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Active Distribution System Planning for Low-carbon Objective using Cuckoo Search Algorithm

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Abstract – In this study, a method for the low-carbon active distribution system (ADS) planning is proposed. It takes into account the impacts of both network capacity and demand correlation to the renewable energy accommodation, and incorporates demand response (DR) as an available resource in the ADS planning. The problem is formulated as a mixed integer nonlinear programming model, whereby the optimal allocation of renewable energy sources and the design of DR contract (i.e. payment incentives and default penalties) are determined simultaneously, in order to achieve the minimization of total cost and CO_2 emissions subjected to the system constraints. The uncertainties that involved are also considered by using the scenario synthesis method with the improved Taguchi's orthogonal array testing for reducing information redundancy. A novel cuckoo search (CS) is applied for the planning optimization. The case study results confirm the effectiveness and superiority of the proposed method.

Keywords: Active distribution system, Low-carbon, Renewable distributed generation, Flexible load, Scenario reduction, Cuckoo Search algorithm

Nomenclature

A. Sets

Ω_F	Set of right-of-ways
Ω_G	Set of RDG connection buses
Ω_L	Set of load buses
Ω	Set of all the system buses

B. Parameters

D^{or}	Forecasted demand of the planning year
C^{ep}	Electricity purchase cost
TH	Number of periods in the planning year
N	Total number of considered scenarios
C^{fdr}/ C^{w}	Capital costs of feeders/ DWG units
C^{wom}	Annual operation and maintenance cost for DWG units
C^{ct}	CO_2 emission tax rate
l	Length of feeders in km
e^{gr}	Emission factor of the main grid
PR	Occurrence probability of scenario

C. Variables

P^{w}	Power output of DWG units
$D^{fl}(\cdot)$	Flexible load of customers
S^{w}	Installed capacity of DWG units
τ	Decision variable of feeder upgrade
E^{gr}	The amount of electricity that purchased
P^{cur}	Curtailed power from DWG
$\cos\varphi$	Power factor of DWG units
ΔV	Deviation of the nodal voltage
I	Current in feeders
$C^{inc}(\cdot)$	Payment incentive for load response
$B^{pen}(\cdot)$	Penalty claimed for response default

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1. Introduction

The increasing CO_2 emission is the major cause of global warming, which poses a huge threat to sustainable development of human society [1]. To tackle this challenge, many countries have proposed long-term regulatory policies to reduce carbon emissions and improve energy efficiency in power sectors [2]-[3]. As the in-service life of electric power infrastructures normally span over several decades, a "carbon lock-in" effect would arise if the system were built up. Therefore, there is a growing consensus that changes should be made in planning methods to achieve the delivery of low-carbon electric power systems [3]-[6].

Most of the exploratory studies concerning the above issue generally focused on the generation side [4]-[6]. This situation is changed with the advent of distributed generation (DG). As DG can be based on renewable energies (such as wind), significant CO_2 reduction would be gained from the grid-side if high penetration of renewable DG (RDG) were accommodated from the distribution level.

However, RDG insertions make the traditional passive network evolve to the active distribution system (ADS).

Technical problems might take place if they were allocated improperly. As such, two types of strategies, i.e., integrated planning [8]-[10] and demand response (DR) [11]-[14] have been suggested. The former group mainly aims to mitigate the network bottleneck by combining RDG installation into network planning to support higher RDG penetration without violating the system constraints. Nevertheless, the actual emission benefits of RDG depend on how it is accommodated by the real-time demand in operations. Due their intermittency and uncertainty, power curtailment would take place if there were a mismatch between RDG production and demand of end-users. Thus, the DR option has aroused lots of interests [11]. The impact of DR on the integration of RDG is examined in [12]-[14]. An evaluation on the low-carbon effect of DR in the ADS is also made through a case study by [15].

Although considerable works have been done, there is an absence of opinions on in what way the DR resources should be enabled and managed so that it could comply with the expectation of DISCO. A key question "how to encourage the customers into special contracts to provide their demand flexibility and actively participate in ADS planning that could enforce optimal overall grid performance" is yet to be answered.

To address this issue, an integrated ADS planning approach towards the low-carbon objective is proposed in this study, where RDG integration (i.e. distributed wind generation (DWG) is selected here) is considered together with DR contract design and network reinforcement planning, with the objective of achieving CO_2 abatement and total cost minimization in the ADS. A new meta-heuristic algorithm, Cuckoo Search (CS) is employed to obtain the optimal solution of the formulated problem. Its performance is also compared with the classic Genetic Algorithm (GA) and investigated.

