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Review

A Review of Optimal Planning Active Distribution System: Models, Methods, and Future Researches

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Abstract: Due to the widespread deployment of distributed energy resources (DERs) and the liberalization of electricity market, traditional distribution networks are undergoing a transition to active distribution systems (ADSs), and the traditional deterministic planning methods have become unsuitable under the high penetration of DERs. Aiming to develop appropriate models and methodologies for the planning of ADSs, the key features of ADS planning problem are analyzed from the different perspectives, such as the allocation of DGs and ESS, coupling of operation and planning, and high-level uncertainties. Based on these analyses, this comprehensive literature review summarizes the latest research and development associated with ADS planning. The planning models and methods proposed in these research works are analyzed and categorized from different perspectives including objectives, decision variables, constraint conditions, and solving algorithms. The key theoretical issues and challenges of ADS planning are extracted and discussed. Meanwhile, emphasis is also given to the suitable suggestions to deal with these abovementioned issues based on the available literature and comparisons between them. Finally, several important research prospects are recommended for further research in ADS planning field, such as planning with multiple micro-grids (MGs), collaborative planning between ADSs and information communication system (ICS), and planning from different perspectives of multi-stakeholders.

Keywords: distributed energy resources; planning model; active distribution system; distribution network planning; optimization program

1. Introduction

For the purpose of security of energy supply and sustainability of energy utilization, renewable energy technology has experienced a rapid development all over the world. At present, renewable energy sources (RESs) share about 5% and 13% of electricity power supply in the United States of America (USA) and the European Union (EU), respectively [1]. With the promoting of "20-20-20", RESs have been greatly developed and advanced in many European countries. In Denmark, for instance, more than 42% of the load demand is supplied by wind power in 2015, where a 100% renewable energy future by 2050 is targeted [2].

Among them, plenty of renewable distributed generations (RDGs), especially distributed photovoltaic (DPVs), and distributed wind generations (DWGs), have been integrated into distribution networks. However, due to the natures of intermittent and difficult prediction, RDGs pose new challenges to distribution networks on several fronts, such as planning, design, and operation [3,4]. In this regard, ADS is introduced and perceived to be one of key technologies to alleviate aforementioned challenges [5–8].

The deterministic methods and the strategy of "fit and forget" are always adopted to deal with integration of RDGs in traditional planning of distribution networks based on the worst and low-probability scenarios, which ignores the uncertainties of RDGs and the different operation conditions. With the widespread use of distributed energy resources (DERs), the drawbacks of these deterministic methods have been increasingly emerging, such as unnecessary distribution grid reinforcements, increasing network losses, and unattainable development and environmental targets. Therefore, traditional planning methods have become barriers to improve the penetration of DERs and are no longer valid in ADS planning.

ADS planning is a complex and comprehensive mission, which needs to give not only the planning scheme of distribution networks, but also the allocation of DERs in the most economic, reliable, and safe way [9–12]. In the meanwhile, high-level uncertainties, coming from DERs, networks, and load demand, etc., increase the complexity of planning model and difficulty of finding a solution. In addition, comparing with traditional planning methods, ADS planning tools need to provide more comprehensive planning analyses from several different criteria, such as economic criterion, technical criterion and environmental criterion, in a multi-objective approach.

Optimal planning of ADS has caught the attention of researchers, and plenty of planning models and methodologies with bright characters and reference significances have emerged. In the meanwhile, several influential and noticeable reviews of optimal planning of distribution networks have been published [13–20]. In [13], authors offer a comprehensive review of the planning of smart distribution networks from the perspectives of intelligent technologies, anticipated functionalities, modern distribution concepts, policies, plans, and policies. The real world optimization problems are investigated considering multi-objective problem and multi-stakeholders in the literature review. In [14], an extended review on the planning of distribution networks is given and the differences between traditional distribution networks planning models and active planning models are discussed. Moreover, a generic multi-dimensional framework for optimal active distribution network planning is proposed to overcome the limitations of the current researches. In [15], 77 selected papers that were published from 2007 to 2014 are reviewed from perspectives of planning models and solving methods to analyze and classify the current research status of distribution networks planning problems. After that, several crucial research areas are introduced briefly to identify the future research trends of this filed. Kazmi et al. [16] also focuses on the planning problem of distribution networks, and especially provides a comprehensive review about the multi-objective models and solving algorithms in this filed. Furthermore, potential future directions in modern distribution networks planning from a multi-objective perspective have also been highlighted. Different from these review articles, many scholars [17–19] review and summary the literature about the allocation of distributed generations (DGs) and energy storage systems (ESSs) in distribution networks, respectively.

Aiming to provide a guide to distribution system, engineers and researchers on the ADS planning especially from the point view of planning models and solving algorithms, the selected articles in the field of distribution network planning published from 2010 [21–107] are reviewed in this paper. To clarify the latest research achievements, the research achievements published in the last three years accounts for more than half of these selected articles. The planning models and methods proposed in these articles are analyzed and categorized from different perspectives including objectives, decision variables, constraint conditions, and solving algorithms. At the same time, the emphasis is also given on the key theoretical issues and challenges of planning models and methodologies, which are extracted and discussed together with several suitable suggestions, including methods to deal with high-level uncertainties, methods to incorporate operational aspects into planning, integration of ESSs and DR, and methods to deal with multiple time scales. Moreover, based on the review, this paper also provides several recommended research prospects for the guidance of further research in details.

The paper is organized as follows. Section 2 analyzes the key features of ADS planning. Section 3 focuses on the analyses on models and methods of ADS planning. In Section 4, several key theoretical issues and challenges in the ADS planning are extracted and discussed. After that, several recommended research prospects are further given in Section 5. Then, Section 6 concludes this paper with several remarks of summary.

2. Key Features of ADS Planning

2.1. Definition of ADS

The CIGRE introduced the concept of active distribution network (ADN) in 2008; ADNs have systems in place to control a combination of DERs, defined as generators, loads, and storage, where distribution system operators (DSOs) have the possibility of managing the electricity flows using a flexible network topology. DERs take some degree of responsibility for system support, which depends on suitable regulatory environments and connection agreements [9]. In 2012, due to the increasing penetration of DERs, the concept of ADN was extended to ADS [10]. At present, the basic definition and framework of ADS have been well acknowledged by other important academic organization, such as IEEE and CIRED [11,12].

The transformation from traditional distribution networks to ADNs indicates that DERs are no longer integrated passively, but controlled actively and coordinated to improve the utilization of DERs. Moreover, due to the increasing penetration of DERs, the transformation from ADNs to ADSs indicates that ADSs are no longer be considered as just the distribution grids to deliver electric power to the consumers, but the compositive systems including DGs, active networks, dynamical active and flexible load demand, ESSs, and etc.

2.2. Features of ADS Planning

It is obvious that comparing with the planning of traditional distribution networks, both the definition and the connotation of ADS planning have been developed with the following key features.

2.2.1. Optimal Allocation of DGs

Due to the increasing penetration of DGs, the optimal allocation of DGs has become an important part of ADS planning and serves as a crucial available solution to satisfy load growth. If these resources are integrated optimally, many benefits can be obtained, including deferring network upgrade, improving asset utilization, reducing network energy losses, and enhancing system reliability [25,34,50,108].

In order to guarantee the secure and stable operation, DGs should be allocated to satisfy the security constraints of distribution networks. Therefore, the allocation of DGs and planning of networks should be optimized coordinately [45,61,64,87].

2.2.2. Coupling of Operation and Planning

Different from the strategy of "fit and forget", active managements (AMs) adopted in ADS enable DERs be controlled and managed cooperatively to tackle aforementioned challenges [10], as shown in Figure 1.

As shown in Figure 1, with the wide spread of fluctuate REGs and dynamical active load demand in ADSs, the effects of voltage rise/drop at their points of common coupling will be worsen, especially in rural distribution networks. It is one of the main barriers that limit the hosting capacity for dynamic active load demand and the accommodation ability for DDGs and RDGs [109]. Meanwhile, the extensive integration of various types of DGs and power electronic devices also affects the features of reactive power flow in networks. The ordinary reactive power supply such as capacitor banks are not capable of satisfying the demand of reactive power supply and voltage control adequately. Furthermore, the integration of DGs and power electronic devices with high renewable penetration will also impact the fault level brought by bi-direction fault currents, and complicate the fault conditions caused by internal faults of DGs and islanded operation of DGs [12].

