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Research Article

An Optimal Master-Slave Model for Stochastic Planning of AC-DC Hybrid Distribution Systems

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ABSTRACT

In this study, a novel stochastic planning method is proposed for AC-DC hybrid distribution networks. The proposed approach is based on the graph theory, and the optimal AC-DC structure of the network is selected among the system spanning trees. The presented method is a Mixed Integer Nonlinear Programming (MINLP) problem, which is solved using genetic algorithm. The buses and lines of the network can be either AC or DC to minimize the system investment costs in the master optimization problem. The location and capacity of the Distributed Energy Resources (DERs) as well as the site and size of the Electric Vehicle (EV) charging stations are optimized in the slave problem to minimize the network losses and system costs. The proposed model utilizes Monte Carlo simulation to deal with the stochastic variations of the renewable energy resources power and load demands. Besides, the converter efficiency curve in the proposed planning problem is modeled based on a function of its input current using PLECS software. The proposed approach for network design can be applied to different DG resources and AC-DC loads. The comparison between the simulation results of the proposed approach and the conventional AC planning method demonstrates the efficiency of the proposed model in reducing network losses and system costs.

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1. INTRODUCTION

Integration of Distributed Energy Resources (DERs) with Distribution Systems (DSs) has increased the ratio of DERs operation and reduced the investment costs in DSs [1]. Green technology, such as photovoltaic (PV) generation resources, and DC loads, such as electric vehicle (EV) charging stations, are used increasingly and higher levels of reliability and power quality are demanded at the same time. Therefore, the AC power distribution system cannot continue using the traditional approach to manage and control energy effectively in this new condition. Hence, a hybrid AC-DC system is proposed as a solution to improve the network performance in terms of network losses, addressing DERs oscillations, and more flexible settings for the new network structures than the traditional AC systems [2-5].

The planning of AC-DC hybrid DSs is more complicated than the AC planning systems due to the presence of various buses, AC-DC lines, and AC-DC converters. The power electronic converters should be modeled correctly, and analysis of stochastic variations of AC-DC load demands, such as EV charging stations and DERs (PV resources and wind turbines), adds up to the complexity of the hybrid planning problem. Also, determining the optimal size and location of some system components such as EV charging stations and DERs is another important issue that should be considered. Therefore, it is necessary to present suitable methods for AC-DC hybrid systems planning in the researches. However, the studies on hybrid DSs planning are still in the primary stages, and no comprehensive planning approach has yet been proposed to consider all the above-mentioned factors in the AC-DC DSs.

The primary studies in the field of hybrid systems planning have focused on HVDC networks. For instance, the development of Voltage Source Converter (VSC)-based transmission systems was investigated in [6], aiming at reducing investment, operation, and load shedding costs of the system. Also, a multi-objective stochastic planning model was employed in [7] in order to define the HVDC network lines so that the investment costs and the reactive power losses could be minimized. The need to deliver generated electricity by offshore wind farms led to further research on the development of a VSC-based offshore network in [8, 9]. In addition, a transmission expansion planning model was proposed in [10] by utilizing the Benders Decomposition (BD) algorithm in order to reduce system costs, including ES (energy storage) installation costs. However, the studies in [6-10] are suitable for HVDC systems, and they are not efficient

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enough to be applied to complicated DSs with cascaded AC-DC structure.

Due to the development of AC-DC hybrid DSs in recent years, the studies on the planning of these systems have increased in number. For instance, a hybrid system planning approach based on optimal location and size of Renewable Energy Systems (RESs) and ESs was proposed in [11]. Furthermore, a two-level planning technique was presented in [12] that investigated N-1 security criterion. At the first level of this model, the system investment and operation costs were minimized. Then, the second level of the planning problem (as a robust optimization problem) enhunced the system reliability. Also, a flexible multi-stage distribution expansion planning model is introduced in [13] to analyze the variations caused by the output power of DGs and loads demand. A hybrid planning model based on Benders analysis was also proposed in [14] to minimize the power losses in commercial buildings. Besides, an AC-DC planning strategy was presented in [15] for distribution network, which considered the uncertainties caused by generation resources, loads, and energy prices. This method considers the environmental concerns as well as system investment and operation costs, and it also enables network islanding to improve the system reliability.

In the microgrid connected to the main grid, a planning model was presented in [16], where the total system costs were minimized by determining bus types and optimal size of DGs. Moreover, a two-stage planning approach was proposed in [17], which defined the optimal size of power electronic converters and the microgrid type in the islanding mode.

However, the studies in [16, 17] are limited to the predefined network structures, while the configuration definition of AC-DC network among all probable network structures is one of the main concerns in the upgrading of AC network to AC-DC system.

Currently, a few studies have considered the planning of hybrid distribution systems by determining the type of network lines and buses (AC or DC). For instance, in [18], a conceptual planning model was presented for hybrid DSs which minimized the system costs by determining optimal AC-DC configuration of network buses and lines as well as optimal size of converters. However, in this method, all possible AC-DC structures of the network are not considered, and only a limited number of them are investigated. Besides, the studies in [19, 20] employed binary matrices to introduce VSC-based AC-DC networks and investigated all possible structures of the network in order to reach the optimal configuration of the AC-DC hybrid DSs. Nevertheless, the studies in [19, 20] did not cover various combinations of DG resources in terms of location and size.

On the other hand, most studies in the field of hybrid systems planning have either presented an accurate model of converter losses and approximated converter losses [8-11, 19, 20] or have completely ignored the matter for the sake of simplicity of calculations [5, 15-16, 18].

In this study, a stochastic planning method is presented for AC-DC hybrid DSs based on graph theory. The proposed model utilizes the Monte Carlo scenario generation method to investigate the stochastic variations of the renewable energy resource output and AC-DC load demand. In addition, VSC is used for power conversion. The planning problem is solved as a Mixed Integer Nonlinear Programming (MINLP) problem using Genetic Algorithm (GA) in MATLAB. The proposed method is evaluated by comparing the results of the presented AC-DC hybrid approach with those of the traditional AC solution.

The main contributions of this paper are as follows:

1) A stochastic master-slave planning strategy for AC-DC DSs is presented based on the graph theory.
2) The optimal network configuration is determined by investigating all radial configurations of the AC-DC network.
   All radial structures of the system are defined as the network spanning trees, and they are generated using the Spantree program in MATLAB.
3) A comprehensive planning model is proposed for AC-DC hybrid DSs. The site and capacity of distributed energy resources and electric vehicle charging stations are optimized by DERs and EVs planning in the slave optimization problem.
4) The converter efficiency curve is modeled in the AC-DC planning formulation.
   In the first step, the converter losses are modeled as a function of converter input power in PLECS (Piecewise Linear Electrical Circuit Simulation) software. In the next step, the converter efficiency curve is employed in the load flow equations in order to reach more accurate results in the planning problem solution.

The rest of the paper is organized as follows. Section 2 presents the planning problem outline. The details of the proposed planning formulation are described in Section 3. Section 4 is devoted to the analysis of simulation results. Section 5 summarize the conclusions.

2. PROBLEM OUTLINE

As shown in Figure 1, AC-DC hybrid DSs include different AC-DC loads, AC-DC generation resources, and AC-DC buses and lines. These loads and DGs are connected to the network via AC-DC converters. The AC and DC buses also use AC-DC converters to connect to each other.