The reminder of this paper is: the modeling of wind generation and DR load are introduced in Section 2; the method of scenario synthesis applied for dealing with system uncertainties is described in Section 3; the mathematical model formulation is presented in Section 4; Section 5 gives the optimization procedures by using CS; the application of the proposed method in the IEEE 34-node system is analyzed in Section 6; finally, conclusions are given in Section 7.

2. Modeling of Wind Generation and Demand

2.1 Wind generation

For planning purpose, wind speed can be normally regarded following the Weibull distribution, the expression of which can be found in [10].

The relationship between wind turbine output versus wind speed v_g is expressed as

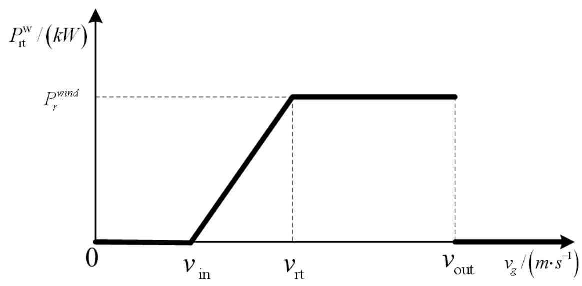

Fig. 1. Wind turbine output versus the wind speed

$$P_g^{\mathrm{w}} = \begin{cases} 0 & v_g < v_{\mathrm{in}}^{\mathrm{cut}} \text{ or } v_g > v_{\mathrm{out}}^{\mathrm{cut}} \\ \dfrac{v_g - v_{\mathrm{in}}^{\mathrm{cut}}}{v_{\mathrm{rated}} - v_{\mathrm{in}}^{\mathrm{cut}}} \cdot P_{\mathrm{rated}}^{\mathrm{w}} & v_{\mathrm{in}}^{\mathrm{cut}} \le v_g \le v_{\mathrm{rated}} \\ P_{\mathrm{rated}}^{\mathrm{w}} & v_{\mathrm{rated}} \le v_g \le v_{\mathrm{out}}^{\mathrm{cut}} \end{cases} \tag{1}$$

where v_{in}^{cut}, v_{out}^{cut}, v_{rated} and P_{rated}^{w} represent the cut-in, cut-off, rated speeds and capacity of the wind turbine.

An illustration of Eq. (1) is shown in Fig. 1.

2.2 System demand with flexible loads

Flexible load (FL) belongs to a type of incentive-based DR program. That is, DISCO pays customers a certain amount of incentives as defined by the bilateral contract if they are involved, whereas the customers would also be faced with penalty if they fail to fulfill their obligation (load reduction) [16]. Therefore, more customers would be attracted to join if they feel higher profits could be gained. Such relationship is herein represented by a linear function as

$$D^{\mathrm{fl}}(t) = a[\sum_{t=1}^{TH} C^{\mathrm{int}}(t) - \sum_{t=1}^{TH} B^{\mathrm{pen}}(t)] + b \tag{2}$$

where $C^{inc}(t)$ and $B^{pen}(t)$ are the payment incentive and default penalty for per kW of load response fulfillment/ violation by customers in the time period t.

The demand of an ADS with FLs is then calculated as

$$D^{\mathrm{dr}}(t) = \begin{cases} D^{\mathrm{or}}(t) - D^{\mathrm{fl}}(t), & t \in \mathbf{T_{pe}} \\ D^{\mathrm{or}}(t) + D^{\mathrm{fl}}(t), & t \in \mathbf{T_{in}} \end{cases} \tag{3}$$

where $\mathbf{T_{pe}}$ and $\mathbf{T_{in}}$ represent the incentive or penalty hours in a day, as stipulated by the contract.

However, as customers' behaviors upon incentive signals are totally voluntary and it is also possible that they may occasionally fail to answer the load reduction order due to many unforeseen factors, $D^{fl}(t)$ in (3) is an uncertain variable in real practice. We here assume that the capacity of FL that available in operations follows a Gaussian distribution [16].