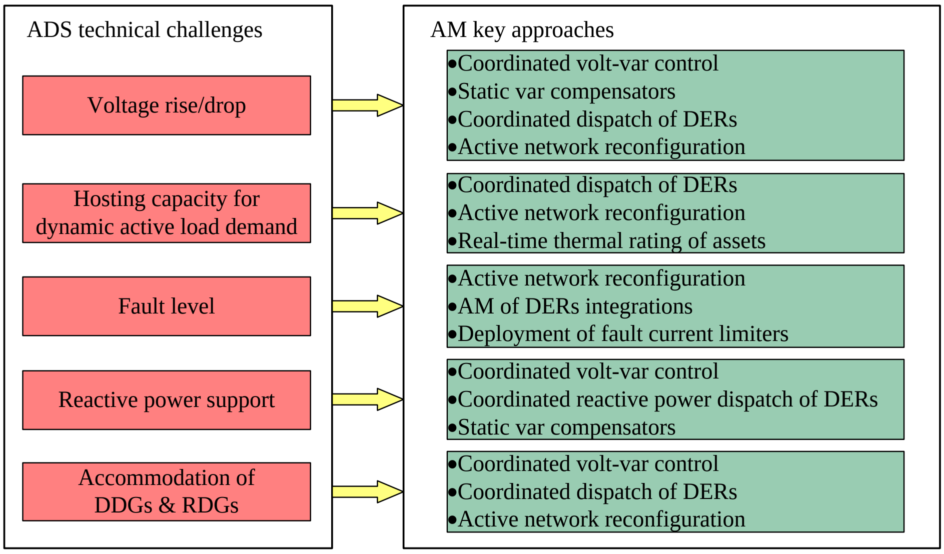


Figure 1. Technical challenges and corresponding active managements (AM) key approaches.

Aiming to addressing these undesirable conditions, several AM key approaches are introduced and listed in Figure 1. All these AM approaches, such as active network reconfiguration [35,77,97,110], coordinated volt-var control [98,109], coordinated dispatch of DERs, including DGs [22,52,94], ESSs [46,71,88,111], demand response (DR) [53,65,89,112], and optimal charging strategy of electric vehicles (EVs) [55,99], offer many potential benefits to the planning of ADSs and affect quality of the planning solution. The coupling of operation and planning is able to achieve the simultaneous optimization of planning and operation, and to identify the benefits and the effects of optimal operation on the planning solution. Therefore, operation models of AMs should be integrated into planning models to defer or avoid network expansion or reinforcement.

2.2.3. High-Level Uncertainties

High proportion of DERs integration makes ADS planning methods take comprehensive account of high-level uncertainties which come from several aspects, including DGs, networks, load demand, and wholescale market, as shown as Figure 2.

All of these aspects of high-level uncertainties have a great influence on the planning models and solving algorithms. Moreover, the combined effects among these uncertainties may further aggravate the aforementioned influence.

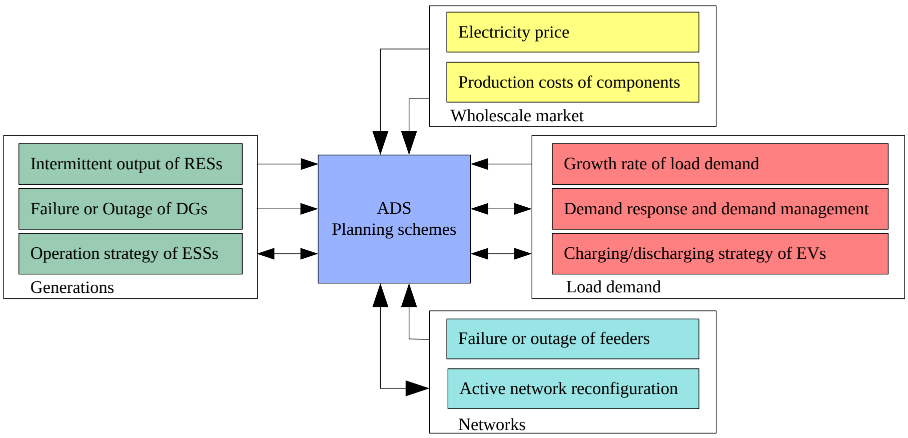


Figure 2. Multiple aspects of high-level uncertainties.

2.2.4. Optimal Allocation of ESSs

Thanks to the flexibility of power regulation, ESSs perform multiple important roles in ADSs, including peak load shaving and valley load filling [90], network upgrade deferral [93,105], frequency-voltage control [46], power quality and reliability improvement [20,60,78,101,104,105], alleviating the fluctuation of RDGs [46], obtaining arbitrage benefit [60,105], reducing energy losses [60], and providing a time varying power energy management, etc.

Therefore, the allocation of ESSs (sizing and sitting) has a great impact on the ADS planning and has been perceived to be one of indispensable parts of ADS planning [67].

2.2.5. Multiple Objective Approach

When it comes to traditional distribution networks, economic criterion is always adopted to be the optimization objective for selecting planning schemes. However, there are more objectives for ADS planning.

In ADS, due to the natures of intermittency and difficult prediction, DERs' integration poses great challenges for secure and stable operation of ADS. In the meanwhile, more and more electric devices require higher power quality. Therefore, the system reliability and power quality have become crucial objectives for ADS planning.

Moreover, the limited utilization of the installed renewable source based power generators has become too severe to increase the penetration of RDGs, and the wind/solar power curtailment has become a frequent occurrence. The environmental and economic benefits brought by RDGs are greatly reduced. Therefore, how to improve the penetration and utilization of RDGs should be integrated into the planning targets.

On the whole, ADS planning is a multi-objective optimal problem for both planning of networks and allocations of DERs under the conditions of high-level uncertainties, in process of which operation models of AMs are integrated into ADS planning for the purpose of increasing economic efficiency, enhancing system reliability, and improving the utilization of RDGs.

3. ADS Planning Model

3.1. Problem Formulation

The optimal mathematic model of ADS planning is similar to traditional distribution network planning, which can be formulated as a typical optimization problem. However, comparing with the traditional one, there are more decision variables, more comprehensive objectives, more complex constraints, and higher level uncertainties in ADS planning models. The basic mathematic model of ADS planning is shown as:

$$\begin{aligned} &\min F(x_{st}, y_{st}) = [OF_1, OF_2, \ldots, OF_M] \\ &\text{s.t.} \begin{cases} G(x_{st}, y_{st}) = 0 \\ H(x_{st}, y_{st}) \leq 0 \\ 1 \leq st \leq N_{\mathrm{ST}} \end{cases} \end{aligned} \tag{1}$$

where, x_{st}, y_{st} are the decision variables for planning networks and allocations of DERs, including possible network topologies, possible locations, sizes and types of substations and DERs. OF_1, OF_2, … , OF_{M}, are the optimal objectives of planning model, such as investment, maintenance and operation costs, indexes of reliability, and power curtailment level of RDGs. $G(.)$ and $H(.)$ are the equality constraints and inequality constraints. Moreover, N_{ST} is the number of planning stage; when $N_{\mathrm{ST}} = 1$, the planning model is a static planning model, otherwise the model is a dynamic multi-stage planning model.

3.2. Decision Variables

The decision variables of ADS planning consist of the variables of traditional distribution networks, as well as the additional variables of DERs, as shown in Table 1. The distribution of decision variables in these surveyed papers is shown in Figures 3 and 4.

Table 1. Decision variables of ADS planning models.

Types	Decision Variables	References
Traditional variables	Locations and sizes of new substations	[26,29,30,32,36,38,54,55,58,66,80,85,89]
	Sizes of existing substations for reinforcement	[24,26,27,29,32,34,36,38,42,52,54,58,64,66,73,80,85,89,95,96,99]
	Locations and sizes of new feeders	[24,26,28–32,38,39,43,49,50,54–56,58,63,66,71,74,80,84,85,89,91,106]
	Sizes of existing feeders for reinforcement	[21,23,24,26,27,29,31,34–37,41–43,48–50,52,53,59,66,67,71,73,75,81,84,86,95,96,99]
	Locations of reserve feeders and interconnection switches	[23,24,28,29,31,32,36,38,50,66,81,82,101]
Additional variables	Locations, sizes, and types of dispatchable distributed generations (DDGs)	[23–25,27,31–35,38–43,45,48,50,61,66,72,77,81,83,84,86,96,97,100,102]
	Locations, sizes, and types of RDGs	[22,25,34,35,44,48,51,53,58,62,64–66,68,74–76,79,81,88,89,93,98,99,103,107]
	Locations of new dynamic active load demand (e.g., charging station of EVs)	[23,47,54,55,78,80,82,85]
	Locations, sizes, and types of centralized/distributed ESSs	[32,46,57,60,69–72,75,83,87,90,92,94,101,104,105]
	Locations and sizes of voltage control devices (e.g., capacitor banks and Static var compensator (SVC))	[37,41,52,63,68,75,77,79,88,96]

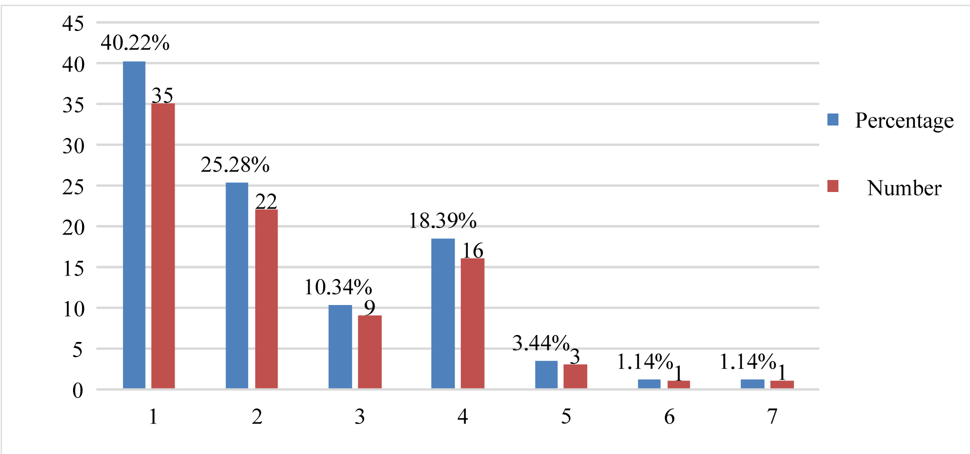


Figure 3. Distribution of the considered numbers of decision variables.

