objective function. Scenarios with the highest costs are considered extreme events and are included in the ADDNP process. Using the AVaR criterion, which focuses on these events, risk management has been addressed. The objective is to obtain a scheme that minimizes planning costs and the costs of extreme events (using the AVaR criterion to evaluate these events).

The main contributions are outlined as follows:

- The uncertainty in load demand and the output power of renewable resources in ADDNP leads to possible behavior of the network. This behavior can lead to violations of constraints, such as bus voltage and line loading, which are the main sources of risk.
- The uncertainty of network parameters is modeled using the K-means algorithm. By defining scenarios with the highest costs as extreme events, risk management has been addressed in the planning problem using the AVaR criterion. The objective of the planning problem is to achieve an optimal network scheme while minimizing planning costs and the costs of extreme events (by employing the AVaR criterion).
- Risk evaluation was conducted on the problem of ADDNP under different confidence levels and voltage tolerance values, and the results were compared.

2. ADDNP Model

The conventional distribution network is typically an AC network, where both the buses and the lines are AC. However, with the increasing presence of DC loads and DGs, implementing an ADDN, which comprises both AC and DC equipment, become a viable option [9]. Fig. 1 illustrates an example of an ADDN.

The scheme of the ADDN consists of:

- The types of network buses
- The connections between buses
- The types of connection lines between buses

Each of the above items is expressed as a matrix. Therefore, the scheme of the ADDN is composed of three matrices: the matrix of network bus types, the matrix of connection lines between buses, and the matrix of the connection line types between buses (indicating whether the equipment is AC or DC).

Additionally, the ADDNP problem consists of parameters that exhibit possible behavior. This behavior arises from the randomness of certain data. In this paper, the main factors influencing the possible behavior of the ADDNP include the random nature of AC and DC load demands, as well as the random nature of the output power of renewable DGs such as wind and PV. On the contrary, the possible behavior of the network could lead to increased operational costs or damage to specific equipment. In ADDNP, if the random behavior of parameters is not considered, constraints such as bus voltage and line loading limits are always satisfied in the problem. However, by modeling the stochastic behavior of parameters, these constraints may exceed their allowable limits. Moreover, a violation of these constraints leads to risks in the problem. It is essential to model and manage the risks arising from these violations. This paper integrates the cost of damages due to risks into the objective function of the modeled problem. It is important to recognize that achieving zero risk in a network is impossible due to the inherent uncertainty of load and renewable resource output.

Various methods have been proposed to model uncertainties in the network. These approaches aim to enhance the reliability and efficiency of decision-making processes by accurately modeling the inherent and unpredictable variability of system components. Employing these methods can significantly contribute to more robust power system planning and operation [26–29]. In ADDNP, the randomness of output power of renewable DGs, load demand, and EV demand is considered. The K-means algorithm is employed to model this uncertainty. In this method, a specific number of points are initially selected randomly as the target clusters. Subsequently, the data is allocated to one of these clusters based

Table 1. Review of the studies conducted.

Reference	Advantages	Disadvantages
[5]	• AC-DC distribution network planning • Determining the types of buses and lines • Modeling uncertainty in load and renewable resources using MCS technique	• Not considering risk
[6]	• AC-DC distribution network planning • Determining the types of buses and network lines	• Not considering the uncertainty in the problem • Ignoring risk
[7]	• AC-DC distribution network planning • Determining the optimal location and capacity of EV and renewable resources	• Not considering the uncertainty in the problem • Ignoring risk
[8]	• AC-DC distribution network expansion planning • Modeling uncertainty in load and renewable resources using the multi-stage scenario tree method	• Ignoring risk
[9]	• AC-DC distribution network expansion planning • Determining the optimal location and capacity of converters and the types of lines • Modeling uncertainty in load and renewable resources using multi-scenario method	• Ignoring risk
[10]	• AC-DC distribution network expansion planning • Considering the N-1 security criterion for AC/DC lines	• Not considering the uncertainty in the problem • Ignoring risk
[11]	• AC-DC distribution network planning • Providing a bi-level planning model	• Not considering the uncertainty in the problem • Ignoring risk
[12]	• AC-DC distribution network planning • Providing a bi-level model • Determining the optimal number and location of PV and energy storages	• Not considering the uncertainty in the problem • Ignoring risk
[23]	• AC-DC distribution network planning • Determining the types of buses and lines • Modeling uncertainty in load and renewable resources using k-means method • Risk modeling as a problem constraint	• Not modeling the risk caused by violating the technical constraints of the problem • Not considering risk management

on proximity. This process leads to the creation of new clusters. By repeating this procedure, new centers can be calculated in each iteration by averaging the data, and the data can be reassigned to the updated clusters. This iteration continues until no further changes are observed in the data. Upon completion of the algorithm, the cluster centers of random parameters are obtained. Moreover, the set of scenarios is attained from the combination of the centers of the parameter clusters [30].

Hence, scenarios with the highest cost but low probabilities of occurrence, along with significant impacts, are defined as extreme events. These events are assessed for their effects on network efficiency under risk evaluation. Effective network planning must ensure resilience during these extreme events while minimizing overall planning costs. Despite their low probability, such events can lead to significant damages, necessitating heightened focus in the decision-making process. The risk measurement tool of AVaR concentrates on these events, facilitating the calculation of costs associated with extreme events.

3. ADDNP Problem Formulation

The ADDNP problem is a mixed-integer nonlinear programming problem with discrete derivatives. This problem cannot be solved through conventional modeling techniques. Consequently, it is divided into two parts. The first part focuses on modeling the mixed-integer programming (MIP) problem. In this part, the planning problem has been resolved using an optimization algorithm within the MATLAB environment. The second part involves modeling the nonlinear problem with discontinuous derivatives (DNLP). In this part, the optimal power flow (OPF) problem has been modeled. Since the OPF problem is a DNLP, it is modeled in the GAMS environment. The CONOPT nonlinear solver is employed to solve the problem. Consequently, to resolve the planning problem, GAMS and MATLAB have been linked together, and the problem has been solved. A schematic modeling of the planning problem is also illustrated in Fig. 2.

3.1. Cost Objective

In this paper, the ADDNP problem is modeled as a multi-objective optimization problem. The objectives include minimizing

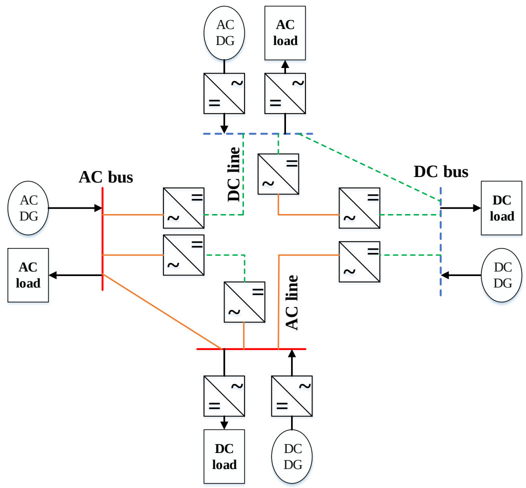

Fig. 1. An example of ADDN.