3. Scenario Synthesis and Redundancy Reduction

As wind speed and FL capacity are probabilistic uncertainties, different techniques could be used to deal with them, including Monte-Carlo [17], point estimation [18], etc. In this study, a well-known scenario synthesis method is adopted [8]. The probability of any scenario s is calculated as

$$PR_s = \int_{D^{\mathrm{fl}}_{\mathrm{l},s}}^{D^{\mathrm{fl}}_{\mathrm{u},s}} \int_{v_{\mathrm{l},s}}^{v_{\mathrm{u},s}} f^{\mathrm{w}}(v) \cdot f^{\mathrm{d}}(D^{\mathrm{fl}}) \cdot dv \cdot d\varepsilon \tag{4}$$

It is seen that the creation of scenarios totally depends on the choice of range width by the decision-maker. A narrow range leads to more accurate and credible planning solutions, but would be at the expense of a surge in scenario quantity. If the system is large, the computational burden may become too heavy to be tolerated. Hence, we employ the Taguchi's orthogonal array testing (TOAT) [19] with the probability re-assignment that developed in our study for reducing information redundancy, as given below:

Step 1: Normalize the wind and FL capacity series into a number of ranges between 0 and 1 with equal intervals (e.g., [0, 0.1], (0.1, 0.2], etc.), so that the variation of each uncertain variable can fall into one of these ranges.

Step 2: Use the rank of each range to be the corresponding input variable for the TOAT. For example, [0, 0.1] corresponds to 1, (0.1, 0.2] to 2, etc.

Step 3: Construct the orthogonal arrays (OAs) [19] in a size of m rows and n columns, where m is the number of refined scenarios generated by the TOAT and n is the number of uncertain variables input from Step 2. m is much smaller than the number of initial scenarios, and they are regarded as the representative scenarios while preserving good statistical information.

Step 4: Redundancy reduction makes the cumulative probability of all the refined scenarios no longer equate to 1, thus a probability re-assignment should be performed. For this purpose, the following strategy is designed and used here: For the lower/upper bounds of uncertain variable xi in scenario s (Eq. (4)), if $xi_{\mathrm{l},s}=xi_{\mathrm{u},s-1}$ and $xi_{\mathrm{u},s}=xi_{\mathrm{l},s+1}$ are not satisfied simultaneously, check whether it is resulted by the decreased scenarios. If 'yes', expand the upper/lower bounds of scenario s and the two adjacent scenarios until either of them meets at the same point. The magnitude that the upper bound enlarges should be equal to that the lower bound diminishes so as to keep the mean value constant. These new points are considered as the adjusted bounds. Noted that as x_1 is normalized to the interval [0,1], so $xi_{\mathrm{l},1}$ and $xi_{\mathrm{u},1}$ needs to be specified as 0 and 1, respectively. Repeat above procedures for all the uncertain variables.

Step 5: Recalculate the probability of each scenario with adjusted bounds by using Eq. (4).

4. Mathematical Model Formulation

4.1 Objective function

To construct a low-carbon ADS, environmental aspect should be the main concern, whereas the economic cost is another equally important factor. As CO_2 emissions can be translated into the monetary metrics as carbon tax, the objective of DISCO in ADS planning is to determine the optimal plan for network reinforcement, DWG installation and contract prices offered to end-users such that the total cost of the system can be minimized, which is formulated as

$$\begin{aligned} F = & [\sum_{(i,j)\in\Omega_F} C^{\mathrm{fdr}} l_{ij} \tau_{ij} + \sum_{g\in\Omega_G} (C^{\mathrm{w}} + C^{\mathrm{wom}}) S^{\mathrm{w}}_g] \\ & + \sum_{ss=1}^{N} PR_{ss} \{ (C^{\mathrm{ep}} E^{\mathrm{gr}}_{ss} + C^{\mathrm{ct}} e^{\mathrm{gr}} E^{\mathrm{gr}}_{ss}) \\ & + \sum_{t=1}^{TH} \sum_{k\in\Omega_L} [C^{\mathrm{int}}(t) D^{\mathrm{fl}}_k(t) - B^{\mathrm{pen}}(t) D^{\mathrm{fl}}_k(t)] \} \end{aligned} \tag{5}$$

In above equation, the first line represents the network reinforcement and DWG costs (including capital investment and O&M cost). η is the annualization operator. $\eta=[d(1+d)^T]$ / $[(1+d)^T-1]$, where d is the discount rate, and T is the interval of the planning. The second and third lines are expected variable costs involved in the system operation stage, which include the energy purchase cost, CO_2 taxation payment (due to generation emissions induced in the main grid), as well as the expenses paid or received from DR activities.