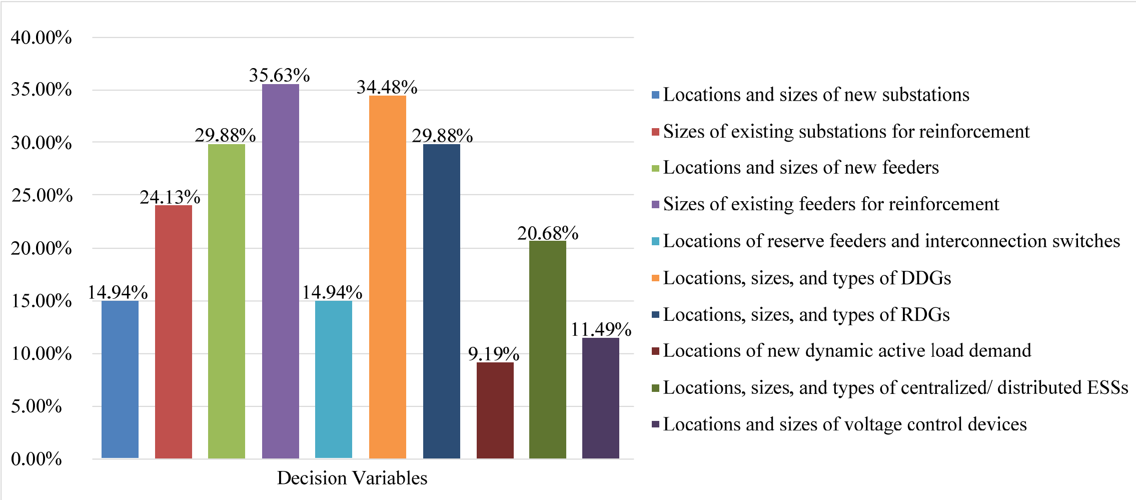


Figure 4. Distribution of decision variables in the literature survey.

Based on the results shown in Figure 3, the numbers of decision variables in most of these articles are smaller than 5. That is because the increase of variable number will complicate the planning problem and aggravate the calculation burden of planning models. The planning model proposed in [66] is the only one involving seven decision variables to satisfy load growth, including optimal reinforcement of existing feeders and substations, or installation new ones, locations of reserve feeders, and optimal locations and sizes of DDGs and RDGs. In [32], the optimal allocations of ESSs and DDGs are integrated into distribution network expansion planning model and serve as the decision variables together with the planning of existing feeders, substations and new ones. In the process of planning, the roles of ESSs are taken into consideration including peak load shaving and reliability improvement. But the integrated planning model does not involve the allocation of RDGs.

Among these decision variables in Table 1, the variables of (1) reinforcement of existing feeders; (2) allocations of DDGs; (3) locations and sizes of new feeders; and, (4) allocations of RDGs, have attracted the most attention. Articles involving these four decision variables account for 35.63%, 34.48%, 29.88%, and 29.88%, respectively. On the contrary, few of these papers take the variables of (1) locations of reserve feeders and interconnection switches; (2) allocation of voltage control devices; and, (3) new dynamic active load demand into consideration. However, it is worth noting that these three variables are associated with AM approaches of active network reconfiguration, coordinated volt-var control, and DR, respectively. It means that, to some extent, these three AM approaches have not received sufficient attentions, which will hinder integration and utilization of DERs.

In [23,24,28,31,32,36,38,50,66,81,101], optimal locations of reserve feeders and switches are introduced into the ADS planning model to improve system reliability and reduce the financial loss brought by interrupted power supply. Different from these papers, an optimal allocation model of EVs charging station is proposed in [82], where the optimal allocation of tie lines is considered to alleviate load capability constraints in networks. The AM approach of active network reconfiguration is also beneficial to improve RES hosting capacity.

In [75], an ADS planning model is proposed to determine optimal allocation of RDGs, ESSs, and capacitor banks, as well as enforcement schemes of networks. The planning results suggest that optimal allocations of ESSs and capacitors are beneficial to improving penetration and utilization level of RDGs and achieving the upgrade deferral. Similar with [75], the benefits brought by optimal allocation of voltage control devices on accommodation of RDGs are also verified in [41,68,79,88,96].

3.3. Planning Objectives

The planning objectives of ADS can be classified as economic objectives, technical objectives, and environmental objectives. Figure 5 provides several primary planning objectives, and other objectives not on the list are always the deformations of these primary objectives. Figure 6 provides the information about number of objectives.

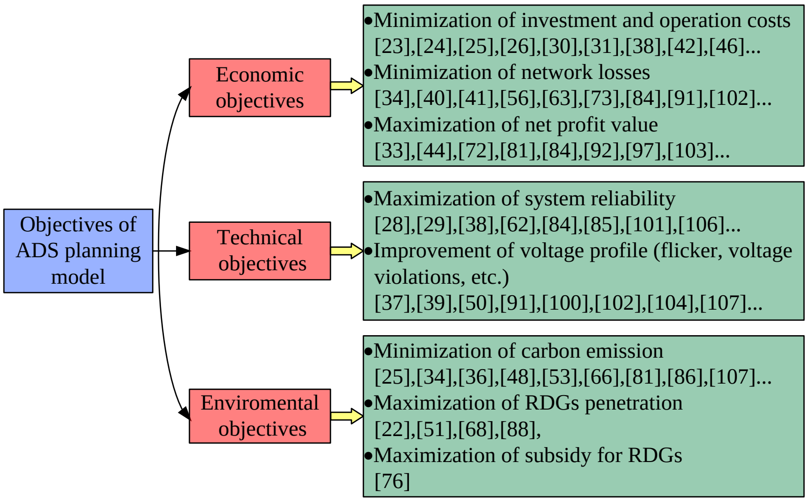


Figure 5. Planning objectives of ADS.

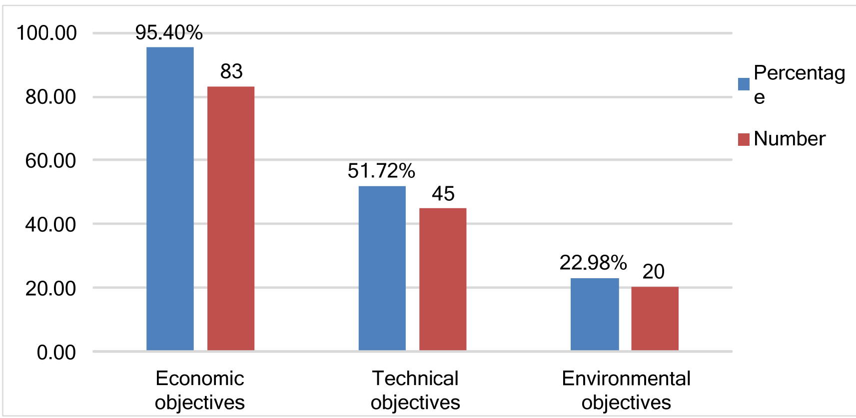


Figure 6. Distribution of the considered numbers of planning objectives.

As shown in Figure 6, economic objectives are the most common planning objectives, and 95.40% of the surveyed papers involve economic objectives. On the contrary, only 22.98% of these planning models focus on the environmental objectives.

Moreover, 71% of the surveyed papers take the single objective planning approach and the rest are multiple objective models. Although more than 53% of these single objective models also involve the technical and/or environmental factors, all of these factors are converted to economic ones by economic parameters, such as reliability costs [24,31,32,34,36,41–43,56,60,63,64,66,71,75,76,87,91] and emission costs [25,34–36,48,53,66,75,81,86,92,94,107]. However, these economic parameters are always experience dependent, and may affect the objectivity of planning solutions.

At present, the methods to deal with multiple objective planning models can be classed as the weight coefficient methods and the Pareto-based methods.