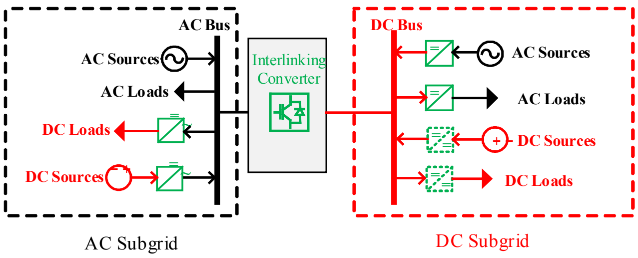

Figure 1. General structure of AC-DC hybrid DSs

In this study, the main objective of the planning problem is finding the optimal AC-DC structure for hybrid DSs. For this purpose, planning decision variables are divided into two categories as follows:

A) The variables that determine the AC-DC radial structure of the network including 1) system bus type (AC or DC), 2) existence of the connection between two buses, and 3) network lines type (AC or DC).
B) The variables related to DERs or EVs planning including the location and capacity of DERs and also the site and size of EV charging stations.

In this study, VSC is utilized to connect different AC-DC loads and generation resources to the network buses as well as power conversions. In the following, the modeling procedure of the converter efficiency curve is presented in order to be employed in Load Flow (LF) calculations.

2.1. Converter model

The AC-DC systems consist of AC and DC subnetworks where AC and DC components can be connected by VSC. Equation (1) shows the relationship between the voltages of the two sides of the converter in terms of modulation index, M [19].

$$V^{pu}_{dc,c} = M^{-1} \times V^{pu}_{ac,c} \tag{1}$$

VSC is used in two operating modes, including inverter mode and rectifier mode. The relationship between the input and output power of the converter in two operating modes is determined by Equations (2) and (3), respectively, where η is the converter efficiency. The value of η can be obtained by Equation (4) in terms of input power, P_{in}, output power, P_{out}, and converter losses, $P_{loss,c}$.

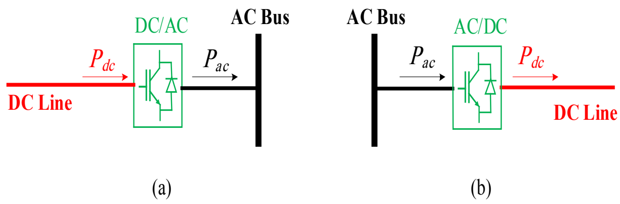

Figure 2. The operating modes of converter: (a) inverter mode and (b) rectifier mode

$$P_{out,c} = P_{ac} = \eta \times P_{dc} \tag{2}$$

$$P_{out,c} = P_{dc} = \eta \times P_{ac} \tag{3}$$

$$\eta = \frac{P_{out}}{P_{in}} = \frac{P_{in} - P_{loss,c}}{P_{in}} \tag{4}$$

The amount of power losses is dependent on the converter input power. The converter efficiency is a function of the input power of the converter. Therefore, the converter efficiency is not a constant value, and can be obtained by the converter efficiency curve. Accordingly, using the application of the converter efficiency curve to model its losses in power flow equations yields more accurate results in LF solution.

In this paper, the converter efficiency curve is obtained for a typical converter that has six IGBT switches from an ABB "HiPak" module 5SNA 0650J450300, designed to be used as a single IGBT-diode pair rated for 4500 V and 650. The converter efficiency curve is used in the power flow equations according to the following steps:

Step (1): The converter loss calculation by simulation in PLECS

Total VSC loss is equals to the sum of conduction, switching and fixed losses. The VSC conduction losses includes transistor conduction losses and diode conduction losses, and they are expressed as follows [21]:

$$P^{cond}_{total} = 6 \times (P^{cond}_{igbt} + P^{cond}_{diode}) \tag{5}$$

The switching losses of the converter include the total switching losses of the diode and transistor, which is made up of two sections: switching-off losses and switching-on losses. The switching losses equal:

$$E^{SW}_{igbt/diode} = a_{igbt/diode}\, i(t) e^{b_{igbt/diode}} + c_{igbt/diode}\, i(t) e^{d_{igbt/diode}} \tag{6}$$

where $E^{SW}_{igbt/diode}$ represents the switching losses of transistor or diode, in which {a, b} and {c, d} are the curve fitting constants for switching-on and switching-off losses, respectively.

The total switching losses are described as [22]:

$$P^{sw}_{total} = 6 \times f_S \times (E^{sw}_{igbt} + E^{sw}_{diode}) \tag{7}$$

In addition, fixed losses include inductor inductance losses, filters and transformers, controller circuit losses, leakage current losses, and so on. Therefore, the total converter losses are obtained as follows:

$$P^{loss}_{total} = P^{cond}_{total} + P^{sw}_{total} + P^{constsnt} \tag{8}$$

In this stage, the converter losses are calculated by simulation in PLECS for different input powers of the converter. The circuit contains a heat-sink unit, and its junction temperature range is adjusted by the R_{th} resistor between 25 ºC and 150 ºC.

Step (2): Fitting the converter efficiency curve

According to the values of power losses calculated in Step 1, the converter efficiency is fitted as a function of the input power to the converter in Equation (9). For the converter used in this paper, the efficiency curve is given in Figure 3.

$$\eta = f(P_{in,c}) \tag{9}$$

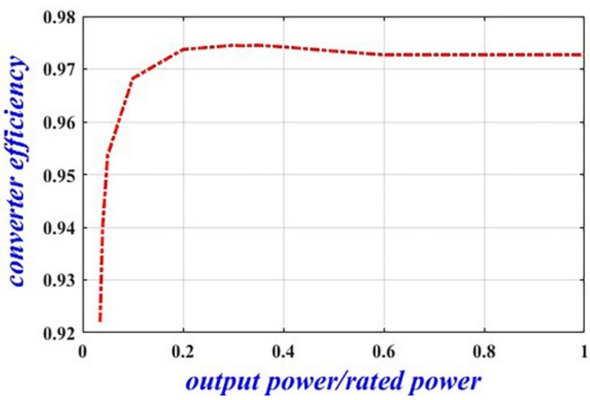

Figure 3. The converter efficiency curve for typical converter

Step (3): Modeling the converter efficiency curve in power flow equations

In this stage, the relationship between the output and input powers of the converter is obtained for both converter operating modes by combining Equations (2), (3), and (9) as:

$$P_{out,c} = f(P_{in,c}) \times P_{in,c} \tag{10}$$

The accurate value of converter losses is calculated by considering Equation (10) in load flow solution.

Figure 4 demonstrates the conducted process for modeling converter efficiency in power flow equations.

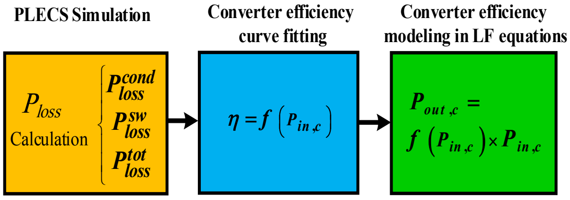

Figure 4. Steps of modeling the converter efficiency curve in LF equations

2.2. Scenarios definition

In this study, the uncertainties related to the generation of renewable resources and power demand in EV charging stations are expressed by Johnson's distribution function as Equation (11). The Pareto distribution function according to Equation (12) is also used to consider the stochastic nature of the load demand. Moreover, to model the stochastic variations of the input parameters in the proposed programming problem, scenario modeling is used, in which scenarios are generated by the Monte Carlo Simulation (MCS) method.

$$CDF(X) = \frac{1}{\sqrt{2\pi}} \int_{0}^{\gamma_1 + \gamma_2 \ln\left(\frac{z}{z-1}\right)} e^{-0.5t^2} dt \tag{11}$$

$$CDF(X) = 1 - \left(1 + \lambda_1 \frac{(x - \lambda_2)}{\lambda_3}\right)^{-\frac{1}{\lambda_1}}, \quad \lambda_1 \neq 0 \tag{12}$$

where CDF(X) represents the cumulative distribution function of stochastic varaible X; γ_1, γ_2, and λ_1 are shape parameters; $z = \frac{x-\gamma_4}{\gamma_3}$; γ_4 and λ_2 are location parameters; scale paremeters are γ_3 and λ_3.