It should be noted that as the power loss cost appears in terms of total power purchased from the main grid and DWG, thus there is thus no explicit energy loss cost presented in (5) as a separate term as it has already been incorporated implicitly inside the energy acquisition cost.

4.2 Constraints

The above optimization is subjected to a number of equality and inequality constraints, as presented below:

1) Power balance constraints

$$\mathbf{H}(\mathbf{z}_{i,ss}) = \mathbf{0} \quad \forall i \in \Omega, \forall ss \tag{6}$$

In above equation, $\mathbf{H}(\cdot)$ represents the conventional active and reactive power flow equations, with the vector of system control and state variables, as denoted by $\mathbf{z}_{i,ss}$.

2) Limit of DWG capacity in each node

$$0 \le S^w_g \le S^w_{g,\max} \qquad \forall g \in \Omega_G \tag{7}$$

3) Binary nature of feeder upgrade decision

$$\tau_{ij} \in \{0,1\} \qquad \forall ij \in \Omega_F \tag{8}$$

4) Limit of voltage variation

$$0.95 \le \Delta V_{i,ss} \le 1.05 \quad \forall i \in \Omega, \forall ss \tag{9}$$

4) Feeder current limit

$$0 \le I_{ij,ss} \le I_{ij,\max} \quad \forall ij \in \Omega_F, \forall ss \tag{10}$$

5) Operating limits of DWG units

$$0 \le P_{g,ss}^{\text{cur}} \le P_{g,ss}^{\text{w}} \qquad \forall g \in \Omega_G, \forall ss \tag{11}$$

$$\cos\varphi_{g,ss} = \frac{P_{g,ss}^{w} - P_{g,ss}^{cur}}{\sqrt{(P_{g,ss}^{w} - P_{g,ss}^{cur})^2 + (Q_{g,ss}^{w} - Q_{g,ss}^{cur})^2}} = 1 \quad \forall g \in \Omega_G, \forall ss \tag{12}$$

6) Limits for the setting of contract prices

$$0 \le B^{\text{pen}}(t) \le B_{\max}^{\text{pen}} \qquad \forall t \tag{13}$$

$$0 \le C^{\text{int}}(t) \le C_{\max}^{\text{int}} \qquad \forall t \tag{14}$$

4.3 Decision variables

In the above problem, the decision variables include the capacity of DWG units to be installed in each candidate location (i.e. S_g^{w}), and binary decision for feeder upgrade (i.e. τ_{ij}), which is same to [8]-[10]. Besides, as DR option is incorporated, the contract design should be considered. Therefore, the value of payment incentive and default penalty offered to customers are another two important decision variables in our model. The complete set of decision variables is summarized as:

$$\mathbf{Z} = [\mathbf{S}^{\text{w}}, \boldsymbol{\tau}, \ \mathbf{C}^{\text{int}}, \mathbf{B}^{\text{pen}}] \tag{15}$$

5. Solution Methodology

5.1 Overview of cuckoo search algorithm

The CS is a new nature-inspired meta-heuristic algorithm which was proposed by Yang and Deb in 2009 [20]. It is inspired by the parasitism behavior of cuckoos to incubate their chicks in the nature. Cuckoo is a typical kind of parasitic birds, which lay their eggs in the nests of other species. However, if the host bird discovers such intrusion, it will either throw them away or abandon this nest. Therefore, cuckoo eggs (offspring) can only survive with a certain probability. If the host bird happens to have oval, egg color, and incubation period similar to the cuckoos, the survival rate of cuckoo eggs would be higher. As CS is simple in concept, less in parameters, and easy to use, it has proved to be a powerful tool for the optimization problems in power systems [21].