1. Weight coefficient methods, where the multi-objective model is transformed into a single objective model by means of weight coefficients. Several approaches are adopted to determine these weight

coefficients for each objective, such as user-defined fixed weight [39,65], analytic hierarchy process [57,107], stochastic weights [63], fuzzing mathematics method [83], and bargaining function [85]. These weight coefficient methods with a priori articulation of preferences have the advantages of simplicity and convenience, but have the drawback of subjectivity at the same time.

2. Pareto-based methods, where a Pareto-optimal set or a Pareto-optimal frontier, can be obtained by means of non-dominated ranking algorithm to deal with candidate solutions. The most important advantage of this method with a posteriori articulation of preferences is that all the different objectives can be taken into account with equal attention. A set of optimal solutions can be made as available options for decision-makers from different perspectives. As a result, more than 68% of these aforementioned multi-objective planning methodologies adopt this approach to deal with multiple objectives. However, comparing with weight coefficient methods, more computation time and computational memory are required for Pareto-based methods.

3.4. Constraints

In order to grantee the feasibility of planning solutions, many aspects of equality and inequality constraint conditions must be strictly obeyed in ADS planning formulation, including technical, economic, and installation conditions.

The most common technical constraints include: (1) radial operation of networks and full connectivity; (2) size limits of substations and feeders; (3) power flow equality constraints; (4) active/reactive power balance equations; (5) permissible range of bus voltage magnitude; (6) position limits on-load tap changer (OLTC); (7) ramp constraints of DDGs; (8) power production constraints of DDGs and RDGs; (9) operation constraints of ESSs; and, (10) operation constraints of DR. It is noteworthy that constraints 7 to constraint 10 are the additional ones for ADSs, and constraint 2 and constraint 5 are the main obstacles to increase the penetration of DERs.

The economic constraints mainly refer to the budget limits for DSOs to build substations and feeders, and budget limits for distributed generation operators (DGOs) and DSOs to install DGs. Moreover, some articles, such as [33], introduce the constraints of maintaining positive profit for each individual DG investor to make the investment more attractive.

Additionally, installation condition constraints mean the geographical condition, landscape aesthetics constraints to install DGs, such as DWGs, DPVs, gas turbine, and gas transmission pipeline.

3.5. Solving Algorithms

Based on the above analyses, most of the proposed planning models are complex mixed integer nonlinear optimization problem with multiple decision variables and multiple constraint conditions, which poses a great challenge to the solving algorithms. How to obtain the optimal planning solutions and keep high computational efficiency is one of the key ADS planning issues.

There are two main classes of algorithms to solve these planning models, including the numerical methods and the heuristic methods. The adoption situations of different algorithms are provided in Figure 7. It can be seen that genetic algorithm (GA), particle swarm optimization (PSO), and software tools based on the numerical methods are mostly adopted in these articles. The numerical methods depend on the first-order and second-order gradient information of objectives and constraints to find the optimal solutions. Several common numerical methods have been utilized to solve ADS planning problems, such as linear programming, nonlinear programming, dynamic programming (DP), and ordinal optimization (OO).

In [45], for the purpose of minimizing the cost of DGO and maximizing the profit of DGO, a bi-level non-liner planning model is proposed to determine sittings and sizes of DDGs in ADS. To deal with this problem, the planning model is turned into an equivalent single-level mixed-integer linear programming problem and it is solved by CPLEX. A mixed integer second-order cone a programming problem that is formulated to determine the allocation scheme of ESSs in [57]. GUROBI is adopted to solve this problem. Similar with [57], the same methods are adopted in [58] to solve the joint planning problem of substations, feeders, and RDGs in ADS. In [55], the allocation of EVs charging station is integrated into ADS planning model considering both charging and discharging behaviors of EVs, and the OO theory is adopted to solve this mixed-integer nonlinear programming problem. Different from [55], the mixed-integer nonlinear programming problem proposed in [36] is solved by DP.

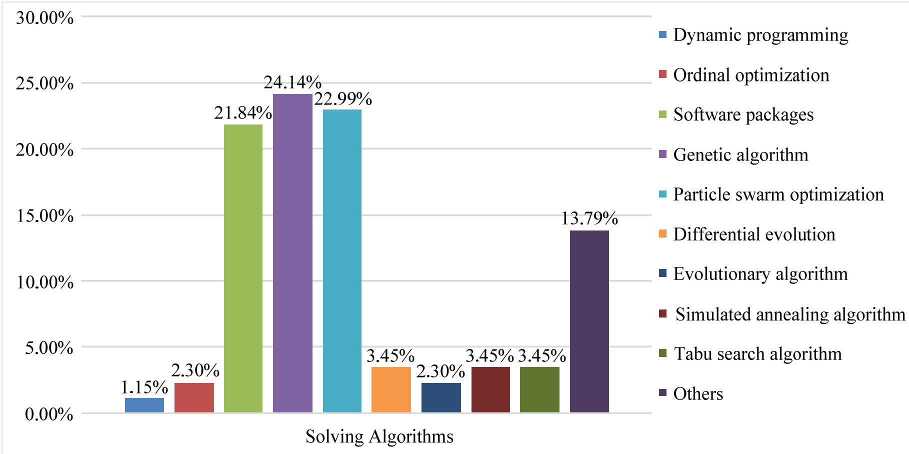


Figure 7. Distribution of solving algorithms.

In general, these classical numerical methods and the software tools based on these numerical methods (CONOPT [51,63,69], IPOPT [65,98], SNOPT [96], GUROBI [57,58,71,89], etc.) have been widely used to solve the ADS planning problem. However, due to the high-level uncertainties, these large-scale combinatorial optimization problems are easily to suffer from the "curse" of dimensionality. Therefore, it will take a large amount of computation time for solving these large-scale problems. In the meanwhile, some simplification actions for these planning models are required to be taken, which, in some extent, will result in the computational accuracy reduction of obtained planning results.

When comparing with these classic numerical methods, heuristic methods have the advantage to balance computational efficiency and accuracy. Nowadays, many kinds of heuristic methods have been widely served for power system optimization. GA, PSO, differential evolution (DE), and artificial bee colony algorithm (ABC) are the successful examples to tackle the planning problems of ADS.

However, each of the heuristic algorithms has different strengths and weaknesses. GA has a good convergence property, but a drawback of complexity because of encoding and decoding. PSO s good at convergence speed, but easily trapped into the local optimum. DE needs less control parameters, and it has the advantage of better flexibility and the drawback of slow convergence speed. Therefore, the solution algorithm should be selected according to the features of different planning models. In addition, a hybrid algorithm based on different algorithms is also another good choice to enhance advantage and avoid disadvantage.

In [50], a modified PSO algorithm is developed by a new mutation operation and is adopted to solve a multi-objective multi-stage distribution expansion planning problem. The mutation operation is adopted to improve the global searching ability and to restrain the premature convergence to local optimal solution. In [38], the PSO algorithm is included in the shuffled frog leaping algorithm structure and implemented to cope with the optimization problem of the multi-stage ADS expansion planning problem. ABC is adopted to solve a multi-stage expansion and unit commitment planning for ADSs in [43]. In the process of computational simulation, performances of the ABC algorithm are compared with the comprehensive learning PSO and the traditional multi-objective non-linear quadratic programming optimization method. The results indicate that ABC has a better convergence performance to solve the proposed planning model.

3.6. Case Study

This section quotes a case study of ADS planning, introduced in [89], to illustrate the mathematic model and solving algorithm for ADS planning. The emphasis is also given to the comparison between traditional network reinforcement and the application of AM schemes.

To provide a reliable and cost effective service to consumers while ensuring that voltages and power quality are within standard ranges, minimizing the total cost serves as the optimization objective including (1) substations expansion cost; (2) new substations installation cost; (3) feeders' replacement cost; (4) new feeders installation cost; (5) installation cost of DG units; (6) operation cost of DG units; (7) cost of purchased energy; (8) system power loss cost; and, (9) AM schemes cost including DR incentive cost, and operation and maintenance (O&M) cost of ESS.

There are four decision variables need to be determined in the planning scheme: (1) expansion capacity of existing substations; (2) sizes of existing substations for reinforcement; (3) locations and sizes of new feeders; and (4) locations and sizes of RDGs.

The constraints mainly consist of (1) the radiality constraint; (2) connection constraint; (3) power flow equations; (4) DG units' operating constraints; (5) DG units' maximum penetration constraint; (6) voltage constraint; (7) thermal limits of feeders and substations; (8) AM constraints and, (9) ESS operation constraints.

The 54-node, 33 kV network is adopted to investigate the availability and effectiveness of the proposed model and the GUROBI solving tool. The planning schemes are given in Figure 8.

