Gao *et al.*
Protection and Control of Modern Power Systems (2023) 8:62
https://doi.org/10.1186/s41601-023-00335-5

Protection and Control of
Modern Power Systems

ORIGINAL RESEARCH

Open Access

Bi-level stackelberg game-based distribution system expansion planning model considering long-term renewable energy contracts

Hongjun Gao[1], Renjun Wang[1], Shuaijia He[1*], Zeqi Wang[1] and Junyong Liu[1]

Abstract

With the deregulation of electricity market in distribution systems, renewable distributed generations (RDG) are being invested in by third-party social capital, such as distributed generations operators (DGOs) and load aggregators (LAs). However, their arbitrary RDG investment and electricity trading behavior can bring great challenges to distribution system planning. In this paper, to reduce distribution system investment, a distribution system expansion planning model based on a bi-level Stackelberg game is proposed for the distribution system operator (DSO) to guide this social capital to make suitable RDG investment. In the proposed model, DSO is the leader, while DGOs and LAs are the followers. In the upper level, the DSO determines the expansion planning scheme including investments in substations and lines, and optimizes the variables provided for followers, such as RDG locations and contract prices. In the lower level, DGOs determine the RDG capacity and electricity trading strategy based on the RDG locations and contract prices, while LAs determine the RDG capacity, demand response and electricity trading strategy based on contract prices. The capacity information of the DRG is sent to the DSO for decision-making on expansion planning. To reduce the cost and risk of multiple agents, two long-term renewable energy contracts are introduced for the electricity trading. Conditional value-at-risk method is used to quantify the RDG investment risk of DGOs and LAs with different risk preferences. The effectiveness of the proposed model and method is verified by studies using the Portugal 54-bus system.

Keywords Distribution system expansion planning, Distributed generation, Distribution system operators, Distributed generation operator, Prosumers, Load aggregators

1 Introduction

The electricity market in China has been deregulated gradually over recent years. Consequently, third-party social capital is being granted permits to invest in renewable distributed generation (RDG). These organisations with capital to invest can be divided into distributed generation operators (DGOs) and load aggregators (LAs), where DGOs sell all renewable energy while LAs use part of the renewable energy for their own needs and sell the surplus. Accordingly, distribution system operators (DSOs), DGOs, and LAs co-exist in the distribution system. The arbitrary RDG investment and electricity trading behavior of DGOs and LAs pose great challenges to the security and reliability of the distribution system. Consequently, it is important for a DSO to integrate those trading aspects in the planning-level issues to guarantee both unimpeded renewable electricity trading and physical security.

In the numerous traditional distribution system expansion planning (DSEP) studies, the co-optimization method is commonly employed to jointly optimize the investments in substations, lines and various kinds of

*Correspondence:
Shuaijia He
shuaijiahe@scu.edu.cn
[1] College of Electrical Engineering, Sichuan University, Chengdu 610065, China

flexible resources, (i.e., controllable load, RDG and energy storage systems) [1–3]. The traditional co-optimization method generally considers flexible resources that belong to the DSO, while the objective of the co-optimization method in the DSEP problem is usually to maximize all social welfare. However, in the deregulated market, these flexible resources belong to the third-party social capitals, and consequently, pursuing the maximization of the whole social welfare is contrary to the practical electricity market operation. In recent years, the DSEP problem in the deregulated market has been researched in several studies [4–9]. Reference [4] proposes a DSEP model considering the interaction among DSOs, DGOs, and end users. This model is analyzed using the Stackelberg game and robust optimization. In [5], a dynamic DSEP model is established with interactive trading among distribution companies, DGOs, and independent distribution network operators, and it is analyzed based on the Benders decomposition framework. Reference [6] develops a DSEP model with various market agents, analyzed using a tetra-level decomposition algorithm. In [7], a distribution network planning method is proposed based on the multilateral incomplete information evolutionary game, where DGOs, electricity retailers, and DSOs are all included. In [8], a risk-based stochastic optimization framework is proposed to model DSO participation in DEP problems in the presence of an electricity wholesale multimarket. Although these studies focus on modeling the impact of RDG investment and electricity trading behavior on system expansion, multi-agent cooperation is not involved. Reference [9] proposes an incentive-based DSEP model with the interaction between a DSO and DGOs, where the DSO provides incentive prices to guide RDG investment. Profits of both parties are improved because of the suitable RDG investment. However, these studies ignore some practical factors such as the RDG investment on the demand side (i.e., some LAs) and the possibility of trading between DGOs and end users, and it may yield idealistic results. At the distribution level, LAs possess large amount of small-scale RDG assets, and differ from DGOs in investment and trading behavior [10–12]. Moreover, trading between DGOs and end users may affect the electricity consumption of users. Therefore, the presence of prosumers and trading between DGOs and end users are important factors for long-term distribution system expansion planning.

The DSEP problem faced by a DSO is a hierarchical interactive problem with imperfect information exchange [13]. This can be simulated by the Stackelberg game. This game has been applied in various fields such as congestion management [14], demand-side management [15], and microgrid transactions [16], and has been extensively used to effectively deal with the 'one-leader and multi-follower' problem. This paper proposes a bi-level Stackelberg framework to handle the DSEP problem under multi-agent interactive trading. In the framework, the DSO is the leader, while DGOs and LAs are the followers. It is also to be noted that the decisions of the DSO are subject to the reactions of DGOs and LAs, and vice versa. Thus, a DSO may face two main concerns in the DSEP problem: (1) how to precisely model the investment behavior of DGOs under uncertainty; and (2) what price strategy should a DSO adopt to properly and positively guide the RDG investment decisions. Reference [17] summarizes that the anticipated market returns of RDG investments is not only based on multiple uncertainty sources, namely, RDG output uncertainty and short-term market price, but also heavily influenced by investor opinion. That is to say, aside from the behavior difference between DGOs and LAs, these agents may have different attitudes towards risk under uncertainty [18]. It is also demonstrated in [19] that assuming risk neutrality could result in poor and unrealistic solutions in certain conditions. The above-mentioned studies [4–9] adopt various uncertainty methods to deal with the DSEP problem under uncertainty from the viewpoint of the DSO. However, most studies neglect the risk of RDG investment projects under uncertainty. This neglect adversely affects the accuracy of DGOs' investment model and ultimately results in decreased effectiveness of the expansion option of the DSO.

In this paper, the conditional value-at-risk (CVaR) method is introduced to model the RDG investment uncertainties. CVaR can help quantify the potential losses that may occur in extreme scenarios. These are often difficult to estimate but may have a significant impact on investment decisions. In addition, the generally used feed-in tariff may lead to the unwillingness of some potential RDG investors to invest in RDG assets due to the gradually decreased subsidy. Therefore, it is important for a DSO to design suitable long-term contracts for them to ensure basic investment profit. As a consequence, two long-term contracts called power purchase agreement (PPA) and contract of difference (CFD) applicable for renewable energy trading are introduced to enable DGOs and LAs to realize more steady income than participating in the short-term electricity market. Consequently, a DSO can affect their investment decisions in a financial fashion and ultimately defer system expansion.

Based on the aforementioned discussion, a novel bi-level Stackelberg game-based distribution system expansion planning model considering long-term renewable energy contracts is proposed here. The leader and multi-follower pursue their maximum profit and are allowed to exchange imperfect information with each other. As the leader, the DSO determines the long-term contract pricing strategy, RDG location, and substation and line investment option. As the followers, DGOs determine the installed RDG capacity and renewable energy trading scheme, while LAs determine the PV capacity and location investment, and electricity trading solution. Then, two long-term renewable energy contracts with different performance of risk aversion and complexity are introduced. These enable the DSO to move towards an optimal substation and line investment option by providing flexible price signals to guide the RDG decisions. The main contributions of the paper are as follows:

(1) Within the context featuring different kinds of DG investors and electricity trading between DGOs and LAs, a bi-level one-leader and multi-follower Stackelberg theoretical framework is proposed for the DSO to facilitate ever-expanding RDG integration in the DSEP problem.
(2) The CVaR method is applied to qualify the RDG investment risk with long-term contracts in the RDG investment decision of DGOs and LAs. The different attitudes of RDG investors towards risk are taken into special consideration instead of assuming the particular instance of risk neutrality.
(3) Two contracts applicable for long-term renewable energy trading are introduced. These enable the DSO to provide flexible price signals to guide the privately-motivated DG investment decisions towards the least network investment cost solution.

The rest of the paper is organized as follows: Sect. 2 explains the framework in the multi-agent interactive trading context, and the planning model for each agent is established in Sect. 3, which includes the DSEP model, and the DGOs' investment model, LAs' investment model and the trading models between DGOs and LAs. A specific solution structure is designed to analyze the proposed model in Sect. 4, while in Sect. 5 the effectiveness of the proposed model is verified by a simulation of the Portugal 54-node system. Conclusions are drawn in Sect. 6.