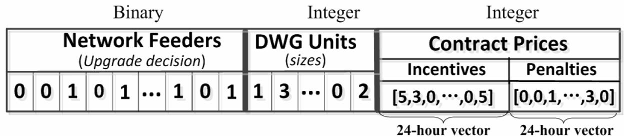

Fig. 2. Structure of coded candidate solutions

5.2 Application of CS for Low-carbon ADS planning

The main procedures of CS for ADS planning are given as follows:

1) Initialize the algorithm parameters, which include population size of host nests, intrusion detection rate, and maximum iteration number.
2) Generate the initial population of nests (candidate planning solutions). The individuals are coded with the mixed binary-integer strategy as shown in Fig. 2.
3) Perform the load flow and calculate the fitness of each candidate solution. Here, the fitness function is taken to be the reciprocal of the objective function (Eq. (5)).
4) All the nests are sorted in the descending order based on their fitness values.
5) Update the locations of the current nests by using the following equation:

$$x_m^{q+1} = x_m^q + \alpha \otimes \text{Lévy}(\lambda) \tag{16}$$

where x_m^q and x_m^{q+1} represents the location of the *m*th nest that cuckoos targeted in the *q* and *q*+1th time of searching. α is the step length [21]. Lévy(λ) stands for a random searching vector following the Lévy distribution. It describes the random walk process of cuckoos, which can be further expanded as:

$$\text{Lévy} \otimes u = t^{-\lambda} \quad 1<\lambda<3 \tag{17}$$

6) The inferior nests in the previous generation will be replaced by the ones selected from the current population that has higher fitness value.
7) The procedures of Step 3) to 6) are repeated until the termination criteria, i.e. the maximum iteration times, is reached. Export the so-far-best nest as the final solution.

6. Case Study

6.1 Test system and basic data

The proposed planning model is tested on the IEEE 34-node system [22], as is shown in Fig. 3.

The system contains a mix of residential, commercial, and industrial customers, which is connected to the main grid via a substation at Bus-0. The chronological daily

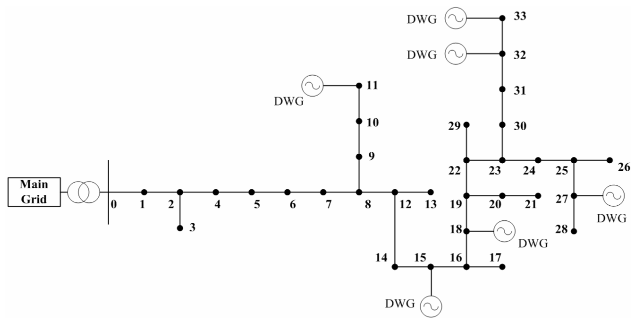

Fig. 3. IEEE 34-node distribution system test case

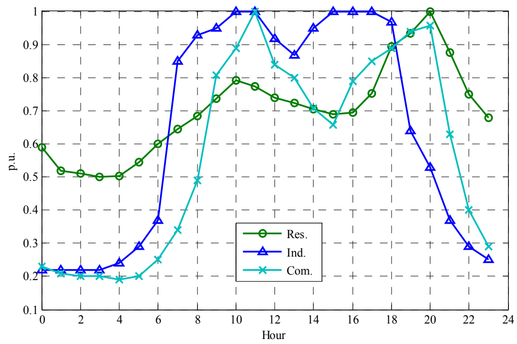

Fig. 4. Daily fluctuation of customer demand

fluctuation of demand is presented in Fig. 4.

Candidate DWG locations are chosen arbitrarily as Buses 11, 15, 18, 27, 32, and 33. The planning horizon is assumed to be 10 years, with the peak load of 4880.72+j2865.31kVA required to be served.

The feeder upgrade cost is $8427/km; the capital and O&M cost of DWG units is $556/kW and $35/kW, respectively. The electricity purchase cost is assumed to be 3.9cent/kWh. The technical parameters of DWG units are extracted from [10].

Besides, the maximum DWG capacity at each node is assumed to be 1MW, the voltage deviation limit is set as ±5% of the nominal value. The carbon tax and grid emission intensity is taken as $10/t and 0.92 kg CO_2/kWh.

Four different cases are assumed for comparison study.

#1: Conventional least-cost planning, without DWG installation and DR option (base case);

#2: Same as Case-1, but with the consideration of the low-carbon objective;

#3: Network reinforcement and DWG installation;

#4: Integrated planning of network, and DWG units with the consideration of DR (the proposed method).

6.2 Simulation results

Table 1 shows the optimization results, while the details of DWG installation in different cases are tabulated in Table 2. It should be noted that all the costs presented here are the annualized values.