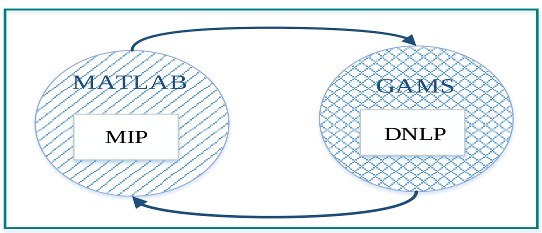

Fig. 2. Schematic modeling of ADDNP problem.

planning costs and AVaR, as outlined in Eq. (1). The planning costs comprise investment and operation costs, which are described in Eq. (2). The investment cost consists of the cost of the line and converter. The operation cost includes equipment maintenance and optimal operating costs. The optimal operating cost is obtained from solving the OPF problem. This cost consists of three terms, as represented in Eq. (3). The first term is related to the cost of energy generation from resources. The second and third terms are related to the costs of damage caused by violations of bus voltage and line loading, respectively.

$$\min \mathrm{OF} = [\mathrm{E}(\mathrm{C}_{\mathrm{t}}^{\mathrm{sc}})\mathrm{AVaR}] \tag{1}$$

$$C_t^{sc} = \underbrace{C_{\text{line}} + C_{\text{vsc}}}_{C_{\text{ic}}} + \underbrace{\sum_{\text{tr}\in\vartheta_t} \frac{C_{\text{mc}} + C_{\text{oper}}^{sc,\text{tr}}}{(1+I_d)^{\text{tr}}}}_{C_{\text{oc}}} \tag{2}$$

$$C_{\text{oper}}^{sc,tr} = 8760 \times \left(\sum_{so\in\vartheta_s} P_s^{so,sc} \cdot C_s^{so,sc}\right) + \sum_{n\in\vartheta_b} C_{\text{dam}-\text{uov}}^{n,sc} + \sum_{n\in\vartheta_b}\sum_{n'\in\vartheta_b} C_{\text{dam}-\text{lo}}^{n,n',sc} \tag{3}$$

The uncertainty in load demand and the power of renewable resources leads to violations of bus voltage and line loading constraints. According to Fig. 3, the bus voltage is composed of three regions: region U, the permissible region, and region O. If the bus voltage is lower than the minimum allowed voltage (V^{mn}), under-voltage occurs (the bus voltage is in region U). Conversely, if the bus voltage is higher than the maximum allowed voltage (V^{mx}), over-voltage occurs (the bus voltage is in region O). The cost of damage caused by a violation of bus voltage is calculated in Eq. (4). The damage function due to under-voltage (region U) and over-voltage (region O) is obtained in Eq. (5). Additionally, if the bus voltage is between the minimum and maximum allowed voltages, it resides in the permissible region. Therefore, the risk of bus voltage violation is zero [31].

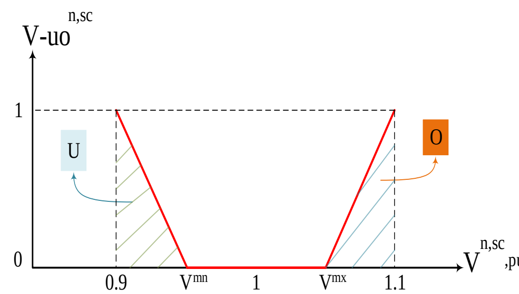

Fig. 3. Bus voltage modeling.

$$C_{\text{dam}-\text{uov}}^{n,sc} = C_{\text{dam}-\text{uov}}^{\text{mx}} \times P_l^{n,sc} \times V_{\text{uo}}^{n,sc} \tag{4}$$

$$V_{\text{uo}}^{n,sc} = \begin{cases} \frac{V^{\text{mn}} - V^{n,sc}}{V^{\text{mn}} - 0.9}, & \text{if} 0.9 \le V^{n,sc} \le V^{\text{mn}} \\ \frac{V^{n,sc} - V^{\text{mx}}}{1.1 - V^{\text{mx}}}, & \text{if} V^{\text{mx}} \le V^{n,sc} \le 1.1 \end{cases} \tag{5}$$

According to Fig. 4, line loading is divided into two regions: the permissible region and region I. If the line loading is less than 90% of the nominal value, it is in the permissible region, and the risk of line loading violation is zero. If the line loading exceeds 90% of its nominal value, an overload has occurred in the line. The cost of damage caused by the violations of line loading is illustrated in Fig. 4 [31, 32]. This cost is obtaine d as Eq. (6) based on the line type (AC or DC). Consequently, the costs of damage caused by the violations of DC and AC lines are obtained as Eqs. (7) and (8), respectively.

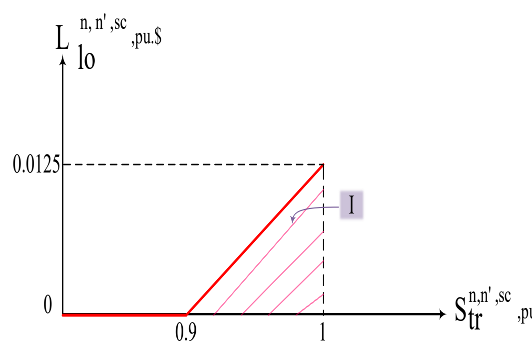

Fig. 4. Line loading modeling.

$$C_{\text{dam-lo}}^{(n,n',sc)} = M_{\text{str}}^{n,n'} \times \left(C_{\text{dam-ol-dc}}^{(n,n',sc)} + C_{\text{dam-ol-ac}}^{(n,n',sc)}\right) \tag{6}$$

$$C_{\text{dam-lo-dc}}^{(n,n',sc)} = 2 \times L_{\text{lo}}^{(n,n',sc)} \times C_{\text{con}} \times \text{Dis}^{n,n'} \times Q_{\text{str}}^{n,n'} \tag{7}$$

$$C_{\text{dam}-\text{lo}-\text{ac}}^{n,n',sc} = 3 \times L_{\text{lo}}^{n,n',sc} \times C_{\text{con}} \times \text{Dis}^{n,n'} \times (1 - Q_{\text{str}}^{n,n'}) \tag{8}$$

Additionally, the constraints of real and imaginary power balance Eqs. (9) and (10), bus voltage angle Eq. (11), converter modulation index Eq. (12), and the limits of real and imaginary power of generating units Eqs. (13) and (14) must be satisfied in the OPF problem [33].

$$P_{\text{inj}}^{n,sc} = P_{\text{cal}}^{n,sc} \quad \forall n \in \vartheta_b = \vartheta_b^{AC} \cup \vartheta_b^{DC}, \quad \forall sc \in \vartheta_{sc} \tag{9}$$

$$Q_{\text{inj}}^{n,sc} = P_{\text{cal}}^{n,sc}, \quad \forall n \in \vartheta_b, \quad \forall sc \in \vartheta_{sc} \tag{10}$$

$$\theta^{\text{mn}} \leq \theta^{n,sc} \leq \theta^{\text{mx}} \quad \forall n \in \vartheta_b, \quad \forall sc \in \vartheta_{sc} \tag{11}$$

$$M_{mo}^{n,n',mn} \leq M_{mo}^{n,n',sc} \leq M_{mo}^{n,n',mx}, \quad \forall n, n' \in \vartheta_b, \forall sc \in \vartheta_{sc} \tag{12}$$

$$P_s^{so,mn} \leq P_s^{so,sc} \leq P_s^{so,mx}, \quad \forall so \in \vartheta_s = \vartheta_s^{AC} \cup \vartheta_s^{DC}, \quad \forall sc \in \vartheta_{sc} \tag{13}$$

$$Q_s^{so,mn} \leq Q_s^{so,sc} \leq Q_s^{so,mx}, \quad \forall so \in \vartheta_s, \quad \forall sc \in \vartheta_{sc} \tag{14}$$