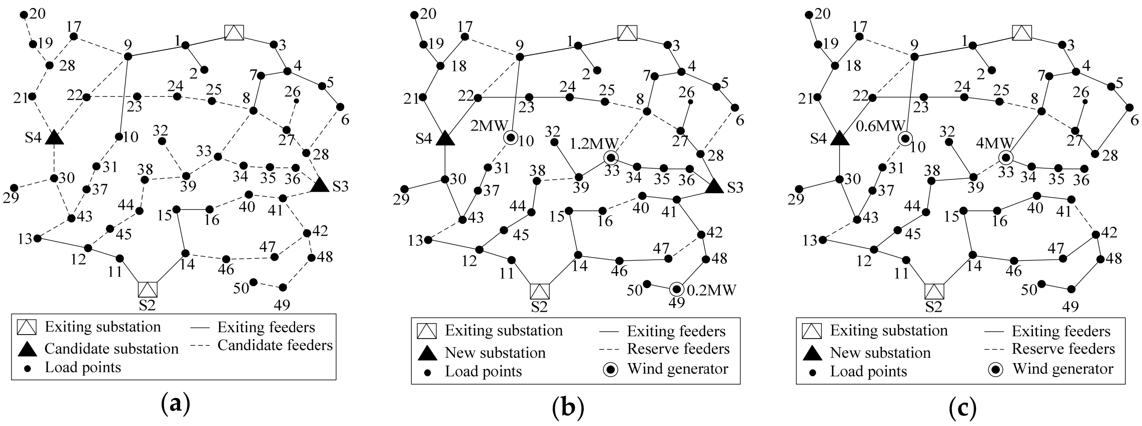


Figure 8. Case study based on 54-node distribution network (adapted from [89]). (**a**) Initial network; (**b**) Expanded network without active managements (AMs); (**c**) Expanded network with AMs.

It can be observed that the main AM approaches adopted in this articles (operation of ESSs and DR) have a recommendable effect on upgrade deferral: the planning result considering these no-network solutions does not need to install substation S3 and corresponding feeders. As a result, the total cost decreases by 13.47%. Meanwhile, the total penetration of DWG increases by 35.29% due to the implementation of these main AM approaches.

The case in [89] can illustrate the typical ADS planning models including objectives, decision variables, and constraints. The results also prove that the AM schemes should be properly considered in planning models and will bring several benefits for the planning solutions.

4. Key Issues of ADS Planning

4.1. Methods to Deal with High-Level Uncertainties

As aforementioned, more and more uncertainties will be faced in ADSs brought by changes in demand, generations, prices, and even policy. How to deal with these high-level uncertainties is a key problem that needs to be considered. At present, probabilistic approaches and multi-scenario based approaches are most common methods to cope with these multiple aspects of uncertainties.

1 Probabilistic approaches

When probabilistic approaches are used to deal with uncertainties, there is an assumption that the probability distribution function (PDF) of input parameters is known. As the main sources of uncertainties, wind speed, solar irradiance, and load demand, are approximately assumed to follow Weibull distribution, Beta distribution, and normal distribution, respectively, as shown from Equations (2)–(4). Therefore, these PDFs are adopted to represent the high fluctuation and randomness features of wind speed, solar irradiance, and load demand in many articles [25,35,44,48,53,65,66,75,81,90].

$$f_v(v) = \left(\frac{k}{\lambda}\right)\left(\frac{v}{\lambda}\right)^{k-1} e^{-\left(\frac{v}{\lambda}\right)^k} \tag{2}$$

$$f(E) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\left(\frac{E}{E_{\max}}\right)^{\alpha-1}\left(1-\frac{E}{E_{\max}}\right)^{\beta-1} \tag{3}$$

$$f_{\mathrm{L}}(P_{\mathrm{L}}) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left(\frac{(P_{\mathrm{L}}-\mu)^2}{2\sigma^2}\right) \tag{4}$$

where, c and k are scale parameter and shape parameter of Weibull distribution, respectively; v is the wind speed at the height of the hub of wind turbine. E is the sunlight intensity, α and β are the shape coefficients of Beta distribution. Γ is the Gamma function. μ and σ are average value and standard deviation of load demand.

When the input parameters, such as k, v, α, β, μ, σ, are obtained, the required solar irradiance, wind speed, and load demand can be simulated by means of Monte Carlo Simulation, Latin Hypercube Sampling, etc. Then, the power outputs of DWG and DPV can be got by power output functions. The process is shown in Figure 9.

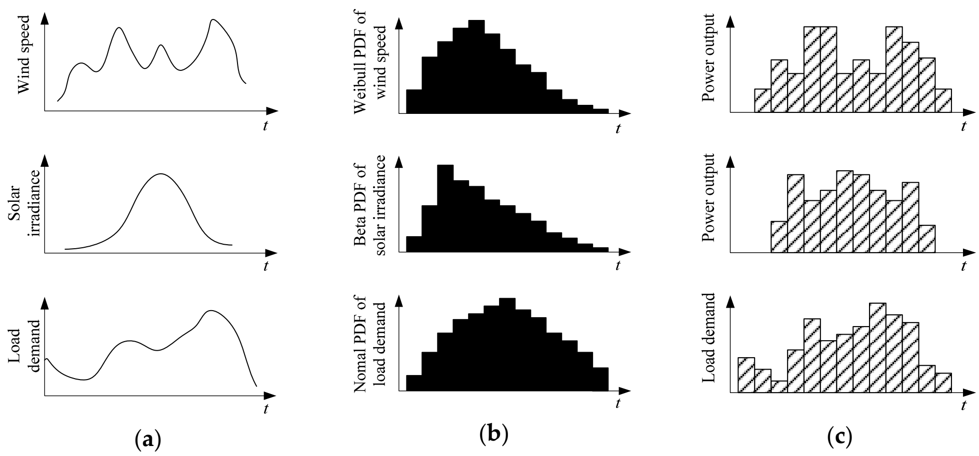


Figure 9. Simulation of power outputs and load demand based on probabilistic approaches. (**a**) Prediction data; (**b**) probability distribution function (PDF); (**c**) Simulated data.

Then, combined with the approaches of probabilistic optimal power flow [44,60,79], chance constrained programming [62,70], etc., these simulated data of RDGs and load demand could be used in ADS planning models considering high-level uncertainties.

Although, these probabilistic approaches have the ability to reflect the intermittent nature of DWG, DPV and load demand, they can not give full expression to the time-variable nature of these RDGs and load demand (e.g., autocorrelation). Therefore, using these approaches based on PDF may lead to the neglect of annually inherent simultaneity of multiple RDGs and load demand, and probably generating incorrect operation point combinations. At the same time, the seasonal/diurnal complementariness may escape from researchers' notice. In [53], although joint probability density functions are adopted to simulate these complementary features between DWG and load demand, the simulation results still need further improvement.

Moreover, due to the strict time sequential operation constraints of ESSs and DR, these probabilistic approaches, which can not capture the time-variable nature and represent the behaviors of AMs, are not suitable for ADS planning models coupled with operation of ESSs and DR.

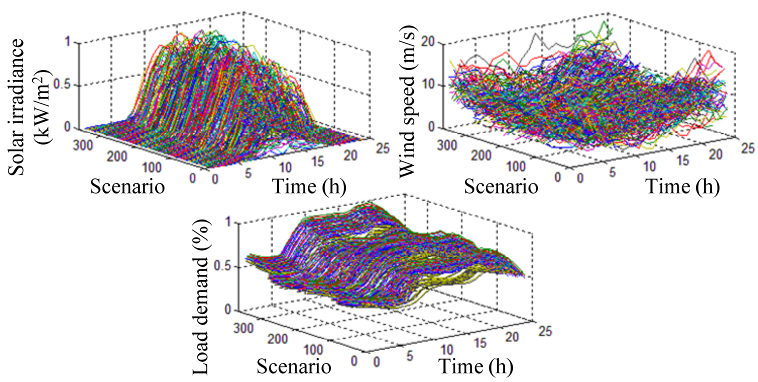
2 Multi-scenario based approaches

In the approaches based on multi-scenario, a set number of typical scenarios are formed based on forecasting data to capture the combinations of different uncertainty factors, such as wind speed, solar irradiance, load demand, and market electricity prices. Then, these typical scenarios serve as the basic data to solve ADS planning models. Obviously, a large number of clusters will bring about more accurate planning solutions, but would be at the cost of a surge in scenario quantity and the burden of computation. Therefore, in order to balance computational efficiency and accuracy, scenario reduction is always adopted in many articles [25,53,75].

In several articles, such as [22,60,71,84,95], the fewer seasonal typical scenarios are adopted to represent the random fluctuations of RDGs and load demand. It is obvious that the computational burden is eased, but the computational accuracy of planning solutions is reduced at the same time.