As is observed, an obvious CO_2 abatement and an

Table1. Comparison of planning results in different cases

		#1	#2	#3	#4
Investment cost (M $)	Feeders	0.183	0.239	0.151	0.145
	DWG units	N/A	N/A	0.174	0.191
Operation cost (M $)	O&M	N/A	N/A	0.073	0.081
	Power purchase	0.769	0.753	0.528	0.372
	Carbon tax	0.181	0.178	0.125	0.087
Net cost of FL deployment (M $)		N/A	N/A	N/A	0.091
Total cost (M $)		1.133	1.170	1.051	0.967
CO_2 emissions (t)		18100	17800	12500	8700
CO_2 reduction (%)		-	1.65	30.93	51.93

Table 2. DWG installations in different cases

Candidate locations	#1	#2	#3 (MW)	#4 (MW)
Bus-11	N/A	N/A	0.3	0.5
Bus-15			0.2	0.2
Bus-18			0	0
Bus-27			0	0
Bus-32			0.8	0.8
Bus-33			0.8	0.8

improvement of overall benefits are achieved in Cases 2 to 4, which is consistent with our expectation.

The solution of Case 2 has much higher network reinforcement cost than Case-1, although it is only slightly better in the total cost and CO_2 emissions. This is because the network losses imposes more significant impact on the planning decision under such problem formulation. As such, the foremost role played by network losses drives this supply-side-based planning towards selecting feeder conductors with larger capacities than the economic design, so as to assure lower loss-related emissions. The results indicate that the planning of low-carbon ADS would be difficult and not economic-effective if only focusing on the issue of network losses.

In Case-3, the effect of DWG on the system benefit improvement is revealed. The zero-carbon wind power alleviates energy import from the main grid, which makes a saving of $82000 in the total cost and a reduction of 5600 t in CO_2 emissions, as compared with the base case.

When DWG and DR are collaboratively utilized in Case-4, the DWG capacity rises from 2.1 to 2.3 MW, whereas the lowest CO_2 emissions and system cost is also achieved. Fig. 5 shows the optimization results of the payment incentives and defaults penalties to the provision of FL in each time period of one day.

It is seen that the optimal incentive and penalty values vary considerably in a day. Such results are determined due to the temporal correlation between DWG production and load demand patterns. To illustrate this, Fig. 6 compares the daily fluctuation of load demand before and after the participation of DR in Case-4.

When DR is excluded, there is a load scarcity at late night and early morning. As such, wind generation cannot