2 Problem statement

2.1 Multiple participants in the deregulated market

In recent years, some policies, such as feed-in tariff, in many countries grant permits to the third-party social capitals (i.e., DGOs) to invest in RDG in distribution systems. As a result, the scale of RDG units installed by DGOs is growing rapidly. Moreover, many traditional consumers gradually transform to prosumers by setting up rooftop photovoltaics. However, individual consumers have resources of limited flexibility, and this hampers their ability to meet flexible energy demand. To overcome the challenge, neighboring prosumers and consumers can form a virtual alliance called an LA, which integrates flexible resources, such as renewable energy and controllable load facilities, to better meet the flexibility requirements and improve overall energy efficiency. In each LA, prosumers prioritize the provision of renewable energy to alliance members at an affordable price, while any surplus renewable energy is exchanged with the DSO through the LA agent. By forming the virtual alliance, participants can share resources and collaborate to address challenges arising from changes in the energy market and the increasing availability of dispatchable energy resources. From a system perspective, each LA is considered as an individual entity with bi-directional power interaction with the DSO. This paper regards Residential LA (RLA), Commercial LA (CLA), and Industrial LA (ILA) as separate entities. Accordingly, the DSO, LAs (including prosumers and pure consumers), and DGOs are taken into consideration in the deregulated market as shown in Fig. 1. As seen, the DSO is responsible for operating the distribution system while RDG units are installed by both DGOs and LAs.

In addition, the risk preference issue is specially incorporated to precisely model the RDG investment decisions. Residential LAs are used as an example to model the similar risk preference since the number of residential consumers is usually larger than those of commercial and industrial consumers. RLAs and DGOs are categorized into three risk profiles: risk-averse, risk-neutral, and risk-seeking. Additionally, it is noteworthy that apart from purchasing electricity from the DSO, LAs can trade with DGOs to reduce the electricity consumption costs.

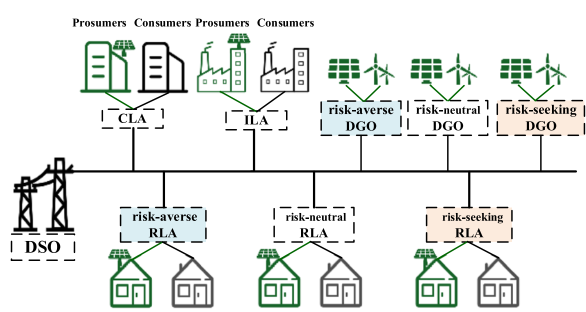

Fig. 1 The participants in the deregulated market

2.2 Long-term renewable energy contracts

Risk aversion is a primary focus for many investors [17], while long-term contracts can avoid the price uncertainties for the investors in renewable energy investments [20]. In this paper, two long-term contracts are introduced, as shown in Fig. 2, to mitigate the investment risks for DGOs and LAs, and prompt the collaboration of the DSO, DGOs and LAs. The DSO can guide DGOs and LAs to invest in RDG reasonably by providing suitable RDG locations and contract prices. Therefore, substation and line upgrading of DSO can be deferred. Those two contracts are different in terms of the risk aversion and the implementation process.

(1) *Power Purchase Agreement (PPA)*: A PPA generally exists in the early stages of the electricity market. This long-term contract is based on the installed capacity of RDG, which means that sellers sell all the electricity production to buyers at a fixed price. The short-term operation risk arising from RDG uncertainty the responsibility of buyers. Thus, the buyers are required to have high-risk tolerance and large renewable energy absorption capacity if they sign PPA contracts. PPA contracts offer simplicity and convenience in execution but lack flexibility, and are suitable for the sellers who are very confused about their future trading rules when there is uncertainty. In this study, a PPA is considered in the trading process when LAs sell electricity to the DSO. The anticipated benefit and risk of each LA signing a PPA are given as:

$$f(x,\xi_s) = \sum_{t=1}^{T} [f_{s,t}^{\text{load}}(P_{s,t}^{\text{DG}} - P_{s,t}^{\text{sell}}) + f^{\text{PPA}} P_{s,t}^{\text{sell}}] \quad \textit{where } P_{s,t}^{\text{buy}} - P_{s,t}^{\text{sell}} = P_{s,t}^{\text{load}} - P_{s,t}^{\text{DG}} \tag{1}$$

$$F(x,\beta) = \beta + \frac{1}{1-\alpha}\sum_{s=1}^{S}\pi(s)[f(x,\xi_s)-\beta]^{+} \quad \textit{where } [t]^{+} = \max\{0,t\} \tag{2a}$$

$$CVaR = \min F(x,\beta) \tag{2b}$$

Equation (1) denotes that as the long-term price of a PPA is fixed, the benefit fluctuation of each LA signing a PPA is associated with the actual active power output of the RDG, the actual active load, and the actual price of power charged to end users. Equation (2) represents the corresponding CVaR model calculated in discrete multi-scenario simulation [21].

(2) *Contract for Difference (CFD)*: As the electricity market develops, the long-term CFD contract becomes more prevalent. This long-term contract is based on the electricity generation of an RDG during a specific time period, which means that sellers primarily sell renewable energy in long-term trading while the surplus electricity is sold in the short-term market. CFD is a highly flexibly financial contract because it does not compel sellers to meet the exact contracted electricity amount. Meanwhile, the buyers face lower risks in CFD than in a PPA because they are not responsible for the surplus electricity. Although CFD performs better than PPA in terms of risk, it is very complex, because the seller and buyer need to collaborate to make the hourly electricity curve. The complexity makes CFD more applicable for DGOs to sell renewable energy, while LAs may find it challenging to create the hourly electricity curve considering their own electricity needs.. In this study, CFD is considered in the trading process. The expected revenue and risk of each DGO signing a CFD are:

$$\begin{aligned} f(x,\xi_s) &= f_1(x) + f_2(x,\xi_s) \\ &= \sum_{t=1}^{T} f^{\text{CFD}} P_t^{\text{CFD}} + \sum_{t=1}^{T} f_{s,t}^{\text{WS}}\left(P_{s,t}^{\text{DG}} - P_t^{\text{CFD}}\right) \end{aligned} \tag{3}$$

$$F(x,\beta) = \beta + \frac{1}{1-\alpha}\sum_{s=1}^{S}\pi(s)[f_2(x,\xi_s)-\beta]^{+} \quad \textit{where } [t]^{+} = \max\{0,t\} \tag{4a}$$

$$CVaR = \min F(x,\beta) \tag{4b}$$

Equation (3) denotes that as the long-term price and the electricity of a CFD in the first term are fixed, the revenue fluctuation of sellers signing a CFD is associated with the actual surplus electricity and the wholesale market price. Analogously, Eq. (4) represents the corresponding CVaR function.

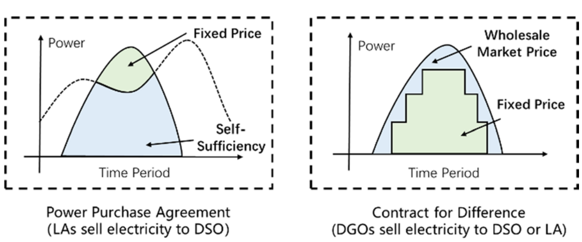

Fig. 2 Form of signing power purchase agreement and signing contract for difference

2.3 Bi-level stackelberg framework

A bi-level Stackelberg theoretical framework is proposed to deal with the DSEP problem, where the DSO is the leader, and DGOs and LAs are the followers when considering the interactive trading among all three. Each agent is regarded as an individual, making investment and trading decisions to maximize their profits. The interaction among these three agents is depicted in Fig. 3.

From the perspective of the leader, the target of the DSO is to obtain the optimal substation and line investment option and long-term renewable energy pricing strategy. The diagram reveals that the DSO can simultaneously provide the long-term contract prices and the network topology for DGOs and LAs. Moreover, it is noteworthy that the DSO can also provide the RDG installation locations for DGOs.

As followers, each DGO aims to obtain the optimal installed RDG capacity according to the CFD prices and RDG location signals from the DSO. Analogously, the target of each LA is to obtain the optimal installed PV capacity and location option, and demand-side flexible load scheduling scheme according to the PPA price signal from the DSO. After investing in RDG, each DGO considers the possibility of electricity trading with the LA based on the network topology, and then provides CFD prices for LAs. Each LA then makes the electricity trading strategy and the flexible loads re-scheduling scheme according to the price signals from DGOs.

After the followers have made investment and trading decisions, they provide the electricity trading schemes as feedback to the DSO. Based on the feedback, the DSO can regulate the substation and line investment decisions, update and publish the signals including renewable energy prices, network topology and RDG locations to DGOs and LAs.

In summary, the bi-level Stackelberg framework mainly contains four parts: the distribution system investment and contract price decision of the DSO, the RDG investment of DGOs, the PV investment

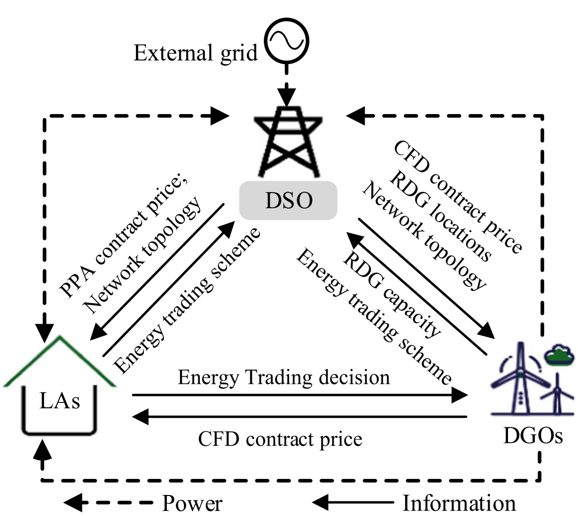

Fig. 3 The flow of power and information between the multiple agents

and demand side management of LAs, and the trading between DGOs and LAs. The processes of the bi-level game interaction are modeled in Sect. 3.