The obtained scenarios from discrete probability distribution sets for wind turbine generation, P_{WT}, photovoltaic generation, P_{PV}, load consumption, P_L, and EV charging station demand, P_{EV}, are defined as follows [23]:

$$\begin{cases} P_{WT} = \{(\alpha_{WT,1}, \beta_{WT,1}), (\alpha_{WT,2}, \beta_{WT,2}), \dots, (\alpha_{WT,n}, \beta_{WT,n})\} \\ \sum_{n} \beta_{WT,n} = 1 \end{cases} \tag{13}$$

$$\begin{cases} P_{PV} = \{(\alpha_{PV,1}, \beta_{PV,1}), (\alpha_{PV,2}, \beta_{PV,2}), \dots, (\alpha_{PV,n}, \beta_{PV,n})\} \\ \sum_{n} \beta_{PV,n} = 1 \end{cases} \tag{14}$$

$$\begin{cases} P_{L} = \{(\alpha_{L,1}, \beta_{L,1}), (\alpha_{L,2}, \beta_{L,2}), \dots, (\alpha_{L,n}, \beta_{L,n})\} \\ \sum_{n} \beta_{L,n} = 1 \end{cases} \tag{15}$$

$$\begin{cases} P_{EV} = \{(\alpha_{EV,1}, \beta_{EV,1}), (\alpha_{EV,2}, \beta_{EV,2}), \dots, (\alpha_{EV,n}, \beta_{EV,n})\} \\ \sum_{n} \beta_{EV,n} = 1 \end{cases} \tag{16}$$

where $\alpha_{WT,n}$, $\alpha_{PV,n}$, $\alpha_{L,n}$, and $\alpha_{EV,n}$ represent the nth stochastic variables for wind generation, photovoltaic generation, load consumption, and EV charging station demand, respectively. The corresponding probability with each of the mentioned variables is demonstrated as $\beta_{WT,n}$, $\beta_{PV,n}$, $\beta_{L,n}$, and $\beta_{EV,n}$, respectively.

Furthermore, all generated uncertainty sets should be combined to create an uncertainty scenario set, and the sum of the probabilities of generated scenarios must be equal to 1. Therefore, we have:

$$\begin{cases} S = P_L \times P_{WT} \times P_{PV} \times P_{EV} \\ \sum_{s \in S} \beta_L \times \beta_{WT} \times \beta_{PV} \times \beta_{EV} = 1 \end{cases} \tag{17}$$

Finally, the Kantorovich scenario reduction method is used to reduce the calculations of the optimization problem. More details can be found in [23].

3. PROPOSED MODEL

In this study, the planning model is an MINLP problem with discrete derivatives, which is not optimized in one optimization model because of its complexity. Hence, the proposed planning approach is formulated as a master-slave model. The master optimization problem is a Mixed Integer Programming (MIP) problem and it defines the network AC-DC structure using the GA, while the slave optimization problem is a Non-Linear Programming (NLP) problem that defines the location and size of DERs and EV charging stations.

3.1. The master problem

According to the proposed framework for AC-DC hybrid DSs planning, the decision for defining the network radial structure and the location and the capacity of the resources is made in the first year of the planning horizon time.

The main purpose of the proposed planning problem is to determine the optimal AC-DC network topology with the aim of minimizing system costs and network losses, by considering the constraints of the optimization problem, which is defined as:

$$\begin{cases} \text{Min } F_{Master} = \begin{bmatrix} C_{NP} & P_{Loss} \end{bmatrix} \\ C_{NP} = C_{Inv} + C_{OM} \end{cases} \tag{18}$$

$$\text{s.t} \quad n_b \le L_{max} \qquad \forall b \in NB,\ s \in S \tag{19}$$

where C_{NP} is the network planning cost. Also, the system investment cost, C_{Inv}, including the investment cost of lines, C_{Line}, and the investment cost of converters, C_{Conv}.

Because the optimal structure is selected from a set of spanning trees of the network graph, the system buses are not isolated. Therefore, only the maximum bus connection limit is investigated as Equation (19). Also, the radial structure constraint of the network in this study is achieved using the Spantree program in MATLAB.

3.2. Optimization problem for DERs and EVs planning (the slave problem)

The objective function of slave optimization problem determines the optimal location as well as optimal capacity of DERs and EV charging stations to minimize the operation cost and network losses. Therefore, it is formulated as follows:

$$\text{Min } F_{Slave} = \begin{bmatrix} C_{OM} & P_{Loss} \end{bmatrix} \tag{20}$$

$$F_{Slave} = \left[\sum_{S=1}^{N_S} \sum_{t=1}^{T_P} \sum_{h} \left(\frac{1}{1+D} \right)^t \times \left(\psi^s \times \sum_{j=1}^{N_{PG}} C_j \times P_{G,j}^{s,t,h} + \beta C_{Inv} \right) \quad P_{Loss} \right] \tag{21}$$

$$\text{s.t} \quad \begin{cases} P_b^{inj} = P_b^{cal} \\ Q_b^{inj} = Q_b^{cal} \end{cases} \quad \forall b \in NB \tag{22}$$

$$\begin{cases} V_{min} \le V_b^s \le V_{max} \\ \theta_{min} \le \theta_b^s \le \theta_{max} \end{cases} \quad \forall b \in NB,\ s \in S \tag{23}$$

$$\begin{cases} P_{G,j,min} \le P_{G,j}^s \le P_{G,j,max} \\ Q_{G,j,min} \le Q_{G,j}^s \le Q_{G,j,max} \end{cases} \quad \forall\ s \in S\ ,\ j \in NG \tag{24}$$

$$\begin{cases} S_{L,i}^s \le S_{L,max} \\ S_{C,n}^s \le S_{C,max} \end{cases} \quad \forall\ i \in NL\ ,\ s \in S,\ n \in NC \tag{25}$$

$$M_{min} \le M_c^s \le M_{max} \quad \forall\ c \in NC\ ,\ s \in S \tag{26}$$

$$P_{EV,k,min} \le P_{EV,k}^s \le P_{EV,k,max} \quad \forall\ s \in S\ ,\ k \in NEV \tag{27}$$

Equation (20) calculates the system operation and maintenance cost in the planning horizon, C_{OM}, and it is formulated as an NLP problem; D is the discount rate; β shows the annual maintenance cost; ψ^s is the probability of S scenario; $P_{G,j}^{s,t,h}$ is the generation cost of unit j in scenario s; T_P is the planning horizon; $C_j$is the generation cost of unit j; and P_{Loss} is the total losses of network, including the line losses and converters losses.

Furthermore, Equations (22-26) express the constraints of the slave optimization problem. Constraint (22) ensures the power balance among the network buses, which is obtained by equalizing the calculated power to the injected pure power in each network bus. To solve (22), the AC-DC load flow method in [24] is used.The voltage stability constraint of the network buses is defined by (23). Constraint (24) investigates the limits of the power generated by DGs. The capacity limit of network lines as well as the converters capacity constraint are considered by (25). Also, (26) guarantees the modulation index of converters between upper and lower limits. Finally, the capcity constraints of EV charging satations are considered as (27).

3.3. The solution procedure of planning problem

The goal of the proposed planning is to determine the optimal AC-DC configuration by investigating all possible radial structures of the network. The presented model is defined as an MINLP problem that is solved by GA.