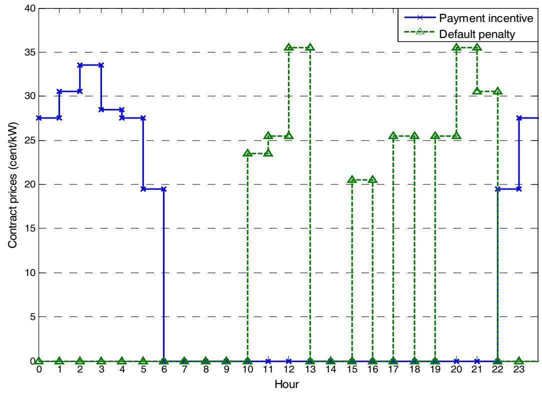

Fig. 5. Optimization results of the DR contract prices

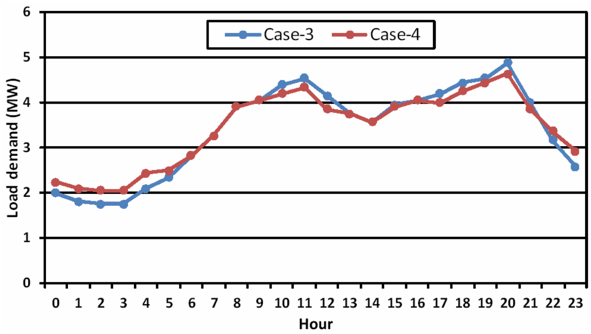

Fig. 6. Wind power and load patterns with and without DR

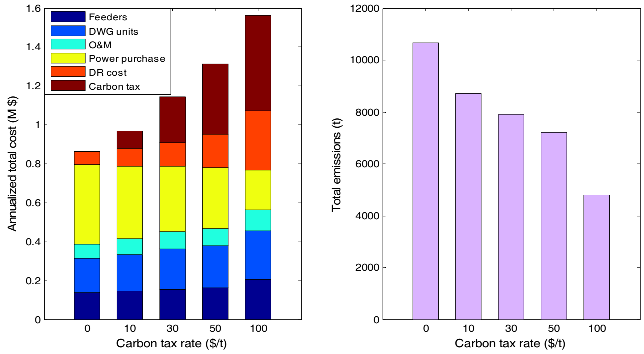

Fig. 7. Sensitivity analysis on the volatility of carbon tax

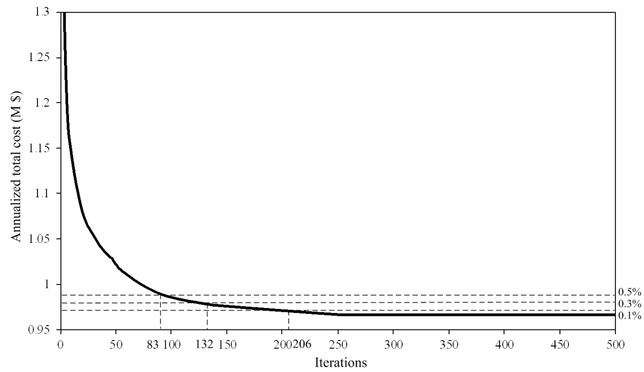

Fig. 8. Convergence characteristic of CS

reach their full potential and it is liable that wind curtailment may happen. The demand flexibility motivated by the dynamic contract incentives shaves the peak consumption (i.e. 10:00-12:00, and 17:00-20:00) and fills the valley hours (i.e. 22:00 to 5:00). This renders a closer matching between the availability of wind and customer consumption. Consequently, the production of DWG is accommodated more effectively in the high wind hours, which leads to a pleasant 66.3% increase in terms of the overall energy generation as compared to Case-3. These results demonstrate that DR has a synergic effect on RDG operations, the optimal solution obtained by the proposed planning method is superior in terms of both economic and environmental benefits.

6.3 Discussion on the CO_2 emission tax volatility

Unpredictable drivers for carbon market mechanism can yield dramatic changes in CO_2 emission tax [23]. To investigate the effect of CO_2 tax volatility upon the planning results. The carbon tax is taken from 0 up to $100/t. The variations of total cost and CO_2 emissions for the designed system are presented in Fig. 7.

As tax rate increases, the surge in generation emission cost makes the total cost increases dramatically. However, it yields lower system emissions: CO_2 emissions created at the rate of $100/t is only 56.3% of that with $10/t case. The composition of the system cost also changes. The DWG and DR investment increase to different extent. These showthat the optimal planning solutions under low-carbon objective are sensitive to the exerted tax rate. When the level is high enough to influence the overall benefit of the system, the schemes that outperform in the environmental aspect would be preferred. Consequently, the policies concerning carbon tax levy are crucial to the decarbonization of power sector, leaving a big issue for the policy-makers of government in the future.

6.4 Performance analysis of CS algorithm

To investigate the performance of CS, the simulation is run 1000 times on a Core2 machine with 2.53-GHz CPU and 1-GB RAM. The convergence characteristic of the best performance is shown in Fig. 8. It is observed that the CS algorithm converges very fast in the beginning of the search, and the optimal solution finally derived is slightly better in the objective value than GA, which is 0.967 v.s. 1.023. Besides, it requires 83 iterations by CS v.s. 97 iterations by GA to reach the 0.5% threshold, 132 v.s. 180 iterations to reach the 0.3% threshold, and 206 v.s. 239 iterations to reach the 0.1% threshold, with the total computation time of 53 min and 78 min, respectively. This demonstrates the superior searching performance of CS with respect to GA.

7. Conclusion

In this paper, a novel solution algorithm called cuckoo search is used in the ADS planning for achieving CO_2 emission reduction. DR is put in and considered as an attractive planning option along with RDG integration and network reinforcement to satisfy the load growth requirement with the low-carbon objective. Such an integrated and coordinated planning paradigm allows attainment of more advantage in the utilization of renewable energy resources, reduction of energy losses and improvement of overall benefits in the system. Through a sensitivity analysis, it is also shown that the variation of carbon tax is a momentous factor that influences the optimal decision of ADS planning and its corresponding benefits. In this study, the optimization performance of CS has been compared with the classic GA. The results demonstrate that the CS has superior convergence, robustness and seldom suffers from searching efficacy tardiness when applied in the large-scale planning problems.

For long-term planning, another key factor yet to be considered is the energy efficiency (EE). A further exploration on the interaction of EE improvement upon demand price-responsivity and its influences on the ADS planning should be a meaningful subject of future work.

Acknowledgements

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