3 Mathematical formulation

3.1 DSEP model of the leader

In the DSEP model, the DSO aims at obtaining an optimal investment decision (substation and line), multiple contract price and RDG connected location (bus). The optimal decisions are derived from the following model:

$$\max PS = PS^{\text{LA}} - CS^{\text{DGO}} + PS^{\text{net}} - CS^{\text{loss}} - CS^{\text{Sub}} - CS^{\text{inv}} \tag{5}$$

The objective of (5) maximizes the profit of the DSO. In (5), the first term represents the profit of the DSO trading with LAs, the second term represents the cost to the DSO of purchasing electricity from DGOs, the third term represents the network usage fee charged by the DSO when DGOs trade with LAs, the fourth term represents the power loss cost, the fifth term represents the cost of the DSO purchasing electricity from the external grid, and the last term denotes the cost of the existing substation upgrading, new substation installation, existing line upgrading and new line installation. The mathematical formulations for each of the costs in (5) are shown in (6a)–(6g) as:

$$PS^{\text{LA}} = \sum_{s=1}^{S} \pi(s) \sum_{t=1}^{T} \sum_{j\in\Omega^{\text{LA}}} \left(f_{s,t,j}^{\text{load}} P_{s,t,j}^{\text{buy}} - f^{\text{PPA}} P_{s,t,j}^{\text{sell}} \right) \tag{6a}$$

$$\begin{aligned} CS^{\text{DGO}} &= \sum_{s=1}^{S} \pi(s) \sum_{t=1}^{T} \sum_{i\in\Omega^{\text{DG}}} f_{s,t}^{\text{WS}} (P_{s,t,i}^{\text{DG}} - z_i^{\text{DG}} P_t^{\text{DG,CFD}}) \\ &+ \sum_{t=1}^{T} \sum_{i\in\Omega^{\text{DG}}} \sum_{j\in\Omega^{\text{LA}}} (1 - \lambda_{i,j}^{\text{DGO,LA}}) f^{\text{DG,CFD}} z_i^{\text{DG}} P_t^{\text{DG,CFD}} \end{aligned} \tag{6b}$$

$$PS^{\text{net}} = \sum_{t=1}^{T} \sum_{i\in\Omega^{\text{DG}}} \sum_{j\in\Omega^{\text{LA}}} \lambda_{i,j}^{\text{DGO,LA}} f^{\text{net}} l_{i,j}^{\text{DGO,LA}} z_i^{\text{DG}} P_t^{\text{DG,CFD}} \tag{6c}$$

$$\delta^{\Psi} = \frac{r(1+r)^{LT}}{(1+r)^{LT} - 1}, \Psi \in \{\text{sub,line}\} \tag{6d}$$

$$\begin{aligned} CS^{\text{inv}} &= \delta^{\text{sub}} \sum_{i\in\Omega^{\text{US}}} \sum_{a\in A} c_a^{\text{US}} x_{i,a}^{\text{US}} + \delta^{\text{sub}} \sum_{i\in\Omega^{\text{NS}}} \sum_{a\in A} c_a^{\text{NS}} x_{i,a}^{\text{NS}} \\ &+ \delta^{\text{line}} \sum_{ij\in\Omega^{\text{UL}}} \sum_{b\in B} c_b^{\text{UL}} x_{ij,b}^{\text{UL}} l_{ij}^{\text{UL}} + \delta^{\text{line}} \sum_{ij\in\Omega^{\text{NL}}} \sum_{b\in B} c_b^{\text{NL}} x_{ij,b}^{\text{NL}} l_{ij}^{\text{NL}} \end{aligned} \tag{6e}$$

$$CS^{\text{loss}} = \sum_{s=1}^{S} \pi(s) \sum_{t=1}^{T} \sum_{ij\in\Omega} c^{\text{loss}} I_{s,t,ij}^2 r_{ij} \tag{6f}$$

$$CS^{\text{sub}} = \sum_{s=1}^{S} \pi(s) \sum_{t=1}^{T} \sum_{i\in\Omega^{\text{sub}}} f_{s,t}^{\text{WS}} P_{s,t,i}^{\text{sub}} \tag{6g}$$

which are subject to:

$$f^{\text{PPA,min}} \le f^{\text{PPA}} \le f^{\text{PPA,max}} \tag{7a}$$

$$f^{\text{CFD,min}} \le f^{\text{DG,CFD}} \le f^{\text{CFD,max}}, \text{DG} \in \{\text{PV,WTG}\} \tag{7b}$$

$$\sum_{a\in A} x_{i,a}^{\text{sub}} \le 1, \forall i \in \Omega^{\text{sub}}, \text{sub} \in \{\text{US,NS}\} \tag{8a}$$

$$\sum_{b\in B} x_{ij,b}^{\text{line}} \le 1, \forall ij \in \Omega^{\text{line}}, \text{line} \in \{\text{UL,NL}\} \tag{8b}$$

$$N^{\text{EL}} + \sum_{ij\in\Omega^{\text{Line}}} \sum_{b\in B} z_{ij,b}^{\text{NL}} = N^{\text{Nodes}} - N^{\text{ES}} - \sum_{i\in\Omega^{\text{Sub}}} \sum_{a\in A} z_{i,a}^{\text{NS}} \tag{9}$$

$$P_{s,t,j}^{\text{inj}} = \sum_{k\in\delta(j)} P_{s,t,jk} - \sum_{i\in\pi(j)} \left(P_{s,t,ij} - I_{s,t,ij}^2 r_{ij}\right) \tag{10a}$$

$$Q_{s,t,j}^{\text{inj}} = \sum_{k\in\delta(j)} Q_{s,t,jk} - \sum_{i\in\pi(j)} \left(Q_{s,t,ij} - I_{s,t,ij}^2 x_{ij}\right) + b_j \tilde{V}_{s,t,j} \tag{10b}$$

$$V_{s,t,j}^2 = V_{s,t,i}^2 - 2\left(P_{s,t,ij} r_{ij} + Q_{s,t,ij} x_{ij}\right) + I_{s,t,ij}^2 \left(r_{ij}^2 + x_{ij}^2\right), \forall s \in S, \forall t \in T, \forall ij \in E \tag{10c}$$

$$I_{s,t,ij}^2 = \frac{P_{s,t,ij}^2 + Q_{s,t,ij}^2}{V_{s,t,i}^2}, \forall s \in S, \forall t \in T, \forall ij \in E \tag{10d}$$

$$S_{s,t,i}^2 \le \left(S_i^{\text{ini}} + \sum_{a\in A} S_{i,a}^{\text{US,max}} z_{i,a}^{\text{US}}\right)^2 \tag{11a}$$

$$S_{s,t,i}^2 \le \left(\sum_{a\in A} S_{i,a}^{\text{NS,max}} z_{i,a}^{\text{NS}}\right)^2 \tag{11b}$$

$$S_{s,t,i}^2 = P_{s,t,i}^2 + Q_{s,t,i}^2, \forall s \in S, \forall t \in T, \forall i \in \Omega^{\text{sub}} \tag{11c}$$

$$I_{s,t,ij}^2 \le \left(I_{ij}^{\text{ini}}\right)^2 (1 - x_{ij,b}^{\text{UL}}) + \left(I_{ij,b}^{\text{UL,max}}\right)^2 x_{ij,b}^{\text{UL}}, \forall s \in S, \forall t \in T, \forall ij \in \Omega^{\text{UL}} \tag{12a}$$

$$I_{s,t,ij}^2 \le \left(I_{ij,b}^{\text{NL, max}}\right)^2 x_{ij,b}^{\text{NL}}, \forall s \in S, \forall t \in T, \forall ij \in \Omega^{\text{NL}} \tag{12b}$$

$$V_j^{\min} \le V_{s,t,j} \le V_j^{\max}, \forall s \in S, \forall t \in T, \forall j \in \Omega \tag{13}$$

$$\sum_{j\in\Omega^{\text{DG}}} z_j^{\text{DG}} = x^{\text{DG}} \tag{14a}$$

$$0 \le z_j^{\text{DG}} \le N_j^{\text{DG,max}}, \forall j \in \Omega^{\text{DG}} \tag{14b}$$

$$P_{s,t,j}^{\text{DG}} = z_j^{\text{DG}} P_{s,t}^{\text{DG,pre}}, \forall s \in S, \forall t \in T, \forall j \in \Omega^{\text{DG}} \tag{14c}$$

Equations (7a) and (7b) define the multiple contract price constraints, while (8a) and (8b) define the substation and line investment constraints. Equation (9) defines the system radial topology constraint, and (10a)–(10d) define the typical branch flow model (BFM) in a distribution system. Equations (11a)–(11c) define the substation capacity constraints, Eqs. (12a)-(12b) define the branch current constraints considering the line investments, Eq. (13) defines the voltage constraint, and (14a)–(14c) define the constraints of DG location.