The master optimization problem is an MIP problem with binary decision variables. At this level of optimization, the type of buses and lines (AC or DC) as well as the type of the supplying path of the feeders are determined by GA. Radial network structures are given as input to GA which are generated by Steps (1) to (4) as follows:

(1) The network is modeled as a graph, G; each bus represents a vertex and each line represents an edge. The weights of the edges represent the distance of the buses from each other.

(2) The information of the graph, G, is given to the Spantree (spanning trees generation using the network graph) program in MATLAB.

(3) The Spantree program generates all spanning trees of G, i.e., all possible radial structures of the network, $g = [g_1,\ldots, g_r,\ldots, g_R]$, where R is the number of all spanning trees of the network and g_r is the rth spanning tree of G.

(4) The radial structures are numbered based on the total weight of the edges and given as input to the GA optimizer.

Then, the GA determines the type of buses and lines of g_r according to the planning goals. Thus, the AC-DC structure of g_r is defined.In the slave problem, the DERs and EVs planning is optimized. For the AC-DC structure of g_r, the location and size of the DERs and EV charging stations are optimized to minimize the network losses and system costs. The decision variables in the slave optimization problem include the location and size of DERs and EV charging stations. The MCS technique is utilized for addressing the stochastic variations in DERs output and load demands.

For all possible radial structures of the network (i.e., r=1:R), the master-slave optimization planning problem is solved.

Finally, the AC-DC structure with minimum planning cost is introduced as the optimal solution. Figure 5 shows the flowchart of the proposed planning strategy.

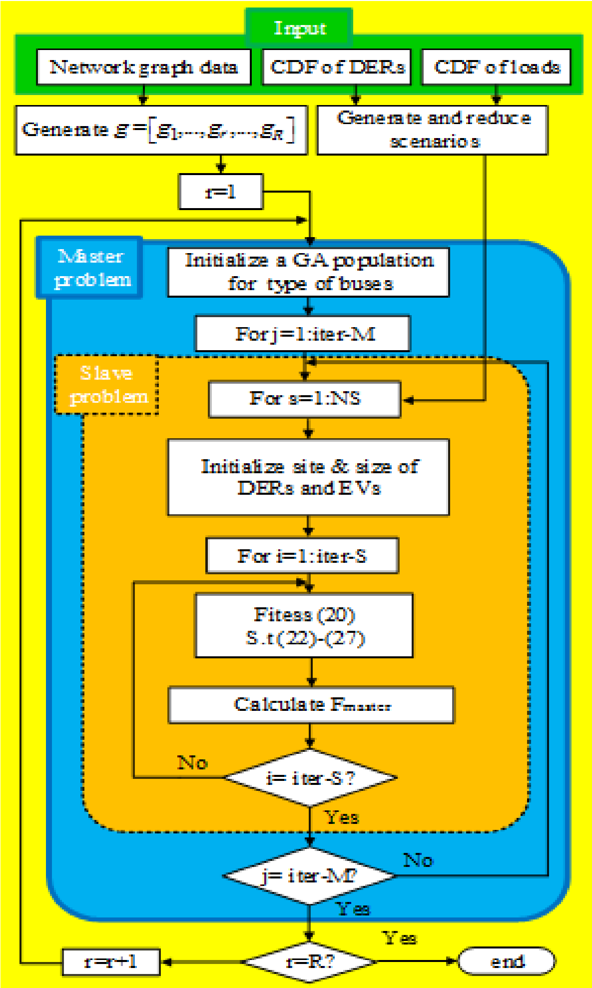

Figure 5. Flowchart of the proposed planning model

4. CASE STUDY

In this section, a test system is presented to implement and evaluate the hybrid planning method.

4.1. Test system

A 13-zone network is selected as the case study in Figure 6. The network includes different DERs and AC-DC loads, whose default locations are depicted in the Figure. The network is assumed as a directed graph, in which each zone is the node and every connection between the two zones is a weighted edge. According to the planning objectives, the lines and buses of the network can be AC or DC. Also, the location and capacity of DERs as well as the location and capacity of EV charging stations can vary. The capacity constraints of EV charging stations are $P_{EV,k,min}$ = 250 kW and $P_{EV,k,max}$ = 1800 kW. Figure 7 shows maximum load demand in each network bus. The maximum generated power rates of the wind generator and PV resources are 1000 kW and 2500 kW, respectively. The active and reactive power limits of other generation units and the energy price are listed in Tables 1 and 2. The distance between the network buses is the shortest possible path between two buses. Also, the effect of physical location of loads and resources on the distance of buses is considered. All possible paths between network buses are defined as the matrix arrays represented in the Appendix. The impedance for the DC and AC lines is 0.4415 Ω/mile and 0.4435 + j0.726 Ω/mile, respectively. Besides, the line price is 28 k$/mile [19].

The system base values include S_b = 10 MVA, V_{ac}^{b} = 4.16 kV, and V_{dc}^{b} = 6.8 kV. The power factor of converters is 0.95. The voltage stability limits are V_{max} = 1.05 p.u., V_{min} = 0.95 p.u., θ_{max} = 45 deg, and θ_{min} = -45 deg. Also, the modulation index limits are M_{max} = 1, and M_{min} = 0.97. The maximum converter capacity is 2 MVA and the converter price is 195 $/kVA. The bus connectivity constraint is considered as L_{max} = 4. The planning horizon time is 10 years. The values of discount rate, D, and annual maintenance cost, β, are 0.07 and 0.06, respectively. The annual load growth is assumed to be 2 %. Moreover, the presented data in [19] is used to describe the stochastic behavior of DERs, loads, and EV charging stations. To consider the uncertainty of stochastic variables in the proposed model, first, the MCS method is used to generate 1000 scenarios, including all possible network states. Then, the scenario reduction method is used to select the most probable states including probable severe network states, and the optimal power flow is performed in the planning problem considering the most probable scenarios and the probable extreme scenarios under uncertainties caused by generation resources and load demands.