3.2. Evaluation of Extreme Events

To analyze significant events, it is essential to utilize risk measurement tools. Among these tools are value at risk (VaR) and AVaR. VaR represents the additional cost over the expected cost that will not be exceeded in α percent of all scenarios. VaR at a specific confidence level α is equal to the minimum value γ for which $\Pr(C_t^{\text{sc}} \leq \gamma) \geq \alpha$ is obtained. The VaR value is calculated as Eq. (15). Although VaR is a widely used measure for assessing risk, it lacks certain mathematical properties such as additivity and convexity. Furthermore, it is only an inherent risk measure when based on the standard deviation from a normal distribution. However, in reality, the loss distribution is often not normal. Therefore, VaR cannot be considered an inherent risk measure. In contrast, AVaR indicates the expected cost that is likely to be incurred under certain probability ($\alpha\%$) and unfavorable conditions. Thus, AVaR is a focused metric on extreme events, considering only the $(1-\alpha)\%$ of scenarios that impose the highest costs on the network within a confidence level of $\alpha\%$. To calculate AVaR, only scenarios with costs exceeding $\text{E}(C_t^{\text{sc}}) + \gamma$ are considered. Consequently, the set N_y is defined as Eq. (16). Therefore, the value of AVaR is obtained as Eq. (17).

$$\begin{aligned} &\text{VaR}_\alpha(C_t^{sc}) = \\ &[\gamma | \Pr(C_t^{sc} \leq \gamma) \geq \alpha], \quad 0 \leq \alpha \leq 1 \end{aligned} \tag{15}$$

$$C_t^{sc} \geq \text{E}(C_t^{sc}) + \gamma, \quad \forall sc \in \mathcal{N}_y \tag{16}$$

$$\begin{aligned} &\text{AVaR} = \\ &\gamma + \tfrac{1}{1-\alpha} \sum_{sc \in N_y} \Pr^{sc} \left(C_t^{sc} - E(C_t^{sc}) - \gamma \right) \end{aligned} \tag{17}$$

For a better understanding of AVaR calculation, an example is provided below. The cost and probabilities of 20 scenarios from the network are shown in Table 2.

According to Table 2, the expected cost is equal to 3.61. To compute VaR (using the cumulative distribution function) under $\alpha = 0.95$, the cumulative probability of scenario 19 is equal to 0.95 and the cost of this scenario is equal to 68. Thus, $\mathbb{E}(C - t^{\text{sc}}) + \gamma$ is equivalent to 68. Therefore, $\text{VaR} = \gamma = 6.7$ is obtained. To calculate AVaR, Eq. (16) must be examined to identify the set N_y. This relationship is valid only for scenarios 19 and 20. According to Eq. (17), AVaR is calculated as 8.7. In fact, AVaR represents the expected value that must be paid in $(1-\alpha)\%$ of the scenarios with the highest costs, in addition to the expected cost.

In many studies on DNs, a constant voltage tolerance of $\pm 5\%$ is commonly used. However, this value can be adjusted to $\pm 10\%$ [34]. Fig. 5 illustrates the function of damage caused by violation of bus voltage under different voltage tolerance values. The comparison of the bus voltage violation interval at a $\pm 5\%$ voltage tolerance versus a $\pm 2.5\%$ voltage tolerance indicates that the interval is larger at $\pm 2.5\%$. Conversely, at a voltage tolerance of $\pm 7.5\%$, the bus voltage violation interval is smaller.

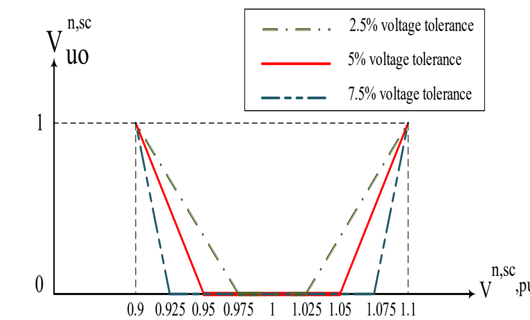

Fig. 5. Comparison of different bus voltage tolerance values.

Among multi-objective optimization algorithms, the non-dominated sorting genetic algorithm (NSGA-II) is particularly popular due to its ease of implementation. Consequently, it has been extensively applied to various multi-objective optimization problems. This optimization algorithm will be utilized to address the presented problem. Each chromosome represents the network scheme matrices, which consist of two parts. The first part consists of two sub-strings that represent the connections between buses ("M_{str}") and the types of connections ("Q_{str}"), respectively. The second part of the chromosome indicates the types of network buses ("A_{str}"). Furthermore, the following constraints must be satisfied for each chromosome:

- The network scheme matrices are all binary.
- To avoid congestion connections with any bus must be satisfied constraint Eq. (18).
- To avoid bus isolation must be satisfied constraint Eq. (19).

The proposed chromosome is depicted in Fig. 6.

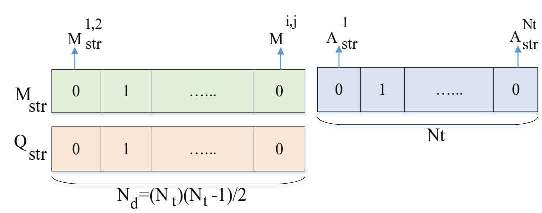

Fig. 6. Proposed chromosome for optimization algorithm.

$$\sum_{n' \in \vartheta_b} M_{\text{str}}^{n,n'} \leq N_{\text{li}}^{\text{mx}} \; N_{\text{li}}^{\text{mn}} \leq N_{\text{li}}^{\text{mx}} \leq |\vartheta_b| - 1, \quad \forall n \in \vartheta_b \tag{18}$$

$$\sum_{n' \in \vartheta_b} M_{\text{str}}^{n,n'} \geq N_{\text{li}}^{\text{mn}} \; 1 \leq N_{\text{li}}^{\text{mn}} \leq N_{\text{li}}^{\text{mx}}, \quad \forall n \in \vartheta_b \tag{19}$$

Therefore, the output of the optimization algorithm is an optimal Pareto front. This Pareto front consists of a set of solutions. Based on the user's opinion, any output from the Pareto front solutions (PFSs) may act as a suggested solution to the problem. In this study, the fuzzy method is utilized to identify the suggested solution.

Table 2. Data for calculating AVaR.

# sc	Cost	Pr	# sc	Cost	Pr	# sc	Cost	Pr	# sc	Cost	Pr
1	55	0.05	6	59	0.05	11	61	0.05	16	66	0.05
2	56	0.05	7	59	0.05	12	61	0.05	17	67	0.05
3	56	0.05	8	59	0.05	13	61	0.05	18	67	0.05
4	57	0.05	9	60	0.05	14	62	0.05	19	68	0.05
5	58	0.05	10	60	0.05	15	64	0.05	20	70	0.05

Thus, the objective of the planning problem is to determine the types of buses, lines, and the network scheme. The approach considers a plan that minimizes not only the planning costs but also the costs associated with extreme events, thereby addressing risk management within the planning.