3.2 The followers decision model

3.2.1 RDG investment model of DGOs

From the perspective of DGOs, their decision variables in this part are the installed RDG capacity (including PV and WTG) according to the CFD contract price signals from the DSO. The investment decision for the optimal RDG capacity is derived from the following model:

$$\max PG = -CG^{\text{inv}} + PG^{\text{oper}} - \eta^{\text{DGO}} CG^{\text{CVaR}} \tag{15}$$

The objective function (15) maximizes the profit of each DGO. It is noteworthy that the objectives and constraints are the same, but the risk preference coefficient η^{DGO} may be different for different DGOs. The mathematical formulations for the objective functions are shown in (16a)–(16c), as:

$$CG^{\text{inv}} = \frac{r(1+r)^{LT}}{(1+r)^{LT} - 1} c^{\text{DG}} x^{\text{DG}} \tag{16a}$$

$$PG^{\text{oper}} = f_1(x) + \sum_{s=1}^{S} \pi(s) f_2(x, \xi_s)$$
$$= \sum_{t=1}^{\text{T}} f^{\text{DG,CFD}} x^{\text{DG}} P_t^{\text{DG,CFD}} + \tag{16b}$$
$$\sum_{s=1}^{\text{S}} \pi(s) \sum_{t=1}^{\text{T}} f_{s,t}^{\text{WS}} (P_{s,t}^{\text{DG}} - x^{\text{DG}} P_t^{\text{DG,CFD}})$$

$$CG^{\text{CVaR}} = \beta^{\text{DGO}} + \frac{1}{1-\alpha^{\text{DGO}}} \sum_{s} \pi(s) [f_2(x, \xi_s) - \beta^{\text{DGO}}]^+ \tag{16c}$$

which are subject to:

$$CG^{\text{inv}} \le CG^{\text{inv,max}} \tag{17}$$

$$0 \le P_{s,t}^{\text{DG}} \le x^{\text{DG}} P_{s,t}^{\text{DG,pre}}, \forall s \in S, \forall t \in T \tag{18}$$

The objective function (16a) represents the cost of RDG investments, while in (16b), the first term represents the certain profit with the price and electricity of CFD fixed, and the second term represents the uncertain profit under uncertainties of RDG output and wholesale market price. Equation (16c) represents the corresponding CVaR function, Eq. (17) defines the budget limitation for any investment, and (18) defines the constraint of the RDG output.

3.2.2 PV investment and DSM model of LA

From the perspective of LAs, their decision variables in this part are the prosumers' PV capacity and location according to the PPA price signals from the DSO, and the demand-side flexible demand scheduling (mainly transferrable load). The optimal PV investment and transferrable load scheduling scheme are derived from the following model:

$$\min CL = CL^{\text{inv}} + CL^{\text{oper}} + \eta^{\text{LA}} CL^{\text{CVaR}} \tag{19}$$

The objective function (19) minimizes the cost of each LA, including a risk-neutral CLA, a risk-neutral ILA, and multiple RLAs with different risk preferences η^{LA}. The mathematical formulations for the components of the objective function are shown in (20a)-(20d), as:

$$CL^{\text{inv}} = \frac{r(1+r)^{LT}}{(1+r)^{LT}-1} \sum_{j \in \Omega^{\text{LA}}} c^{\text{PV}} x_j^{\text{PV,PSM}} \tag{20a}$$

$$CL^{\text{oper}} = \sum_{s=1}^{S} \pi(s) \sum_{t=1}^{T} \sum_{j \in \Omega^{\text{LA}}} \left(f_{s,t,j}^{\text{load}} P_{s,t,j}^{\text{buy}} - f^{\text{PPA}} P_{s,t,j}^{\text{sell}} \right) \tag{20b}$$

$$f(x, \xi_s) = \sum_{t=1}^{T} \sum_{j \in \Omega^{\text{LA}}} [f_{s,t}^{\text{load}} (P_{s,t,j}^{\text{PV,PSM}} - P_{s,t,j}^{\text{sell}}) + f^{\text{PPA}} P_{s,t,j}^{\text{sell}}] \tag{20c}$$

$$CL^{\text{CVaR}} = \beta^{\text{LA}} + \frac{1}{1-\alpha^{\text{LA}}} \sum_{s} \pi(s) \left[f(x, \xi_s) - \beta^{\text{LA}} \right]^+ \tag{20d}$$

which are subject to:

$$CL^{\text{inv}} \le CL^{\text{inv,max}} \tag{21}$$

$$0 \le x_j^{\text{PV,PSM}} \le N_j^{\text{PV,max}}, \forall j \in \Omega^{\text{LA}} \tag{22}$$

$$P_{s,t,j}^{\text{buy}} - P_{s,t,j}^{\text{sell}} = P_{s,t,j}^{\text{load}} - P_{s,t,j}^{\text{PV,PSM}} - \Delta P_{s,t,j}^{\text{TL}} \tag{23}$$

$$u_{s,t,j}^{\text{sell}} + u_{s,t,j}^{\text{buy}} \le 1 \tag{24a}$$

$$0 \le P_{s,t,j}^{\text{sell}} \le u_{s,t,j}^{\text{sell}} P_{t,j}^{\text{sell,max}} \tag{24b}$$

$$0 \le P_{s,t,j}^{\text{buy}} \le u_{s,t,j}^{\text{buy}} P_{t,j}^{\text{buy,max}} \tag{24c}$$

$$0 \le P_{s,t,j}^{\text{PV,PSM}} \le x_j^{\text{PV,PSM}} P_{s,t,j}^{\text{PV,pre}} \tag{25}$$

$$\sum_{t=1}^{\text{T}} \Delta P_{s,t,j}^{\text{TL}} = 0 \tag{26a}$$

$$0 \le \Delta P_{s,t,j}^{\text{TL}} \le \Delta P_{t,j}^{\text{TL,max}}, \forall s \in S, \forall t \in T, \forall j \in \Omega^{\text{LA}} \tag{26b}$$

The objective function (20a) represents the PV investment cost of prosumers in each LA, and (20b) represents the operational cost of each LA. Equation (20c) represents the anticipated benefit of installed PV units from self-sufficiency and electricity sale from multiple uncertain sources, namely, PV output uncertainty, active load and the price of electricity purchased from the DSO, whereas (20d) represents the corresponding CVaR function. Equation (21) defines the budget limitation for any investment, Eq. (22) defines the capacity limitation of the PV installation at each node, and (22) defines the power balance constraint. Equations (24a)-(24c) define the constraints that only one state (e.g., electricity purchasing or selling) can be permitted at the same time. Equation (25) defines the PV output constraint, and (26a)–(26b) define the constraints of transferrable load based on the principle that the total electricity consumption during 24 h remains unchanged.

3.2.3 DGOs and LAs interactive trading model

The premise of electricity trading between each DGO and LA is that both participants can thereby obtain higher profits than by trading with the DSO. From the perspective of DGOs, the decision variables are the CFD contract pricing strategies and trading decisions, whereas from the perspective of LAs, the decision variables are the trading decisions based on the price signals from DGOs. Their optimal electricity trading decisions are derived from the following model:

$$\max PG^{\text{trans}}=CS^{\text{DGO}}+PG^{\text{LA}}+PS^{\text{net}} \tag{27a}$$

$$CL^{\text{trans}}=PS^{\text{LA}}+PG^{\text{LA}} \tag{27b}$$

$$CL_j^{\text{trans}}\le CL_j^{\text{oper}} \tag{27c}$$

The objective function (27a) maximizes the profit of each DGO considering the network usage cost. The network usage fee increases with the increasing distance and electricity exchange. In (27a), the first term is shown in (6b), the second term is shown in (28), and the third term is shown in (6c). Equations (27b) and (27c) ensure that the operational costs of LAs trading with DGOs in (18) are not less than the operational costs of LAs trading with the DSO in (10b) at each node *j*.

$$PG^{\text{LA}}=\sum_{t=1}^{T}\sum_{i\in\Omega^{\text{DG}}}\sum_{j\in\Omega^{\text{LA}}}\lambda_{i,j}^{\text{DGO,LA}}f_{i,j}^{\text{DGO,LA}}z_i^{\text{DG}}P_t^{\text{DG,CFD}} \tag{28}$$

and are subject to (24), (26), and the constraints as follows:

$$f^{\text{DG,PFD}}\le f_{i,j}^{\text{DGO,LA}}\le f^{\text{DG,max}},\forall i\in\Omega^{\text{DG}},\forall j\in\Omega^{\text{LA}} \tag{29}$$

$$\sum_{j\in\Omega^{\text{LA}}}\lambda_{i,j}^{\text{DGO,LA}}\le 1,\forall i\in\Omega^{\text{DG}} \tag{30a}$$

$$\sum_{i\in\Omega^{\text{DG}}}\lambda_{i,j}^{\text{DGO,LA}}\le 1,\forall j\in\Omega^{\text{LA}} \tag{30b}$$

$$\sum_{j\in\Omega^{\text{LA}}}\lambda_{i,j}^{\text{DGO,LA}}\le z_i^{\text{DG}},\forall i\in\Omega^{\text{DG}} \tag{30c}$$

$$\sum_{i\in\Omega^{\text{DG}}}\lambda_{i,j}^{\text{DGO,LA}}z_i^{\text{DG}}P_{t,i}^{\text{DG,CFD}}\le P_{s,t,j}^{\text{load}}-\Delta P_{s,t,j}^{\text{TL}}, \quad \forall s\in S,\forall t\in T,\forall j\in\Omega^{\text{LA}} \tag{30d}$$

$$P_{s,t,i}^{\text{DG}}\le z_i^{\text{DG}}P_{s,t}^{\text{DG,pre}},\forall s\in S,\forall t\in T,\forall i\in\Omega^{\text{DG}} \tag{31}$$

$$P_{s,t,j}^{\text{buy}}-P_{s,t,j}^{\text{sell}}=P_{s,t,j}^{\text{Load}}-P_{s,t,j}^{\text{PV,PSM}}-\lambda_j^{\text{DGO,LA}}P_{t,i}^{\text{DG,CFD}} -\Delta P_{s,t,j}^{\text{TL}},\forall s\in S,\forall t\in T,\forall i\in\Omega^{\text{DG}},\forall j\in\Omega^{\text{LA}} \tag{32}$$

The first term in (28) represents the cost of each LA purchasing electricity from the DSO, and the second term represents the cost of each LA purchasing electricity from DGOs. Equation (29) defines the pricing limitation of each DGO selling electricity to LAs. Equations (30a) and (30b) define the constraints that an installed RDG node of DGOs can only trade with an end-user node, and vice versa. Equation (30c) defines the renewable electricity trading premise that DGOs have set up RDG at the corresponding nodes, while (30d) defines the renewable energy trading premise that an LA needs to absorb all the electricity purchasing from DGOs. It is noteworthy that the PV output of prosumers is excluded in (30d) because the prosumers' PV electricity trading scheme of each LA will be adjusted according to the trading and demand response results. Equation (31) defines the constraint of RDG output at each node, and (32) defines the power balance constraint of an LA, which is different from (23).