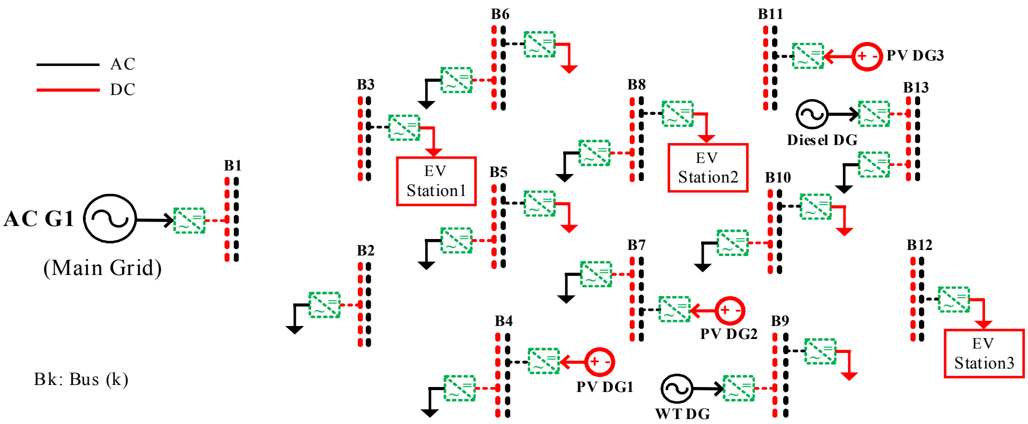

Figure 6. 13-bus test system

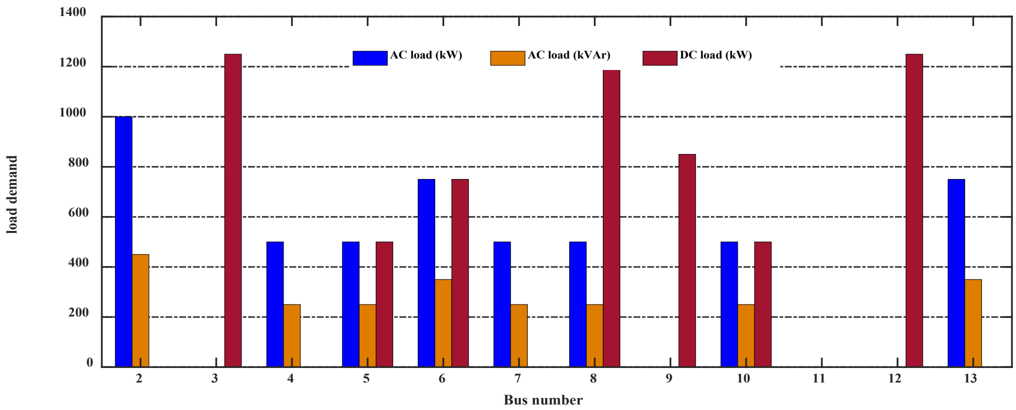

Figure 7. Maximum load demand

Table 1. Generators data

Unit	P_{min}^{Gen} (p.u.)	P_{max}^{Gen} (p.u.)	Q_{min}^{Gen} (p.u.)	Q_{max}^{Gen} (p.u.)	Energy price ($/MWh)
AC G1	0.100	-	0.080	0.480	0.02
Diesel DG	0.100	0.200	0.010	0.096	0.20

5. RESULTS AND DISCUSSION

Four scenarios are defined in the following to evaluate the proposed approach in this work.

Scenario 1: AC planning without DERs and EVs planning

In this scenario, no binary variable exists. All buses and lines are AC. Besides, the location and the size of all DERs and EV charging stations in the AC network are defined as Figure 7 and the presented values in Table 2. The structure of the radial network is defined based on minimization of the objective function.

Scenario 2: AC planning including optimal DERs and EVs planning

For the AC system in this scenario, the radial structure of the network as well as the optimal size and location of DERs and EV charging stations are variable and are determined based on the planning objectives.

Scenario 3: AC-DC hybrid planning without DERs and EVs planning

The AC-DC structure of the network is unknown in this scenario. The system buses and lines can be AC or DC. The capacity and location of DERs and EV charging stations are considered as known parameters of the planning problem. The specified parameters are given in Figure 6 and Table 2.

Scenario 4: AC-DC hybrid planning including optimal DERs and EVs planning

In this case, the AC-DC network structure is defined according to the flowchart of Figure 5 by determining the type of buses and lines, as well as the optimal size and location of DERs and EV charging stations.

The optimal planning solution for Scenarios 1 to 4 is presented in Figures 8-11, respectively. The capacity of the converters connected to the network buses is calculated considering the annual load growth in the planning horizon, and the obtained values for the hybrid planning and AC planning are depicted in Figures 12 and 13, respectively. In Scenario 3, the capacities of the converters installed in the network lines (C1, C2, C3) are 1500 kVA, 900 kVA, and 1000 kVA, respectively. However, in Scenario 4, the capacities of C1, C2, and C3 are 1200 kVA, 1000 kVA, and 800 kVA, respectively. The capacities of the generation units and EV charging stations for the second and fourth scenarios are presented in Table 2. Figure 14 shows the system operation cost. The network planning cost and the average value of network losses over a 10-year horizon are listed in Table 3.

The analysis of planning results in different scenarios is described as follows:

1) Comparison of the first and third scenarios shows that the lower installation capacity of converters and AC lines in hybrid planning has led to the following:
    - The investment cost is significantly lower than AC traditional planning so that the investment cost in the third scenario is decreased by 785.75 k$ in comparison with the first scenario.
    - The network loss in the hybrid structure is 63.5 kW less than its value in the AC structure.
    - The system operation cost in AC-DC planning is reduced by 1077.48 k$ in comparison with AC planning.

    Therefore, the hybrid planning has saved the total cost of planning by 4.75 % compared to traditional planning and reduced network losses by 10.5 %.

2) According to the comparison of the results from the first to fourth Scenarios, planning with the definition of the optimal size and location of DERs and EV charging stations has brought about the following outcomes:
    - The investment and operation costs of the system in the fourth scenario are reduced by 199.15 k$ and 611.51 k$, respectively, in comparison with the third scenario. Also, in the second scenario, there

are 86.7 k$ and 314.01 k$ savings in the system investment cost and the system operation cost, respectively, in comparison with the first scenario.

- The planning cost and power losses of the network in the fourth scenario are decreased by 2.17 % and 8 %, respectively, in comparison with the third scenario. Besides, in the second scenario, the planning cost and power loss cost are reduced by 1.02 % and 7.6 %, respectively, in comparison with the first scenario.