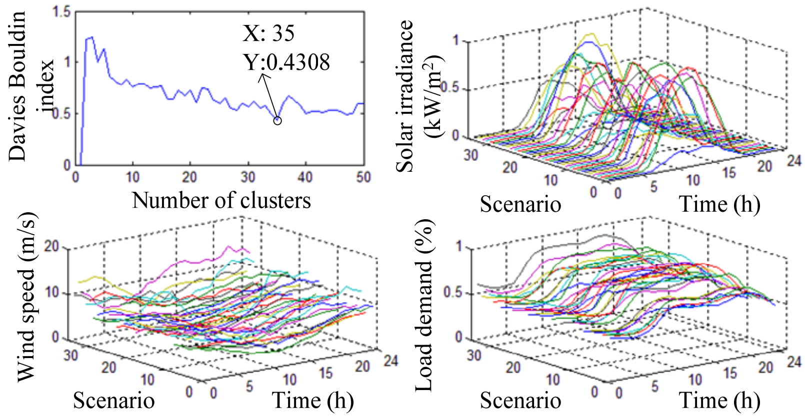
A recommendable approach based on multi-scenario is adopted in several articles. In these papers, the annual time-dependent data are segmented into 365 daily intervals and are normalized. Then, these 365 daily intervals are created as a matrix that contains the 24 (h) of data of the load, solar irradiance, and wind speed. By means of fuzzy clustering algorithm [99] or K-means clustering algorithm [57,58,75,89], the typical scenarios with similar characteristics are clustered.

The approach has the ability to keep the diversity of scenarios, while eases the computational burden. By this means, these typical daily scenarios can be extracted from these annual prediction data and assumed to be sufficiently representative of the sequential behaviors and inherent simultaneity between multiple RDGs and load demand. Therefore, it is one of recommendable approaches to handle high-level uncertain factors. However, in the process of clustering, the number of cluster is determined without deliberateness, and few of the abovementioned references take the quality and diversity of these selected typical daily scenarios into account adequately. In this regard, several property validity indices, such as Davies Bouldin index [113], Cluster cardinality index [114], and Xie & Beni index [115], should be adopted to determine the proper number of typical daily scenarios with high quality and diversity. A simple numerical example is adopted to illustrate the process of scenario clustering based on Davies Bouldin index, shown as Figure 10.



(a)

Figure 10. *Cont.*



(**b**)

Figure 10. Simulation results by multi-scenario based approaches with Davies Bouldin index. (**a**) Annual time-dependent data; (**b**) Typical scenarios after clustering.

4.2. Methods to Incorporate Operational Aspects into Planning Model

When comparing with traditional distribution networks, the ability to control DERs by means of AM schemes is the most prominent feature of ADS. These AMs and control schemes, defined as no-network solutions, offer many potential benefits to the planning of ADSs and have become valuable alternatives to network expansion or reinforcement [10]. Therefore, the planning consideration and operation consideration should not be optimized separately any more.

In [60,63,69,71], in order to optimize operation and planning of ADSs coordinately, the bi-level structure is introduced to formulate the ADS planning models and achieve the coordinate optimization between planning and operation, as shown in Equation (5).

$$\begin{array}{l} \min F(x_{st}, y_{st}, z_{st,sc,t}) = [OF_1, OF_2, \ldots, OF_M] \\ \text{s.t.} \begin{cases} G(x_{st}, y_{st}) = 0 \\ H(x_{st}, y_{st}) \leq 0 \\ 1 \leq st \leq N_{\text{ST}} \\ \text{where } z_{st,sc,t} \text{ should be solved from:} \\ \qquad \min f(x_{st}, y_{st}, z_{st,sc,t}) = [of_1, of_2, \ldots, of_n] \\ \qquad \text{s.t.} \begin{cases} g(x_{st}, y_{st}, z_{st,sc,t}) = 0 \\ h(x_{st}, y_{st}, z_{st,sc,t}) \leq 0 \\ 1 \leq t \leq 24 \\ 1 < sc \leq N_{\text{SC}} \end{cases} \end{cases} \end{array} \tag{5}$$

where, x_{st}, y_{st} are the decision variables of planning of networks and allocations of DERs. OF_1, OF_2, ... , OF_M, are the optimal objectives of planning model. $G(.)$ and $H(.)$ are the equality constraints and inequality constraints. $z_{st,sc,t}$ is the decision variables of operation, which are solved in lower level models. of_1, of_2, ... , of_n, are the optimal objectives of operation model in lower level. $g(.)$ and $h(.)$ are the equality constraints and inequality constraints. sc and t denotes the scenario sc and time t, respectively. Moreover, N_{ST} is number of planning stage; when N_{ST} = 1, the planning model is a static planning model, otherwise the model is a dynamic multi-stage planning model.

The bi-level models adopted in these papers belong to the multi-level programming, which is first introduced to model the extension problem of the Stackelberg Games by Candler and Norton [116]. At present, the multi-level programming has become a hot topic in the optimization field research, and has been widely used for varieties fields of sciences, engineering, and economics. In a bi-level model, each level of the model has its objectives and decision spaces, which are affected by variables controlled at another level. That enables the optimization objectives and the interaction of different decision makers be taken into account. Meanwhile, the execution of decisions is sequential, from higher to lower level, which is consistent with the logical relationship between planning and operation. These features of bi-level model enable itself to be suitable for hybrid optimization of ADS planning and operation. The ADS planning structure based on bi-level programming is shown in Figure 11.

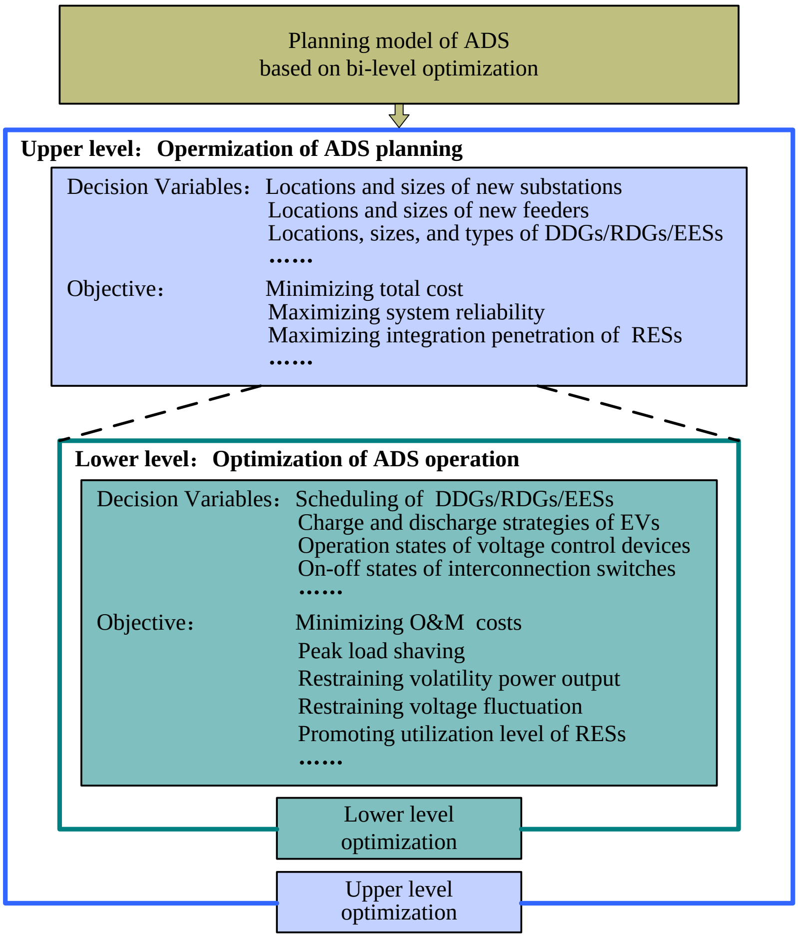


Figure 11. The active distribution systems (ADS) planning structure based on bi-level programming.

In this structure, the upper level model serves as a leader and plays a decisive role to determine the planning schemes of ADS. The lower level model serves as a follower and determines the operation conditions of ADS under the candidate planning scheme that is obtained by the upper level. At the same time, the evaluation indicators obtained by the lower level, such as operation costs, reliability indexes, and the utilization level of RDGs, will be fed back to the upper level and impact the optimal planning schemes. Finally, the optimal planning schemes can be obtained as well as the optimal operation situations, by the iterative optimization mentioned above.

Authors in [25] adopt the bi-level structure to solve an allocation problem of DGs, where capacities, types, and locations of DGs are obtained in the master optimization problem (upper level model), and the optimal active and reactive power outputs of DG units are determined in the sub-optimization problem (lower level model). Similar with [25], a bi-level model is adopted to formulate an allocation of DGs in [62]. But, the lower level model serves to examine the feasibility of candidate planning schemes by the voltage profiles and reliability performance.

A case study is adopted to illustrate the utilization of bi-level models in ADS planning. A bi-level optimization problem is proposed in [60] to model the planning of ESSs in ADS, where the planning problem and operation problem are optimized in the upper level and lower level, respectively.