3.3 Solution method

The solution structure as shown in Fig. 4 is designed to analyze the proposed one-leader and multi-follower model. As demonstrated, the proposed model is divided into a master problem and a subproblem which are solved following a specific sequence. The particle swarm optimization (PSO) method is introduced to find the best long-term contract prices, and the CPLEX solver is used to solve the decision model of each agent.

3.3.1 The master problem

The target of the master problem is to calculate the optimal substation and line investment solution under the best contract pricing strategy. First, a particle swarm of the contract prices is generated. Secondly, each DGO and LA make investment and trading decisions according to the price signals, and then provide their electricity trading schemes to the DSO as feedback. Subsequently, the DSO calculates the net injection power of each node based on the feedback and makes the optimal substation and line investment decision. Finally, the net saving for the DSO is taken as the fitness function to make the optimal pricing strategy.

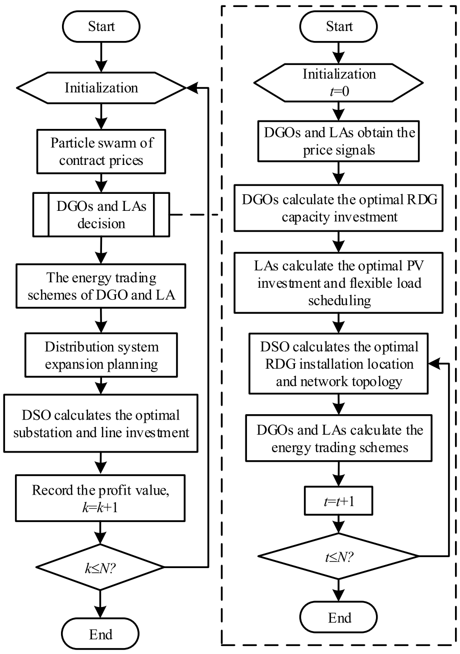

Fig. 4 Flowchart for solving the proposed model

3.3.2 The subproblem

The target of the subproblem is to calculate the optimal RDG capacity and location, and the electricity trading strategy of DGOs and LAs. First, each DGO calculates the optimal RDG capacity investment option according to the price signals, and provides the investment plan for the DSO. Simultaneously, each LA calculates the optimal PV investment and transferrable load scheduling option. Secondly, the DSO calculates the optimal RDG location of DGOs and network topology based on the principle of minimizing substation and line investment costs, and then provides the network topology for DGOs and LAs to compute the electricity network usage costs. Finally, each DGO calculates the optimal contract pricing strategy in the renewable electricity trading process between the DGO and the LA. Meanwhile, each LA calculates the optimal electricity trading scheme and flexible load re-scheduling option.

4 Numerical results

4.1 Basic data

The proposed model is tested on the Portugal 54-node distribution system, where the rated voltage is 15 kV. The initial network topology can be found in [22], and comprises 2 existing substations and 17 existing lines. The predicted total load is 48.67 MW and the system power factor is 0.9. There are 34 new load nodes, 2 candidate new substations, and 44 new candidate lines. The parameters of the candidate substations can be found in [22] and [23]. The parameters of the candidate lines are shown in Table 1, and the parameters of the candidate RDGs are shown in Table 2.

Table 1 Parameters of the candidate lines

Line type	R (Ω)	X (Ω)	Current limit (A)	Cost (10^4\$)
A1	0.85	0.4	150	12.4
A2	0.45	0.35	275	16
A3	0.24	0.32	450	23
A4	0.13	0.12	600	30.2
A5	0.08	0.06	800	38

Table 2 Parameters of the candidate RDGs

DG	Capacity (MW)	Cost (10^4\$)	CFD electricity of each unit during 24 h (MWh)
WTG	0.1	20	0.78
PV	0.2	40	1.52

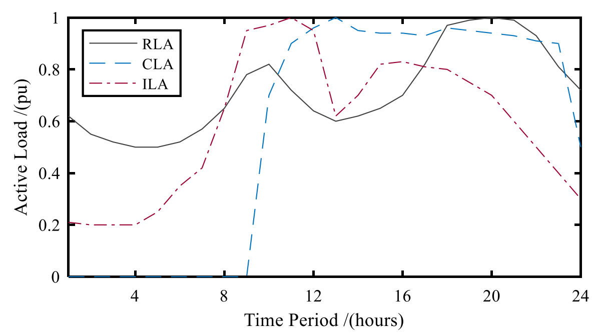

Fig. 5 The active load curve of residential, commercial, and industrial loads

The typical predicted loads, i.e. residential, commercial and industrial, are shown in Fig. 5. The predicted active loads of resident, commerce and industry are 32.48 MW, 9.66 MW and 6.53 MW, respectively. Based on different risk preferences, DGOs and RLAs are respectively divided into three types, including risk-averse, risk-neutral and risk-seeking. The three types are respectively defined as: $\eta^{\mathrm{RLA1}} = \eta^{\mathrm{DGO1}} = 0.1, \eta^{\mathrm{RLA2}} = \eta^{\mathrm{DGO2}} = 0.5$, $\eta^{\mathrm{RLA3}} = \eta^{\mathrm{DGO3}} = 0.9$. The risk preferences of the CLA and ILA are regarded as risk-neutral where $\eta^{\mathrm{CLA}} = \eta^{\mathrm{ILA}} = 0.5$.

The typical prices of electricity purchased from the external grid, and electricity sold to end users, are shown in Fig. 6. The electricity network usage price is set to 0.5 \$/(MWh·km) and power loss price is set to 50 \$/MWh. The predicted output of wind power and PV can be

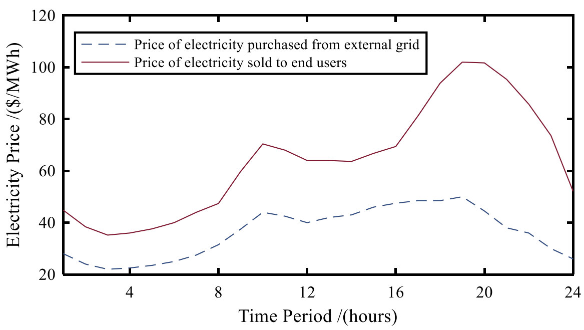

Fig. 6 Price curves for the DSO purchasing electricity from the external grid and selling electricity to users

found in [1]. Considering the uncertainty of the RDG, prices and active loads, 10,000 uncertainty scenarios are generated by Monte Carlo simulation. Then, the K-means clustering method is used to select 12 discrete scenarios.

The penetration of RDG in the system is assumed to be above 30%. The price ranges of CFD contracts for DGOs' PV units and WTG units are 62–73 $/MWh and 56–66 $/MWh, respectively, while the price range of a PPA contract for LAs' PV units is 40–60 $/MWh. The number of particles is set to 50 and the number of iterations is set to 20.

4.2 Results and analysis

To demonstrate the effectiveness of the proposed model, three cases are considered:

Case 1: DSEP with RDG assets of DGOs;

Case 2: DSEP with RDG assets of DGOs and LAs;

Case 3: DSEP with RDG assets of DGOs and LAs considering the electricity trading between them.

The results of these case studies are summarized in Tables 3, 4, 5, 6. Table 3 depicts the distribution system expansion option including substation and line investments, Table 4 reveals the two long-term contract prices provided for DGOs and LAs, Table 5 lists the RDG assets investments of DGOs and LAs, and Table 6 reveals the costs and revenues of DSO in the DSEP problem.