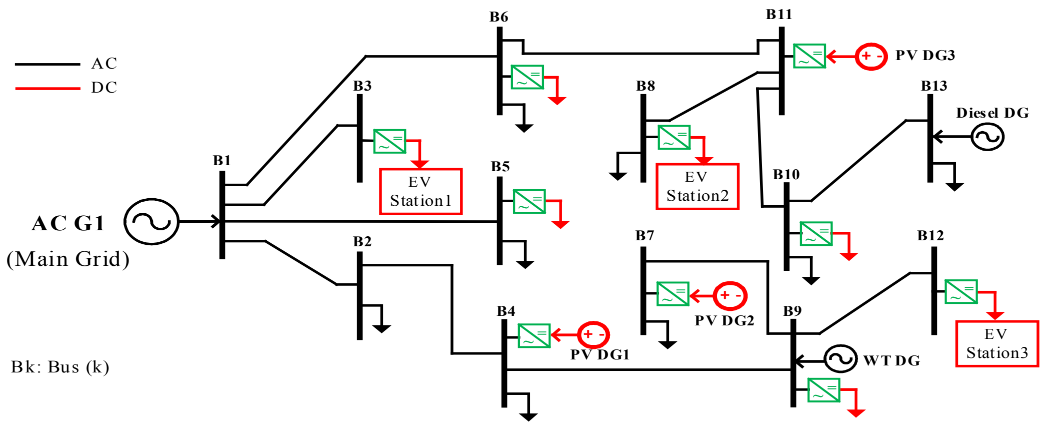

Figure 8. AC planning solution for Scenario 1

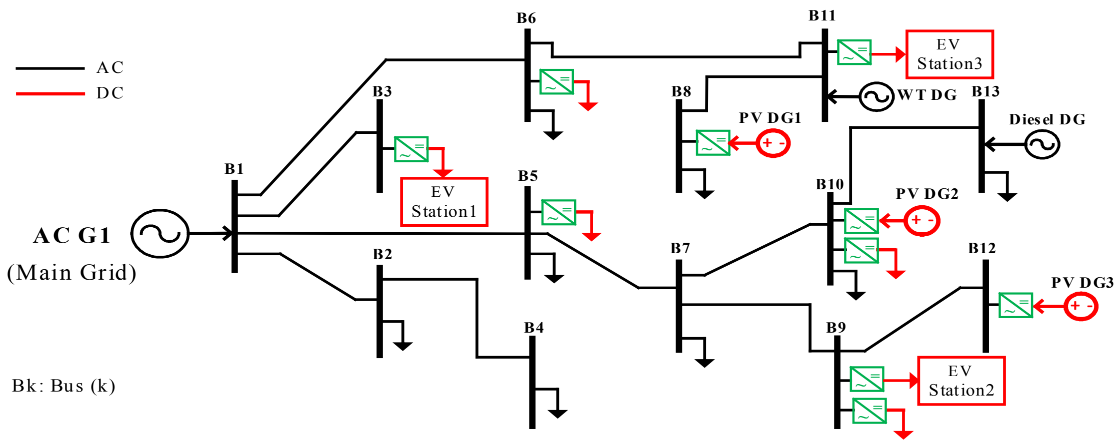

Figure 9. AC planning solution for Scenario 2

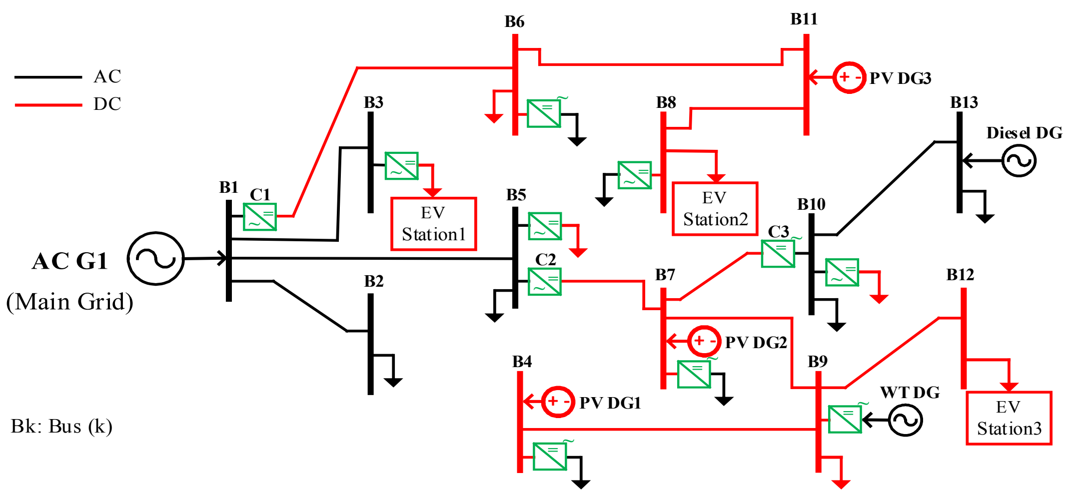

Figure 10. Hybrid planning solution for Scenario 3

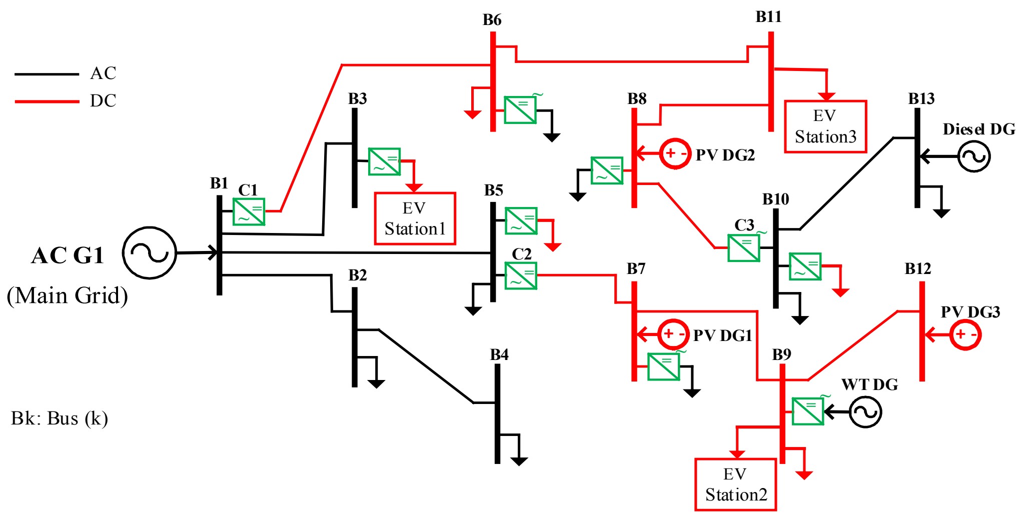

Figure 11. Hybrid planning solution for Scenario 4

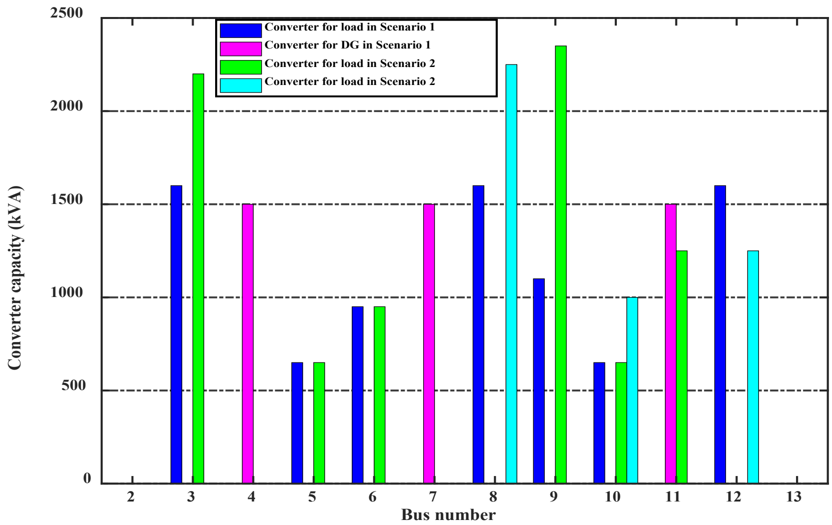

Figure 12. The capacities of converters connected to the network buses for AC planning

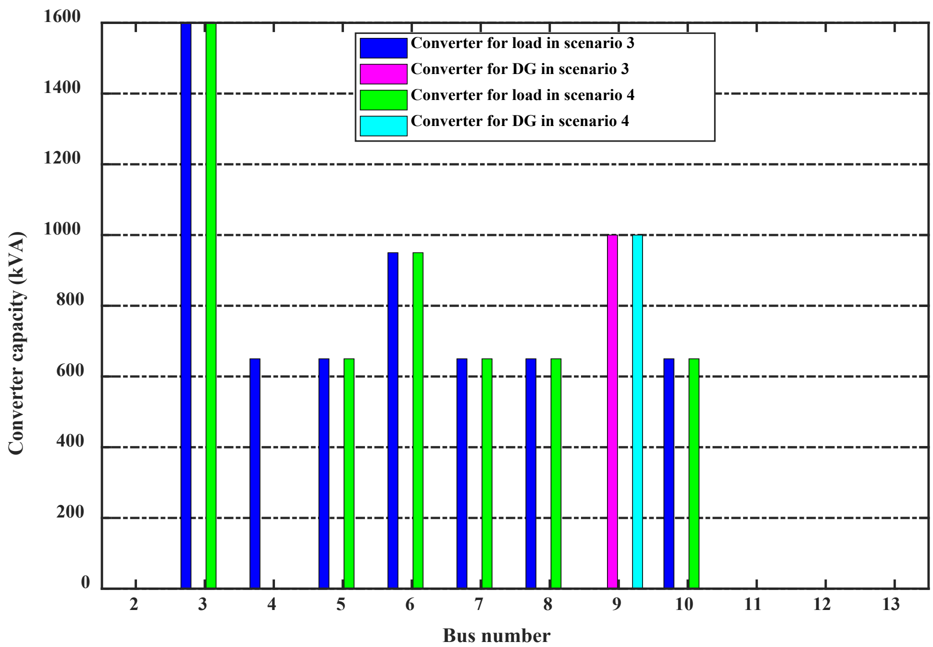

Figure 13. The capacities of converters connected to the network buses for hybrid planning

Table 2. The capacities of DGs and EV Stations (kW)

Unit	Scanario 1	Scenario 2	Scenario 3	Scenario 4
PV DG1	1500*	2250	1500**	1350
PV DG2	1500*	1000	1500**	1900
PV DG3	1500*	1250	1500**	1250
EV Station1	1250*	1750	1250**	1350
EV Station2	1250*	850	1250**	700
EV Station3	1250*	1000	1250**	1700
Diesel DG	2000*	1800	2000**	1650