For the planning aspect, minimizing the total costs of the ADS and ESS serves as the objective of the upper level, including (1) minimization of the storage investment cost; (2) minimization of O&M cost; (3) minimization of reliability cost; and, (4) minimization of the number of technical constraints' violations. For the operation aspect, ESS operation scheduling is obtained for three purposes simultaneously including peak shaving, voltage regulation, and reliability enhancement in the lower level. These roles of ESSs are modeled as operation costs, reliability costs, and the penalty factor, and are fed back to the upper level. To address this problem, PSO serves as the basic frame of the hybrid solving strategy to determine the allocation of ESS in the upper level. Tabu search serves as the algorithm embedded in the basic frame to obtain ESS scheduling in the lower level. The 21-node, 13.8 kV network is adopted to investigate the availability and effectiveness of the proposed model and the hybrid solving strategy, shown as Figure 12. The planning results are given in Table 2, including the optimal locations, capacities, and power ratings of the ESSs in different wind penetration.

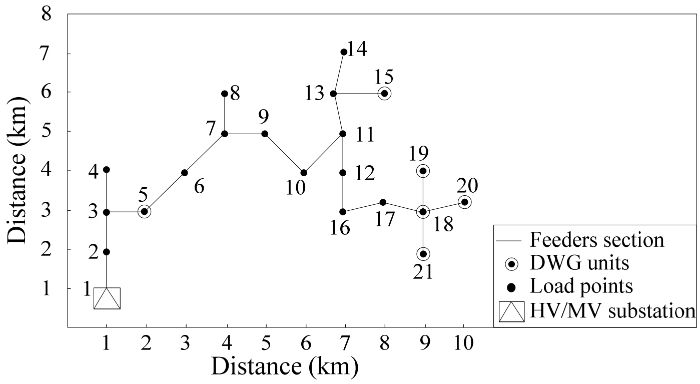


Figure 12. Case study based on 21-node distribution network (adapted from [60]).

Table 2. Different planning results for different distributed wind generations (DWG) penetration.

DWG penetration = 0%	Location (Node No.)	15	19	20	21	-	Total
	Capacity (kWh)	590	80	630	630	-	1930
	Power rating (kW)	120	45	125	120	-	410
DWG penetration = 10%	Location (Node No.)	13	15	17	19	20	Total
	Capacity (kWh)	780	770	800	715	710	3775
	Power rating (kW)	150	170	150	150	160	780
DWG penetration = 30%	Location (Node No.)	11	13	15	19	20	Total
	Capacity (kWh)	1680	1880	1840	1820	1365	8585
	Power rating (kW)	275	300	290	290	245	1400

It can be observed that with the increase of DWG penetration, the required capacities of ESSs increase considerably, which reveals the improvement effect of ESS on the accommodation of fluctuate RDGs. It also can be found that these ESSs tend to be located far from the HV/MV substation to alleviate the challenge of higher power losses, voltage fluctuation, and outage probability [60]. In addition, the comparing of the cost items, including operation cost, reliability cost, penalty factor, and average power losses, also indicates that the utilization of ESS reduces all of these cost items separately, even if minimizing the total costs serves as the optimization objective.

Generally speaking, shown as the case study in [60], the bi-level optimization model enables us to take into account how optimal operation consideration of ADS in the lower level can affect and be affected by the optimal planning of ADS in the upper level, which has the ability to bring potential benefits from operational strategies to the planning studies.

4.3. Integration of ESSs and DR

With the increasing application of ESSs and DR, the success of these programs makes ESSs and DR be perceived as virtual distributed resources. The benefits brought by operation of ESSs and DR have attracted researches' attention. However, most of these researches focus on the operational challenges rather than planning aspects [10]. Only 20% of the selected articles integrate optimal operation of ESSs into ADS planning, while less than 10% of the selected papers involve the performance of DR.

Authors in [32] integrate the allocation of ESSs into multi-stage distribution expansion planning model, where several operation strategies are proposed for DGs and ESSs operation to cut peak load demand and enhance system reliability. In [46], authors introduce a planning model to determine the allocation of customer-side ESS to deal with voltage fluctuation problem in ADS with high penetration of PV systems. A suitable connection agreement is adopted to allow the DSO to control the operation output of customer-side ESS during a specific time period in exchange for a subsidy, which can be used to reduce the initial cost of ESS. Similar with [32], a multi-stage distribution network expansion planning model is proposed incorporating ESSs in [67]. A straightforward operation strategy of ESSs is introduced to shave the peak demand and to reduce the planning cost. In [72], the optimal operation of ESSs and DGs is incorporated into the coordinated planning on the ESSs and DGs. It is noteworthy that both active power and reactive power of ESSs are adequately addressed and discussed, which is less common in other papers.

As the most representative dynamic active load demand, charging load demands of EVs have a major impact on ADS planning. Moreover, EVs also have the ability to discharge and participate energy management in ADS. Therefore, it is required to investigate the important impact of EVs on optimal planning of ADS.

In [83], a fuzzy load model of EVs is adopted to investigate the impacts of EVs' uncertainties on ADS planning. Optimal allocation of EESs and DDGs serves as the solution to deal with the undesirable impacts mentioned above. But optimal charging and discharging strategies of EVs are not involved in this paper. Authors in [99] propose an ADS expansion planning model to support increasing penetrations of EVs, where the uncertainties and charging behaviors of EVs are taken into consideration. The results indicate that the ordered charging behaviors of EVs can reduce the investment and operation costs of ADS, and have noteworthy beneficial effects on ADS planning.

Different from these two references, the allocation of EVs charging station is integrated into ADS planning model in [54,55,80,82,85]. Among them, authors in [54,80,82,85] introduce the traffic flow index into the proposed planning models to present the convenience of charging service. By means of the proposed models, the ADS and transportation systems are optimized collaboratively.

Besides of EVs, other flexible load demands can also be considered as virtual DERs to participate energy management in ADS by means of time-based programs, incentive-based programs, and market-based programs [84]. The success of DR programs is beneficial to improving the utilization of RDGs [48,81], reducing the operation costs [81,89] and energy losses [89], decreasing load peak and off-peak difference, and mitigating the mismatch between load demand and outputs of RDGs.

Authors in [48] propose an integrated ADS planning model to optimize reinforcement scheme of networks and allocation of DGs. In the process, a truncated Gaussian distribution is applied to represent the elasticity variations of price responsiveness in DR programs. What is noteworthy is that the smart metering devices are taken into consideration in the ADS planning methodology. In [81,84,89,96], DR serves as an AM scheme integrated into ADS planning model. Among them, authors in [81] adopt the flexible load as a kind of virtual energy storage unit with bi-directional power output to reduce the operation costs. In [84], DR programs are integrated in a multi-level and multi-objective ADS expansion planning model, where DR specifications are optimized by means of sensitivity analysis in lower level and feedback to other level, so that the optimal DR programs can be taken into account in ADS planning modes effectively.

Many of the references select simple models to represent the optimal operation of ESSs, DR programs, and EVs. However, these AM schemes, especially ESSs, have the strict operational constraints and flexible operational strategies, which cannot be captured and represented by simple models. Therefore, further studies are needed about the operational models integrated into planning models.

4.4. Methods to Deal with Multiple Time Scales

As mentioned above, the co-optimization between planning in long-time scale and operation in short-time scale is a key issue for ADS planning models. This requires the definition of adequate time-series models to be able to adequately represent the behaviors of active approaches in the planning calculations [10,20]. Therefore, the coordination of multiple time scales is an important problem to determine what extent operational aspects need to be modelled in planning models.

In terms of planning consideration, there are three kinds of ADS planning problems including long-term planning, median-term planning, and short-term planning. Correspondingly, the planning horizons of them are 16–30 years [35,41,52,64], 6–15 years [34,42,59,61,71,96,97], and 1–5 years [31,38,43,67,84,86], respectively. In most of the articles, capital recovery factor is adopted to calculate the net present value of equal annual cash flows and economic objectives. Moreover, discounted payback period and benefit-cost ratio also can be taken into consideration [92].

In terms of operation consideration, the time scales are closely associated with the different response time of AM schemes, such as seconds, or minutes, and hours [69]. Taking the operation of ESSs as an example, super-capacitor and battery normally have different response rates, therefore they play different roles in ADS operation.

There is no doubt that the fine granularities have a better ability to capture operation situations. But in the process of planning models, the simplistic representations in hour interval will barely affect the quality of planning solutions and have the ability to ease the calculating burden [10,20]. Therefore, it is widely accepted to take one hour as the elementary interval in the planning calculations.

Moreover, because of the daily cycling operation of ESSs, DR programs, and EVs, the time scales of planning and operation can be united by diurnal evaluation criteria based on the probabilistic multi-scenario, such as diurnal investment and operation costs, and the diurnal reliability index. The expectation values of these criteria calculated by multiple scenarios and corresponding probabilities can be adopted to iterative optimization, shown as Figure 13.