4.2.1 Results of case 1

In this case, the DSO makes the distribution system expansion decisions considering RDG assets of DGOs. Table 6 reveals that the annual net savings for the DSO in the planning horizon are 1.721×10^6 $. The total cost and revenue of the DSO are the highest in the three case studies since the DSO is the sole supplier of electricity to end-users. The total distribution system investment cost is 4.887×10^6 $, of which 41.64% is the cost of line investments. Table 3 reveals that the existing substation S2 is reinforced and the new substation

Table 3 The optimal distribution system expansion option of the DSO

Network assets	Case1	Case 2	Case3
Substation	**S2 (13.3)**	**S1 (16.7)**	**S3(22.2)**
	S4 (22.2)	S4 (22.2)	S4(22.2)
Existing line	51–1 (A4)	51–1 (A4)	51–1 (A4)
	51–3 (A3)	51–3 (A3)	51–3 (A3)
	3–4 (A3)	3–4 (A3)	3–4 (A3)
	4–7 (A2)	4–7 (A2)	4–7 (A2)
	4–5 (A2)	7–8 (A2)	7–8 (A2)
	7–8 (A2)	1–9 (A2)	1–9 (A2)
	1–9 (A2)	52–14 (A2)	52–14 (A2)
	52–14 (A5)	14–15 (A2)	14–15 (A2)
	14–15 (A3)	52–11 (A3)	52–11 (A3)
	15–16 (A3)	11–12 (A3)	11–12 (A3)
	52–11 (A4)		
	11–12 (A3)		
New line	19–20 (A1)	19–20 (A1)	19–20 (A1)
	18–19 (**A2**)	18–19 (**A1**)	18–19 (**A1**)
	18–17 (**A3**)	18–17 (**A1**)	18–17 (**A3**)
	21–18 (**A5**)	21–18 (**A3**)	21–18 (**A5**)
	54–21 (**A4**)	54–21 (**A5**)	54–21 (**A3**)
	54–22 (**A5**)	54–22 (**A5**)	54–22 (**A3**)
	23–22 (**A2**)	23–22 (**A3**)	23–22 (**A5**)
	24–23 (**A4**)	24–23 (**A4**)	24–23 (**A5**)
	25–24 (**A2**)	25–24 (**A5**)	25–24 (**A4**)
	26–27 (**A1**)	26–27 (**A2**)	26–27 (**A1**)
	28–27 (**A2**)	28–27 (**A3**)	28–27 (**A4**)
	54–30 (**A5**)	54–30 (**A4**)	54–30 (**A4**)
	29–30 (**A1**)	29–30 (**A3**)	29–30 (**A3**)
	43–30 (**A5**)	43–30 (**A2**)	43–30 (**A2**)
	37–43 (A1)	37–43 (A1)	37–43 (A1)
	31–37 (A1)	31–37 (A1)	31–37 (A1)
	45–12 (**A3**)	45–12 (**A2**)	45–12 (**A2**)
	44–45 (A2)	44–45 (A2)	44–45 (A2)
	38–44 (A2)	38–44 (A2)	38–44 (A2)
	39–38 (A1)	39–38 (A1)	39–38 (A1)
	32–39 (A1)	32–39 (A1)	32–39 (A1)
	33–34 (A1)	35–34 (A1)	35–34 (A1)
	36–35 (A1)	36–35 (A1)	36–35 (A1)
	53–36 (A1)	53–36 (A1)	53–36 (A1)
	53–28 (**A1**)	53–28 (**A2**)	53–28 (**A2**)
	53–41 (**A1**)	53–41 (**A2**)	53–41 (**A2**)
	40–41 (**A2**)	40–41 (**A1**)	40–41 (**A1**)
	16–40 (A2)	42–41 (**A1**)	42–41 (**A2**)
	48–42 (A1)	48–42 (A1)	48–42 (A1)
	49–48 (A1)	49–48 (A1)	49–48 (A1)
	50–49 (A1)	50–49 (A1)	50–49 (A1)
	47–42(A1)	47–42(A1)	47–42(A1)
	46–47 (A2)	14–46 (A1)	14–46 (A1)
	14–46 (**A2**)		

Table 4 The optimal renewable energy contract pricing strategy

Contract	DG assets	Prices ($/MWh)		
		Case1	Case 2	Case3
CFD	PV	62.8	68	68
	WTG	65.87	56.57	56.57
PPA	PV	–	40	40

Table 5 The optimal RDG investment option of DGOs and LAs

Agents	RDG type	The location and capacity (MW) of RDG assets		
		Case1	Case 2	Case3
DGOs	PV	10 (0.4)	5 (1)	5 (1)
		16 (0.2)	8 (0.6)	10 (1)
		32 (1)	9 (0.2)	16 (1)
		33 (1)	10 (1)	20 (0.4)
		39 (0.4)	16 (1)	31 (0.6)
		50 (1)	20 (0.2)	32 (0.4)
			31 (0.4)	33 (1)
			32 (0.4)	37 (0.6)
			33 (1)	38 (1)
			37 (0.6)	39 (0.6)
			38 (1)	50 (0.4)
			39 (0.6)	
	WTG	1 (1)	1 (0.1)	1 (0.2)
		8 (1)	8 (1)	8 (1)
		26 (1)	32 (1)	32 (1)
		27 (1)	33 (1)	33 (1)
		32 (0.2)	49 (0.6)	49 (0.5)
		33 (1)	50 (0.3)	50 (0.33)
		34 (1)		
		35 (0.9)		
		36 (0.9)		
		40 (1)		
		41 (0.7)		
		49 (0.3)		
		53 (1)		
LA	PV	–	3 (0.4)	3 (0.4)
			4 (0.6)	4 (0.6)
			7 (0.4)	7 (0.4)
			9 (0.6)	9 (0.6)
			26 (0.6)	26 (0.6)
			28 (0.4)	28 (0.4)
			36 (0.2)	36 (0.2 s)

S4 is installed. This is the most economical planning option in the three case studies. The distribution system investment and RDG assets investment options are

Table 6 Profits of the DSO in the three case studies

Cost and revenue of DSO ($10^6$$)	Case 1	Case 2	Case 3
Cost of substation investments	2.852	3.667	3.667
Cost of line investments	2.035	1.620	1.629
Cost of power loss	0.887	0.507	0.530
Cost of electricity purchased from external grid	8.735	8.775	8.752
Cost of electricity purchased from DGO	3.753	2.675	1.708
Cost of electricity purchased from LA	/	0.020	0.020
Revenue earned from selling electricity to LA	19.982	19.162	18.104
Revenue earned from network usage	/	/	0.006
Total cost	18.261	17.263	16.265
Total revenue	19.982	19.199	18.110
Net savings for DSO	1.721	1.936	1.845

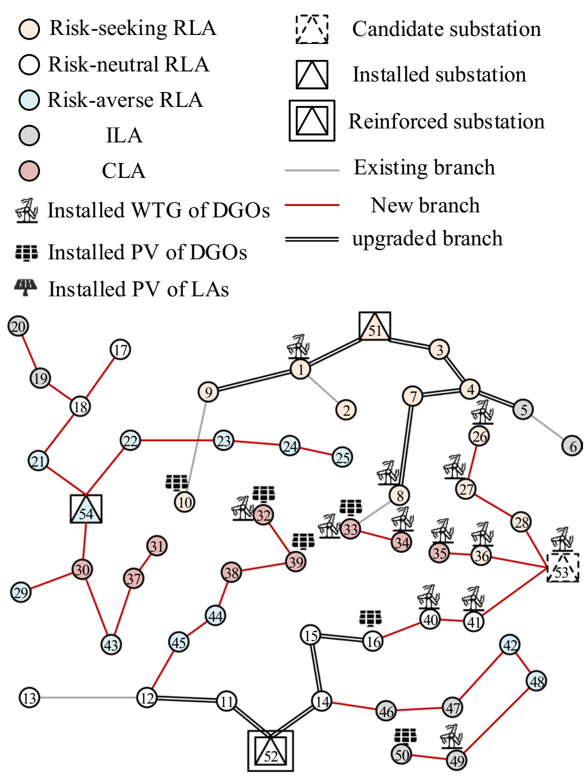

Fig. 7 The distribution system expansion option in Case 1

shown in Fig. 7. The schematic diagram demonstrates that the candidate substation S3 is not installed owing to an immense amount of WTG units integrated into the neighboring nodes. However, both the existing line upgrading investments and new line installation investments in Case 1 are the largest in these case studies. That is to say, the DSO in Case 1 defers the substation expansion but increases the line investments.

The total cost of the DSO purchasing electricity is 12.488×10^6 \$, of which 30.05% is the cost of the DSO purchasing electricity from DGOs. As demonstrated in Table 4, the CFD contract prices of the electricity generated by WTG and PV are 62.8 \$ and 65.87 \$, respectively. As shown in Table 5, the total installed RDG capacity is 16 MW and the penetration of RDG is 32.88% in the system, which is the highest in the three cases. Moreover, Fig. 7 also reveals that the locations of the PV units optimized by the DSO are mainly in the commercial and industrial load nodes, while few PV units are installed in residential load nodes.

4.2.2 Results of case 2

In this case, the RDG assets of DGOs and LAs are taken into account in the DENP problem. Table 6 reveals that the annual net saving for the DSO in the planning horizon is 1.936×10^6 \$, which is the most profitable option among the three case studies. Compared with Case 1, the revenue of the DSO has decreased from 19.982×10^6\$ to 19.162×10^6\$ as a result of the end-user electricity consumption characterized by partial self-sufficiency. The total distribution system investment cost is 5.287×10^6 \$, of which 30.64% is the cost of line investments. The distribution system investment and RDG assets investment options are shown in Fig. 8. It can be demonstrated from Table 3 and Fig. 0.8 that the substation and line investment option in Case 2 is significantly different from that in Case 1. The substation investments in Case 2 are reduced where the candidate new substations S3 and S4 are installed, and the line investments in Case 2 are reduced where the existing branch 4–5 and branch 15–16 are not upgraded, and the candidate new branch 16–40 and branch 46–47 are replaced by branch 53–51.