The flowchart of the ADDNP problem is illustrated in Fig. 7 and consists of the following steps:

Step 1: Forming the initial population of the optimization algorithm. In this step, the chromosome of the optimization algorithm, which contains the network scheme matrices, is determined. Each chromosome of the algorithm is shown in Fig. 6.

Step 2: Modeling the random parameters of the problem, which include AC/DC load demand and the power of renewable resources using the K-means algorithm. In this step, the number of clusters is determined.

Step 3: Determining the distance between the data and clustering the data.

Step 4: Updating the cluster center.

Step 5: Calculation of the objective function of the K-means algorithm. If the objective function is minimized, then the center of the clusters of random parameters is obtained. Otherwise, steps 3 to 5 are repeated.

Step 6: Forming a set of scenarios that result from combining the centers of clusters of random parameters.

Step 7: Solving the OPF problem for the scenario.

Step 8: Calculation of planning costs and AVaR for all chromosomes, along with the evaluation of objective functions and constraints of the optimization algorithm.

Step 9: Investigating the stopping criteria of the optimization algorithm. If the stopping criterion of the algorithm is satisfied. The suggested solution to the problem is obtained using the fuzzy method. Otherwise, the processes of crossover and mutation are executed to update the population of the optimization algorithm. Additionally, steps 2 to 9 are repeated to establish the stopping criteria of the optimization algorithm.

Furthermore, all ADDNP procedures considering extreme events are illustrated schematically in Fig. 8.

4. Test Results

To compare and validate the proposed method with other methods, the studied network [33] was utilized for planning. This network, comprises 13 buses, one distribution substation, three PVs, three EVs, one wind turbine, one diesel generator, eight AC loads, and four DC loads, as depicted in Fig. 9. It includes both AC and DC loads and generation units. Some of the input data is outlined in Table 3, while the remaining data was used according to reference [33]. The distribution network planning (DNP) problem has been addressed in three cases. First, the problem is solved without considering risk and compared with the solution from [33]. This case shows the correctness of the proposed method. In cases 2 and 3, the solution of the scheme [33] has been calculated under different confidence levels and voltage tolerance values, respectively. The results from scheme [33] have been compared with the obtained PFSs. The purpose is to illustrate the status of the obtained PFSs compared to the solution from [33]. In all cases, improvements in the PFSs were evident. Moreover, the importance of discussing risk in the planning problem shows how considering risk from the beginning can lead to both realistic and optimal planning.

Table 3. Some of the input data.

Parameter	Value
Maximum cost of damage caused by violation of bus voltage	112000 ($/MW) [31]
Population	200
Number of iterations	100
Probability of crossover operator	0.9
Probability of mutation operator	0.125
Number of clusters for each random parameter	3

A) Case 1: DNP and comparison

In this case, to demonstrate the efficiency of the optimization method, AC distribution network planning (ADNP) and ADDNP have been implemented on the test network. The objective is to minimize total distribution network costs, including investment and operation costs.

B) Case 2: DNP under extreme events and various confidence levels

In this case, planning has been conducted under extreme events. Additionally, ADNP and ADDNP under different confidence levels have been discussed. The confidence levels of 0.92, 0.95, and 0.98 are considered. Furthermore, a voltage tolerance value of $\pm 5\%$ is included.

C) Case 3: DNP under extreme events and different voltage tolerance values

In this case, similar to the previous one, the ADNP and ADDNP have been conducted considering extreme events, but under different voltage tolerance values of $\pm 2.5\%$, $\pm 5\%$, and $\pm 7.5\%$. Moreover, a confidence level of 0.95 is considered.

D) Planning result and analysis

To ensure the accuracy and reliability of the solutions presented in this paper, the planning problem was initially executed on a test network without considering extreme events. The results obtained from this case were then compared to the reference [33]. The findings indicate that the optimal scheme from reference [33] is identical to the optimal scheme resulting from the execution of this case. A comparison of the cost results obtained from this case and reference [33] is presented in Table 4. Therefore, the congruence of the optimal scheme and the results suggest that the proposed method has been implemented correctly.

Table 4. Comparison of DNP results.

Type	AC		AC-DC	
Case	[33]	Case 1	[33]	Case 1
$\mathbf{C_{vsc}}$ (M$)	2.0485	2.0485	1.7595	1.7595
$\mathbf{C_{ic}}$ (M$)	1.7136	1.7136	1.2264	1.2264
$\mathbf{C_{line}}$ (M$)	3.7621	3.7621	2.9859	2.9859
$\mathbf{C_{t}}$ (M$)	47.3567	47.3564	45.6596	45.6586

From the implementation of the planning problem at a confidence level of 0.92, the PFSs for ADNP and ADDNP have been shown in Fig. 10-a and Fig. 10-b. In these figures, the solutions are labeled as solution E, solution A, and solution S, corresponding