* The known value for Scenario 1
** The known value for Scenario 3

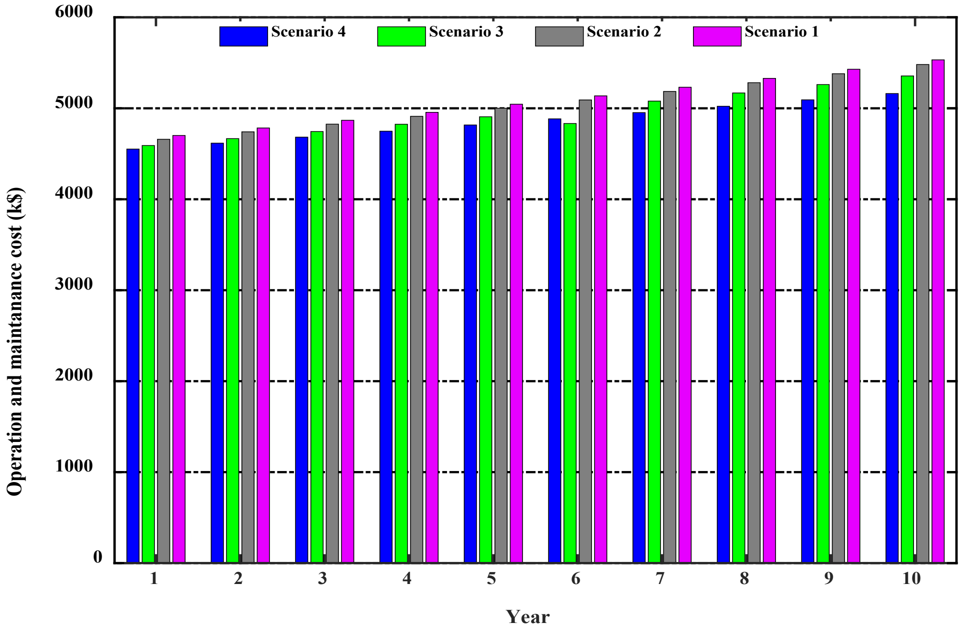

Figure 14. The comparison of system operation cost for different scenarios

Table 3. Planning results

Costs and values	Scenario 1	Scenario 2	Scenario 3	Scenario 4
C_{Line} (k$)	1226.40	1159.20	918.40	924.00
C_{Conv} (k$)	2466.75	2447.25	1989.00	1784.25
C_{Inv} (k$)	3693.15	3606.45	2907.40	2708.25
C_{OM} (k$)	35471.38	35157.37	34393.90	33782.39
C_{NP} (k$)	39164.53	38763.82	37301.30	36490.65
Average of P_{Loss} (kW)	474.30	438.10	410.80	378.30

6. CONCLUSIONS

A novel stochastic planning approach for AC-DC hybrid networks was proposed in this study. The optimal network structure was defined based on investigating all possible AC-DC system configurations. The presented planning model was formulated as a master-slave optimization problem. The master optimization problem defines the type of network buses and lines in order to minimize the system investment costs. The slave problem was formulated to solve the optimal power flow equations so that the size and the location of the DERs and EV charging stations could be determined to minimize the both system operation cost and network power losses simultaneously. The stochastic variation of the loads consumption and the output of the DERs were modeled by generating scenarios with the MCS method. In the next step, the Kantorovich scenario reduction method was applied to reduce the calculations burden of the planning problem. The efficiency curve of the converter was employed to model the converter losses accurately in the power flow equations. Finally, the proposed approach was applied to designing a 13-zone case study system, including different AC-DC loads and resources. The results showed that the presented approach could effectively reduce the system costs. The proposed method is useful for future designers of hybrid DSs due to its advantages and efficiency.

7. ACKNOWLEDGEMENT

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NOMENCLATURE

Sets	
S	Set of scenarios
NB	Set of network buses
NL	Set of network lines
NC	Set of converters
NG	Set of generation units
NEV	Set of electric vehicle charging stations
Indices	
s	Index for scenarios
b	Index for network buses
i	Index for network lines
c	Index for converters
j	Index for generation unit
t	Index for years
k	Index for electric vehicle charging stations
Parameters	
S_b	Base value of the network power (MVA)
V_{ac}^{b}	AC Voltage base value (kV)
V_{dc}^{b}	DC Voltage base value (kV)
NS	Number of scenarios
f_s	Switching frequency (Hz)
Variables	
P_b^{inj}/Q_b^{inj}	Injected active/reactive power into bus b (kW/kVAR)
P_b^{cal}/Q_b^{cal}	Calculated active/reactive power at bus b (kW/kVAR)
$P_{G,j}/Q_{G,j}$	Active/reactive power of generation unit j (kW/kVAR)
$P_{IGBT}^{cond}/P_{diode}^{cond}$	Conduction losses in the IGBT/diode (kW)
$E_{IGBT}^{SW}/E_{diode}^{SW}$	Switching losses in the IGBT/diode (kW)
P_{total}^{cond}	The total conduction losses of the converter (kW)
P_{total}^{SW}	The total switching losses of the converter (kW)
$P^{constant}$	The fixed losses of the converter (kW)
S_L	Power passing through the network lines (kVA)
S_C	Power passing through the converters installed in network lines (kVA)
$V_{ac,c}$	Voltage at AC side of the converter (p.u.)
$V_{dc,c}$	Voltage at DC side of the converter (p.u.)
V	Voltage amplitude (p.u.)
θ	Voltage angle (deg.)
M	Modulation index of converter
X_{min}	Minimum limit of variable X
X_{max}	Minimum limit of variable X

APPENDIX

The distance between the buses of 13-bus test system used in this study is given by:

$$D(m,n)=A_m(n) \quad \forall\, m \in \{2,3,...,13\},\ n \in \{1,2,...,12\} \tag{28}$$

where D(m,n) indicates the distance between bus m and bus n of the system in miles; and values of $A_m(n)$ are defined as:

$A_2=[1.0]$
$A_3=[1.0\ 1.4]$
$A_4=[2.0\ 1.0\ 2.4]$
$A_5=[1.4\ 1.0\ 1.0\ 1.4]$
$A_6=[2.0\ 2.4\ 1.0\ 2.8\ 1.4]$
$A_7=[2.4\ 1.4\ 2.0\ 1.0\ 1.0\ 2.4]$
$A_8=[2.4\ 2.0\ 1.4\ 2.4\ 1.0\ 1.0\ 1.4]$
$A_9=[3.4\ 2.4\ 3.0\ 1.4\ 2.0\ 3.4\ 1.0\ 2.4]$
$A_{10}=[2.8\ 2.4\ 2.4\ 2.0\ 1.4\ 2.0\ 1.0\ 1.0\ 1.4]$
$A_{11}=[3.4\ 3.0\ 2.4\ 3.4\ 2.0\ 1.4\ 2.4\ 1.0\ 2.8\ 1.4]$
$A_{12}=[3.8\ 2.8\ 3.4\ 2.4\ 2.4\ 3.0\ 1.4\ 2.0\ 1.0\ 1.0\ 2.4]$
$A_{13}=[3.8\ 3.4\ 2.8\ 3.0\ 2.4\ 2.4\ 2.0\ 1.4\ 2.4\ 1.0\ 1.0\ 1.4]$