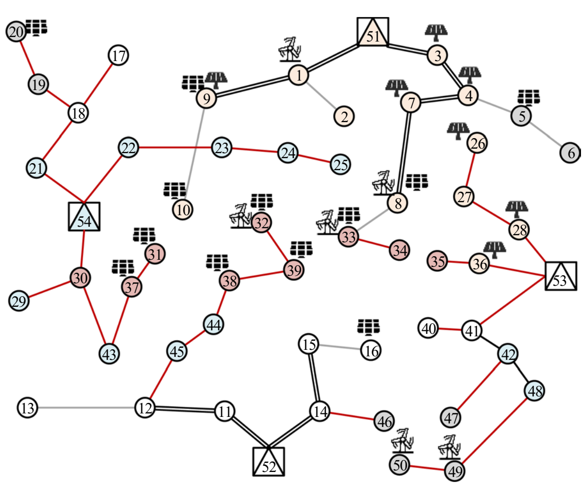

Fig. 8 The distribution system expansion option in Case 2

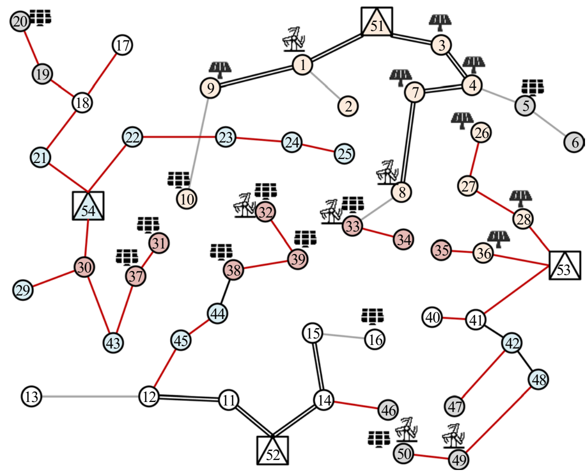

Fig. 9 The distribution system expansion option in Case 3

The power loss cost in Case 2 is the lowest among the three case studies, which is 57.5% of that in Case 1.

The total cost of the DSO purchasing electricity is 11.47×10^6 \$, of which 23.32% is the cost of the DSO purchasing electricity from DGOs and 0.2% is the cost of the DSO purchasing electricity from an LA. As demonstrated in Table 4, the PPA price and two kinds of CFD prices are 40 \$/MWh, 68 \$/MWh, and 56.57 \$/MWh, respectively, where the wind electricity price is lower and the solar electricity price is higher than in Case 1. As shown in Table 5, the total installed RDG capacity is 14.8 MW and the penetration of RDG is 30.41%.

From the perspective of the LA, the benefits of RDG installation come from two sources, namely, electricity self-sufficiency with a proportion of 96.24%, and electricity sold to the DSO in the amount of of 3.76%. The results demonstrate that prosumers may set up an RDG without considering selling electricity to the DSO. On the other hand, the impact of long-term contract price on DGOs is more significant than that on prosumers.

4.2.3 Results of case 3

In this case, the RDG assets of DGOs and LAs and the electricity trading between those agents are both taken into consideration. The results reveal that the annual net saving for DSO in the planning horizon are 1.845×10^6 \$. The annual total cost and total revenue of DSO are the lowest in these cases as a result of the end-user electricity consumption being supplied from three sources including DSO, DGOs, and LAs. The total distribution system investment cost is 5.296×10^6 \$, of which 30.76% is the cost of line investments. The distribution system investment and RDG assets investment options are shown in Fig. 9, which reveals that the network topology and substation investments in Case

Table 7 Energy Trading results of DGOs and LAs in Case 3

RDG assets of DGOs	RDG integration locations	End-user load locations	Load types	RDG capacity (MW)	Price ($/MWh)
PV	5	5	Industry	1	80.52
	10	10	Resident	1	70.54
	16	16	Resident	1	69.38
	19	20	Industry	0.4	83.4
	50	50	Industry	0.4	75.18
WTG	1	1	Resident	0.2	66.18
	8	8	Resident	1	69.38
	50	50	Industry	0.3	74.1

3 are the same as those in Case 2. But it can be demonstrated from Table 3 that the DSEP results of those two cases are significantly different in the type alternatives of new line investments.

The total cost of the DSO purchasing electricity is 10.48×10^6 \$, of which 16.30% is the cost of the DSO purchasing electricity from DGOs and 0.2% is the cost of DSO purchasing electricity from LA. As demonstrated in Tables 4 and 5, the contract prices and total capacity of installed RDG in Case 3 are the same as those in Case 2. However the locations of the RDG are different in the two cases.

From the perspective of DGOs, the total revenue of selling renewable energy is 2.803×10^6 \$, of which 60.92% is from selling to the DSO and 39.08% is from selling to LAs. The renewable energy trading results between DGOs and LAs are shown in Table 7. This reveals that 47.5% of installed PV units and 37.5% of installed WTG units are involved in the electricity trading between DGOs and LAs. Except for where the DGO at node 19 trades with the LA at node 20, all electricity trading processes between DGOs and LAs are implemented locally. The results reveal that the price of electricity sold to ILA is higher than that to RLAs. It means that there is a higher probability of electricity transactions between DGOs and ILA than between DGOs and other LAs.

Comparisons of the active load in node 5 and the total load are shown in Fig. 10. The schematic diagram reveals that considering the electricity trading between DGOs and LAs can affect the distribution system investments since the LAs may actively change their electricity consumption habits to adapt to the renewable energy trading with DGOs.

Finally, it is assumed that the DSO and DGOs also sign PPA in the long-term renewable energy trading process. In this light, a comparison of the renewable energy prices with different contracts is performed and shown in Fig. 11. It can be seen that when the risk

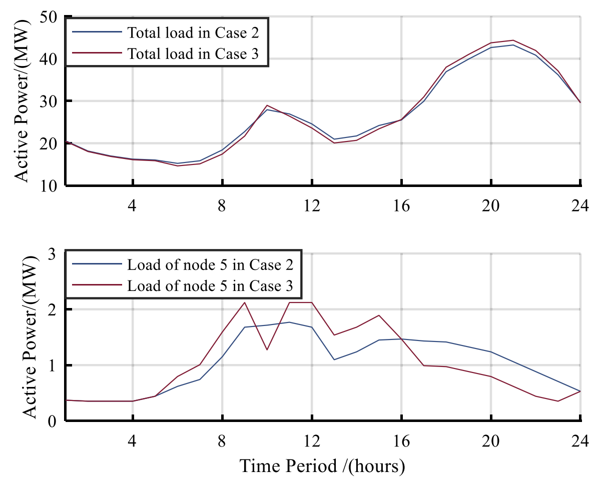

Fig. 10 The active load of node 5 and the total load in Case 2 and Case3

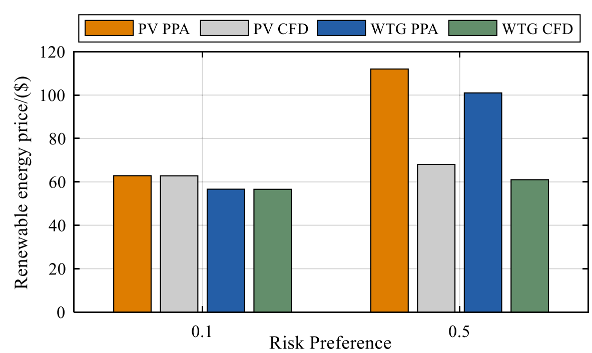

Fig. 11 The prices of PV and WTG electricity with different long-term contracts

preference of a DGO is risk-neutral, the risk of a DGO investing in RDG with CFD is significantly lower than that with PPA, where the CFD price is nearly 60% of the PPA price. It means that when the RDG penetration is nearly 30% and half of the RDG units belong to risk-neutral DGO, the proposed CFD contract can reduce the cost for the DSO purchasing renewable energy from DGOs by 20%, thus reducing the total cost of the DSO purchasing electricity by 4.88%.

5 Conclusions

A bi-level Stackelberg framework is established to address the distribution system expansion planning problem in the electricity trading context, featuring different RDG investors, namely, DGOs and prosumers, and the electricity trading between DGOs and LAs. Two long-term contracts are introduced to adapt to the renewable energy trading process between multiple agents, and the CVaR method is used to model the investment and trading behaviors of DGOs and LAs with different risk preferences. The numerical studies reveal that whether the prosumers are present in the distribution system or DGOs intend to trade with end users, the proposed model enables the DSO to flexibly adjust contract pricing strategy and RDG location to defer distribution system expansion, i.e., the proposed model provides the DSO with great flexibility and initiative in the DSEP problem with the ever-expanding renewable energy. Compared with only considering feed-in tariff, the pattern of the two long-term contracts can encourage renewable energy investments at a lower cost. When the RDG penetration is 30%, the proposed pattern can reduce the annual cost of a DSO purchasing renewable energy from DGOs by 20% and the annual total cost of a DSO purchasing electricity by 4.88%.