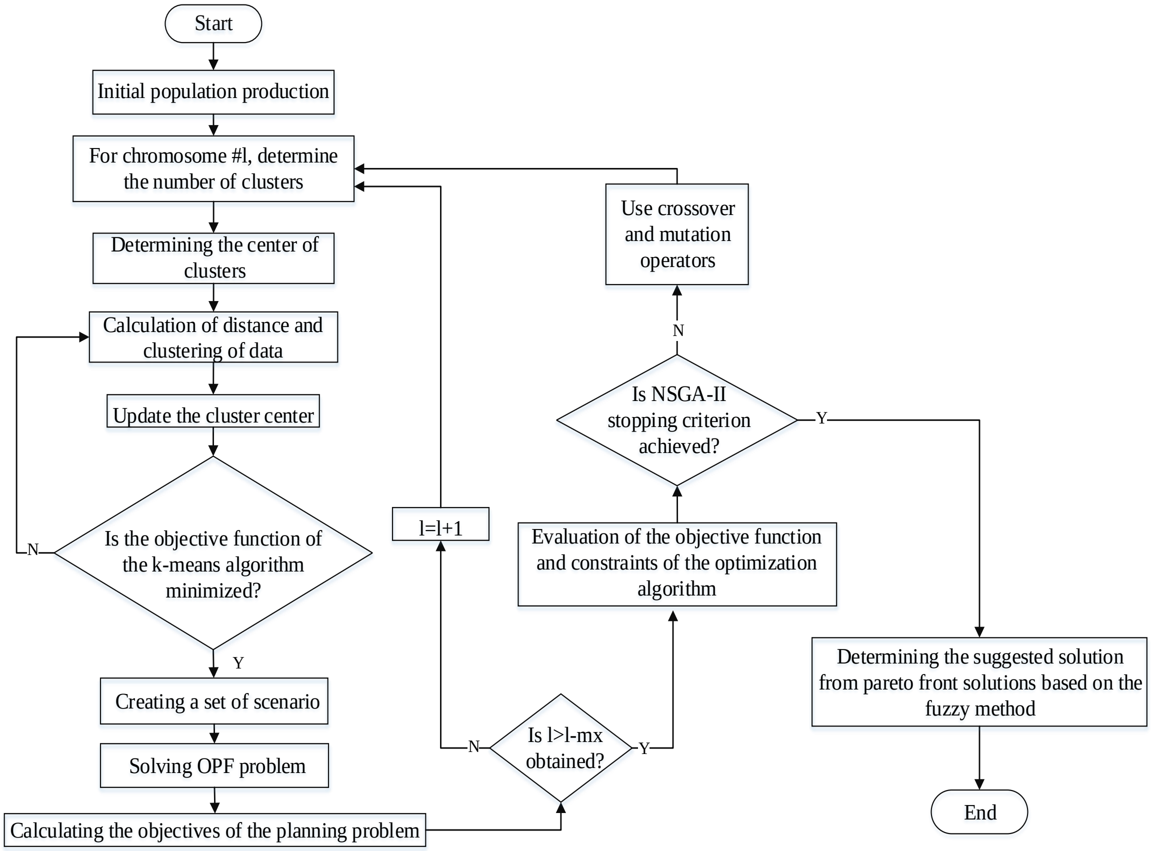

Fig. 7. The flowchart of the ADDNP problem.

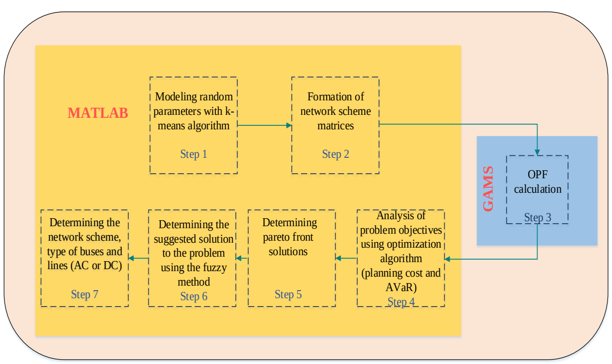

Fig. 8. Procedures of ADDNP.

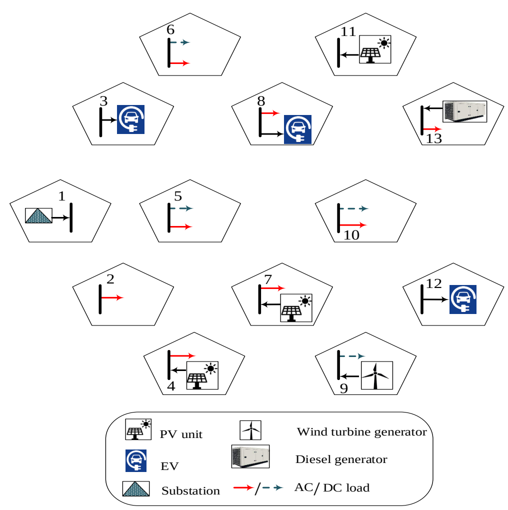

Fig. 9. The network under study.

to the minimum expected cost, minimum AVaR, and suggested solution, respectively. According to these figures, for solution A of ADDNP compared to ADNP, the expected cost and AVaR values have decreased by 7.2811% and 13.1448%, respectively. Similarly, solution E of ADDNP, when compared to ADNP, shows a reduction in expected cost and AVaR by 8.1064% and 9.9583%, respectively. Additionally, the cost results for scheme [33] at the confidence level of 0.92 are presented in Table 5. To demonstrate the improvements in the obtained solutions, the maximum expected cost (solution A) and maximum AVaR (solution E) were compared with the value from scheme [33]. Consequently, the PFSs have been compared with the solution from [33] at the confidence level of 0.92. The comparison indicates that the PFSs are lower than those of solution [33]. In both ADNP and ADDNP, the expected cost of solution A has decreased by 2.6204% and 6.3225%, respectively, compared to solution [33]. Furthermore, the AVaR values of solution E of ADNP and ADDNP have also decreased by 39.9486% and 35.8999%, respectively, when compared to the AVaR value of solution [33].

From the implementation of the planning problem at a confidence level of 0.95, the PFSs for ADNP and ADDNP have been illustrated in Fig. 11-a and Fig. 11-b. According to these figures, in the planning under the confidence level of 0.95, the expected cost and AVaR of solution A of ADDNP have decreased by 7.5996% and 12.6938%, respectively, compared to ADNP.

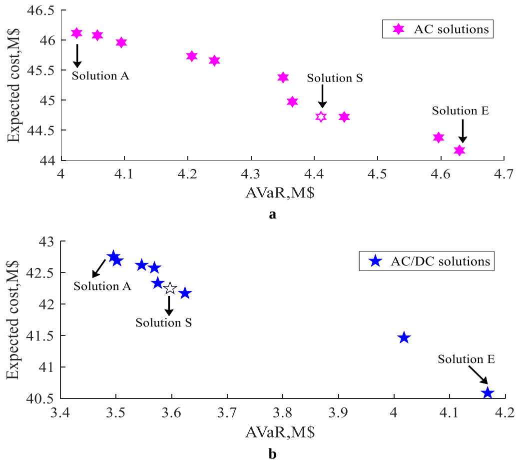

Fig. 10. PFSs (a) ADNP under a confidence level of 0.92 (case 2), (b) ADDNP under a confidence level of 0.92 (case 2).

Table 5. Cost results of scheme [33] under different confidence levels.

Type	AC			AC-DC		
Confidence Level	0.92	0.95	0.98	0.92	0.95	0.98
$\mathbf{E(C_t)}$ (M$)	47.3562	47.3562	47.3562	45.6434	45.6434	45.6434
AVaR (M$)	7.7089	8.2339	8.4410	6.5028	6.9605	7.1542

Similarly, the expected cost and AVaR of solution E of ADDNP are reduced by 8.2574% and 17.1787%, respectively, compared to ADNP. Additionally, the results of solution [33] under this confidence level are provided in Table 5. Thus, in ADNP, the expected cost for solution A has decreased by 1.5922% compared to solution [33]. In ADDNP, the expected cost for solution A has decreased by 5.6586% compared to solution [33]. Furthermore, the AVaR of solution E in ADNP and ADDNP has decreased by 37.2205% and 38.4929%, respectively, compared to the AVaR of solution [33]. For solution A of ADNP under the 0.95 confidence level compared to the 0.92 confidence level, the expected cost and AVaR have increased by 1.0558% and 2.4376%, respectively. For solution E in ADNP under the 0.95 confidence level, the expected cost and AVaR have increased by 1.9693% and 11.6627%, respectively, compared to the 0.92 confidence level. For solution A of ADDNP under the 0.95 confidence level, the expected cost and AVaR have increased by 0.7086% and 2.9696%, respectively, compared to the 0.92 confidence level. For solution E of ADDNP planning under the 0.95 confidence level, the expected cost has increased by 1.8017% and AVaR has increased by 2.7085% compared to the 0.92 confidence level. The scheme for solution E regarding ADNP and ADDNP is illustrated in Fig. 12-a and Fig. 12-b. Cost results for solution E are also presented in Table 6.

Table 6. The results of solution E under a confidence level of 0.95.