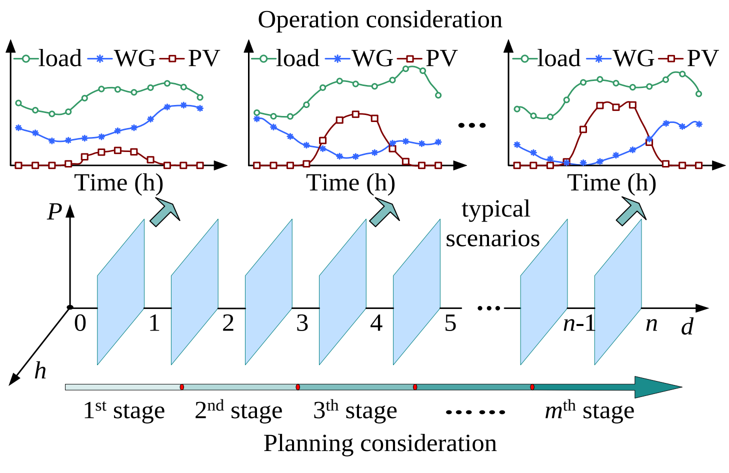


Figure 13. Methods to deal with multiple time scales by multiple scenarios.

5. Recommendation for Future Works of ADS Planning

5.1. ADS Planning with Multiple Micro-Grids

MGs have the ability to aggregate many DERs, such as DGs and distributed energy devices, and operate as a controlled and efficient energy unit for economic and reliability purposes by fast acting power electronics. Furthermore, MGs also can improve the utilization of RDGs and take some degree of responsibility to support ADS [117]. Therefore, more and more RDGs are prone to be integrated by means of MGs. So that a new pattern that can be referred as multi-MGs has emerged in ADS, shown as Figure 14. In this architecture, the goal of global coordination in ADS and regional autonomy in MGs can be achieved [118–120].

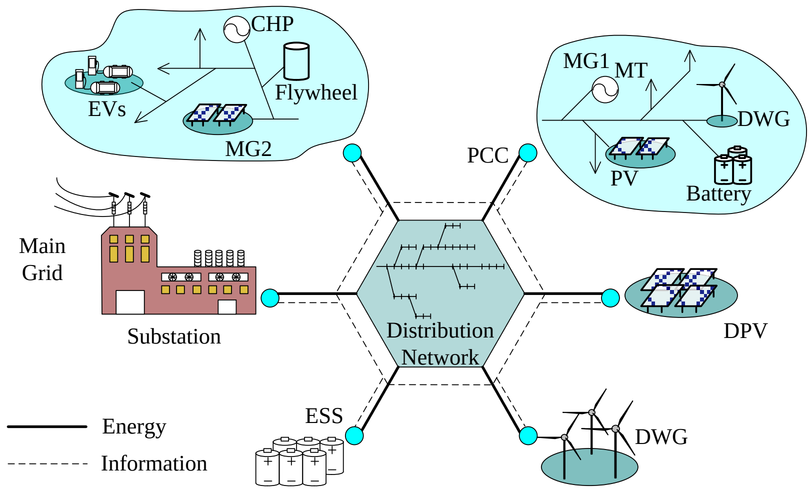


Figure 14. ADS architecture with multi-MGs.

At present, ADSs with multi-MGs have been studied in some literature. However, most existing literature are directed towards the operation issues but not planning problems [118–122]. Even though there has been a small part of literature that spends efforts on the planning of ADS with multi-MGs, there are many problems that remain unsolved [117,123]. First of all, it requires rethinking ADS planning models with appropriate optimization objectives to satisfy the different planning goals of stakeholders. Secondly, more uncertain factors need to be handled in the planning process, such as various operation states combined with different islanding/connecting operation of multi-MGs. Moreover, how to integrate control strategies of multi-MGs into ADS planning is another important issue to be considered.

Therefore, ADS planning with multi-MGs is a valuable and recommendable topic that needs to be further researched.

5.2. Collaborative Planning Methods of ADS and Information Communication System

In ADSs, the real-time energy optimization and coordinative AMs between a mass of DERs and multi-MGs bring great challenges on the information and communication technologies (ICT). The reliability of ICS directly impacts the observability and the controllability of ADS, which is the firm foundation for the secure and stable operation of ADS [124–127]. Therefore, the allocation of ICS devices and planning of ADS should no longer to be optimized as separate tasks. The collaborative planning of ADS and ICS is another recommendable topic that needs to be further researched.

To realize situational awareness and autonomous decision-making of DERs, ICS components should be allocated according to the management strategies and physical architecture of ADS. Only in this way, can the massive, distributed and heterogeneous data resources be captured, transmitted, processed, and utilized.

In the collaborative planning, the co-simulation approaches of ADS and ICS need to be further studied to simulate power delivery and communications networks simultaneously. In terms of economic assessment, the investment and operation costs of ICS components should be integrated into the economic objectives. More importantly, in terms of reliability assessment, the potential impacts of ICS operation quality (e.g., accuracy, security, availability, performance) on ADS reliability should be evaluated accurately and taken into account adequately.

5.3. ADS Planning from Different Perspectives of Multi-Stakeholders

With the liberalization of electricity markets, many new stakeholders have emerged to participate the market operation. More and more DDGs, RDGs, and EESs are invested by the independent DGOs instead of DSOs. This is the typical scenario in Ontario, Canada and Sacramento Municipal Utility District in California, USA [33,35]. These DGOs would like to take part in market competition and realize the profits by means of selling electricity to the grid and the arbitrage by ESSs.

Therefore, the different and even conflicting planning goals of system stakeholders should be taken into account, shown as Table 3. However, except for [33,35,45,46,71,81,84], the other papers all lose sight of this problem and assume that DGs all belong to DSOs. It means that the liberalization of the electricity market environment has not been adequately taken into consideration.

Table 3. Different planning goals of distribution system operators (DSOs) and distributed generation operators (DGOs) [10].

	Planning Goals
DSOs	Increased customer services (e.g., being able to connect generation customers and demand customers more quickly and cost effectively)
	Better system performance metrics (e.g., reliability and electric power quality)
	Reducing the investment, maintenance, and operation costs
	... ...
DGOs	Quicker and cheap connections
	Investment incentives
	... ...

Hejazi et al. [33] are the early scholars to plan ADS from the different perspectives of stakeholders, where maximizing the DSO's profit is adopted to be the objectives, while maintaining positive profit for each independent DGOs serves as a constraint condition to assure DG investment attractive. In [45], the game relationship between DGOs and DSOs is modeled appropriately by a bi-level programming. The minimizing investment and operation costs of DSOs and maximizing the profit value of DGOs are adopted to be the objectives of the upper level and lower level, respectively. The contract prices of DGs between DGOs and DSOs are optimized together with the allocation of DDGs. From the different perspectives of stakeholders, authors in [81,84] use the multi-level programing to determine the optimal reinforcement schemes of ADS and allocation of DGs under the condition of a competitive market environment.

Judging based on the present condition; further study may be still needed to find optimal compromise planning solutions for the conflicting objectives of different stakeholders.

6. Conclusions

This paper presents a timely overview of ADS planning models and methodologies from different perspectives. The key issues and research prospects in the field of ADS planning methods are analyzed and discussed with several remarkable conclusions.

1. The environmental issues and allocation of reserve feeders, voltage control devices, and dynamic active load demand are deserving of more attention from the perspectives of optimization objective and decision variable, respectively.

2. Probabilistic multi-scenario based approaches and the multi-level programming are recommendable approaches to handle the key issues related with high-level uncertainties, the incorporating operational aspects into planning model, the integration of ESSs and DR, and the methods to deal with multiple time scales.

3. ADS planning with multi-MGs, collaborative planning methods between ADS and ICS, and ADS planning from different perspectives of multi-stakeholders are the valuable and recommendable topics that need to be further researched.

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Abbreviations

ABC	Artificial Bee Colony
ADN	Active Distribution Network
ADS	Active Distribution System
AM	Active Management
CHP	Combined Heat and Power
DDG	Dispatchable Distributed Generations
DE	Differential Evolution
DER	Distributed Energy Resource
DG	Distributed Generation
DGO	Distributed Generation Operator
DP	Dynamic Programming
DR	Demand Response
DSO	Distribution System Operator
DPV	Distributed Photovoltaic
DWG	Distributed Wind Generation
EV	Electric Vehicle
ESS	Energy Storage System
GA	Genetic Algorithm
MG	Micro-Grid
MT	Micro Turbine
OLTC	On-load Tap Changer
OO	Ordinal Optimization
O&M	Operation and Maintenance
PCC	Point of Common Coupling
PDF	Probability Distribution Function
RDG	Renewable Distributed Generation
RES	Renewable Energy Source
PSO	Particle Swarm Optimization
SVC	Static Var Compensator
ICS	Information Communication System
ICT	Information Communication Technology

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