Abbreviations

Indices and Sets

i, j	Index for buses
ij	Index for lines
s, t	Index for scenarios and time period
A, B	Set of substations and lines types
Ω, E	Set of system buses and branches
$\Omega^{US}, \Omega^{NS}, \Omega^{UL}, \Omega^{NL}$	Set of installation buses for candidate upgraded substation, new substation, upgraded lines and new lines
Ω^{LA}	Buses set of LA
Ω^{DG}	Buses set of candidate DG installation

Parameters

δ	Coefficient of investment cost
LT	Lifespan of each device
r	Discount rate
$c_a^{US}, c_a^{NS}, c_b^{UL}, c_b^{NL}$	Price of substations and lines investments
$c^{DG}, c^{PSM,PV}$	Price of DG investment
l_{ij}^{UL}, l_{ij}^{NL}	Candidate upgraded and new lines length
c^{Loss}	Price of power loss
$f_{s,t}^{load}$	Price of electricity charged to end users
$f_{s,t}^{WS}$	Price of electricity purchased from the external grid
$f^{PPA,min}, f^{PPA,max}$	Upper limit and lower limit of PPA price provided for LA
$f^{CFD,min}, f^{CFD,max}$	Upper limit and lower limit of CFD price provided for DGO
$N^{Nodes}, N^{EL}, N^{ES}$	Numbers of system nodes, existing lines and existing substation
$S_i^{ini}, S_{i,a}^{NS,max}, S_{i,a}^{NS,max}$	Upper capacity limits of initial substation, upgraded substation and new substation
$I_{ij}^{ini}, I_{ij,b}^{UL,max}, I_{ij,b}^{NL,max}$	Upper branch current limits of the initial, upgradedand new lines
V_j^{min}, V_j^{max}	Upper limit and lower limit of voltage
η^{DGO}, η^{LA}	Different risk preferences of DGO and LA
$\alpha^{DGO}, \alpha^{LA}$	Confidence of DGO and LA
β^{DGO}, β^{LA}	VaR values of DGO and LA
$CG^{inv,max}, CL^{inv,max}$	Upper limits of capitals of each DGO and LA
$N_j^{DG,max}$	Upper limit of DG installation of DGO at node j
$N_j^{PV,max}$	Upper limit of PV installation of prosumers at node j
$P_t^{DG,CFD}$	Active power of CFD contract decomposition curve
$P_{s,t,j}^{LA,Load}$	Active load of end users
$P_{t,j}^{buy,max}, P_{t,j}^{sell,max}$	Upper limits of LA purchasing and selling electricity
$\Delta P_{t,j}^{TL,max}$	Upper limit of transferable load

Variables

$x_{i,a}^{US}, x_{i,a}^{NS}, x_{ij,b}^{UL}, x_{ij,b}^{NL}$	Investment variables of substation and line
x^{DG}	DG investment variable of DGO
$z_j^{DG}, x_j^{PV,PSM}$	DG investment variables of DGO and prosumers at node j
$f^{DG,CFD}$	CFD price of DSO purchasing electricity from DGO
f^{PPA}	PPV price of DSO purchasing electricity from LA
$f_{i,j}^{DGO,LA}$	CFD price of LA purchasing electricity from DGO
$P_{s,t,j}^{inj}, Q_{s,t,j}^{inj}$	Node injection active power and reactive power
$\tilde{V}_{s,t,j}, \tilde{I}_{s,t,ij}$	Square of voltage and current
$P_{s,t,j}^{DG}, P_{s,t,j}^{PV,PSM}$	Active power of DG units
$\lambda_{i,j}^{DGO,LA}$	Electricity trading variable between DGO and LA
$z_j^{PSM,PV}$	Investment decision variable of prosumers' PV
$P_{s,t,j}^{PSM,PV}$	PV active power of prosumers
$P_{s,t,j}^{LA,Buy}, P_{s,t,j}^{LA,Sell}$	Variables of LA purchasing and selling electricity
$u_{s,t,j}^{LA,Buy}, u_{s,t,j}^{LA,Sell}$	Status of LA purchasing and selling electricity
$\Delta P_{s,t,j}^{TL}$	Load variation under demand side management

Acknowledgements
Not applicable

Author contributions
HG: Conceptualization, Methodology, Writing- Reviewing and Editing. RW: Data curation, Writing—Original draft preparation. SH: Writing—Reviewing and Editing. ZW: Writing—Reviewing and Editing. JL: Supervision.

Funding
This work was supported by the National Science Foundation of China under Grant 52077146 and 52307123, the Sichuan Science and Technology Program under Grant 2023NSFSC1945 and 2023YFSY0032.

Availability of data and materials
The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Received: 5 February 2023 Accepted: 2 November 2023
Published online: 01 December 2023

References

1. Gao, H., Wang, R., Liu, Y., Wang, L., Xiang, Y., & Liu, J. (2020). Data-driven distributionally robust joint planning of distributed energy resources in active distribution network. *IET Generation, Transmission and Distribution, 14*(9), 1653–1662.
2. Roy Ghatak, S., Sannigrahi, S., & Acharjee, P. (2020). Multiobjective framework for optimal integration of solar energy source in three-phase unbalanced distribution network. *IEEE Transactions on Industry Applications, 56*(3), 3068–3078.
3. Ehsan, A., & Yang, Q. (2019). Coordinated investment planning of distributed multi-type stochastic generation and battery storage in active distribution networks. *IEEE Transactions on Sustainable Energy, 10*(4), 1813–1822.
4. He, Y., Yang, N., Dong, B., Ding, L., Qin, T., Huang, Y., & Chen, C. (2019). Incremental distribution network source-load collaborative planning method considering uncertainty and multi-agent game. *Proceedings CSEE, 39*(09), 2689–2702.
5. Munoz-Delgado, G., Contreras, J., & Arroyo, J. M. (2019). Distribution system expansion planning considering non-utility-owned DG and an independent distribution system operator. *IEEE Transactions on Power Systems, 34*(4), 2588–2597.
6. Huang, C., Wang, C., Xie, N., Sun, K., Chen, F., & Huang, J. (2019). Distribution expansion planning based on strong coupling of operation and spot market. *Proceedings CSEE, 39*(16), 4716–4731.
7. Yang, N., Li, X., Liu, Y. et al. (2023) Research on distribution network planning method based on multi-lateral incomplete information evolutionary game in power market, *Power System Technology.* https://doi.org/10.13335/j.1000-3673.pst.2022.2502.
8. Nourollahi, R., Gholizadeh-Roshanagh, R., Feizi-Aghakandi, H., Zare, K., & Mohammadi-Ivatloo, B. (2022). Power distribution expansion planning in the presence of wholesale multimarkets. *IEEE Systems Journal, 17*(1), 1684.
9. Alotaibi, M. A., & Salama, M. M. A. (2018). An incentive-based multistage expansion planning model for smart distribution systems. *IEEE Transactions on Power Systems, 33*(5), 5469–5485.
10. Hu, J., Yang, G., Ziras, C., & Kok, K. (2019). Aggregator operation in the balancing market through network-constrained transactive energy. *IEEE Transactions on Power Systems, 34*(5), 4071–4080.
11. Attarha, A., Scott, P., & Thiébaux, S. (2020). Affinely adjustable robust ADMM for residential DER coordination in distribution Networks. *IEEE Transactions on Smart Grid, 11*(2), 1620–1629.
12. Han, L., Morstyn, T., & McCulloch, M. (2019). Incentivizing prosumer coalitions with energy management using cooperative game theory. *IEEE Transactions on Power Systems, 34*(1), 303–313.
13. Lu, T., Wang, Z., Wang, J., Ai, Q., & Wang, C. (2019). A data-driven stackelberg market strategy for demand response-enabled distribution systems. *IEEE Transactions on Smart Grid, 10*(3), 2345–2357.
14. Fattaheian-Dehkordi, S., Tavakkoli, M., Abbaspour, A., Fotuhi-Firuzabad, M., & Lehtonen, M. (2021). An incentive-based mechanism to alleviate active power congestion in a multi-agent distribution system. *IEEE Transactions on Smart Grid, 12*(3), 1978–1988.
15. Ming, H., Xia, B., Lee, K. Y., Adepoju, A., Shakkottai, S., & Xie, L. (2020). Prediction and assessment of demand response potential with coupon incentives in highly renewable power systems. *Protection and Control of Modern Power Systems., 5*(1), 1–14.
16. Valinejad, J., Marzband, M., Korkali, M., Xu, Y., & Al-Sumaiti, A. S. (2020). Coalition formation of microgrids with distributed energy resources and energy storage in energy market. *Journal of Modern Power Systems and Clean Energy, 8*(5), 906–918.
17. Chinmoy, L., Iniyan, S., & Goic, R. (2019). Modeling wind power investments, policies and social benefits for deregulated electricity market: A review. *Applied Energy, 242*, 364–377.
18. Anwar, M. B., Stephen, G., Dalvi, S., Frew, B., Ericson, S., Brown, M., & O'Malley, M. (2022). Modeling investment decisions from heterogeneous firms under imperfect information and risk in wholesale electricity markets. *Applied Energy, 306*, 117908.
19. Tekiner-Mogulkoc, H., Coit, D. W., & Felder, F. A. (2015). Mean-risk stochastic electricity generation expansion planning problems with demand uncertainties considering conditional-value-at-risk and maximum regret as risk measures. *International Journal of Electrical Power and Energy Systems, 73*, 309–317.
20. Salci, S., & Jenkins, G. P. (2018). An economic analysis for the design of ipp contracts for grid-connected renewable energy projects. *Renewable and Sustainable Energy Reviews, 81*, 2410–2420.
21. Xuan, A., Shen, X., Guo, Q., & Sun, H. (2021). A conditional value-at-risk based planning model for integrated energy system with energy storage and renewables. *Applied Energy, 294*, 116971.
22. Miranda, V., Ranito, J. V., & Proenca, L. M. (1994). Genetic algorithms in optimal multistage distribution network planning. *IEEE Transactions on Power Systems, 9*(4), 1927–1933.
23. Yao, W., Zhao, J., Wen, F., Dong, Z., Xue, Y., Xu, Y., & Meng, K. (2014). A multi-objective collaborative planning strategy for integrated power distribution and electric vehicle charging systems. *IEEE Transactions on Power Systems, 29*(4), 1811–1821.