Type	AC	AC-DC
$E(C_t)$ (M$)	45.0334	41.3148
AVaR (M$)	5.1692	4.2812
VaR (M$)	4.7783	4.1103
$\mathbf{C_{vsc}}$ (M$)	2.0485	1.3175
$\mathbf{C_{line}}$ (M$)	1.5120	1.2040
$\mathbf{C_{ic}}$ (M$)	3.5605	2.5215

From the implementation of the planning problem at a confidence level of 0.98, the PFSs for ADNP and ADDNP are displayed in Fig. 13-a and Fig. 13-b. According to these figures, solution A of ADDNP, when compared to ADNP, shows a decrease in expected cost by 6.2265% and a reduction in AVaR by 5.4901%. Solution E of ADDNP, in comparison to ADNP,

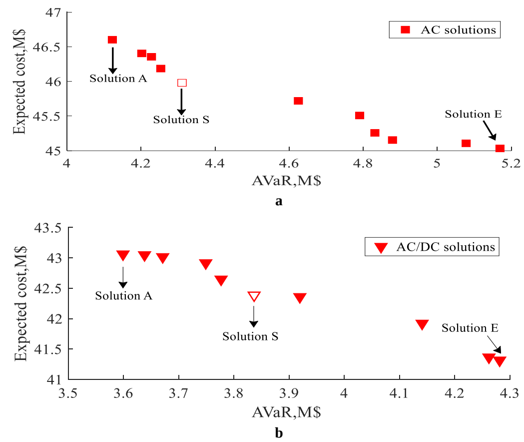

Fig. 11. PFSs (a) ADNP under a confidence level of 0.95 (case 2), (b) ADDNP under a confidence level of 0.95 (case 2).

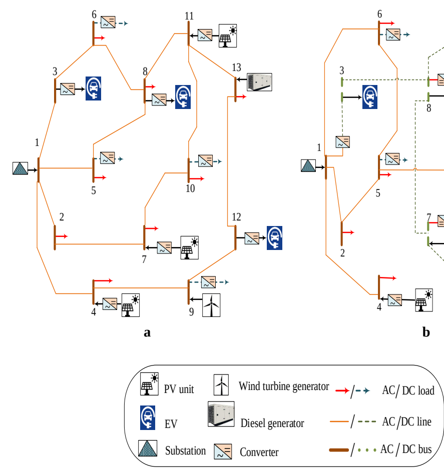

Fig. 12. The scheme (a) Solution E of ADNP under confidence level of 0.95, (b) Solution E of ADDNP under confidence level of 0.95.

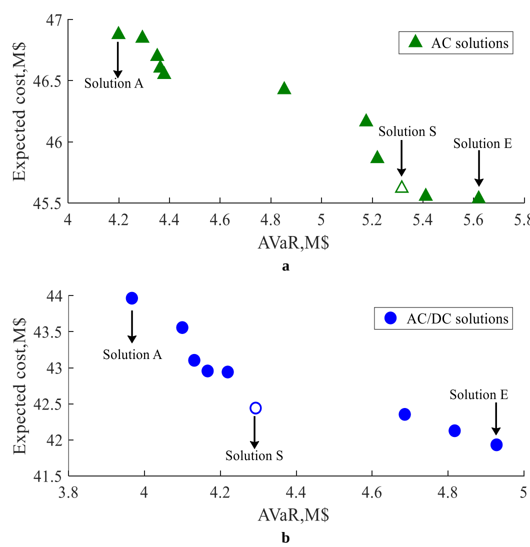

Fig. 13. PFSs (a) ADNP under a confidence level of 0.98 (case 2), (b) ADDNP under a confidence level of 0.98 (case 2).

results in a reduction in expected cost and AVaR by 7.4966% and 14.2595%, respectively. Additionally, the results of solution [33]

Table 7. The results of solution S under a confidence level of 0.98.

Type	AC	AC-DC
$\mathbf{E(C_t)}$ (M$)	45.6193	42.4346
AVaR (M$)	5.3166	4.2942
VaR (M$)	4.6437	3.7593
$\mathbf{C_{vsc}}$ (M$)	2.0485	1.5045
$\mathbf{C_{line}}$ (M$)	1.5456	1.2208
$\mathbf{C_{ic}}$ (M$)	3.5941	2.7253

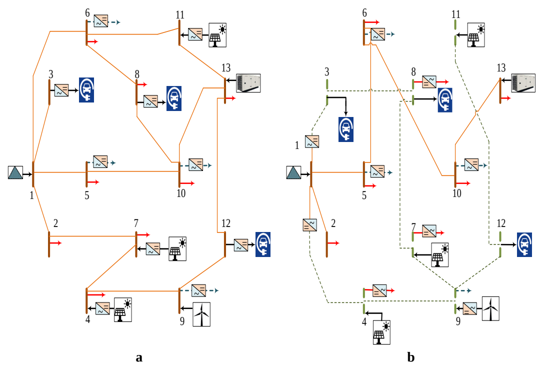

Fig. 14. The scheme (a) Solution S of ADNP under a confidence level of 0.98, (b) Solution S of ADDNP under a confidence level of 0.98.

at this confidence level are provided in Table 5. In ADNP, the expected cost of solution A has decreased by 1.0121% compared to solution [33]. In ADDNP, the expected cost of solution A has decreased by 3.6923% compared to solution [33]. Furthermore, the AVaR value of solution E in both ADNP and ADDNP has decreased by 33.4190% and 32.6452%, respectively, compared to the AVaR value of solution [33]. Solution A of ADNP planning at the 0.98 confidence level, compared to the 0.95 confidence level, shows increases in expected cost and AVaR by 0.5895% and 1.8435%, respectively. Solution E of ADNP at the 0.98 confidence level shows increases in expected cost by 1.1112% and in AVaR by 8.7228% compared to the 0.95 confidence level. For solution A of ADDNP at a confidence level of 0.98, the expected cost and AVaR have increased by 2.0843% and by 10.2467%, respectively, compared to the confidence level of 0.95. For solution E of ADDNP at the confidence level of 0.98, the expected cost and AVaR have increased by 1.9497% and 12.5549%, respectively, compared to the confidence level of 0.95. The scheme for solution S in ADNP and ADDNP is illustrated in Fig. 14-a and Fig. 14-b. Cost results for solution S are also presented in Table 7. According to the results in this table, the suggested scheme of ADDNP has lower planning costs and AVaR than ADNP. Therefore, optimal planning can be achieved with ADDNP.

In addition, the trend of changes in expected cost and AVaR values for solutions A and E under different confidence levels are depicted in Fig. 15-a to Fig. 15-d. Additionally, these figures display the solution from scheme [33] at different confidence levels. The figures indicate that as the confidence level increases from 0.92 to 0.98, the expected cost and AVaR values rise for all solutions. Furthermore, the obtained solutions exhibit lower expected cost and AVaR values compared to the solutions from scheme [33]. Thus, it demonstrates the improvement of the obtained solutions.