REFERENCES

1. Eajal, A.A., Shaaban, M.F., Ponnambalam, K. and El-Saadany, E.F., "Stochastic centralized dispatch scheme for AC/DC hybrid smart distribution systems", ***IEEE Transactions on Sustainable Energy***, Vol. 7, No. 3, (2016), 1046-1059. (https://doi.org/10.1109/TSTE.2016.2516530).
2. Peyghami, S., Mokhtari, H. and Blaabjerg, F., "Autonomous operation of a hybrid AC/DC microgrid with multiple interlinking converters", ***IEEE Transactions on Smart Grid***, Vol. 9, No. 6, (2018), 6480-6488. (https://doi.org/10.1109/TSG.2017.2713941).
3. Wang, T., Li, C., Mi, D., Wang, Z. and Xiang, Y., "Coordinated modulation strategy considering multi-HVDC emergency for enhancing transient stability of hybrid AC/DC power systems", ***CSEE Journal of Power and Energy Systems***, Vol. 6, No. 4, (2020), 806-815. (https://doi.org/10.17775/CSEEJPES.2019.02000).
4. ElNozahy, M.S. and Salama, M.M.A., "Uncertainty-based design of a bilayer distribution system for improved integration of PHEVs and PV arrays", ***IEEE Transactions on Sustainable Energy***, Vol. 6, No. 3, (2015), 659-674. (https://doi.org/10.1109/TSTE.2015.2405411).
5. Kurohane, K., Senjyu, T., Yona, A., Urasaki, N., Goya, T. and Funabashi, T., "A hybrid smart AC/DC power system", ***IEEE Transactions on Smart Grid***, Vol. 1, No. 2, (2010), 199-204. (https://doi.org/10.1109/TSG.2010.2053392).
6. Lotfjou, A., Fu, Y. and Shahidehpour, M., "Hybrid AC/DC transmission expansion planning," ***IEEE Transactions on Power Delivery***, Vol. 27, No. 3, (2012), 1620-1628. (https://doi.org/10.1109/TPWRD.2012.2194515).
7. Doagou-Mojarrad, H., Rastegar, H. and Gharehpetian, G.B., "Probabilistic multi-objective HVDC/AC transmission expansion planning considering distant wind/solar farms", ***IET Science, Measurement & Technology***, Vol. 10, No. 2, (2016), 140-149. (https://doi.org/10.1049/iet-smt.2015.0173).
8. Meng, K., Zhang, W., Qiu, J., Zheng, Y. and Dong, Z.Y., "Offshore transmission network planning for wind integration considering AC and DC transmission options", ***IEEE Transactions on Power Systems***, Vol. 34, No. 6, (2019), 4258-4268. (https://doi.org/10.1109/TPWRS.2019.2912414).
9. Torbaghan, S.S., Gibescu, M., Rawn, B.G. and Meijden, M., "A market-based transmission planning for HVDC grid-Case study of the North Sea", ***IEEE Transactions on Power Systems***, Vol. 30, No. 2, (2015), 784-794. (https://doi.org/10.1109/TPWRS.2014.2332762).
10. Moradi-Sepahvand, M. and Amraee, T., "Hybrid AC/DC transmission expansion planning considering HVAC to HVDC conversion under renewable penetration", ***IEEE Transactions on Power Systems***, Vol. 36, No. 1, (2021), 579-591. (https://doi.org/10.1109/TPWRS.2020.2988195).
11. Huang, L., Chen, Z., Cui, Q., Zhang, J., Wang, H. and Shu, J., "Optimal planning of renewable energy source and energy storage in a medium- and low-voltage distributed AC/DC system in China", ***The Journal of Engineering***, Vol. 2019, No. 16, (2019), 2354-2361. (https://doi.org/10.1049/joe.2018.8546).
12. Wu, Z., Liu, P., Gu, W., Huang, H. and Han, J., "A bi-level planning approach for hybrid AC-DC distribution system considering N-1 security criterion", ***Applied Energy***, Vol. 230, (2018), 417-428. (https://doi.org/10.1016/j.apenergy.2018.08.110).
13. Wu, Z., Sun, Q., Gu, W., Chen, Y., Xu, H. and Zhang, J., "AC/DC hybrid distribution system expansion planning under long-term uncertainty considering flexible investment", ***IEEE Access***, Vol. 8, (2020), 94956-94967. (https://doi.org/10.1109/ACCESS.2020.2990697).
14. Frank, S.M. and Rebennack, S., "Optimal design of mixed AC–DC distribution systems for commercial buildings: a nonconvex generalized benders decomposition approach", ***European Journal of Operational Research***, Vol. 242, No. 3, (2015), 710-729. (https://doi.org/10.1016/j.ejor.2014.10.008).
15. Bagheri, A., Monsef, H. and Lesani, H., "Integrated distribution network expansion planning incorporating distributed generation considering uncertainties, reliability, and operational conditions", ***International Journal of Electrical Power & Energy Systems***, Vol. 73, (2015), 56-70. (http://dx.doi.org/10.1016/j.ijepes.2015.03.010).
16. Lotfi, H. and Khodaei, A., "AC versus DC microgrid planning", ***IEEE Transactions on Smart Grid***, Vol. 8, No. 1, (2017), 296-304. (https://doi.org/10.1109/TSG.2015.2457910).

17. Hamad, A.A., Nassar, M.E., El-Saadany, E.F. and Salama, M.M.A., "Optimal configuration of isolated hybrid AC/DC microgrids", ***IEEE Transactions Smart Grid***, Vol. 10, No. 3, (2019), 2789-2798. (https://doi.org/10.1109/TSG.2018.2810310).

18. Ghadiri, A., Haghifam, M.R. and Larimi, S.M.M., "Comprehensive approach for hybrid AC/DC distribution network planning using genetic algorithm", ***IET Generation, Transmission & Distribution***, Vol. 11, No. 16, (2017), 3892-3902. (https://doi.org/10.1049/iet-gtd.2016.1293).

19. Ahmed, H.M.A., Eltantawy, A.B. and Salama, M.A., "A planning approach for the network configuration of AC-DC hybrid distribution systems", ***IEEE Transactions on Smart Grid***, Vol. 9, No. 3, (2018), 2203-2213. (https://doi.org/10.1109/TSG.2016.2608508).

20. Ahmed, H.M.A., Eltantawy, A.B. and Salama, M.M.A., "A reliability-based stochastic planning framework for AC-DC hybrid smart distribution systems", ***International Journal of Electrical Power & Energy Systems***, Vol. 107, (2019), 10-18. (https://doi.org/10.1016/j.ijepes.2018.11.003).

21. Blaabjerg, F., Jaeger, U. and Munk-Nielsen, S., "Power losses in PWM-VSI inverter using NPT or PT IGBT devices", ***IEEE Transactions on Power Electronics***, Vol. 10, No. 3, (1995), 358-367. (https://doi.org/10.1109/63.388002).

22. Islam, M.M., Rahman, M.A. and Islam, M.R., "Power loss and thermalimpedance modeling of multilevel power converter with discontinuous modulation", ***IEEE Transactions on Energy Conversion***, Vol. 36, No. 1, (2020), 36-47. (https://doi.org/10.1109/TEC.2020.3000596).

23. Ebrahimi, J., Abedini, M., Rezaei M.M. and Nasri M., "Optimum design of a multi-form energy in the presence of electric vehicle charging station and renewable resources considering uncertainty", ***Sustainable Energy, Grids and Networks***, Vol. 23, (2020), 100375. (https://doi.org/10.1016/j.segan.2020.100375).

24. Sabzian Molaee, Z., Rokrok, E. and Doostizadeh M., "A unified power flow approach using VSC-efficiency for AC-DC distribution systems operating at grid connected and islanded modes", ***International Journal of Electrical Power & Energy Systems***, Vol. 130, (2021), 106906. (https://doi.org/10.1016/j.ijepes.2021.106906).