From the implementation of the planning problem under a voltage tolerance of ±2.5%, the PFSs for ADNP and ADDNP are illustrated in Fig. 16-a and Fig. 16-b. Solution A of ADDNP, in comparison to ADNP, shows a decrease in expected cost by 7.7576% and a reduction in AVaR by 13.4701%. Similarly, solution E of ADDNP, when compared to ADNP, exhibits a decrease in expected cost and AVaR by 7.8833% and 8.9281%, respectively. Additionally, the solution results [33] under this

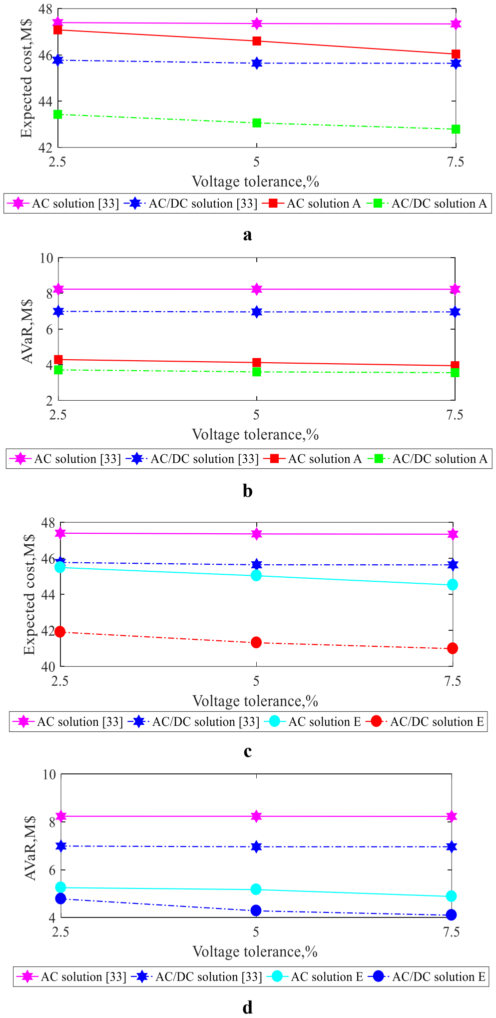

Fig. 15. Changes in problem objectives under different confidence levels (a) The values of expected cost for solution A and [33], (b) The values of AVaR for solution A and [33], (c) The values of expected cost for solution E and [33], (d) The values of AVaR for solution E and [33].

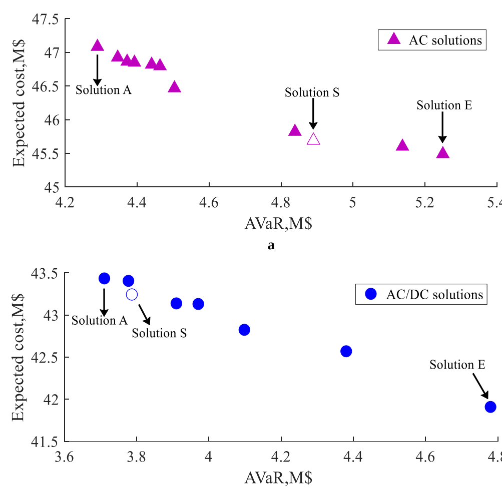

Fig. 16. PFSs (a) ADNP under voltage tolerance value of ±2.5% (case 3), (b) ADDNP under voltage tolerance value of ±2.5% (case 3).

Table 8. Cost results of scheme [33] under different voltage tolerance values.

Type	AC			AC-DC		
Voltage Tolerance	±2.5%	±5%	±7.5%	±2.5%	±5%	±7.5%
$\mathbf{E(C_t)}$ (M$)	47.3976	47.3562	47.3403	45.7723	45.6434	45.6380
AVaR (M$)	8.2348	8.2339	8.2289	6.9890	6.9605	6.9603

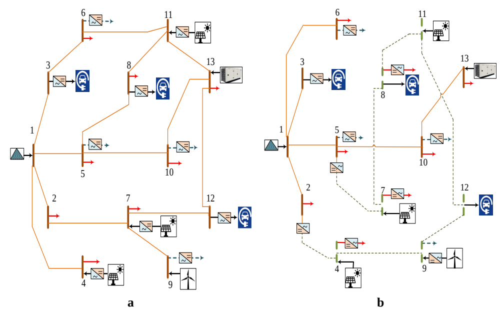

Fig. 17. The scheme (a) Solution A of ADNP under voltage tolerance of ±2.5%, (b) Solution A of ADDNP under voltage tolerance of ±2.5%.

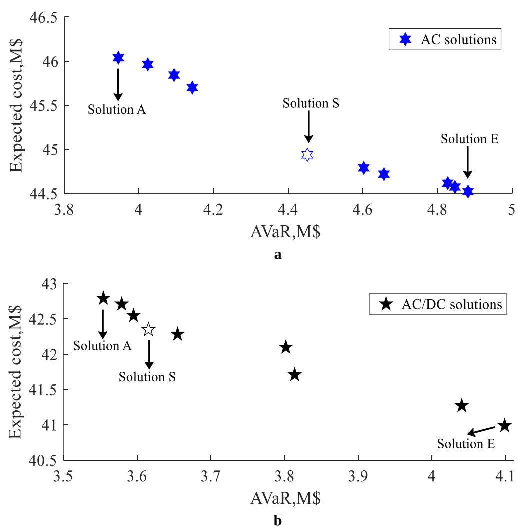

Fig. 18. PFSs (a) ADNP under voltage tolerance value of ±7.5% (case 3), (b) ADDNP under voltage tolerance value of ±7.5% (case 3).

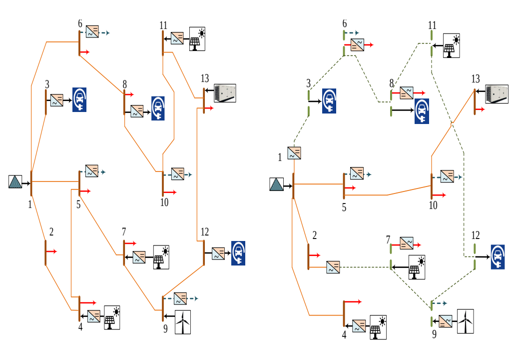

Fig. 19. The scheme (a) Solution S of ADNP under voltage tolerance of ±7.5%, (b) Solution S of ADDNP under voltage tolerance of ±7.5%.

Table 9. The results of the solution A under voltage tolerance of ±2.5%.

Type	AC	AC-DC
$\mathbf{E(C_t)}$ (M$)	47.0829	43.4304
AVaR (M$)	4.2895	3.7117
VaR (M$)	4.2891	3.6603
$\mathbf{C_{vsc}}$ (M$)	2.0485	1.7595
$\mathbf{C_{line}}$ (M$)	1.5456	1.1704
$\mathbf{C_{ic}}$ (M$)	3.5941	2.9299

Table 10. The results of solution S under voltage tolerance of ±7.5%.

Type	AC	AC-DC
$\mathbf{E(C_t)}$ (M$)	44.9375	42.3471
AVaR (M$)	4.4510	3.6154
VaR (M$)	4.1871	3.6147
$\mathbf{C_{vsc}}$ (M$)	2.0485	1.6575
$\mathbf{C_{line}}$ (M$)	1.3944	1.1200
$\mathbf{C_{ic}}$ (M$)	3.4429	2.7775

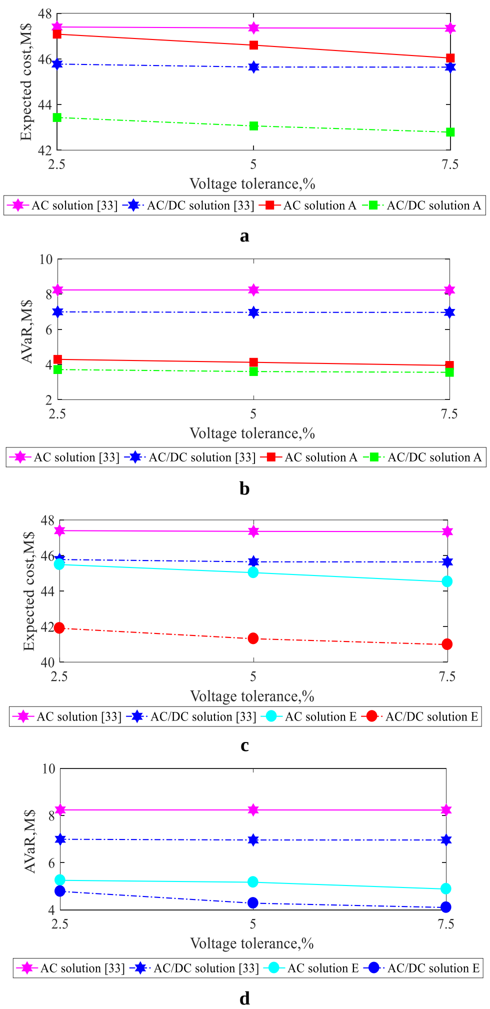

Fig. 20. Changes in problem objectives under different voltage tolerance values (a) The values of expected cost for solution A and [33], (b) The values of AVaR for solution A and [33], (c) The values of expected cost for solution E and [33], (d) The values of AVaR for solution E and [33].

voltage tolerance are presented in Table 8. In ADNP, the expected cost of solution A has decreased by 0.6640% compared to solution [33]. In ADDNP, the expected cost of solution A has decreased by 5.1164% compared to solution [33]. Furthermore, the AVaR value of solution E in both ADNP and ADDNP has decreased by 36.2498% and 31.5925%, respectively, when compared to the AVaR value of solution [33]. The scheme of solution A for ADNP and ADDNP is shown in Fig. 17-a and Fig. 17-b. Cost results for solution A are also provided in Table 9.

On the other hand, the distribution network planning has been conducted under different voltage tolerance values, considering a confidence level of 0.95. Consequently, the planning results under a confidence level of 0.95 with ±5% voltage tolerance have already been evaluated. Only the comparison of ADNP and ADDNP under ±5% voltage tolerance against ±2.5% voltage tolerance is presented. Thus, for solution A of ADNP under ±5% voltage tolerance, the expected cost and AVaR values have decreased by 1.0210% and 3.8932%, respectively, compared to ±2.5% voltage tolerance. For solution E of ADNP under a voltage tolerance of ±5%, the expected cost is reduced by 1.0040% and AVaR is reduced by 1.5334% compared to a voltage tolerance of ±2.5%. Additionally, for solution A of ADDNP under a voltage tolerance of ±5% compared to a voltage tolerance of ±2.5%, the expected cost and AVaR values have decreased by 0.8515% and 3.0310%, respectively. For solution E of ADDNP under a voltage tolerance of ±5% compared to a voltage tolerance of ±2.5%, the expected cost has decreased by 1.4061%, while AVaR has decreased by 10.4539%.

From the implementation of the problem under a voltage tolerance of ±7.5%, the PFSs for the ADNP and ADDNP are shown in Fig. 18-a and Fig. 18-b. According to these figures, for solution A of ADDNP compared to ADNP, the expected cost and AVaR values have decreased by 7.0524% and 9.9037%, respectively. For solution E of ADDNP compared to ADNP, the expected cost is reduced by 7.9375% and AVaR is reduced by 16.0453%. Additionally, the solution results [33] under this voltage tolerance are provided in Table 8. Thus, in ADNP, the expected cost of solution A has decreased by 2.7530% compared to solution [33]. In ADDNP, the expected cost of solution A has decreased by 6.2398% compared to solution [33]. Furthermore, the AVaR value of solution E in ADNP and ADDNP has also decreased by 40.6749% and 41.1160%, respectively, compared to the AVaR value of solution [33]. For solution A of ADNP under a voltage tolerance of ±7.5% compared to a voltage tolerance of ±5%, the expected cost is reduced by 1.2128% and AVaR is reduced by 4.3056%. For solution E of ADNP under a voltage tolerance of ±7.5% compared to a voltage tolerance of ±5%, the expected cost and AVaR values have decreased by 1.1389% and 5.5599%. In solution A of ADDNP under a voltage tolerance of ±7.5%, the expected cost and AVaR have decreased by 0.6277% and 1.2475% compared to a ±5% voltage tolerance. In solution E of ADDNP under a voltage tolerance of ±7.5%, the expected cost and AVaR are reduced by 0.7941% and 4.2675% compared to a ±5% voltage tolerance. The scheme for solution S in ADNP and ADDNP is illustrated in Fig. 19-a and Fig. 19-b. Cost results for solution S are also presented in Table 10. According to the results obtained in this table, the suggested scheme for ADDNP planning has a lower planning cost and AVaR than ADNP. Therefore, under different voltage tolerance values, as well as different confidence levels, optimal planning can be achieved with ADDNP.

On the other hand, the trend of changes in expected cost and AVaR for solutions A and E under different voltage tolerance values is depicted in Fig. 20-a to Fig. 20-d. These figures also show the solution of scheme [33] under different voltage tolerance values. According to these figures, as the voltage tolerance increases from ±2.5% to ±7.5%, the expected cost and AVaR values decrease for all solutions. Additionally, the obtained solutions exhibit lower expected cost and AVaR values compared to the solution of scheme [33]. Therefore, it shows an improvement in the obtained solutions.

5. CONCLUSION

This paper discusses AC-DC distribution network planning (ADDNP) considering extreme events. The randomness in load demand and the output power of renewable resources can lead to possible behaviors in the network that may violate bus voltage and line loading constraints. These violations introduce risks to the system. To model these uncertainties, the K-means algorithm is employed. Scenarios with the highest costs are categorized as extreme events, and risk management is addressed using the Average Value at Risk (AVaR) criterion, which focuses on such events. The planning problem, considering extreme events, is a multi-objective problem with objectives including planning costs and AVaR. To demonstrate the effectiveness of the proposed method, planning is implemented on a 13-bus distribution network across three cases. Case 1 involves planning without considering extreme events to validate the method's correctness. In Cases 2 and 3, planning is conducted with extreme events under varying confidence levels and voltage tolerance values, respectively. The results from Case 2 show that as the confidence level increases, both the planning costs and AVaR rise. In contrast, Case 3 demonstrates that as voltage tolerance increases, both planning costs and AVaR decrease. These findings indicate that variations in voltage tolerance and confidence levels significantly influence planning outcomes. Additionally, planning was executed for both ADDNP and ADNP, and the results were compared. The findings reveal that ADDNP results in lower planning costs and AVaR compared to ADNP. Thus, optimal planning in ADDNP can be achieved by determining the types of buses and lines.

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